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A swarm intelligence based sample average approximation algorithm for the capacitated reliable facility location problem

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ABSTRACT

We present a novel hybrid method, swarm intelligence based sample average approximation (SIBSAA), for solving the capacitated reliable facility location problem (CRFLP). The CRFLP extends the well-known capacitated fixed-cost facility problem by accounting for the unreliability of facilities. The standard SAA procedure, while effectively used in many applications, can lead to poor solution quality if the selected sample sizes are not sufficiently large. With larger sample sizes, however, the SAA method is not practical due to the significant computational effort required. The proposed SIBSAA method addresses this limitation by using smaller samples and repetitively applying the SAA method while injecting social learning in the solution process inspired by the swarm intelligence of particle swarm optimization. We report on experimental study results showing that the SIBSAA improves the computational efficiency significantly while attaining same or better solution quality than the SAA method.

1. Introduction

Facility location and strategic supply chain decisions require significant investment and planning for uncertain future events. One example of an uncertain event is the disruption of critical facilities (Schütz et al., 2009), which can be due to natural disaster or be man-made (i.e., terrorist attacks, labor strikes, etc.). In certain cases, a regional disruption may affect or migrate through other parts of the supply chain (Masihtehrani, 2011). Recent examples of such disruptions include the 2011 earthquake in Japan which affected Toyota's ability to ship parts and finish vehicles (The Guardian, 2011; Brennan, 2011), hurricanes Katrina and Rita in 2005 which disrupted the nation's oil refineries, and the 2000 fire at the Royal Philips Electronics radio frequency chip manufacturing plant in Albuquerque which halted the production of Ericsson and Nokia products (Snyder et al., forthcoming).

Following a disruption event, it is difficult to rapidly change the supply chain substructure (Snyder et al., forthcoming). A common recourse is to reassign customers to other facilities or arrange alternative sources of supply. In either case, the cost of serving the customer demand increases due to issues such as higher transportation costs. The effect such disruptions have on supply chain network design has received significant attention in the literature over the past decade. In Snyder and Daskin's (2005) exemplary study, a reliability-based formulation for Uncapacitated Facility Location Problem (UFLP) was developed and the authors also proposed a Lagrangean relaxation based algorithm. More recently, Shen et al. (2011) studied a variant of the reliable UFLP in Snyder and Daskin (2005) called uncapacitated reliable facility location problem (URFLP). Shen et al. (2011) proposed highly efficient approximation algorithms for URFLP by exploiting the problem's special structure. However, these approximations cannot be applied to the general class of facility location problems such as capacitated reliable facility location problems (CRFLPs).

In practice, capacity and location decisions are jointly considered. Further, facility capacity often cannot be changed in the event of a disruption. Following a facility failure, customers can be assigned to other facilities only if these facilities have sufficient available capacity. Thus, capacitated reliable facility location problems are more complex than their uncapacitated counterparts (Shen et al., 2011). The studies considering capacitated reliable facility location problem are limited. Snyder and Ülker (2005) study the CRFLP and propose an algorithm based on Sample Average Approximation (SAA) embedded with Lagrangean relaxation. Gade (2007) applied the SAA method in combination with a dual decomposition method to solve CRFLP. Peng et al. (2011) proposed a hybrid metaheuristic based on genetic algorithm to solve a related problem where the objective is to minimize the total fixed and transportation cost while limiting the disruption risk based on the p-robustness criterion. In summary, the earlier work on CRFLP uses either SAA based approximation or metaheuristic methods to overcome the

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computational complexity associated with a large number of scenario realizations.

In this study, we develop a novel technique, called Swarm Intelligence Based Sample Average Approximation (SIBSAA), hybridizing the swarm intelligence and SAA method to efficiently solve the CRFLP. While the standard SAA procedure is effective with sufficiently large samples, the required sample size can be quite large for the desired confidence level. Further, the SAA procedure selects the best performing sample solution and discards the remaining sample solutions which contain valuable information about the problem's uncertainty. The proposed hybrid method re-uses the embedded information in sample solutions by iteratively solving the sample problems while injecting social learning in the solution process. The swarm intelligence injection is based on the Particle Swarm Optimization (PSO). Our experimental results indicate that the proposed hybrid method significantly improves computational efficiency while attaining the same or better solution quality as the SAA method.

The rest of this paper is organized as follows. In Section 2, we review the relevant literature. In Section 3, we present the capacitated reliable facility location problem and its formulation, briefly summarize the SAA and PSO methods, and then describe the proposed hybrid algorithm in detail. In Section 4, we report on the computational experiments comparing the solution quality and CPU time efficiency of the SAA algorithm and the proposed hybrid algorithm. We conclude with discussion and future research directions in Section 5.

2. Literature review

Developing efficient methods for solving large-scale stochastic problems is an optimization challenge. There are several exact methods such as Progressive Hedging Algorithm (Rockafeller and Wets, 1991) and L-shaped Decomposition (Van Slyke and Wets, 1969) for solving stochastic programming problems. However, these exact methods become impractical when the number of scenarios is very large. Therefore, we herein focus on two types of approximate methods: sampling based methods and metaheuristics. Sampling methods can be applied in either interior or exterior mode (Linderoth et al., 2006). In the interior mode, the algorithm aims to solve the full problem and only select a sample when an approximate value is needed (Higle and Sen, 1991). In the exterior mode, a sample is randomly selected among all possible scenarios and an approximation of the objective value for the true problem is determined by solving the sample. The SAA method uses exterior sampling and has become a popular technique in solving large-scale stochastic programming problems. This is primarily due to its ease of application. It has been shown that the solutions obtained by the SAA converge to the optimal solution when the sample size is sufficiently large (Ahmed and Shapiro, 2002). However these sample sizes could be quite large and the actual rate of convergence depends on the problem conditioning. Several studies reported successful application of SAA to various stochastic programs (Verweij et al., 2002; Kleywegt et al., 2001; Shapiro and Homem-de-Mello, 1998). The SAA approach is also extensively used in solving stochastic facility location and network design problems (Snyder and Ülker, 2005; Gade, 2007; Santoso et al., 2005; Schütz et al., 2009; Chouinard et al., 2008).

Metaheuristic methods such as Genetic Algorithms (GAs), Tabu Search (TS), and Simulated Annealing (SA) have been used to solve stochastic programming problems as an alternative to sampling methods. Kratica et al. (2001) applied GA to solve simple facility location problems. Wang et al. (2008) proposed a stochastic programming-based genetic algorithm to determine a profitable capacity planning and task allocation plan for a resource portfolio planning problem. They reported that using a stochastic sampling procedure improves the effectiveness of the genetic algorithm. Arostegui et al. (2006) compared the TS, SA, GA methods' performances by solving various facility location problems under time-limited, solution-limited, and unrestricted conditions. They reported that the TS method gives better performance overall than both the SA and the GA methods. In this study, we integrate swarm intelligence within the SAA algorithm in an effort to reduce the need to increase sample sizes for improved solution quality. The proposed hybrid method utilizes a swarm intelligence concept similar to that of PSO and enables the swarm learning to take place between the sample solutions of the SAA (i.e., swarm). This combined approach differs from the previous studies using metaheuristics to solve stochastic programming problems in two ways. First, the solution methodology is based on SAA where the solutions in the swarm are obtained by exact solution of the sample subproblems (e.g., rather than an update mechanism such as random crossover operation in GA and velocity update in PSO). Second, the swarm learning is incorporated into the objective function by penalizing deviations from a balanced solution combining the swarm's best solution found thus far and the swarm's average solution. Hence, the swarm learning is an integral part of the solution generation process in the proposed SIBSAA method.

3. Problem statement and methodology

In this section, we first present Capacitated Reliable Facility Location Problem (CRFLP) formulation. Next, we summarize the standard SAA and PSO heuristic methods and describe the proposed hybrid SIBSAA methodology in detail.

3.1. Capacitated reliable facility location problem (CRFLP)

We now introduce the notation used throughout this paper. Let D denote the set of customers (i.e., demand points) and F denote the set of possible facility sites. The fixed cost for facility $i \in F$ is denoted by f_i and incurred if the facility is opened. Let d_j be the demand for customer $j \in D$ and c_{ij} denote the cost of satisfying each unit demand of customer j from facility i and include such variable cost drivers as transportation and production costs. Each facility i has a limited capacity and can serve at most b_i units of demand. Facilities are subject to failure and may be unavailable in the event of a disruption. A customer j cannot be served by any of the facilities whenever all facilities fail, there is not sufficient capacity among the surviving facilities to meet customer j's demand, or the cost of serving customer j's demand via surviving facilities is prohibitive. In such cases, the customer j is assigned to an emergency facility and a large penalty cost is incurred for each unit of unsatisfied demand. The emergency facility can represent an alternative supply source and the large penalty cost then represents the outsourcing cost. In the absence of an alternative supply, the emergency facility corresponds to the lost-sale with the penalty cost of forfeited profit. For simplicity, we denote the last facility in F as the emergency facility and the cost $c_{|F|j}$ as the customer j's unit demand penalty cost.

We formulate the CRFLP as a two-stage stochastic programming problem. In the first stage, the location decisions are made before random failures of the located facilities. In the second stage, following the facility failures, the customer-facility assignment decisions are made for every customer given the facilities that have survived. The goal is to identify the set of facilities to be opened while minimizing the total cost of open facilities and the expected cost of meeting customer demand from the surviving facilities and the emergency facility. In the scenario-based