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Stochastic resource allocation using a predictor-based heuristic for optimization via simulation

Sharif H. Melouk [a,*], Belleh A. Fontem [a], Emily Waymire [b], Shane Hall [c]

[a] Department of Information Systems, Statistics, and Management Science, The University of Alabama, Tuscaloosa, AL 35487, United States
[b] Naval Surface Warfare Center, Panama City Division, Panama City, FL 32407, United States
[c] Department of Operational Sciences, Air Force Institute of Technology, Wright-Patterson AFB, OH 45433, United States

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ABSTRACT

Some combinatorial stochastic resource allocation problems lack algebraically defined objective functions and hence require optimization via simulation as a mechanism for obtaining good solutions. For this class of problems, we propose a new predictor-based heuristic that uses a distance criterion to perform the solution search. To demonstrate our solution approach, we apply this heuristic to the problem of selecting the proper design configuration of an unmanned aerial system (UAS) fleet so as to maximize mission effectiveness. We compare our approach to black box optimization via simulation approaches (two tabu search-based procedures and a greedy heuristic) and glean both methodological and practical insights.

1. Introduction

Resource allocation problems encompass a large collection of optimization problems in which a limited resource must be assigned to pre-determined entities while adhering to system constraints. Typically, allocation of the resource to the entities occurs in discrete units. For instance, in the classic cutting stock problem, the master paper roll (i.e., the resource) may only be cut into smaller rolls (i.e., entities) of pre-determined various-sized widths. Another example involves investing a fixed monetary budget by composing a portfolio of assets from a larger array of assets to maximize returns while minimizing risk. In this case, the fixed monetary budget serves as the resource while the potential assets serve as the entities. In general, the problem solution space consists of the set of feasible configurations in which the resource may be allocated. Typically, an optimal solution to the problem contains a mix of all involved entities.

In certain instances, the lack of an algebraic expression for the objective function requires the use of simulation optimization techniques to obtain high quality solutions. Some of these techniques involve updating prior beliefs on parameters characterizing the uncertainty on the function being optimized (i.e., Bayesian methods). Frazier and Powell [1] determine sufficient conditions under which sequential measurements converge to global optimality. Essentially, the goal is to select only those measurements that yield the most benefit in knowledge according to some previously expressed preference (e.g., expectation, minimax). Mockus and Mockus [2] compared expected and minimax Bayesian approaches to global and stochastic optimization on continuous spaces. A very well-known Bayesian global optimization strategy is the look-ahead policy first introduced by Gupta and Miescke [3].

Other policies such as those by Chen et al. [4–6] propose measurement strategies that pick points sequentially for sampling in order to improve the probability of ultimately selecting the best point after sampling terminates. Glynn and Juneja [7] and Broadie et al. [8] develop strategies to allocate a simulation budget so as to maximize the probability of selecting the best performing point in the solution space. While good theoretical bounds on the performance of some of these Bayesian methods exist, they require significant implementation effort.

The main contribution of this research is a heuristic which uses a predictor in the context of simulation optimization to solve discrete resource allocation problems with objective functions whose algebraic forms are unknown. We also develop tabu search-based heuristics as well as a greedy heuristic and test all the approaches on a problem pertaining to the design of fleets of unmanned aerial systems. The remainder of this paper is organized as follows. Section 2 reviews the literature pertaining to related simulation optimization approaches. Section 3 describes a specific stochastic resource allocation problem and presents its formulation. Section 4 introduces and explains the developed predictor-based heuristic. Section 5 presents alternate solution approaches as a basis for comparison with the newly developed heuristic procedure. Section 6 discusses the results of numerical

* Corresponding author. Tel.: +1 205 348 3217.
E-mail address: smelouk@cba.ua.edu (S.H. Melouk).

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experimentation. In the last section, we summarize our findings and discuss possible areas for extension.

2. Literature review

The goal of a combinatorial optimization problem is to find the best solution vector that maximizes or minimizes a certain objective function. Often, uncertainty exists regarding the algebraic structure of the objective function such that optimization via simulation provides a viable alternate solution approach to find high quality solutions. In terms of searching the solution space, heuristic methods prove useful in tackling such problems and provide several advantages over completely random search methods [9]. A large family of randomized methods exist with learning capabilities that allow smart adaptation through a random process of finding a global optimum.

Tabu search [10], simulated annealing [11], and genetic algorithms, in pure as well as in hybrid forms successfully, address multi-objective resource allocation problems such as the ones studied by Lin and Gen [12] and Osman et al. [13]. In recent years, swarm intelligence methods, which mimic the global intelligence of decentralized units, have gained considerable importance. The most popular approaches derive from the collective action of food-searching insects such as ants [14] and bees [15].

Simulating solution points to estimate their performances also allows for the construction of a metamodel to capture the response of the unknown objective function with respect to control and environmental variables (e.g., kriging). Ankenman et al. [16] develop a kriging model incorporating uncertainty stemming from the unpredictability of simulation replications as well as that of the unknown response surface. In a traditional multi-stage stochastic programming framework with a well-defined objective function (discrete or continuous), the merit of a candidate solution is an evaluation of a feasible policy describing the actions to be successively taken in an uncertain environment. In other words, decision-making with the possibility of recourse is a defining characteristic.

Xu et al. [17] develop a three-phase approach (termed Industrial Strength COMPASS) to search discrete spaces defined by convex linear constraints. Shi and Olafsson [18] propose a nested space partitioning method for discrete deterministic problems and prove assured convergence to a global optimum. Later, an extension was developed for discrete stochastic problems [19] although convergence to a global optimum was shown only to be asymptotic. The superiority of the nested partitions method lies in that it makes no a priori assumptions on the structure of the solution space, and it has been combined with other ranking methods to generate a faster hybrid [20]. However, bounds on the rate of convergence are unknown, and the convergence of this method strongly depends on the moment generating function of the random performance (response) of solutions being finite.

Our optimization approach, within a simulation optimization context, consists of a predictor-based heuristic that employs a distance criterion to guide the solution search process. Even though the moment generating function characterizing the response uncertainty in this problem is unknown, the predictor-based heuristic approach does not hinge on it taking any specific form. Through experimentation with a military vehicle design problem, we compare its performance to a tabu search-based metaheuristic (two versions) as well as a specially designed greedy heuristic.

In the next section, we introduce the actual discrete resource allocation problem (with an unknown algebraic expression for the objective function) on which we apply our solution procedures. The detailed description of the problem aids in understanding the newly developed predictor-based heuristic as well as the structure of the “black box” solution approaches.

3. UAS design problem

3.1. Background

Problems related to unmanned aerial systems (UASs) have recently been gaining currency in light of the increasing relevance of missions in areas with difficult terrain. Besides minimizing direct human intervention and consequently mitigating exposure to harm, there are numerous reasons for increased UAS use including cost savings and increased options with advantages for search strategy and operations. UASs may also be broadly used for gathering intelligence and tracking targets as well as for search and rescue purposes [21]. However, there are complex challenges associated with the deployment of UASs including control and routing issues which have been studied extensively. In the relevant literature, researchers have applied numerous heuristic techniques to solve pure routing [22], task assignment [23], or even integrated versions that combine both aspects [21,24]. In general, assignment problems have been widely researched since the seminal work of Kuhn [25].

While these operational assignment challenges are significant, they only come into play once the actual UAS fleet has been properly designed and configured. Given a set of hardware components with specific capabilities, the task of selecting the optimal subset of components to construct a UAS is not straightforward because the performance of the selected components depends considerably on random events beyond the control of the designer. As such, no algebraic mapping is available to predict the performance of a certain system hardware configuration in a mission. In addition, certain component combinations may violate aerodynamic or budget constraints, hence feasibility is a complicating issue. Even though the hardware makeup of a UAS is fundamental to its performance, no previous work has considered this aspect of UAS optimization.

Given a budget constraint, the problem is to optimally determine the number of UASs comprising a fleet and the number and type of components that provide each UAS with mission capability. Components are defined as sensors, radars, and weapons payload. More specifically, each UAS is composed of visual components (one or more sensors plus a single radar) and payload components (possibly belonging to different weight classes). The quality of a particular solution (i.e., UAS fleet configuration) is assessed by a mission effectiveness performance measure which is to be maximized. The fleet is homogeneous in that all of the UASs are identical. While fleet configuration may be a tactical decision at times, we focus on the its operational aspect in which quick decision-making is vital to mission success.

3.2. Simulation model

A discrete event simulation model represents the mission (i.e., searching for targets) of a UAS fleet. Model output from a single replication comes in the form of percent targets destroyed. Over independent multiple replications, an expected value (average) serves as an evaluation of a particular UAS fleet configuration. The cyclical flow of decisions made by each UAS during the course of simulating a solution is shown in Fig. 1. The whole arrows indicate true boolean values while the dashed arrows are false boolean values.

Referring to Fig. 1, if any target lies in the field of vision (FOV) of the sensor or radar of a UAS, the model calculates an identification probability. If this probability lies above a certain threshold, then available payload from a given weapon type is dropped on the target. Heavier weapons have a greater probability of eliminating an impacted target. The flowchart in Fig. 1 is valid for each UAS in the fleet irrespective of the fleet population. Essentially, the simulation model depicts a fleet of UASs flying over a collection of targets, all enclosed within the boundaries in a two-dimensional grid called