

Chapter XIV

Evolutionary Multi-Objective Optimization in Military Applications*

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ABSTRACT

Evolutionary methods are used in many fields to solve multi-objective optimization problems. Military problems are no exception. This chapter looks at a variety of military applications that have utilized evolutionary techniques for solving their problem.

INTRODUCTION

Many real world problems in the military are inherently multi-objective problems (MOPs). Quite often, the problem contains competing objectives, where the optimization of one objective degrades the value of another such as mission success vs. resource survival. To solve some of these problems, researchers have applied numerous optimization techniques. The technique applied usually depends on the complexity of the problem. For a

simple single objective optimization problem, a deterministic method such as depth-first search, the simplex technique or Tabu search might be the most appropriate method. But for a highly complex, high dimensional NP-complete problem, a stochastic algorithm may be the better choice in finding an acceptable solution in a reasonable amount of time. Multi-objective Evolutionary Algorithms (MOEAs) are a stochastic search method with the ability to find sets of acceptable tradeoff solutions. Also, their performance as addressed in

this chapter is less susceptible to the shape of the search landscape and the associated Pareto front (Coello, Van Veldhuizen, & Lamont 2002).

For the modern military there are many complex MOPs that require effective solutions to be provided in an efficient manner. Military MOPs come from a variety of disciplines but usually can be symbolically formulated with objectives and constraints and thus, are reflected in a mathematical or computational model (Coello et al., 2002). In this chapter we consider a variety of explicit military applications including military communication networks (design, routing and layout), resource management (facilities, engine maintenance), mission planning, dynamic simulation and technical resource design optimization (low energy laser, autopilot). Other applications are briefly mentioned. Through these problem domain and MOEA discussions, we wish to motivate the use of MOEA stochastic search techniques to find efficiently “good” solutions to complex multi-objective military problems.

COMMUNICATION NETWORKS

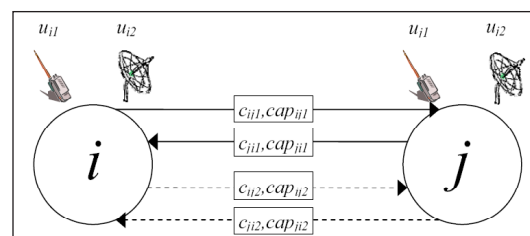
Because of the impact of military communication networks on overall performance, various network problems are addressed. For example, consider a network design problem that attempts to find the best network configuration with respect to total cost and average number of hops. Another presented example develops routing optimization possibilities and layout optimizations of wireless sensor networks. Network sensor layout for wireless sensors and associated management are other important military applications which are discussed.

Network Design

Computer networks are vital for the military in order to relay information quickly. Kleeman (2007a) research the network design problem,

which is a critical piece for network centric warfare. The MOP was derived from the single objective problem introduced by Erwin (2006). The problem is a variation of the **multicommodity capacitated network design problem (MCNDP)**. For this problem, a network consists of nodes and arcs. Additionally, each node can have a number of interfaces (interfaces can be different types of connection points in the network—such as satellite, infrared or hardwired connections). Each interface can be connected to every other node (through the same interface type) via an arc, but it does not have to be a fully connected graph. The arcs are unidirectional and each has a fixed capacity. The capacities for each arc can be different. Each node can have a commodity (messages, packets, etc.) that it needs to send to every other node in the network. Each commodity has a bandwidth requirement. This problem is detailed enough that the optimization process can determine where bottlenecks may be in the network and find routes to overcome the bottlenecks. We let u_{if} denote the number of interfaces of type f at node i . The fixed cost of including an arc from node i to node j via interface type f in the network is denoted c_{ijf} . The capacity of each arc is given by cap_{ijf} . In the following arc representation we let the number of interface types be fixed at 2. We use solid and dashed arcs to distinguish between the different interface

Figure 1. Modified Monte Carlo results for the 2nd instance of a 10 node problem (Kleeman, 2007a)



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