

Chapter 8

MULTIOBJECTIVE COMBINATORIAL OPTIMIZATION – THEORY, METHODOLOGY, AND APPLICATIONS

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Abstract This chapter provides an annotated bibliography of multiple objective combinatorial optimization, MOCO. We present a general formulation of MOCO problems, describe their main characteristics, and review the main properties and theoretical results. One section is devoted to a brief description of the available solution methodology, both exact and heuristic. The main part of the chapter consists of an annotation of the existing literature in the field organized problem by problem. We conclude the chapter by stating open questions and areas of future research. The list of references comprises more than 400 entries.

Keywords: Combinatorial optimization, multiple objectives, metaheuristics, exact methods, bibliography

1. Introduction

Combinatorial Optimization is a field extensively studied by many researchers. Due to its potential for application in real world problems it has prospered over the last few decades. A good survey of the state of the art is provided by [74]. But as far as real world decision making is concerned, it is also well known, that decision makers have to deal with several – usually conflicting – objectives. The growth in the interest in theory and methodology of multicriteria decision making (MCDM) over the last thirty years as documented by the chapters in this volume, the survey of the activities in the field [366] and a bibliography of MCDM applications [421] is witness of this fact.

Thus it is somewhat surprising that a combination of both, i.e. multicriteria or multiobjective combinatorial optimization (MOCO) has not been studied widely. A few papers in the area have been published in the seventies, then the classical problems have been investigated in the eighties. Only in recent years – approximately since 1990 – a profound interest in the topic is evident. Since then several PhD theses have been written, specific methodologies have been developed, and the number of research papers in the field has grown considerably.

In this chapter we intend to give an overview over the literature in the field of multiobjective combinatorial optimization. In the following sections, we first present a brief introduction to the field, including a general problem formulation, description of several types of MOCO problems, and the most important theoretical properties of these problems (Sections 2 and 3). In Section 5 we explain the classification of literature that we used. This consists first of a classification of the problem treated and secondly of the methodology applied to solve it. Then we review existing methods to solve MOCO problems in Section 4. The main part of the chapter is devoted to the annotation of the literature (Section 6). The chapter is concluded by a brief discussion of open questions and areas of future research (Section 7).

Let us now describe the focus of this chapter. We compiled the literature on multiobjective combinatorial optimization accessible to us. We mainly consider papers that deal specifically with MOCO problems, thus our bibliography is certainly not complete on 0-1 programming with multiple objectives, and exclude most of the literature on general multiobjective integer programming. A similar statement can be made with respect to scheduling. Scheduling problems are specific problems with their own theory and methodology, which we will not describe in detail, but refer to Chapter 7.3. We should also mention, that there exist earlier survey papers related to MOCO, one general [398], and two specifically

devoted to multiobjective network design, [53, 54]. Our bibliography contains all the relevant literature listed there. However, it is more complete, e.g. we could include the new direction of using metaheuristics for MOCO problems. However, we are aware of the fact, that despite our best efforts the list will not be complete, so we apologize for any omissions.

The aim of the bibliography is twofold. First we want to provide a starting point for researchers and students interested in the field, giving a brief introduction and commenting on, thus guiding through, existing literature. For the experienced researcher the list is intended as structured overview of the field.

2. Multiple Objective Combinatorial Optimization Problems

The feasible set of a (multiobjective) combinatorial problem is defined as a subset $X \subseteq 2^A$ of the power set of a finite set $A = \{a_1, \dots, a_n\}$. For example, consider the minimum spanning tree problem. $G = (V, A)$ is a graph with node set V and edge set A , the feasible set is the set of spanning trees of G and $X = \{S \subseteq A : S \text{ is a spanning tree of } G\}$.

Typically, in combinatorial optimization two types of objective functions are considered, namely the sum and the bottleneck objective:

$$z(S) = \sum_{a \in S} w(a), \text{ or}$$

$$z(S) = \max_{a \in S} w(a),$$

where $S \in X$ and $w : A \rightarrow \mathbb{Z}$ is some weight function.

A combinatorial problem can also be formulated in terms of binary variables. For this purpose we introduce a variable x_i for each element $a_i \in A$. Then, a feasible solution $S \in X$ can be represented by a binary vector $x \in \{0, 1\}^n$ if we define

$$x_i = \begin{cases} 1 & e_i \in S \\ 0 & \text{else.} \end{cases}$$

With this definition $S = \{a_i : x_i = 1\}$. It is therefore equivalent to speak about feasible solutions as subsets of A or about their representations by binary vectors. Accordingly S will be represented by a subset of $\{0, 1\}^n$.

In terms of the feasible set, this definition comprises (multiobjective versions of) the shortest path, minimum spanning tree, assignment, knapsack, travelling salesperson, or set covering problems, to mention only a few.

In a multicriteria combinatorial problem several weight functions $w_j : A \rightarrow \mathbb{Z}$ are given, yielding several objective functions z^j , $j = 1, \dots, Q$ (usually of the sum or bottleneck type). The problem is then to solve

$$\text{"min"}_{S \in X} (z^1(S), \dots, z^Q(S)) \quad (\text{MOCO})$$

where the meaning of "min" has still to be defined.

Most often the minimization in (MOCO) is understood in the sense of efficiency (or Pareto optimality). A subset $S \in X$ is called efficient if there does not exist another feasible solution $S' \in X$ such that $z^j(S') \leq z^j(S)$ for all $j = 1, \dots, Q$ with strict inequality for at least one of the objectives. The corresponding vector $z(S) = (z^1(S), \dots, z^Q(S))$ is called nondominated. The set of Pareto optimal (efficient) solutions of (MOCO) will be denoted by E , the set of nondominated vectors by ND throughout the chapter. Sometimes we shall use the term non-dominated frontier for the set of all nondominated vectors.

However, besides efficiency, there are other definitions of the "min" term in the formulation of (MOCO). For example, one could consider lexicographic minimization, when objective vectors are compared lexicographically: $z(S_1) <_{lex} z(S_2)$ if $z^j(S_1) < z^j(S_2)$, where j is the smallest index such that $z^j(S_1) \neq z^j(S_2)$. This could be done with respect to one, or all permutations of the objective functions z^j .

Another possibility is to minimize the worst objective function, i.e.

$$\min_{S \in X} \max_{j=1, \dots, Q} z^j(S).$$

We call this the max-ordering problem (following [94]) in order to distinguish it from the single objective bottleneck problem (note that both are often called min-max problems, which may create confusion).

A combination of the latter two is the lexicographic max-ordering problem, where the vector of objective values $z(S)$ is first resorted in a nonincreasing order of its components, and the resulting vectors are compared lexicographically, see [83, 85] for details.

In a real world decision context, finally a compromise has to be made among the many efficient solutions that (MOCO) may have. This is the reason why often the existence of a utility function is implicitly or explicitly assumed. A utility function assigns each criterion vector $z(S)$ a scalar overall utility. Then methods are developed to find a solution of maximum utility. This is a typical approach in interactive methods described later.

Closely related to combinatorial problems are multiobjective integer programming problems. These can be formulated as follows.

$$\begin{array}{ll}
\text{"min"} & Cx \\
\text{subject to} & Ax = b \\
& x_i \geq 0, \text{ integer } i = 1, \dots, n
\end{array} \quad (\text{MOIP})$$

Here C is a $Q \times n$ objective matrix, A is an $m \times n$ constraint matrix, and $x \in \mathbb{R}^n$. There is a considerable amount of literature on these problems. We refer to some surveys that exist but will not consider the literature in detail. In this respect, [43, 381, 429] provide surveys of techniques to find efficient solutions for (MOIP), [380] gives an overview of interactive methods for (MOIP), and [313] surveys (MOIP) with binary variables.

In general, combinatorial optimization problems can be considered as special cases of integer (in particular binary) programming. A MOCO problem is distinguished by a specific set of constraints, that provides a structure to the problem. We focussed on such problems and do not intend to review literature on general multiobjective binary or integer programming.

To conclude this section, let us mention one particular case, namely, when the set of feasible solutions is an explicitly given finite set, e.g. $X = A$. In this case, all problems discussed above are efficiently solvable. Algorithms can be found in [86, 87] and [218]. For this reason, these problems are mathematically not particularly interesting and we omit them from further discussion.

To summarize, (MOCO) is a discrete optimization problem, with n variables x_i , $i = 1, \dots, n$, Q objectives z^j , $j = 1, \dots, Q$ and a specific constraint structure defining the feasible set X .

3. Properties of MOCO Problems

In this section we discuss some of the properties of MOCO problems. It is in order to mention here that there is a considerable number of erroneous statements, even in papers published in international standard refereed journals. We will point out the most important of these throughout the chapter, in the appropriate places.

By its nature, multiobjective combinatorial optimization deals with discrete, non continuous problems, although the objectives are usually linear functions. An essential consequence of this fact when trying to determine the set of all efficient solutions (or nondominated vectors in objective space) is, that it is not sufficient to aggregate the objectives through weighted sums.

It is long known that for multiobjective linear programming problems

$$\min\{Cx : Ax = b, x \geq 0\}$$

the set of efficient solutions is exactly the set of solutions that can be obtained by solving LP's

$$\min \left\{ \sum_{j=1, \dots, Q} \lambda_j c^j x : Ax = b, x \geq 0 \right\},$$

where $\sum_{j=1}^Q \lambda_j = 1, \lambda_j > 0, j = 1, \dots, n$, see e.g. [183]. But the discrete structure of the MOCO problem makes this result invalid. Thus there usually exist efficient solutions, which are not optimal for any weighted sum of the objectives. This is true even in cases where the constraint matrix is totally unimodular, contrary to a proposition in [216] (see [399] for an example). These solutions are called nonsupported efficient solutions *NE*, whereas the remaining are called supported efficient solutions, *SE*. In early papers referring to MOCO, *NE* was usually not considered. Most authors focussed on scalarizing the objectives by means of weighting factors λ_j .

Nevertheless, the set *NE* is important. With more than one sum objective there are many more nonsupported than supported efficient solutions, see e.g. [413] for numerical results. But empirical results show that this is not necessarily the case when at most one objective is of the sum type and the others are bottleneck objectives [259, 261, 262].

Moreover, the nonsupported solutions contribute essentially to the difficulty of MOCO problems. Below, we shall briefly discuss the concepts of computational complexity of (MOCO). For introductions to the theory of *NP*-completeness and *#P*-completeness we refer to [128] and [407, 408, 409], respectively. These notions deal with the difficulty of finding a, respectively counting the number of solutions of a (MOCO).

In order to transfer the notions of *IP*, *NP* and *#P* to MOCO we first introduce a decision problem related to (MOCO) in a straightforward manner:

Given constants $k_1, \dots, k_Q \in \mathbb{Z}$,
does there exist a feasible solution
 $S \in X$ such that $z^j(S) \leq k_j, j =$
 $1, \dots, Q$?

D(MOCO)

The corresponding counting problem is:

How many feasible solutions $S \in$
 X do satisfy $z^j(S) \leq k_j, j =$
 $1, \dots, Q$?

#(MOCO)

It turns out that the respective versions of (MOCO) in the sense of finding or counting efficient solutions are in general NP - and $\#P$ -complete, respectively. This is true even for problems which have efficient algorithms in the single objective case. We refer to [102, 347] and [89] for results in this respect. Therefore the development of heuristics with guaranteed worst case performance (bounded error) is interesting. However, not much is known in this regard: [89] gives some general results on approximating the efficient set by a single solution, [303] uses a Tchebycheff metric to measure the error, and [326, 327] consider the existence of such algorithms. Some specific results about flow problems, shortest path, knapsack problems, and the TSP are discussed in Section 6.

Another aspect related to the difficulty of MOCO is the number of efficient solutions. It turns out that it may be exponential in the problem size, thus prohibiting any efficient method to determine all efficient solutions. Such results are known for the spanning tree, matroid base, shortest path, assignment, and travelling salesperson problems (see [103, 149, 349] for details). Consequently such problems are called intractable. Even the size of the set SE may be exponential, see [324]. However, numerical results available on the knapsack problem [413] show the number of supported solutions grows linearly with the problem size, but the number of nonsupported solution grows following an exponential function. However, other investigations indicate that for problems with bottleneck objectives (at most one sum objective), the ratio between the size of SE and NE is independent of the problem size in the asymmetric TSP [261], and that the number of efficient solutions decreases with increasing number of constraints for multi-constrained knapsack problems [262].

As far as the other definitions of optimality in (MOCO) are concerned, we note that the max-ordering problem with sum objectives is NP -hard in general (see [41]), but can be reduced to a single objective problem in the case of bottleneck objectives [86]. Bounds and heuristic methods for the former problem have been investigated in [307]. At least one solution of the max-ordering problem is always efficient, but possibly nonsupported. Similarly, a lexicographic max-ordering solution, although always efficient and optimal for the max-ordering problem may be nonsupported, [86].

For lexicographic optimization it is known that a lexicographically optimal solution is always efficient, and even a supported efficient solution, see [149]. Lexicographic optimization can also be viewed as a special case of algebraic optimization, see [428].

In view of the new trend to apply metaheuristics and local search in MOCO problems (see Section 4 below), it is interesting to consider the issue of neighbourhoods of feasible solutions, and their relations to efficient solutions. Using a neighbourhood corresponding to Simplex basis pivots for the shortest path problem and exchanges of one edge for the spanning tree problem it was shown in [92, 93] that the set of efficient solutions can be an unconnected subset of X with respect to the neighbourhood. So it is possible that local search methods (in principle) cannot find all efficient solutions.

4. Solution Methods for MOCO Problems

In the context of multiobjective programming (MOP), it is usual to distinguish the methods following the role of the decision maker in the resolution process. Information provided by the decision maker often concerns his preferences. In “a priori mode”, all the preferences are known at the beginning of the decision making process. The techniques used seek for a solution on the basis of these parameters. The best example is given by goal-programming methods. In “a posteriori mode” the set of all efficient solutions is generated for the considered problem. At the end, this set is analyzed according to the decision maker’s preferences. Many approximation (heuristic) methods are conceived following this resolution mode. In the “interactive mode”, the preferences are introduced by the decision maker during the resolution process. The methods involve a series of computing steps alternated with dialogue steps and can be viewed as the interactive determination of a satisfying compromise for the decision maker. Thus they require a high participation level on the part of the decision maker. Practical problems are often resolved according to the interactive mode.

The appropriate resolution mode is chosen considering the situation of the decision process. The method involved in the process could be exact or approximation methods.

4.1. Exact Methods

Here we discuss some of the methods used to solve MOCO problems. Many of these essentially combine the multiple objectives into one single objective. The most popular, and the one used first, is weighted sum scalarization. The problem solved is

$$\min \left\{ \sum_{j=1}^Q \lambda_j z^j(x) : x \in X \right\}, \quad (P_\lambda)$$

where $0 \leq \lambda_j \leq 1$ and $\sum_{j=1}^Q \lambda_j = 1$. Varying the weights, it is known that all supported efficient solutions can be found, using results from [183] and linear programming [132]. The advantage of the method (especially for problems where the single objective version is solvable in polynomial time) is that for each $\lambda \in \mathbb{R}^Q$ the problem (with sum objectives) is only as difficult as the single objective counterpart of (MOCO). Parametric programming can be used to solve the problem for all λ .

The approach has been applied to many MOCO problems: see [166, 420] for shortest path, [7, 77, 78, 184, 363] for the transportation problem, [69] for assignment, [202, 227, 248] for network flow, [149, 341, 342] for spanning tree, [81, 321] for knapsack and [245] for location problems. In many of these papers, the existence of nonsupported efficient solutions was either not known, or ignored. When a sum and a bottleneck objective are present, the minimization of the sum of the objectives has been discussed in [266] and [306] for general combinatorial optimization problems.

Besides weighted sum scalarization the most important method for multiobjective programming involves constraints on some objective values. The ε -constraint problem, described in detail in [35], is the following

$$\begin{aligned} & \min_{x \in X} z^k(x) \\ & \text{subject to } z^j(x) \leq \varepsilon_j \quad j \neq k. \end{aligned}$$

Its usefulness for MOCO problems depends on the objective function type. With more than two sum objectives, the ε -constraint problem is often *NP-hard*, see e.g. [128, problem ND30] for constrained shortest path. If, however, at most one sum objective is present, the constraints can be applied to the bottleneck objectives, and simply imply the exclusion of feasible solutions containing elements $a \in A$ with $z^j(a) > \varepsilon_j$ for some $j \neq k$. Moreover, assuming integer weights, the values of ε_j can be restricted to all integers between $\min_{a \in A} w_j(a)$ and $\max_{a \in A} w_j(a)$. Applications of the method to such cases are described for assignment, spanning tree, and 1-tree problems in [259, 260, 262], for asymmetric TSP in [261], and for knapsack problems in [264]. Recently a modification of

the method has been used to solve large scale bicriteria set-partitioning problems (with sum objectives) arising in airline crew scheduling [95].

Another well known approach in multicriteria optimization is the compromise solution method [424], where one tries to minimize the distance to an ideal point z^I or to a utopian point $z^U = z^I - \epsilon e$, where $e = (1, \dots, 1) \in \mathbb{R}^Q$ is the vector of all ones, and $\epsilon > 0$. The ideal point is defined according to the individual minima of each objective

$$z_j^I := \min_{x \in X} z^j(x).$$

Usually, the Tchebycheff norm is used as distance measure:

$$\min \left\{ \max_{j=1}^Q \{ \lambda_j |z^j(x) - z_j^I| \} : x \in X \right\}.$$

Unfortunately, when we consider sum objectives, this type of problem is usually *NP*-complete, see e.g. [277] for references on the shortest path problem. This explains why it is rarely used, even though, theoretically the whole of the efficient set can be found, see e.g. [332]. Using another norm, e.g. an l_p norm, $p \notin \{1, \infty\}$ leads to nonlinear objectives, and we found only one reference [405] using l_p norms for MOCO. Note that for $p = 1$, the compromise solution method coincides with the weighted sums approach.

A special approach to multiobjective optimization is goal programming, see e.g. [179, 229] and Chapter 7 for details. Here, for each of the objectives a target value (goal) is specified by the decision maker. The overall aim is to minimize the deviation from the specified goals. This approach is very popular and although it is sometimes considered a different field from multiobjective optimization we list the references here.

One approach that is popular for bicriteria problems is the use of ranking methods. First, define

$$z_j^I = \min_{x \in X} \{z^j(x)\}, \quad j = 1, 2 \quad (8.3)$$

and then

$$z_j^N := \min_{x \in X} \{z^j(x) : z^i(x) = z_i^I\}, \quad j = 1, 2; \quad i \neq j. \quad (8.4)$$

The ideal point $z^I = (z_1^I, z_2^I)$ and Nadir point $z^N = (z_1^N, z_2^N)$ define lower and upper bounds on the objective values of efficient solutions. Then

starting from a solution with $z^1(x) = z_1^I$, and finding second best, third best, ..., K -best solutions with respect to the first objective until z_1^N is reached, the efficient set can be determined. The approach has been used for the shortest path problem [44, 255] and the transportation problem [77]. Note that computation of the Nadir point z^N in the bicriteria case essentially means the solution of two lexicographic optimization problems.

A generalization of this approach to more than three objectives is not possible without knowledge of the Nadir point, which is difficult to obtain when $Q > 2$, see [214]. Note that a generalization of (8.4) (stated without proof in [255]) does not necessarily provide an upper bound on objective values of efficient solutions. Not even considering lexicographic optimization with respect to all permutations of objectives is guaranteed to produce upper bounds on objective values of efficient solutions, see [97, 98] for a recent discussion.

Moreover, the ranking approach can be effectively used to solve max-ordering problems with any number of criteria. First a weighting vector is chosen, then K -best solutions x^K are created according to the combined objective $\sum \lambda_j z^j$. When for the first time

$$\min_{k=1, \dots, K-1} \max_{j=1, \dots, Q} z^j(x^k) \leq \sum_{j=1}^Q \lambda_j z^j(x^K)$$

an optimal solution is among $\{x^1, \dots, x^K\}$. We refer to [84, 146], and [149] for applications to the uniform matroid, network flow problem, and spanning tree problem, respectively and [96] for a general procedure.

Let us now look at methods adapted from single objective combinatorial optimization. Among the very well established procedures is dynamic programming [21]. The method applies to sequential decision problems, which admit a recursion formula such as

$$\min \left(g_N(x_n) + \sum_{k=0}^{N-1} g_k(x_k, u_k) \right),$$

where g is a cost function depending on the state variable x_k and control variable u_k at stage k . Theoretically, this recursion can easily be adapted to the multiobjective case. Therefore dynamic programming algorithms appear most often for problems, where they have been established for the single objective versions earlier. These are the shortest path problem

[34, 165, 166, 215, 311, 319, 330, 358, 384], the knapsack problem [33, 38, 81, 199, 200, 201], the TSP [112, 391] and the transportation problem [123].

An implicit enumeration algorithm, which is widely used to solve hard combinatorial optimization problems is branch and bound. Its philosophy is to partition the problem into mutually disjoint and jointly exhaustive subproblems. Bounds are computed for subproblems and the process continues until an optimal solution is found. Much to our surprise, we could only find a few papers applying branch and bound for MOCO – to the knapsack problem, [396, 400, 413], the max-ordering shortest path problem, [311], and the cutting stock problem [210]. The adaptation of branch and bound poses one difficult problem. Since we deal with nondominated vectors, bounds play the role of ideal/Nadir points for subproblems. Thus they may be difficult to compute, or bad, i.e. not discarding enough feasible, nonefficient solutions. Research on replacing single points as bounds by bound sets to better reflect the multicriteria nature (efficient frontier) has recently been initiated in [90].

Many authors used available single objective methods for a particular problem and adapted them to the multiobjective case. The more natural such a generalization is, the bigger the number of papers pursuing such an approach. We note the following.

- Shortest Path: [157, 251] for label setting and [26, 50, 52, 272, 356, 392, 393, 411] for label correcting methods
- Spanning Tree: [49, 149] for adaptations of Prim's algorithm and [341, 347] for the greedy algorithm
- Assignment: [247, 396, 399] for the Hungarian method
- Network Flow: [88, 226, 227, 228] for the out-of-kilter algorithm and [31, 109, 305, 345] for the network simplex method
- TSP: [89] for Christofides' algorithm

Finally, we explain a general framework for the exact solution of the problem of determining the efficient set for bicriteria (MOCO), the two phases method. The name goes back to [396] and [399] and is telling: In the first phase *SE* is found using the scalarization technique, and solving single objective problems. The necessary weights are easy to compute using information generated in the process. The second phase consists

of finding the nonsupported efficient solutions by problem specific methods, using bounds, reduced costs, etc. In fact, most of the algorithms known to the authors (with exception of the shortest path problem) that are capable of determining the whole of E are some modification of the two phases method, e.g. [88, 228, 346] (Network Flow), [396, 413], (Knapsack), [399] (Assignment) and [310] (Spanning Tree).

4.2. Approximation Methods

The last two decades have been highlighted by the development and the improvement of approximative resolution methods, usually called “heuristics and metaheuristics”. In the context of combinatorial optimization, the term heuristic is used as a contrast to methods that guarantee to find a global optimum, such as the “Hungarian method” for solving the assignment problem, or Johnson’s method for 2-machine sequencing, or implicit enumeration schemes such as branch and bound or dynamic programming.

A heuristic is defined by [316] as a technique which seeks good (i.e. near-optimal) solutions at a reasonable computational cost without being able to guarantee optimality (or feasibility), or even in many cases to state how close to optimality a particular feasible solution is. Often heuristics are problem-specific, so that a method which works for one problem cannot be used to solve a different one.

In contrast, metaheuristics are powerful techniques applicable generally to a large number of problems. A metaheuristic refers to an iterative master strategy that guides and modifies the operations of subordinate heuristics by combining intelligently different concepts for exploring and exploiting the search space [134, 289]. A metaheuristic may manipulate a complete (or incomplete) single solution or a collection of solutions at each iteration. The family of metaheuristics includes, but is not limited to, constraint logic programming, genetic algorithms, evolutionary methods, neural networks, simulated annealing, tabu search, non-monotonic search strategies, greedy randomized adaptive search, ant colony systems, variable neighbourhood search, scatter search, and their hybrids. A comprehensive list of 1380 references on the theory and application of metaheuristics is presented in [289]. The success of these methods is due to the capacity of such techniques “to solve in practice” some hard combinatorial problems. As in the single objective case, a reasonable alternative to exact methods for solving large-scale instances of MOCO problem is to derive an approximation method. Such methods yield a good tradeoff between the quality of an approximation of the efficient solutions set denoted by \hat{E} , and the time and memory requirements.

The introduction of metaheuristic techniques for the solution of MOP problems has mushroomed over the last ten years. This activity has given birth to multiobjective metaheuristics (MOMH), aiming to approximate the (sub)set of Pareto-optimal solutions. Chronologically, the literature reports methods based on genetic algorithms (GA, Schaffer 1984), artificial neural networks (ANN, Malakooti 1990), simulated annealing (SA, Serafini 1992), and tabu search (TS, Gandibleux 1997).

Two characteristics are found in the first methods: They are inspired exclusively either by evolutionary algorithms, or by neighborhood search algorithms. Future researchers may see methods which are inspired simultaneously by the two schools. Also, the pioneer methods were a direct derivation of single objective optimization metaheuristics. They have small adaptations in order to integrate the concept of efficient solution to optimize multiple objectives.

Evolutionary Algorithms. Evolutionary algorithms (EA) make use of a population of solutions. By maintaining a population of solutions such a method can search for many efficient solutions in parallel via self adaptation and cooperation mechanisms. Self adaptation means that the individuals evolve independently while cooperation implies an exchange of information among the individuals. Here the whole population contributes to the evolution process toward the efficient set. The generation mechanism is parallel along the frontier and we talk about “global convergence-based methods”. This characteristic makes population-based methods very attractive for solving multiobjective problems with the advantage of being independent of the problem.

The first to introduce a multiobjective metaheuristic was Schaffer [337, 338]. He developed Vector Evaluated Genetic Algorithm (VEGA), which was an extension of Grefenstette’s GENESIS program [140] to include multiple objective functions. The vector extension concerns only the selection procedure. The main idea of VEGA is to divide the population into equal sized subpopulations. Each subpopulation is entrusted with optimization of a single objective. The selection procedure is performed independently for each objective while evolution (crossover and mutation operators) are performed on the union of subpopulations. As VEGA selects individuals who excel in one dimension of performance without looking at the other dimensions the speciation problem can arise from this approach. It implies that individuals with balanced performance on all objectives will not survive under this selection mechanism. Although some serious drawbacks are known, VEGA has had a strong influence up to now, and was at the origin of the Multiobjective Evolutionary Algorithms (MOEA) wave. Most MOMH are based on MOEA.

A list maintained on the web [48] counts several hundred papers only for multiobjective genetic algorithms, see also Chapter 5.1.

For a long time, the problems investigated were often unconstrained bi-objective problems with continuous variables and non-linear functions. EA are appreciated by the communities of engineers. This can explain the large number of applications of MOEA (in mechanical design, electronics, etc.) for solving real world problems. Surprisingly, few MOEA have been applied to solve MOCO problems. One only finds [130, 131] (Transportation Problem), [426] (Spanning Tree Problem), [188] (Travelling Salesperson Problem) [2, 127] (Knapsack Problem), [432] (Multi-constraint Knapsack Problem), [237] (Set Covering Problem), [390] (Containership Loading Design) and [271, 291, 379] (Scheduling Problems).

Neighborhood Search Algorithms. In neighborhood search algorithms (NSA) the generation relies upon one individual, a current solution x_n , and its neighbours $\{x\} \subseteq \mathcal{N}(x_n)$. Basically, starting from an initial solution and a weight vector $\lambda \in \Lambda$, the procedure approximates a part of the nondominated frontier corresponding to the search direction λ . A local aggregation mechanism of the objectives, often based on a weighted sum, produces the effect to focus the search on a part of the nondominated frontier. It defines a sequential generation implying a local convergence, i.e. a convergence located in an area of the efficient frontier. The principle is repeated for several search directions to approximate completely the nondominated frontier. NSA present an aggressive convergence due to less dispersion of the search. However, they need more effort in diversification to cover the efficient frontier completely.

The comparison of $x \in \mathcal{N}(x_n)$ with x_n according to Q objectives $z^j(x)$, $j = 1, \dots, Q$ raises three possible situations. If $\Delta z^j = z^j(x) - z^j(x_n)$ is the difference between solution x and x_n in the objective j :

$\forall j \Delta z^j \leq 0$: All the objectives are improved for solution x . x dominates the current solution x_n and is always accepted.

$\exists j, j' \Delta z^j < 0$ and $\Delta z^{j'} > 0$: An improvement and a deterioration occur simultaneously for different criteria. Both solutions x and x_n are potentially efficient.

$\forall j \Delta z^j \geq 0$: All objectives are deteriorated with at least one strict inequality. Solution x is dominated by x_n .

For the two last cases a scalarizing function $s(z(x), \lambda)$ is often used to project the multidimensional objective space into a monodimensional one using λ . Such a function allows to produce a “local agregation”

of the objectives in order to compute the “weighted distance” $\Delta s = s(z(x), \lambda) - s(z(x_n), \lambda)$ between $z(x)$ and $z(x_n)$.

The majority of the methods developed on the principle of NSA were applied to bi-objective problems with discrete variables, linear functions and linear constraints (combinatorial optimization).

Recent methods are more and more hybridized. For example, a population of solutions comes into NSA based methods [62, 153]. This coupling aims at breaking the independent character of each search process, inherent to the sequential generation principle, by exploiting information available in the population.

4.2.1 Multiobjective Evolutionary Algorithms (MOEA).

Since VEGA, significant progress concerns corrections of shortcomings observed in previous algorithms and propositions of new algorithmic primitives to generate a better approximation of E (like the use of non-domination ranking suggested by Goldberg [136]). Among the elements playing a significant role in a MOEA one finds the elite solutions. Zitzler underlines that recent studies suggest the use of elitism to improve MOEAs [223]. The results of numerical experiments show that the use of elite solutions must come with a strong rate of mutation in order to prevent a too fast specialization of the population. The contribution of elite solutions in the generation of the efficient frontier in the case of MOCO problems has been investigated by Gandibleux et al. [127, 271]. For the knapsack problem the use of greedy solutions or efficient supported solutions in the population has clearly shown a much better aptitude of the algorithm to generate the efficient solutions.

In the continuation of VEGA a lot of methods have contributed to the methodologic development of MOEAs. The most outstanding among them are briefly mentioned. Readers can find a complete survey on these methods in [46, 47, 114, 194].

[113]: **Multiple Objective Genetic Algorithm (MOGA93)** by Fonseca and Fleming, 1993. MOGA93 uses a ranking procedure where the rank of an individual is equal to the number of solutions which dominate this individual.

[361]: **Nondominated Sorting Genetic Algorithm (NSGA)** by Srinivas and Deb, 1994. NSGA implements Goldberg’s ranking idea where the rank of an individual is equal to its domination layer computed by ranking the population on the basis of domination.

[172]: **Niched Pareto Genetic Algorithm (NPGA)** by Horn, Nafpliotis and Goldberg, 1994. NPGA combines the Pareto dominance princi-

ple and a Pareto tournament selection where two competing individuals and a set of individuals are compared to determine the winner of the tournament.

[275]: **Multiple Objective Genetic Algorithm (MOGA95)** by Murata and Ishibuchi, 1995. MOGA95 is not based on the Pareto ranking principle but on a weighted sum of objective functions to combine them into a scalar fitness function using weight values generated randomly in each iteration.

[431]: **Strength Pareto Evolutionary Algorithm (SPEA)** by Zitzler and Thiele, 1998. SPEA takes the best features of previous MOEAs and includes them in a single algorithm. Using the multiobjective multi-constraint knapsack problem as benchmark, SPEA shows advantages over the other MOEA under consideration in convergence to the efficient frontier [432].

[205]: **Pareto Archived Evolution Strategy (PAES)** by Knowles and Corne, 1999. PAES is an evolution strategy employing local search for the generation of new candidate solutions using a reference archive to compute the solution quality.

Other Methods Related to Evolutionary Algorithms: [20, 47, 48, 152, 151, 190].

4.2.2 Simulated Annealing. Serafini [348] was the first to use simulated annealing as a technique for multiobjective optimization problems. All multiobjective simulated annealing-based methods since then are still closely related to the original single objective method. They extend the single objective algorithm to cope with the notion of efficiency [396]. The most recent methods include dynamic diversification mechanisms exploiting the set of potential efficient solutions to drive the approximation process [62, 295].

The methods presented subsequently are differentiated primarily by four points: (1) the rule for acceptance of a new solution with some probability depending on the temperature; (2) the scheme of decreasing the temperature; (3) the mechanism which guides the browsing of the efficient frontier; (4) the use of information drawn from a population of individuals. Often the authors tested various forms and definitions of acceptance rules. A lot of them have been suggested and discussed in [348].

[396]: **Multi-Objective Simulated Annealing (MOSA)** by Ulungu, 1993. The method uses a predefined set of weights. An independent SA process is then executed for each weight value. Each process generates a

set of potential solutions, which are then merged and filtered to provide the final approximation. Other references: [100, 241, 382, 394, 401, 402, 403].

[62]: **Pareto Simulated Annealing** (PSA) by Czyzak and Jaskiewicz, 1996. PSA introduces the use of a sample of solutions which are simultaneously optimized toward the efficient frontier while they are dispersed over the whole frontier. Other references: [63, 64, 161, 159, 160, 161, 162, 163, 187, 191, 193].

[105, 295]: **The revised Engrand method**. This method is not based on a principle of search directions, and it does not need an aggregation mechanism for the objectives. Each objective is considered separately. Advanced strategies using the population of potential efficient solutions drive the approximation mechanism ensuring the detection of the whole efficient frontier. Other references: [106, 373, 374].

Other methods related to Simulated Annealing. The trip planning problem [135], interactive method for 0-1 multiobjective problems [5], bicriteria scheduling problems on a single machine [209].

4.2.3 Tabu Search. Metaheuristics dealing with multiple objective optimization problems are sometimes presented wrongly as MOMH. This occurs when multiobjective problems are solved with a single objective strategy, looking for a unique compromise solution. In this case the original multiobjective problem is transformed or managed as the optimization of one or several single objective problems. It is the case for the first papers describing the use of TS as technique for solving MOP [289]. In [66] a family of (P_λ) problems are solved to generate a subset of \hat{E} . In [168] the method consists in solving a sequence of single objective problems considering in turn each objective z^j associated with a penalty term. Methods able to generate an approximation of the efficient solutions have been introduced later.

[126]: **Multiobjective Tabu Search** (MOTS) by Gandibleux et al., 1997. Its principle is based on a scalarizing function driven by a tabu search mechanism to browse, in an equilibrium way, the nondominated frontier. Intensification, diversification and tabu daemon are designed for the multiobjective case. Two tabu memories are used, one on the decision space, the second on the objective space. The former is an attribute-based tabu list preventing return to already visited solutions. The latter is connected with the objectives and based on an improvement measure of each objective. It is used for updating of weights using the pseudo criterion concept to diversify the search in the objective space. Other references: [124, 125].

[369]: **Interactive procedure using Tabu Search** by Sun, 1997. It is an interactive procedure for general multiple objective combinatorial optimization problems. The procedure works in a way similar to that of the Combined Tchebycheff/Aspiration Criterion Vector Method [365]. Tabu search is used to solve subproblems in order to find approximately efficient solutions. Other references: [3].

[153]: **Tabu Search approach inspired by PSA method (MOTS*)** by Hansen, 1998. A set of “generation solutions”, each with its own tabu list is considered. These solutions are dispersed along the objective space in order to allow a search in different areas of the nondominated frontier. Weights are defined for each solution to force the search into a direction of the nondominated frontier and away from other current solutions that are efficient with respect to it. Diversification is ensured by the set of generation solutions and a drift criterion. Other references: [154, 410].

[18]: **TS algorithm for finding Pareto optimal solutions** by Baykasoglu et al., 1999. A candidate list is introduced as an opportunity to diversify the search. The components of the method are designed to handle any type of variables (integer, zero-one, continuous and mixed). Other references: [16, 17].

Other methods related to Tabu Search. A hybrid resolution process based on TS and GA [2], a hybrid and interactive resolution process based on SA and TS [5], the trip planning problem [135], scheduling problems [240].

4.2.4 Other Approaches and New Developments. At the beginning of the Nineties, the first works using Artificial Neural Networks (ANN) to solve MOP were published. However, the ANN approach remains marginal [244, 370, 371]. The first links of ant colony systems to MOMH are recent, meriting thus their presence in this section [182, 138, 351]. [207] presents a dedicated heuristic and [377] a stochastic search method. We mention also a paper concerning a comparison of neighbourhood search techniques for MOP [249].

Several aspects concerning MOMH and MOCO were discussed during recent international conferences. One finds new adaptations of meta-heuristic such as GRASP, scatter search, ant systems, etc. Also, MOCO problems rarely tackled hitherto are now studied. One can find time-tabling problems, space allocation problems, multi-period distribution management problems, vehicle routing problems, etc. Finally, aspects related to the computer are them also examined. Efficient data structures, such as the quad-tree have proven their efficiency to manage non-

dominated criterion vectors [142, 372]. Reusable software as object-oriented frameworks for multiobjective local search is in development. These new trends promise a lot of forthcoming papers.

5. Classification of the Literature

In this section, we describe the classification scheme we used below to annotate the references. We classify a paper according to four categories, namely combinatorial structure, objective function type, problem type, and method applied. The first three pertain to the description of the problem discussed in a given paper.

As indicated in Section 2, to classify a certain paper, we first have to identify the problem discussed. This consists of the combinatorial structure (i.e. shortest path, knapsack, etc.), the type and number of objectives (i.e. sum, bottleneck, or occasionally something else), and the type of problem (e.g. finding the efficient set, max-ordering, lexicographic).

In addition to the identification of the problem, we give the methodology used in the paper. We can distinguish between exact and approximation (or heuristic) methods, where exact means that the optimal solutions mentioned in the problem description are found, whereas approximation means that only some solutions representing this set, not necessarily optimal, are found.

So, we introduce a classification using positions

$$Pos1/Pos2/Pos3/Pos4:.$$

Below, we provide tables where the different entries for each position are listed.

Entries for *Pos2* do not need a table, they simply define the number and type of objective functions considered. We could restrict ourselves to the sum and bottleneck objectives, with occasional exceptions explained where appropriate. Most of the papers that deal with other types of objectives are listed separately, because almost each of them would have required its own entry here. Note that Q stands for an arbitrary number of objectives.

We remark that sometimes two entries appear in one position. This means that one paper falls under two categories or that the approach applied in the paper is a combination of two methods. It may also happen that a single paper appears under several classifications if more than one problem was considered, or several methods proposed.

Table 8.1. Entries for *Pos1*: Combinatorial structure.

Entry	Explanation
P	Shortest Path Problem
AP	Assignment Problem
TP/TS	Transportation resp. Transshipment Problem
F	Network Flow Problem
ST	Spanning Tree Problem
MB/MI	Matroid Base resp. Matroid Intersection Problem
TSP	Travelling Salesperson Problem
KP	Knapsack Problem
SCH	Scheduling Problem
DL/NL	Discrete resp. Network Location Problem
SCP/SPA	Set Covering resp. Set Partitioning Problem
U	Unconstrained Problem
QAP	Quadratic Assignment Problem
VRP	Vehicle Routing Problem
FLP	Facility Layout Problem

Table 8.2. Entries for *Pos3*: Type of problem.

Entry	Explanation
E	Finding the efficient set
e	Finding a subset of the efficient set
SE, NE	Finding (non)supported efficient solutions
se, ne	Finding a subset of the (non)supported efficient solutions
$\hat{\bullet}$	Finding an approximation of \bullet
lex	Solving the lexicographic problem (preemptive priorities)
MO	Max-ordering problem
lexMO	Solving the lexicographic max-ordering problem
U	Optimizing a utility function
C/S	Finding a compromise respectively satisfying solution

6. Annotation of the Literature Problem by Problem

In this section we will give an annotated overview over the literature. We found it most convenient to organize the section according to the combinatorial structure of MOCO problems. Thus, we introduce eleven subsections, dealing with the most important combinatorial problems, in

Table 8.3. Entries for Pos4: Solution method applied.

Entry	Explanation
SP	Exact algorithm specifically designed for the problem
LS/LC	Label setting resp. label correcting method
DP	Algorithm based on dynamic programming
BB	Algorithm based on branch and bound
ϵ C	Algorithm based on ϵ -constraint method
IA	Interactive method
H	Heuristic specifically designed for the problem
SA	Simulated annealing algorithm
TS	Tabu search algorithm
GA	Genetic or evolutionary algorithm
GP	Goal programming
2P	Two phases method
A	Approximation algorithm with worst case performance bound
LP	Method based on linear programming
DEA	Method using data envelopment analysis
Fuzzy	Method using fuzzy programming

terms of the number of papers available. In a last subsection we briefly mention other MOCO problems that have appeared in papers, but to a definitely smaller extent.

As an exception to this order, we briefly mention PhD theses in the subject, since they are also witness of the growing research efforts in the field. An increasing number of dissertations have been written on MOCO in recent years. Those that we found were not all dedicated to MOCO specifically, but use some MOCO problems in another context: [52] deals with the multiobjective shortest path problem for routing of hazardous material, [238] contains information about bicriteria spanning trees, [45, 204, 274, 430] are about evolutionary techniques in multiobjective optimization, and [86] presents some general results for certain general MOCO problems. Among those which are specifically dedicated to MOCO problems we mention [108] and [226] on the flow problem, [171] and [385] in scheduling. [153, 191] explores the use of metaheuristics for MOCO, and [396] introduces the two-phases method and develops it for the assignment and knapsack problem. [135] introduces the “Trip Planning Problem”, as a preferences-based multiobjective traveling salesman problem with activity and lodging selection. [100] uses the MOSA method to solve a multiple objective Vehicle Routing Problem

with time windows. Finally fast approximation algorithms for MOCO problems are discussed in [326].

6.1. Shortest Path Problems

The multiobjective shortest path problem consists in finding in a network with vector weights on the edges “optimal” paths. The papers we found usually consider the problem with specified starting and ending node, or from a given starting node to all other nodes. The shortest path problem belongs to the most widely studied MOCO problems. There exists a survey on the topic [397], a bibliography on the Internet containing an abstract collection [254], and a classification of algorithms [355]. Our list contains all papers mentioned there, too.

Most problems in this category are *NP-complete*: See [347] for the efficient paths problem with two sum objectives, [157] for intractability of the same problem. In [157] ten bicriteria shortest path problems are introduced and analyzed. In [92] an example shows that a result from [251] about the connectedness of efficient solutions is wrong, *NP-completeness* of the max-ordering problem is mentioned in [277]. However, the multicriteria shortest path problem is an exceptional kind of problem, because a fully polynomial time approximation scheme is known, as presented in [415].

A variety of algorithms based on dynamic programming (e.g. [166, 215, 358]), label setting [157, 251] and label correcting methods (e.g. [26, 272, 356]) are available, with computational experiments [26, 174, 356] comparing different methods. In the biobjective case an algorithm based on ranking paths has also been proposed, [44, 255]. The general idea is also applicable to other MOCO problems with two objectives, as explained in Section 4.

Besides, several papers present formulations of specific problems in terms of multicriteria shortest paths, or consider other variations of the classical problem.

- $P/2-\sum/E/LC$: [26, 356, 392]
- $P/2-\sum/E/LS$: [157]
- $P/2-\sum/E/2P,LC$: [272]
- $P/2-\sum/E/SP$: [44, 174]
- $P/2-\sum/E/DP$: [65, 166]
- $P/2-\sum/\hat{E}/A$: [157]
- $P/1-\sum 1-\max/E/SP$: [157, 252, 296]

- $P/2-\Sigma/C/IA$: [61, 110]
- $P/2-\Sigma/U/SP$: [166]
- $P/2-\Sigma/U/IA$: [278]
- $P/2-\Sigma/ne/IA$: [51]
- $P/3-\Sigma/E/LC$: [122]
- $P/3-\Sigma/C/IA$: [122]
- $P/Q-\Sigma/SE/SP$: [166, 420]
- $P/Q-\Sigma/E/LS$: [251]
- $P/Q-\Sigma/E/LC$: [50, 52, 393, 411]
- $P/Q-\Sigma/E/DP$: [165, 215, 312, 330, 358, 384]
- $P/Q-\Sigma/E/SP$: [11, 367]
- $P/Q-\Sigma/\hat{E}/A$: [415]
- $P/Q-\Sigma/C/IA$: [167]
- $P/Q-\Sigma/C/SP$: [418]
- $P/Q-\Sigma/U/DP$: [34]
- $P/Q-\Sigma/U/SP$: [10, 268]
- $P/Q-\Sigma/MO/DP,BB$: [311]
- $P/Q-\Sigma/MO/LC$: [277]
- $P/Q-\Sigma/MO/SP$: [290]
- $P/Q-\Sigma/\widehat{MO}/A$: [406, 415]
- $P/Q-ND^1/C/DEA$: [70]
- $P/Q-\Sigma^2/E/SP$: [267]
- Other particular multiobjective path problems: [56, 57, 58, 59, 60, 75, 76, 143, 331, 422]
- Problems formulated as multiobjective shortest path problems, or where these appear as subproblems: [4, 250, 253, 256, 357]

¹Any nondominated objective vectors.

²Weights are time-dependent nonnegative functions

6.2. The Assignment Problem

The multiobjective assignment problem is the following

$$\begin{aligned}
 & \text{“min”} \quad Cx \\
 & \text{subject to} \quad \sum_{j=1}^n x_{ij} = 1 \quad i = 1, \dots, n \\
 & \quad \quad \quad \sum_{i=1}^n x_{ij} = 1 \quad j = 1, \dots, n \\
 & \quad \quad \quad x_{ij} \in \{0, 1\}
 \end{aligned} \tag{MOAP}.$$

Total unimodularity of the constraint matrix guarantees that an optimal integer solution is found by linear programming methods, when only a single objective is considered. With the Hungarian method (see e.g. [279]), a very efficient algorithm is available.

The (MOAP) literature is again focussed on the determination of (supported) efficient solutions. In fact, (MOAP) belongs to the first MOCO problems studied. However, the first papers only deal with *SE*, using convex combinations of objectives [69], or goal programming [36]. However, nonsupported efficient solutions exist [399], and the problem is *NP*-complete [347] and *#P*-complete [283] and an exponential number of efficient solutions may exist.

Exact algorithms to determine the whole set *E* [247, 399] have been developed. They make use of single objective methods and duality properties of the assignment problem. Recently we can also observe the application of metaheuristic techniques for the problem [394]. Quite a few papers deal with a special version of the problem: [19, 36, 419]. Other papers deal with variations of the problem or applications. These cannot really be classified according to the problem and methodology applied or discussed in detail. We list them separately.

- AP/2- Σ /SE/SP: [69]
- AP/2- Σ /E/2P,SP: [247, 396, 399]
- AP/2- Σ / \widehat{E} /SA: [394]
- AP/2- Σ /lex/SP: [302]
- AP/2- Σ /C/IA: [300]
- AP/4- Σ /SE/SP: [265]
- AP/Q- Σ /E/SP: [343]

- AP/ Q - \sum/\widehat{E} /SA: [382]
- AP/ Q - \sum /S/GP: [36, 362]
- AP/ Q - \sum /C/IA: [133]
- AP/ 1 - \sum 1-max, 2-max/ E , $SE/\varepsilon C$: [259, 260, 263]
- AP/ 1 - \sum 2-max, 3-max/ E , $SE/\varepsilon C$: [262, 263]
- Papers related to assignment models: [9, 13, 14, 19, 181, 225, 230, 235, 257, 258, 276, 298, 299, 419, 425]

6.3. Transportation and Transshipment Problems

Both are generalizations of the assignment problem, where the right hand side of the constraint may take positive integer values, and the variables any nonnegative integer. The transshipment problem has transshipment nodes in addition to demand and supply nodes. The transportation problem is given below.

$$\begin{array}{ll}
 \text{"min"} & Cx \\
 \text{subject to} & \sum_{j=1}^n x_{ij} = a_i \quad i = 1, \dots, m \\
 & \sum_{i=1}^m x_{ij} = b_j \quad j = 1, \dots, n \\
 & x_{ij} \geq 0, \text{ integer.}
 \end{array} \tag{MOTP}$$

The transshipment problem has transshipment nodes in addition to supply and demand nodes. Again, in the single objective case total unimodularity and integer right hand sides imply that an optimal solution of the linear relaxation is also an optimal solution of the problem itself. Making use of this fact, most of the papers use a scalarization by means of weighted sums or goal programming approaches.

- TP/ 2 - \sum / SE /LP: [7, 364]
- TP/ 1 - \sum 1-max/ SE /LP: [7, 82, 309, 363]
- TP/ 1 - \sum 1-max/S/GP: [233]
- TP/ Q - \sum / se , S/IA: [42, 319]
- TP/ Q - \sum / SE /LP: [77, 78, 184, 352]

- TP/ Q - \sum / SE /DP: [123]
- TP/ Q - \sum /S/SP: [67]
- TP/ Q - \sum / \hat{E} /GA: [130, 131]
- TS/ Q - \sum /S/GP: [219, 220, 270, 368]
- TP/ Q - \sum /C/SP: [236]
- TP/ Q - \sum /C/Fuzzy: [101]
- Other related problems and applications: [8, 203, 206, 224, 234, 287, 301, 314, 376, 378, 395]

6.4. Network Flow Problems

The network flow problem is a problem that actually is on the borderline between combinatorial and linear optimization. Its formulation is

$$\begin{array}{ll}
 \text{“min”} & Cx \\
 \text{subject to} & Ax = 0 \\
 & l \leq x \leq u,
 \end{array} \quad (\text{MOFP})$$

where A is the node-arc incidence matrix of a network. It is well known that with a single objective there always exist integer optimal solutions of the LP, due to the unimodularity of A , which is the reason for considering it a combinatorial problem.

In the multiobjective case we have to distinguish between the linear and the integer case. In the linear case, we know that $SE = E$. We deal with the papers in their relevance for the integer case. [324] demonstrated that an exponential number (in the number of node of the network) of extreme points among SE may occur. Most of the algorithms in the literature generalize methods for the single objective flow problem, e.g. the out-of-kilter method [227, 248] or elements from network simplex [31, 305, 345]. The algorithms for MO and lexMO problems [88, 146] are based on ranking approaches. For linear bicriteria network flow problems algorithms approximating the efficient set to any given precision ϵ are presented in [27, 121, 325] and generalized to bicriteria quadratic network flow problems in [423].

- F/2- \sum / SE /SP: [202, 227, 248, 305]
- F/2- \sum / SE /LP: [345]

- $F/2-\sum/\widehat{SE}/A$: [27, 121, 325, 328]
- $F/2(3)-\sum/E/SP$: [109, 173, 226, 228, 281, 282, 346]
- $F/Q-\sum/SE/SP$: [202]
- $F/Q-\sum/E/SP$: [88]
- $F/Q-\sum/lex/SP$: [30, 31]
- $F/Q-\sum/MO/SP$: [146]
- $F/Q-\sum/lexMO/SP$: [88]
- $F/Q-\sum/C/IA$: [108, 111]
- Other network flow problems: [8, 203, 253, 280, 315, 423]

6.5. The Spanning Tree Problem

The spanning tree problem is to find among all spanning trees of a given graph one that is “minimal” with respect to the edge weights. This problem appears in network design. It is known that the problem to find efficient solutions is *NP*-complete [32] and intractable [149]. *NP*-completeness also holds for the max-ordering problem [149]. The complexity status of a variety of multiobjective spanning tree problems, involving other than the typical sum and bottleneck objectives is studied in [32, 72, 73]. The algorithms that have been proposed to find efficient trees range from minimizing weighted sums [308, 341, 342] over generalizations of Prim’s [49] and Kruskal’s [342] method to approximation [149] and genetic algorithms [426]. A counterexample to a sufficient condition for a spanning tree to be efficient [49] has been given in [149]. As far as local search methods are concerned, it is important to note that, defining trees to be adjacent if they have $n - 2$ edges in common, can imply that the set of efficient spanning trees is not connected [92].

- $ST/2-\sum/SE/SP$: [149]
- $ST/1-\sum 1\text{-max}/SE/SP$: [308]
- $ST/2-\sum/E/2P,SP$: [310]
- $ST/2-\sum/\widehat{E}/H$: [6, 149]
- $ST/Q-\sum/SE/SP$: [341, 342]
- $ST/Q-\sum/E/SP$: [49]

- ST/Q- \sum/\widehat{E} /GA: [426]
- ST/Q- \sum /MO/SP: [149]
- ST/1- \sum 1-max, 2-max/E, SE/ ϵ C: [259, 260, 263]
- ST/1- \sum 2-max, 3-max/E, SE/ ϵ C: [262, 263]
- Other spanning tree problems with different objectives: [72, 73, 177, 178, 344]

6.6. Matroids and Matroid Intersections

The matroid base problem is a generalization of the spanning tree problem. With a single objective it can be solved by the greedy algorithm. A generalization of this result for finding efficient bases is given in [347]: For each efficient basis B , there exists a topological sorting of the elements (e.g. edges of a graph), such that the greedy algorithm finds B . A topological sorting is a total or linear order that respects the partial order given by the vector weights. The problem is *NP*-complete, as was shown e.g. in [84, 347]. A matroid intersection problem is to find a set of minimal weight which is independent with respect to two matroids.

Few papers deal with these problems in the multiobjective case. We identified the following, mostly presenting exact algorithms, theoretical properties [137, 414], and complexity issues [84, 347].

- MB/2- \sum /SE, E/SP: [84, 347]
- MI/Q- \sum , 1-max 1- \sum /Lex/SP: [427]
- MB/Q- \sum /MO/SP: [84, 137]
- MB/Q- \sum / \widehat{MO} /H: [414]

6.7. The Travelling Salesperson Problem

In combinatorial optimization, the TSP is widely studied. To find a shortest tour among n cities is *NP*-complete even with one objective, for both the sum and bottleneck case. Moreover, the number of efficient solutions is expected to be exponential, see [103]. For approximation results, we refer to [89], where limits on the possibility of approximating efficient solution by one heuristic solution are derived and generalizations of the tree and Christofides heuristic are analyzed.

These might be reasons why investigation of the multiobjective version is not so common, and why research concentrates on exact algorithms

based on dynamic programming as well as heuristics. Some papers discuss special versions or generalizations of the TSP, such as various formulations of vehicle routing problems.

- TSP/1- \sum 1- Π^3 /E/DP: [112]
- TSP/1- \sum 1-max/ \widehat{SE} /H [353]
- TSP/1- \sum 1-max/E, $SE/\varepsilon C$ / [261]
- TSP/2,3- \sum / \widehat{E} /GA: [188]
- TSP/3- \sum /E/SP: [24]
- TSP/Q- \sum /E/DP: [391]
- TSP/Q- \sum / \widehat{E} /A: [89]
- TSP/Q- \sum / \widehat{E} /TS: [155]
- TSP/Q- \sum / \widehat{MO} /H: [141]
- TSP/3- \sum , 4- \sum / \widehat{E} /SA: [192]
- Other versions of the problem, e.g. vehicle routing (VRP): [56, 135, 170, 196, 197, 292, 293, 294, 375]

6.8. Knapsack Problems

The knapsack problem is one of the fundamental *NP*-complete combinatorial optimization problems. Its multiobjective formulation is

$$\begin{aligned} & \text{“min”} \quad Cx \\ & \text{subject to} \quad \sum_{i=1}^n a_i x_i \leq b \\ & \quad \quad \quad x_i \in \{0, 1\}, \end{aligned} \tag{MOKP}$$

where all parameters are assumed to be positive integers. All papers that we found deal with the problem to identify or approximate SE or E . Finding E or SE are obviously *NP*-complete, too. Thus it is not surprising that the algorithms proposed are either based on implicit enumeration methods such as dynamic programming [81, 199, 200, 201], branch and bound [396, 400] or apply heuristic procedures, especially

³ Π denotes an objective defined by the products of weights.

metaheuristics to approximate E [125, 153, 328, 329]. Recently a polynomial time approximation scheme was developed in [107]. Some papers also deal with an extension to time-dependent knapsack problems [200, 201]. An interactive decision support system for the capital budgeting problem is proposed in [383]. Metaheuristics have been used to solve multi-constraint knapsack problems [189, 432].

- KP/1- \sum 1-max/SE/BB: [264]
- KP/2- \sum /SE/SP: [321]
- KP/2- \sum /SE/DP: [81]
- KP/2- \sum /E/DP: [33]
- KP/2- \sum / \widehat{SE} /H: [321]
- KP/2- \sum /E/2P,BB: [396, 400, 413]
- KP/2- \sum / \widehat{E} /TS: [125]
- KP/2- \sum / \widehat{E} /H: [329]
- KP/2- \sum / \widehat{E} /H: [328]
- KP/2- \sum / \widehat{E} /GA+TS: [2]
- KP/2- \sum / \widehat{e} /SA+TS: [5]
- KP/2- \sum / \widehat{E} /GA: [127]
- KP/Q- \sum /E/DP: [199, 200, 201]
- KP/Q- \sum / \widehat{E} /A: [107]
- KP/Q- \sum / \widehat{E} /TS: [153, 154]
- KP/Q- \sum / \widehat{E} /SA: [64, 382, 401, 402]
- KP/Q- \sum /SE/IA: [80]
- KP/Q- \sum /U/DP: [38]
- KP/Q- \sum /S/GP: [22, 71, 150, 195]
- KP/Q- \sum / \widehat{E} /IA+GA: [291]

6.9. Multiobjective Scheduling Problems

The scheduling problems constitute a particular category. Although these problems can often be formulated using 0-1 variables, they have generally no particular structure. Moreover, they have a usual classification defined according the shop organization which they refer to (single machine, parallel machines, flow shop, job shop, open shop, etc.). Also, the usual objective functions in scheduling have a specific sense (the makespan, the total flow time, the tardiness, etc.).

For example we look at [212]. Let us consider n jobs to be processed on a single machine at time zero. Let p_i and d_i denote the processing time and the due date of job i respectively. Let

$$\begin{aligned} J_i &: \text{job } i, i = 1, \dots, n \\ C_i(\sigma) &: \text{completion time of job } i \text{ in schedule } \sigma \\ F(\sigma) &: \text{total flowtime of jobs in schedule } \sigma \\ T_{max}(\sigma) &: \text{maximum tardiness of schedule } \sigma \\ \Omega &: \text{set of all possible sequences.} \end{aligned}$$

Then the objective is to find a schedule σ^* such that

$$f(F(\sigma^*), T_{max}(\sigma^*)) = \min_{\sigma \in \Omega} f(F(\sigma), T_{max}(\sigma)),$$

where

$$F(\sigma) = \sum_{i=1}^n C_i(\sigma), \quad T_{max}(\sigma) = \max_i \{\max(C_i(\sigma) - d_i, 0)\}$$

and f is any arbitrary nondecreasing function of $F(\sigma)$ and $T_{max}(\sigma)$.

This problem is denoted by $1/d_i/f(\sum C_i, T_{max})$. A sequence σ is efficient with respect to total flowtime and maximum tardiness if there does not exist a sequence σ' with $F(\sigma') \leq F(\sigma)$ and $T_{max}(\sigma') \leq T_{max}(\sigma)$ with at least one of the above holding as a strict inequality.

We observe a constant interest on multiobjective scheduling problems during the last years, because the consideration of more than one objective is more in line with the real context of such practical problems. In a recent survey [388] and Chapter 7.3 more than one hundred papers are classified according to the usual notation introduced by Graham and extended by T'Kindt and Billaut to the multiobjective case. Also, the approximate resolution algorithms for scheduling problems and related problems (like [161, 209, 271, 379, 410]) often are inspired by multiobjective metaheuristic methods developed for MOCO problems. For these

reasons, we mention actual developments for this category of problems but for more details about multiobjective scheduling problems we refer to Chapter 7.3 and [37, 171, 385, 388].

- Single machine problems:
 - [12, 207, 208, 212, 213, 417], (SCH/2/ \hat{E} /SA);
 - [209, 271, 328] (SCH/2/ \hat{E} /GA);
 - [379] (SCH/Q/ \hat{E} /GA);
- Multiple machine problems: [25, 175, 269, 336, 386, 389];
- Surveys: [387, 388];
- PhD theses: [171, 385];
- Papers on other scheduling or production management problems: cell formation problem (SCH/Q/CS/TS) [168] and resource constrained project scheduling (SCH/Q/ \hat{E} /SA,TS) [410].

6.10. Location Problems

Location planning is an active area of research. The objective in a location problem is to find one (or more) locations, such that some objective, usually related to the distance to a set of existing facilities is minimized or maximized. These objectives usually are the weighted sum or maximum of individual distances. Moreover, location problems can be divided into three categories, namely planar, network and discrete problems. In planar location, the feasible set is (a subset of) the Euclidean plane. Network location problems deal with a network of nodes and arcs, new facilities can be built either on the nodes only, or also on arcs. Finally, for discrete location problems a set of potential sites is specified. Problems of the latter category are usually formulated as mixed integer programs. From the point of view of MOCO, we will consider only network and discrete location problems. For details about planar problems and single objective location problems, we refer to the specialized literature, e.g. [222, 221] for surveys. We refer also to two reviews on the topic in MOCO context, [55] and [317]. Most of the applications use a goal programming approach.

- NL/1- \sum , 1-max/ E /SP: [412]
- NL/2- \sum / E /SP: [357]
- NL/Q- \sum /lex, E /SP: [147]

- NL/ Q - \sum / E , SE /SP,IA: [322]
- NL/ Q - \sum / E /SP: [158]
- NL/ Q - \sum , Q -max/ E /SP: [148]
- NL/ Q - \sum /MO,lexMO/SP: [94]
- DL/ Q - \sum , Q -max/ E /SP: [286]
- DL/ Q - \sum / E /DP: [304]
- DL/ Q - \sum / SE /SP: [245]
- DL/ Q - \sum /lexMO/SP: [285]
- DL/ Q - \sum /U,S/IA,GP: [246]
- DL/ Q - \sum /S/GP: [15]
- Warehouse location: [99, 139, 232]
- Others and applications: [169, 176, 211, 231, 288, 318, 323, 339, 340, 359]

6.11. Set Covering and Partitioning Problems

The set covering problem is concerned with selecting subsets of a set that cover all elements of the set at minimal cost. The variables are binary variables for each subset that may be chosen. Thus, the IP formulation of this *NP*-complete problem is given as follows:

$$\begin{aligned}
 & \text{“ min ” } Cx \\
 & \text{subject to } \sum_{i=1}^n a_{ji}x_i \geq 1 \quad j = 1, \dots, m \\
 & \quad x_i \in \{0, 1\},
 \end{aligned}
 \tag{MOSCP}$$

where $a_{ji} = 1$ if element j is contained in subset i , and all coefficients of C are assumed positive.

The SCP has applications in the location of emergency facilities. Suppose there are m sites of potential emergency and n potential locations for emergency facilities, incurring cost c_i to build this site. Then the aim is to select – at minimal cost – enough sites to cover all risks.

The multiobjective set partitioning problem (MOSPA) requires equality constraints and the multiobjective set packing problem “ \leq ” constraints (MOSPP). Other applications of set covering and set partitioning problems arise in scheduling and rostering.

(MOSCP) and (MOSPA) have not gained much attention in the literature, and we found no references for (MOSPP). The main results in one of the references [333] are wrong. [164] deals with a particular problem. Note also that some of the problems discussed in the shortest path section 6.1 above and in the other MOCO problems section 6.12 below deal with aspects of “covering”.

- SCP/ Q - \sum / E /SP: [333]
- SCP/ Q - \sum / SE /SP: [68]
- SCP/3- \sum / S /GP: [40]
- SPA/2- \sum / $E/\varepsilon C, BB$: [95]
- Others: [144, 334]

6.12. Other MOCO Problems

In the previous sections we have discussed the most important multiobjective combinatorial optimization problems. Besides these there is some literature on other problems: Some classical problems have been discussed only in a few papers, others deal with problems that are so specific that they would require their own category. All of these are discussed summarily here.

In [145] a lexicographic flow problem is used to determine minimal cuts with a minimal number of arcs in a network. [354] deals with the one dimensional cutting stock problem with two objectives in a lexicographic context (priorities on the objectives). Both an exact and a heuristic algorithm are given. In [210] a branch and bound procedure to find all Pareto-optimal solutions is given, and [39] use a combination of objectives. In [1] an interactive approach is proposed to solve the multiobjective cutting stock problem.

We also found few references [185, 243] on the quadratic assignment problem (QAP) in a multicriteria context. This is closely related to the facility layout problem which is discussed in a number of papers. They actually propose approaches based on the quadratic assignment problem: [79, 115, 242, 320, 404]. Other references on the facility layout problem (FLP) are [185, 217, 350, 416]

Many of the papers listed in the surveys [53] and [54] about multiobjective transportation and routing problems also are among these specific problems. A variety of multiobjective routing problems is also discussed in [23], [100], and [135]. For network design problems we refer to [116, 117, 118, 119, 120, 129, 180, 186, 239, 284, 297]. Another problem which is combinatorial in nature has been discussed in [66]

(the channel minimization problem). In [273] a GA based heuristic is proposed to solve an extended formulation of the nominal airline crew rostering problem with two objectives.

The problem of minimizing several functions over the set of all permutations of a finite set is discussed in [104].

[28] presents a two step approach for a multicriteria timetabling problem. First, high quality timetables are generated with respect to each criterion separately. Second a compromise solution is searched. In [29], a hybrid heuristic using a population is described. Results are reported for a real instance of a biobjective space allocation problem.

[259] considers, among others 1-tree problems with one sum and one bottleneck objective or two bottleneck objectives. 1-trees are important as relaxations of the TSP. A 1-tree is a spanning tree on nodes $2, \dots, n$ together with two edges incident on node 1.

7. Open Questions and Conclusions

Our survey of the state of the art in multiobjective combinatorial optimization clearly identifies potential areas of research and weak points in the existing literature. We briefly outline these below.

7.1. General Remarks

- (a) Three is more than two plus one. Many of the existing methods concern the biobjective case (to various extents, depending on the problem). The multiobjective case is still hard to be solved, not only due to the computational complexity, but also due to the higher number of more efficient solutions of the MOCO problem.
- (b) Theoretical results. Very few theoretical results are available about the properties of MOCO problems, like characterization of efficient solutions, the number of efficient solutions (supported and nonsupported) both in the worst case or on average, the topology of the nondominated frontier, the elicitation of lower and upper bounds, etc. Taking into account the fact that MOCO problems are almost always very hard in terms of computational complexity the need for a thorough theoretical understanding of MOCO problems is all the more evident. It is also clear that a better theoretical comprehension of these problems will contribute to the development of efficient solution methods.
- (c) Adaptation of well known methods versus new methods. Many of the current extensions of methods useful for single objective optimization to the multiobjective situation have exhibited some diffi-

culties for finding E . One such example is the the VEGA method. MOCO problems have specific properties and need specific techniques to cope in an efficient way with these. Some adaptations such as MOSA, PSA, etc. could produce good results on a particular problem like the knapsack problem. The question is, whether such method show good performance when applied to other problems. From the evolution of these methods over the last years, one can have some doubts. No comparative studies on the performance of solution strategies like branch and bound or dynamic programming on a variety of problems are available.

- (d) Applications of MOCO. Few papers refer to practical application of MOCO problems. Moreover, when the MOCO problem is extracted from a practical context, the resolution is often reduced to a single objective problem. For example, this is the case to the channel minimization problem of [66], but also for a lot of scheduling problems (see [385]). Thus there is a need to attract the attention of decision makers to the area of MOCO and solve the problems arising in practice in a real multicriteria context.

7.2. Remarks on Exact Methods

- (a) Two versus many criteria. Especially for exact methods, i.e. those identifying the whole of E there is a huge gap between the bicriteria and the general case. Many procedures have been developed especially for bicriteria problems and cannot be modified to deal with the general case, a remark that is especially true for the two phases method. This gap is probably caused by the lack of theoretical understanding of MOCO problems with three or more objectives, as pointed out above.
- (b) The two phases approach. As far as we know there are no procedures to compute supported efficient solutions in the multiobjective case. This would be of course the first step to an application of the two phases method in three or more criteria MOCO. Some difficulties are pointed out in [96] for max-ordering problems and in [360] for finding supported efficient solutions.
- (c) Computation of bounds. For the effective adaptation of some bicriteria methods to the general case, knowledge of good lower and upper bounds on the efficient set is needed. The computation of the Nadir point (which is pretty easy in bicriteria problems) is an unsolved problem in general. Another research area would be to consider the computation of sets of solutions that constitute a set

of lower and upper bounds on E . The lack of such results makes it impossible to adapt certain procedures to general MOCO at this time. Some preliminary results are presented in [90].

- (d) Problems not treated as MOCO. There is a wide variety of combinatorial problems that have not or hardly ever been investigated in a multicriteria context, as is evident from the problems list in Section 6.
- (e) Level set approach. An important concept in MOP is that of level sets. It can be seen as a general framework for MOP, which allows a characterization of efficient solutions [91], as well as interactive procedures. Applications to MOCO could be promising but are not existing now.

7.3. Remarks on Heuristic Methods

- (a) A real multiobjective metaheuristic for MOCO. Closely related to the remark about adaptation of single objective methods is the question of multiobjective metaheuristics to solve MOCO problems. We are not convinced of the efficiency of a real metaheuristic in the sense of a meta-method able to solve efficiently any MOCO. Each problem has its own specifics and a general MOMH cannot cope with all of these.
- (b) Methods for obtaining quickly a first approximation of E . If a heuristic method defined according to the “a posteriori mode” is available, it is easy and always possible to transform it to the “interactive mode”. The main challenge for heuristic methods is then how to obtain very quickly a good approximation of the whole nondominated frontier. With such an approximation, the procedure could then be to continue either in increasing the approximation quality for the nondominated frontier or in focusing the approximation on a part of the nondominated frontier following the preference of a decision maker in the context of an interactive procedure.
- (c) The quality of approximated solutions. This is an important question in the context of approximation methods: How to measure and compare approximations, and how to evaluate the quality of an approximation, especially for problems with multiple objectives? Ideas have been put forward in [156, 335, 394, 198]. Some attributes like coverage, uniformity and cardinality to judge the approximation to be satisfactory or not by a decision maker have

been defined. Such attributes are also useful when defining stopping rules in approximation methods, and again when the tuning of heuristic algorithms is examined. New attributes are then especially welcome.

- (d) Using bounds and domination conditions to reduce the search space. In the continuation of the previous remark, all available information to bracket and reduce the decision space is welcome. Such information could be used for scanning the “core” of the problem, identifying and discarding irrelevant aspects of the problem investigated. Information could be derived from the decision space as well as from the objective space.
- (e) Combination of exact and heuristic methods. For some MOCO problems, the resolution could be decomposed in several steps. For example, in a first step the procedure could try to identify the supported efficient solution using an exact method. Information could be extracted from the first results to reduce the search space and in a second step try to identify the nonsupported solutions by a heuristic method. Such a “semiexact” method is especially attractive for problems that can be efficiently solved as single objective combinatorial problems.

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