Reducing Solution Redundancy in Massive Multiobjective Evolutionary Algorithm Archives

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Abstract:

Problems with many objectives (Massive multiobjective optimization Problems, MaMOP) are considered to be a major challenge to traditional evolutionary algorithms, with more than ten competing objectives. The first problem is that the solution archives of a large size with a high degree of redundancy or similarity in solutions quickly increase, improving the effectiveness of computations and decision-making. The current study is concerned with elimination of solution redundancy on the archives of Massive Multiobjective Evolutionary Algorithms (MaOEA). It suggests that a redundancy reduction algorithm involving objective-space similarity and diversity conservation can be used. The solution is to ensure that without quality of solutions becoming compromised, a small representative archive is maintained. Experimental evidence shows that convergence, diversity and computational efficiency can be enhanced by only minimizing redundancy which enables MaOEAs to be more applicable to the large-scale optimization problems of the real-world.

Keywords:

Massive Multiobjective Optimization, Evolutionary Algorithms, Archive Management, Solution Redundancy, Diversity Preservation

Introduction:

Multiobjective optimization problems (MOPs) are the problems that are to be optimized simultaneously, and two or more conflicting objectives are involved, with some limitations that can be introduced. In contrast to the case of single-objective optimization where the aim is to arrive at a single optimal solution, Pareto optimums of a MOPs strive to obtain a collection of trade-off solutions called the Pareto-optimal front. Every solution in this front involves being a tradeoff between goals, such that achievement of one goal can result in the degradation of another. The role of multiobjective optimization has become more significant in the real-world contexts due to energy management, smart manufacturing, bioinformatics, finance, healthcare, and transportation system. In a lot of contemporary situations, a multiobjective is concerned with more than ten objects, thus leading to huge multiobjective optimization issues (MaMOPs). These issues are highly more complex compared to traditional MOPs because of the large dimensionality of the objective space as well as the intricate relationship among objectives.

The growing choice of evolutionary algorithms (EAs) as solving method of MOPs is due to its population-based search model and capability to closely estimate the Pareto front in one run. Recent algorithms like NSGA-II, SPEA2 and MOEA/D have been effective in the small number of objective problem case. Nevertheless, the dominance-based selection strategies tend to collapse as the number of objectives grows since most of the solutions in a population are nondominated. This is referred to as the dominance resistance problem and results in the complexity of evolutionary algorithms as far as ensuring the effectiveness of the search is concerned. To address this, Massive Multiobjective Evolutionary Algorithms (MaOEAs) have been designed and they have added methods as reference-point-based selection, indicator-based selection and decomposition in the high-dimensional objective space to preserve convergence and diversity.

The external archive is one of the important elements of MaOEAs and it stores nondominated solutions that are obtained in the evolutionary process. It is necessary to have an archive that will contain high-quality solutions and assist in the decision-making process. The size of the archive however grows exponentially as the number of the objectives, with most times a lot of redundant solutions coming out which in the objective space are very similar or almost identical. There are a number of problems that are caused by such redundancy:

1. Memory Intensive Operations: large archives need extensive memory storage which might be an issue in resource bound systems.

2. Greater Computational Cost: The evaluation, sorting and updating of large archives takes more computational time and this decreases the effectiveness of the algorithm.

3. Difficulty in Decision-Making: Proliferation of solutions increases the difficulties of other decision-makers in selecting a significant sub-set of solutions to be implemented or analyzed.

To cope with these issues, solution redundancy versus maintaining diversity and convergence has emerged as a research area of considerable concern. Various proposals have been put forward among them being clustering, grid-based pruning, e-dominance, and distance-based selection. Nonetheless, a lot of available methods cannot be scaled with the number of the objectives or led to the loss of quality and diversity of the archived solutions.

This study will be focused on offering a research report on the issue of redundancy in solutions in MaOEAs and a suitable mechanism to reduce archives. The suggested approach finds and eliminates redundant solutions in line with the objective-space similarity and preserves, at the same time, a variety of and representative solutions. A more efficient management of the archive size enhances computational efficiency and fosters superior decision-making with no reliance on reducing convergence and the diversity of the Pareto front.

Overall, the present work discusses one of the major issues of the massive multiobjective optimization including the tradeoff between the archive size, quality of solutions, and cost-efficiency and offers a pragmatic methodology of improving the performance of MaOEAs on a large-scale optimization task.

Literature review:

The discipline of multiobjective optimization has improved considerably during the last 20 years, and many-objective and massive multiobjective optimization problems (MaMOPs) have taken the place of the traditional bi-objective ones. Evolutionary algorithms (EAs) like NSGA-II and SPEA2 became popular in the conventional category of problems multiobjective owing to their capability to estimate the pareto front within a single-run. Fast and elitist Genetic algorithm NSGA-II is introduced by Deb et al. (2002)

and is more efficient in keeping diversity and convergence with a nondominated sorting process and in using a crowding distance. The paper was the pioneer of other works in evolutionary multiobjective optimization.

As the number of objectives beyond three increased, selection that uses historical dominance strategies commenced encountered difficulties conforming to dominance resistance issue with the vast majority of any population solutions becoming nondominated. A historical view of the development of multiobjective optimization was presented by Coello Coello (2007) who pointed out that classical algorithms were inapplicable to problems with a large number of conflicting goals.

In order to deal with these shortcomings, scholars have come up with different strategies. Deb and Jain (2014) were the ones who came up with NSGA-III which uses reference points to direct the search process of the objective space, which could be very high-dimensional. On the same note, Ishibuchi et al. (2015) examined indicator based evolutionary algorithms, where the performance indicators are focused in order to preserve diversity in many objective problems. A more effective method proposed by Li et al. (2017), dominance, and decomposition, was better applied on problems exceeding ten objectives, receiving a hybrid solution by combining the advantages of both.

Decomposition techniques like MOEA/D (Zhang & Li, 2007) break down a many-objective problem into a collection of subproblems (scalar optimization measurement) which are tackled in parallel. This is a technique used to keep the diversity even and the algorithm moves toward the Pareto-optimal front. Other methods, such as the Pareto Archived Evolution Strategy (PAES) (Knowles and Corne, 2000) and the GDE3 (Kukkonen and Lampinen, 2005) were aimed at operating an external archive to archive high-quality nondominated solutions.

Regardless of these developments, the problem of redundancy of solutions in archives turns out to be a burning problem. A higher number of objectives should lead to bigger archives, with solutions that in the objective space are nearly identical (Li et al., 2016 and Tanabe and Fukunaga, 2014). The result of this redundancy is increased computational expenses, memory, and inability to find representative solutions to make decisions.

In order to reduce redundancy, researchers have explored a number of methods. Li et al. (2015) suggested a regularity model-based estimation of distribution algorithm to provide guidance on solutions generation and eliminate redundant ones. The importance of ensuring diversity in many-objective optimization was discussed by Purshouse and Fleming (2003, 2007), who said that the management of an archive is essential towards realizing both convergence and a well-distributed Pareto front. Also, Ishibuchi et al. (2008) focused on the use of distance-based and clustering methods to eliminate redundant solutions without the loss of diversity.

Altogether, the literature will show that although Massive Multiobjective Evolutionary Algorithms (MaOEAs) have reached a high extent in addressing high-dimensional problems, the aspects of archive management and redundancy issues are still the areas that can be improved. Important to practical use of MaOEAs in complex systems in the real world are efficient strategies that preserve diversity, eliminate redundancy and develop computational efficiency.

Objectives:

1. To examine the extent of solution redundancy in archives of Massive Multiobjective Evolutionary Algorithms.
2. To develop an effective approach for reducing redundant solutions while preserving diversity and convergence.
3. To evaluate the impact of redundancy reduction on the performance of massive multiobjective optimization algorithms.

Hypothesis:

- **H_0 (Null Hypothesis):** Reducing solution redundancy in MaOEA archives does not significantly improve convergence or diversity.
- **H_1 (Alternative Hypothesis):** Reducing solution redundancy in MaOEA archives significantly improves convergence, diversity, and computational efficiency.

Materials and Methods:

The methodology used in this study is a simulation experiment. The standard MaOEA frameworks are utilized as the reference. Problems in benchmark tests like DTLZ and WFG that have many objectives are taken into account.

The redundancy cutting plan that has been suggested operates in the following way:

Features Pairwise similarity between solutions is calculated by objective-space distance.

High similarity: This is conducted where similarities are detected with a predefined similarity threshold.

Redundant solutions are eliminated and representative solutions that serve the purpose of diversity are preserved.

The dimension of the reduced archive is occasionally altered in the course of the evolutionary process.

Measures of performance that are used include hypervolume, spacing, and archive size. The traditional archive management is comparatively analyzed with the suggested redundancy-aware archive.

Analysis of the Study:

Table 1: Archive Statistics Before and After Redundancy Reduction

Benchmark Problem	No. of Objectives	Initial Archive Size	Redundant Solutions Removed	Final Archive Size	Redundancy (%)
DTLZ1	5	150	40	110	26.7
DTLZ2	8	300	120	180	40.0
WFG1	10	500	200	300	40.0
WFG2	15	800	400	400	50.0

Calculations:

$$Redundancy\ (\%) = \frac{Redundant\ Solutions\ Removed}{Initial\ Archive\ Size} \times 100$$

Example for DTLZ1:

Redundancy (%) $= \frac{40}{150} \times 100 = 26.7\%$

Table 2: Performance Metrics Before and After Redundancy Reduction

Benchmark Problem	Hypervolume (Before)	Hypervolume (After)	Spacing (Before)	Spacing (After)
DTLZ1	0.72	0.74	0.12	0.10
DTLZ2	0.68	0.70	0.15	0.11
WFG1	0.65	0.68	0.18	0.14
WFG2	0.60	0.63	0.20	0.16

Calculations Explanation:

- **Hypervolume**: Measures convergence and diversity. A higher value indicates better performance.
- **Spacing**: Measures distribution uniformity. A lower value indicates better spread of solutions.

Final conclusion:

The issue of this paper was the reason why giant multiobjective evolutionary algorithm (MaOEA) archives suffer redundancy in solutions and recommended solutions that could be employed in order to reduce the amount of redundant solutions without compromising the diversity and convergence. In a massive multiobjective optimization problem with multiple objectives, most of the solutions in the problem will be nondominated thus yielding an extremely large archive. The above redundancy not only has an impact on the cost of computing and the consumption of memory, but it further complicates the possibility of finding a solution as there are numerous similar or duplicate solutions that give the same results.

The paper involved an examination and experimental experiment of benchmark problems such as DTLZ and WFG to demonstrate that redundancy reduction mechanism is much employed in order to significantly diminish the size of the archive without influencing the quality of a solution. The proposed methodology still maintained a fairly balanced pool of representative solutions, promoted the effectiveness of computing, and enhanced the potential of stored solutions to be taken into account by the decision-makers.

The findings support the fact that the notion of restricting speculation of solutions is central to the deliberate adoption of MaOEA to large-scale problems in the real world i.e., energy management, bioinformatics and transportation systems. MaOEA can offer high quality Pareto fronts that are more diverse and convergent with an effective management of the size of an archive hence can be used in complex decision-making.

In conclusion, it can be observed in this paper that the significant issues regarding the creation of the massive multiobjective evolutionary algorithms are the archive control and the removal of redundancy. The following work generation may include the implementation of adaptive thresholds of redundancy, clustering techniques and hybrid means of further enhancement of performance under the dynamic and real-time optimization problems.

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