A Review on Swarm Intelligence and Evolutionary Algorithms for Solving Flexible Job Shop Scheduling Problems

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***Abstract*— Flexible job shop scheduling problems (FJSP) have received much attention from academia and industry for many years. Due to their exponential complexity, swarm intelligence (SI) and evolutionary algorithms (EA) are developed, employed and improved for solving them. More than 60% of the publications are related to SI and EA. This paper intents to give a comprehensive literature review of SI and EA for solving FJSP. First, the mathematical model of FJSP is presented and the constraints in applications are summarized. Then, the encoding and decoding strategies for connecting the problem and algorithms are reviewed. The strategies for initializing algorithms? population and local search operators for improving convergence performance are summarized. Next, one classical hybrid genetic algorithm (GA) and one newest imperialist competitive algorithm (ICA) with variables neighborhood search (VNS) for solving FJSP are presented. Finally, we summarize, discus and analyze the status of SI and EA for solving FJSP and give insight into future research directions.**

***Index Terms*—Evolutionary algorithm, flexible job shop scheduling, review, swarm intelligence.**

I. Introduction

FLEXIBLE job shop scheduling problems (FJSP) evolve from job shop scheduling problems (JSP). An FJSP consists of two sub-problems, machine assignment and operation sequencing [1]–[2]. The former is to select a machine from a candidate set for each operation while the latter is to schedule all operations on all machines to obtain satisfactory schedules. It extensively exists in many industries, such as automobile assembly, textile manufacturing, chemical material processing and semiconductor manufacturing [1]–[4]. FJSP is very complex and has been proven to be an NP-hard problem [3]–[4]. Owing to such complexity, traditional mathematic optimization methods are difficult to tackle within a reasonable amount of time [5]. More and more swarm intelligence (SI) and evolutionary algorithms (EA) have thus been employed to solve FJSP in recent years, including genetic algorithm (GA) [6]–[48], particle swarm optimization (PSO) [49]–[62], ant colony optimization (ACO) [63]–[70], tabu search (TS) [71]–[81], artificial bee colony (ABC) [82]–[93], harmony search (HS) [94]–[99], memetic algorithm (MA) [100]–[105], evolutionary algorithm (EA) [106]–[117], neighborhood search (NS) [118]–[126], meta-heuristics [127]–[133], biogeography-based optimization (BBO) [134]–[135], estimation of distribution algorithm (EDA) [136]–[141], immune algorithm (IA) [5], [142]–[145], and some emerging ones. The emerging algorithms include Chemical-reaction optimization (CRO), migrating birds optimizer (MBO), fruit fly optimization (FFO), imperialist competitive algorithm (ICA), shuffled frog-leaping algorithm (SFLA), Social Spider Optimization (SSO), and virus optimization algorithm (VOA) [146]–[164].

Till Dec. 2018, about 520 publications could be found under "Web of Science Core Collection" database in Web of Science with keywords "flexible job shop scheduling" in titles. More than 60% of them include various SI and EA algorithms. From them, this study selects the literature in major journals [4]–[164] and top-level conferences [165]–[177] to analyze and review the topic about SI and EA for solving FJSP. Some newer research outcomes [178]–[184], which are not yet included in the Web of Science database, are also reviewed.

The remainder of this paper is organized as follows. Section II presents FJSP model and real-life constraints in various applications. The SI and EA framework for solving FJSP is described and some strategies to improve SI and EA are summarized in Section III. We will discuss and analyze the SI

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TABLE I
PUBLICATIONS HANDLING VARIOUS OBJECTIVES

Objective	References
C_{Max}	[5] [6] [8] [12] [14]–[16] [19]–[22] [24] [26]–[27] [52]–[54] [60] [62]–[63] [66] [68] [73] [83] [86]–[87] [92] [95] [102]–[103] [112] [118] [120] [123] [125] [127] [129] [135]–[137] [144] [147] [165] [168] [169] [170] [171] [173] [176]
C_{Total}	[58] [13] [165] [167] [169]
W_{Max}	[4] [7] [10] [50]–[51] [71] [82] [84]–[85] [89]–[90] [99] [106] [110] [124] [128] [134] [138] [140] [143] [146] [157] [160] [165] [169] [176]
W_{Total}	[7] [10] [51] [71] [82] [84]–[85] [100] [106] [110][128] [138] [143] [146] [160] [176]
E/T	[18] [58] [65] [77] [94] [96]–[97] [121] [130] [171]
Stability metric	[14] [108] [111] [183]
Multi-objective	[33] [61] [71] [77] [82] [84]–[85] [94] [100]–[101] [106] [110] [121] [128] [133] [138] [140] [142] [146] [172] [174] [183]
Others	[9][30] [54] [101] [158] [171] [172] [175] [178]–[181] [184]

and EA used to solve FJSP in Section IV. Finally, conclusions and some future research directions are given in Section V.

II. FLEXIBLE JOB SHOP SCHEDULING PROBLEMS

A. Mathematical Model of FJSP

A job in a flexible job shop consists of a sequence of operations. An operation requires only one machine out of a bank of candidates. Each operation must be processed on only one machine at a time, and each machine can handle only one operation at a time. The following notations and assumptions are needed to formulate a multi-objective FJSP.

1) $J=\{_{Ji}\}$, $1 \le i \le n$ is a set of n jobs to be scheduled. q_i denotes the total number of operations of job $J=\{1, 2, \ldots, n\}$.

2) Let $M = \{M_k\}$, $1 \le k \le m$, be a set of m machines.

3)Job J_i consists of a predetermined sequence of operations. Let $O_{i,h}$ be operation h of J_i.

4) Each operation $O_{i,h}$ can be processed without interruption on one of the set of candidate machines$M(O_{i,h})$. $P_{i,h,k}$ denotes the processing time of $O_{i,h}$ on machine M_k.

5) Decision variables

$$x_{i,h,k} = \begin{cases} 1, \text{if machine } k \text{ is selected for operation } O_{i,h} \\ 0, \text{otherwise} \end{cases}$$

where the completion time of operation $O_{i,h}$ is denoted as $c_{i,h}$.

6)There are many objectives in published literature for FJSP, including completion time, flowtime, machine workload, due date, cost, and energy consumption. These objectives are formulated as follows:

The maximum completion time of all jobs called Makespan: $C_{Max}=\max_{(1\le i\le n)}c_i$, where c_i is the completion time of job J_i;

The total flow time, $C_{Flow}=\sum_{(1\le i\le n)}c_i$, where c_i is the completion time of job J_i.

The maximum machine workload, $W_{Max} = \max_{(1\le j\le m)} w_j$, where w_j is the workload of machine M_j.

The total machine workload, $W_{Total}=\sum_{(1\le j\le m)}w_j$, where w_j is the workload of machine M_j.

Minimize the earliness or tardiness, $\Delta_i=|c_i-d_i|$, where d_i is the due date of J_i.

Some publications optimized two or more objectives simultaneously. When two or more objectives are optimized simultaneously, decreasing one function may cause the other function or functions increasing. It makes the bi-objective or multi-objective FJSP more difficult to solve than FJSP with a single objective. A summary of publications for FJSP with various objectives is recorded in Table I. Flexible job shop rescheduling is a new trend for dealing with some constraints. Stability metric is an objective to evaluate the changing to existing schedule. We list it as one objective separately in Table I even if the number of related publications is few.

B. FJSP with Considering Constraints

In a real-world engineering environment, many constraints must be considered for solving FJSP. These constraints include uncertain or stochastic processing time, machine breakdown or disruptions, resource-constrains, operation transportation time, new job dynamic insertion, maintenance or preventive maintenance, setup time, operation overlapping, and cost or energy consumption. They, in general, increase the difficulty of obtaining high-quality solutions for FJSP. Some researchers consider one or more of these aforementioned mentioned constraints when solving FJSP. A summary of publications considering various constraints is shown in Table II.

III. SI AND EA ALGORITHMS FOR SOLVING FJSP

A. General Framework of SI and EA

SI and EA own a similar framework for optimization problems. First, the population is initialized with some solutions generated randomly or by simple heuristics, like dispatch rules. The values of all decision variables should be in their defined range or domain. Then, the initial solutions are evaluated by counting their objective functions. Next, an iteration process is repeated to generate new solutions with different algorithms. New solutions are evaluated and replace the solutions in the population based on some rules that are often set in advance. The objective values of corresponding solutions are updated. The iteration process is executed repeatedly until some stop criterion is met. Finally, the best solution and corresponding objective results are output. The general framework of SI and EA algorithms are shown in Fig. 1. For different SI and EA algorithms, the ways to generate new solutions are different. For specific algorithms, the methods to initialize population and perform local search are often different.

TABLE II
THE PUBLICATIONS REPORTING FJSP SOLUTIONS HANDLING DIFFERENT CONSTRAINTS

Constraints	No. of publications	Reference list
Machine breakdown or disruptions	5	[14] [18] [30] [54] [111]
Uncertain processing time	13	[15] [20] [60] [86] [89]–[90] [97] [123] [135] [137] [139] [147] [182]
Resource-constrained	1	[61]
Transportation time	1	[16]
New job insertion	3	[87] [90] [183]
Maintain (Preventive) maintenance	2	[68] [146]
Setup Time	4	[21] [66] [121] [125]
Operation overlapping	2	[22] [103]
Cost or energy consumption	7	[28] [158] [178]–[181] [184]

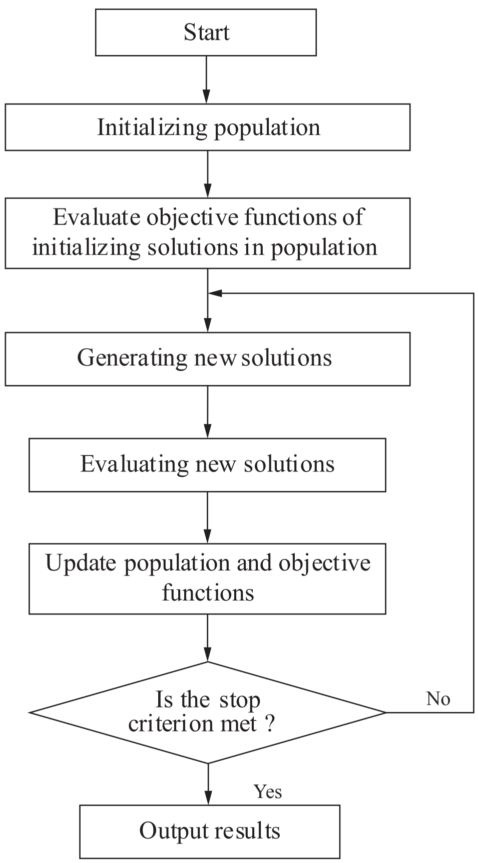

Fig. 1. General procedures framework of SI and EA algorithms.

B. Encoding and Decoding Strategies

When using SI and EA algorithms for solving FJSP, the key steps to connect problems and algorithms involve encoding scheduling schemes to solution vectors in the population for their optimization, and to decode solution vectors to scheduling schemes to evaluate their quality. The design of high-quality encoding and decoding strategies is an important issue, which affects the efficiency of encoding and decoding, and the convenience to integrate SI and EA with local search operators. The four most commonly used encoding and decoding strategies are summarized as follows.

1) Binary-alphabet-based Strategy [177]

This strategy is proposed for GA based on a binary alphabet, which designs a special strategy in a matrix for jobs' operations and machines. For an operation, the entry in this matrix is set to "0" if a machine cannot process it. The value is set "1" if this operation can be processed on this machine only. If it can be processed by more than one candidate machines, the value is set to symbol "*". Finally, the value is set to start time and end time on this machine if this machine is selected to process it.

2) Machine-based Assignment and Operation Sequences [4]

In this strategy, there are two vectors filled by discrete machine indices and operation indices for encoding. The first one is for machine assignment, which assigns one processing machine for each operation. The second is for an operation sequence on all machines, in which the operation sequences on each machines are connected before and after.

3) Unified Encoding Strategy [5], [6]

This strategy considers machine assignment and operation sequence together in one vector. Each element in the vector consists of three values: job index, operation index, and selected machine index. This encoding strategy is also used by many researchers due to its simplicity to decode solutions to schemes.

4) Machine Assignment and operation Sequence [7], [8]

This strategy is similar to the second one to a certain extent. However, the operation sequence setting method differs. In this strategy, an operation sequence is encoded using job indices. When the job index first appears, it represents the first operation of this job. The second appearance depicts the second operation of this job. The operation sequence can be encoded by analogy, in which the operation sequences of all machines are intertwined together. Table III shows an example of this strategy. The first row is an operation index, while the second and third rows show the machine assignment and operation sequence vectors. The values of the second and third rows are the machine indices and job indices, respectively. This encoding method is used by many researchers owing to the convenience and simplicity to a generate new operation sequence and to do local search for better solutions.

Among four encoding strategies, the third and fourth ones are more suitable for FJSP and are easier to design operations

TABLE III
AN EXAMPLE OF THE FOURTH ENCODING STRATEGY

Operation index	$O_{1,1}$	$O_{1,2}$	$O_{1,3}$	$O_{2,1}$	$O_{2,2}$	$O_{2,3}$	$O_{3,1}$	$O_{3,2}$	$O_{3,3}$
Machine assignment	3	1	4	2	2	1	4	3	4
Operation sequence	1	3	3	2	1	2	3	1	2

TABLE IV
REFERENCE LIST OF ENCODING AND DECODING STRATEGIES

Order	No. of publications	Reference list
1)	1	[177]
2)	4	[4]
3)	9	[5] [6] [89] [90] [97] [106] [118] [120] [143]
4)	3	[7]–[8] [15] [19] [22] [27] [60] [63] [82] [84] [86]–[87] [94] [96] [133]–[134] [137]–[138] [158]

TABLE V
REFERENCE LIST OF INITIALIZING STRATEGIES

Order	No. of publications	Reference list
a)	3	[6] [84] [106]
b)	6	[5] [6] [73] [89] [106] [118]
c)	9	[5] [6] [22] [84] [87] [89] [94] [118] [138]
d)	3	[89] [94] [96]
e)	2	[94] [97]
f)	12	[5] [6] [22] [84] [87] [89] [94] [96] [106] [118] [138] [185]
g)	12	[5] [6] [22] [84] [87] [89] [94] [96] [106] [118] [138] [185]
h)	1	[77]
i)	2	[83] [85]–[86] [136] [186]

for generating new solutions in each iteration of the algorithm. The third is easier to match operations to selected processing machine, and to decode a solution to a schedule. The fourth is easier to design operations to generate new solutions and to integrate local search operators for a better operation sequence. The represent studies adopting four encoding and decoding strategies are given in Table IV.

C. *Improvement Strategies of SI and EA Algorithms*

1) Initializing Strategies

The quality of initial solutions affects the convergence speed and global searching performance of SI and EA algorithms. Many initial strategies, including dispatch rules, simple heuristics, and the ensembles of dispatch rules and simple heuristics are proposed to improve the quality of initial populations. We summarize and analyze these strategies for population initialization. Strategies a through e are used for initializing machine assignment, f and g are for initializing operation sequences, and h and i are for initializing both machine assignment and operation sequences. Their publications are listed in Table V.

a) Operation Minimum Processing Time [6]

For each operation, a machine with the minimum processing time is selected from candidate machines to process it. With this rule, all operations are assigned to the machines with the minimum processing time. For a single operation, the processing time is indeed the minimal, yet, there may be many operations queuing on the same machine. Thus, the machine workload and makespan may increase.

b) Local Minimum Processing Time [5]

This heuristic develops an operation minimum processing time rule. It adds the processing time of the current operation to the machine workload. The selection criterion involves r adding the processing time of the current operation, then selecting the machine with the minimum workload. This rule considers single operation processing time and machine workload together.

c) Global Minimum Processing Time [5]

This heuristic selects the minimum processing time from all-machine processing time for all operations. Similar to heuristic b, the processing time is also added to machine workload. This rule starts with finding the global minimum processing time of all operations with considering the maximum machine workload. The disadvantage is lack of diversity.

d) Minimum Completion Time [89]

For one operation with two or more candidate machines, their completion time is compared based on their earliest start tine and processing time and then the machine with the smallest completion time is selected for the operation. This rule is conducive to the minimization of the maximum completion time.

TABLE VI
REFERENCE LIST OF LOCAL SEARCH OPERATORS AND APPROACH

Order	No. of publications	Reference list
a)	4	[82] [84] [135] [158]
b)	3	[28] [51] [101]
c)	3	[19] [146] [147]
d)	7	[10] [83] [85] [94] [96] [106] [136]
e)	3	[7] [71] [86]
f)	2	[68] [87] [186]
g)	2	[30] [137]

e) MinEnd Heuristic [94]

In this heuristic, an operation sequence is randomly decided. The processing machine for each operation is assigned based on an operation sequence. This heuristic has the following steps: i) Shuttle all operations of all jobs randomly to obtain an operation sequence. ii) Repair an operation sequence, and ensure that the operations of the same job can satisfy the processing priority. iii) For each operation in an operation sequence, evaluate the completion time on each selectable machine. The machine with the minimum completion time is selected for processing it.

f) Most Work Remaining Rule [5]

This rule is for operation sequence initialization. It first orders the jobs in a descending order based on remaining work. The job with the most remaining work is selected first and put into an operation sequence, the iteration is then repeated until all operations of all jobs have been sequenced. This method is based on the remaining work, which is calculated from the processing machine and the processing time. Hence, machine assignment must be decided before this heuristic is used.

g) Most Operations Remaining Rule [6]

This rule is for operation sequence initialization. It selects jobs based on the number of remaining operations. The job with the most un-sequenced operations is selected first. This method relies on the total number of remaining operations rather than machine assignment.

h) Two-step Greedy Heuristic [77]

In this heuristic, the operations are sorted in ascending order based on the number of selectable machines. Ascending order of processing time is used to break ties when there is an equal number of selectable machines. The machines are sorted by using their workload in non-decreasing order. The operation is taken from the operations list and the first machine that belongs to the machine list is assigned to the operation. The workload of this machine is updated, and the machine sorting is also updated. The process iterates until all operations have been assigned to machines. The two-step greedy rule is proposed for the minimization of the maximum tardiness. The performance of this heuristic is unsatisfactory in terms of makespan and workload.

i) Ensemble of Multiple Strategies [83]

In the initializing stage, some dispatch rules and simple heuristics are integrated to generate the initial solutions of certain quality and diversity. An ensemble strategy can utilize the advantage of various simple heuristic rules and improve the quality of initial solutions in population. It can also improve the convergence speed of SI and EA algorithms.

2) Local Search Operators

To solve FJSP effectively and efficiently, some local search strategies and operators are proposed to improve the convergence speed and local optimal searching performance of SI and EA algorithms. These local search strategies and operators are embedded in the iterative process of SI and EA algorithms as one part of algorithms. Here, we summarize and analyze the commonly used local search operators and strategies in SI and EA algorithms for solving FJSP. Their related publications are recorded in Table VI.

a) Insertion, Swap and Reverse Operators [82]

These three operators are commonly used local search operators for operation sequences, especially for the ones generated by the fourth encoding strategy. Operator insert is to move one operation from its current position to other positions in an operation sequence, which changes the position of the inserted operation and the positions of the following operations after the insertion point. Operator swap is used to exchange positions of two operations, which just changes two operations' positions in an operation sequence. Operator reverse is to reverse the order of some operations, which change the positions of some connected operations in an operation sequence.

b) Simulated Annealing Based Local Search Operation [28]

Simulated Annealing (SA) represents an effective and general form of optimization. It is useful in finding the global optima in the presence of numerous local optima. It can be used for solving FJSP by itself or integrated into other algorithms as a local search approach for searching local optimal solutions.

c) Tabu Search (TS) Based Local Search [19]

TS is a local search-based metaheuristic, which uses a local or neighborhood search procedure to iteratively move from one potential solution to an improved one in the neighborhood, until some stopping criterion is satisfied, e.g., an attempt limit or a score threshold, which is set in advance. Similar to SA, TS can be used for FJSP by itself [71]–[81] or embedded into other SI or EA algorithms as a local search operator.

d) Critical Path Based Local Search Operator [10]

This operator is to move the operations on critical paths to other place in order to get a new schedule with a smaller objective. For example, the makespan of a solution is defined by the length of its critical paths. The makespan cannot be reduced while maintaining its current critical paths. The purpose of the critical path operator is to identify and break the existent critical paths to obtain solutions with smaller makespan values. To execute it, a disjunctive graph is used to find the critical paths of a solution.

e) Variables Neighborhood Search (VNS) [187]

VNS is a modern meta-heuristic based on systematic changes of a neighborhood structure within a search to solve combinatorial optimization problems. Systematic change of neighborhood within a possibly randomized local search is a simple principle of VNS. For solving FJSP, neighborhood structures are considered to generate operation sequence and machine assignment. VNS is used in some SI and EA algorithms as a local search operator to improve their performance and it can also be employed for solving FJSP by itself.

f) Ensemble [68]

An ensemble is an integration strategy for multiple local search operators, which use them to obtain better performance. It takes their respective advantages and avoids their disadvantages. Generally, it consists of a finite set of local search operators but typically allows for much more flexible neighborhood structures among them. Here, we summarize three high-quality ensembles (E1-E3) which integrate different simple heuristics and local search operators.

E1:

Step 1: Generate a processing time table of all machines for all operations.

Step 2: Order all operations regardless of operation priority.

Step 3: Perform machine assignment by using the local minimum processing time heuristic.

Step 4: Calculate workload for each machine

Step 5: Generate an operation sequence by using the most-work-remaining rule.

E2:

Step 1: Generate machine assignment (MA1) by selecting processing machine randomly.

Step 2: Calculate workload for each machine.

Step 3: Generate an operation sequence by using the most-work-remaining rule.

Step 4: Select one processing machine for each operation by using the minimum-completion-time rule to obtain a new machine assignment (MA2).

Step 5: Compare the completion time of machine assignments MA1 and MA2.

Step 6: Select the one with smaller completion time as a final machine assignment.

E3:

Step 1: Count the total operation number for each job.

Step 2: Generate an operation sequence by using the most-work-remaining rule and break ties by random selection.

Step 3: For each operation in operation sequence, select one processing machine by using the minimum completion time rule.

Ensemble E1 promotes the randomness of both machine assignment and operation sequence to improve algorithms' global search performance. Ensemble E2 is for optimizing workload and makespan objectives in operation sequence and machine assignments, respectively. Ensemble E3 considers the minimization of makespan.

g) Left-shift or right-shift decoding [30]

In a decoding phase, there are strategies to obtain better objective values for a same solution. The left-shift and right-shift decoding strategies are commonly used to decode solutions to schedules. The left-shift operator inserts one operation into a gap among the decoded operations to reduce the makespan or other objectives values while the right-shift operator is to reschedule the operations after machine disruptions or breakdown or to meet other dynamic constraints.

D. Representative SI and EA algorithms

To show SI and EA algorithms for solving FJSP with and without constraints, this section presents a classical hybrid GA (hGA) algorithm [7] and a newest ICA algorithm with VNS [184]. The hGA was proposed in 2008 [7] and is a highly cited paper. The ICA with VNS is a new algorithm published online in 2018.

1) hGA with variable neighborhood descent [7]

The hGA algorithm embeds two local search operators based on a critical path to GA. The operators with moving one or two operations from the critical path to find solutions with a better critical path. The procedures of the local search by moving one operation is shown as follows.

```
Procedures of local search by moving one operation:
Identify a critical path P for a solution S.
Select the first operation O1 in P.
Do
   Delete O1 from S
   Search for an assignable time interval for O1 in S
   If there is no assignable interval
      Select the next operation in P
   Else
      Allocate O1 in the interval and obtain S'
         Break out
    Endif
 While (P is not traversed)
 If exists S',
    Update S by using S'
 Else
    Remain S
 Endif
```

Based on the local search with moving one operation, the one with moving two operations are proposed. From the first operation in one critical path, it selects two operations once and finds assignable time interval for them. If the assignable time intervals are found, the solution is updated. The local search by moving one operation is implemented until the local optimal are found or the critical path is traversed. Owing to its computational complexity, the local search with moving two operations is implemented only once in each iteration. The procedures of the hGA are shown as follows with the detail information about crossover, mutation operators being at [7].

Procedure of hGA:

1. Initialize population using the fourth encoding strategy.
2. Evaluate objective values.
3. Do
4. Crossover operation
5. Mutation operation
6. Improve the solutions by using the local search with moving one operation
7. Improving the solutions by using the local search with moving two operations
8. Update solutions

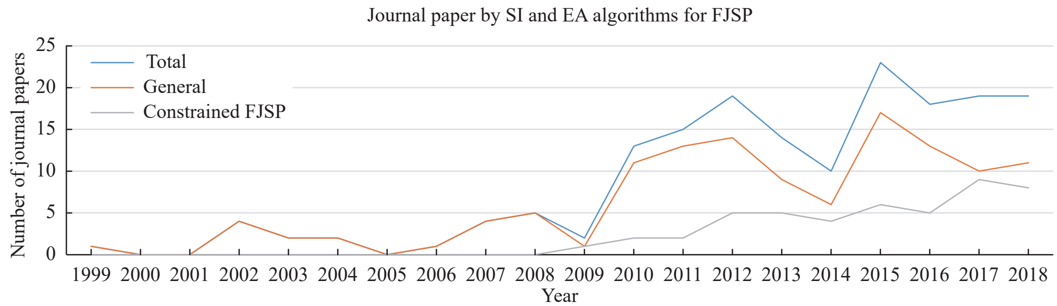

Fig. 2. Published journal papers presenting SI and EA algorithms for FJSP from 1999 to 2018.

9. While (stop condition is not met)
10. Output best solution and corresponding schedule

2) ICA with VNS [184]

ICA is a novel meta-heuristic, which is inspired by imperialistic competition. In [184], an ICA algorithm with VNS is proposed for solving multi-objective FJSP with the consideration of energy consumption. It consists of two phases, ICA and VNS. ICA is to explore new solutions of FJSP for optimizing makespan, total tardiness and total energy consumption, and obtains a set of nondominated solutions. VNS is based on the insertion, swap and revise operators to find new solutions in the corresponding three neighborhoods. It tries to improve the makespan and total tardiness performance further for the nondominated solutions. The dominated standard is redefined based on the results of total energy consumption. The procedures of ICA with VNS are shown as follows with assimilation of colonies, revolution of colonies, exchange colony and imperialist, and imperialist competition being at [184].

Procedures of ICA with VNS:
1. Initialize population and construct a set Ω for nondominated solutions.
2. Construct initial empires
3. Do
4. Assimilation of colonies
5. Revolution of colonies
6. Exchange colony and imperialist if possible
7. Imperialist competition
8. updated Ω
9. While (stop condition is not met)
10. Obtain final Ω
11. For the first solution S in Ω
12. Generate a new solution S' by using one neighborhood
13. If S' dominates S
14. Replace S with S' and update Ω
15. Else
16. Try remaining two neighborhoods
17. Endif
18. S will be substituted by another solution S'' if the number of its executions exceeds a threshold β
19. Execute 12-18 for all solutions in Ω

IV. Analysis and Discussions

A. Publications for FJSP

To discuss and analyze publications presenting SI and EA algorithms for solving FJSP, the journal papers from 1999 to 2018 are counted and shown in Fig. 2. It can be summarized that the number of journal papers is almost increasing year by year and achieves 5 for the first time in 2008. From 2010 to 2018, there are at least 10 journal papers per year. It means that SI and EA algorithms are more and more frequently employed for solving FJSP. Fig. 2 also shows the journal paper counts for general FJSP and constrained FJSP. Before 2008, all publications are for general or standard FJSP without considering constraints. From 2009, some researchers start to consider constraints when they solve FJSP implying that researchers start to solve FJSP in a real-life environment, where some constraints have to be considered to match real-life requirements. The theory research of FJSP is moving to engineering applications.

B. Algorithms for FJSP

This section summarizes the publications about various SI and EA algorithms for solving FJSP from 1999 to 2018. The total numbers of publication by using various algorithms are recorded and shown in Fig. 3. The algorithms with more than 5 journal papers are counted individually. All the ones with less than five journal papers are included in “Others”. It can be seen from Fig. 3 that GA is most popular among them and appears in 46 journal papers. The second most popular is PSO, which has more than 10 journal papers. For “Others”, even if the publication count of an individual algorithm is less than 5, the total number of journal papers is 30, which is more than 15% of all SI and EA algorithms. They appear only in recent years.

To further analyze and discuss the number of journal papers presenting specific algorithms, the number of journal papers based on their presented algorithms is counted by year and shown in Fig. 4. It shows the results from 2008 to 2018 and only the algorithms with at least 5 journal papers in the 10 years are recorded individually. It is obvious that the number of algorithms for solving FJSP is increasing, especially after 2010. The number of GA-related journal papers increases from 2008 to 2012, and decreases after that. From 2011, the number of journal papers by the “Others” algorithms is increasing year by year. Most algorithms in the “Others” are recently emerging algorithms, e.g., Chemical-reaction optimization (CRO), Migrating birds optimizer (MBO),

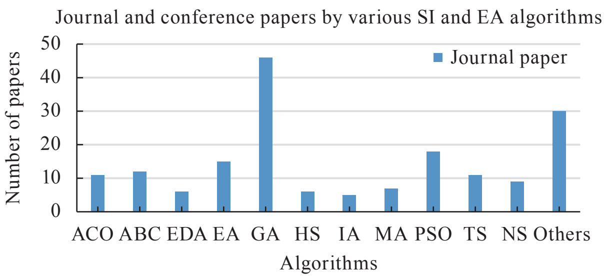

Fig. 3. Total publication presenting SI and EA algorithms from 1999-2018.

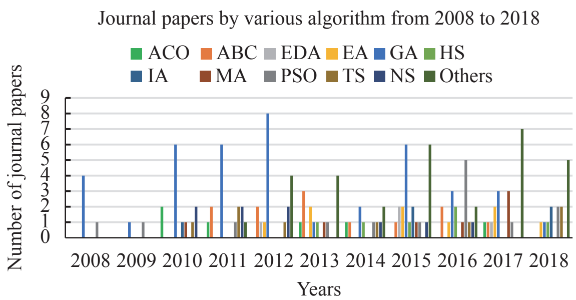

Fig. 4. Publication counts of specific SI and EA algorithms from 2008 to 2018.

Firefly algorithm (FFA), Imperialist competitive algorithm (ICA), Shuffled frog-leaping algorithm (SFLA), Social Spider optimization (SSO), and Virus optimization algorithm (VOA). It is a trend that more and more novel algorithms are employed for solving FJSP.

V. Conclusions and Future Directions

This paper attempts to provide an overall picture of the state-of-the-art research on swarm intelligence and evolutionary algorithms for solving flexible job shop scheduling problems (FJSP). Starting with an introduction to flexible job shop scheduling problems, we discuss the mathematic model of FJSP and the framework of swarm intelligence and evolutionary algorithms for solving FJSP. Next, the strategies for improving the performance of algorithms are summarized and analyzed, including simple heuristics and dispatching rules for population initialization and local search operators in an iteration progress. Finally, we analyze and discuss the publications from 1999 to 2018. The publications start from theory research on general FJSP to engineering applications by considering real-life constraints. Various SI and EA algorithms' publications are also discussed and analyzed, including publications numbers of various algorithms and the distributions of different algorithms in the past 10 years. From 2011, some emerging algorithms are employed and improved for solving FJSP by considering various real-life constraints.

Based on the discussions and analysis on the research trend of swarm intelligence and evolutionary algorithms for solving FJSP, we give some research directions from the aspects of problems and algorithms for future research.

1) Real-world constraints must be considered if we wish to solve FJSP in industrial environments. By considering the real-life constraints, we can put theory research results into a specific filed or for a specific product.

2) Minimizing energy consumption and enhancing environmental protection are two new objectives to seek in solving production scheduling problems[188]–[189], including FJSP. Thus, we can achieve low-carbon and green production.

3) Multiple objectives even many objectives have to be optimized for satisfying different performance indicators.

4) Simple and efficient swarm intelligence and evolutionary algorithms are key to solving FJSP effectively. The design ensembles of various strategies to improve the algorithms' performance is an important issue for swarm intelligence and evolutionary algorithms.

5) The models and scheduling strategies for multi-objective and many-objective optimization remain a challenging issue and have to be further studied for FJSP.

References

[1] M. R. Garey, D. S. Johnson, and R. Sethi, "The complexity of flow shop and job shop scheduling," *Math. Oper. Res.*, vol. 1, no. 2, pp. 117–129, 1976.

[2] P. Brucker, R. Schlie, "Job-shop scheduling with multi-purpose machines," *Computing*, vol. 45, no. 4, pp. 369–375, 1990.

[3] A.S. Jain, S. Meeran, "Deterministic job-shop scheduling: past, present and future," *Eur. J. Oper. Res.*, vol. 113, no. 2, pp. 390–434, 1998.

[4] I. Kacem, S. Hammadi, P. Borne, "Approach by localization and multi-objective evolutionary optimization for flexible job shop scheduling problems," *IEEE Trans. Syst., Man, Cybern*, vol. 32, no. 1, pp. 1–13, Jan. 2002.

[5] A. Bagheri, M. Zandieh, I. Mahdavi, and M. Yazdani, "An artificial immune algorithm for the flexible job-shop scheduling problem," *Future Gener. Comput. Syst.*, vol. 26, no. 4, pp. 533–541, 2010.

[6] F. Pezzella, G. Morganti, G. Ciaschetti, "A genetic algorithm for the Flexible Job-shop Scheduling Problem," *Comput. Oper. Res.*, vol. 35, no. 10, pp. 3202–3212, 2008.

[7] J. Gao, L. Y. Sun, M. Gen, "A hybrid genetic and variable neighborhood descent algorithm for flexible job shop scheduling problems," *Comput. Oper. Res.*, vol. 35, no. 9, pp. 2892–2907, 2008.

[8] G. H. Zhang, L. Gao, Y. Shi, "An effective genetic algorithm for the flexible job-shop scheduling problem," *Expert Syst. Appl.*, vol. 38, no. 4, pp. 3563–3573, 2011.

[9] M. T. Jensen, "Generating robust and flexible job shop schedules using genetic algorithms," *IEEE Trans. Evolut. Comput.*, vol. 7, no. 3, pp. 275–288, 2003.

[10] J. Gao, M. Gen, L. Y. Sun, X. H. Zhao, "A hybrid of genetic algorithm and bottleneck shifting for multiobjective flexible job shop scheduling problems," *Comput. Ind. Eng.*, vol. 53, no. 1, pp. 149–162, 2007.

[11] J. Gao, M. Gen, L.Y. Sun, "Scheduling jobs and maintenances in flexible job shop with a hybrid genetic algorithm," *J. Intel. Manuf.*, vol. 17, no. 4, pp. 493–507, 2006.

[12] G. L. De, F. Pezzella, "An improved genetic algorithm for the distributed and flexible job-shop scheduling problem," *Euro. J. Oper. Res*, vol. 200, no. 2, pp. 95–408, 2010.

[13] X.B. Huang, L.X. Yang, "A hybrid genetic algorithm for multi-objective flexible job shop scheduling problem considering transportation time," *Int. J Intell. Comput. Cyber.*, vol. 12, no. 2, pp. 154–174, 2019.

[14] N. Al-Hinai, T. Y. ElMekkawy, "Robust and stable flexible job shop scheduling with random machine breakdowns using a hybrid genetic algorithm," *Int. J. Prod. Res.*, vol. 132, no. 2, pp. 279–291, 2011.

[15] D. M. Lei, "A genetic algorithm for flexible job shop scheduling with fuzzy processing time," *Int. J. Prod. Res.*, vol. 48, no. 10, pp. 2995–3013, 2010.

[16] L. Sun, L. Lin, M.S. Gen, H.J. Li, "A hybrid cooperative coevolution

algorithm for fuzzy flexible job shop scheduling," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 5, pp. 1008–1022, 2019.

[17] J. C. Chen, C. C. Wu, C. W. Chen, K. H. Chen, "Flexible job shop scheduling with parallel machines using genetic algorithm and grouping genetic algorithm," *Expert Syst. Appl.*, vol. 39, no. 11, pp. 10016–10021, 2012.

[18] M. Gholami, M. Zandieh, "Integrating simulation and genetic algorithm to schedule a dynamic flexible job shop," *J. Intel. Manuf.*, vol. 20, no. 4, pp. 481–498, 2009.

[19] A. Corominas, A. Garcia-Villoria, N.A. Gonzalez, R. Pastor, "A multistage graph-based procedure for solving a just-in-time flexible job shop scheduling problem with machine and time-dependent processing cost," *J. Oper. Res. Soc.*, vol. 70, no. 4, pp. 620–633, 2019.

[20] D. M. Lei, "Co-evolutionary genetic algorithm for fuzzy flexible job shop scheduling," *Appl. Soft Comput.*, vol. 12, no. 8, pp. 2237–2245, 2012.

[21] F. M. Defersha, M. Y. Chen, "A parallel genetic algorithm for a flexible job-shop scheduling problem with sequence dependent setups," *Int. J. Adv. Manuf. Tech.*, vol. 49, no. 1-4, pp. 263–279, 2010.

[22] Y. Demir, S.K. Isleyen, "An effective genetic algorithm for flexible job-shop scheduling with overlapping in operations," *Int. J. Prod. Res.*, vol. 52, no. 13, pp. 3905–3921, 2014.

[23] C. Gutierrez, I. Garcia-Magarino, "Modular design of a hybrid genetic algorithm for a flexible job-shop scheduling problem," *Knowl-Based Syst.*, vol. 24, no. 1, pp. 102–112, 2011.

[24] N. Al-Hinai, T.Y. ElMekkawy, "An efficient hybridized genetic algorithm architecture for the flexible job shop scheduling problem," *Flex. Serv. Manuf. J.*, vol. 23, no. 1, pp. 64–85, 2011.

[25] I. Driss, K.N. Mouss, A. Laggoun, "A new genetic algorithm for flexible job-shop scheduling problems," *J. Mech. Sci. Tech.*, vol. 29, no. 3, pp. 1273–1281, 2015.

[26] H. C. Chang, Y. P. Chen, T. K. Liu, J. H. Chou, "Solving the flexible job shop scheduling problem with Makespan optimization by using a hybrid taguchi-genetic algorithm," *IEEE Access*, vol. 3, pp. 1740–1754, 2015.

[27] S. Ishikawa, R. Kubota, K. Horio, "Effective hierarchical optimization by a hierarchical multi-space competitive genetic algorithm for the flexible job-shop scheduling problem," *Expert Syst. Appl.*, vol. 42, no. 24, pp. 9434–9440, 2015.

[28] A. Jalilvand-Nejad, P. Fattahi, "A mathematical model and genetic algorithm to cyclic flexible job shop scheduling problem," *J. Intel. Manuf.*, vol. 26, no. 6, pp. 1085–1098, 2015.

[29] W. Sun, Y. Pan, X.H. Lu, Q.Y. Ma, "Research on flexible job-shop scheduling problem based on a modified genetic algorithm," *J. Mech. Sci. Tech.*, vol. 24, no. 10, pp. 2119–2125, 2010.

[30] Y. M. Wang, H. L. Yin, K. D. Qin, "A novel genetic algorithm for flexible job shop scheduling problems with machine disruptions," *Int. J. Adv. Manuf. Tech.*, vol. 68, no. 5-8, pp. 1317–1326, 2013.

[31] G. Z. Rey, A. Bekrar, V. Prabhu, D. Trentesaux, "Coupling a genetic algorithm with the distributed arrival-time control for the JIT dynamic scheduling of flexible job-shops," *Int. J. Prod. Res.*, vol. 52, no. 12, pp. 3688–3709, 2014.

[32] H. Piroozfard, K.Y. Wong, W.P. Wong, "Minimizing total carbon footprint and total late work criterion in flexible job shop scheduling by using an improved multi-objective genetic algorithm," *Resour. Conserv and Recy.*, vol. 128, pp. 267–283, 2018.

[33] M. Rohaninejad, A. Kheirkhah, P. Fattahi, B. Vahedi-Nouri, "A hybrid multi-objective genetic algorithm based on the ELECTRE method for a capacitated flexible job shop scheduling problem," *Int. J. Adv. Manuf. Tech.*, vol. 77, no. 1–4, pp. 51–66, 2015.

[34] D. Cinar, J. A. Oliveira, Y. I. Topcu, P. M. Pardalos, "A priority-based genetic algorithm for a flexible job shop scheduling problem," *J. Ind. Manag. Optim*, vol. 12, no. 4, pp. 1391–1415, 2016.

[35] R. Agrawal, L.N. Pattanaik, S. Kumar, "Scheduling of a flexible job-shop using a multi-objective genetic algorithm," *J. Adv. Manag. Res.*, vol. 9, no. 2, pp. 178–188, 2012.

[36] K. Ida, K. Oka, "Flexible job-shop scheduling problem by genetic algorithm," *Electr. Eng. Jpn.*, vol. 177, no. 3, pp. 28–35, 2011.

[37] Ha. C. Chang, T. K. Liu, "Optimisation of distributed manufacturing flexible job shop scheduling by using hybrid genetic algorithms," *J. Intel. Manuf.*, vol. 28, no. 8, pp. 1973–1986, 2017.

[38] W. Zhang, J. B. Wen, Y. C. Zhu, Y. Hu, "Multi-objective scheduling sumulation of flexible job-shop based on multi-population genetic algorithm," *Int. J. Simu. Model.*, vol. 16, no. 2, pp. 313–321, 2017.

[39] X. J. Wang, L. Gao, C. Y. Zhang, X. Y. Li, "A multi-objective genetic algorithm for fuzzy flexible job-shop scheduling problem," *Int. J. Comput. Appl. Tech.*, vol. 45, no. 2–3, pp. 115–125, 2012.

[40] P. H. Lu, M. C. Wu, H. Tan, Y. H. Peng, Ch. F. Chen, "A genetic algorithm embedded with a concise chromosome representation for distributed and flexible job-shop scheduling problems," *J. Intel. Manuf.*, vol. 29, no. 1, pp. 19–34, 2018.

[41] X. J. Wang, W. F. Li, Y. Zhang, "An improved multi-objective genetic algorithm for fuzzy flexible job-shop scheduling problem," *Int. J. Comput. Appl. Tech.*, vol. 47, no. 2–3, pp. 280–288, 2013.

[42] P. Kaweegitbundit, T. Eguchi, "Flexible job shop scheduling using genetic algorithm and heuristic rules," *J. Adv. Mech. Des. Syst. Manuf.*, vol. 10, no. 1, JAMDSM0010, 2016.

[43] S. Yokoyama, H. Iizuka, M. Yamamoto, "Priority rule-based construction procedure combined with genetic algorithm for flexible job-shop scheduling problem," *J. Adv. Comput. Intel. Inform.*, vol. 19, no. 6, pp. 892–899, 2015.

[44] R. Wu, Y. B. Li, S. S. Guo, W. X. Xu, "Solving the dual-resource constrained flexible job shop scheduling problem with learning effect by a hybrid genetic algorithm," *Adv. Mech. Eng.*, vol. 10, no. 10, pp. 1–14, 2018.

[45] M. E. Meziane, N. Taghezout, "A hybrid genetic algorithm with a neighborhood function for flexible job shop scheduling," *Multi-Agent Grid Syst.*, vol. 14, no. 2, pp. 161–175, 2018.

[46] Z. S. Zhang, Y. M. Chen, Y. J. Tan, J. G. Yan, "Non-crossover and multi-mutation based genetic algorithm for flexible job-shop scheduling problem," *IEICE Trans. Fund. Electron. Commun. Comput. Sci.*, vol. 99, no. 10, pp. 1856–1862, 2016.

[47] Y. Demir, S. K. Isleyen, "Note to Scheduling jobs and maintenances in flexible job shop with a hybrid genetic algorithm," *J. Intel. Manuf.*, vol. 25, no. 1, pp. 209–211, 2014.

[48] H. J. Huang, T. P. Lu, "Solving a multi-objective flexible job shop scheduling problems with timed petri nets and genetic algorithm," *Discrete Math. Algorithms Appl.*, vol. 2, no. 2, pp. 221–237, 2010.

[49] G. H. Zhang, X. Y. Shao, P. G. Li, L. Gao, "An effective hybrid particle swarm optimization algorithm for multi-objective flexible job-shop scheduling problem," *Comput. Ind. Eng.*, vol. 56, no. 4, pp. 1309–1318, 2009.

[50] G. Moslehi, M. Mahnam, "A Pareto approach to multi-objective flexible job-shop scheduling problem using particle swarm optimization and local search," *Int. J. Prod. Econ.*, vol. 129, no. 1, pp. 14–22, 2011.

[51] X.Y. Shao, W.Q. Liu, Q. Liu, C.Y. Zhang, "Hybrid discrete particle swarm optimization for multi-objective flexible job-shop scheduling problem," *Int. J. Adv. Manuf. Tech.*, vol. 67, no. 9-12, pp. 2885–2901, 2885.

[52] M. Nouiri, A. Bekrar, A. Jemai, S. Niar, A. C. Ammari, "An effective and distributed particle swarm optimization algorithm for flexible job-shop scheduling problem," *J. Intel. Manuf.*, vol. 29, no. 3, pp. 603–615, 2018.

[53] M. R. Singh, S. S. Mahapatra, "A quantum behaved particle swarm optimization for flexible job shop scheduling," *Comput. Ind. Eng.*, vol. 93, pp. 36–44, 2016.

[54] M. Nouiri, A. Bekrar, A. Jemai, D. Trentesaux, A. C. Ammari, S. Niar, "Two stage particle swarm optimization to solve the flexible job shop predictive scheduling problem considering possible machine breakdowns," *Comput. Ind. Eng.*, vol. 112, pp. 595–606, 2017.

[55] S. Huang, N. Tian, Y. Wang, Z. C. Ji, "Multi-objective flexible job-shop scheduling problem using modified discrete particle swarm optimization," *SPRINGER PLUS*, vol. 5, no. 1, pp. 1432, 2016.

[56] S. Nourali, N. Imanipour, "A particle swarm optimization-based algorithm for flexible assembly job shop scheduling problem with sequence dependent setup times," *Sci. Iran*, vol. 21, no. 3, pp. 1021–1033, 2014.

[57] H. Boukef, M. Benrejeb, P. Borne, "Flexible job-shop scheduling problems resolution inspired from particle swarm optimization," *Stud. Inform. Control*, vol. 17, no. 3, pp. 241–252, 2008.

[58] M. R. Singh, M. Singh, S. S. Mahapatra, N. Jagadev, "Particle swarm

optimization algorithm embedded with maximum deviation theory for solving multi-objective flexible job shop scheduling problem," *Int. J. Adv. Manuf. Tech.*, vol. 85, no. 9–12, pp. 2353–2366, 2016.

[59] W. Teekeng, A. Thammano, P. Unkaw, J. Kiatwuthiamorn, "A new algorithm for flexible job-shop scheduling problem based on particle swarm optimization," *Artif. Life Robo.*, vol. 21, no. 1, pp. 18–23, 2016.

[60] T. Jamrus, C. F. Chien, M. Gen, K. Sethanan, "Hybrid particle swarm optimization combined with genetic operators for flexible job-shop scheduling under uncertain processing time for semiconductor manufacturing," *IEEE Trans. Semicond. Manuf.*, vol. 31, no. 1, pp. 32–41, 2018.

[61] J. Zhang, J. Jie, W. L. Wang, X. L. Xu, "A hybrid particle swarm optimisation for multi-objective flexible job-shop scheduling problem with dual-resources constrained," *Int. J. Comput. Sci. Math.*, vol. 8, no. 6, pp. 526–532, 2017.

[62] H. Daliria, H. Mokhtari, I. N. Kamalabadi, "A particle swarm optimization approach to joint location and scheduling decisions in a flexible job shop environment," *Int. J. Eng.*, vol. 28, no. 12, pp. 756–1764, 2015.

[63] L. N. Xing, Y. W. Chen, P. Wang, Q. S. Zhao, J. Xiong, "Knowledge-based ant colony optimization for flexible job shop scheduling problems," *Appl. Soft Comput.*, vol. 10, no. 3, pp. 888–896, 2010.

[64] A. Rossi, G. Dini, "Flexible job-shop scheduling with routing flexibility and separable setup times using ant colony optimisation method," *Robot. Comput.Integr. Manuf.*, vol. 23, no. 5, pp. 503–516, 2007.

[65] R. H. Huang, C. L. Yang, W. C. Cheng, "Flexible job shop scheduling with due window a two-pheromone ant colony approach," *Int. J. Prod. Econ.*, vol. 141, no. 2, pp. 685–697, 2013.

[66] A. Rossi, "Flexible job shop scheduling with sequence-dependent setup and transportation times by ant colony with reinforced pheromone relationships," *Int. J. Prod. Econ*, vol. 153, pp. 253–267, 2014.

[67] B. Z. Yao, C. Y. Yang, J. J. Hu, J. B. Yao, J. Sun, "An improved ant colony optimization for flexible job shop scheduling problems," *Adv. Sci. Lett.*, vol. 4, no. 6–7, pp. 2127–2131, 2011.

[68] F. El Khoukhi, J. Boukachour, A.E. Alaoui, "The dual-ants colony: a novel hybrid approach for the flexible job shop scheduling problem with preventive maintenance," *Comput. Ind. Eng.*, vol. 106, pp. 236–255, 2017.

[69] D. L. Luo, H. P. Chen, S. X. Wu, Y. X. Shi, "Hybrid ant colony multi-objective optimization for flexible job shop scheduling problems," *J. Internet Tech.*, vol. 11, no. 3, pp. 361–369, 2010.

[70] L. Wang, J. C. Cai, M. Li, Z. H. Liu, "Flexible job shop scheduling Pproblem using an improved ant colony optimization," *Sci. Program.*, pp. 9016303, 2017.

[71] J. Q. Li, Q. K. Pan, Y. C. Liang, "An effective hybrid tabu search algorithm for multi-objective flexible job-shop scheduling problems," *Comput. Ind. Eng.*, vol. 59, no. 4, pp. 647–662, 2010.

[72] J. Q. Li, Q. K. Pan, P. N. Suganthan, T. J. Chua, "A hybrid tabu search algorithm with an efficient neighborhood structure for the flexible job shop scheduling problem," *Int. J. Adv Manuf. Tech.*, vol. 52, no. 5–8, pp. 683–697, 2011.

[73] S.-M. Mohammad, F. Parviz, "Flexible job shop scheduling with tabu search algorithms," *Int. J. Adv. Manuf. Tech.*, vol. 32, no. 5–6, pp. 563–570, 2007.

[74] Q. Zhang, H. Manier, M. A. Manier, "A genetic algorithm with tabu search procedure for flexible job shop scheduling with transportation constraints and bounded processing times," *Comput. Oper. Res.*, vol. 39, no. 7, pp. 1713–1723, 2012.

[75] X.Y. Li, L. Gao, "An effective hybrid genetic algorithm and tabu search for flexible job shop scheduling problem," *Int. J. Prod. Econ*, vol. 174, pp. 93–110, 2016.

[76] S. Jia, Z. H. Hu, "Path-relinking Tabu search for the multi-objective flexible job shop scheduling problem," *Comput. Oper. Res, vol. 47, pp.11-26*, vol. 47, pp. 11–26, 2014.

[77] G. Vilcot, J. C. Billaut, "A tabu search algorithm for solving a multicriteria flexible job shop scheduling problem," *Int. J. Prod. Res.*, vol. 49, no. 23, pp. 6963–6980, 2011.

[78] R. Logendran, A. Sonthinen, "A Tabu search-based approach for scheduling job-shop type flexible manufacturing systems," *J. Oper. Res. Soc.*, vol. 48, no. 3, pp. 264–277, 1997.

[79] A.T. Eshlaghy, S.A. Sheibatolhamdy, "Scheduling in flexible job-shop manufacturing system by improved tabu search," *Afr. J. Bus. Manag.*, vol. 5, no. 12, pp. 4863–4872, 2011.

[80] B. Marzouki, O. B. Driss, K. Ghedira, "Multi-agent model based on combination of chemical reaction optimisation metaheuristic with Tabu search for flexible job shop scheduling problem," *Int. J. Intel. Eng. Inform.*, vol. 6, no. 3-4, pp. 242–265, 2018.

[81] J. Q. Li, P. Y. Duan, J. D. Cao, X. P. Lin, Y. Y. Han, "A hybrid Pareto-based Tabu search for the distributed flexible job shop scheduling problem with E/T criteria," *IEEE Access*, vol. 6, pp. 58883–58897, 2018.

[82] J. Q. Li, Q. K. Pan, K. Z. Gao, "Pareto-based discrete artificial bee colony algorithm for multi-objective flexible job shop scheduling problems," *Int J. Adv. Manuf. Tech.*, vol. 55, no. 9–12, pp. 1159–1169, 2011.

[83] L. Wang, G. Zhou, Y. Xu, S.Y. Wang, Liu Min, "An effective artificial bee colony algorithm for the flexible job-shop scheduling problem," *Int. J. Adv. Manuf. Tech.*, vol. 60, no. 1-4, pp. 303–315, 2012.

[84] J. Q. Li, Q. K. Pan, M. F. Tasgetiren, "A discrete artificial bee colony algorithm for the multi-objective flexible job-shop scheduling problem with maintenance activities," *Appl. Math. Model.*, vol. 38, no. 3, pp. 1111–1132, 2014.

[85] L. Wang, G. Zhou, Y. Xu, M. Liu, "An enhanced Pareto-based artificial bee colony algorithm for the multi-objective flexible job-shop scheduling," *Int. J. Adv. Manuf. Tech.*, vol. 60, no. 9–12, pp. 1111–1123, 2012.

[86] L. Wang, G. Zhou, Y. Xu, M. Liu, "A hybrid artificial bee colony algorithm for the fuzzy flexible job-shop scheduling problem," *Int. J. Prod. Res*, vol. 51, no. 12, pp. 3593–3608, 2013.

[87] K. Z. Gao, P. N. Suganthan, T. J. Chua, C. S. Chong, T. X. Cai, Q. K. Pan, "A two-stage artificial bee colony algorithm scheduling flexible job-shop scheduling problem with new job insertion," *Expert Syst. Appl.*, vol. 42, no. 21, pp. 7652–7663, 2015.

[88] J. Q. Li, Q. K. Pan, S. X. Xie, S. Wang, "A hybrid artificial bee colony algorithm for flexible job shop scheduling problems," *Int. J. Comput. Commun. Control*, vol. 6, no. 2, pp. 286–296, 2011.

[89] K. Z. Gao, P. N. Suganthan, Q. K. Pan, T. J. Chua, C. S. Chong, T. X. Cai, "An improved artificial bee colony algorithm for flexible job-shop scheduling problem with fuzzy processing time," *Expert Syst Appl.*, vol. 65, pp. 52–67, 2016.

[90] K. Z. Gao, P. N. Suganthan, Q. K. Pan, M. F. Tasgetiren, A. Sadollah, "Artificial bee colony algorithm for scheduling and rescheduling fuzzy flexible job shop problem with new job insertion," *Knowl-Based Syst.*, vol. 109, pp. 1–16, 2016.

[91] D. M. Lei, "Multi-objective artificial bee colony for interval job shop scheduling with flexible maintenance," *Int. J. Adv. Manuf. Tech.*, vol. 66, no. 9–12, pp. 1835–1843, 2013.

[92] X. X Li, Z. Peng, B. G. Du, J. Guo, W. X. Xu, K. J. Zhuang, "Hybrid artificial bee colony algorithm with a rescheduling strategy for solving flexible job shop scheduling problems," *Comput. Ind. Eng.*, vol. 113, pp. 10–26, 2017.

[93] T. Meng, Q.K. Pan, H.Y. Sang, "A hybrid artificial bee colony algorithm for a flexible job shop scheduling problem with overlapping in operations," *Int J. Prod. Res*, vol. 56, no. 16, pp. 5278–5292, 2018.

[94] K. Z. Gao, P. N. Suganthan, Q. K. Pan, T. J. Chua, T. X. Cai, C. S. Chong, "Pareto-based grouping discrete harmony search algorithm for multi-objective flexible job shop scheduling," *Inform. Sci.*, vol. 289, pp. 76–90, 2014.

[95] Y. Yuan, H. Xu, J.D. Yang, "A hybrid harmony search algorithm for the flexible job shop scheduling problem," *Appl. Soft Comput.*, vol. 13, no. 7, pp. 3259–3272, 3259.

[96] K. Z. Gao, P. N. Suganthan, Q. K. Pan, T. J. Chua, T. X. Cai, C. S. Chong, "Discrete harmony search algorithm for flexible job shop scheduling problem with multiple objectives," *J. Intel. Manuf.*, vol. 27, no. 2, pp. 363–374, 2016.

[97] K. Z. Gao, P. N. Suganthan, Q. K. Pan, M. F. Tasgetiren, "An effective discrete harmony search algorithm for flexible job shop scheduling problem with fuzzy processing time," *Int. J. Prod. Res*, vol. 53, no. 19, pp. 5896–5911, 2015.

[98] A. Maroosi, R. C. Muniyandi, E. Sundararajan, A.M. Zin, "A parallel

membrane inspired harmony search for optimization problems: A case study based on a flexible job shop scheduling problem," *Appl. Soft Comput.*, vol. 49, pp. 120–136, 2016.

[99] M. Gaham, B. Bouzouia, N. Achour, "An effective operations permutation-based discrete harmony search approach for the flexible job shop scheduling problem with makespan criterion," *Appl. Intel.*, vol. 48, no. 6, pp. 1423–1441, 2018.

[100] Y. Yuan, H. Xu, "Multiobjective flexible job shop scheduling using memetic algorithms," *IEEE Trans. Auto. Sci. Eng.*, vol. 12, no. 1, pp. 336–353, 2015.

[101] M. Frutos, O. A. Carolina, F. Tohme, "A memetic algorithm based on a NSGAII scheme for the flexible job-shop scheduling problem," *Ann. Oper. Res.*, vol. 181, no. 1, pp. 745–765, 2010.

[102] W. C. Yi, X. Y. Li, B. L. Pan, "Solving flexible job shop scheduling using an effective memetic algorithm," *Int. J. Comput. Appl. Tech.*, vol. 53, no. 2, pp. 157–163, 2016.

[103] H. Farughi, B.Y. Yegane, M. Fathian, "A new critical path method and a memetic algorithm for flexible job shop scheduling with overlapping operations," *Simul-T Soc. Mod. Sim.*, vol. 89, no. 3, pp. 264–277, 2013.

[104] C. Wang, N. Tian, Z.C. Ji, Y. Wang, "Multi-objective fuzzy flexible job shop scheduling using memetic algorithm," *J. Stat. Comput. Sim.*, vol. 87, no. 14, pp. 2828–2846, 2017.

[105] A. Phu-ang, A. Thammano, "Memetic algorithm based on marriage in honey bees optimization for flexible job shop scheduling problem," *Memetic Comput.*, vol. 9, no. 4, pp. 295–309, 2017.

[106] T. C. Chiang, H. J. Lin, "A simple and effective evolutionary algorithm for multiobjective flexible job shop scheduling," *Int. J. Prod. Econ.*, vol. 141, no. 1, pp. 87–98, 2013.

[107] I. T. Tanev, T. Uozumi, Y. Morotome, "Hybrid evolutionary algorithm-based real-world flexible job shop scheduling problem: application service provider approach," *Appl. Soft Comput.*, vol. 5, no. 1, pp. 87–100, 2004.

[108] X. N. Shen, X. Yao, "Mathematical modeling and multi-objective evolutionary algorithms applied to dynamic flexible job shop scheduling problems," *Inform. Sci.*, vol. 298, pp. 198–224, 2015.

[109] R. Zarrouk, I.E. Bennour, A. Hemai, "A two-level particle swarm optimization algorithm for the flexible job shop scheduling problem," *Swarm Intell.*, vol. 13, no. 2, pp. 145–168, 2019.

[110] S. H. A. Rahmati, M. Zandieh, M. Yazdani, "Developing two multi-objective evolutionary algorithms for the multi-objective flexible job shop scheduling problem," *Int. J. Adv. Manuf. Tech.*, vol. 64, no. 5–8, pp. 915–932, 2013.

[111] E. Ahmadi, M. Zandieh, M. Farrokh, S.M. Emami, "A multi objective optimization approach for flexible job shop scheduling problem under random machine breakdown by evolutionary algorithms," *Comput. Oper Res.*, vol. 73, pp. 56–66, 2016.

[112] X. L. Wu, S. M. Wu, "An elitist quantum-inspired evolutionary algorithm for the flexible job-shop scheduling problem," *J. Intel. Manuf.*, vol. 28, no. 6, pp. 1441–1457, 2017.

[113] A. Rossi, G. Dini, "An evolutionary approach to complex job-shop and flexible manufacturing system scheduling," *P. I. Mech. Eng. J-J Eng.*, vol. 215, no. 2, pp. 233–245, 2001.

[114] I. Kacem, S. Hammadi, P. Borne, "Correction to 'Approach by localization and multiobjective evolutionary optimization for flexible job-shop scheduling problems (vol 32, pg 1, 2002)," *IEEE Trans. Syst. Man Cybrn. C Appl. Rev*, vol. 32, no. 2, pp. 172–172, 2002.

[115] M. B. S. S Reddy, C. Ratnam, G. Rajyalakshmi, V. K. Manupati, "An effective hybrid multi objective evolutionary algorithm for solving real time event in flexible job shop scheduling problem," *Measurement*, vol. 114, pp. 78–90, 2018.

[116] C. Wang, Z. C. Ji, W. Yan, "Multi-objective flexible job shop scheduling problem using variable neighborhood evolutionary algorithm," *Mod. Phys. Lett B*, vol. 31, pp. 19–21, 2017.

[117] T. K. Liu, Y. P. Chen, J. H. Chou, "Evolutionary scheduling system using a universal encoding operator in a distributed and flexible job-shop manufacturing environment," *J. Chin Soc. Mech. Eng.*, vol. 36, no. 3, pp. 221–232, 2015.

[118] M. Yazdani, M. Amiri, M. Zandieh, "Flexible job-shop scheduling with parallel variable neighborhood search algorithm," *Expert Syst. Appl.*, vol. 37, no. 1, pp. 678–687, 2010.

[119] A. Ishigaki, Y. Matsui, "Effective neighborhood generation method in search algorithm for flexible job shop scheduling problem," *Int. J. Autom. Tech.*, vol. 13, no. 3, pp. 389–296, 2019.

[120] M. Amiri, M. Zandieh, M. Yazdani, A. Bagheri, "A variable neighbourhood search algorithm for the flexible job-shop scheduling problem," *Int. J. Prod. Res.*, vol. 48, no. 19, pp. 5671–5689, 2010.

[121] A. Bagheri, M. Zandieh, "Bi-criteria flexible job-shop scheduling with sequence-dependent setup times-Variable neighborhood search approach," *J. Manuf. Syst.*, vol. 30, no. 1, pp. 8–15, 2011.

[122] D. M. Lei, X. P. Guo, "Variable neighbourhood search for dual-resource constrained flexible job shop scheduling," *Int. J. Prod. Res.*, vol. 52, no. 9, pp. 2519–2529, 2014.

[123] D. M. Lei, X. P. Guo, "Swarm-based neighbourhood search algorithm for fuzzy flexible job shop scheduling," *Int. J. Prod. Res.*, vol. 50, no. 6, pp. 1639–1649, 2012.

[124] Y. L. Zheng, Y. X. Li, D. M. Lei, "Multi-objective swarm-based neighborhood search for fuzzy flexible job shop scheduling," *Int. J. Adv. Manuf. Tech.*, vol. 60, no. 9–12, pp. 1063–1069, 2012.

[125] T. F. Abdelmaguid, "A neighborhood search function for flexible job shop scheduling with separable sequence-dependent setup times," *Appl. Math. Comput.*, vol. 260, pp. 188–203, 2015.

[126] S. Huang, N. Tian, Z. C. Ji, "Particle swarm optimization with variable neighborhood search for multiobjective flexible job shop scheduling problem," *Int. J. Model. Simul. Sci. Comput.*, vol. 7, no. 3, UNSP 1650024, 2016.

[127] A. Baykasoglu, "Linguistic-based meta-heuristic optimization model for flexible job shop scheduling," *Int. J. Prod. Res.*, vol. 40, no. 17, pp. 4523–4543, 2002.

[128] N. Shahsavari-Pour, B. Ghasemishabankareh, "A novel hybrid meta-heuristic algorithm for solving multi objective flexible job shop scheduling," *J. Manuf. Syst.*, vol. 32, no. 4, pp. 771–780, 2013.

[129] V. Roshanaei, A. Azab, H. ElMaraghy, "Mathematical modelling and a meta-heuristic for flexible job shop scheduling," *Int. J. Prod. Res.*, vol. 51, no. 20, pp. 6247–6274, 2013.

[130] V. M. Dalfard, G. Mohammadi, "Two meta-heuristic algorithms for solving multi-objective flexible job-shop scheduling with parallel machine and maintenance constraints," *Comput. Math. Appl.*, vol. 64, no. 6, pp. 2111–2117, 2012.

[131] M. E. T Araghi, F. Jolai, M. Rabiee, "Incorporating learning effect and deterioration for solving a SDST flexible job-shop scheduling problem with a hybrid meta-heuristic approach," *Int. J. Comput. Integ. Manuf.*, vol. 27, no. 8, pp. 733–746, 2014.

[132] M. Yazdani, M. Zandieh, R. Tavakkoli-Moghaddam,, F. Jolai, "Two meta-heuristic algorithms for the dual-resource constrained flexible job-shop scheduling problem," *Sci. Iran*, vol. 22, no. 3, pp. 1242–1257, 2015.

[133] R. Wu, Y. B. Li, S. S. Guo, X. X. Li, "An efficient meta-heuristic for multi-objective flexible job shop inverse scheduling problem," *IEEE Access*, vol. 6, pp. 59515–59527, 2018.

[134] S.H.A. Rahmati, M. Zandieh, "A new biogeography-based optimization (BBO) algorithm for the flexible job shop scheduling problem," *Int. J. Adv. Manuf. Tech.*, vol. 58, no. 9–12, pp. 1115–1129, 2012.

[135] J. Lin, "A hybrid biogeography-based optimization for the fuzzy flexible job-shop scheduling problem," *Knowl-Based Syst.*, vol. 78, pp. 59–74, 2015.

[136] L. Wang, S.Y. Wang, Y. Xu, G. Zhou, M. Liu, "A bi-population based estimation of distribution algorithm for the flexible job-shop scheduling problem," *Comput. Ind. Eng.*, vol. 62, no. 4, pp. 917–926, 2012.

[137] S.Y. Wang, L. Wang, Y. Xu, M. Liu, "An effective estimation of distribution algorithm for the flexible job-shop scheduling problem with fuzzy processing time," *Int. J. Prod. Res.*, vol. 51, no. 12, pp. 3778–3793, 2013.

[138] L. Wang, S.Y. Wang, M. Liu, "A Pareto-based estimation of distribution algorithm for the multi-objective flexible job-shop scheduling problem," *Int. J. Prod. Res.*, vol. 51, no. 12, pp. 3574–3592, 2013.

[139] B. J. Liu, Y. S. Fan, Y. Liu, "A fast estimation of distribution algorithm for dynamic fuzzy flexible job-shop scheduling problem," *Comput. Ind. Eng.*, vol. 87, pp. 193–201, 2015.

[140] R. Perez-Rodriguez, A. Hernandez-Aguirre, "A hybrid estimation of

distribution algorithm for flexible job-shop scheduling problems with process plan flexibility," *Appl. Intel.*, vol. 48, no. 10, pp. 3707–3734, 2018.

[141] H. W. Ge, L. Sun, X. Chen, Y. C. Liang, "An efficient artificial fish swarm model with estimation of distribution for flexible job shop scheduling," *Int. J. Comput. Intel. Syst.*, vol. 9, no. 5, pp. 917–931, 2016.

[142] X. J. Wang, L. Gao, C. Y. Zhang, X. Y. Shao, "A multi-objective genetic algorithm based on immune and entropy principle for flexible job-shop scheduling problem," *Int. J. Adv. Manuf. Tech.*, vol. 51, no. 5–8, pp. 757–767, 2010.

[143] N. Shivasankaran, P. S Kumar, K. V. Raja, "Hybrid sorting immune simulated annealing algorithm for flexible job shop scheduling," *Int. J. Comput. Intel. Syst.*, vol. 8, no. 3, pp. 455–466, 2015.

[144] W. Xiong, D. M. Fu, "A new immune multi-agent system for the flexible job shop scheduling problem," *J. Intel. Manuf.*, vol. 29, no. 4, pp. 857–873, 2018.

[145] X. Liang, M. Huang, T. Ning, "Flexible job shop scheduling based on improved hybrid immune algorithm," *J. Amb. Intel. Hum. Comput.*, vol. 9, no. 1, pp. 165–171, 2018.

[146] J. Q. Li, Q. K. Pan, "Chemical-reaction optimization for flexible job-shop scheduling problems with maintenance activity," *Appl. Soft Comput.*, vol. 12, no. 9, pp. 2896–2912, 2012.

[147] J. Q. Li, Q. K. Pan, "Chemical-reaction optimization for solving fuzzy job-shop scheduling problem with flexible maintenance activities," *Int. J. Prod. Econ.*, vol. 145, no. 1, pp. 4–17, 2013.

[148] Z.C. Li, B. Qian, R. Hu, L.L. Chang, J.B. Yang, "An elitist nondominated sorting hybrid algorithm for multi-objective flexible job-shop scheduling problem with sequence-dependent setups," *Knowl-Based Syst.*, vol. 27, no. 5, pp. 1008–1022, 2019.

[149] L. Gao, Q. K. Pan, "A shuffled multi-swarm micro-migrating birds optimizer for a multi-resource-constrained flexible job shop scheduling problem," *Inform. Sci.*, vol. 372, pp. 655–676, 2016.

[150] Y. Yuan, H. Xu, "Flexible job shop scheduling using hybrid differential evolution algorithms," *Comput. Ind. Eng.*, vol. 65, no. 2, pp. 246–260, 2013.

[151] D. Y. Ma, C. H. He, S. Q. Wang, X. M. Han, X. H. Shi, "Solving fuzzy flexible job shop scheduling problem based on fuzzy satisfaction rate and differential evolution," *Adv. Prod. Eng. Manag.*, vol. 13, no. 1, pp. 44–56, 2018.

[152] H. J. Zhang, Q. Yan, G. H. Zhang, Z. Q. Jiang, "A chaotic differential evolution algorithm for flexible job shop scheduling," *Theory*, *Methodology*, *Tools and Applications for Modeling and Simulation of complex systems*, *II*, vol. 644, pp. 79–88, 2016.

[153] X. L. Zheng, L. Wang, "A knowledge-guided fruit fly optimization algorithm for dual resource constrained flexible job-shop scheduling problem," *Int. J. Prod. Res.*, vol. 54, no. 18, pp. 5554–5566, 2016.

[154] Q. Liu, M. M. Zhan, F. O. Chekem, X. Y. Shao, B. S. Ying, J. W. Sutherland, "A hybrid fruit fly algorithm for solving flexible job-shop scheduling to reduce manufacturing carbon footprint," *J. Clean. Prod.*, vol. 168, pp. 668–678, 2017.

[155] M. Zandieh, A. R. Khatami, S. H. A. Rahmati, "Flexible job shop scheduling under condition-based maintenance: Improved version of imperialist competitive algorithm," *Appl. Soft Comput.*, vol. 58, pp. 449–464, 2017.

[156] S. Karimi, Z. Ardalan, B. Naderi, M. Mohammadi, "Scheduling flexible job-shops with transportation times: Mathematical models and a hybrid imperialist competitive algorithm," *Appl. Math. Model*, vol. 41, pp. 667–682, 2017.

[157] J. Q. Li, Q. K. Pan, S. X. Xie, "An effective shuffled frog-leaping algorithm for multi-objective flexible job shop scheduling problems," *Appl. Math. Comput.*, vol. 218, no. 18, pp. 9353–9371, 2012.

[158] D. M. Lei, Y. L. Zheng, X. P. Guo, "A shuffled frog-leaping algorithm for flexible job shop scheduling with the consideration of energy consumption," *Int. J. Prod. Res.*, vol. 55, no. 11, pp. 3126–3140, 2017.

[159] W. Teekeng, A. Thammano, "A combination of shuffled frog leaping and fuzzy logic for flexible job-shop scheduling problems," *Procedia Computer Science*, vol. 6, pp. 69–75, 2011.

[160] H.T. Tang, R. Chen, Y.B. Li, *et al*, "Flexible job-shop scheduling with tolerated time interval and limited starting time interval based on hybrid discrete PSO-SA: An application from a casting workshop," *Appl. Soft Comput.*, vol. 78, pp. 176–194, 2019.

[161] M. A. Cruz-Chavez, M. G. Martinez-Rangel, M. H. Cruz-Rosales, "Accelerated simulated annealing algorithm applied to the flexible job shop scheduling problem," *Int. Trans. Oper. Res.*, vol. 24, no. 5, pp. 1119–1137, 2017.

[162] R. Zeng, Y.Y. Wang, "A chaotic simulated annealing and particle swarm improved artificial immune algorithm for flexible job shop scheduling problem," *Eursip J. Wirel. Comm.*, vol. 2018, no. 101, 2018.

[163] S. Kavitha, P. Venkumar, N. Rajini, P. Pitchipoo, "An efficient social spider optimization for flexible job shop scheduling problem," *J. Adv. Manuf. Syst.*, vol. 17, no. 2, pp. 181–196, 2018.

[164] C. Lu, X.Y Li, L. Gao, W. Liao, Y. Jin, "An effective multi-objective discrete virus optimization algorithm for flexible job-shop scheduling problem with controllable processing times," *Comput. Ind. Eng.*, vol. 104, pp. 156–174, 2017.

[165] I Kacem, "Genetic algorithm for the flexible job-shop scheduling problem," in *Proc. IEEE-SMC*, Washington, DC, USA, 2003, pp. 3464–3469.

[166] K. F. Guimaraes, M. A. Fernandes, "An approach for flexible job-shop scheduling with separable sequence-dependent setup time," in *Proc. IEEE-SMC*, Taipei, China, 2006, pp. 3727–3731.

[167] J. Q. Li, Q. K. Pan, S. X. Xie, "Flexible job shop scheduling problems by a hybrid artificial bee colony algorithm," in *Proc. IEEE-CEC*, New Orleans, LA, USA, 2011, pp. 78–83.

[168] W. P. Ma, Y. Zuo, J. L. Zeng, S. Liang, L. C. Jiao, "A memetic algorithm for solving flexible job-shop scheduling problems," in *Proc. IEEE-CEC*, Beijing, China, 2014, pp. 66–73.

[169] L. C. F. Carvalho, M.A. Fernandes, "Multi-objective flexible job-shop scheduling problem with DIPSO: more diversity, greater efficiency," in *Proc. IEEE-CEC*, Beijing, 2014, pp. 282–289.

[170] N. B. Ho, J. C. Tay, "LEGA: An architecture for learning and evolving flexible job-shop schedules," in *Proc. IEEE-CEC*, Edinburgh, Scotland, 2005, pp. 1380–1387.

[171] X. N. Shen, Y. Sun, M. Zhang, "An improved MOEA/D for multi-objective flexible job shop scheduling with release time uncertainties," in *Proc. IEEE-CEC*, Vancouver, Canada, 2016, pp. 2950–2957.

[172] J. J. Ma, Y. Lei, Z. Wang, L.C. Jiao, R.C. Liu, "A memetic algorithm based on immune multi-objective optimization for flexible job-shop scheduling problems," in *Proc. IEEE-CEC*, Beijing, China, 2014, pp. 58–65.

[173] H. W. Ge, L. Sun, "Intelligent scheduling in flexible job shop environments based on artificial fish swarm algorithm with estimation of distribution," in *Proc. IEEE-CEC*, Vancouver, Canada, 2016, pp. 3230–3237.

[174] X. Y. Li, L. Gao, "A collaborative evolutionary algorithm for multi-objective flexible job shop scheduling problem," in *Proc. IEEE-SMC*, Anchorage, AK, USA, 2011, pp. 997–1002.

[175] Y. Mati, N. Rezg, X. L. Xie, "An integrated greedy heuristic for a flexible job shop scheduling problem," in *Proc. IEEE-SMC*, Tucson, AZ, 2001, pp. 2534–2539.

[176] I. Kacem, S. Hammadi, P. Borne, "Approach by localization and genetic manipulation algorithm for flexible job-shop scheduling problem," in *Proc. IEEE-SMC*, Tucson, AZ, USA, 2001, pp. 2599–2604.

[177] H. X. Chen, J. Ihlow, C. Lehmann, "A genetic algorithm for flexible job shop scheduling," in *Proc. ICRA*, Detroit, MI, USA, 1999, pp. 1120–1125.

[178] T. H. Jiang, G.L. Deng, "Optimizing the low-carbon flexible job shop scheduling problem considering energy consumption," *IEEE Access*, vol. 6, pp. 46346–46355, 2018.

[179] X. L. Wu, Y. J. Sun, "A green scheduling algorithm for flexible job shop with energy-saving measures," *J. Clean. Prod.*, vol. 172, pp. 3249–3264, 2017.

[180] H. Wang, Z.G. Jiang, Y. Wang, H. Zhang, Y.H. Wang, "A two-stage optimization method for energy-saving flexible job shop scheduling based on energy dynamic characterization," *J. Clean. Prod.*, vol. 188, pp. 575–588, 2018.

[181] X. Gong, T. D. Pessemier, L. Martens, W. Joseph, "Energy-and labor-aware flexible job shop scheduling under dynamic electricity pricing: a many-objective optimization investigation," *J. Clean. Prod.*, vol. 209,

pp. 1078–1094, 2019.

[182] J. Lin, "Backtracking search based hyper-heuristic for the flexible job shop scheduling problem with fuzzy processing time," *Eng. Appl. Artif. Intel.*, vol. 77, pp. 186–196, 2019.

[183] K. Z. Gao, F. J. Yang, M. C. Zhou, Q. K. Pan, P. N. Suganthan, "Flexible job shop rescheduling for new job insertion by using discrete Jaya algorithm," *IEEE Trans. Cybern.*, *to be published*, .

[184] D. M. Lei, M. Li, L. Wang, "A two-phase meta-heuristics for multi-objective flexible job shop scheduling problem with total energy consumption," *IEEE Trans. Cybern.*, *to be published*, .

[185] P. Brandimarte, "Routing and scheduling in a flexible job shop by tabu search," *Ann. Oper. Res.*, vol. 41, pp. 157–183, 1993.

[186] K. Z. Gao, P. N. Suganthan, Q. K. Pan, M. F. Tasgetiren, "Effective ensembles of heuristics for scheduling multi-objective flexible job shop problem with new job insertion," *Comput. Ind. Eng.*, vol. 90, pp. 107–117, 2015.

[187] S. Jun, S. Lee, H. Chun, "Learning dispatching rules using random forest in flexible job shop scheduling problems," *Int. J. Prod. Res.*, vol. 57, no. 10, pp. 3290–3310, 2019.

[188] X.Y. Li, C. Lu, L. Gao, S.Q. Xiao, L. Wen, "An Effective Multi-Objective Algorithm for Energy Efficient Scheduling in a Real-Life Welding Shop," *IEEE Trans. Ind. Inform.*, vol. 14, no. 12, pp. 5400–5409, 2018.

[189] Y.P. Fu, G.D. Tian, A.M. Fathollahi-Fard, A. Ahmadi, C.Y, "Zhang. Stochastic multi-objective modelling and optimization of an energy-conscious distributed permutation flow shop scheduling problem with the total tardiness constraint," *J. Clean. Prod.*, 2019.

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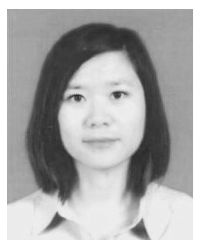

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