



DECOR: Differential Evolution using Clustering based Objective Reduction for many-objective optimization



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ABSTRACT

Challenges like scalability and visualization which make multi-objective optimization algorithms unsuitable for solving many-objective optimization problems, are often handled using objective reduction approaches. This work proposes a novel many-objective optimization algorithm, viz. Differential Evolution using Clustering based Objective Reduction (DECOR). Correlation distance based clustering of objectives from the approximated Pareto-front, followed by elimination of all but the centroid constituent of the most compact cluster (with special care to singleton cluster), yields the reduced objective set. During optimization, the objective set periodically toggles between full and reduced size to ensure both global and local exploration. For finer clustering, number of clusters is eventually increased until it is equal to the remaining number of objectives. DECOR is integrated with an Improved Differential Evolution for Multi-objective Optimization (IDEMO) algorithm which uses a novel elitist selection and ranking strategy to solve many-objective optimization problems. DECOR is applied on some DTLZ problems for 10 and 20 objectives which demonstrates its superior performance in terms of convergence and equivalence in terms of diversity as compared to other state-of-the-art optimization algorithms. The results have also been statistically validated. Source code of DECOR is available at <http://decor.droppages.com/index.html>.

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1. Introduction

Optimization algorithms help to find the best alternative from a set of available choices for any problem at hand. Meta-heuristic optimization algorithms have gained popularity by providing a decent approximation of the optimal solution [15,16,30], even for hard problems. To solve the problems with multiple conflicting objectives, Multi-Objective Optimization (MOO) algorithms are used [14]. In this class of optimization algorithms, when number of objectives is four or more, several challenges come into play. Hence, this sub-class of problems forms an essential research topic and is called Many-Objective Optimization (MaOO) problems [20]. Some practical applications of MaOO algorithms from varied domains are nurse scheduling problem [27], problem of designing factory-shed truss [2], space trajectory design problem [22], feature selection problem for motor imagery brain signal classification [28], software refactoring problem [26] and cyclone geometry design problem [12].

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Literature has in abundance several MOO algorithms. Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [8], Decomposition based Multi-Objective Evolutionary Algorithms (MOEA/D) [32], Hypervolume Estimation (HypE) algorithm [11], Differential Evolution for Multi-objective Optimization (DEMO) [33], Pareto Envelope-based Selection Algorithm (PESA) [7], and Strength Pareto Evolutionary Algorithm 2 (SPEA2) [35] are some of the popular ones. The most prominent issues of applying MOO algorithms to MaOO problems are as follows:

1. With increase in number of objectives, the number of solutions needed to approximate the Pareto-optimal set grows as polynomial in length of encoded input, if not exponentially [13,31]. Handling such a large population in every iteration of evolutionary algorithms, increases the computational burden.
2. The popular Pareto-dominance based selection, in several MOO algorithms [8], fails to provide sufficient selection pressure for MaOO problems. Thus, when MOO algorithms are scaled beyond 8 to 10 objectives, the population is saturated by non-dominated solutions at an early generation [2,17]. Relaxations to Pareto-dominance like ϵ -dominance [20], favour relation [11,20], modified favour relation [20,34], fuzzy Pareto-dominance [17] and many more, are available in the literature to handle this situation.
3. Beyond three objectives, decision-making is difficult as the objective space cannot be visualized [3,18].

To assist in decision-making, one of the options is to rely on performance measures to assess the quality of the result. Different performance metrics [1,2,8,20] consider different features of the MaOO algorithms like the convergence of solution, the diversity of Pareto-front, the speed of convergence, or a combination of two or more of these features. For example, a study for optimizing four scalable functions, each having 2–8 objectives, was performed to compare NSGA-II (excelled in diversity and speed), PESA (excelled in convergence) and SPEA2 (excelled in diversity) [24]. Another study [29] emphasizes the need to visualize the Pareto-front by showing that MaOO can result in conflicting decisions on the basis performance measures. Even being associated with several problems, the most popular performance metrics are convergence metric and Hypervolume Indicator [29]. Thus, the other option for decision making is to develop visualization methods like Buddle Chart [18], Parallel Coordinates [5,18], Heatmaps [5,18], Radial Visualization (or RadViz) [5,18] and Self-organizing Maps [5,18]. Parallel coordinates is found as the most popular visualizing tool due to its simplicity.

The mentioned issues for MaOO problems are often tackled by objective reduction where the most conflicting m objectives out of M objectives ($m \leq M$) are chosen. If this achieves $m \leq 3$, the MaOO problem reduces to a MOO problem. Even when $4 \leq m < M$, the computational burden reduces as lesser number of points could approximate the Pareto-front and thus the algorithm could converge faster [2,21]. The size of the full and reduced objective sets are denoted as M and m , respectively, throughout the present work. There are two groups of objective reduction algorithms in literature [21,30]: (i) m is specified by the users, and (ii) m is automatically determined. Some of the recent objective reduction algorithms which have gained attention are δ -Minimum Objective Sub-Set (δ -MOSS) and Objective Sub-Set of size k with Minimum Error (k -EMOSS) [4], Principal Component Analysis NSGA-II (PCA-NSGA-II) [9], k -sized Objective Sub-Set Algorithm (kOSSA) and mixed search scheme of kOSSA [21], α -DEMO and α -DEMO-revised [2]. All these schemes, except [4], quantify the conflict between objectives using correlation among the objectives. Motivated by these characteristics of objective reduction techniques, the authors propose an optimization algorithm in this paper which uses objective reduction in the background of a multi-objective optimization algorithm such that many-objective optimization problems are efficiently addressed.

Outline of the rest of the paper is as follows. A brief description of the previous works that are related to the proposed algorithm, is mentioned in Section 2 while highlighting the primary contributions of the proposed work. The modifications of the base optimization algorithm (DEMO) to yield Improved DEMO (or IDEMO) are presented in Section 3 and the proposed objective reduction based optimization approach (viz. Differential Evolution using Clustering based Objective Reduction or DECOR) is described in Section 4. Performance analysis and the results of statistical significance test are presented in Section 5, and the major observations are further discussed in Section 6. Finally, the conclusion is drawn and open research scopes are discussed in Section 7.

2. Motivation for the work

This section briefly describes the shortcomings of the existing works which help to understand the motivation behind studying the proposed work. Subsequently, the characteristic features of the proposed work are mentioned which distinguish it from the existing works by highlighting its novelties.

2.1. Related works and their drawbacks

The existing approaches suffer from some severe drawbacks. In δ -MOSS and k -EMOSS [4], a greedy approach is followed where the minimal alteration in induced Pareto-dominance relation is searched by removing one objective in every turn. The high time complexity of this approach makes it unsuitable for practical applications [4]. To quicken the process, online objective reduction [21] is adopted by performing reduction during search. However, when online reduction is of one objective at a time like in mixed search scheme of kOSSA [21], the procedure is still slow. Hence, the provision of removal of multiple objectives at a time is adopted, like in α -DEMO and α -DEMO-revised [2], and the approach proposed in [30]. The presented algorithms in [2] require the users to specify m . However, the apriori determination of m is not possible, and for desirable performance, repeated evaluations by varying m is time-consuming and not user-friendly. Considering all

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