Genetic Algorithms, Building Blocks, and Multiobjective Optimization

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1 Introduction

The process of solving Multiobjective Optimization Problems (MOPs) with Multiobjective Evolutionary Algorithms (MOEAs) presents several unique challenges (e.g., vector-valued fitness, *sets* of solutions, evolutionary operator complexity). For a good introduction to the relevant issues and past EA-based approaches, see the articles by Van Veldhuizen and Lamont [5], Coello [1], and by Fonseca and Fleming [2]. This paper focuses on the traditional notion of *building blocks*, extending the concept to the MOP domain in an effort to develop more effective and efficient MOEAs. This is a new, innovative MOEA approach.

2 MOPs and Building Blocks

When considered at a meta-level, standard EAs (which are predicated upon building block use) often perform much better than random search, implying their use of building blocks (problem domain knowledge) is responsible for their effectiveness and/or efficiency. It then appears that building blocks are useful in *some* problem solving situations. We center our attention on the explicit use of building blocks when solving MOPs.

The Schema Theorem has been historically thought of, described, and analyzed in terms of single-objective functions. However, the building block concept remains applicable when extended to MOPs. We first point out that building blocks are not structurally modified by the simultaneous optimization of more than one function. To illustrate, assume a binary-valued genotype of length l containing several building blocks. Single-objective optimization maps this genotype to a single value; this is the genotype's associated fitness or phenotype. In MOPs the same genotype maps to a *multi*-valued fitness vector. However, the genotype's structure and its building blocks have not changed in any way. It is simply that two or more fitness functions have been evaluated with respect to a *single* genotype resulting in multiple associated fitnesses.

Single-objective optimization attempts to find a genotype(s) mapping to "high" fitness; MOPs attempt the same. While single-objective optimization problems generally search for a (possibly) unique single solution, MOPs often focus on a *set* of efficient solutions which may well have very *dissimilar* building blocks! Good MOP building blocks drive search towards solutions in the Pareto optimal set, which defines the trade-off surface of the MOP from which some decision maker implicitly indicates acceptable solutions. These solutions may have no clearly apparent relationship besides their membership in the Pareto optimal set. In fact, building blocks which are "good" for some Pareto optimal solution(s) may be "not good" for an arbitrarily chosen other (or subset).

3 The Multi-Objective mGA (MOMGA)

We initially consider the mGA [3] as a vehicle with which to define and investigate MOP building blocks. We select this algorithm for several reasons, although primarily because it was designed to explicitly manipulate appropriate building blocks in order to arrive at an optimal solution and its enumeration of all possible building blocks of a specified size.

Additionally, we choose the mGA code as it is freely available, its operation well understood, and its structure modifiable to solve MOPs. We modify mGA features in producing the MOMGA including fitness evaluations and storage, selection, and the competitive template concept. We also employ a form of sharing. Figure 1 graphically shows the MOMGA's operation.

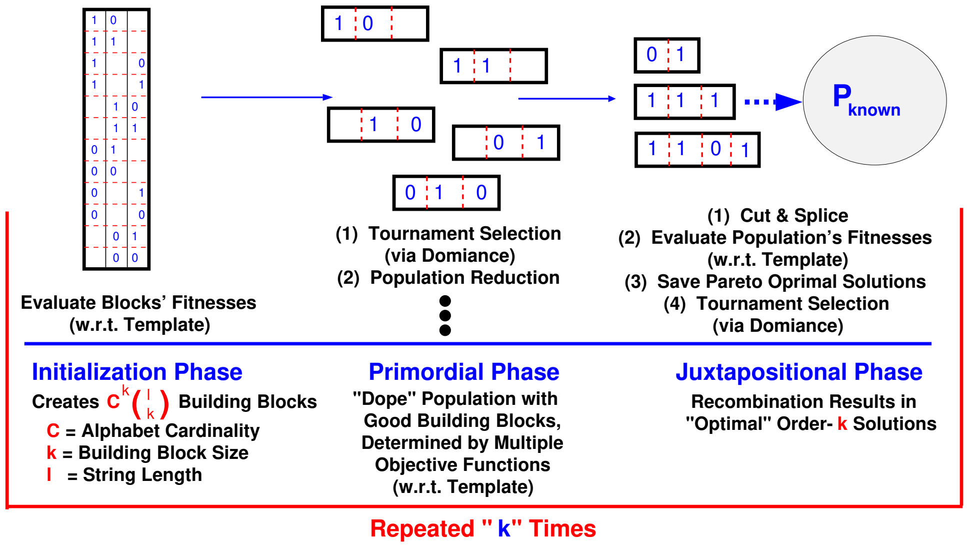

Figure 1: MOMGA Operation

4 Initial Experimental Results

We implemented the MOMGA and executed it against several numeric MOPs in our proposed MOEA test function suite [6]. Although numeric test functions provide a common basis for MOEA comparison, these comparisons are still empirical unless the Pareto front is known. For most MOPs of any complexity this is not the case, however, there is a way to determine the Pareto front at a given computational resolution by enumerating the entire search space. Other algorithms using the same resolution can then be absolutely compared against the determined MOP optimum. This methodology, which uses parallel computation, is discussed elsewhere [6]. We are now using the MOMGA in more complex experiments and refining our experimental metrics.

5 Conclusions and Future Work

The building block concept is valid when extended to MOPs. Our MOMGA specifically manipulates building blocks in its search for desired MOP solutions. It produces statistically comparative solutions as compared to other MOEAs over a comprehensive test suite [4, 6].

We plan to extend other building block-based EAs to the MOP domain. This results not only in an alternate building block MOP solution method, but also offers a different view of the solution process and gene linkage, possibly unearthing essential theoretical information.

References

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