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Integrated civilian–military pre-positioning of emergency supplies: A multiobjective optimization approach

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ABSTRACT

Emergency supplies pre-positioning is crucial to improve the speed of response and mitigate the effects of disasters. According to the requirements of emergency preparedness for both civilian and military operations in China, the paper presents a problem of integrated civilian–military emergency supplies pre-positioning, the aim of which is to maximize both the expected military operational efficiency and the expected civilian operational efficiency while minimizing the overall cost of pre-positioning. To solve the problem, the paper proposes a solution method that uses a multiobjective algorithm to evolve a population of main location solutions and uses another single-objective algorithm to search optimal allocation sub-solutions for each main solution. Among different heuristics, we select water wave optimization (WWO) to design a multiobjective algorithm for the main problem and select biogeography-based optimization (BBO) for the subproblem, and demonstrate that they have competitive performance advantage in comparison with a set of well-known algorithms.

1. Introduction

Natural and man-made disasters often strike us with little warning. In order to shorten the response time and improve the efficiency of relief distribution, a widely adopted strategy is to pre-position the supplies at strategic locations such that they are readily available when needed [1]. However, selecting the locations of storage facilities (i.e., distribution centers), determining the types and amounts of supplies, and allocating the supplies to demand points make up a difficult integrated problem, involving subproblems commonly known as facility location and resource allocation in the literature [2].

In many countries, such as China, military forces play a key role in disaster relief operations [3]. This fact indicates that the facilities often need to store emergency supplies for both civilian and military use. In other words, military operations and civilian operations need to share the facilities and supplies in order to increase efficiency and decrease cost. Inevitably, such an integration further increases the difficulty of pre-positioning decisions. However, to our best knowledge, there is no report on integrated civilian–military emergency pre-positioning problems.

In this paper we present a problem of integrated civilian–military emergency supplies pre-positioning, which is to determine the locations of emergency facilities and the allocations of emergency supplies in a set of potential military operational scenarios and civilian relief operational scenarios, such that the military operational efficiency, the civilian operational efficiency, and the pre-positioning cost are simultaneously optimized. To solve the problem, we propose a multiobjective optimization method that cooperatively optimizes solutions to the main allocation problem and sub-solutions to the allocation subproblem. By testing a variety of evolutionary metaheuristics, we find that water wave optimization (WWO) [4] and biogeography-based optimization (BBO) [5] exhibit competitive performance on the main problem and the subproblem, respectively. The main contribution of the paper is twofold:

- The considered problem, to our knowledge, is the first study on integrated civilian–military emergency pre-positioning in the literature.

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- The hybrid WWO/BBO algorithm, which is also the first that combines and adapts the two metaheuristics for combinatorial optimization, shows performance advantage over many well-known algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO) on the pre-positioning problem.

In the remainder of the paper, Section 2 reviews the related work, Section 3 presents the mathematical formulation of the problem, Section 4 describes the proposed solution method, Section 5 presents the computational experiments, and finally Section 6 concludes with discussion.

2. Related work

Facility location [6] and location-allocation [7] are well-known operations research problems used to select the optimal locations for setting up facilities and to design optimal distribution networks. Both the discrete and the planar location-allocation problems have been shown to be NP-hard [8–10]. In comparison with location-allocation in regular supply chains, the problems in emergency supply chains are commonly with uncertain demands and conflicting objectives which can present significant methodological and computational challenges.

Wen and Iwamura [11] consider a problem of determining the locations of capacitated facilities in continuous space and allocating each customer to the facilities so that the total distribution cost is minimized. The customer demands are represented by fuzzy variables, and the fuzzy optimization problem is transformed into an α-cost minimization model under the Hurwicz criterion. A hybrid intelligent algorithm integrating the simplex algorithm, fuzzy simulations and GA is proposed for the problem. But the problem does not consider any constraint on the location of facilities in continuous space.

Rawls and Turnquist [12] present a two-stage stochastic mixed integer programming (MIP) model for the pre-positioning of emergency supplies for disaster response. The first stage is to determine the locations and sizes of storage facility and types of supplies, and the second-stage is to distribute supplies in response to a set predefined scenario. The authors use the Lagrangian L-shaped method to divide the problem into subproblems which can be solved by a greedy algorithm and a linear programming algorithm. The decomposition strategy makes the algorithm scale well to large instances.

Campbell and Jones [13] present another problem of emergency supplies pre-positioning which considers both risk and inventory levels without the use of scenarios. In particular, they develop a cost model for determining the optimal stocking quantity and the total expected delivery costs. The authors show that the cost model can be embedded within a variety of existing location algorithms, among which they choose a heuristic algorithm based on the translation of the objective function into a sum of one-median objective functions [7]. But their approach does not constrain on the distance between demand points and distribution centers.

Paul and Hariharan [14] develop a location-allocation planning framework that addresses different types of delays and takes into account the impact of disaster-specific casualty characteristics. The basic problem model is a MIP model with the objective function to minimize the social cost which is the sum of fatality costs and stock piles maintenance costs. Moreover, when there exists uncertainty regarding the scenarios, they use the mini-max regret decision making rule [15] for choosing across the scenarios and employ robust optimization that takes the worst-case scenario into account to obtain final solutions. Vidyarthi and Jayaswal [16] further consider a class of location-allocation problems with immobile servers and stochastic demand and congestion, which often arise in contexts such as location of emergency medical clinics and preventive healthcare centers. By simulating user demand arrivals and stochastic congestion based on Poisson processes, the problem is set up as a network of independent queues, and the result nonlinear integer program is solved by piecewise linear approximation and the constraint generation. However, queues used in the model is limited to pattern $M/G/1$.

Shariff et al. [17] apply a maximal covering location-allocation model for healthcare facility planning in Malaysia. They develop a GA-based algorithm which shows high performance on large-size instances where the classical CPLEX algorithm fails. In [18] Saeidian et al. compare the performance of GA and bees algorithm (BA) on a set of simulated and realistic instances of the emergency facility location-allocation problem. Their results indicate that the convergence of BA is gradual while GA is relatively stepwise, and in general the performance of the GA is better.

Mestre et al. [19] propose two location-allocation problem models for hospital network planning, which consider a two-tier hierarchical structure with district and central hospitals and flows between those hierarchical levels. The first model is to design facilities allocation under certainty, and the second is to allocate resources according to demand estimates in different scenarios. They develop a solution method based on ε-constrained multiobjective programming, and test the method on a case study based in the South Region of Portugal. Liu et al. [20] present a two-stage optimization problem of emergency material reserve layout planning for coping with pollution accidents. At the first stage, hierarchical clustering analysis is used to identify newly-built emergency material warehouses for risk sources; at the second stage, a material warehouse location and emergency material allocation model is solved by interval mixed-integer programming to produce emergency material reserve plans. Their approach is applied to emergency management system planning in Jiangsu province, China.

Verma and Gaukler [21] propose two models for location disaster response facilities: The first is a deterministic model incorporating distance-dependent damages to facilities, and the second further considering the damage intensity as a random variable. They show that, when only a few facilities can be placed, the stochastic model has cost advantage. They also develop a solution method based on Benders decomposition to solve the stochastic model. Nevertheless, determining the distribution of those random variables increase the burden of the user.

Nevertheless, to our best knowledge, there is no study on integrated civilian–military emergency location-allocation models. Our work is also the first to combine two relatively new heuristics, WWO and BBO, for this kind of combinatorial optimization problem, and the experimental results show that the approach outperforms a set of state-of-the-art multiobjective evolutionary algorithms.

3. A model of integrated civilian–military supplies pre-positioning

We consider an integrated civilian–military supplies pre-positioning problem, which is to determine a set of locations of emergency facilities and the types and quantities of emergency supplies stored in each facility and delivered from each facility to each demand point, in order to satisfy the potential demands of both military operations and civilian relief operations. We use scenario planning to determine a set of potential military operational scenarios and civilian relief operational scenarios, and then model the distribution of demand points and their demands for supplies in each scenario. The input variables of the problem are presented in Table 1. The decision variables consist of the following three parts: