Are the "Best" Solutions to a Real Optimization Problem Always Found in the Noninferior Set? Evolutionary Algorithm for Generating Alternatives (EAGA)

Emily M. Zechman and S. Ranji Ranjithan

North Carolina State University, CB 7908, Raleigh, NC 27695, USA
{emzechma,ranji}@eos.ncsu.edu

1 Introduction

Evolutionary algorithms (EAs) continue to offer an effective, powerful, and sometimes exclusive way to search for solutions to real optimization problems. While these algorithms can help solve a complex optimization problem, whether the results represent the "best" choices for making decisions about a solution to a real problem is questionable. In decision-making problems that are ill posed, all objectives may not be defined clearly and therefore not quantitatively captured in the optimization model [1]. The noninferior set of solutions to the optimization model being solved may not necessarily contain the best solution to the actual problem.

The search for "good" solutions to a real optimization problem with unmodeled objectives should not be focused only on the noninferior set. Exploring the inferior region is important to make better decisions. As described in [2], the Modeling to Generate Alternatives (MGA) approach implements a systematic exploration to generate a small number of alternative solutions that are good within the modeled objective space while being maximally different in the decision space. A target constraint in the objective value is specified to allow search in a small region of the non-inferior space. Resulting alternative solutions are likely to provide truly different choices, all performing similarly with respect to the modeled objectives but differently with respect to unmodeled objectives, enabling exploration of the decision space for good solutions while considering unmodeled objectives when making decisions. The focus of this paper is to present a new EA-based approach for generating good alternative solutions for real problems with unmodeled objectives.

2 Evolutionary Algorithm for Generating Alternatives (EAGA)

EAGA is designed to generate a small number of good but maximally different alternatives, where subpopulations collectively and simultaneously search for different solutions. Each solution is represented by one subpopulation that undergoes an evolutionary search procedure. The survival of solutions in each subpopulation depends upon the performance of a solution with respect to the modeled objectives as well as upon how far that solution is from the others in decision space. The main steps of the algorithm are described below.

E. Cantú-Paz et al. (Eds.): GECCO 2003, LNCS 2724, pp. 1622–1623, 2003.

Step 1. Initialization – create an initial population with P subpopulations (each with a population size of K), where P is the number of alternative solutions being sought. Let SP_p (p=1, …,P) represent the index for subpopulation p. First subpopulation (SP_1) is dedicated to the search for the optimal solution to the modeled problem, and this solution will serve as the benchmark for setting the relaxation constraint.
Step 2. In SP_1, evaluate and identify the best solution with respect to the modeled objective.
Step 3. In SP_p, p=2, …, P, evaluate all solutions with respect to the modeled objective. Solutions that meet the target constraint are assigned a "feasible" flag, and the others an "infeasible" flag.
Step 4. Apply elitism operator to all subpopulations $SP_{p.}$
Step 5. Check for termination criteria. Stop the algorithm if termination criteria (e.g., a maximum number of iterations) are met. Otherwise, go to Step 6.
Step 6. For each SP_p, identify the centroid in decision space.
Step 7. For each solution k in subpopulation q ($q \neq 1$), calculate a distance measure $D^{k,q}$ in the decision space between that solution and other subpopulations. This distance represents the minimum distance between solution k in subpopulation q and the centroids of all other subpopulations.
Step 8. In each subpopulation SP_p, apply binary tournament selection. In SP_1, the selection is based on how good the solution is with respect to the modeled objectives. In SP_p, $p \neq 1$, the selection is based on the goodness of the solution with respect to the modeled objectives (feasibility) as well as its distance from other subpopulations ($D^{k,p}$).
Step 9. In each subpopulation, apply crossover and mutation operators to the solutions selected in Step 8, and repeat Step 2.

3 Final Remarks

The new method EAGA extends the powerful alternatives generation notions that are established in the mathematical programming and operations research literature to evolutionary search. By enabling the EA to systematically search in slightly inferior regions for maximally different solutions in the decision space, their value in offering good solutions to real problems is enhanced.

References

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