European Journal of Operational Research xxx (2013) xxx–xxx

Contents lists available at ScienceDirect

European Journal of Operational Research

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

Decision Support

An interactive evolutionary multi-objective optimization algorithm with a limited number of decision maker calls

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ARTICLE INFO

Article history:
Received 4 September 2011
Accepted 29 August 2013
Available online xxxx

Keywords:
Evolutionary multi-objective optimization
Multiple criteria decision-making
Interactive multi-objective optimization

ABSTRACT

This paper presents a preference-based method to handle optimization problems with multiple objectives. With an increase in the number of objectives the computational cost in solving a multi-objective optimization problem rises exponentially, and it becomes increasingly difficult for evolutionary multi-objective techniques to produce the entire Pareto-optimal front. In this paper, an evolutionary multi-objective procedure is combined with preference information from the decision maker during the intermediate stages of the algorithm leading to the most preferred point. The proposed approach is different from the existing approaches, as it tries to find the most preferred point with a limited budget of decision maker calls. In this paper, we incorporate the idea into a progressively interactive technique based on polyhedral cones. The idea is also tested on another progressively interactive approach based on value functions. Results are provided on two to five-objective unconstrained as well as constrained test problems.

1. Introduction

The evolutionary multi-objective optimization (EMO) algorithms have demonstrated their ability in solving complicated multiple objective problems (Deb, 2001; Coello, VanVeldhuizen, & Lamont, 2002). They have been successful in handling two to three objective test problems, but thereafter, the deterioration in performance becomes noticeable (Deb, Thiele, Laumanns, & Zitzler, 2005; Deb & Saxena, 2006; Knowles & Corne, 2007) both in terms of convergence[1] and diversity[2] (Deb, 2001). The deterioration in performance while solving problems with larger number of objectives is primarily due to stagnation in search as the Pareto-dominance looses its discriminatory potential in higher dimensions. Moreover, the requirement of an exponentially increasing population size to explore the Pareto-optimal front leads to a huge computational expense. Difficulty in visualization of the objective space further leads to additional challenges related to performance evaluation of the algorithm as well as decision making. These difficulties are inherent to an optimization problem with a larger number of objectives, and efficient procedures are required. In this paper, we introduce a methodology, which can be integrated with any evolutionary multi-objective optimization algorithm allowing it to effectively handle problems with multiple objectives.

The EMO algorithms aim for well spread solutions close to the Pareto-optimal front for two to three objective problems. The decision maker (DM) is expected to choose the most suitable point from an array of approximately Pareto-optimal points found by the EMO algorithm. However, in this paper we propose to integrate the DM with the optimization run of an EMO algorithm in a way such that the preferences of the DM can be incorporated into the intermediate generations of the algorithm. Such an integration leads to progress towards the most preferred point.[3] This point is of course unknown at the start of the optimization run and the proposed algorithm tries to get as close to this point as possible, based on the preference information provided by the DM. Such a procedure, where a DM is involved in the intermediate generations of an EMO algorithm, is called a *progressively interactive EMO approach* (PI-EMO) (Deb, Sinha, Korhonen, & Wallenius, 2010; Branke, Greco, Slowinski, & Zielniewicz, 2009). A progressively interactive approach is a DM-oriented approach, which allows the DM to guide the algorithm towards the most preferred point. The working of such an approach can be observed from Fig. 1 for a two-objective maximization problem. The advantage associated with seeking the most preferred point, instead of the entire Pareto-optimal front, is that it saves us

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[1] In evolutionary multi-objective optimization, convergence refers to the proximity of the solutions to the Pareto-optimal frontier.

[2] In evolutionary multi-objective optimization, diversity refers to the spread of solutions approximating the Pareto-optimal frontier.

[3] The most preferred point is the point on the Pareto-optimal front which gives maximum utility/satisfaction to the DM when compared with other points on the front.

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http://dx.doi.org/10.1016/j.ejor.2013.08.046

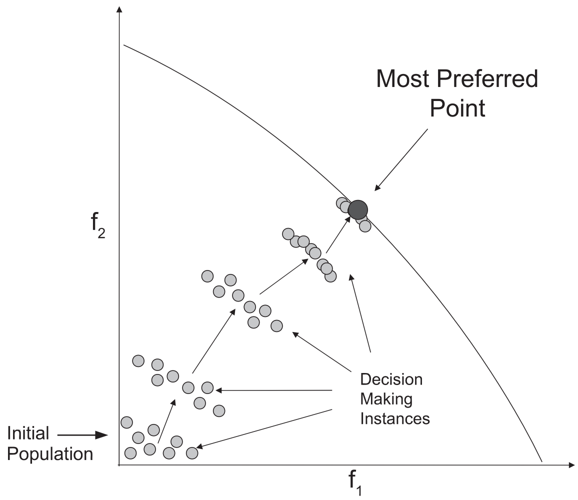

Fig. 1. Progressively interactive approach to handle a multi-objective optimization problem.

from the intricacies involved in exploring the entire multi-dimensional front.

This paper proposes a simple scheme, which could be integrated into any progressively interactive EMO algorithm to approach the most preferred point in limited number of interactions with the decision maker. The budget of DM calls[4] is taken as input at the start of the optimization run, and then the decision maker is invited to provide preference statements whenever required. The concept is integrated with a progressively interactive EMO approach based on polyhedral cones (PI-EMO-PC) (Sinha, Deb, Korhonen, & Wallenius, 2010), which is elaborately discussed in the paper. The scheme of limited budget of DM calls is generic, and is also demonstrated on another progressively interactive EMO approach based on value functions (PI-EMO-VF) (Deb et al., 2010). Results are provided for three unconstrained and two constrained test problems having two to five objectives.

2. A survey of preference-based evolutionary methods

A multi-objective optimization problem inherently consists of two tasks, namely, search and decision making. These two tasks can be combined in various ways to generate procedures, which can be classified into three broad categories, i.e. apriori approach, aposteriori approach and interactive approach. In this section, we provide a review for the methods falling in each of these categories. Discussion about preference-based methods can also be found in the review papers by Rachmawati and Srinivasan, 2006 and Branke, 2008.

In the apriori approach, preferences are elicited before the start of the algorithm; then the optimization task is executed by incorporating the preference information, and the most preferred solution is identified. Biased niching based EMO (Branke & Deb, 2004), the reference direction based EMO (Deb & Kumar, 2007), reference point-based EMO approaches (Deb, Sundar, Uday, & Chaudhuri, 2006; Thiele, Miettinen, Korhonen, & Molina, 2009), and the light beam approach based EMO (Deb & Kumar, 2007) represent some of the efforts in the direction of utilizing preference information before the start of an EMO algorithm. Once the information is available in the form of a reference direction or reference point, the algorithm finds the most-preferred point without any further interaction with the DM. Deb et al., 2006 used the concept of the reference point, but did not apply an Achievement Scalarizing Function; they rather used a weighted Euclidean distance to rank population members. In a later study, Thiele et al., 2009 implemented a similar idea using the Achievement Scalarizing Function. Another simple algorithm based on this approach is to modify dominance based on ranks obtained for a few alternatives from the DM. Such an approach was used by Greenwood, Hu, and D'Ambrosio, 1996 in their study. Tiwari, Wiecek, and Fadel, 2008 used pre-determined preference cones in an evolutionary algorithm to converge to a part of the Pareto-optimal frontier. They considered two objective test problems in their study.

Information in an apriori approach is elicited towards the beginning, therefore, the solution obtained after executing the algorithm is usually not the best solution and may not even be close to the most preferred solution. The preference structure of the DM at the beginning might be different from the preference structure at the Pareto-optimal front. Therefore, the approach is highly error prone, as even slight deviations in providing preference information at the beginning may lead to entirely different solutions.

Most of the evolutionary multi-objective algorithms (Deb, Agrawal, Pratap, & Meyarivan, 2002; Zitzler, Laumanns, & Thiele, 2001) which aim to find the entire frontier, are classic examples of the aposteriori approach. In such methods, the decision making aspect is ignored and the entire Pareto-optimal frontier is generated before incorporating the DM. However, as already mentioned, there are enormous difficulties in finding the entire Pareto-optimal front for a problem having a large number of objectives. Choosing the most preferred solution from this front makes the problem even more challenging.

Realizing the various difficulties associated with the above two approaches, in recent years there has been interest towards development of interactive EMO algorithms, particularly for problems having a large number of objectives. A variety of interactive methods have been presented in the literature, but our focus is on progressively interactive techniques. As already mentioned, progressively interactive methods converge towards a particular region of the frontier by incorporating preferences obtained from the DM in the dominated regions of the objective space. Preference elicitation is performed during the course of optimization such that a progress towards the most preferred point is made. Some of the recent work in the direction of progressively interactive techniques are Phelps and Koksalan, 2003, Fowler et al., 2009, Jaszkiewicz, 2007, Branke et al., 2009, Koksalan and Karahan, 2010, Deb et al., 2010. Next, we briefly highlight the salient features of these studies.

Phelps and Koksalan, 2003 periodically accept preferences from the DM and construct a linearly weighted sum of objectives, which is optimized in the subsequent generations using an evolutionary algorithm. Fowler et al., 2009 send a few solutions to the DM for ranking, and construct a convex preference cone, which is used to rank the members not considered by the DM. The study assumes a quasi-concave preference structure for the DM, and presents the results on multi-dimensional knapsack problems. Jaszkiewicz, 2007 also uses linear value functions, however, his strategy is to select a set of compatible linear value functions from randomly generated linear value functions. The selected value functions are then used within the EMO algorithm to explore the preferred regions on the frontier. In fact, many algorithms use linear value functions, but they have limitations in handling problems where the most preferred point lies on a non-convex part of the Pareto-optimal front. Branke et al., 2009 implemented the GRIP (Figueira, Greco, & Slowinski, 2009) methodology, where the preference information from the DM is used to construct all possible additive value functions conforming to the preferences. This guides the

[4] A DM call is an event where the algorithm seeks preference information from the DM.

Please cite this article in press as: Sinha, A. et al., An interactive evolutionary multi-objective optimization algorithm with a limited number of decision maker calls, European Journal of Operational Research (2013), http://dx.doi.org/10.1016/j.ejor.2013.08.046