Chapter 15
Comprehensive Survey of the Hybrid Evolutionary Algorithms

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ABSTRACT

Multiobjective evolutionary algorithm based on decomposition (MOEA/D) and an improved non-dominating sorting multiobjective genetic algorithm (NSGA-II) are two well known multiobjective evolutionary algorithms (MOEAs) in the field of evolutionary computation. This paper mainly reviews their hybrid versions and some other algorithms which are developed for solving multiobjective optimization problems (MOPs. The mathematical formulation of a MOP and some basic definitions for tackling MOPs, including Pareto optimality, Pareto optimal set (PS), Pareto front (PF) are provided in Section 1. Section 2 presents a brief introduction to hybrid MOEAs. The authors present literature review in subsections. Subsection 2.1 provides memetic multiobjective evolutionary algorithms. Subsection 2.2 presents the hybrid versions of well-known Pareto dominance based MOEAs. Subsection 2.4 summarizes some enhanced Versions of MOEA/D paradigm. Subsection 2.5 reviews some multimethod search approaches dealing optimization problems.

1. INTRODUCTION

A multiobjective optimization problem (MOP) can be stated as follows:[1]

minimize $F(x) = (f_1(x),..., f_m(x))^T$ (1)

subject to $x \in \Omega$

where Ω is the decision variable space, $x = (x_1, x_2,..., x_n)^T$ is a decision variable vector and x_i, i =1.... n are called decision variables, $F(x)$: $\Omega \rightarrow R^m$ consist of m real valued objective functions and R^m is called the objective space.

If Ω is closed and connected region in R^n and all the objectives are continuous of x, a problem (1) is said to be a continuous MOP.

Very often, the objectives of the problem (1) are in conflict with one another or are incommensurable. There doesn't exist a single solution in the search space Ω that can minimize all the objectives functions simultaneously. Instead, one has to find the best tradeoffs among the objectives. These tradeoffs can be better de-fined in terms of Pareto optimality. The Pareto optimality concept was first introduced by eminent economists Pareto and Edgeworth (Edgeworth, 1881). A formal defi-

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nition of the Pareto optimality is given as follows (Coelle Coello, Lamont, & Veldhuizen, 2002); (Deb, 2002); (Deb, 2001); (Miettinien, 1999):

Definition: Let $u = (u_1, u_2,..., u_m)^T$ and $v = (v_1, v_2,..., v_m)^T$ be any two given vectors in R^m. Then u is said to dominate v, denoted as $u \prec v$, if and only if the following two conditions are satisfied.

1. $u_i \leq v_i$ for every$i \in \{1, 2,..., m\}$
2. $u_j < v_j$ for at least one index $j \in \{1, 2,..., m\}$.

Remarks: For any two given vectors, u and v, there are two possibilities:

1. Either u dominates v or v dominates u
2. Neither u dominates v nor *does v dominate u*.

Definition: A solution $\mathbf{x}^* \in \Omega$ is said to be a Pareto Optimal to the problem (1) if there is no other solution $x \in \Omega$ such that $F(x)$ dominates $F(x^*)$. $F(x)$ is then called Pareto optimal (objective) vector.

Remarks: Any improvement in a Pareto optimal point in one objective must lead to deterioration in at least one other objective.

Definition: The set of all the Pareto optimal solutions is called Pareto set (PS): $PS = \{x \in \Omega, F(y) \prec F(x)\}$

Definition: The image of the *Pareto optimal set (PS)* in the objective space is called *Pareto front (PF)*, $PF = \{F(x)|x \in PS\}$.

Weight Sum Approach: the weighted sum of the m objectivists is defined as $g^{ws}(x, \lambda) = \lambda^1 f_1(x) + \lambda^2 f_2(x) +... + \lambda^m f_m(x)$, where $\sum_{j=1}^{m} \lambda^j = 1$ and $\lambda^j \geq 0$.

In other words, a set of all Pareto optimal solutions form a tradeoff surface in the objective space. The basic definitions of dominance and Pareto optimality played an important role in the development of effective MOEAs. However, in MOP, Pareto domination does not define a complete ordering among the solutions in the objective space. Secondly, it does not measure that how much one solution is better than another one. There are some other definitions of optimality such as: strong and weak Pareto domination (Deb, 2002), fuzzy domination (Talukder, Kirley, & Buyya, 2008), -domination (Laumanns, Thiele, Deb, & Zitzler, 2002), cone-domination (Collette & Siarry, 2003), etc. All these mentioned definitions are also used in various MOEAs and cab found in the existing literature of the evolutionary multiobjective optimization.

Recent years have witnessed significant development in MOEAs for dealing MOPs. In last two decades, a variety of MOEAs have been proposed. The success of most MOEAs depends on the careful balance of two conflicting goals, exploration (i.e., searching new Pareto-optimal solution) and exploitation (i.e., refining the obtained PS). To achieve these two goals, hybridization is good strategy (Ishibuchi, Yoshida, & Murata, 2003). The following section introduces hybrid algorithms.

2. HYBRID MULTIOBJECTIVE EVOLUTIONARY ALGORITHMS

Hybrid MOEAS or combination of MOEAs with efficient techniques have been investigated for more than one decade (Knowles & Corne, 2005). Hybridization uses desirable proper-ties of different techniques for better algorithmic improvements. Hybridization can be done in several ways:

1. To use one algorithm to generate a population and then apply another technique to improve it,
2. To use multiple operators in an evolutionary algorithm, and
3. To apply local search to improve the solutions obtained by MOEAs (Thangaraj, Pant, Abraham, & Bouvry, 2011).

Multiobjective memetic algorithms (MOMAs) is a special type of hybrid MOEAs. MOMAs arepopulation based algorithms inspired by the