Advances in Engineering Software 76 (2014) 1–8

Contents lists available at ScienceDirect

Advances in Engineering Software

journal homepage: www.elsevier.com/locate/advengsoft

Comparison of many-objective evolutionary algorithms using performance metrics ensemble

Z. He, G.G. Yen *

School of Electrical and Computer Engineering, Oklahoma State University, Stillwater, OK 74078, USA

ARTICLE INFO

Article history:
Received 9 March 2014
Received in revised form 13 April 2014
Accepted 25 May 2014
Available online 24 June 2014

Keywords:
Performance metrics ensemble
Many-objective optimization problem
Evolutionary algorithms
Double elimination tournament selection
Many-objective evolutionary algorithms
Performance metrics

ABSTRACT

In this study, we have thoroughly researched on performance of six state-of-the-art Multiobjective Evolutionary Algorithms (MOEAs) under a number of carefully crafted many-objective optimization benchmark problems. Each MOEA apply different method to handle the difficulty of increasing objectives. Performance metrics ensemble exploits a number of performance metrics using double elimination tournament selection and provides a comprehensive measure revealing insights pertaining to specific problem characteristics that each MOEA could perform the best. Experimental results give detailed information for performance of each MOEA to solve many-objective optimization problems. More importantly, it shows that this performance depends on two distinct aspects: the ability of MOEA to address the specific characteristics of the problem and the ability of MOEA to handle high-dimensional objective space.

1. Introduction

Evolutionary algorithms (EAs) with meta-heuristic character and population-based property provide powerful search ability to generate both converged and diversified Pareto-optimal fronts in multiobjective optimization problems (MOPs), which generally involve two or three conflicting objectives. On the other hand, there are many real-world problems with multiple conflicting objectives (in most cases, more than five) needed to be optimized simultaneously, which are called many-objective optimization problems (MaOPs). In the literature, Multiobjective Evolutionary Algorithms (MOEAs) have been effectively applied to search for the Pareto-optimal fronts in MOPs, but render much worse performance in MaOPs [1]. This subject has been gaining an increasing interest in recent years. Compared with low-dimensional MOPs, the curse of dimensionality in MaOPs has presented several challenges for MOEAs.

First, in MaOP, Pareto optimality loses its selection pressure in the evolution process due to the increasing number of objectives. In MOPs, Pareto optimality based MOEAs, such as NSGA-II [2] and SPEA2 [3], perform very well in that Pareto optimality is effective to select nondominated individual and facilitates the convergence of the population in low-dimensional space. However, in high-dimensional space, the proportion of nondominated individuals rises quickly with the number of objectives [4]. This leads to severely diminishing selection pressure during the evolutionary process no matter how the MOEA is designed, if it is based on Pareto dominance relation.

Second, the high-dimensional objective space of MaOP is extremely large. This large search space makes it difficult to determine the population size in the evolution process. If the population size is too small, the evolution process will prematurely approach the local Pareto solutions, making the whole population settle into local fronts. Also, the small population size makes most of solutions apart from each other. It becomes hard to measure the diversity of the whole population. On the other hand, if the population size is too large, the huge computation effort will paralyze the evolution process. Meanwhile, even with the large population size, two distant solutions may still generate offsprings far from them.

Besides the deficiency in the definition of Pareto dominance and extremely large objective space stated above, other complications such as visualization of high-dimensional objective spaces [1] and a very high computational cost (due to a large number of individuals needed to obtain a good representation of the Pareto front) [5] have contributed to the challenges in solving MaOPs.

From the above discussions, difficulties caused by a large number of objectives have rendered the existing MOEAs ineffective to solve MaOPs. The efforts in addressing this issue have led to the developments of new algorithms, often called Many Objective Evolutionary Algorithms (MaOEAs). In literature, there are mainly four types of MOEAs that have been proposed to solve MaOPs.

* Corresponding author. Tel.: +1 (405)7447743; fax: +1 (405)7449198.
E-mail addresses: zhenan@okstate.edu (Z. He), gyen@okstate.edu (G.G. Yen).

http://dx.doi.org/10.1016/j.advengsoft.2014.05.006
0965-9978/

First, MOEAs are constructed using modified Pareto dominance design. The relaxing form of the Pareto dominance including Pareto α-Dominance [6], Pareto ε-Dominance [6], and Pareto cone ε-Dominance [6] makes one individual dominates others easier in high-dimensional space by the heuristically chosen parameters. Based on this idea, ε-Domination Based Multi-Objective Evolutionary Algorithm (ε-MOEA) [7] is proposed and shows a good performance [8]. On the other hand, fuzzy concept is incorporated into Pareto dominance for new fitness evaluation mechanism to continuously differentiate individuals into different degrees of optimality beyond the classification of the original Pareto dominance. Based on it, a fuzzy Pareto dominance (FD) relation is defined and incorporated into the designs of NSGA-II, so called FD-NSGA-II [4].

The second class is based on the idea of performance indicators. For example, Hypervolume Estimation Algorithm for Multiobjective Optimization (HypE) [9], has been shown to be effective in solving MaOPs. Also, there are some other designs in a similar spirit such as Indicator-Based Evolutionary Algorithm (IBEA) [10] and SMS-EMOA [11].

The third class is decomposition based designs, such as multiobjective evolutionary algorithm based on decomposition (MOEA/D) [12] and reference-point based many-objective NSGA-II (MO-NSGA-II) [13]. This type of methods decomposes a multiobjective optimization problem into a number of scalar optimization subproblems and optimizes them simultaneously. In the evolution process, aggregation functions, such as Tchebycheff in [12] and Achievement Scalarizing Function in [13], are applied for fitness assignment and individual selection instead of Pareto-dominance. Nowadays, this method is very popular to solve MaOPs.

The last class is the grid-based method. From [14], a grid can reflect the status of both convergence and diversity simultaneously. Grid-Based Evolutionary Algorithm (GrEA) [14] exploits this grid approach to strengthen the selection pressure toward the optimal direction, while maintaining an extensive and uniform distribution among solutions. Territory Defining Multiobjective Evolutionary Algorithm (TDEA) [15] defines a territory around each individual to prevent crowdness in any region.

Although numerous MOEAs exist for many-objective optimization problems, there is no comprehensive study conducted to reveal advantages and weaknesses of the underlying MOEAs and at determining the best performance algorithm to specific class of problem characteristics [16]. Recently, multiple comparisons between latest improvements on NSGA-II and MOEA/D for many-objective optimization problems have been made in [17–19]. In those experiments, only single performance metric is used therein. However, every metric can merely provide some specific, but incomplete, quantifications of performance and can only be effective under specified conditions. For a specific test problem, we cannot ascertain which metrics should be applied in order to faithfully quantify the performance of MOEAs. The conclusion, if any is drawn, is often indecisive and reveals no additional insight pertaining to the specific problem characteristics that proposed MOEA would perform the best [20,21].

To overcome these deficiencies and arrive at a fair evaluation of MOEAs, performance metrics ensemble with double elimination tournament [22] is used in this research work. The ensemble method uses multiple metrics collectively to obtain a better assessment than what could be obtained from any single performance metric alone. Metrics ensemble not only can give a comprehensive comparison between different algorithms, but avoid the choosing process and can be directly used to assessing MOEAs.

In the remaining paper, Section 2 provides the literature review on the MOEAs for comparison. In Section 3, we give detailed information for performance metrics. Section 4 describes the performance metrics ensemble approach in detail, including the double elimination tournament selection operator. In Section 5, we elaborate on the experiment results for selected benchmark problems. Finally, a conclusion is drawn in Section 6 along with pertinent observations.

2. Literature review on many-objective evolutionary algorithms

In this study, six state-of-the-art MOEAs are chosen for competition. They are FD-NSGA-II [4], HypE [9], MOEA/D [12], GrEA [14], ε-MOEA [7], and MO-NSGA-II [13]. Here, FD-NSGA-II is of the first type of algorithms modifying Pareto dominance. HypE based on performance indicator comes from the second type. MOEA/D is the decomposition-based method and belongs to the third type. The grid-based method GrEA is from the fourth type. ε-MOEA not only modifies the Pareto dominance, but also uses the grid to improve the diversity, so it is a combination of both the first and the fourth types. MO-NSGA-II is also a hybrid method and contains both decomposition and grid ideas from the third and the fourth types, respectively. A brief overview of each chosen MOEA is given below.

FD-NSGA-II is the improved NSGA-II by adopting the fuzzy Pareto dominance relations and the corresponding fuzzy fitness assignment process. In the proposed design, fuzzy Pareto dominance relation is applied to determine the rank value of each individual instead of Pareto dominance in the original NSGA-II. After the rank value is determined, the same crowding-distance is used as the original design of NSGA-II. The fuzzy fitness assignment process ensures one individual is fuzzy nondominated with respect to others in the same rank.

HypE is a hypervolume-based evolutionary many objective optimization algorithm. It applies Monte Carlo simulation to approximate the exact hypervolume value, and assigns ranks of solutions induced by the hypervolume indicator. These ranks of solutions can be used in fitness evaluation, mating selection, and environmental selection. Overall, it balances the accuracy of the estimates and the computation cost of the Hypervolume calculation.

MOEA/D decomposes a MOP into a number of scalar optimization subproblems and optimizes them simultaneously. Each subproblem has a different weight vector and a single solution. For each subproblem, a certain number of the nearest subproblems are defined as its neighbors based on the Euclidean distance between their weight vectors. Each subproblem is optimized by only using information from its several neighboring subproblems. For each subproblem, a new solution is generated by current solutions in its neighboring subproblems and is compared with current solutions in the neighboring subproblems.

Grid-Based Evolutionary Algorithm (GrEA) exploits the potential of the grid-based approach to strengthen the selection pressure towards the global Pareto front while maintaining an extensive and uniform distribution among solutions. Two concepts, grid dominance and grid difference, were introduced to determine the mutual relationship of individuals in a grid environment. Then, three grid-based criteria, grid ranking, grid crowding distance, and grid coordinate point distance, are incorporated into the fitness of individuals to distinguish them in both the mating and environmental selection processes. GrEA uses the basic framework of NSGA-II while modifying three main steps of evolution process: fitness assignment, mating selection, and environmental selection.

ε-MOEA is a steady-state algorithm based on the ε-dominance relation. It divides the objective space into hyperboxes by a size of ε. Each hyperbox is assigned at most a single solution on the basis of ε-dominance. From [7], ε-MOEA provides a tradeoff among convergence, diversity, and computational time. Furthermore, it could be made interactive with a decision-maker which implies ε can be chosen by decision-maker according to user's preference.