Multi-objective optimization algorithms for flow shop scheduling problem: a review and prospects

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Abstract: Since multi-objective flow shop scheduling problem (MFSP) plays a key role in practical scheduling, there has been an increasing interest in MFSP according to the literature. However, there still have been wide gaps between theories and practical applications, and the review research of multi-objective optimization algorithms in MFSP (objectives > 2) field is relatively scarce. In view of this, this paper provides a comprehensive review of both former and the state-of-the-art approaches on MFSP. Firstly, we introduce a broad description and the complexity of MFSP. Secondly, a taxonomy of multi-objective optimizations and an analysis of the publications on MFSP are presented. It is noteworthy that heuristic and meta-heuristic methods and hybrid procedures are proven much more useful than other methods in large and complex situations. Finally, future research trends and challenges in this field are proposed and analyzed. Our survey shows that algorithms developed for MFSP continues to attract significant research interest from both theoretical and practical perspectives.

***Keywords*:** Decision making, Flow shop, Multi-objective optimization, Scheduling.

1. Introduction

The flow shop scheduling problem (FSP) is an important component of scheduling problems. Its importance and practical relevance to industry have attracted researchers to study it from different perspectives for decades. Because of its powerful engineering backgrounds, it is very significant to develop effective algorithms to solve this problem which can enhance production efficiency, improve the optimization of production resources, and increase competitive strength [1].

The majority of the literature of handling FSP has been concentrated on single-criterion scheduling. However, several objectives must be considered in many real-world situations. That is to say, the multi-objective must be satisfied simultaneously over these criteria conflicted with others, and FSP with a single optimization objective is not sufficient for practical applications. It is necessary to search for the trade-off solutions among these objectives, particularly in conflicting situations. Models of multi-objective FSP (MFSP) are established to capture optimization solutions, often called the Pareto optimal solutions, in knotty problems. Besides, there is not even a universally accepted achievement of optimization as that in single-objective optimization. Research on approaches of tackling MFSP is with no doubt a very important and challenging project, and there are still many open questions in this domain.

The conventional approaches to solve single-objective FSP can be mainly categorized into two types, namely, exact and approximation methods. Exact methods, such as enumeration, dynamic programming, branch-and-bound (B&B) method, have been successfully applied to tackle small-sized flow shop problems. However, despite the relative success of exact algorithms, they are still incapable of solving medium and large instances and are too complex for real-world problems. For the medium- and large-scale problems, approximation methods are superior to the exact methods. Actually, multi- objective FSP is encountered much more frequently in real- world engineering applications. In the last decades, there has been an increase in the design of multi-objective programming techniques to handle FSP with multiple objectives, which can be seen in Fig. 1 (started in 1995). It also suggests that an interesting issue appears in the FSP field. The most successful and popular of the exact methods is the B&B algorithms which use the latest theoretical developments to improve their performances. Approximation methods, especially meta-heuristic methods developed in recent years, are attractive alternatives and are also used to tackle MFSP with Pareto solutions. These efficient meta-heuristic methods mainly include genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), simulated annealing (SA), tabu search (TS), and differential evolution (DE). However, the comprehensive surveys in the literature about methods of dealing with multi-machine flow shop with several objectives, especially in future trends and challenges, are relatively scarce. There have been a few surveys [2–6] about multi-criteria scheduling published in the technical literature. The review studied by Minella et al. [6] is much more comprehensive than others. But it does not discuss further researches and challenges thoroughly, and several other approaches have arisen since the publication of that paper. The intention of the present work was to provide researchers an updated survey and the future research trends of theoretical and practical areas on MFSP.

The remainder of this paper is organized as follows. In Section 2, we introduce the description of MFSP and common measures of performance. In Section 3 and 4, we review the status researches in the development of algorithms on MFSP including the classification and main applications respectively. At last, some conclusions are made in Section 5.

2. Basic concepts and description

MFSP studies n jobs which are processed on m different machines sequentially. The set of n jobs is $J=\{1, 2,\ldots,n\}$ and the set of m machines is $M=\{1, 2,\ldots,m\}$. Machines are available continuously. A job is processed on one machine at a time without preemption, and a machine processes no more than one job at a time. The optimization objectives are ≥ 2. When the sequence in which the jobs are to be processed is the same for each machine, the scheduling problems are named permutation FSP (PFSP). A hybrid flow shop is a generalization of the flow shop and the parallel machine environments. Instead of m machines in series, there are c stages in series with a number of identical machines in parallel at each stage. Each job has to be processed first at stage 1, then at stage 2, and so on. A stage functions as a bank of parallel machines; at each stage, job j requires processing on only one machine and any machine can be chosen [7].

Scheduling problems can be described by a three-field notation $\alpha|\beta|\gamma$ in [8]. The first field, α, describes the shop (machine) environment. The formula $\alpha=\alpha_1\alpha_2$ is taken here, where α_1 denotes the shop environment and α_2 gives the number of machines. The second field, β, indicates a number of job characteristics such as preemption. The third field, γ, denotes the optimality objectives.

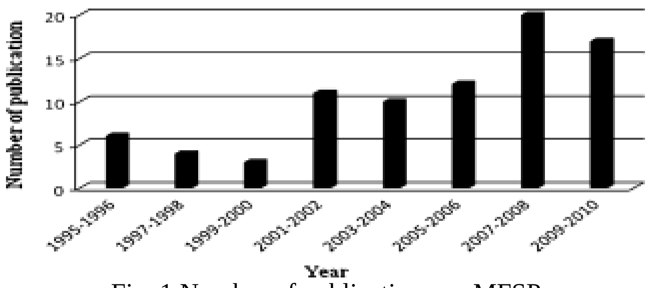

Fig. 1 Number of publications on MFSP

3. Literature group and analysis

MFSP has received great attention due to its importance in many industrial areas. The methods to solve MFSP can be classified according to decision-making process as follows: *a priori* methods, *a posteriori* methods, and *interactive* methods [12]. In this section, the description of these three kinds of methods is introduced, as well as the applications on MFSP according to particular methods.

3.1. A priori methods

The simplest methods of these approaches are a priori methods which enable the decision maker to intervene before the resolution process. This group of techniques includes those approaches assuming that either certain desired achievable goals or a certain pre-ordering of the objectives can be performed by the decision maker prior to the research. These approaches mainly include lexicographic ordering, linear fitness combination, and nonlinear fitness combination methods [13]. A lexicographic method is described as sorting the objectives according to weightiness and then selecting an objective to be optimized in order, or selecting an objective randomly in each evolutionary step [14]. B&B (e.g., [15]) and other heuristic methods (e.g., [16]) are studied for MFSP in this group. The linear fitness combination approaches give each sub-objective different weight by relative importance and combine them in a linear aggregating function. Thus, a multi-objective flow shop scheduling problem is turned into a single-optimization problem. B&B (e.g. [17]), SA method (e.g., [18]), TS method (e.g., [19]), ACO algorithm (e.g., [20]), PSO approach (e.g., [21]), and other effective strategies (e.g., [22]) are using linear fitness combination techniques to solve MFSP.

The advantages of this group technique are the easy performance and fast implementation in small instance FSP. Whereas, researchers must define a way to gain the weighted value of each objective firstly and only a single solution is returned solution per algorithm run. It is not fit for dealing with MFSP, especially large-scale problems.

3.2 A posteriori methods

The decision-making process comes after completing the search in a posteriori methods. Pareto solutions, obtained by implementing a posteriori approaches, are different from conventional optimization. These techniques do not need priori preference information from the decision maker. The Pareto front solutions obtained are all “best” solutions to the problem in multi-objective cases, and there is no strong dominance relationship among these solutions. From a widespread set of Pareto solutions obtained, administrators will select the only satisfied solution according to the decision maker’s preferences. A posteriori methods are more popular than a priori methods in the literature for engineering applications. They mainly include independent sampling, criterion selection, aggregation selection (linear, nonlinear), and Pareto sampling (Pareto-based selection, Pareto deme-based selection, Pareto elitist-based selection, Pareto rank- and niche-based selection) [13]. The independent sampling methods use a single-objective searching technique to obtain solutions of a multi-objective problem. The weights of sub-objectives are varied during a number of separate multi-objective scheduling method runs. This sort of method is relatively simple and effective in solving MFSP. The number of publications of GA using this technique is the largest (e.g., [23, 24]). The applications using this technique in Pareto sampling techniques are based on Pareto distributive strategy and search all members of non-dominated solutions in each evolutionary run. This sort of method is most popular and effective in solving MFSP. Applications of a posteriori methods in multi- objective scheduling fields are much more plentiful than applications of a priori methods. Besides these mentioned approaches (e.g., B&B, PSO, ACO) in instances of using a priori technique, algorithms like GA [25], DE [26], and IA are proposed in this domain. What is more is that the state-of-the-art theoretical developments are presented to deal with MFSP by adopting posteriori strategies.

3.3 Interactive methods

The interactive approaches are studied less than the other two kinds of approaches. They mainly emphasize the interactive process between solution searching and decision making. Generally speaking, decision makers do not get the relation among the objectives of the problem at the beginning. As for the decision-making process, as well as the observation of intermediate results, decision makers gain a more clear preference and give quantitative descriptions on the objectives in this way. Therefore, these techniques can be summarized as follows. Firstly, find a non-dominated solution using multi-objective algorithms. Then, get the reaction of the consideration of the decision maker about this non-dominated solution and modify the preferences of the objectives accordingly. Lastly, repeat the two previous steps until the decision maker is satisfied or no further improvement is accomplished. Obviously, this method is more appropriate for solving real-world problems. However, few literatures solved the MFSP with the interactive methods being applied due to the complex and difficult nature of its theory. Shi considers that researches about this interactive method should be paid more attention to.

4. Method review in literature

The concise introduction and analysis of each algorithm are discussed in this section. Table 1 gives a summary of these methods in settling MFSP. The first column of the table indicates the handled problems, the second indicates the used methods, and the last column indicates the references, including authors and years. It is obvious that the B&B algorithms in the exact methods are used most successfully, and GA is the most popular meta-heuristic algorithm of approximation methods.

Table 1 Summary of applications in MFSP field

Problem	Algorithm	Reference
$F2\|\|(C_{max},N_T)$, (C_{max},T)	B&B	Liao et al. (1997)
$F2\|\|C_{max}, F$	B&B	Sayın and Karabat (1999)
$F2\|\|C_{max}, F$	B&B	Yeh (2001)
$F2\|\|C_{max}, F$	B&B	Lin and Wu (2006)
$F2\|\|C_{max}, F$	B&B	Nagar et al. (1995) [2]
$F2\|\|C_{max}, F$	B&B	Yeh (1999)
$F2\|\|F, T$	B&B	Lee and Wu (2001)
$F2\|prmu\|C_{max}, F$	B&B, heuristic	Sivrikaya-Serifoğlu and Ulusoy (1998)
$F2\|\|C_{max}, F$	B&B, heuristics	T'kindt et al. (2003) [15]
$Fm\|prmu\|C_{max}, T$	B&B, Parallelism	Lemesre et al. (2007) [17]
$Fm\|prmu\|C_{max}, F$	SA	Suresh and Mohanasundaram (2004)
$F\|prmu\|many$	SA	Loukil et al. (2005)
$HF2(PM)\|SDST\|C,T$	SA	Naderi et al. (2009) [18]
$Fm\|prmu\|C_{max}, F$	SA	Varadharajan and Rajendran (2005)
$HFm\|\|F_{ave}, T_{max}$	SA, TS	Hatami et al.(2010)
$Fm\|\|many$	MOTS	Loukil et al. (2000)
$Fm\|prmu\|C_{max}, T_{max}$	TS	Armentano and Arroyo (2004)
$F2\|ST\|C,T$	TS, heuristics	Eren and Güner (2006) [19]
$F2\ \|\|C,C_{max}$	TS, heuristic	Eren and Güner (2008)
$F2\|\|C_w,T, C_{max}$	TS, heuristic, EDD	Eren and Güner (2008)

$Fm\|\|(C_{max},T), (C_{max},T,F)$	GA	Murata et al. (1996) [23]
$4F2\|\|C_{max}, F$	GA	Nagar et al. (1996) [24]
$F2\|\|(C_{max}, F), (C_{max},T,F)$	GA	Neppalli et al.(1996)
$Fm\|\|C_{max}, F, I_{sum}$	GA	Sridhar and Rajendran (1996)
$Fm\|\|C_{max},T$	GA	Cavalieri and Gaiardelli (1998)
$Fm\|\|(C_{max},T), (C_{max}, T, F)$	GA	Ishibuchi and Murata (1998) [25]
$Fm\|\|C_{max},T$	C-MOGA	Murata et al. (2001)
$Fm\|\|(C_{max}, T), (C_{max}, T, F)$	GA	Chang et al. (2002)
$F2\|\|C_{max}, F$	HGA	Yeh (2002)
$Fm\|prmu\|(C_{max}, T), (C_{max}, T, F)$	GA and LS	Ishibuchi et al. (2003)
$Fm\|prmu\|C_{max}, F$	PGA-ALS	Pasupathy et al. (2006)
$Fm\|\|C_{max}, I_{sum},C_{ave}$	TSP-GA	Ponnambalam et al. (2004)
$Fm\|\|(C_{max},T_{max}), (C_{max}, T)$	GA	Arroyo and Armentano (2005)
$Fm\|\|C_{max},T$	PGA	Melab et al. (2006)
$Fm\|\|C_{max},T$	HQGA	Li and Wang (2007)
$F2\|prmu\|C_{max},C$	SPGA	Chang et al. (2007)
$HFm(PM)\|retr\|Z_{bottle},C_{max}$	L-NSGA,	Dugardin et al. (2010)
$HFm(PM)\|SDST\|C_{max}, T_w$	Multi-phase GA	Karimi et al. (2010)
$F2\|\|C_{max}, F$	ACO	T’kindt et al. (2002) [20]
$Fm\|\|C_{max}, T, I_{sum}$	ACO	Yagmahan and Yenisey (2008)
$Fm\|ovlp\|T, I_{sum}, W$	ACO	Huang and Yang (2009)
$Fm\|\|C_{max}, F$	ACO	Yagmahan and Yenisey (2010)
$Fm\|prmu\|C_{max},T$	ACO	Rajendran and Ziegler (2004)
$Fm\|prmu\|C_{max}, T_{max}$	ACO, Path Relinking	Pasia et al. (2006)
$Fm\|ST, lst\|C_{max}, T$	ACO,TA	Marimuthu et al. (2009)
$Fm\|prmu\|F, I_{sum}$	HPSO	Rahimi-Vahed and Mirghorbani (2007)
$Fm\|prmu\|C_{max}, T$	DPSO	Guo et al. (2007)
$Fm\|lst\|E_w, T_w$	NBM, DPSO	Tseng and Liao (2008) [21]
$Fm\|prmu\|many$	HPSO	Li et al. (2008)

5. Conclusion

In this paper, we provide a comprehensive review of the most popular approaches for solving MFSP together with some insights of the research of their operations. The study of MFSP has attracted a great many researchers to develop effective and efficient approaches. The approaches involved are EA, GA, TS, SA, GP, ACO, PSO, IA, TA, DE, local search, B&B, and some other dispatching rules, which could be classified into three groups: a priori methods, interactive methods, and a posteriori methods. This review can be a good reference in this field with helpful suggestions for further research.

This survey starts with a broader introduction of FSP and the complexity of it under the criteria being used frequently in single-objective FSP. A simple and clear description of HFSP and PFSP is discussed. Three-category literature groups and analysis of multi-objective optimization are introduced as well as the main methods review. Later, some subjects of further studies on MFSP are given. The review clearly shows that some interesting progress has already been made in the area, but much more research still needs

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