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A multiobjective evolutionary algorithm based on decomposition with normal boundary intersection for traffic grooming in optical networks

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ABSTRACT

This paper presents a multiobjective optimization algorithm for solving tri-objective optimization problems with objectives of very different scales. As a version of the Multiobjective Evolutionary Algorithm based on Decomposition (MOEA/D), it adopts the Normal Boundary Intersection (NBI) based Tchebycheff approach to decompose a multiobjective optimization problem into a number of single objective subproblems. Particular attention has been paid to set the weight vectors of these subproblems for handling disparately scaled objectives. We have applied our proposed algorithm to a traffic grooming problem in the telecommunication fields. We also propose to use an indirect encoding approach to handle this very complicated problem. Our experimental studies show that our proposed method is able to produce very promising results for this real-world telecommunication problem.

1. Introduction

Over the last decade, multiobjective optimization problems (MOOP) [4] have attracted much attention [7,24]. No single solution can optimize all the objectives in a MOOP at the same time. Instead, the set of Pareto-optimal solutions is often required by a decision maker. In a Pareto optimal solution, any improvement in one objective must lead to deterioration to at least one other objective. Many multiobjective evolutionary algorithms (MOEAs) have been proposed for approximating the set of Pareto optimal solutions in a single run. Most existing MOEAs can be classified them into three categories: *Pareto dominance based methods*, *Indicator-based ones*, and *decomposition based ones*.

Among the most popular methods based on Pareto dominance are the Pareto Archived Evolution Strategy (PAES [14]), the Fast Non-Dominated Sorting Genetic Algorithm (NSGA-II [5]), and the Strength Pareto Evolutionary Algorithm 2 (SPEA2 [35]). These Pareto dominance based algorithms treat a MOOP as a whole and use the Pareto dominance relationship to rank solutions. It is not always easy to obtain a set o uniformly distributed Pareto optimal solutions.

Indicator-based algorithms use an indicator function such as the hypervolume measure [36] to evaluate solutions. the most popular indicator-based approaches includes Indicator-based Evolutionary Algorithm (IBEA) [34] and S-metric Selection Evolutionary Multiobjective Optimisation Algorithm (SMS-EMOA) [1]. A main drawback of these methods are that they often involve very heavy computational overheads.

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Examples of decomposition based methods are Multiobjective Genetic Local Search (MOGLS [10–12]) and the Multiobjective Evolutionary Algorithm based on Decomposition (MOEA/D [27]). These algorithms use aggregation functions to guide their search. In MOGLS, an aggregation function with random weight vectors is constructed to evaluate solutions at each iteration. MOEA/D decomposes a MOOP into a number of single objective subproblems with preselected weight before its search, and optimize these subproblem in a collaborative manner by using a population search strategy. The two commonly-used aggregation techniques in MOEA/D are the weighted Tchebycheff approach and the weighted sum approach. However, both approaches are sensitive to the scale of the objectives.

Actually, many researchers have suggested that the normalization of the objective space should be made in MOEAs to tackle disparately scaled objectives. However, in the case of more than two objectives, a set of uniformly distributed solutions in the normalized objective space (Fig. 1(c)) may not be uniformly distributed in the original objective space as shown in Fig. 1(d).

The *COV measure* and *Mesh ratio* are used to measure the uniformity of solution distributions [9]. Given a set of n points $\{z_i\}_{i=1}^{n}$, the minimum distance between z_i and the other points is $\gamma_i = \min_{j \neq i} |z_i - z_j|$. The *COV measure* is defined as:

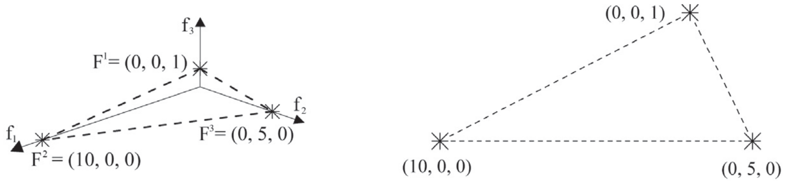
$$COV\ measure = \sqrt{N \frac{\sum_{i=1}^{n} \gamma_i^2}{\left(\sum_{i=1}^{n} \gamma_i\right)^2}} \tag{1}$$

and the *Mesh ratio* as:

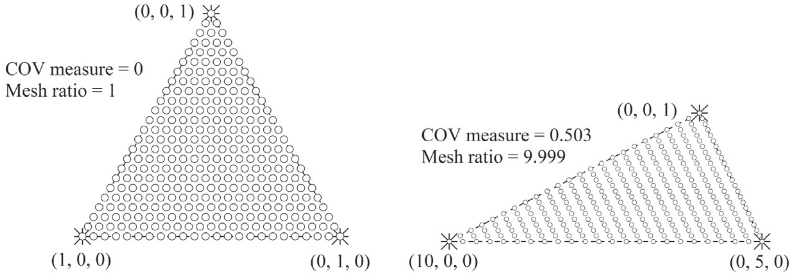
$$Mesh\ ratio = \frac{\max_{i=1,\ldots,n}\ \gamma_i}{\min_{i=1,\ldots,n}\ \gamma_i} \tag{2}$$

For a perfectly uniform mesh, $\gamma_1 = \gamma_2 = \cdots = \gamma_n$, and the *COV measure* = 0 and the *Mesh ratio* = 1. In both metrics, the smaller the value is, the more uniform is the mesh. For further information, please refer to [9].

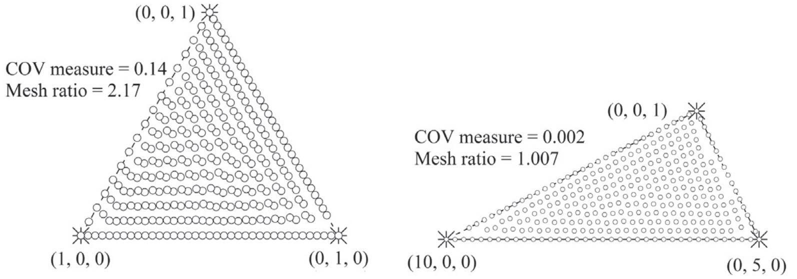
In order to improve the performance and effectiveness of the MOEA/D for real-world optimization problems with disparately scaled objectives, we use an improved version of the MOEA/D with combination of the Normal Boundary



(a) 3D representation (b) 2D representation



(c) Normalized Objective Space (d) Real Objective Space



(e) Normalized Objective Space (f) Real Objective Space

Fig. 1. A set of uniformly distributed solutions in the normalized objective space may not be uniformly distributed in the original (real) objective space.