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Development of Pareto-based evolutionary model integrated with dynamic goal programming and successive linear objective reduction

Baehyun Min [a], Changhyup Park [b,*], Ilsik Jang [c], Joe M. Kang [d], Sunghoon Chung [d]

[a] Center for Petroleum and Geosystems Engineering, The University of Texas at Austin, Austin, TX 78712, USA
[b] Department of Energy and Resources Engineering, Kangwon National University, Chuncheon, Kangwon, Republic of Korea
[c] Department of Energy and Resources Engineering, Chosun University, Gwangju, Republic of Korea
[d] Department of Energy Systems Engineering, Seoul National University, Seoul, Republic of Korea

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ABSTRACT

This study investigates the coupling effects of objective-reduction and preference-ordering schemes on the search efficiency in the evolutionary process of multi-objective optimization. The difficulty in solving a many-objective problem increases with the number of conflicting objectives. Degenerated objective space can enhance the multi-directional search toward the multi-dimensional Pareto-optimal front by eliminating redundant objectives, but it is difficult to capture the true Pareto-relation among objectives in the non-optimal solution domain. Successive linear objective-reduction for the dimensionality-reduction and dynamic goal programming for preference-ordering are developed individually and combined with a multi-objective genetic algorithm in order to reflect the aspiration levels for the essential objectives adaptively during optimization. The performance of the proposed framework is demonstrated in redundant and non-redundant benchmark test problems. The preference-ordering approach induces the non-dominated solutions near the front despite enduring a small loss in diversity of the solutions. The induced solutions facilitate a degeneration of the Pareto-optimal front using successive linear objective-reduction, which updates the set of essential objectives by excluding non-conflicting objectives from the set of total objectives based on a principal component analysis. Salient issues related to real-world problems are discussed based on the results of an oil-field application.

1. Introduction

The term *many-objective problems* (MOPs) refers to problems that involve four or more objectives, in general [1]. The purpose of optimizing MOPs is to yield trade-off optimal responses in posterior space (objective space) by adjusting decision variables in prior space (variable space) [2]. More than 90% of multi-objective optimization approaches have been based on Pareto-optimality using meta-heuristic techniques [3]. Most meta-heuristic methods have adopted evolutionary algorithms of which population-based properties strengthen a multi-points search toward an optimal solution domain called a Pareto-optimal front (POF), i.e. a set of Pareto-optimal solutions [4–6]. Pareto-optimality is a state of optimal allocation of resources in which no response can be improved without deteriorating other responses [7]. A variety of evolutionary multi-objective optimization (EMO) algorithms have been proposed to represent the POF by achieving two orthogonal goals simultaneously: convergence of solutions as close to the POF as possible and diversity of solutions as uniformly distributed along the POF as possible [8–25].

Many Pareto-based EMO algorithms have demonstrated their applicability in solving two or three-objective problems [11,14,16–23]. Given a finite population size, however, it is difficult to capture the entire POF in high-dimensional objective space because the structure of the POF becomes more complicated in proportion to the number of conflicting objectives [24,25]. High computational cost, poor scalability, and hardness in visualizing the multi-dimensional POF are the main difficulties associated with the increasing complexity of the POF. In short, these difficulties are called a *curse of dimensionality* [26]. POF is a $M-1$ dimensional hyperplane under regularity condition if M objectives conflict with each other in the optimal solution domain [27]. At least L^{M-1} data points are required to approximate the POF provided that L data points be necessary to represent the one-dimension of objective space [26]. Assuming that L is 3 and the population consists of 50 solutions, for example, this population size is too small to

* Corresponding author. Tel.: +82 33 250 6259; fax: +82 33 259 5544.
E-mail address: changhyup@kangwon.ac.kr (C. Park).

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approximate the four-dimensional POF because at least 81 data points are needed. As a result, a bias of solutions on a certain part of the POF is inevitable when using population-based algorithms for solving MOPs. Increasing the population size might give rise to enormous computational cost. Furthermore, a large number of objectives deteriorate the convergence speed toward the POF owing to the increasing probability that most non-dominated solutions become stagnated in the non-optimal solution domain [9]. As a compromise, the degeneration of objective space has been investigated for balancing the number of objectives and the population size.

Objective-reduction approaches compress the objective space by selecting an essential objective set that can preserve a similar dominance relationship in a total objective set on the basis of feature selection [28–39]. This dimensionality-reduction of objective space is based on the premise that redundant objectives exist in the given MOPs [29]. The POF in reduced objective space needs to be identical to the POF in the original objective space [30]. The redundancy among objectives can be measured in terms of the degree of dependences between pairs of objective vectors obtained from the fitness evaluation of solutions. The redundant objectives omitted in the current generation are excluded from the evolutionary process in subsequent generations. The limitation of the objective-reduction scheme is that an improvement of convergence speed toward a reduced POF is insignificant if the number of essential objectives is greater than four [37]. Furthermore, it is difficult to capture the true Pareto-relation among objectives from non-optimal solutions in high-dimensional objective space. To the best of our knowledge, only a few references pointed out that applying the preference-ordering scheme to the degenerated objective space could delineate the POF more reliably [38,39].

Preference-ordering approaches focus on finding solutions that satisfy the aspiration levels reflecting the decision maker (DM)'s preference on the objectives [40–89]. Compared with the objective-reduction scheme, the preference-ordering scheme regards every objective as essential. The most distinguishing feature of these approaches combined with an EMO algorithm is to accelerate the convergence toward a specific part of the POF while enduring a loss in diversity of non-dominated solutions. Otherwise, the computational cost increases exponentially in proportion to the dimension of the POF. With reference to Ishibuchi et al.'s review [40], preference-ordering techniques can be classified as follows: modifying Pareto-dominance relation [41–50]; using scalarizing functions [51–60]; using indicator functions [61–67]; assigning different ranks to solutions [68–72]; and allocating reference points [45,46,73–77]. The drawback of the above techniques is that increasing the selection pressure excessively might provide only a few biased Pareto-optimal solutions. The degree of selection pressure is related to how the preference is articulated on the objectives. Hence, the adaptive preference is of importance for solving complex MOPs since it is difficult to find non-dominated solutions that satisfy every preference simultaneously in high-dimensional objective space [78]. Preference information does not affect the evolution of non-dominated solutions, in the case where all solutions either satisfy or fail to achieve the given preference [79–81]. Meanwhile, the importance of the adaptive control has led some researchers to extend reinforcement learning [82–86] to sequential multi-objective decision-making analyses [87–89]. Nevertheless, it is a job to separate the benefits associated with each objective for identifying trade-offs solutions in the domain of multi-objective reinforcement learning.

This study investigates the coupling effects of preference-ordering and objective-reduction schemes on the search efficiency of the evolutionary process for resolving the scalability issue in exploring the high-dimensional POF. Dynamic goal programming (DGP) for prioritizing solutions that satisfy the aspiration levels for the essential objectives and successive linear objective-reduction (SLOR) for updating the set of essential objectives are developed individually, and then combined with a multi-objective genetic algorithm (MOGA). Non-dominated Sorting Genetic Algorithm-II (NSGA-II), one of the widely used MOGAs, is adopted in the proposed framework to provide a set of non-dominated solutions with regard to the essential objectives [18]. DGP adjusts both the aspiration levels and the constraints allocated to the essential objectives adaptively, thereby inducing the convergence of the evolved solution set toward the POF. The induced solutions facilitate a degeneration of the POF using SLOR, which updates the set of essential objectives by excluding non-conflicting objectives based on a principal component analysis. For brevity, this framework is named DS-MOGA (MOGA combined with DGP and SLOR) in this paper. The performance of DS-MOGA is demonstrated in redundant benchmark test problems, non-redundant benchmark test problems, and a subsurface modeling problem.

2. Theoretical background of multi-objective optimization

This section explains the parameterization of MOP (see Section 2.1) and the Pareto-dominance relation (see Section 2.2) in brief.

2.1. Parameterization of many-objective problem

Eq. (1) generalizes a multi-objective minimization problem:

$$\begin{aligned} &\text{Minimize} \quad y = f(x) = f(x_1, \ldots, x_N) = \{f_1(x), \ldots, f_M(x)\} \\ &\text{Subject to} \quad x \in X, f(x) \in Y, \end{aligned} \tag{1}$$

where x is a variable vector in prior space X, f is an objective estimator to compute an objective vector $f(x)$ in posterior space Y, x_i is the ith decision variable in x, $f_j(x)$ is the jth objective value in $f(x)$, N is the number of decision variables, and M is the number of objectives. Computing $f(x)$ is called forward modeling, while estimating x from $f(x)$ is called inverse modeling. Optimization is an iterative process of forward and inverse modeling in order to explore a set of optimal solutions, minimizing $f(x)$ in objective space. In this paper, the term *solution* refers to the variable vector x and its corresponding objective vector $f(x)$ interchangeably. In reservoir characterization, for example, the solution indicates a reservoir model of which the variable vector x is a set of static rock and fluid properties to be adjusted (porosity, permeability, capillary pressure) and the objective vector $f(x)$ is a set of dynamic responses to be matched (time-series production/injection data measured at wells).

2.2. Pareto-dominance relation

Pareto-optimality is a state of an optimal allocation of resources [7]. Mathematically, Pareto-optimality is defined as the best non-domination that is a state of equivalence where no solution can be improved with respect to any objective without worsening at least one other objective [9]. Assuming a minimization problem, a variable vector $x_1 \in X$ is said to dominate a variable vector $x_2 \in X$ if and only if Eq. (2) is satisfied:

$$\forall i \in \{1, \ldots, M\} : f_i(x_1) \le f_i(x_2) \wedge \exists j \in \{1, \ldots, M\} : f_j(x_1) < f_j(x_2). \tag{2}$$

Dominance of x_1 over x_2 implies that x_1 is superior to and then preferred over x_2 for decision making. Simply, $f(x_1) \prec f(x_2)$. If Eq. (2) is not satisfied, x_1 is said to conflict with x_2. Both x_1 and x_2 are non-dominated to each other, thus regarded as equivalent solutions.x_1 becomes a member of the Pareto-optimal solutions if no other variable vector x dominates x_1 in the M-dimensional