Guest Editorial: Special Issue on Evolutionary Multiobjective Optimization

MOST problems in nature have several objectives (normally conflicting with each other) that need to be achieved at the same time. These problems are called "multiobjective," "multicriteria," or "vector" optimization problems, and were originally studied in the context of economics. However, scientists and engineers soon realized the importance of solving multiobjective optimization problems, and the development of techniques to deal with such problems became an important area within operations research.

Because of the conflicting nature of their objectives, multiobjective optimization problems do not normally have a single solution and, in fact, they even require the definition of a new notion of "optimum." The most commonly adopted notion of optimality in multiobjective optimization is that originally proposed by Edgeworth [5] and later generalized by Pareto [13]. Such a notion is called *Edgeworth-Pareto optimality* or, more commonly, *Pareto optimality*.

Then, in multiobjective optimization the aim is to find a set of solutions called the *Pareto optimal set*. The vectors corresponding to the solutions included in the Pareto optimal set are called *nondominated*. The image of the Pareto optimal set under the objective functions is called *Pareto front*.

Over the years, operations researchers have developed an important number of techniques to deal with multiobjective optimization problems of any type (e.g., combinatorial, numerical, linear, nonlinear, etc.) [12]. These techniques, however, normally require an initial search point and only generate a single nondominated solution per run. These methods are also susceptible to the shape or continuity of the Pareto front and, therefore, their applicability may be severely limited in many real-world applications.

This context gives the main motivation for using evolutionary algorithms for solving multiobjective optimization problems. First, evolutionary algorithms use a population and, therefore, they allow the generation of several members of the Pareto optimal set in a single run. Additionally, evolutionary algorithms are less susceptible to the shape or continuity of the Pareto front and do not require an initial search point defined by the user (the initial population can be randomly generated).

The first implementation of a multiobjective evolutionary algorithm (MOEA) dates back to the mid-1980s [16], [17], but it was not until the mid-1990s that the field now called "evolutionary multiobjective optimization" started to take shape. Important algorithms were designed at that time, from which it is worth mentioning the Multi-Objective Genetic Algorithm (MOGA) [6], the Nondominated Sorting Genetic Algorithm (NSGA) [18], and the Niched–Pareto Genetic Algorithm (NPGA) [11]. Concerns about test functions and metrics that could allow a quantitative comparison of approaches came later [2], [20], [21], [4]. On the other hand, other important aspects, such as the theoretical foundations of MOEAs, have received little attention until recently [14], [15], [7], [8], [9].

During the last few years, the amount of research in this field has experienced an important growth [1].[1] The growing interest in evolutionary multiobjective optimization has allowed the organization of special sessions at international conferences and even a (more specialized) *Conference on Evolutionary Multi-Criterion Optimization*, which celebrates its second year, in Portugal in 2003[2] after the success of the first conference, which was held in Zurich in 2001 [22].

This Special Issue contains seven papers. The first contribution, by Knowles and Corne, addresses the implementation of external archives to store nondominated vectors found throughout the evolutionary process. The use of external archives has become a popular practice in the last few years since Horn's suggestion [10] and after the success of the Strength Pareto Evolutionary Algorithm (SPEA) [24]. However, very few researchers have studied the different issues associated with the implementation of a secondary memory for an MOEA (e.g., how to decide what nondominated vectors must be retained and which can be eliminated). Knowles and Corne provide an in-depth study of archiving algorithms for use in MOEAs and analyze several related concepts such as convergence and spread of points.

The performance assessment of MOEAs has been a critical issue that has worried researchers since the origins of the field (when only graphical comparisons were normally used to compare MOEAs). Several metrics have been proposed in the literature, but most of them have been found to be misleading under certain conditions [19], [1]. The second paper, by Zitzler *et al.*, provides a formal framework that allows the authors to perform a rigorous analysis and classification of performance assessment measures for MOEAs. As part of this study, several current metrics are classified and analyzed, identifying their limitations and incompatibilities with each other.

The third paper, by Jaszkiewicz, also refers to performance assessment, but from a more pragmatic point of view. The study presented here compares single and multiobjective evolutionary algorithms, and single and multiobjective memetic algorithms.

[1]See the EMOO repository (which contains over 1100 bibliographical entries). [Online] Available: http://delta.cs.cinvestav.mx/~ccoello/EMOO, with mirrors at http://www.lania.mx/~ccoello/EMOO/ and http://www.jeo.org/emo/.

[2][Online] Available: http://conferences.ptrede.com/emo03/main.py/index.

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The main rationale behind this comparative study is the claim by the author regarding the importance of ensuring that an MOEA is competitive with a single objective evolutionary algorithm, both in terms of quality of solutions and computational efficiency. To allow such an assessment, the author proposes a methodology which he applies to the set-covering problem.

Van Veldhuizen *et al.* provide in the fourth paper a detailed discussion of parallel and distributed MOEAs which covers issues such as design and implementation, suitability, hardware and software, and testing. The authors also discuss innovative concepts regarding migration and replacement and niching in parallel MOEAs. Some important development guidelines and even a small performance assessment study (using the multiobjective knapsack problem) complement this paper, which should be considered a good starting point for anyone wishing to design and/or use parallel MOEAs.

The fifth paper, by Bosman and Thierens, deals with one of the several dilemmas that characterizes this field: how to balance closeness to the true Pareto front with good spread of points when designing an MOEA. The authors argue that this balance is really a nonrealistic design goal, because it turns out to be multiobjective as well! The possible multiobjective nature of these two issues (diversity and proximity to the Pareto front), however, does not invalidate the current research efforts in the field, but instead suggests that new algorithmic frameworks may be required. In fact, the authors suggest a possible multiobjective algorithmic framework and include an example of its use.

The sixth paper, by Weicker *et al.*, describes a novel application of MOEAs: the positioning of base station transmitters of a mobile phone network assigning frequencies to the transmitters. The authors propose a new MOEA which is found to be competitive with respect to the NSGA-II [3] and SPEA2 [23] in a real world problem.

Last, but not least, the paper by Ishibuchi *et al.*addresses the importance of hybridizing genetic and local search to improve the performance of a MOEA in the context of multiobjective combinatorial optimization. The critical balance between genetic and local search is analyzed and a comparative study is performed, using flowshop scheduling problems.

The papers in this Special Issue are representative of the state-of-the-art in the field and are indicative of the research trends that will be followed in the years to come. It is expected that the contents of this Special Issue, as well as the many other ongoing activities in the field, will motivate researchers and students to enter this exciting research discipline. Being a young research area, evolutionary multiobjective optimization still has many opportunities to offer to newcomers, making it fertile land for new contributions for those who may be interested.

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