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Multiobjective evolutionary algorithm based on multimethod with dynamic resources allocation

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ABSTRACT

In the last two decades, multiobjective optimization has become main stream and various multiobjective evolutionary algorithms (MOEAs) have been suggested in the field of evolutionary computing (EC) for solving hard combinatorial and continuous multiobjective optimization problems. Most MOEAs employ single evolutionary operators such as crossover, mutation and selection for population evolution. In this paper, we suggest a multiobjective evolutionary algorithm based on multimethods (MMTD) with dynamic resource allocation for coping with continuous multi-objective optimization problems (MOPs). The suggested algorithm employs two well known population based stochastic algorithms namely MOEA/D and NSGA-II as constituent algorithms for population evolution with a dynamic resource allocation scheme. We have examined the performance of the proposed MMTD on two different MOPs test suites: the widely used ZDT problems and the recently formulated test instances for the special session on MOEAs competition of the 2009 IEEE congress on evolutionary computation (CEC'09). Experimental results obtained by the suggested MMTD are more promising than those of some state-of-the-art MOEAs in terms of the inverted generational distance (IGD)-metric on most test problems.

1. Introduction

Many real-world search and optimization problems are naturally posed as multi-objective optimization problems (MOPs). All these types of problems usually contain conflicting objective functions in their formulation and need to be optimized simultaneously. The stationary gas turbine combustion process optimization [1], optimization of material distribution of functionally graded materials (FGMs) [2–4], optimization of vehicle crashworthiness design problems [5] and improvement of energy consumption in wireless sensor networks are some practical examples of optimization problems. For more details the interested readers may refer to [6,7,5,8–11]. Without any loss of generality, we consider the optimisation problem:

$$\begin{aligned} &\text{minimize} \quad F(x) = (f_1(x), \ldots, f_m(x))^T \\ &\text{subject to} \quad x \in \Omega \end{aligned} \tag{1}$$

where Ω is the decision variable space, $x = (x_1, x_2, \ldots, x_n)^T$ is a decision variable vector and x_i, $i = 1, \ldots, n$ are their decision variables, $F(x) : \Omega \rightarrow R^m$ involves $m \geq 2$ real valued conflicting objective functions and R^m is the objective space.

If Ω is closed and connected region in R^n and all the objective functions are continuous in x then problem (1) will be a continuous MOP. Furthermore, If $m = 1$, then a problem (1) will become a single objective problem (SOP). If $m \leq 3$, then problem (1) will called MOPs. However, if $m \geq 3$, then problem (1) is normally known many objectives function problem.

A solution $u = (u_1, u_2, \ldots, u_n) \in \Omega$ is said to be Pareto optimal if there exist no another solution $v = (v_1, v_2, \ldots, v_n) \in \Omega$ such that $f_j(u) \leq f_j(v)$ for all $j = 1, \ldots, m$ and also $f_j(u) < f_j(v)$ for at least index k. An objective vector is said to be Pareto optimal if their corresponding decision vector is Pareto optimal. All Pareto optimal solutions in the decision space of MOP is called Pareto set (PS) and their corresponding image in their objective space is called Pareto front (PF). The idea Pareto optimality was first proposed by Francis Ysidro Edgeworth in 1881 and then later on generalized by Vilfredo Pareto in 1986 as discussed in [12,13].

Multiobjective evolution optimization has become main stream in last two decades. Since the development of first multiobjective evolutionary algorithm (MOEA) known as "vector evaluated genetic algorithm (VEGA) [14]" by David Schaffer in 1985, different kinds MOEAs have been designed in the field evolutionary computing and successfully applied to different complicated problems [15–17]. MOEAS are mainly inspired by the biological process of

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evolution and operate on set of solutions. They are nature inspired stochastic method and need no derivative information. Dur to population based nature, they can find a diversified set of solutions for the given MOPs in single simulation run unlike traditional techniques [18,9,19,11,20]. In general, classical MOEAs can be divided into three main different classes, namely, the Pareto dominance based MOEAs (e.g., [21–29]), the decomposition based MOEAs (e.g., [30–40,19,41,42]), and Indicator Based algorithms (e.g., [43–49]).

Among above mentioned three classes, Pareto dominance based MOEAs are very commonly used in the existing specialized literature of EC. These algorithms utilize Pareto dominance concepts and different diversity maintenance techniques to evaluate their population in the whole process of optimization. In this category, a fast elitist multiobjective non-dominated sorting genetic algorithm: NSGA-II [22] and SPEA2: Improve strength Pareto evolutionary algorithm [24] are two leading stochastic approaches. NSGA-II [22] evaluates their population using Pareto ranking procedure together with crowding distance technique. SPEA 2 [24] is also exercises Pareto dominance concept along with clustering methods in the selection process of their offspring population. Both these algorithms are using the crowding distance technique and clustering strategies for the purposes to prevent premature convergence and improve diversity in their current population to ensure convergence and uniformly distributive set of solutions. Furthermore, the fitness assignment mechanisms exploited in both NSAG-II [22] and SPEA2 [24] promote an adequate selection pressure to drive their population toward the true Pareto front with good convergence manner. However, employing the same strategies without modification in NSAG-II [22] framework are not suitable for many objective optimization problems. Recently, various modification have been proposed in original version of NSGA-II framework of [22] and several enhanced versions have been proposed in the existing literature [50–56] for solving many objective optimization problems.

Recently indicator based EAs (IBEAs) are another promising frameworks. They directly involve performance indicator such as hypervolume in the selection process of their offspring solution. IBEAs with the hypervolume measure have strong theoretical support and high search ability. In [44], Hypervolume also called S metric selection evolutionary multiobjective optimization algorithms (SMS-EMOA) is recently developed. It exactly uses the hypervolume function to measure their solutions consuming high time complexity as resultant this approach is unsuitable and undesirable for problems with high dimensionality. However, high time complexity issues have been properly resolved in general indicator-based evolutionary algorithm (IBEA) [43,46]. General IBEA approximates the hypervolume contributions by aggregating the hypervolume differences of pairwise solutions in minimum time. A scalarizing function-based hypervolume approximation method has been suggested in general IBEA [43]. In [57], the idea scalarizing function-based hypervolume approximation method has been introduced and solved many objective optimization problems with great success.

MOEA/D[1]: multiobjective evolutionary based on decomposition [32] is another newly efficient developed paradigm that decomposes a MOP under attack into a number of different single objective optimization subproblems and then optimize all these subproblems simultaneously using generic EA. To date, MOEA/D [32] have many enhanced version (i.e., For example: [35,36,40,11,19,41,42,58]). One of the key features of this paradigm is neighbourhood structure that defined based on Euclidean distance between weight vectors of decomposition functions. In [35], two different neighbourhood schemes in combination with restricted replacement strategy have been introduced for solving complicated problems. In MOEA/D, different subproblems require different amounts of computational resources. In [36], dynamical resource allocation strategy for different subproblems has been introduced. In [59], a Gaussian process model have been embed in MOEA/D [32] for solving expensive MOPs. In [60], each subproblem records more than one solution to maintain search diversity in their population evolution. Multiple search operators with self-adaptive procedures have been suggested for population evolution [61,41,40]. Two well-known MOEA/D and NSGA-II [62] have combined at population level in [63] for solving hard optimization and search problems. In [64], two different aggregation functions have been simultaneously incorporated. A new NBI-style Tchebycheff approach has been introduced in [65] to handle the portfolio optimization problems. A decomposition-based multiobjective evolutionary algorithm with an ensemble of neighborhood sizes (ENS-MOEA/D) has been proposed for solving CEC'09 test instance [66]. In ENS-MOEA/D, two ensemble neighbourhood sizes (NSs) with online self-adaptation manner has been proposed for the purpose to overcome the user-specific tuning of neighbourhood size (T) parameter used in MOEA/D [36]. In [67], ant colony optimization (ACO) has been incorporated into MOEA/D for solving the multiobjective Knapsack problems (MOKPs) and the multiobjective traveling salesman problem (MTSPs). An improved version of MOEA/D with adaptive weight vector adjustment (MOEA/D-AWA) has been proposed in [68]. MOEA/D uses fixed weight vectors which cannot work if Pareto fronts (PFs) of the considered MOPs are complicated (i.e., discontinuous PF or PF with sharp peak or low tail).

Different strategies/techniques/search operators have different strengths at different stages of population evolution. Pareto dominance concepts and concept of decomposition are two well-known procedures. Each one have its some own key features and limitations. Therefore, combined use of these two concepts in a master algorithm can bring significant advancement and success to field of evolutionary computation. Inspired from their remarkable achievements and some existing works in the EC literature [69,70,62,40,41,37,42], We have suggested novel MOEA based on multimethod (MMTD) with dynamic resource allocation in this paper. The suggested algorithm exploits two popular algorithms known as MOEA/D [32] and NSGA-II [22] and evolve their population in dynamical manners. We have tested our MMTD on CEC'09 benchmark functions [71] and ZDT test problems [72] using inverted generational distance (IGD) as a performance indicator. MMTD have been tackled almost all test problems in robust manner as compared to state-of-the-art MOEAs selected in our comparative analysis.

The core contributions of the proposed algorithm are summarized and highlighted as follow:

- The proposed MMTD employs both Pareto dominance-based concept and decomposition strategy in their evolutionary process for population evolution.
- The proposed algorithm employs two well-known MOEAs based their individual performances simultaneously and dynamically.
- The proposed MMTD is flexible and many algorithms or even different multiple operators can be accommodated as a constituent algorithms/search operators in their whole process of population evolution. The impact analysis of different operators in MMTD constituent algorithms is also part of research work in this paper.
- Experimental results demonstrate that MMTD has significantly performed better than state-of-the-art MOEAs such as MOEA/D [32], NSGA-II [22], AMALGAM [70], MOPSO: A proposal for multiple objective particle swarm optimization [73], MOSaDE [74],

[1] The source codes of MOEA/D can be found in Qingfu Zhang's homepage, Jmetal, MOEA Framework, Dr. Shih-Hsin Chen's Web and MOS web.