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IT-CEMOP: An iterative co-evolutionary algorithm for multiobjective optimization problem with nonlinear constraints

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Abstract

Over the past few years, researchers have developed a number of multiobjective evolutionary algorithms (MOEAs). Although most studies concentrate on solving unconstrained optimization problems, there exit a few studies where MOEAs have been extended to solve constrained optimization problems. Most of them were based on penalty functions for handling nonlinear constraints by genetic algorithms. However the performance of these methods is highly problem-dependent, many methods require additional tuning of several parameters.

In this paper, we present a new optimization algorithm, which is based on concept of co-evolution and repair algorithm for handling nonlinear constraints. The algorithm maintains a finite-sized archive of nondominated solutions which gets iteratively updated in the presence of new solutions based on the concept of ε-dominance. The use of ε-dominance also makes the algorithms practical by allowing a decision maker to control the resolution of the Pareto set approximation by choosing an appropriate ε value, which guarantees convergence and diversity. The results, provided by the proposed algorithm for six benchmark problems, are promising when compared with exiting well-known algorithms. Also, our results suggest that our algorithm is better applicable for solving real-world application problems.

Keywords: Multiobjective nonlinear programming; Multiobjective evolutionary algorithms; Genetic algorithms; ε-Dominance

1. Introduction

When attempting to optimize a decision in industrial and scientific applications, the designer is frequently faced with the problem of achieving several design targets, some of which may be conflicting and noncommensurable and wherein a gain in one objective is at the expense of another. This problem can be generally reduced to multiobjective optimization problems (MOPs) in operational description, which has been in the spotlight of operations research communities over years. Usually, there is no unique optimal solution, but rather a set of

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alternative solutions and these solutions are optimal in the wider sense that no other solutions in decision space are superior to them when all objectives are considered. They are known as Pareto-optimal solutions, also termed nondominated noninferior, admissible, or efficient solutions [20].

During the past decade, various multiobjective evolutionary algorithms (MOEAs) have been proposed and applied in MOPs [8]. A representative collection of these algorithms includes the vector evaluated genetic algorithm (VEGA) by Schaffer [25], the niched Pareto genetic algorithm (NPGA) [12] and the nondominated sorting genetic algorithm (NSGA) by Srinivas and Deb [26], the nondominated sorting genetic algorithm II (NSGA-II) by Deb et al. [3], the strength Pareto evolutionary algorithm (SPEA) by Zitzler and Thiele [28], the strength Pareto evolutionary algorithm II (SPEA-II) by Zitzler et al. [29], the Pareto archived evolution strategy (PAES) by Knowles and Corne [14] and the memetic PAES (M-PAES) by Knowles and Corne [15]. Although these MOEAs differ from each other in both exploitation and exploration, they share the common purpose, searching for a near-optimal, well-extended and uniformly diversified Pareto-optimal front for a given MOP. However, this ultimate goal is far from being accomplished by the existing MOEAs as documented in the literature, e.g., [8].

On the other hand, there exist a few studies where an MOEA is specifically designed for handling constraints. Among all methods, the usual penalty function approach [13,18,19] where a penalty proportional to the total constraint violation is added to all objective functions. When applying this procedure, all constraints and objective functions must be normalized.

Deb et al. [3,5] defined a constraint-domination principle, which differentiates from feasible solutions during the nondominated sorting procedure.

Kurpati et al. [16] suggested four constraint handling improvements for MOGA. These improvements are made in the fitness assignment stage of a MOGA and are all based upon a "Constraint-First-Objective-Next" model.

Chafekar et al. [6] propose two approaches for solving constrained multiobjective optimization problems using steady state GAs. One method called objective exchange genetic algorithm for design optimization (OEGADO) runs several GAs concurrently with each GA optimizing one objective and exchanging information about its objective with the others. The other method called objective switching genetic algorithm for design optimization (OSGADO) runs each objective sequentially with a common population for all objectives. Despite all these developments, there seem to be not enough studies concerning procedure for handling constraints.

In this paper, we present a new optimization system (IT-CEMOP), which is based on concept of co-evolution and repair algorithm for handing constraints. Also, it is based on the ε-dominance concept which maintains a finite-sized archive of nondominated solutions which gets iteratively updated according to the chosen ε-vector, also it guarantees convergence and diversity.

The remainder of the paper is organized as follows. In Section 2 we describe some preliminaries on MOPs, and in Section 3 we present constraint multiobjective optimization via genetic algorithm. Experimental results are given and discussed in Section 4. Section 5 indicates our conclusion and notes for future work.

2. Preliminaries

2.1. Problem formulation

A general multiobjective optimization problem is expressed by
MOP:

$$\begin{aligned} \text{Min} \quad & F(x) = (f_1(x), f_2(x), \ldots, f_m(x))^{\mathrm{T}} \\ \text{s.t.} \quad & x \in S \\ & x = (x_1, x_2, \ldots, x_n)^{\mathrm{T}} \end{aligned} \tag{1}$$

where $(f_1(x), f_2(x), \ldots, f_m(x))$ are the m objectives functions, $(x_1, x_2, \ldots, x_n)$ are the n optimization parameters, and $S \in R^n$ is the solution or parameter space. Obtainable objective vectors, $\{F(x) | x \in S\}$ are denoted by Λ, so $\{F{:}S \to \Lambda\}$, S is mapped by F onto Λ. This situation is represented in Fig. 1 for the case $n = 2$, $m = 3$.