Post Pareto Analysis in Multi-objective Optimization

P.M.Chaudhari
Ph.D. Student
Post Graduate Department of Computer Science & Engineering, G. H. Raisoni College of Engineering, Nagpur, India
(Currently at PIET, Nagpur, India)

R.V. Dharaskar, Ph.D
Director
Matoshri Pratishthan's Group opf Institutions (MPGI) Integrated Campus,
Nanded, India

V. M. Thakare, Ph.D
Professor & Head
Post Graduate Department of Computer Science,
Faculty of Engineering &Technology,
S.G.B. Amravati University, Amravati. India

ABSTRACT
The proposed methodology is based on efficient clustering technique for facilitating the decision-maker in the analysis of the solutions of multi-objective problems .Choosing a solution for system implementation from the Pareto-optimal set can be a difficult task, generally because Pareto-optimal sets can be extremely large or even contain an infinite number of solutions. The proposed technique provides the decision-maker a smaller set of optimal tradeoffs.

Keywords
Multi-objective problems, Pareto-optimal sets, clustering technique

1. INTRODUCTION
In many engineering optimization problems, it is not rare to face a challenge when there are several criteria or problem objectives to be satisfied simultaneously. Considering that generally such objectives are in conflict with each other, and then the problem becomes one of finding the best possible solution that satisfies the competing objectives under different tradeoff scenarios. With several multiple objectives and constraints taken into consideration, an accurate optimization formulation can be determined. This type of problems is known as multi-criteria problems [1]. Because of their nature, multi-objective optimization problems may not have one solution which is best (global minimum or maximum) with respect to all objectives. Instead, there may be a set of solutions which are superior to the rest of the solutions in the search space when all objectives are considered, but are inferior to other solutions in the search space in one or more objectives. These solutions are known as Pareto-optimal solutions or non-dominated solutions [2]. Although several methods for solving multi-objective optimization problems have been developed and studied, little prior work has been done on the evaluation of results obtained in multi-objective optimization. Value function is used to help the decision-maker identify the most preferred solution in multi-objective optimization problems. Greedy Algorithm (GR) is analyzed to obtain a sub-set of Pareto optima from a larger Pareto set. The selection of the sub-set was based on maximizing a function of the vector of percentile ordinal rankings of the Pareto optima within the large set. However, choosing a solution for system implementation from the Pareto-optimal set can be a difficult task, generally because Pareto-optimal sets can be extremely large or even contain an infinite number of solutions. [3]

This discussion makes clear that there is a need to achieve smaller practical sets of promising solutions. Thus, the motivation for the current work stems from challenges encountered during the post-Pareto analysis phase. A practical approach is proposed to help in the analysis of the solution of multi-objective optimization and provide the decision-maker a workable sized set of solutions to analyze

[4].This method is based on an unsupervised cluster analysis technique, in which the solutions in the Pareto optimal set are clustered so that the Pareto optimal front is reduced to a set of k clusters [5]. Each cluster consists of solutions with similar properties, and therefore the decision maker only has to investigate one solution per cluster; in this case, the closest solution to each cluster centroid. Moreover, with this method, once the optimal number of clusters is identified, the decision maker can focus to the "knee" cluster, which contains the solutions that are likely to be more interesting to the decision maker [6].

To illustrate the method, some well-known optimization problems will be formulated as multiple objective problems. To solve them, the fast elitist non-dominated sorting genetic algorithm (NSGA-II) will be initially used to determine a set of Pareto solutions [7]. To reduce the size of the Pareto-optimal solutions, a partitional clustering algorithm will be used to directly decompose the Pareto-optimal set into a set of disjoint clusters. This method does not require a priori knowledge of the relative importance of the conflicting objectives, providing the decision-maker a smaller set of optimal tradeoffs [8].

2. CLUSTER ANALYSIS
Cluster analysis, also known as unsupervised learning, is one of the most useful methods in the cluster analysis process for discovering groups. Clustering aims to organize a collection of data items into clusters, such that objects within the same cluster have a high degree of similarity, while objects belonging to different clusters have a high degree of dissimilarity. Cluster analysis makes it possible to look at properties of whole clusters instead of individual objects. This is a simplification that is useful when handling large amounts of data [9].

According to the method adopted to define clusters, the algorithms can be broadly classified into the following types: Partitional and Hierarchical [10]. Partitional clustering attempts to directly decompose the data set into a set of disjoint clusters. Probably, one of the most popular partitional methods is the k-means clustering algorithm. The k-means clustering algorithm is well known for its efficiency in clustering data sets [11]. The grouping is done by calculating the centroid for each cluster, and assigning each observation to the group with the closest centroid. For the membership function, each data point belongs to its nearest center, forming a partition of the data. A frequent problem that many clustering algorithms encounter is the choice of the number of clusters. Thus, different cluster validity indices have been suggested to address this problem, since this is an important issue for partitional clustering in general. A cluster validity index indicates the quality of a resulting clustering process. The silhouette plot method is one of these cluster validity techniques [12]. Then, the clustering partition that optimizes the validity index under consideration is chosen as the best partition. The silhouette plot is used to evaluate the quality of a clustering allocation, independently of the clustering technique that is used [13].

3. LITERATURE SURVEY

Various different classical generating methods were discussed which are either quite well-known or are in oblivion due to lack of available resources and some of which were even suggested before the inception of evolutionary methodologies [14]. A tabu search algorithm was proposed for finding the Pareto solutions of multi-objective optimal design problems [15]. When the relative importance of different criteria cannot be quantified, there is no single optimal solution, but a possibly very large set of Pareto-optimal solutions. Computing this set completely is in general very costly and often infeasible in practical applications. Several methods were considered that apply algorithms for soft CSP to this problem [16]. Although MOEAs can find multiple Pareto-optimal solutions, often, users need to impose a particular order of priority to objectives [17]. Significant improvements in the efficiency of evolutionary search can be achieved by running multiple optimization algorithms simultaneously using new concepts of global information sharing and genetically adaptive offspring creation called as a multi-algorithm, genetically adaptive multi-objective, or AMALGAM, method, to evoke the image of a procedure that merges the strengths of different optimization algorithms [18]. An overview of the multi-objective shortest path problem (MSPP) and a review of essential and recent issues regarding the methods to its solution explore a multi-objective evolutionary algorithm as applied to the MSPP and described its behavior in terms of diversity of solutions, computational complexity, and optimality of solutions [19]. The ranking algorithm presented was based on the filtration of a set of Pareto optimal solutions by using the undifferentiating interval method. The generated subsets of non-dominated solutions are given different ranks, which should contribute to an adequate crossover operation [20]. An approach to construct multiple Pareto-optimal fuzzy systems based on a multi-objective genetic algorithm was proposed [21].

4. PRESENT METHODOLOGY

4.1 Classical generating methods- In solving multi-objective optimization problems, evolutionary methods have been adequately applied to demonstrate that multiple Pareto-optimal solutions can be found in a single simulation run. Various different classical generating methods were discussed which were either quite well-known or were in oblivion due to lack of available resources and some of which were even suggested before the inception of evolutionary methodologies. These generating methods specialized either in finding multiple Pareto-optimal solutions in a single simulation run or specialized in maintaining a good diversity by systematically solving a number of scalarizing problems. Most classical generating methodologies were classified into four groups mainly based on their working principles and one representative method from each group is chosen in the present study for a detailed discussion and for its performance comparison with a state-of-the-art evolutionary method.

4.2 Multi-objective shortest path problem- An overview of the multi-objective shortest path problem (MSPP) and a review of essential and recent issues regarding the methods to its solution explore a multi-objective evolutionary algorithm as applied to the MSPP and described its behavior in terms of diversity of solutions, computational complexity, and optimality of solutions. Results proved that the evolutionary algorithm can find diverse solutions to the MSPP in polynomial time.

4.3 Order of priority to objectives- Since the beginning of the 1990s, research and application of muliti-objective evolutionary algorithms (MOEAs) had attracted increasing attention. This is mainly due to the ability of evolutionary algorithms to find multiple Pareto-optimal solutions in one single simulation run. Although MOEAs can find multiple Pareto-optimal solutions, often, users need to impose a particular order of priority to objectives.

4.4 Multiple Pareto-optimal fuzzy systems- An approach to construct multiple Pareto-optimal fuzzy systems based on a multi-objective genetic algorithm was proposed. First, in order to obtain a good initial fuzzy system, a modified fuzzy clustering algorithm was used to identify the antecedents of fuzzy system, while the consequents were designed separately to reduce computational burden. Second, a Pareto multi-objective genetic algorithm based on NSGA-II and the interpretability- driven simplification techniques were used to evolve the initial fuzzy system iteratively with three objectives: the precision performance, the number of fuzzy rules and the number of fuzzy sets. Resultantly, multiple Pareto- optimal fuzzy systems were obtained.

4.5 Method of ranking Pareto optimal solutions- A new method of ranking Pareto optimal solutions, which form a numerous set of non-dominated solutions, by using the notion of optimality in the sense of an undifferentiating interval, was studied. The ranking algorithm presented was based on the filtration of a set of Pareto optimal solutions by using the undifferentiating interval method. The example presented proved that the generated subsets of non-dominated solutions were given different ranks, which should contribute to an adequate crossover operation.

Solving real-life engineering problems requires often multi-objective, global and efficient (in terms of objective function evaluations) treatment. In the proposed approach, the problems of this type are considered by discussing some drawbacks of the current methods and a new method is then introduced to find the most significant solution from the large result set of Multi-objective Evolutionary Algorithms by applying clustering technique.

5. PROPOSED APPROACH

This approach is suitable for decision-makers that do not have a priori knowledge of the relative importance of the conflicting objectives in multi-objective optimization problem.

The developed approach is based on the following steps:

5.1 Obtain the entire Pareto-optimal set or sub-set of solutions by using a multiple-objective evolutionary algorithm (MOEA).

5.2 Apply an efficient cluster analysis algorithm to form clusters on the solutions contained in the Pareto set.

5.3 To determine the "optimal" number of clusters in the Pareto-optimal set.

5.4 To select a representative solution.

5.5 Analyze the results.

A Matlab code will be developed to perform the steps of the proposed technique. From standardized data, the code will run the clustering algorithm and from two to a specified number of means it will calculate the average silhouette values and it will return the value of k suggesting the most optimal allocation. After this, it will also return the "knee cluster" of the optimal partition, the k representative solutions of the Pareto front, and in both cases, the solution closest to the ideal or utopian point.

6. CONCLUSION

The proposed methodology based on cluster analysis is implemented to assist the decision-maker in the analysis of the solutions of multi-objective problems .Choosing a solution for system implementation from the Pareto-optimal set can be a difficult task, generally because Pareto-optimal sets can be extremely large or even contain an infinite number of solutions. The proposed method provides the decision-maker a smaller set of optimal tradeoffs .

Over the past few years, the research on evolutionary algorithms has demonstrated their role in solving multi-objective optimization problems, where the goal is to find a number of Pareto-optimal solutions in a single simulation run. Many studies have depicted different ways evolutionary algorithms can progress towards the true Pareto-optimal solutions with a widely spread distribution of solutions. However, none of the multi-objective evolutionary algorithms (MOEAs) has a proof of convergence to the true Pareto-optimal solutions with a wide diversity among the solutions.

Thus, the motivation for the current work stems from challenges encountered during the post-Pareto analysis phase. A practical approach is proposed to help in the analysis of the solution of multi-objective optimization and provide the decision-maker a workable sized set of solutions to analyze.

The proposed methodology is very much feasible taking into the account the work carried out by the researchers internationally.

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