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Adaptive composite operator selection and parameter control for multiobjective evolutionary algorithm

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The multiobjective evolutionary algorithm based on decomposition (MOEA/D) has shown a superior performance in tackling some complicated multiobjective optimization problems (MOPs). However, the use of different evolutionary operators and their various parameter settings has a significant impact on its performance. To enhance its algorithmic robustness and effectiveness, this paper proposes an adaptive composite operator selection (ACOS) strategy for MOEA/D. Four evolutionary operator pools are used in ACOS and their advantages are combined to provide stronger exploratory capabilities. Regarding each selected operator pool, an online self-adaptation for the parameters tuning is further employed for performance enhancement. When compared with other adaptive and improved strategies designed for MOEA/D, our proposed algorithm is found to be effective and competitive in solving several complicated MOPs.

1. Introduction

Multiobjective optimization problems (MOPs) widely exist in many scientific and engineering applications, which are aimed at optimizing several (often conflicting) objectives simultaneously [10,13,40]. No single solution can find the optimum for all the objectives simultaneously due to the fact that the enhancement of one objective may result in the deterioration of another one. Therefore, the target of MOPs is to find a set of equally-optimal solutions, called *Pareto-optimal set* (*PS*), which can be provided to the decision maker as the alternative solutions for various application cases.

Nature-inspired heuristic algorithms, such as evolutionary algorithms (EAs) [11,48,59], artificial immune algorithms [5,33,34,43] and particle swarm optimization algorithms [8,51], have shown the promising performance in tackling MOPs. Due to their population-based nature, they are suitable for solving MOPs because, if properly manipulated, they can generate multiple Pareto-optimal solutions in a single run. Particularly, during the last decades, numbers of multiobjective evolutionary algorithms (MOEAs) have been proposed [2,6,14,26,35,58]. Most MOEAs are designed based on the use of the Pareto dominance relationship or a decomposition approach [16]. As the Pareto dominance relationship is very simple and straightforward to apply, Pareto-based MOEAs were the most popular in the specialized literature during many years [50]. The most popular MOEAs, *e.g.*, NSGA-II [11] and SPEA2 [60], were all designed based on the Pareto dominance relationship. Until now, there are still many improved Pareto-based MOEAs reported in the literature [12,21,27,31,32,46]. However, as pointed out in

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[36,53], Pareto-based MOEAs have some difficulties to approach the true *Pareto-optimal front* (*PF*) when tackling some complicated MOPs. Thus, a novel MOEA based on decomposition (MOEA/D) was proposed in [36,53]. It decomposes MOPs into a set of single-objective optimization subproblems (SOPs) and then optimizes all the SOPs cooperatively. The objective of each subproblem is a (linear or nonlinear) weighted aggregation of all the objectives in a MOP. Neighborhood relationships among these subproblems are defined based on the Euclidean distances of their aggregation weight vectors and they can be exploited to enhance the performance of MOEA/D.

Due to the superior performance provided by MOEA/D in solving some complicated MOPs, many enhanced strategies such as dynamical resource allocation [39,55], enhanced evolutionary operators [36,37,45], adaptive control methods [29,47,57], and matching strategies [28,30], have been designed based on the framework of MOEA/D. On the dynamical resource allocation, MOEA/D-DRA [55] was proposed based on the fact that different subproblems may have different computational difficulties. This approach designs a dynamic computational resource allocation strategy to assign more computational resources to the non-convergent subproblems. Another dynamic resource allocation scheme for MOEA/D was investigated in [39] to reward the better crossover operator. In this approach, the better one between the simplex crossover operator and the center of mass crossover operator can gain more computational resources. About the enhanced evolutionary operators, differential evolution (DE) was used in [36,45] to replace simulated binary crossover for effectively producing the new trial vectors, while an opposition-based learning strategy was employed in [37] to accelerate the convergence speed during the evolutionary process. Regarding the adaptive control methods designed in MOEA/D variants, a new version of MOEA/D with an ensemble of different neighborhood sizes (ENS-MOEA/D) was proposed in [57] to decrease the impact of neighborhood size on the performance of MOEA/D. This approach dynamically determines the selection of different neighborhood sizes using their previous search experience, and consequently, this online self-adaptation strategy significantly improves the performance of MOEA/D. In [47], an adaptive DE for MOPs (ADEMO/D) was reported. This approach adopts probability matching and adaptive pursuit as two adaptive strategy selection principles. A DE mutation strategy is picked up from a candidate's DE pool according to a probability that depends on the successful rate to produce better solutions. To adaptively select the preferred recombination operator, a novel bandit-based adaptive operator selection was presented for MOEA/D (MOEA/D-FRRMAB) in [29]. In this approach, the application rates of different DE operators are decided dynamically by their recent performance. A sliding window is used to track the dynamics of the search process by recording the recent fitness improvement rates of different operators, and a decay mechanism is employed to raise the selection probability of the best operator. At last, considering the matching strategies designed for solutions and subproblems, a stable matching model has been proposed for MOEA/D (MOEA/D-STM) in [28]. This approach assigns each promising solution to a subproblem according to the respective preferences. It maintains the good convergence speed and population diversity, and outperforms other enhanced MOEA/D algorithms, such as ENS-MOEA/D and MOEA/D-FRRMAB. Similarly, an improved inter-relationship model [30] was built to match the solutions and subproblems based on their mutual-preferences. Different from the stable matching model that aims to produce a trade-off between convergence and population diversity, it is essentially a diversity first and convergence second strategy, which enables superior solutions to explore the entire *PF*.

Moreover, some weight generation strategies [17,23,41] were also designed to achieve a better approximation for complex Pareto-optimal fronts (PFs). Unlike traditional MOEA/D algorithms that decompose MOPs into a set of subproblems, a new MOEA/D algorithm [4,7] was proposed to decompose the objective space into different sub-objective spaces using numbers of distinct direction vectors. Each sub-objective space at least owns a solution in order to maintain properly the population diversity. This idea of decomposition using direction vectors was also studied in [22] to combine with a co-evolutionary algorithm, giving rise to the so-called DVCMOA. To extend MOEA/D for high-dimensional MOPs, a generalized decomposition approach was designed in [15], while a systematic sampling approach was presented in [1] to generate uniformly distributed reference points coupled with two independent distance measures and a simple preemptive distance comparison scheme.

It is noted that most of the above MOEA/D variants adopt DE coupled with polynomial mutation as their evolutionary operators. However, several research studies on DE operators have revealed that the use of hybridized DE operators provides an enhanced optimization performance and algorithmic robustness for solving different types of SOPs, because the use of single DE operator may present several limitations in tackling some difficult problems characterized by certain complex features [20,49]. Since a decomposition approach transforms a MOP into a number of SOPs, it is possible that the competitive approaches designed for solving SOPs are also suitable for MOEA/D. Although an adaptive operator selection for MOEA/D was recently investigated in MOEA/D-FRRMAB to enhance its exploratory capability, four basic DE mutation operators (*i.e.*, "DE/rand/1", "DE/rand/2", "DE/current-to-rand/2" and "DE/current-to-rand/1") were selected in MOEA/D-FRRMAB to compose the operator pool. This combination of DE mutation strategies may not lead to optimal performance, as the composite DE operator pools studied in [49] seem to be more competitive. Working on the research direction suggested by MOEA/D-FRRMAB, this paper proposes an adaptive composite operator selection and parameter control strategy for MOEA/D (called MOEA/D-CDE). The core idea is to design an adaptive MOEA/D algorithm with superior performance. Four composite DE operator pools are adaptively employed (such operators were selected based on their previously reported performance), and their recent fitness improvement rates are stored using a sliding window. An adaptive control strategy is also designed to adjust the parameters in each composite DE pool. Our experimental results validate that MOEA/D-CDE is able to find a good approximated subset of *PS* when solving several complicated MOPs, *e.g.*, the Unconstrained Functions (UF) adopted at the competition held at the *2009 IEEE Congress on Evolutionary Computation* (CEC'2009) [56] and the Walking Fish Group (WFG) problems [18]. When compared with other enhanced variants of MOEA/D, *e.g.*, MOEA/D-DE [36], MOEA/D-DRA [55], ENS-MOEA/D [57], MOEA/D-FRRMAB [29] and MOEA/D-STM [28], MOEA/D-CDE performs best on most of the UF and WFG test