

Yu, Wuyang

Article

A robust model for emergency supplies prepositioning and transportation considering road disruptions

Operations Research Perspectives

Provided in Cooperation with:

Elsevier

Suggested Citation: Yu, Wuyang (2023) : A robust model for emergency supplies prepositioning and transportation considering road disruptions, Operations Research Perspectives, ISSN 2214-7160, Elsevier, Amsterdam, Vol. 10, pp. 1-10, <https://doi.org/10.1016/j.orp.2023.100266>

This Version is available at:

<https://hdl.handle.net/10419/325752>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

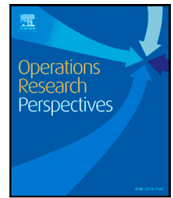
Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>



A robust model for emergency supplies prepositioning and transportation considering road disruptions

Wuyang Yu

School of Management, Hangzhou Dianzi University, Zhejiang 310018, China

ARTICLE INFO

Keywords:

Emergency supply prepositioning
Road disruption
Uncertainty
Robust optimization

ABSTRACT

Proper prepositioning of emergency supplies can dramatically improve the efficiency of emergency response work. However, the uncertainties of emergency demands and road conditions bring difficulties to the prepositioning of emergency supplies. This paper proposes a two-stage robust model to locate emergency supply points and preposition the corresponding storage amount of emergency supplies, in which we presented two budget sets to describe the uncertainties of demands and road conditions, respectively. The innovative use of variables in the model to limit road capacities addresses the representation of different road interruption scenarios. We proposed an algorithm based on Benders decomposition by transforming the second-stage model into a binary linear programming model. Computational experiments based on the Sioux Falls network demonstrate the validity of the model and algorithm. We conducted sensitivity analyses for some important parameters in the model, such as two uncertainty control parameters, unit transportation cost, budget for the construction of emergency supply points, etc. We find that the uncertainty of road disruptions has a greater impact on the model than the uncertainty of demands. In addition, when the control parameter of the road disruptions exceeds a certain threshold, its influence on the model remains essentially constant.

1. Introduction

Over the past two decades, frequent natural disasters (e.g., hurricanes, earthquakes, floods, and tsunamis) have caused huge casualties and damages or loss of properties. Total global disaster losses from 2002 to 2021 exceeded \$5271 billion [1]. It has been recognized from the practice of responding to disasters that the implementation of scientific disaster management strategies is essential to reduce the impact of disasters. Among the various disaster management strategies, emergency supply planning plays an important role in providing timely emergency supplies for post-disaster relief through pre-disaster preparations.

Proper prepositioning of emergency supplies can dramatically improve the efficiency of emergency response. However, the uncertainty of both emergency demands and road conditions poses a great difficulty in pre-disaster emergency supplies prepositioning. For the former, since the degree of losses caused by different disasters varies greatly, it is almost impossible to accurately estimate the demands of emergency supplies at different points before a disaster. Moreover, due to the low frequency nature of some disasters, historical data are not sufficient to derive the probability distribution of emergency demands. For the latter, the uncertainty of road disruptions makes it difficult to predict the structure of the transportation network available after a disaster. At the same time, it is almost impossible to obtain probability distributions for

specific road disruptions because the mechanisms inherent in disasters-induced road disruptions are not known. Therefore, the uncertainty of both emergency demands and road disruptions can only be expressed in the form of intervals in many cases.

By using two budget sets to describe the uncertainty of demand and road conditions, this paper proposes a two-stage robust model to locate emergency supply points and preposition the corresponding storage amount of supplies. Since the unit transportation cost between point pairs is closely related to the structure of available transportation network after a specific road disruption, the cost of transporting emergency supplies after a disaster cannot be determined using traditional transportation models. This difficulty is solved by using a network flow model with uncertain capacity constraints on the edges in our proposed two-stage robust model.

In this study, we make the following main contributions:

- The innovative use of binary variables to limit road capacities addresses the representation of different road disruption scenarios.
- The network flow model is used to solve the problem of uncertainty in the path between supply and demand points due to road disruptions.
- The designed Benders decomposition algorithm can find the exact solution of pre-disaster prepositioning of emergency supplies and give the distribution plan under the worst-case scenario.

E-mail address: yu_wuyang@163.com.

<https://doi.org/10.1016/j.orp.2023.100266>

Received 6 August 2022; Received in revised form 7 January 2023; Accepted 8 January 2023

Available online 10 January 2023

2214-7160/© 2023 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

The remainder of the article is organized as follows. Section 2 gives a review of related literature. Section 3 presents the mathematical formulation of our two-stage robust model. Section 4 provides the algorithm based on Benders decomposition by linearizing the second-stage model. Section 5 reports the computational experiments with sensitivity analysis results on some important parameters and some valuable management insights. The final section provides concluding remarks and discusses some future work.

2. Literature review

Numerous studies of emergency supply planning have shown that integrating pre- and post-disaster operations allows for better pre-positioning of emergency supplies. To deal with the uncertain effects of disasters, stochastic programming and robust optimization are the two most common approaches in the relevant literature.

Most articles using stochastic programming describe uncertainty by defining a set of scenarios and assuming that the occurrence of each scenario conforms to some random distribution, or directly giving the corresponding probability. Paul and Zhang [2] developed a two-stage stochastic programming model for hurricane preparedness by using probability distributions to estimate the impact of hurricanes. The goal of the model is to determine the location of distribution points, medical supply levels, and transportation capacity in the first stage, and transportation decisions in the second stage. Jiang and Ouyang [3] formulated a mixed-integer nonlinear program to solve the positioning and allocation of emergency resources by considering the probabilistic risk of station disruptions. Sütüçen et al. [4] proposed a scenario-based two-stage stochastic programming to study the stochastic interdependent infrastructure reinforcement and repair problem. Wang and Nie [5] incorporated the effects of traffic congestion into the problem of emergency supplies pre-positioning and post-disaster transportation. They formulated the problem as a mixed-integer nonlinear programming model and solved by a generalized Benders decomposition algorithm. Wang and Nie [6] further incorporated network mitigation decisions and dynamic factors after disasters with the traffic congestion effects in the emergency supplies pre-positioning problem. Shehadeh and Tucker [7] proposed three new stochastic optimization models to study the problem of location and inventory pre-positioning of relief supplies, they addressed the uncertainty and distributional ambiguity of important random factors. Sanci and Daskin [8] proposed an integer L-shaped algorithm to solve the two-stage stochastic programming model, which is formulated to optimize the number and locations of the emergency response facilities and restoration resources. Wang et al. [9] proposed a two-stage stochastic model for emergency supply planning to facilitate cooperation and coordination in a regional healthcare coalition. Kizito et al. [10] proposed a multi-stage stochastic program to optimize the reliability and resilience of the microgrid during a week-long power outage.

The above assumptions about uncertainty in stochastic programming methods are not realistic for certain disasters, such as earthquakes, tsunamis, etc. The corresponding probability distribution information for these disaster-related uncertainties is difficult to obtain due to reasons such as scarcity of data or unclear mechanisms involved. Robust optimization (RO) is a methodology to solve optimization problems that contain uncertain parameters. RO avoids the difficulty of obtaining the parameter probability distribution by assuming that the values of the uncertain parameters lie in some user-defined set of uncertainties. Soyster [11] first proposed a mathematical model of robust formation with interval data uncertainty. Ben-Tal and Nemirovsky [12] addressed the issue of over-conservatism in Soyster's model by defining the ellipsoid uncertainty set, but their robust counterpart model does not conserve the complexity of the original problem. Bertsimas and Sim [13] presented a robust formulation that leads to the same complexity of the original problem while maintaining the flexibility to adjust the degree of conservativeness in the solutions.

In the field of emergency management research, robust optimization methods have been widely used to deal with various uncertainties. For example, Liu et al. [14] applied the robust optimization approach to cope with the uncertainties in demand and transportation time and deduced the robust counterpart of the proposed model. Rahmani et al. [15] proposed a scenario-based robust optimization approach to sweep away the uncertain parameters in the design process of humanitarian relief supply chains. Paul and Wang [16] incorporated various uncertainties, such as facility damage, casualty by severity, and travel time, for optimizing the location and capacity of distribution centers in the earthquake preparedness stage. Two types of robustness are modeled in their paper: parameter uncertainty within a scenario and relative regret between scenarios. Yu [17] developed a two-stage model to determine the location of warehouses and storage of emergency commodities before disasters. In this paper, both randomness and uncertainty are considered in the preparation stage. Sun et al. [18] developed a robust optimization model for a combination of facility location and casualty transport in the presence of uncertainty in the number of casualties. Yang et al. [19] studied the multi-period dynamic pre-positioning of emergency supplies considering the static pre-disaster stage and dynamic post-disaster stage. They proposed a distributionally robust optimization model to handle the time-varying uncertain demands in the post-disaster stage. Sun et al. [20] developed a scenario-based robust bi-objective optimization model to decide medical facility location, casualty transportation, and relief commodity allocation. Zhang et al. [21] proposed a distributionally robust optimization model for the emergency rescue network design problem, where the objective function is the sum of the preparation cost and the expected penalty cost of demand shortage. Hafezalkotob et al. [22] proposed a linear robust formulation to study the collaborative behaviors among human resource allocation problem. In their model, information uncertainty is considered the right-hand side parameters.

Table 1 summarizes the uncertain parameters, representation methods and solution strategies in the above literature. The first half of the table is modeled by stochastic programming, while the second half is modeled by robust optimization.

We find that most of the literature proposing robust models for emergency management focuses on the uncertainty of demand or casualties, while very little research has been done on the uncertainty of transportation network conditions. This may be caused by the difficulty of representing the post-disaster conditions of the transportation network with a suitable uncertainty set. After representing road disruptions as decision variables, our model implicitly allocates emergency material flows between supply and demand points using road capacity constraints, thus avoiding the difficulty of explicitly calculating unit transportation costs under a large number of post-disaster network structures.

3. Model formulation

Pre-positioning emergency supplies is an important strategic decision that can increase preparedness for natural disasters. The problem can be divided into two stages. In the first stage (pre-disaster stage), decision makers decide where to establish emergency supply points and the corresponding storage levels. In the second stage (post-disaster stage), based on the available road network after the disaster and the actual requirements at each demand point, decision makers decide on the emergency supplies distribution plan from supply points to demand points. If some demands cannot be fully met by pre-stored emergency supplies at the supply points, it is assumed that these unmet portions of demands can be compensated by other, more costly means. In this paper, we consider an undirected graph $G(V, E)$ with node set $V = \{1, 2, \dots, n\}$ and edge set $E = \{(i, j) | i, j \in V\}$. Where $V_d \subseteq V$ denotes the set of demand points (DP), and $V_s \subseteq V$ denotes the set of candidate locations of emergency supply points (SP). A subset $E_1 \subseteq E$ of the edge

Table 1
Uncertain parameters, representation methods and solution strategies in literature.

Literature	Uncertain parameters	Representation methods	Solution strategies
Paul and Zhang [2]	Casualty, Supply, Cost, Time	Scenarios-based	Cplex
Jiang and Ouyang [3]	Station disruption	Probability	Approximation
Sütiçen et al. [4]	Infrastructure disruption	Scenarios-based	Genetic algorithm
Wang and Nie [5]	Traffic flow, Supply, Demand	Scenarios-based	Exact algorithm
Wang and Nie [6]	Time, Supply, Demand, Arc capacity	Scenarios-based	Exact algorithm
Shehadeh and Tucker [7]	Supply, Demand, Road capacity	Probability	Approximation
Sanci and Daskin [8]	Demand, Damage rate, Repair time	Scenario-based	Exact algorithm
Wang et al. [9]	Supply, Demand, Cost	Scenario-based	Gurobi
Kizito et al. [10]	Power output, Power demand	Scenario-based	Exact algorithm
Liu et al. [14]	Demand, Transportation time	Interval	Cplex
Rahmani et al. [15]	Demand, Facility disruption	Scenario-based	Exact algorithm
Paul and Wang [16]	Casualty, Facility damage, Time	Scenario-based	Cplex
Yu [17]	Demand, Supply, Facility damage	Interval, Probability	Exact algorithm
Sun et al. [18]	Casualty	Interval	Cplex
Yang et al. [19]	Demand	Interval	Approximation
Sun et al. [20]	Casualty, Cost	Scenario-based, Interval	Cplex
Zhang et al. [21]	Demand	Interval, Probability	Matlab
Hafezalkotob et al. [22]	Referral, Treatment time	Interval	Game theory

set E consists of edges representing roads that are at risk of disruption. The following notations are used for the development of the model:

- Parameters:
- f_i : Fixed cost of establishing a emergency supplies point at SP point $i, \forall i \in V_s$, and set $f_i := +\infty, \forall i \in V \setminus V_s$;
 - C_i : Capacity of potential SP point i to store emergency supplies, $\forall i \in V_s$, and set $C_i := 0, \forall i \in V \setminus V_s$;
 - d_i : The unit procurement cost of emergency supplies at potential SP point i in the pre-disaster stage, $i \in V_s$;
 - s_i : The unit compensation cost for unmet demand component at DP point i in the post-disaster stage, $i \in V_d$;
 - $[\beta_i, \beta_i + \Delta_i]$: The interval in which uncertain demand of DP point i lies, $\forall i \in V_d$, and set $\beta_i := 0, \Delta_i := 0, \forall i \in V \setminus V_d$;
 - c_{ij} : The unit cost of transporting emergency supplies along edge $(i, j) \in E$;
 - Γ_1 : The parameter is used to control the uncertainty of the total number of disrupted roads;
 - Γ_2 : The parameter is used to control the uncertainty of the total demand at DPs;
 - G : The total budget for the construction of emergency supply points in the pre-disaster stage;
 - M : A large positive number;
- Variables:
- x_i : The amount of emergency supplies stored at node i in the pre-disaster stage, $i \in V$;
 - f_{ij} : The flow of emergency supplies on road (i, j) in the post-disaster stage, $(i, j) \in E$;
 - \hat{x}_i : The amount of emergency supplies provided by SP point i in the post-disaster stage, $i \in V$;
 - z_i : The amount of unmet demand at DP point i (i.e., the amount of compensation) in the post-disaster stage, $i \in V_d$;
 - y_i : If the potential SP point $i \in V_s$ is selected as supply point, then $y_i = 1$, otherwise $y_i = 0$;
 - r_{ij} : If the edge (i, j) is disrupted in the post-disaster stage, then $r_{ij} = 1$, otherwise $r_{ij} = 0, (i, j) \in E$;
 - t_i : The proportion of Δ_i in the demand $\beta_i + t_i \Delta_i$ for DP point $i, 0 \leq t_i \leq 1, i \in V$.

The purpose of the model is to determine the location of supply points and the amount of emergency supplies stored at each supply point to minimize the total operating cost: procurement cost of pre-positioned emergency supplies before the disaster, transportation cost and compensation cost of emergency supplies after the disaster. The corresponding constraints are that the construction cost of emergency supply points does not exceed the given budget, and the storage level of emergency supplies at each selected point does not exceed its capacity. Since it is impossible to predict before the disaster which scenario will

occur after the disaster, the decision in the pre-disaster stage takes into account the operating costs of the worst-case scenario in the post-disaster stage. Therefore, the decision problem in the first stage can be modeled as follows:

$$\min Z = \sum_{i \in V_s} d_i x_i + Q(x, \Gamma_1, \Gamma_2) \tag{1}$$

$$\text{(FM) s.t.} \begin{cases} \sum_{i \in V} f_i y_i \leq G & \text{(a)} \\ x_i \leq C_i y_i, \forall i \in V & \text{(b)} \\ x_i \geq 0, y_i \in \{0, 1\}, \forall i \in V & \text{(c)} \end{cases} \tag{2}$$

The first item in the objective function (1) is the procurement cost of emergency supplies in the pre-disaster stage. Given the the amount of emergency supplies stored at each supply point in the first stage (x_i) and two robust control parameters (Γ_1, Γ_2), the second item of the objective function (1) represents the optimal objective function value corresponding to the second stage model. Constraint (2)(a) indicates that the total fixed cost for constructing emergency supply points cannot exceed the budget G . Constraints (2)(b) mean that the amount of emergency resources available at each supply point is limited by its capacity.

In this paper, we assume that there is uncertainty in the amount of emergency supplies required at each demand point and whether a specific road in the transportation network is disrupted after a disaster. To better express these two types of uncertainties, we first define two budget uncertainty sets as follows:

$$\Gamma_1 := \left\{ r_{ij} \in \{0, 1\}, \forall (i, j) \in E \mid \sum_{(i,j) \in E_1} r_{ij} \leq \Gamma_1, \sum_{(i,j) \in E \setminus E_1} r_{ij} = 0 \right\} \tag{3}$$

$$\Gamma_2 := \left\{ 0 \leq t_i \leq 1, \forall i \in V \mid \sum_{i: \{\Delta_i > 0, i \in V\}} t_i \leq \Gamma_2 \right\} \tag{4}$$

The uncertainty set (3) indicates that the total number of disrupted roads does not exceed the control parameter Γ_1 , and the uncertainty set (4) implies that for those demand points with uncertainty, the total fluctuations does not exceed the parameter Γ_2 . Thus, the demand for emergency supplies at point $i \in V$ after a disaster can be expressed as $\beta_i + t_i \Delta_i$, here $t_i \in \Gamma_2$.

$Q(x, \Gamma_1, \Gamma_2)$ denotes the required transportation costs and compensation costs under the worst-case scenario obtained from the combination of the two uncertainties. Once the specific values of the two uncertainties are clarified after a disaster, optimal decisions can be made to minimize transportation costs and compensation costs. Thus, the second-stage problem can be modeled as maximum–minimum model that uses the decision of the first-stage model and two robust control

parameters as its input parameters. For any given scenario, We model the problem of determining transportation and compensation decisions as a network flow problem rather than a traditional transportation problem. This is due to the fact that road disruptions can be directly represented in the network flow model using the edge capacity limit constraints. Conversely, if a transportation model is used, the unit transportation costs between supply and demand point pairs are difficult to represent as a function of disrupted roads. According to the robust modeling method proposed by Bertsimas and Sim [13], the problem of transportation and compensation of emergency supplies in the second stage can be expressed as follows:

$$Q(x, \Gamma_1, \Gamma_2) = \max_{r_{ij} \in T_1, t_i \in T_2} \min \left(\sum_{(i,j) \in E} c_{ij} f_{ij} + \sum_{i \in V_d} s_i z_i \right) \quad (5)$$

$$(SM) \quad s.t. \begin{cases} \sum_{j:(i,j) \in E} f_{ij} - \sum_{j:(j,i) \in E} f_{ji} = \hat{x}_i + z_i - (\beta_i + t_i \Delta_i), \forall i \in V & (a) \\ 0 \leq f_{ij} \leq M(1 - r_{ij}), \forall (i, j) \in A & (b) \\ 0 \leq z_i \leq \beta_i + t_i \Delta_i, \forall i \in V & (c) \\ 0 \leq \hat{x}_i \leq x_i, \forall i \in V & (d) \end{cases} \quad (6)$$

The two items in the objective function (5) are the transportation cost of emergency supplies and the compensation cost of unmet demands, respectively. The maximum–minimum form of the objective function indicates that the aim of the second-stage model is to find the worst-case scenario among all scenarios represented by $r_{ij} \in T_1, t_i \in T_2$. $Q(x, \Gamma_1, \Gamma_2)$ denotes the minimum cost of transportation and compensation in the worst-case scenario of the post-disaster stage, given the decision x in the first stage and the values of the parameters Γ_1, Γ_2 . Constraints (6)(a) mean that the flow balance condition is satisfied for each node $i \in V$. From the definition of r_{ij} , it is clear that $r_{ij} = 1$ indicates that the road (i, j) is disrupted, so constraints (6)(b) restrict the flow on the edge (i, j) with $r_{ij} = 1$ to 0. Conversely, the flow on the edge (i, j) corresponding to $r_{ij} = 0$ has no capacity limit. Constraints (6)(c) indicate that the number of compensated emergency supplies does not exceed the actual requirement at each demand point. Constraints (6)(d) imply that the amount of emergency supplies shipped from each supply point does not exceed the amount pre-stored at that point.

4. Model linearization and the algorithm

The maximum–minimum form of $Q(x, \Gamma_1, \Gamma_2)$ is difficult to solve. Since the minimization part (i.e. the network flow problem) is a linear programming, we can obtain its dual problem, which is a maximization problem and can be merged with the maximization over $r_{ij} \in T_1$, and $t_j \in T_2$, the results are as follows:

Theorem 1. $Q(x, \Gamma_1, \Gamma_2)$ equivalent to the following model:

$$\max \sum_{i \in V} [-\beta_i + t_i \Delta_i](\pi_i + \omega_i) - x_i \theta_i - \sum_{(i,j) \in A} M(1 - r_{ij}) u_{ij} \quad (7)$$

$$s.t. \begin{cases} \pi_i - \pi_j - u_{ij} \leq c_{ij}, \forall (i, j) \in A & (a) \\ -\pi_i - \omega_i \leq s_i, \forall i \in V & (b) \\ -\pi_i - \theta_i \leq 0, \forall i \in V & (c) \\ \sum_{(i,j) \in A_1} r_{ij} \leq \Gamma_1 & (d) \\ \sum_{i: \{\Delta_i > 0, i \in V\}} t_i \leq \Gamma_2 & (e) \\ u_{ij} \geq 0, r_{ij} \in \{0, 1\}, \forall (i, j) \in A & (f) \\ \omega_i \geq 0, \theta_i \geq 0, 0 \leq t_i \leq 1, \forall i \in V & (g) \end{cases} \quad (8)$$

Proof. For given $r_{ij} \in T_1, t_i \in T_2$, the minimization part of $Q(x, \Gamma_1, \Gamma_2)$ is the following linear programming:

$$\min \left(\sum_{(i,j) \in A} c_{ij} f_{ij} + \sum_{i \in V} s_i z_i \right) \quad (9)$$

$$s.t. \begin{cases} \sum_{j:(i,j) \in A} f_{ij} - \sum_{j:(j,i) \in A} f_{ji} - \hat{x}_i - z_i = -(\beta_i + t_i \Delta_i), \forall i \in V & (a) \\ f_{ij} \leq M(1 - r_{ij}), \forall (i, j) \in A & (b) \\ z_i \leq \beta_i + t_i \Delta_i, \forall i \in V & (c) \\ \hat{x}_i \leq x_i, \forall i \in V & (d) \\ f_{ij} \geq 0, \forall (i, j) \in A & (e) \\ z_i \geq 0, \hat{x}_i \geq 0, \forall i \in V & (f) \end{cases} \quad (10)$$

Denote the dual variables of constraints (10)(a)–(10)(d) as $\pi_i, u_{ij}, \omega_i, \theta_i$, respectively. Then the dual problem of the linear programming is:

$$\max \sum_{i \in V} [-\beta_i + t_i \Delta_i] \pi_i - (\beta_i + t_i \Delta_i) \omega_i - x_i \theta_i - \sum_{(i,j) \in A} M(1 - r_{ij}) u_{ij} \quad (11)$$

$$s.t. \begin{cases} \pi_i - \pi_j - u_{ij} \leq c_{ij}, \forall (i, j) \in A & (a) \\ -\pi_i - \omega_i \leq s_i, \forall i \in V & (b) \\ -\pi_i - \theta_i \leq 0, \forall i \in V & (c) \\ u_{ij} \geq 0, \forall (i, j) \in A & (d) \\ \omega_i \geq 0, \theta_i \geq 0, \forall i \in V & (e) \end{cases} \quad (12)$$

Now this maximization problem can be merged with the maximization part ($\max_{r_{ij} \in T_1, t_i \in T_2}$). From the definitions of T_1 and T_2 we can get that $Q(x, \Gamma_1, \Gamma_2)$ is equivalent to model (7)–(8). ■

Although $Q(x, \Gamma_1, \Gamma_2)$ has been transformed from max–min to maximization, solving the model is still difficult because the objective function (7) is nonlinear. In order to linearize the objective function (7), we need to make a reasonable assumption on the control parameter Γ_2 . Since the parameter Γ_2 represents the total fluctuation of post-disaster demands, it is convenient to take the number of demand points at which demand reaches its upper limit as the value of Γ_2 . Therefore, based on the assumption that Γ_2 is an integer, we give the following linearization result for the solution of $Q(x, \Gamma_1, \Gamma_2)$.

Theorem 2. If Γ_2 is an integer, then the following model can give the optimal solution to $Q(x, \Gamma_1, \Gamma_2)$:

$$\hat{F}(x, \Gamma_1, \Gamma_2) = \max \sum_{i \in V} [-\beta_i(\pi_i + \omega_i) - \Delta_i v_i - x_i \theta_i] - M \sum_{(i,j) \in A} k_{ij} \quad (13)$$

$$s.t. \begin{cases} \pi_i - \pi_j - u_{ij} \leq c_{ij}, \forall (i, j) \in A & (a) \\ -\pi_i - \omega_i \leq s_i, \forall i \in V & (b) \\ -\pi_i - \theta_i \leq 0, \forall i \in V & (c) \\ \sum_{(i,j) \in A_1} r_{ij} \leq \Gamma_1 & (d) \\ \sum_{i: \{\Delta_i > 0, i \in V\}} t_i \leq \Gamma_2 & (e) \\ v_i \leq M t_i, \forall i \in V & (f) \\ -v_i \leq M t_i, \forall i \in V & (g) \\ \pi_i + \omega_i - v_i \leq M(1 - t_i), \forall i \in V & (h) \\ -(\pi_i + \omega_i - v_i) \leq M(1 - t_i), \forall i \in V & (i) \\ 0 \leq k_{ij} \leq M(1 - r_{ij}), \forall (i, j) \in A & (j) \\ 0 \leq u_{ij} - k_{ij} \leq M r_{ij}, \forall (i, j) \in A & (k) \\ u_{ij} \geq 0, r_{ij} \in \{0, 1\}, \forall (i, j) \in A & (l) \\ \omega_i \geq 0, \theta_i \geq 0, t_i \in \{0, 1\}, \forall i \in V & (m) \end{cases} \quad (14)$$

Proof. First, we prove the following result: If Γ_2 is an integer, then there is a optimal solution $(\pi^*, r^*, u^*, \omega^*, \theta^*, t^*)$ of model (7)–(8) such that $t_i^* \in \{0, 1\}, \forall i \in V$.

Define the following polytopes:

$$\Omega := \{(\pi, r, u, \omega, \theta) \in R^{|V|} \times R^{|A|} \times R^{|A|} \times R^{|V|} \times R^{|V|} \mid \forall i \in V, (i, j) \in A\} \quad (15)$$

$$s.t. \begin{cases} \pi_i - \pi_j - u_{ij} \leq c_{ij}, \forall (i, j) \in A & (a) \\ -\pi_i - \omega_i \leq s_i, \forall i \in V & (b) \\ \sum_{(i,j) \in A_1} r_{ij} \leq \Gamma_1 & (c) \\ -\pi_i - \theta_i \leq 0, \forall i \in V & (d) \\ \omega_i \geq 0, \theta_i \geq 0, \forall i \in V & (e) \\ u_{ij} \geq 0, r_{ij} \in \{0, 1\}, \forall (i, j) \in A & (f) \end{cases} \quad (16)$$

and

$$\Phi := \left\{ t \in R^{|V|} \mid \sum_{i: \{d_i > 0, i \in V\}} t_i \leq \Gamma_2, 0 \leq t_i \leq 1, \forall i \in V \right\} \quad (17)$$

From the definitions of Ω and Φ , we know that the model (7)–(8) is a bilinear programming, therefore the optimal solution of model (7)–(8) can be taken at a vertex of $\Omega \times \Phi$ [23]. That is, there is an optimal solution $(\pi^*, r^*, u^*, \omega^*, \theta^*, t^*)$ of model (7)–(8) such that $t_i^* \in \{0, 1\}, \forall i \in V$. In other words, t_i^* can be considered as binary variables.

Second, we deal with the nonlinear items in the objective function (7). Let $v_i := t_i(\pi_i + \omega_i)$, we have:

$$\begin{cases} t_i = 0 \rightarrow v_i = 0 & (a) \\ t_i = 1 \rightarrow v_i = \pi_i + \omega_i & (b) \end{cases} \quad (18)$$

Therefore, we can use the following four linear inequalities to express the relationship between the above variables.

$$\begin{cases} v_i \leq M t_i & (a) \\ -v_i \leq M t_i & (b) \\ \pi_i + \omega_i - v_i \leq M(1 - t_i) & (c) \\ -(\pi_i + \omega_i - v_i) \leq M(1 - t_i) & (d) \end{cases} \quad (19)$$

Similarly, let $k_{ij} := (1 - r_{ij})u_{ij}$, we have:

$$\begin{cases} r_{ij} = 1 \rightarrow k_{ij} = 0 & (a) \\ r_{ij} = 0 \rightarrow k_{ij} = u_{ij} & (b) \end{cases} \quad (20)$$

Then the relationships of (20) can be expressed as the following linearized constraints:

$$\begin{cases} 0 \leq k_{ij} \leq M(1 - r_{ij}) & (a) \\ 0 \leq u_{ij} - k_{ij} \leq M r_{ij} & (b) \end{cases} \quad (21)$$

The model (13)–(14) is obtained by replacing $t_i(\pi_i + \omega_i)$ and $(1 - r_{ij})u_{ij}$ with v_i and k_{ij} in the objective function (7), respectively, and combining constraints (19) and (21) into constraints (8). ■

Since the proposed model is in the min-max form, we propose an algorithm based on Benders Decomposition [24,25] to solve it. The algorithm is as follows:

Algorithm:

Step1. Initialization: Given parameters Γ_1 and Γ_2 , randomly generate x_i, y_i satisfying constraints (2)(a)–(2)(c). Then solve the subproblem $\hat{F}(x, \Gamma_1, \Gamma_2)$, let $(\pi_i^1, \omega_i^1, v_i^1, \theta_i^1, u_i^1, k_{ij}^1)$ be the optimal solution of $\hat{F}(x, \Gamma_1, \Gamma_2)$, set $U := +\infty, L := 0, k := 1, x_{best} := x$;

Step2. For given $(\pi_i^k, \omega_i^k, v_i^k, \theta_i^k, u_i^k, k_{ij}^k)$, solve the master problem:

$$\min \sum_{i \in V} d_i x_i + \xi \quad (22)$$

$$s.t. \begin{cases} \xi \geq \sum_{i \in V} [-\beta_i(\pi_i^k + \omega_i^k) - \Delta_i v_i^k - x_i \theta_i^k] - M \sum_{(i,j) \in A} k_{ij}^k & (a) \\ x_i \leq C_i y_i, \forall i \in V & (b) \\ \sum_{i \in V} f_i y_i \leq G & (c) \\ x_i \geq 0, y_i \in \{0, 1\}, \forall i \in V & (d) \end{cases} \quad (23)$$

Denote the optimal solution of the master problem as (x^k, y^k, ξ^k) , update $L := \max\{L, \sum_{i \in V} d_i x_i^k + \xi^k\}$.

Step3. For given x^k , solve the subproblem $\hat{F}(x^k, \Gamma_1, \Gamma_2)$, let the optimal value be \hat{F}^{k+1} and the optimal solution be $(\pi_i^{k+1}, \omega_i^{k+1}, v_i^{k+1}, \theta_i^{k+1}, u_{ij}^{k+1}, k_{ij}^{k+1})$. If there is $U > \sum_{i \in V} d_i x_i^k + \hat{F}^{k+1}$, update $U := \sum_{i \in V} d_i x_i^k + \hat{F}^{k+1}$ and $x_{best} := x^k$, otherwise keep U and x_{best} unchanged.

Step4. If $U \leq L + \epsilon$, stop and output the optimal solution x_{best} , otherwise add the following constraint to the master problem:

$$\xi \geq \sum_{i \in V} [-\beta_i(\pi_i^{k+1} + \omega_i^{k+1}) - \Delta_i v_i^{k+1} - x_i \theta_i^{k+1}] - M \sum_{(i,j) \in A} k_{ij}^{k+1} \quad (24)$$

Update $k := k + 1$, return Step2.

Note: Because the unmet demands are already compensated for in model (5)–(6), the problem under study is always feasible, so there is no need to include feasible cuts in the algorithm.

5. Computational experiments

5.1. Generation of test instance

The Sioux Falls network has been used by numerous researchers to test kinds of models and algorithms. In this paper, we use a simplified Sioux Falls network to test the proposed model. Among the 24 nodes in this simplified network, 8 nodes serve as emergency resource demand points ($V_d = \{4, 8, 10, 12, 13, 14, 17, 21\}$). The remaining 16 nodes are considered as candidate locations of emergency supply points. The set of roads at risk of disruption E_1 consists of 10 of the 38 edges, that is, $E_1 = \{(3, 4), (4, 5), (3, 12), (4, 11), (10, 11), (13, 24), (14, 23), (16, 17), (17, 19), (21, 24)\}$. Fig. 1 shows the structure, road distances (numbers near links, unit: miles), demand points (orange nodes), and possibly disruption roads (red dotted lines) of the simplified Sioux Falls network.

Table 2 lists the parameters of the candidate locations for the emergency supply points, and Table 3 lists the parameters of the demand points.

5.2. Experimental results

The problem is programmed in MATLAB R2018a platform and run on a 64-bit Intel i7-1065G7 portable computer with 1.30 GHz CPU and 16 GB RAM. The commercial solver Gurobi 9.1.1 is used to solve the subproblem in the proposed algorithm. Let $\Gamma_1 = 4, \Gamma_2 = 5, G = 300(\times 10^4)$, and the transportation cost of unit emergency resource c_{ij} set to be c times the distance of edge (i, j) , here $c = 10$. Table 4 shows the optimal location of emergency supply points, the amount of emergency supplies stored at each selected supply point, and the worst-case transport and compensation plan. The optimal objective function value is $Z^* = 1.8664 \times 10^6$ while the operation cost $Q(x^*, \Gamma_1, \Gamma_2) = 1.2796 \times 10^6$. In the penultimate line, z_i^* represents the number of unmet emergency resources at demand point i (i.e. the compensation amount). The last row of Table 4 shows the actual demand for each demand point in the worst case scenario, where the underline indicates that the corresponding demand point reaches the upper boundary of the corresponding demand interval.

As can be seen from Table 4, candidate points 6, 11, 16, 19, and 22 were selected as emergency supply points, with 6 and 16 having emergency supplies stored below their capacity. The emergency supplies required at points 4, 13, and 17 cannot be fully met by supply points and must be supplemented by compensation.

If decision-makers ignore the parameters' uncertainty, it is equivalent to thinking that the robust control parameters $\Gamma_1 = \Gamma_2 = 0$, then the optimal location scheme of emergency supply points and the allocation of emergency supplies are shown in Table 5.

If the optimal allocation scheme obtained from the deterministic model is applied to the uncertain environment, it can be found that

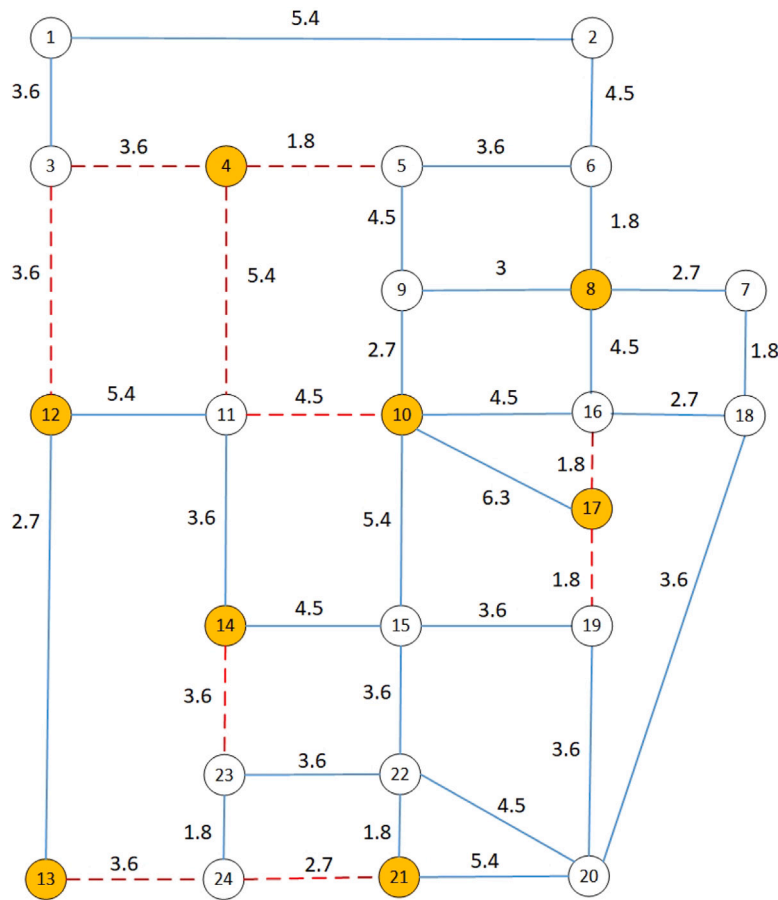


Fig. 1. The simplified Sioux Falls network.

Table 2
Parameters of the candidate locations for the emergency supply points.

V_s	1	2	3	5	6	7	9	11	15	16	18	19	20	22	23	24
$f_i(\times 10^4)$	130	70	50	60	60	70	50	60	60	50	40	40	100	50	60	50
$C_i(\times 10^2)$	14	20	15	15	16	18	12	17	15	12	10	11	23	15	17	15
d_i	140	120	110	90	80	90	110	100	120	90	80	80	120	90	120	100

Table 3
Parameters of the demand points.

V_d	4	8	10	12	13	14	17	21
β_i	1500	880	1290	1000	1320	1370	1450	1020
A_i	300	176	258	200	264	274	290	204
s_i	200	200	240	240	200	220	220	220

Table 4
The allocation scheme for the worst case scenario when $\Gamma_1 = 4, \Gamma_2 = 5, G = 300$.

Selected location	Demand points								Allocated quantity (x_i^*)
	4	8	10	12	13	14	17	21	
6		880	122.9	106.6					1109.5
11	542.6			1093.4		64			1700
16			1167.1						1167.1
19						1100			1100
22						480		1020	1500
z_i^*	1257.4				1584		1740		
Demand quantity	1800	880	1290	1200	1584	1644	1740	1020	

the total operating cost will exceed the optimal decision requirement of the robust model when facing the worst-case scenario. For example, if the deterministic optimal allocation scheme shown in Table 5 (here we denote it as x_d^*) is applied to the uncertain environment of $\Gamma_1 = 4, \Gamma_2 = 5$, the post-disaster transportation and compensation costs can

be obtained by solving the subproblem $Q(x_d^*, \Gamma_1, \Gamma_2) : 1.2424 \times 10^6$. Therefore, the total operating cost is equal to the above costs plus the prepositioning cost of emergency supplies ($\sum_{i \in V_s} d_i x_{di}^* = 766,000$), and the total is 2.0084×10^6 . Obviously, this cost is greater than the total

Table 5
The allocation scheme when ignore parameters' uncertainty $\Gamma_1 = 0, \Gamma_2 = 0, G = 300$.

Selected location	Demand points								Allocated quantity (x_{di}^*)
	4	8	10	12	13	14	17	21	
3	500			1000					1500
6	720	880							1600
11			640			1060			1700
18			650				350		1000
19							1100		1100
22					170	310		1020	1500
z_i^*	280				1150				
Demand quantity	1500	880	1290	1000	1320	1370	1450	1020	

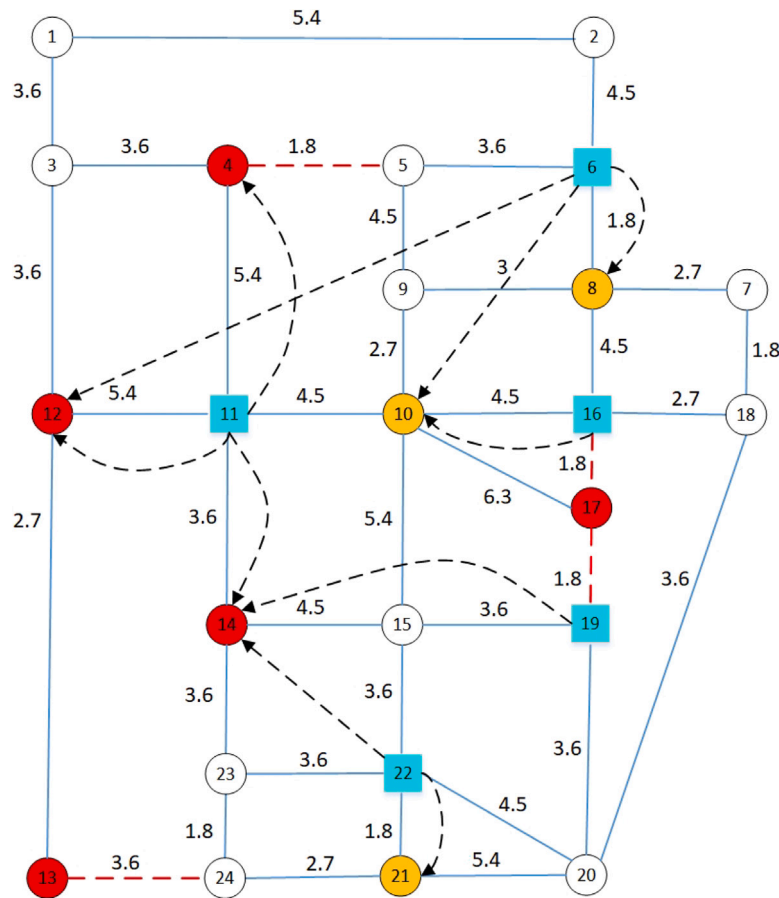


Fig. 2. Location-allocation scheme ($\Gamma_1 = 4, \Gamma_2 = 5, G = 300$).

operating cost of the optimal decision (shown in Table 4) derived from the robust model $Z^* = 1.8664 \times 10^6$. According to the above analysis, when parameters are uncertain, it is better to use robust model than deterministic model for decision-making.

Fig. 2 visualizes the location of the emergency supply and demand points and the supply relationship between them, as well as the worst case scenario of road disruption. In Fig. 2, blue squares represent emergency resource supply points, dots represent demand points (where red dots represent demand points that reach the upper boundary of the corresponding demand intervals), black dashed lines indicate distribution relationships, and red dashed lines denote the disrupted roads in the worst-case scenario.

5.3. Sensitivity analysis

The parameters Γ_1 and Γ_2 play an important role in controlling the uncertainties of the total demand for emergency supplies and the disruption of roads, respectively. We therefore first test the impact of

parameters Γ_1, Γ_2 on the location scheme of emergency supply points and the disruption of roads in the worst-case scenario. Now, we keep $\Gamma_2 = 5$ and $G = 300$ unchanged, and let Γ_1 change from 0 to 10, the location scheme of supply points, the disrupted roads and the corresponding operating costs (Z^*) are shown in Table 6. Note that these results are calculated based on the worst-case scenario among possible scenarios that satisfy constraints with the given parameters Γ_1 and Γ_2 .

As can be seen from Table 6, operating costs Z^* first increase as Γ_1 and remain constant as Γ_1 increases further. According to different values of Γ_1 , there are 5 different location schemes for the emergency supply points. It can be found that for different values of Γ_1 , (6, 11, 19, 22) are selected as emergency supply points, which indicates that these candidate points are well adapted for various road disruption scenarios. Another interesting phenomenon is that when Γ_1 reaches a certain level, further increases in its value will no longer affect the location scheme of emergency supply points and the corresponding

Table 6
The location scheme in the worst-case scenario when $\Gamma_2 = 5, G = 300$.

Γ_1	Location scheme	Disrupted roads	$Z^*(\times 10^6)$
$\Gamma_1 = 0$	(3,6,11,18,19,22)	-	1.6451
$\Gamma_1 = 1$	(6,11,16,18,19,22)	(17-19)	1.6930
$\Gamma_1 = 2$	(6,11,18,19,22,24)	(13-24) (17-19)	1.7573
$\Gamma_1 = 3$	(6,11,18,19,22,24)	(13-24) (16-17) (17-19)	1.8235
$\Gamma_1 = 4$	(6,11,16,19,22)	(4-5) (13-24) (16-17) (17-19)	1.8664
$\Gamma_1 = 5$	(6,11,16,19,22)	(4-5) (13-24) (14-23) (16-17) (17-19)	1.8750
$\Gamma_1 = 6$	(6,11,16,18,19,22)	(4-5) (4-11) (13-24) (14-23) (16-17) (17-19)	1.8752
$\Gamma_1 \geq 7$	(6,11,16,18,19,22)	(3-4) (4-5) (4-11) (13-24) (14-23) (16-17) (17-19)	1.8753

Table 7
The location scheme in the worst-case scenario when $\Gamma_1 = 4, G = 300$.

Γ_2	Location scheme	Disrupted roads	$Z^*(\times 10^6)$
$\Gamma_2 = 0$	(6,11,16,19,22)	(4-5) (4-11) (16-17) (17-19)	1.6037
$\Gamma_2 = 1$	(6,11,16,19,22)	(4-5) (4-11) (16-17) (17-19)	1.6675
$\Gamma_2 = 2$	(6,11,16,19,22)	(4-11) (13-24) (16-17) (17-19)	1.7275
$\Gamma_2 = 3$	(6,11,16,19,22)	(4-11) (13-24) (16-17) (17-19)	1.7803
$\Gamma_2 = 4$	(6,11,16,19,22)	(4-5) (13-24) (16-17) (17-19)	1.8253
$\Gamma_2 = 5$	(6,11,16,19,22)	(4-5) (13-24) (16-17) (17-19)	1.8664
$\Gamma_2 = 6$	(6,11,16,19,22)	(13-24) (14-23) (16-17) (17-19)	1.8996
$\Gamma_2 = 7$	(6,11,16,19,22)	(4-5) (13-24) (16-17) (17-19)	1.9260
$\Gamma_2 = 8$	(6,11,16,19,22)	(4-5) (13-24) (16-17) (17-19)	1.9428

operating costs. When $\Gamma_1 \geq 7$, the set of disrupted roads in the worst-case scenario contains the following results: (3-4), (4-5), (4-11), (13-24), (14-23), (16-17), (17-19).

Next, keep $\Gamma_1 = 4$ and $G = 300$ unchanged, and let Γ_2 change from 0 to 8, the location scheme of supply points, the disrupted roads and the corresponding operating costs (Z^*) are shown in Table 7.

In Table 7, the increase in Z^* with increasing Γ_2 is a predictable result. For different values of Γ_2 , there are only two different location schemes, indicating that Γ_2 has less influence on the location scheme than Γ_1 . Furthermore, we find that while the value of Γ_1 remains constant, the set of disrupted roads corresponding to the worst-case scenario still varies with Γ_2 . This phenomenon suggests that the degree of uncertainty in aggregate demand affects the set of disrupted roads in the worst-case scenario.

To test the adaptability of a given optimal solution (in the case of x^* in Table 4) to random scenarios with different parameters, we first hold $\Gamma_2 = 5$ constant and let Γ_1 change from 1 to 10. Then we generate 100 random scenarios satisfying the conditions of each case (that is, we randomly generate 100 sets of demand data to satisfy total fluctuation of no more than Γ_2 , and randomly select Γ_1 edges from E_1 as disrupted roads). The mean and variance of the operating costs (including procurement costs, transportation costs, and compensation costs) for each scenario are shown in Fig. 3. Note that when $\Gamma_1 = 4, \Gamma_2 = 5$, the operating cost of the optimal solution x^* in the worst-case scenario ($Q(x^*, \Gamma_1 = 4, \Gamma_2 = 5)$) is shown in the figure as a comparison standard.

As can be seen in Fig. 3, the mean of operating cost increases with Γ_1 , while there is no significant correlation between the variance of operating cost and Γ_1 . The former is due to the fact that as Γ_1 increases, the number of disrupted roads also increases, thus increasing the corresponding transportation costs. When $\Gamma_1 \geq 8$, the operating cost in some cases exceeds $Q(x^*, \Gamma_1 = 4, \Gamma_2 = 5) = 1.2796 \times 10^6$, which means that as Γ_1 increases, some post-disaster scenarios are worse than the worst-case scenario corresponding to x^* .

Now hold $\Gamma_1 = 4$ constant, let Γ_2 vary from 1 to 8, and generate 100 random scenarios that satisfy the conditions for each case. The mean and variance of the operating costs are shown in Fig. 4.

The mean value of operating costs in Fig. 4 increases with Γ_2 , and the increasing trend of the curve slows down significantly when $\Gamma_2 \geq 5$. For any value of Γ_2 , the operating cost under all random scenarios is lower than $Q(x^*, \Gamma_1 = 4, \Gamma_2 = 5) = 1.2796 \times 10^6$. This means that the optimal solution x^* can be adapted to all scenarios corresponding to different values of Γ_2 when Γ_1 is held constant. Comparing the impact

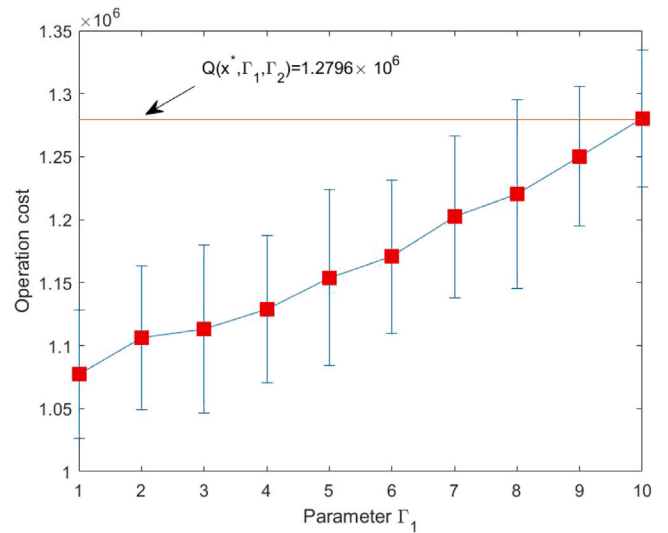


Fig. 3. Operation costs under random scenarios (different Γ_1).

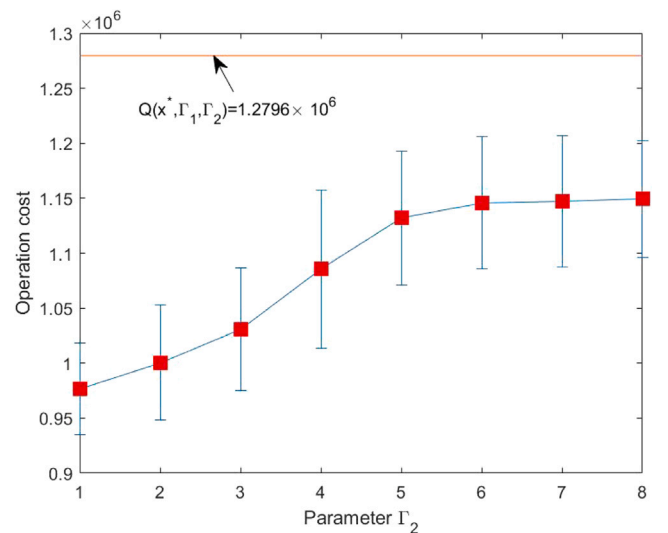


Fig. 4. Operation costs under random scenarios (different Γ_2).

Table 8
The impact of transportation cost per unit distance.

c	$c = 5$	$c = 10$	$c = 15$	$c = 20$
Location scheme	(6,11,16,18,19,22)	(6,11,16,19,22)	(6,9,11,15,22)	(6,9,11,16,22)
Disrupted roads	(4-5)(13-24)(16-17)(17-19)	(4-5)(13-24)(16-17)(17-19)	(4-5)(4-11)(14-23)(16-17)	(4-5)(3-12)(13-24)(16-17)
$Z^*(\times 10^6)$	1.6526	1.8664	1.9879	2.0805

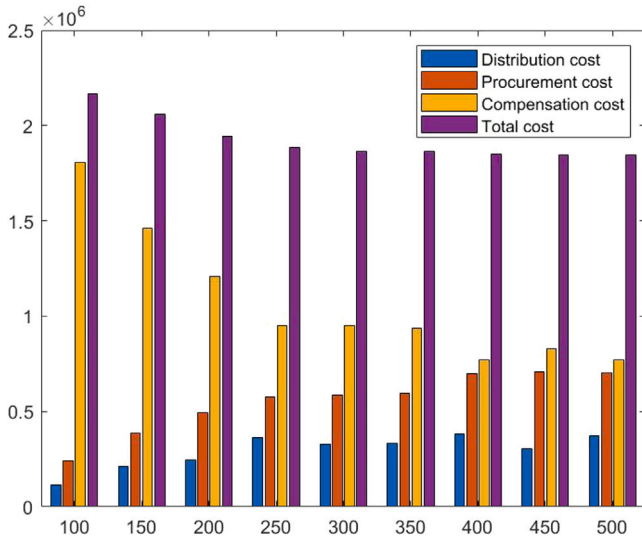


Fig. 5. The relationship between different costs and budgets.

of Γ_1 and Γ_2 on operating costs in Figs. 3 and 4, it can be seen that road disruptions have a greater impact on operating costs than demand.

Since the unit transportation cost c_{ij} is set as c multiplied by the distance of the road (i, j) , we can test the impact of c on the location scheme of supply points and the worst-case scenario of disrupted roads. Keeping other parameters constant, let c vary from 5 to 20 in steps of 5. The results are shown in Table 8.

As can be seen from Table 8, different values of c affect not only the location scheme of the emergency supply points, but also the worst-case scenario disrupted roads.

Finally, we analyze the effect of budget G on the objective function. Let G vary from 100 to 500 in steps of 50. The procurement cost, transportation cost, compensation cost of emergency supplies, and the total cost of these three items are shown in Fig. 5.

As can be seen from Fig. 5, the total cost first decreases as G increases and remains essentially constant when G exceeds a certain threshold. Of these three costs, compensation costs essentially decrease as G increases, while procurement costs show the opposite trend. This is because as G increases, more emergency supply points can be established, which increases the procurement cost of emergency supplies while reducing unmet demands (i.e. lowering the compensation costs).

5.4. Management insights

Some valuable management insights can be drawn from the preceding test case and sensitivity analysis.

First, when decision makers are faced with uncertainties about road disruptions and emergency demands, the former has a greater impact on the prepositioning of emergency supplies, so they need to make more accurate judgements about the possible set of road disruptions and the control parameter for the total number of disruption roads.

Second, for the total number of disrupted roads is large, decision makers can appropriately reduce pre-positioned quantity of emergency supplies, while considering different ways to compensate for emergency supplies in order to reduce compensation costs.

Third, if it is difficult for decision makers to decide the value of the control parameter Γ_1 (i.e. the total number of the disrupted roads), different values of Γ_1 can be used to find out the common locations of emergency supply points. Decision makers can first establish emergency supply points at these locations and then determine the next decision options based on subsequent information obtained.

Finally, the construction cost of emergency supply points is one-time fixed investment, while the operating cost is a long-term investment for each possible disaster. As long as the budget for construction costs reaches a certain threshold, it will basically not affect the subsequent operating costs. Therefore, decision makers need to budget enough for the construction costs of emergency supply points.

6. Conclusion

In this paper, we proposed a two-stage robust optimization model to determine the location of emergency supply points and the corresponding storage levels of emergency supplies. The model describes two types of uncertainty, possible road disruptions and requirements for emergency supplies, using interval data. Since the different available road network conditions after a disaster affect the unit transportation cost of emergency supplies, the tradition location-transportation model faces the difficulty of solving the unit transportation cost under different network structures. These available road network structures are scenarios obtained by combining different disrupted roads, so the number of possible network structures grows exponentially with the number of disrupted roads. The novelty of this paper is that the location and transportation of emergency supplies is modeled as a network flow problem, which utilizes the capacity constraints of edges to incorporate the uncertainty of potentially disrupted roads into this problem.

The second-stage model is transformed from the original maximum–minimum to the maximum form using duality theory. An algorithm based on Benders decomposition is proposed after linearizing the objective function of the second-stage model. Finally, computational experiments demonstrate the validity of the model and algorithm, and give some valuable management insights through sensitivity analysis of different parameters.

The idea of this paper can be further extended to the possibility of candidate supply points being damaged by a disaster, and future work can take into account factors such as the urgency of post-disaster relief and equity between different demand points.

CRediT authorship contribution statement

Wuyang Yu: Conceptualization, Methodology, Software, Writing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgments

The National Social Science Fund of China (22BGL004) supported this work.

References

- [1] Rudden J. Natural disaster losses cost worldwide. 2022, p. 2000–21, <https://www.statista.com/statistics/612561/natural-disaster-losses-cost-worldwide-by-type-of-loss/>.
- [2] Paul JA, Zhang M. Supply location and transportation planning for hurricanes: A two-stage stochastic programming framework. *European J Oper Res* 2019;274:108–25.
- [3] Jiang Z, Ouyang Y. Reliable location of first responder stations for cooperative response to disasters. *Transp Res Part B* 2021;149:20–32.
- [4] Sütüçen TC, Batun S, Çelik M. Integrated reinforcement and repair of interdependent infrastructure networks under disaster-related uncertainties. *European J Oper Res* <http://dx.doi.org/10.1016/j.ejor.2022.10.043>.
- [5] Wang Q, Nie X. A stochastic programming model for emergency supply planning considering traffic congestion. *IIE Trans* 2019;51:910–20.
- [6] Wang Q, Nie X. A stochastic programming model for emergency supply planning considering transportation network mitigation and traffic congestion. *Soc-Econ Plan Sci* 2022;79:101119.
- [7] Shehadeh KS, Tucker EL. Stochastic optimization models for location and inventory prepositioning of disaster relief supplies. *Transp Res Part C: Emerg Technol* 2022;144:103871.
- [8] Sanci E, Daskin MS. An integer L-shaped algorithm for the integrated location and network restoration problem in disaster relief. *Transp Res Part B* 2021;145:152–84.
- [9] Wang Q, Liu Z, Jiang P, Luo L. A stochastic programming model for emergency supplies pre-positioning, transshipment and procurement in a regional healthcare coalition. *Soc-Econ Plan Sci* 2022;82:101279.
- [10] Kizito R, Liu Z, Li X, Sun K. Multi-stage stochastic optimization of islanded utility-microgrids design after natural disasters. *Oper Res Perspect* 2022;9:100235.
- [11] Soyster AL. Convex programming with set-inclusive constraints and applications to inexact linear programming. *Oper Res* 1973;21:1154–7.
- [12] Ben-Tal A, Nemirovski A. Robust solutions for linear programming problems contaminated with uncertain data. *Math Program* 2000;88:411–24.
- [13] Bertsimas D, Sim M. The price of robustness. *Oper Res* 2004;52:35–53.
- [14] Liu Y, Lei H, Zhang D, Wu Z. Robust optimization for relief logistics planning under uncertainties in demand and transportation time. *Appl Math Model* 2018;55:262–80.
- [15] Rahmani D, Zandi A, Peyghaleh E, Siamakmanesh N. A robust model for a humanitarian relief network with backup covering under disruptions: A real world application. *Int J Disaster Risk Reduct* 2018;28:56–68.
- [16] Paul JA, Wang X. Robust location-allocation network design for earthquake preparedness. *Transp Res Part B* 2019;119:139–55.
- [17] Yu W. Pre-disaster location and storage model for emergency commodities considering both randomness and uncertainty. *Saf Sci* 2021;141:105330.
- [18] Sun H, Wang Y, Zhang J, Cao W. A robust optimization model for location-transportation problem of disaster casualties with triage and uncertainty. *Expert Syst Appl* 2021;175:114867.
- [19] Yang M, Liu Y, Yang G. Multi-period dynamic distributionally robust pre-positioning of emergency supplies under demand uncertainty. *Appl Math Model* 2021;89:1433–58.
- [20] Sun H, Li J, Wang T, Xue Y. A novel scenario-based robust bi-objective optimization model for humanitarian logistics network under risk of disruptions. *Transp Res Part E: Logist Transp Rev* 2022;157:102578.
- [21] Zhang J, Li Y, Yu G. Emergency relief network design under ambiguous demand: A distributionally robust optimization approach. *Expert Syst Appl* 2022;208:118139.
- [22] Hafezalkotob A, Fardi K, Aickelin U, Chaharbaghi S, Khorshidi HA. A cooperative robust human resource allocation problem for healthcare systems for disaster management. *Comput Ind Eng* 2022;179:108283.
- [23] Horst R, Pardalos PM, Thoai NY. Introduction to global optimization. Amsterdam: Kluwer Academic Publishers; 2000.
- [24] Witthayapraphakorn A, Charnsethikul P. Benders decomposition with special purpose method for the sub problem in lot sizing problem under uncertain demand. *Oper Res Perspect* 2019;6:100096.
- [25] Muffak A, Arslan O. A benders decomposition algorithm for the maximum availability service facility location problem. *Comput Oper Res* 2023;149:106030.