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Robust vertex *p*-center model for locating urgent relief distribution centers

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ABSTRACT

This work locates urgent relief distribution centers (URDCs) on a given set of candidate sites using a robust vertex *p*-center (RVPC) model. This model addresses uncertain travel times, represented using fixed intervals or ranges instead of probability distributions, between URDCs and affected areas. The objective of locating a predetermined number (p) of URDCs is to minimize worst-case deviation in maximum travel time from the optimal solution. To reduce the complexity of solving the RVPC problem, this work proposes a property that facilitates identification of the worst-case scenario for a given set of URDC locations. Since the problem is *NP*-hard, a heuristic framework is developed to efficiently obtain robust solutions. Then, a specific implementation of the framework, based on simulated annealing, is developed to conduct computational experiments. Experimental results show that the proposed heuristic is effective and efficient in obtaining robust solutions of interest. This work examines the impact of the degree of data uncertainty on the selected performance measures and the tradeoff between solution quality and robustness. Additionally, this work demonstrates the applicability of the proposed model to natural disasters based on a real-world instance. The result is compared with that obtained by a scenario-based, two-stage stochastic model. This work contributes significantly to the growing body of literature applying robust optimization approaches to emergency logistics.

1. Introduction

Emergency response to quick-onset disasters relies heavily on effective and efficient emergency logistics, which have drawn considerable attention in the last decade (e.g., [1–3]) due to the severe impacts of numerous natural disasters and the devastation and casualties they have caused [4]. To support emergency responses, such as evacuation of survivors, search and rescue of the injured, and distribution of medical and relief supplies, all components in an emergency logistics system must be designed and deployed optimally, along with mechanisms that trigger and coordinate activities in and among those components. Of vital importance to an emergency logistics system are urgent relief distribution centers (URDCs), because they serve as hubs with the aim of seamlessly integrating and coordinating inbound and outbound emergency logistics in response to relief demands from affected areas. These hubs also have an inventory management function (*i.e.*, risk pooling)—aggregating relief demands (or their forecasts) across several affected areas to reduce the adverse impact of relief demand variability and uncertainty on the system.

Recognizing that facility location is an essential design variable for URDCs, this work focuses on the URDC location problem. Specifically, this work aims at developing a robust URDC location model that explicitly accounts for uncertain travel times between URDCs and affected areas. Among various facility location models that have been presented in the literature (e.g., [5,6]), the *p*-center model, which aims to locate p facilities to minimize maximum distance (or travel time) between demand nodes and their closest facilities (e.g., [7]), is particularly suitable for emergency applications (e.g., [8–10]). The vertex *p*-center (VPC) model restricts the set of candidate sites to network nodes, while the absolute *p*-center model allows facilities to be anywhere along network arcs. In response to quick-onset disasters, government agencies typically designate existing public buildings (e.g., schools and stadiums) with little or no damage that can be promptly converted to shelters for survivors and/or warehouses for relief supplies as candidate sites instead of establishing new emergency facilities from scratch. Thus, this work considers the URDC location problem as a VPC problem (e.g., [11]).

A robust location model of URDCs must explicitly account for uncertain input data, such as travel times between URDCs and

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affected areas, mainly due to poor measurements based on limited information available during a disaster's aftermath or approximations in the modeling process choosing a distance norm. Two major categories of approaches have been adopted in the literature to deal with uncertain coefficients in facility location models [12], namely, stochastic programming (SP) and robust optimization (RO). The former has been used typically to deal with decision-making for facility locations in risk situations, in which the values of uncertain coefficients are governed by discrete or continuous probability distributions that are known to a decision-maker. The SP approach has been widely applied to emergency logistics for short-notice disasters (e.g., hurricanes, flooding, and wild fires) by assuming that possible impacts of these disasters can be estimated based on historical and meteorological data. A classical example of applying SP to disaster relief is the scenario-based, two-stage stochastic model proposed by Mete and Zabinsky [13], for medical supply location and distribution in disaster management. Other examples can be found, for instance, in [14–16]. A common goal of stochastic location models is to optimize the expected value of a given objective function.

On the other hand, the RO approach attempts to optimize the worst-case system performance in uncertain situations that lack any information about the probability distributions of uncertain coefficients; hence, the RO approach generally describes uncertain data using pre-specified intervals or ranges (e.g., [17–21]). Typical robustness measures include mini-max objective value and mini-max regret in an objective value. The RO approach may be more appropriate in response to quick-onset or no-notice disasters (e.g., earthquakes, tsunamis, and landslides); however, to the best of our knowledge, it has rarely been applied to this context. For quick-onset disasters, because of the difficulty in predicting disaster occurrence and impacts as well as a lack of historical data, probability distributions and scenario data are generally unavailable. For example, an extremely large earthquake, 9.1 on the Richter scale, which hit the northeastern coast of Japan on March 11, 2011, was never considered in that nation's preparedness planning for earthquakes, even though Japan is widely regarded as one of the most advanced countries in earthquake preparedness. Thus, in responding to such a disaster, decision-makers may prefer an alternative method for describing uncertain data (*i.e.*, using intervals to represent uncertain data). The selection of a solution technique (*i.e.*, SP or RO) depends mostly on data availability and the decision-maker's objective.

The p-center problems with interval-represented uncertain data tend to be very difficult because of the mini-max structure. Therefore, analytical results and exact algorithms for the p-center problems with interval data have only been attained in special cases, such as locating a single facility on general networks or multiple facilities on tree networks (e.g., [22,23]). To the best of our knowledge, only Averbakh and Berman [24] reported analytical results for an absolute weighted p-center problem with interval-represented node weights. No study has addressed absolute or vertex multi-center problems with interval-represented edge lengths.

This work develops a robust vertex p-center (RVPC) model for locating URDCs in an emergency logistics network. This model considers explicitly uncertain travel times between URDCs and affected areas. The objective of locating p URDCs is to minimize worst-case deviation in maximum travel time between URDCs and affected areas from the optimal solution. In this model, uncertain travel times are represented using prescribed, continuous intervals (or ranges), rather than probability distributions. This work also proposes a property that facilitates identification of the worst-case scenario for a given set of URDC locations, thereby reducing complexity of solving the problem. Since the problem is *NP*-hard [25], a local search-based algorithmic framework incorporating the property for identifying the worst-case scenarios is developed to find robust solutions within a reasonable amount of computational resources. Then, a specific framework implementation based on simulated annealing (SA) is developed to conduct numerical experiments, including a case study based on the Jiji Earthquake, which hit central Taiwan on September 21, 1999.

This study contributes significantly to literature by (i) modeling the URDC location problem as the vertex multi-center problem with interval-represented edge lengths on general networks; (ii) providing an effective and efficient algorithmic framework for solving these problems; and (iii) shedding light on the applicability and potential benefits of the proposed models to real-world instances.

The remainder of this paper is structured as follows. Section 2 describes the RVPC problem, the representation of data uncertainty, and the property of worst-case scenarios. Section 3 presents the generic heuristic framework and a specific implementation using SA. This is followed by the numerical experiments in Section 4. Section 5 provides a case study demonstrating the applicability of the proposed model to a real instance. Concluding remarks are given in Section 6.

2. Vertex *p*-center problem with data uncertainty

2.1. The deterministic problem

Consider a connected, undirected network $G(N, A)$, where N is the vertex set and A the arc (or edge) set. Let U be the set of candidate sites for URDC locations and V be the set of relief stations in affected areas; $U \cup V = N$, and $U \neq V$. Each possible pair of relief station $i \in V$ and URDC $j \in U$ is connected by an arc $(i, j) \in A$ that is associated with a positive (real or integer) number, t_{ij}, representing travel time between relief station i and URDC j. Each relief station is serviced only by a single URDC. For a given set of predetermined candidate sites, the VPC problem is to locate p ($p < |U|$) URDCs and assign relief stations to these centers, thereby minimizing maximum travel time between relief stations and URDCs. A mixed integer linear programming (MILP) formulation of the problem is as follows (e.g., [11])

$$\text{(VPC) Minimize } z \tag{1}$$

$$\text{Subject to } z \geq \sum_{j \in U} t_{ij} y_{ij}, \quad \forall i \in V \tag{2}$$

$$\sum_{j \in U} y_{ij} = 1, \quad \forall i \in V \tag{3}$$

$$y_{ij} - x_j \leq 0, \quad \forall i \in V, \quad j \in U \tag{4}$$

$$\sum_{j \in U} x_j = p \tag{5}$$

$$x_j \in \{0,1\}, \quad \forall j \in U \tag{6}$$

$$y_{ij} \in \{0,1\}, \quad \forall i \in V, \quad j \in \mathbf{U} \tag{7}$$

The decision variables are binary variables x_j, $\forall j \in U$ and y_{ij}, $\forall i \in V$, $j \in U$. $x_j = 1$ if candidate site j is selected; otherwise, $x_j = 0$. Additionally, $y_{ij} = 1$ if relief station i is serviced by URDC j; otherwise, $y_{ij} = 0$. The objective function (1) minimizes maximum travel time between each relief station and its closest URDC. Constraint (2) defines the lower bound of maximum travel time, which is being minimized. Constraint (3) requires that each relief station be assigned to exactly one URDC. Constraint (4) restricts relief station assignments only to open URDCs. Constraint (5) stipulates that p URDCs are to be located. Constraints (6) and (7) indicate that location and allocation decision variables are binary.