

Production, Manufacturing and Logistics

# On operators and search space topology in multi-objective flow shop scheduling

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Received 19 January 2006; accepted 8 June 2006

Available online 14 August 2006

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## Abstract

Multi-objective optimization using evolutionary algorithms identifies Pareto-optimal alternatives or their close approximation by means of a sequence of successive local improvement moves. While several successful applications to combinatorial optimization problems are known, studies of underlying problem structures are still scarce.

The paper presents a study of the problem structure of multi-objective permutation flow shop scheduling problems and investigates the effectiveness of local search neighborhoods within an evolutionary search framework. First, small problem instances with up to six objective functions for which the optimal alternatives are known are studied. Second, benchmark instances taken from literature are investigated. It turns out for the investigated data sets that the Pareto-optimal alternatives are found relatively concentrated in alternative space.

Also, it can be shown that no single neighborhood operator is able to equally identify all Pareto-optimal alternatives. Taking this into consideration, significant improvements have been obtained by combining different neighborhood structures into a multi-operator search framework.

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*Keywords:* Multiple objective programming; Flow shop scheduling; Local search; Evolutionary computations

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## 1. Introduction

In the last years, metaheuristics have become increasingly popular for solving complex optimization problems. Various successful applications are reported, and research focuses more and more on aspects being of relevance for the real world. Multi-objective models are of particular interest in this context, as practical problems most often imply several aspects that have to be taken into consider-

ation when deriving an overall evaluation of alternatives. As criteria are often conflicting, not a single solution can however be regarded as optimal but a whole set of Pareto-optimal alternatives, leading to an optimization problem where its' resolution has to be seen in the identification of a set of solutions.

Metaheuristic methods try to solve a given problem by successive modification steps applied to given alternatives. This is done using a so called neighborhood  $nh(x)$ , an operator that associates a set of alternatives  $x' \in nh(x), x' \neq x$  to an alternative  $x \in X$ . By means of modification improved alternatives are accepted, while inferior solutions

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are usually discarded from the search. This process is organized with respect to the specific search strategy proposed by the metaheuristic. For the multi-objective case, where the evaluation of an alternative  $x$  is done based on an objective vector  $G(x) = (g_1(x), \dots, g_k(x))$ , multi-objective extensions have been proposed to integrate this aspect into the evaluation of solutions. Important concepts include tabu search [18,24], simulated annealing [39], and foremost evolutionary algorithms [11,15]. Most evolutionary algorithms are based on the concept on Pareto dominance as given in Definition 1 (without the loss of generality) for minimization functions, and try to identify all Pareto-optimal alternatives, the Pareto set  $P$ , given in Definition 2. As they naturally evolve a whole set of alternatives during search, these methods are particularly popular for the resolution of multi-objective optimization problems. An excellent collection of corresponding resources is maintained by Coello Coello under <http://www.lania.mx/~ccoello/EMOO/> for further references. Other important publications on metaheuristics for multi-objective optimization include the work of Jaszkiwicz [27], Gandibleux and Ehrgott [20], and Gandibleux et al. [19].

**Definition 1 (Dominance).** An objective vector  $G(x), x \in X$  is said to dominate a vector  $G(x')$ ,  $x' \in X$  if and only if  $g_i(x) \leq g_i(x') \forall i = 1, \dots, k \wedge \exists i | g_i(x) < g_i(x')$ . The dominance of  $G(x)$  over  $G(x')$  is denoted with  $G(x) \preceq G(x')$ .

**Definition 2 (Efficiency, Pareto-optimality, Pareto set).** An objective vector  $G(x), x \in X$  is said to be *efficient*, if and only if  $\nexists x' \in X | G(x') \preceq G(x)$ . The corresponding alternative  $x$  is called *Pareto-optimal*, the set of all Pareto-optimal alternatives the *Pareto set*  $P$ .

Evolution of alternatives is usually done using two operators: crossover  $nh_{\text{cross}}(x, x')$ , recombining two alternatives, and mutation  $nh_{\text{mut}}(x)$ , taking one alternative as an input. Good neighborhood structures are essential for an effective resolution of the problem at hand. Their influence on the resolution of a certain problem may be described in the context of a fitness landscape, a concept initially proposed by Wright in theoretical biology [41]. A fitness landscape may be described as a triplet  $(\mathcal{S}, nh(x), g(x))$ , comprising the search space  $\mathcal{S}$  which is in many cases equivalent to the set of feasible alternatives  $X$ , a neighborhood  $nh(x)$ , and an evaluation function  $g(x)$  [6]. In the multi-objective case, the evaluation

function  $g(x)$  is replaced by the vector  $G(x)$ . Structures of fitness landscapes may be analyzed in terms of the fitness-distance-correlation of qualitatively good alternatives, and can be exploited by a heuristic search algorithm similar to gradient methods in continuous global optimization [8].

Efficient solutions  $G(x)$  may be very different in terms of their components  $g_1(x), \dots, g_k(x)$ . As evolutionary search is performed on the alternatives, it is however also of importance whether the corresponding alternatives significantly differ or whether they are concentrated in the search space, forming a structure similar to what sometimes is referred to as a ‘big valley’ [9].

While Reeves first investigated combinatorial landscapes for scheduling problems in the single objective case [35,36], a multi-objective analysis has not been conducted yet. First results are however reported for other problems, namely for the multi-objective quadratic assignment by Knowles and Corne [28], and for the multi-objective traveling salesman problem by Borges and Hansen [10]. In their studies, they find evidence that globally optimal solutions of the corresponding multi-objective problems are found relatively concentrated in alternative space.

Besides, a wide literature of metaheuristics for the multi-objective flow shop scheduling problem exists describing the successful resolution of a range of problem instances. Gangadharan and Rajendran [21] and Loukil et al. [29] propose a simulated annealing algorithm, and various evolutionary algorithms are applied by Nagar et al. [32], Basseur et al. [4], Murata et al. [31], Ishibuchi et al. [25,26], and Bagchi [2,3].

The paper presents a study of the search space topology of multi-objective flow shop scheduling problems and is organized as follows. In Section 2, the problem is introduced and suitable neighborhood operators are presented. An analysis of the search space of Pareto-optimal alternatives for the investigated problem is given in Section 3, and the effectiveness of neighborhoods is studied within a metaheuristic evolving a population of alternatives in Section 4. Conclusions are derived in Section 5.

## 2. The multi-objective permutation flow shop scheduling problem

### 2.1. Problem statement

The permutation flow shop scheduling problem consists in the assignment of a set of jobs  $\mathcal{J} =$

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