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Facilities Sites Selection Optimization for Food Emergency Logistics to Meet Urgent Demands

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Abstract: Effective emergency logistics facility site selection is vital for ensuring prompt and fair food supply during crises. This study tackles the intricate task of choosing optimal sites for emergency food logistics facilities by considering varying urgency levels of needs, uncertain demands, and potential facility interruptions. A novel weighted Mahalanobis distance–gray relational analysis–TOPSIS method is devised to evaluate demand urgency and guide site selection decisions. The proposed location model aims to minimize total cost and unmet demand while integrating discrete scenario strategies to address interruption events. Leveraging the Social Network Search (SNS) algorithm, the model is solved, and its effectiveness is validated through a case study analysis. The results highlight the accuracy of the urgency level determination method in capturing demand characteristics and the model's provision of an objective and practical framework for formulating rational facility location strategies. This approach holds significant promise for enhancing the promptness and fairness of food supply assurance during emergencies.

Keywords: emergency logistics; facility sites selection; urgency of food demands; social network search algorithm

MSC: 90B50

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1. Introduction

Frequent sudden events worldwide have a profound impact on residents, economies, and social development. Post disasters, there is a surge in food demand in affected regions, requiring swift supply under resource constraints [1–3]. Optimizing the spatial layout of emergency logistics facilities is a widely employed and effective strategy to reduce material distribution time, manage costs, and enhance material supply efficiency [4–6]. It serves as a crucial practical foundation for emergency logistics system operations and has the potential to significantly enhance the effectiveness of material supply efforts. The optimization process should adhere to the principle of prioritizing urgent demands first. Facilities should be strategically located near areas with high demand urgency, and their capacity should align with the urgency of material requirements. By accounting for demand variations and fully acknowledging the urgency's impact, the development of scientifically driven site selection strategies for emergency logistics facilities can facilitate the establishment of a robust and efficient emergency logistics system. This, in turn, can enhance allocation efficiency, bolster material supply operations during crises, and ensure reliable support [7–14].

Various research endeavors have been pursued to tackle this challenge. Ye Feng et al. introduced an Emergency Warehouse Location Problem (EWLP) model, prioritizing effectiveness in emergency management over efficiency, to investigate the site selection problem for national emergency warehouses in China [15]. Liu Jin et al. advocated emergency material reserve warehouse site selection based on coverage satisfaction and cost-effectiveness [16]. Mansoor et al. presented a comprehensive bilateral location model considering center and customer utilities to enhance service quality and center density [17]. Naranjo et al. proposed a hierarchical facility location model for multi-category facilities, emphasizing storage capacity and coverage rate to optimize overall coverage satisfaction [18]. Regis-Hernández et al. assert that combining location and allocation factors can strengthen the scientific foundation of location decisions [19]. To capture the intricacies and uncertainties of emergencies, Michael et al. developed a multi-capability P-median facility location model that accounts for the diverse needs of individuals following disasters [20]. Guo et al. addressed the intermittent unavailability of established emergency logistics facilities due to capacity constraints or disaster impact in their research on emergency logistics facility location issues [21]. Several groups of researchers have extensively investigated the effects of uncertain demand on location problems [22–25]. Several groups of scholars emphasize the significance of transportation and transit costs in location problems [26–29]. In contrast, other groups of scholars advocate incorporating humanitarian considerations into site selection decisions [30–33].

These studies have given less emphasis to variations in demand urgency. To tackle this gap, Pamucar et al. introduced the fuzzy FUCOM-D'Bonferroni model to prioritize transportation demand management (TDM) issues [34]. Song et al. introduced a novel material dispatching model that accounts for distinct disaster severity levels, ensuring prioritization and concentration on emergency material dispatching in severely affected areas while also considering equity in emergency material distribution across all levels [35]. Furthermore, Song et al. recommended that scheduling decisions should factor in rescue time window constraints across different urgency levels [36]. Zhang et al. proposed a dynamic optimization model that considers demand urgency, arguing that conventional emergency material supply models focus on meeting quantity requirements but overlook the subjective urgent needs of diverse emergency materials and disaster victims, hindering the fair and rational maximization of limited resources' utility [37]. For complex location models, Mišković et al. proposed a variable neighborhood search method to tackle practical problems that the CPLEX solver cannot handle [38]. Filippi et al. introduced a kernel search heuristic to improve the effectiveness of model solutions [39]. Presently, research on emergency material dispatch primarily focuses on medical supplies and specialized rescue equipment, often overlooking the importance of food provision. Emergency food plays a crucial role in not only sustaining life but also maintaining social order, facilitating swift responses, preventing diseases, supporting long-term rescue efforts, and catering to vulnerable populations. Unlike medical supplies that have specific usage guidelines, various types of food can address basic survival requirements. Additionally, food presents distinct challenges like perishability and specific transportation needs. Therefore, in situations with limited resources, it is essential to prioritize various food requirements and make strategic decisions regarding facility locations.

This paper explores the problem of food emergency logistics facility location by fully considering the impact of demand urgency and determining the optimal layout and configuration of these facilities. Firstly, it designs a method for assessing demand urgency and establishes a location model aimed at minimizing total cost and unmet demand, with considerations for potential facility disruptions. Secondly, it develops a solution method for the model and verifies it through case analysis. Finally, this paper summarizes the findings, aiming to improve China's crisis management capabilities and enhance emergency response effectiveness.

2. Model Establishment

2.1. Problem Description and Assumptions

Within an emergency logistics system, emergency logistics facilities primarily comprise emergency logistics centers and distribution centers. The material demand points, representing the disaster-affected areas, can be fulfilled directly by the emergency logistics centers or indirectly through the distribution centers. Emergency logistics centers are divided into permanent and temporary types, with permanent ones established during the prevention and preparation phase. In the aftermath of a sudden incident, the emergency response phase may witness substantial casualties and losses, rendering existing logistics centers inadequate to meet the demand. Hence, it becomes imperative at this juncture to address the two-tier food emergency logistics facility location problem encompassing "logistics centers–distribution centers". The model integrates uncertain demand and demand urgency to formulate the location model for food emergency logistics facilities. To streamline the model, it focuses solely on domestic logistics and considers a single mode of transportation, be it road, waterway, or air transport. Furthermore, the model operates under the following assumptions:

(1) The positions of potential emergency logistics facilities and demand points are predetermined.
(2) Each emergency logistics facility can cater to multiple demand points, and conversely, demand points can be serviced by multiple facilities.
(3) Factors such as demand, damage rate, and damage cost of various material types are not taken into account.
(4) The capacity of emergency logistics facilities is restricted, and can be adjusted as needed, in proportion to construction and operational expenses.

Following a sudden disaster, uncertainty parameters may not exhibit randomness due to information scarcity, and the outcomes of diverse disasters can differ. It is plausible that uncertainty parameters cannot be deduced from historical data or conform to a probability distribution. In such instances, the prerequisites for employing stochastic programming are not fulfilled, prompting the creation of a robust optimization model. To tackle uncertainty parameters in the location selection issue, uncertainty sets are employed to represent demand uncertainty. We devise a food emergency logistics facility location model centered on demand urgency. The symbols utilized in the model are elucidated below:

I: a set of demand points, $I = 1, 2, \ldots, |I|$.

M: a set of established and candidate logistics centers, $M = \{1, 2, \ldots, |M|\}$.

N: a set of candidate distribution centers, $N = \{1, 2, \ldots, |N|\}$.

k: the total categories of emergency food.

q_i, $\overline{q_i^k}$: these, respectively, represent the expected demand of the demand point (I_i) and the actual demand of the demand point (I_i) for materials (k), $k \in K$.

λ_i, λ_i^k: these denote the urgency of emergency demand and the urgency of emergency food (k) demand at the demand point (I_i).

FC_M, FC_N: the unit construction cost of the logistics center and distribution center, $FC_M > FC_N$.

VC_M, VC_N: the unit operating cost of the logistics center and distribution center, $VC_M > VC_N$.

SC: the unit transportation cost refers to the cost of transporting goods per unit distance.

TC: the unit transit cost is the charge for moving each unit of goods from the logistics center to the demand point through the distribution center.

$v_{N\max}$, $\nu_{N\max}$: the maximum and minimum construction capacity (i.e., the volume of materials they can handle) of logistics centers.

s_{mi}, s_{ni}, s_{mn}: the distance from the demand point to the logistics center, the distance from the demand point to the distribution center, and the distance from the logistics center to the distribution center.

w_M, w_N: the decision variable, i.e., the number of emergency logistics centers and distribution centers opened.

$x_m^M \in \{0, 1\}$, $x_n^N \in \{0, 1\}$: The decision variable signifies the opening status of a logistics center (M_m) or distribution center (N_n). A value of 1 indicates that the center is open, while any other value indicates closure. $m \in M$, $n \in N$.

v_m^M, v_n^N: The decision variable. The capacity of a logistics center and distribution center denotes the volume of goods they can hold.

z_{mn}^k, z_{mi}^k, z_{ni}^k: the decision variable representing the allocation quantity of food supply (k) among logistics centers, distribution centers, and demand points.

2.2. Determination of Demand Urgency

Following a sudden event, the urgency of demand for emergency food varies across demand points due to factors like the severity of the disaster, economic conditions, and population demographics. The urgency of demand is influenced by factors such as food importance, production capabilities, transportation challenges, and emergency response efficiency. As a result, demand points exhibit varying levels of urgency for different food types. Therefore, the analysis of demand urgency should consider two aspects: the urgency at demand points and the urgency across food categories. Priority should be given to meeting the needs of high-urgency demand points while also addressing those with lower urgency. This approach allows for centralized coordination by emergency material management centers, rational selection of emergency logistics sites, and efficient resource utilization. It enhances decision-making precision, ensures timely food supply during emergencies with limited resources, reduces management expenses, and boosts rescue effectiveness.

To assess the urgency of food demand at various points, we consider the following indicators: degree of disaster (X_1), extent of building or road damage (X_2), energy demand density (X_3), primary industry GDP (X_4), population density (X_5), and ratio of elderly and young population (X_6). For evaluating the urgency of food demand itself, we choose the following indicators: demand level (Y_1), nutritional demand (Y_2), demand frequency (Y_3), transportation temperature and humidity index (Y_4), lead time (Y_5), demand price elasticity (Y_6), self-sufficiency capacity (Y_7), edible days (Y_9), food energy (Y_9), shelf life (Y_{10}), and convenience of consumption (Y_{11}). To ensure objectivity, we first construct an initial decision matrix and preprocess it. Then, we use the entropy weight method to assign weights. Next, we apply the weighted Mahalanobis distance–gray relational–TOPSIS method to obtain urgency coefficients. Finally, we use hierarchical clustering to determine the urgency levels of demand. The steps are as follows:

Step 1: Interval number type conversion. Liu et al. introduced a method for converting attribute values represented as interval numbers [40].

$$x_{i_e} = x^- + i_e(x^+ - x^-) \tag{1}$$

where i_e are expected indicative values, and the general value is 0.5; x between $[x^-, x^+]$ x^- and x^+ belongs to $\Re$; x^- is less than x^+.

Step 2: Normalization of indicator values. Define set n as the evaluation objects, associated with set m as the evaluation indicators, and create an initial evaluation indicator matrix $\boldsymbol{A} = (a_{ij})_{n \times m}$, where a_{ij} represents the j-th indicator of the i-th object, $1 \leq i \leq n$, $1 \leq j \leq m$. Matrix $\boldsymbol{A}$ is normalized using the min–max method, resulting in matrix $\boldsymbol{B} = (b_{ij})_{n \times m}$.

Step 3: Calculate the information entropy H_j:

$$H_j = -\sum_{i=1}^{n} c_{ij} \ln c_{ij} / \ln n \tag{2}$$

where $c_{ij} = b_{ij} / \sum\limits_{i=1}^{n} b_{ij}$ represents the specific gravity of the indicator. To prevent calculation errors in cases where it equals zero, the lower limit of the normalization interval is set to 0.002.

Step 4: Use $w_j = 1 - H_j / n - \sum\limits_{j=1}^{n} H_j$ to calculate index entropy weight w_j.

Step 5: Calculate the positive ideal solution A^+ and negative ideal solution A^-:

$$A^+ = \{a_1^+, a_2^+, \ldots, a_m^+\} = \left(\max_{1 \leq i \leq n} x_{ij} \middle| j \in J^+, \min_{1 \leq i \leq n} x_{ij} \middle| j \in J^- \right) \tag{3}$$

$$A^- = \{a_1^-, a_2^-, \ldots, a_m^-\} = \left(\min_{1 \le i \le n} x_{ij} \middle| j \in J^+, \max_{1 \le i \le n} x_{ij} \middle| j \in J^- \right) \tag{4}$$

where J^+ and J^- are benefit-type and cost-type index sets, respectively.

Step 6: Calculate the dimensionless Markov distance D_j^+ between each evaluation scheme and the positive ideal solution, $d_i^+ = d(a_i, A^+) = \sqrt{(a_i - A^+)\mathbf{\Omega}\mathbf{\Sigma}^{-1}\mathbf{\Omega}^{\mathrm{T}}(a_i - A^+)^{\mathrm{T}}}$, $D_i^+ = \frac{d_i^+}{\max\limits_{1 \le i \le n} d_i^+}$. Similarly, the dimensionless Markov distance from the negative ideal solution $D_i^- = \frac{d_i^-}{\max\limits_{1 \le i \le n} d_i^-}$, $\mathbf{\Omega} = \mathrm{diag}(\sqrt{w_1}, \sqrt{w_2}, \ldots, \sqrt{w_m})$; $\mathbf{\Sigma}$ is the covariance matrix of matrix $\boldsymbol{A}$; and d_i^+ is the Mahalanobis distance with dimension.

Step 7: Calculate the dimensionless gray correlation degree R_i^+ and R_i^- of each scheme with positive and negative ideal solutions.

Firstly, calculate the weighted normalized matrix $\boldsymbol{C} = \left((b_{ij} * w_j)_{n \times m}\right)^T$. Then, calculate the gray correlation coefficient matrix $r^+ = (r_{ij}^+)_{n \times m}$ of each scheme and positive ideal solution, where $r_{ij}^+ = \frac{\min\limits_i \min\limits_j \left| c_j^+ - c_{ij} \right| + \rho \max\limits_i \max\limits_j \left| c_j^+ - c_{ij} \right|}{\left| c_j^+ - c_{ij} \right| + \rho \max\limits_i \max\limits_j \left| c_j^+ - c_{ij} \right|}$. Finally, the gray correlation degree $R_i^+ = \frac{r_i^+}{\max\limits_{1 \le i \le n} r_i^+}$ with the positive ideal solution is calculated. Here, $r_i^+ = \frac{1}{m} \sum\limits_{j=1}^{m} r_{ij}^+$ and ρ are the resolution coefficients, and $\rho = 0.5$ is generally selected; $c_j^+ = \max(c_j)$; r_{ij}^+ represents the gray coefficient of the i scheme and the positive ideal solution with respect to the j index; and r_i^+ is the gray correlation degree with dimension.

Similarly, the dimensionless gray correlation degree between each scheme and the negative ideal solution is $R_i^- = \frac{r_i^-}{\max\limits_{1 \le i \le n} r_i^-}$.

Step 8: Combine the Mahalanobis distance and the gray correlation degree. The larger D_i^- and R_i^+ are, the closer they are to the positive ideal scheme; conversely, the larger D_i^+ and R_i^- are, the closer they are to the ideal solution.

$$H_i^+ = \alpha D_i^- + \beta R_i^+ \tag{5}$$

$$H_i^- = \alpha D_i^+ + \beta R_i^- \tag{6}$$

where $1 \le i \le n$; $\alpha + \beta = 1$, generally 0.5; H_i^+ and H_i^- are the weighted synthetic values of D_i^- and R_i^+ and the weighted synthetic values of D_i^+ and R_i^-, respectively.

Step 9: Utilize $H_i^* = \frac{H_i^+}{H_i^+ + H_i^-}$ to compute the urgency value H_i^*. A higher proximity value indicates a more urgent demand, correlating to a heightened level of demand urgency.

Step 10: Use the hierarchical clustering method H_i^* to cluster urgent values.

2.3. Construction of Site Selection Model Considering the Urgency of Demand

2.3.1. Location Model

Utilizing the maximum coverage model, a food emergency logistics facility location model, denoted as SAM, is developed with the aim of minimizing total cost and unmet demand while considering demand urgency.

Total construction cost: $TFC = \sum\limits_{m \in M} x_m^M v_m^M FC_M + \sum\limits_{n \in N} x_n^N v_n^N FC_N$.

Total operating cost: $TVC = \sum\limits_{m \in M} x_m^M v_m^M VC_M + \sum\limits_{n \in N} x_n^N v_n^N VC_n$.

Total transportation cost:

$$TSC = \sum_{m \in M} \left(\sum_{i \in I} \sum_{k \in K} z_{mi}^k s_{mi} SC + \sum_{n \in N} \sum_{k \in K} z_{mn}^k s_{mn} SC \right) + \sum_{n \in N} \sum_{i \in I} \sum_{k \in K} z_{ni}^k s_{ni} SC.$$

$$\text{Total transit cost: } TTC = \sum_{n\in N}\sum_{i\in I}\sum_{k\in K} x_n^N z_{ni}^k TC.$$

$$\begin{aligned}&(SAM): \ \min f_1 = TFC + TVC + TSC + TTC \\ &= \sum_{m\in M}\left(x_m^M v_m^M (FC_M + VC_M) + \sum_{i\in I}\sum_{k\in K} z_{mi}^k s_{mi} SC + \sum_{n\in N}\sum_{k\in K} z_{mn}^k s_{mn} SC\right) + \sum_{n\in N}\left(x_n^N v_n^N (FC_N + VC_N) + \sum_{i\in I}\sum_{k\in K}\left(z_{ni}^k s_{ni} SC + x_n^N z_{ni}^k TC\right)\right)\end{aligned} \tag{7}$$

$$\min f_2 = \sum_{i\in I}\sum_{k\in K}\lambda_i^k\left(\overline{q_i^k} - \sum_{m\in M} z_{mi}^k x_m^M - \sum_{n\in M} z_{ni}^k x_m^M\right) + \sum_{i\in I}\lambda_i\left(\sum_{k\in K}\overline{q_i^k} - \sum_{m\in M}\sum_{k\in K} z_{mi}^k x_m^M - \sum_{n\in N}\sum_{k\in K} z_{ni}^k x_n^n\right) \tag{8}$$

$$s.t. \sum_{n\in N} x_n^N = w_N \tag{9}$$

$$\sum_{m\in M} x_m^M = w_M \tag{10}$$

$$\sum_{i\in I}\sum_{k\in K} z_{mi}^k + \sum_{n\in N}\sum_{k\in K} z_{mn}^k \le v_m^M, \forall m \in M \tag{11}$$

$$\sum_{m\in M}\sum_{k\in K} z_{mn}^k \le v_n^N, \forall n \in N \tag{12}$$

$$\sum_{m\in M} z_{mn}^k = \sum_{i\in I} z_{ni}^k, \forall n \in N \tag{13}$$

$$\begin{aligned} z_{mn}^k, z_{mi}^k &= \begin{cases} \ge 0, & x_m^M = 1 \\ 0 \ , & else \end{cases} \\ z_{ni}^k &= \begin{cases} \ge 0, & x_n^N = 1 \\ 0 \ , & else \end{cases}\end{aligned} \tag{14}$$

$$x_m^M, x_n^N \in \{0,1\} \tag{15}$$

$$v_m^M \ge v_{M\min}, 0 \le v_n^N \le v_{N\max} \tag{16}$$

$$\forall i \in I, m \in M, n \in N, k \in K \tag{17}$$

Objective function (7) aims to minimize the total cost, encompassing construction, operating, operating, transportation, and transit costs. Objective function (8) focuses on minimizing the material shortage at demand points based on their urgency, considering both total demand shortfall and specific material deficiencies. Constraint (9) restricts the number of allowable distribution centers. Constraint (10) limits the number of new logistics centers that can be established. Constraints (11) and (12) ensure that material supply at logistics and distribution centers, respectively, does not exceed their capacities. Constraint (13) enforces flow conservation at distribution centers. Constraint (14) mandates that supplies are only provided if the facility is operational. Constraints (15) to (17) define variable type limitations.

In the model SAM, the objective function (8) incorporates an uncertain parameter related to uncertain demand $\overline{q_i^k}$ for food supply k. This paper utilizes the robust counterpart optimization method, employing a "box" uncertainty set to characterize the uncertainty level in demand $\overline{q_i^k}$. It integrates the robust counterpart model introduced by Bertsimas and Sim to convert the objective function (8) into a robust equivalent model.

Assume $\overline{q_i^k} \subseteq \left[q_i^k - a_i^k u_i^k, q_i^k + a_i^k u_i^k\right], \forall i \in I$, where q_i^k is the nominal demand of demand point I, $a_i^k = \varepsilon_i^k q_i^k$ is the demand perturbation, ε_i^k is the perturbation ratio, and u_i^k is the uncertainty factor. In uncertainty set $U^k = \left\{u^k : \sum_{i\in I} u_i^k \le \Gamma_u^k, \forall i \in I\right.$, the parameter Γ_u^k signifies the level of uncertainty within the demand set. This parameter quantifies the conservatism of the constraints, mirroring the decision-maker's risk preference. A higher value of Γ_u^k indicates a more conservative approach. Here, Γ_u^k is a subset of [0, I], while I denotes the count of demand points, suggesting that not all demand points will encounter fluctuations in material (k) requirements. This implies that the demands of up to $\lfloor \Gamma_i^k \rfloor$ demand points can fluctuate within their intervals, with each demand perturbation being $\left(\Gamma_i^k - \lfloor \Gamma_i^k \rfloor\right)\overline{q_i^k}$, while the demands for the remaining demand points remain at their nominal level q_i^k. Under this condition, the resulting robust solution remains viable [41]. Part $\sum_{i\in I}\sum_{k\in K} \lambda_i^k \overline{q_i^k} + \sum_{i\in I}\sum_{k\in K} \lambda_i \overline{q_i^k}$ of objective function (8) containing uncertain demand is sorted out to obtain $\sum_{i\in I}\sum_{k\in K}\left(\lambda_i + \lambda_i^k\right)\overline{q_i^k}$. After applying the method described above, $\sum_{i\in I}\sum_{k\in K}\left(\lambda_i + \lambda_i^k\right)(q_i^k + a_i^k u_i^k)$ is derived. According to the Bertsimas and Sim equivalent model, the inner maximization problem is denoted as $\max \sum_{i\in I}\sum_{k\in K}(\lambda_i + \lambda_i^k) a_i^k u_i^k$, and its constraints are represented as $\sum_{i\in I} u_i^k \le \Gamma_u^k, \forall i \in I, k \in K, 0 \le u_i^k \le 1$ [42].

Applying duality theory involves introducing dual variables φ_k and γ_{ik} to address this maximization problem, resulting in the following outcome:

$$\min \sum_{i\in I}\sum_{k\in K}\left(\lambda_i + \lambda_i^k\right) q_i^k + \sum_{k\in K}\Gamma_u^k \varphi_k + \sum_{i\in I}\sum_{k\in K}\gamma_{ik} \tag{18}$$

$$\varphi_k + \gamma_{ik} \ge \left(\lambda_i + \lambda_i^k\right)\varepsilon_i^k q_i^k \tag{19}$$

$$\varphi_k, \gamma_{ik} \ge 0, \forall i \in I, k \in K \tag{20}$$

Ultimately, Equation (8) is converted into Equation (21).

$$\min f_2 = \sum_{i\in I}\sum_{k\in K}\lambda_i^k\left(q_i^k - \sum_{m\in M} z_{mi}^k x_m^M - \sum_{n\in M} z_{ni}^k x_m^M\right) + \sum_{i\in I}\lambda_i\left(\sum_{k\in K} q_i^k - \sum_{m\in M}\sum_{k\in K} z_{mi}^k x_m^M - \sum_{n\in N}\sum_{k\in K} z_{ni}^k x_n^n\right) + \sum_{k\in K}\Gamma_u^k\varphi_k + \sum_{i\in I}\sum_{k\in K}\gamma_{ik} \tag{21}$$

2.3.2. Site Selection Model Considering Facility Interruption

In light of potential sudden events, particularly natural disasters, that could damage infrastructure, established emergency facilities may face interruptions. When a facility is disrupted, it may lose partial or complete functionality, leading to unmet demands at various points. This necessitates the construction of new facilities or the reassignment of existing ones to address the situation. However, the temporary facilities may be distant and lack sufficient inventory capacity, causing delays in the supply of emergency food materials and impacting rescue operations. A new assumption is introduced, considering the risk of facility interruptions in both emergency logistics centers and distribution centers, with interruptions only considered in cases of complete functional loss. Discrete random scenarios are employed to depict facility interruption events [43]. In addition to the current site selection model, new variables are introduced based on the characteristics of reliability site selection issues. The symbols' meanings are as follows:

Ξ: the scenario set for facility disruptions, $\Xi = \{1, 2, \ldots, |\Xi|\}$, $\xi \in \Xi$.

p_ξ: the probability of occurrence of scenario ξ, $p_\xi \in [0, 1]$.

$y_m^{M\xi}, y_n^{N\xi} \in \{0, 1\}$: In scenario ξ, whether logistics center (M_m) and distribution center (N_n) is interrupted. If it is 1, it is interrupted.

$z_{mn}^{k\xi}, z_{mi}^{k\xi}, z_{ni}^{k\xi}$: the decision variable, denoted as, signifies the allocation of food material (k) among logistics centers, distribution centers, and demand points within scenario ξ.

Building upon model SAM, a location selection model based on discrete scenarios is developed and denoted as model $ISAM$.

Total construction cost: $TFC = \sum_{m\in M} x_m^M v_m^M FC_M + \sum_{n\in N} x_n^N v_n^N FC_N$

Total operating cost: $TVC = \sum_{\xi\in\Xi}\sum_{m\in M} p_\xi x_m^M y_m^{M\xi} v_m^M VC_M + \sum_{\xi\in\Xi}\sum_{n\in N} p_\xi x_n^N y_n^{N\xi} v_n^N VC_N$

Total transportation cost:

$$TSC=\sum_{\xi\in\Xi}\sum_{m\in M}p_{\xi}\left(\sum_{i\in I}\sum_{k\in K}z_{mi}^{k\xi}s_{mi}SC+\sum_{n\in N}\sum_{k\in K}z_{mn}^{k\xi}s_{mn}SC\right)+\sum_{\xi\in\Xi}\sum_{n\in N}\sum_{i\in I}\sum_{k\in K}p_{\xi}z_{ni}^{k\xi}s_{ni}SC$$

Total transit cost: $TSC=\sum\limits_{\xi\in\Xi}\sum\limits_{n\in N}\sum\limits_{i\in I}\sum\limits_{k\in K}p_{\xi}x_n^N y_n^{N\xi}z_{ni}^{k\xi}TC$

$$\begin{aligned}&(ISAM):\ \min f_1=TFC+TVC+TSC+TTC\\&=\sum_{m\in M}x_m^M v_m^M FC_M+\sum_{n\in N}x_n^N v_n^N FC_N+\sum_{\xi\in\Xi}\sum_{n\in N}p_{\xi}x_n^N y_n^{N\xi}v_n^N VC_N+\sum_{\xi\in\Xi}\sum_{m\in M}p_{\xi}\left(x_m^M y_m^{M\xi}v_m^M VC_M+\sum_{i\in I}\sum_{k\in K}z_{mi}^{k\xi}s_{mi}SC+\sum_{n\in N}\sum_{k\in K}z_{mn}^{k\xi}s_{mn}SC\right)\\&+\sum_{\xi\in\Xi}\sum_{n\in N}\sum_{i\in I}\sum_{k\in K}p_{\xi}z_{ni}^{k\xi}\left(s_{ni}SC+x_n^N y_n^{N\xi}TC\right)\end{aligned}\tag{22}$$

$$\min f_2=\sum_{\xi\in\Xi}\sum_{i\in I}\sum_{k\in K}P_{\xi}\lambda_i^k(\overline{q_i^k}-\sum_{m\in M}z_{mi}^{k\xi}x_m^M y_m^{M\xi}-\sum_{n\in N}z_{ni}^{k\xi}x_m^M y_m^{M\xi})+\sum_{\xi\in\Xi}\sum_{i\in I}P_{\xi}\lambda_i(\sum_{k\in K}\overline{q_i^k}-\sum_{m\in M}\sum_{k\in K}z_{mi}^{k\xi}x_m^M y_m^{M\xi}-\sum_{n\in N}\sum_{k\in K}z_{ni}^{k\xi}x_m^M y_m^{M\xi})\tag{23}$$

$$s.t.\sum_{n\in N}x_n^N=w_N\tag{24}$$

$$\sum_{m\in M}x_m^M=w_N\tag{25}$$

$$\sum_{i\in I}\sum_{k\in K}z_{mi}^{k\xi}+\sum_{n\in N}\sum_{k\in K}z_{ni}^{k\xi}\le v_m^M,\forall m\in M,\xi\in\Xi\tag{26}$$

$$\sum_{m\in M}\sum_{k\in K}z_{mn}^{k\xi}\le v_n^N,\forall n\in N,\xi\in\Xi\tag{27}$$

$$\sum_{m\in M}z_{mn}^{k\xi}=\sum_{i\in I}z_{ni}^{k\xi},\forall n\in N,\xi\in\Xi\tag{28}$$

$$\sum_{m\in M}x_m^M y_m^M+\sum_{n\in N}x_n^N y_n^N\ge 1\tag{29}$$

$$\begin{aligned}z_{mn}^{k\xi}&=\begin{cases}\ge 0, & x_m^M y_m^{M\xi}x_n^N y_n^{N\xi}=1\\ 0\ \ , & else\end{cases}\\ z_{mi}^{k\xi}&=\begin{cases}\ge 0, & x_m^M y_m^{M\xi}=1\\ 0\ \ , & else\end{cases}\\ z_{ni}^{k\xi}&=\begin{cases}\ge 0, & x_n^N y_n^{N\xi}=1\\ 0\ \ , & else\end{cases}\end{aligned}\tag{30}$$

$$x_m^M,x_n^N\in\{0,1\}\tag{31}$$

$$v_m^M\ge v_{M\min},0\le v_n^N\le v_{N\max}\tag{32}$$

$$\forall i\in I,m\in M,n\in N,\xi\in\Xi\tag{33}$$

Constraint (29) guarantees the availability of at least one operational emergency facility to deliver emergency supplies to the point of need in all scenarios. The remaining objective functions and constraints convey the same meaning as those in the model SAM.

For the part $\sum\limits_{\xi\in\Xi}\sum\limits_{i\in I}\sum\limits_{k\in K}p_{\xi}\left(\lambda_i+\lambda_i^k\right)\overline{q_i^k}$ of the objective function (23) that contains uncertain parameter $\overline{q_i^k}$, the uncertain set description of "box" is adopted, which is robust and transformed by introducing dual variables. The dual variables θ_k and ρ_{ik} are introduced and converted into Equations (34)–(36), which are put into the objective function, and finally the final form (37) of the objective function (23) is obtained.

$$\min\sum_{\xi\in\Xi}\sum_{i\in I}\sum_{k\in K}p_{\xi}\left(\lambda_i+\lambda_i^k\right)q_i^k+\sum_{k\in K}\Gamma_u^k\theta_k+\sum_{i\in I}\sum_{k\in K}\rho_{ik}\tag{34}$$

$$\theta_k + \rho_{ik} \geq \left(\lambda_i + \lambda_i^k\right)\varepsilon_i^k q_i^k \sum_{\xi\in\Xi} p_\xi \tag{35}$$

$$\theta_k, \rho_{ik} \geq 0, \forall i \in I, k \in K \tag{36}$$

$$\min f_2 = \sum_{\xi\in\Xi}\sum_{i\in I}\sum_{k\in K} P_\xi \lambda_i^k (q_i^k - \sum_{m\in M} z_{mi}^{k\xi} x_m^M y_m^{M\xi} - \sum_{n\in N} z_{ni}^{k\xi} x_m^M y_m^{M\xi}) + \sum_{\xi\in\Xi}\sum_{i\in I} P_\xi \lambda_i (\sum_{k\in K} q_i^k - \sum_{m\in M}\sum_{k\in K} z_{mi}^{k\xi} x_m^M y_m^{M\xi} - \sum_{n\in N}\sum_{k\in K} z_{ni}^{k\xi} x_m^M y_m^{M\xi}) + \sum_{k\in K} \Gamma_u^k \theta_k + \sum_{i\in I}\sum_{k\in K} \rho_{ik} \tag{37}$$

3. Location Model Solving

3.1. Multiobjective Processing

Balancing cost and unmet value as dual objectives poses challenges in real rescue operations due to differing units of measurement, making the traditional linear weighting method impractical. This paper adopts a method to address multi-objective decision-making, where f_1^* and f_2^* represent the optimal values for the respective sub-problems, and α denotes the cost preference weight determined by the decision-maker [44,45].

$$\min f = \alpha \frac{f_1}{f_1^*} + (1-\alpha)\frac{f_2}{f_2^*} \tag{38}$$

3.2. Algorithm Design

This paper employs a novel meta-heuristic algorithm, the Social Network Search (SNS), to tackle the model. The SNS algorithm, introduced by SIAMAK TALATAHARI et al. in 2021, mimics user behaviors in social networks to gain recognition, replicating actions like imitation, dialog, argument, and innovation [46]. These behaviors serve as optimization operators, mirroring how users are influenced and driven to share fresh perspectives. The algorithm accounts for interpersonal relationships, incorporates additional random elements and population diversity, and boasts low computational overhead and rapid convergence speed.

(1) Encoding

The facilities (logistics center, distribution center) for the supply of materials accepted by the demand point are taken as the code, that is, the emergency logistics center and the corresponding rescue provided by the distribution center are taken as the code. Assuming that there are m demand points, each of which can be supplied by n emergency facilities, a vector $m \times n$ dimensional vector (called user individual) is constructed using symbol coding.

$$X = (x_1, x_2, \ldots, x_k, \ldots, x_{2m}) \tag{39}$$

where the value $x_k(1 \leq k \leq 2m)$ of gene location k represents the number of the logistics center or distribution center that provides materials to the corresponding demand point, and the location $k = n(i-1) + j$ corresponds to the number of the Class j facility that supplies materials to the i demand point.

(2) SNS algorithm steps

Step 1: Initialize scale ($nUser$), maximum number of evaluations ($MaxEval$), maximum number of iterations ($MaxEval$), and other parameters.

Step 2: Initialize individual users and evaluate them.

Step 3: Users are randomly selected to enter four behavioral modes of imitation, dialog, argument, and innovation to obtain a new solution. Since the encoded solution is discrete, the SNS algorithm needs to reprocess the solution after it is updated, and the processing method is Formula (40), where UB and LB represent the maximum and minimum values of the variable value range, and $round(\cdot)$ represents the nearest integer value.

$$x_{i\ new} = \begin{cases} LB, & x'_{i\ new} < LB \\ round(x'_{i\ new}), & LB \leq x'_{i\ new} \leq UB \\ UB, & UB < x'_{i\ new} \end{cases} \tag{40}$$

Step 4: If the new solution satisfies the condition, it replaces the old solution and updates the function value. Otherwise, return to Step 3.

Step 5: If the termination conditions are not met, which typically involve reaching the maximum number of iterations or attaining the global optimum, the process returns to Step 3.

The algorithm flowchart is depicted in Figure 1.

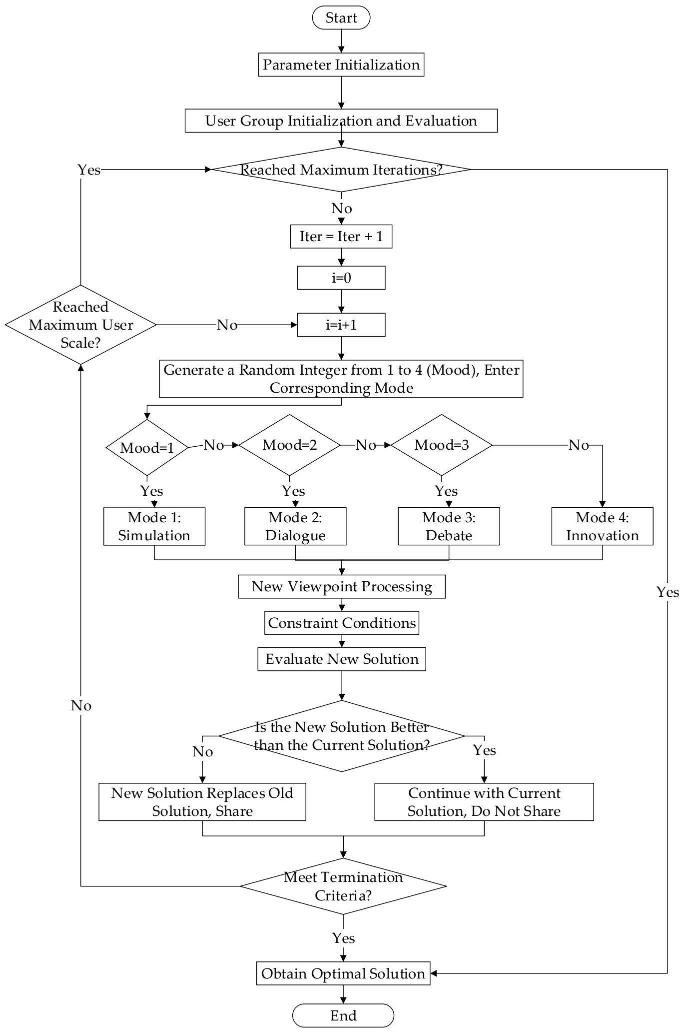


Figure 1. Algorithm flowchart.

4. Example Analysis

4.1. Data Description

This case study delves into a region in China impacted by the novel coronavirus pneumonia event in October 2022. It involves 20 demand points, with their food demand urgency data and demand urgency analysis data detailed in Tables 1 and 2, respectively. Table 2 specifically outlines the food demand data for demand point 14. Assuming logistics centers 1 and 2 are already operational, two additional candidate logistics centers (numbered 3 and 4) and six candidate distribution centers can be added. The food demand at demand points follows a specific distribution, with probabilities of 0.1, 0.15, and 0.19 for three scenarios. The emergency food categories required consist of Material 1, Material 2, and Material 3. The coordinates and relevant demand data for each demand point are provided in Tables 3–5, respectively. The unit construction cost for logistics centers and distribution centers is 2 and 1, respectively. The unit operating costs are 0.05 and 0.03, respectively. The unit transportation cost for goods is 0.012, with a unit transfer cost of

0.001. The minimum construction capacity for logistics centers is 800, while for distribution centers it is 200, with a maximum construction capacity of 1000. The facility interruption scenarios are detailed in Table 6.

Table 1. Urgency of food demand at demand points.

Demand Point Number	Coordinate	X_1	X_2	X_3	X_4	X_5	X_6
1	(20,85)	28.57%	0	2172.86	11.27	1460.04	31.95%
2	(5,45)	14.29%	0	2182.09	5.42	2439.82	32.70%
3	(42,15)	45.45%	0	2172.77	9.11	1416.11	33.92%
4	(38,5)	7.14%	0	2196.79	6.30	2449.44	33.55%
5	(95,35)	98.00%	0	2213.94	0.20	106.57	25.35%
6	(85,25)	89.00%	0	2220.31	0	84.76	25.40%
7	(62,80)	82.00%	0	2238.93	2.70	54.03	22.79%
8	(58,75)	83.00%	0	2235.85	0.50	93.58	22.61%
9	(55,85)	76.00%	0	2241.31	5.40	46.93	27.96%
10	(18,80)	92.00%	0	2236.34	10.2	46.77	26.84%
11	(25,30)	4.00%	0	2158.20	80.87	410.85	40.48%
12	(15,10)	5.00%	0	2161.98	48.58	375.87	44.10%
13	(45,65)	10.27%	0	2201.03	38.65	248.62	29.68%
14	(65,20)	47.37%	0	2178.86	21.74	2529.31	32.19%
15	(31,52)	32.00%	0	2136.60	71.20	315.42	38.78%
16	(2,60)	38.46%	0	2158.16	23.73	336.07	44.75%
17	(5,5)	60.00%	0	2116.64	12.47	985.87	33.70%
18	(57,29)	8.33%	0	2107.92	18.29	159.74	40.81%
19	(4,18)	11.76%	0	2158.06	39.04	202.64	41.31%
20	(26,35)	57.14%	0	2150.47	25.96	152.17	41.93%

Table 2. Analysis data of food demand urgency.

Broad Category	Middle Class	Y_1	Y_2	Y_3	Y_4	X_5	Y_6	Y_7	Y_8	Y_9	Y_{10}	Y_{11}
grain	flour	2	250	3	0.36	0.5	0.32	70.63	4.00	364.00	270	2
	rice	2	250	3	0.69	2.0	0.39	0.47	4.00	120.00	270	2
	corn	2	250	3	0.64	0.5	0.30	57.25	4.00	112.00	16	2
	soya bean	5	30	1	0.34	1.0	0.43	0.59	33.33	390.00	900	2
	other	2	250	3	0.30	0.5	0.70	6.35	4.00	325.00	45	2
vegetable	fresh	3	400	3	0.56	1.5	0.42	194.6	2.50	43.42	6	2
	dehydrated	3	40	3	0.13	0.5	5.34	4.04	25.00	273.16	225	4
	other	3	400	3	0.58	0.5	0.85	10.77	2.50	40.00	9	2
fruit	fresh	3	275	3	0.46	1.0	0.65	41.41	3.64	85.97	25	5
	dried	3	27.5	1	0.33	0.5	7.37	3.54	36.36	338.32	210	5
nut	nut	5	30	1	0.36	2.0	5.35	9.72	33.33	1076.4	300	5
poultry egg	egg	4	45	3	0.52	1.0	0.72	1.25	22.22	147.00	20.0	4
	other	5	45	3	0.52	1.0	0.89	11.88	22.22	204.83	25.0	4
edible salt	edible salt	6	2.5	3	0.11	0.5	0.54	0.00	400.0	0.00	1460	1
edible oil	vegetable	6	27.5	3	0.04	0.5	0.63	10.65	36.36	829.38	360	1
	animal	6	27.5	3	0.04	2.0	0.74	0.01	36.36	867.57	360	1
sugar	sugar	6	5.00	0.5	0.13	1.0	0.56	0.00	200	400.00	630	3
meat	livestock meat	4	55	2.5	0.53	1.0	0.79	7.69	18.18	236.09	1.5	1
	poultry	4	55	2.5	0.53	0.5	0.85	1.90	18.18	284.90	2.5	1

Table 2. *Cont.*

Broad Category	Middle Class	Y_1	Y_2	Y_3	Y_4	X_5	Y_6	Y_7	Y_8	Y_9	Y_{10}	Y_{11}
processed food	convenience food	2	250	3	0.43	0.2	7.31	166.7	4.00	473.00	330	4
	dairy product	5	400	1.5	0.56	2.0	2.06	32.82	2.5	313.25	14.0	5
	beverage	1	160	8	0.04	0.2	0.68	78,505	0.63	37.15	405	5
	processed aquatic products	4	57.5	0.5	0.88	2.5	4.48	7.22	17.39	310.45	138	1

Table 3. Information of candidate logistics centers.

Number of the Built Logistics Center	x-Coordinate	y-Coordinate	Added Candidate Logistics Center Number	x-Coordinate	y-Coordinate
1	55	80	3	20	50
2	20	50	4	43	8

Table 4. Information of candidate distribution centers.

Candidate Number	x-Coordinate	y-Coordinate	Candidate Number	x-Coordinate	y-Coordinate
5	17	15	8	80	21
6	25	70	9	10	25
7	45	46	10	23.3	52

Table 5. Food demand at each demand point.

Demand Point Number	The Demand for Different Situations			Nominal Demand for Different Materials			Demand Point Number	The Demand for Different Situations			Nominal Demand for Different Materials		
	1	2	3	1	2	3		1	2	3	1	2	3
1	200	180	220	50	130	20	11	150	210	170	110	30	10
2	180	240	300	70	60	50	12	220	190	160	150	30	40
3	210	200	170	90	30	90	13	160	230	210	60	20	80
4	220	190	210	50	60	110	14	210	140	190	80	60	70
5	230	220	190	70	50	110	15	170	190	210	70	40	60
6	230	240	210	30	80	120	16	210	210	210	70	70	70
7	190	180	160	60	70	60	17	180	240	230	80	60	40
8	210	260	260	90	50	70	18	190	220	170	40	90	60
9	210	150	230	50	90	70	19	230	170	210	100	50	80
10	170	170	150	70	70	30	20	240	190	220	60	60	120

Table 6. Sets of disruption scenarios of logistics facilities.

Situation	Opportunity	Logistics Facility Code									
		1	2	3	4	5	6	7	8	9	10
situation 1	0.2	1	1	1	1	1	1	1	1	1	1
situation 2	0.05	1	0 *	1	1	1	1	1	1	1	1
situation 3	0.1	1	1	1	1	0	1	1	1	1	1
situation 4	0.1	1	1	1	1	1	1	1	1	1	0

* 0 indicates facility interruption. Source of data.

4.2. Results and Analysis

4.2.1. Model Solution Results

(1) Solution for demand urgency

Using the above method and data for determining demand urgency, we obtained the numerical values for demand urgency and identified the emergency demand urgency level for each demand point through cluster analysis. Given that China categorizes emergency response to sudden events into four levels, we have similarly classified demand urgency into four levels, as shown in Table 7. For demand point 14, which has the highest demand urgency, detailed evaluations of demand urgency for different food categories are provided in Table 8. Additionally, the demand urgency for each demand point across different food categories is presented in Table 9.

Table 7. Comprehensive parameters for food demand urgency evaluation at demand points.

Demand Point Number	Evaluate the Comprehensive Parameter Values						H*	Sort	Urgency Level
	D^+	D^-	R^+	R^-	H^+	H^-			
14	1.8072	2.4434	0.8303	0.6966	1.6369	1.2519	0.5666	1	I
5	1.7104	1.7563	0.9471	0.7033	1.3517	1.2069	0.5283	2	II
6	1.7247	1.9923	0.8152	0.8123	1.4038	1.2685	0.5253	3	II
2	2.1442	2.1346	0.7912	0.7322	1.4629	1.4382	0.5043	4	II
4	2.1624	2.1447	0.8028	0.7360	1.4738	1.4492	0.5042	5	II
10	1.4862	1.6830	0.7350	0.9473	1.2090	1.2167	0.4984	6	II
8	1.8329	1.8761	0.7487	0.8877	1.3124	1.3603	0.4910	7	II
7	1.8452	1.8531	0.7302	0.8877	1.2917	1.3665	0.4859	8	II
16	2.3692	2.0854	0.7810	0.7159	1.4332	1.5426	0.4816	9	II
9	1.9514	1.7347	0.7363	0.9988	1.2355	1.4751	0.4558	10	III
13	2.5738	1.8462	0.9829	0.8365	1.4146	1.7052	0.4534	11	III
20	2.7843	1.8132	0.7801	0.7368	1.2966	1.7606	0.4241	12	III
12	2.6218	1.7583	0.7158	0.8020	1.2371	1.7119	0.4195	13	III
3	2.7077	1.5804	0.7591	0.6953	1.1697	1.7015	0.4074	14	III
17	2.7785	1.5384	0.7513	0.7449	1.1449	1.7617	0.3939	15	III
18	3.0372	1.3996	0.6711	0.8513	1.0353	1.9442	0.3475	16	IV
19	3.1233	1.3375	0.6887	0.8046	1.0131	1.9639	0.3403	17	IV
1	3.0537	1.2186	0.7226	0.7451	0.9706	1.8994	0.3382	18	IV
11	2.9690	1.2881	0.6530	0.8503	0.9706	1.9097	0.3370	19	IV
15	2.9692	1.2551	0.6589	0.8044	0.9570	1.8868	0.3365	20	IV

Table 8. Comprehensive parameters of urgency evaluation of emergency food demand.

Category	Evaluate the Comprehensive Parameter Values						H*	Sort	Urgency Level
	D^+	D^-	R^+	R^-	H^+	H^-			
beverage	7.2821	6.4459	0.7926	0.8075	3.6192	4.0448	0.4722	1	I
nut	8.7383	3.8761	0.7476	0.8262	2.3118	4.7822	0.3259	2	II
convenience food	8.6439	3.7371	0.7102	0.849	2.2237	4.7464	0.3190	3	II
sugar	8.6669	3.7071	0.7021	0.8374	2.2046	4.7521	0.3169	4	II
edible salt	8.5758	3.1473	0.7576	0.8512	1.9525	4.2135	0.3167	5	II
dairy product	8.7621	3.5623	0.7356	0.8382	2.149	4.8002	0.3092	6	II
rice	9.0211	3.4956	0.7313	0.8302	2.1134	4.9257	0.3002	7	III
flour	8.9822	3.3937	0.7048	0.8534	2.0493	4.9178	0.2941	8	III
other vegetables	8.8549	3.325	0.6942	0.8752	2.0096	4.8651	0.2923	9	III
fresh fruit	9.0802	3.3496	0.7292	0.8462	2.0394	4.9632	0.2912	10	III
fresh vegetable	8.9359	3.2866	0.7072	0.8584	1.9969	4.8972	0.2897	11	III
corn	9.0038	3.2249	0.7042	0.8699	1.9645	4.9368	0.2847	12	III
animal fat	9.1666	3.273	0.7037	0.8698	1.9884	5.0182	0.2838	13	III
soya bean	9.6582	3.4051	0.7008	0.8516	2.053	5.2549	0.2809	14	III
vegetable oil	9.1086	3.2161	0.6816	0.8931	1.9489	5.0008	0.2804	15	III
other grain	9.1321	3.1391	0.697	0.8711	1.9181	5.0016	0.2772	16	III
other eggs	9.3358	3.147	0.7044	0.8652	1.9257	5.1005	0.2741	17	III
egg	9.4011	3.1257	0.7086	0.8606	1.9172	5.1308	0.272	18	III
dried fruit	9.5242	2.912	0.7045	0.8662	1.8082	5.1952	0.2582	19	IV
dehydrated vegetable	9.5948	2.9074	0.6923	0.8705	1.7998	5.2327	0.2559	20	IV
processed aquatic products	9.4564	2.8358	0.7131	0.8729	1.7745	5.1647	0.2557	21	IV
poultry	9.4232	2.7813	0.6791	0.9023	1.7302	5.1627	0.251	22	IV
livestock meat	9.5073	2.6917	0.6837	0.895	1.6877	5.2011	0.245	23	IV

Table 9. Urgency of demand for different food materials.

Demand Point	Different Urgency of Food Demand			Demand Point	Different Urgency of Food Demand		
	Category 1	Category 2	Category 3		Category 1	Category 2	Category 3
1	0.6567	0.6752	0.5786	11	0.5688	0.4637	0.4312
2	0.6599	0.6435	0.5416	12	0.6423	0.5381	0.5498
3	0.576	0.5173	0.579	13	0.5760	0.5718	0.5981
4	0.5385	0.5374	0.5971	14	0.5143	0.5381	0.5237
5	0.4693	0.4720	0.5122	15	0.5197	0.4420	0.5124
6	0.4391	0.4438	0.4685	16	0.4637	0.4667	0.4328
7	0.4599	0.4621	0.4610	17	0.6894	0.5973	0.1357
8	0.5675	0.5173	0.5578	18	0.5687	0.5637	0.5173
9	0.4368	0.4839	0.4764	19	0.642	0.6120	0.6389
10	0.4712	0.5713	0.3751	20	0.5364	0.5329	0.6210

According to Table 7, demand point number 14 has an emergency demand urgency level of Level I. This area experiences severe disasters, high per capita energy demand, weak self-supply capabilities, and high population density. There are eight demand points with Level II urgency levels, characterized by relatively lower disaster severity but high energy demand density and lower primary industry GDP. Demand point number 3, despite having a smaller population density, has a higher proportion of elderly and young populations, resulting in a relatively higher urgency level. This demonstrates that the model fully considers various scenarios. There are six demand points with Level III urgency levels, which have higher disaster severity and higher primary industry GDP, but lower demand density and population density. Lastly, there are five demand points with Level IV urgency levels. These points generally have lower disaster severity, low energy demand density, high primary industry GDP, and low population density. They can somewhat meet their own emergency requirements, justifying their classification as Level IV.

Referring to Table 8, Level I comprises 1 class, Level II includes 5 classes, Level III consists of 12 classes, and Level IV encompasses 5 classes. Through the analysis, it is observed that emergency food items sharing the same demand urgency level exhibit consistent attributes. Class I emergency food stands out as a vital resource crucial for human survival and development, representing a life-sustaining element. Class II emergency food embodies emergency characteristics fully. Class III emergency food exhibits high demand, nutritional requirements, and frequency, albeit with subpar performance, making it suitable for scenarios with specific cooking conditions. Grade IV emergency food primarily consists of less essential items with high interchangeability. Thus, it can be inferred that emergency food items with identical demand urgency levels exhibit uniform attributes.

(2) Solve the model without considering the facility interruption

According to the above model (SAM), the SNS algorithm is used to solve the location problem in the prevention and preparation stage. The user group size ($nUser$) is set to 10; the maximum evaluation time ($MaxEval$) is 2000; the maximum iteration time ($MaxIter$) is 200; the probability of constraint violation ($MaxIter$) is 0.1; the stocks of three kinds of materials in the built logistics center 2 and logistics center 3 are, respectively, (1000,700, 400) and (450,400,800); the uncertainty levels of the three different food materials (Γ_u) were 7, 10, and 8, respectively; the disturbance proportion (ε) was 0.1; and the cost target weight (α) was 0.3. The solution results are shown in Tables 10 and 11.

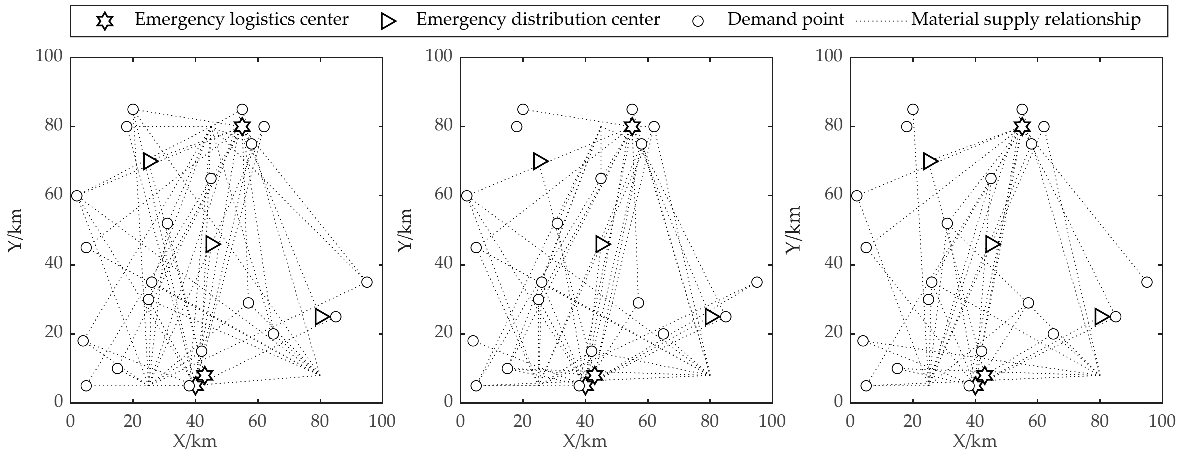
Table 10. The model solution results under the number of different logistics facilities.

w_m	w_n	f	f_1	f_2	f_1^*	f_2^*	f_1/f_1^*	f_2/f_2^*
0	1	1.6685	2383.199	3269.633	919.203	2569.740	2.5927	1.2724
	2	1.7852	2291.492	3620.558	926.595	2429.320	2.4730	1.4904
	3	1.7457	2661.905	3171.083	1097.274	2180.702	2.4259	1.4542
	4	1.2952	4057.208	2586.000	2465.955	2258.323	1.6453	1.1451
	5	1.6590	3533.595	3047.085	1476.86	2266.243	2.3926	1.3446
	6	1.7682	2786.600	3183.405	1200.033	2079.492	2.3221	1.5309
1	1	1.2447	3632.954	2866.138	2585.518	2437.317	1.4051	1.1759
	2	1.0769	3993.407	2716.531	3107.202	2750.483	1.2852	0.9877
	3	1.0558	4238.869	2645.678	3514.828	2668.240	1.2060	0.9915
	4	1.1832	4361.449	2939.336	3368.338	2589.061	1.2948	1.1353
	5	1.1536	4583.603	2547.332	3372.058	2390.743	1.3593	1.0655
	6	1.2344	3358.112	3091.201	2294.003	2720.894	1.4639	1.1361
2	1	1.1986	4057.699	2884.946	2950.936	2569.142	1.3751	1.1229
	2	1.2014	4560.539	2470.400	3396.610	2165.419	1.3427	1.1408
	3	1.0917	4602.188	2596.678	3365.642	2667.117	1.3674	0.9736
	4	1.0756	5248.056	2412.375	3629.812	2631.000	1.4458	0.9169
	5	1.0626	5285.108	2427.910	3860.493	2607.200	1.3690	0.9312
	6	1.3117	3153.151	3094.161	2293.750	2408.368	1.3747	1.2848

Table 11. Solution results of opening facilities and capacity under different number of logistics facilities.

w_m	w_n	**Emergency Logistics Facility Number**							
		3	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0	1	—	—	121.5065	—	—	—	—	—
	2	—	—	1.0163	—	—	110.6026	—	—
	3	—	—	122.8886	220.7189	298.8664	—	—	—
	4	—	—	313.8970	—	405.2732	189.1734	—	313.4505
	5	—	—	574.6851	297.2199	89.4751	54.5037	—	5.3834
	6	—	—	312.6386	224.1756	185.2262	121.0599	109.1487	121.7259
1	1	23.4350	—	—	—	—	—	277.6299	—
	2	—	154.0637	—	—	—	—	488.9404	234.6332
	3	—	152	—	554.2330	838.6398	—	412.5656	—
	4	—	117.4460	497.7070	1258.243	40.27621	29	—	—
	5	100.7196	—	691.0052	408.6187	760.9448	0	177.2688	292.2753
	6	69.6243	—	150.7925	493.5004	210.1093	359.9340	27.2092	75.5644
2	1	121	58	—	—	—	—	588.3328	—
	2	125	75	—	804.0603	844.2429	—	—	—
	3	263.2657	13.32539	—	982.3554	—	286.5072	—	159.9360
	4	200.6965	36.78673	1005.940	—	—	704.9396	613.777	494.0270
	5	255	5	1159.382	778.1607	—	841.4426	103.236	23.9527
	6	53.1681	21.2980	237.9712	222.5209	250.5111	224.9367	86.9911	98.2520

Table 10 shows that the optimal solution involves establishing one new logistics center and three distribution centers, resulting in a minimum comprehensive objective function value of 1.0588. The total cost amounts to 4238.869, with a relatively low unmet demand of 2645.678, indicating economic viability during the rescue phase. In Table 11, it is evident that the optimal solution with the minimum comprehensive objective value designates the new logistics center as number 4, with a capacity of 152. The newly opened distribution centers are numbered 6, 7, and 9, with capacities of 554.2330, 838.6398, and 412.5656, respectively. Figure 2 illustrates the layout of supply points and the supply dynamics between supply points and demand points in this scenario.



(a)Location layout and supply relationship of emergency materials 1
(b)Location layout and supply relationship of emergency materials 2
(c)Location layout and supply relationship of emergency materials 3

Figure 2. Location layout and material supply relationship.

(3) Consider facility interruption model solution

According to the *ISAM* model, the results obtained are shown in Tables 12 and 13.

Table 12. Solution results of target values under different number of emergency facilities in the case of facility interruption.

w_m	w_n	f	f_1	f_2	f_1^*	f_2^*	f_1/f_1^*	f_2/f_2^*
0	1	1.3741	1250.9044	1222.5636	635.5231	1092.0905	1.9683	1.1195
	2	1.4031	1193.6164	1359.3207	632.9688	1136.2676	1.8857	1.1963
	3	1.2836	1016.3025	1400.7349	738.0747	1126.3595	1.3770	1.2436
	4	1.4738	1234.8363	1425.5614	633.7922	1122.1173	1.9483	1.2704
	5	1.3040	1272.7025	1373.4383	819.5163	1147.1680	1.5530	1.1972
	6	1.3275	939.7073	1440.9201	702.6569	1088.8611	1.3374	1.3233
1	1	1.3996	2069.3108	1324.8951	1425.5944	961.9171	1.4515	1.3773
	2	1.4556	2809.1657	1172.0470	1195.7195	1092.8168	2.3494	1.0725
	3	1.5308	3009.3252	1246.6189	1251.9059	1077.7028	2.4038	1.1567
	4	1.2409	2461.4220	1213.1392	1689.2833	1056.4609	1.4571	1.1483
	5	1.3896	2756.3715	1125.5712	1298.8236	1046.4238	2.1222	1.0756
	6	1.5019	2228.5791	1334.5366	1179.5523	999.0318	1.8893	1.3358
2	1	2.0617	2085.0847	1425.5944	546.4425	1088.2535	3.8157	1.3100
	2	1.2356	1934.6315	1146.8449	1150.9369	1097.7588	1.6809	1.0447
	3	1.4820	3027.5659	1150.9369	1372.3786	982.3305	2.2061	1.1716
	4	3.8982	1870.8750	1689.2833	201.0679	1068.3705	9.3047	1.5812
	5	2.2147	2151.8298	1298.8236	485.3437	1027.8230	4.4336	1.2637
	6	1.4334	2442.5397	1179.5523	1310.0228	944.6323	1.8645	1.2487

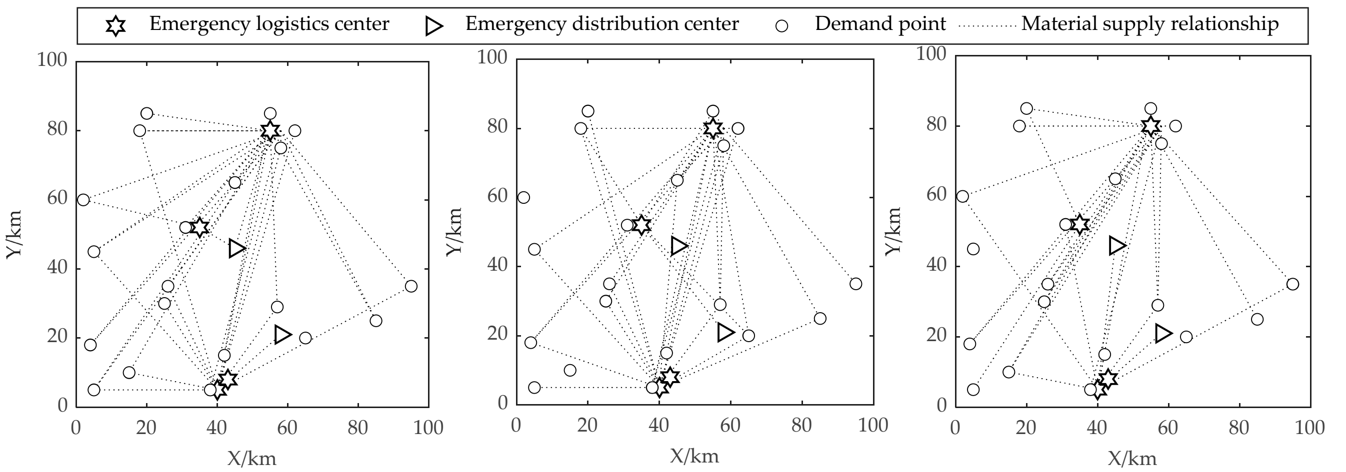
Table 13. Solution results of facility establishment and capacity configuration under different number of emergency facilities.

w_m	w_n	**Emergency Facility Number**							
		3	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0	1	—	—	—	—	—	327.5096	—	0
	2	—	—	—	250.8966	—	86.4852	—	0
	3	—	—	—	187.2122	399.7672	—	—	25.6657
	4	—	—	358.6288	—	301.4494	54.79758	107.7734	—
	5	—	—	243.1211	273.8265	—	121.4983	136.4630	358.3099
	6	—	—	94.8141	304.8282	50.9340	122.0936	130.3203	63.0702

Table 13. *Cont.*

w_m	w_n	Emergency Facility Number							
		3	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	1	—	4.9113	—	—	—	9.1049	—	—
	2	—	49.5300	—	94.5167	—	—	631.6002	—
	3	—	103.4061	—	—	—	942.6161	162.2912	165.3176
	4	161.4599	—	—	306.2215	180.2892	55.6302	—	161.5663
	5	—	417.4045	138.8492	224.1519	559.4366	197.9028	—	86.3463
	6	183.9976	—	156.3549	109.3003	201.5024	87.5131	112.0054	107.1257
2	1	39.9344	2.7841	—	88.3463	—	—	—	—
	2	137.1711	61.1074	—	—	442.7607	532.5178	—	—
	3	206.6114	24.2078	—	—	155.2727	—	875.1702	232.9581
	4	7.5415	1.0695	—	6.7985	17.3177	24.7640	—	12.7616
	5	171.9057	69.8868	—	119.5227	89.8118	164.5950	49.5461	208.8138
	6	53.3865	11.0256	118.9475	275.9588	150.777	222.5826	27.9950	123.1602

Table 12 illustrates that with two new emergency logistics centers and two distribution centers, the minimum comprehensive target value of 1.2356 is achieved, representing the optimal outcome. At this configuration, the total cost amounts to 1934.6315, with unmet demands of 1146.8449 and dimensionless values of 1.6809 and 1.0447, respectively, where the latter is minimized. These solution outcomes effectively mirror the requirements of emergency material support operations. In Table 13, logistics centers 3 and 4 are selected with capacities set at 137.1711 and 61.1074, while distribution centers 7 and 8 have capacities of 442.7607 and 532.5178, respectively. Figure 3 depicts the location layout and the demand–supply dynamics of various materials under this scenario.



(a)Location layout and supply relationship of emergency materials 1
(b)Location layout and supply relationship of emergency materials 2
(c)Location layout and supply relationship of emergency materials 3

Figure 3. Location layout and material supply relationship.

4.2.2. Impact Analysis of Cost Weight

Figure 4 depicts the correlation between cost weight (CW) and the comprehensive target value (CTV) alongside the dimensionless target value (DTV). As CW approaches 0, CTV converges to 0.9764; at CW 0.32, CTV peaks at 1.3469; conversely, as CW nears 1, CTV declines to its lowest point at 0.6829.

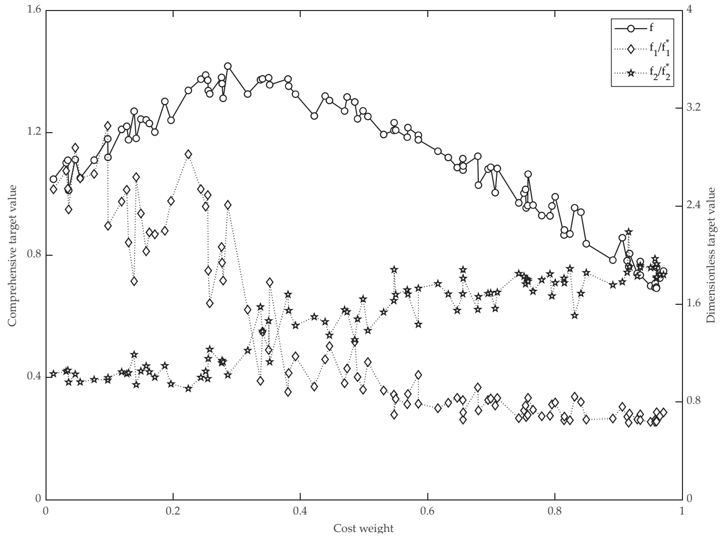


Figure 4. Changes in target values for different cost weights.

Distinct intervals exhibit diverse curve behaviors. Within the range of CW from 0 to 0.32, CTV rises with increasing CW; the dimensionless total cost (C-DTV) fluctuates notably but generally decreases, while the dimensionless unmet demand (D-DTV) stabilizes, narrowing the gap between them.

As CW spans from 0.32 to 0.4, CTV inversely correlates with CW; D-DTV sees a marked upsurge, while C-DTV maintains a downward trajectory at a slower rate. The disparity between them diminishes with rising CW, aligning at a certain threshold before gradually diverging.

In the CW range of 0.4 to 1, CTV sustains its decline with minor oscillations. C-DTV and D-DTV uphold their respective trends, with C-DTV's descent decelerating as D-DTV consistently surpasses C-DTV. The gap between them widens as CW values increase.

Figure 5 illustrates the impact of facility interruption. For CW values between 0 and 0.2, CTV rises with CW, indicating a gradual decline in solution quality. Within this range, C-DTV decreases notably while D-DTV increases slowly, narrowing the gap between them until they equalize around CW 0.18 before diverging again.

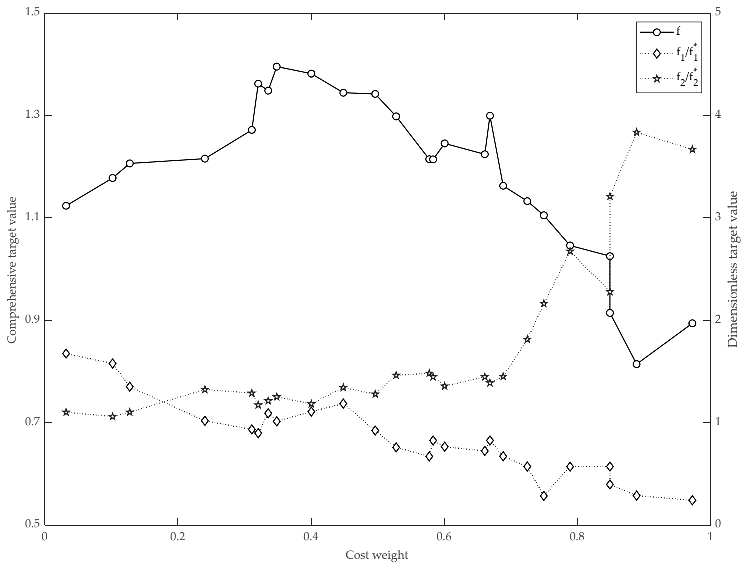


Figure 5. Changes in target values considering different cost target weights for facility outages.

In the CW range of 0.2 to 1, CTV initially rises and then falls, peaking at 0.36 for CW 0.36, representing the least favorable solution, and dropping to its minimum at CW 1. Changes in C-DTV and D-DTV follow similar patterns but with varying rates. C-DTV decreases rapidly with CW, while D-DTV increases. The rate of change accelerates beyond CW 0.72.

Comparing Figures 4 and 5 reveals overall consistency with notable differences at key points. CTV's trend is similar but peaks earlier in Graph 5. D-DTV exhibits a gradual increase followed by a sharp rise, hitting its threshold earlier than C-DTV and after their equalization, underscoring the importance of considering facility interruption in site selection models for decision-makers to grasp the impact of diverse disasters on target values.

Decision-makers can leverage these trends to select CW, factoring in the emergency response stage's characteristics. During the response phase emphasizing demand satisfaction, this aspect should be proritized with CW between 0 and 0.72. As the situation improves, focus should be shifted to cost, opting for CW between 0.72 and 1.

4.2.3. Impact Analysis of Uncertainty Level

Figure 6 illustrates the relationship between the uncertainty level (UL) and the Critical Threshold Value (CTV) of three different emergency food supplies. The ranges between the maximum and minimum CTV values under varying ULs for these supplies are 0.1859, 0.1386, and 0.1727, respectively. Category 1 exhibits the most significant fluctuation in CTV, while Category 3 shows the least, with a gradual and steady upward trend. Category 2, however, experiences the most frequent fluctuations. Consequently, decision-makers should enhance the accuracy of their assessments for Category 1 and 2 emergency supplies prior to making decisions.

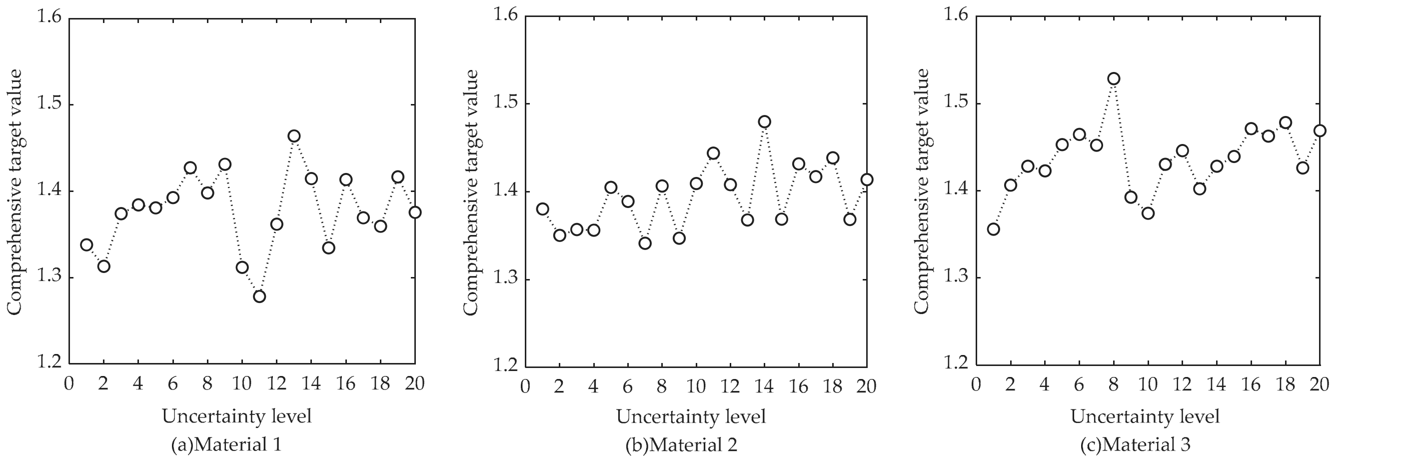


Figure 6. Changes in comprehensive target values at different levels of uncertainty.

Figure 7 presents the maximum and minimum comprehensive objective values under different UL variations for categories 1, 2, and 3 as 1.4692, 1.5110, and 1.5368, and 1.2508, 1.2694, and 1.2998, respectively. The differences between the maximum and minimum values are 0.2184, 0.2416, and 0.2370. The analysis of curve changes reveals that Category 1 has the smallest difference between maximum and minimum values but shows relatively high frequency in curve fluctuations. For Category 2, a notable observation is that the CTV is generally lower in the earlier part than in the latter when dividing the graph at UL 10, suggesting that priority should be given to whether UL exceeds half of its upper limit when locating facilities for this type of supply. Category 3, with the poorest minimum comprehensive value, exhibits significant fluctuations between the maximum and minimum values, and the uncertainty in CTV increases as UL rises. Therefore, decision-makers should exercise increased caution when setting the UL for this category.

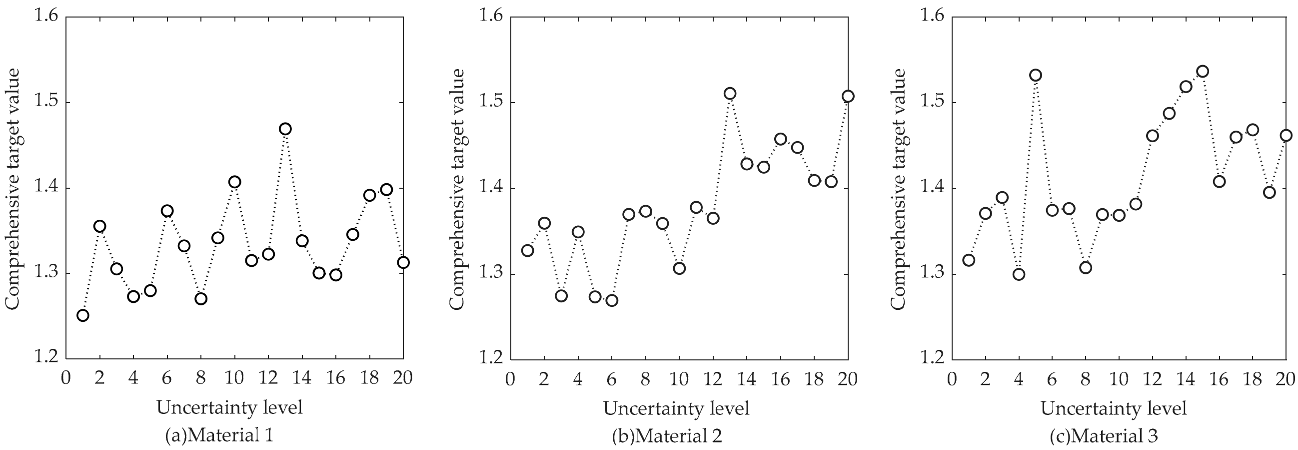


Figure 7. Changes in comprehensive target values at different levels of uncertainty.

The sensitivity analysis comparing scenarios with and without facility interruptions highlights significant differences in how different types of supplies are affected, underscoring the importance of developing separate models for facility interruption occurrences.

4.2.4. Influence Analysis of Disturbance Proportion

Figure 8a shows the relationship between the disturbance proportion (DP) and the comprehensive target value (CTV). The disturbance proportion varies from 0 to 2. The change in the target value depends on the range of the disturbance proportion.

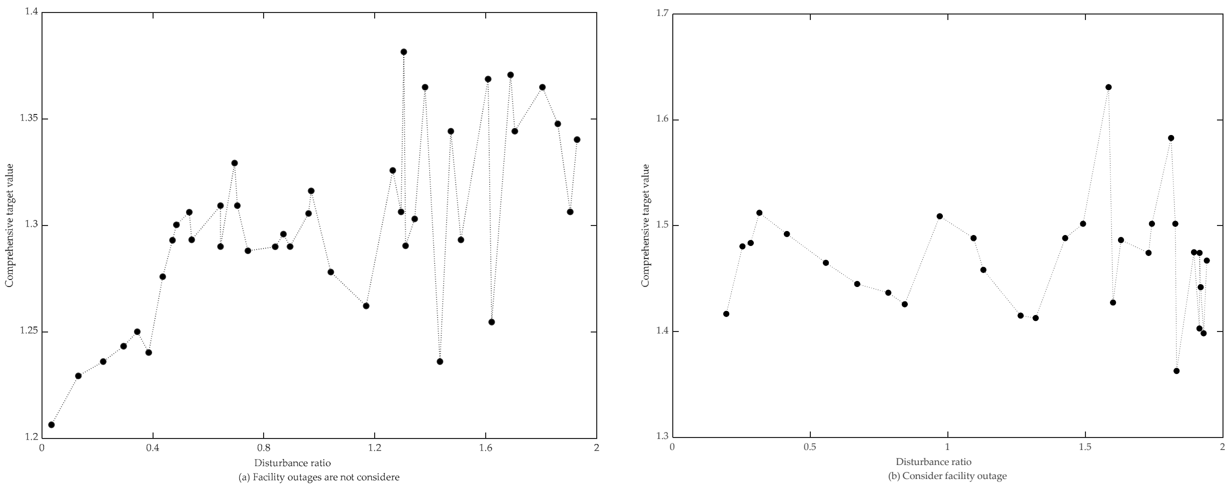


Figure 8. Changes in comprehensive target values of different disturbance proportions.

The relationship changes with DP values. When DP is between 0 and 1, the CTV rises with the DP. This rise is first rapid and then more gradual. When DP is between 1 and 2, the CTV becomes more sensitive to changes in it. CTV oscillates wildly between highs and lows in this range. So, when DP reaches this range, the decision-maker should carefully consider the parameters.

Figure 8b considers the disruption of emergency facilities. In this context, it shows the trend in the CTV with DP. When DP changes in the interval (0, 1), CTV first increases and then decreases as DP increases. The maximum value in this interval is 1.5121, which occurs when DP is 0.32.

When DP is between 1 and 2, CTV varies erratically as DP rises. The fluctuation frequency is high. CTV is more sensitive to DP in this range. The maximum value is 1.6309 when the weight is 1.58, and the minimum value is 1.3627 when the weight is 0.83. As a result, the minimum and maximum values differ by 0.2689, which is a large value.

Compare the results of the sensitivity analysis. First, look at the results in the 0–1 interval without considering facility outages. Without facility outages, CTV always maintains a upward trend. Second, look at the results with facility outages. CTV first rises and then declines. But the interval between 1 and 2 gives different results. The relationship shows large fluctuations and high frequency with or without outages. This confirms that when DP reaches this level, the parameter should be calculated precisely. Decision-makers should not rely on experience alone.

5. Conclusions

This paper presents several innovative aspects in exploring the location problem of emergency logistics facilities. Firstly, food is essential for human survival, making its demand both necessary and important. This paper treats food as emergency supplies, enriching previous studies that primarily focused on medical supplies and specialized rescue materials, thereby expanding the research scope in this field. Secondly, by recognizing the urgency of food demands, the model incorporates this critical factor and devises an effective method for its determination, enhancing the model's realism. Thirdly, it thoroughly examines the location problem within the context of potential facility disruptions, establishing location models for various scenarios and enriching the model's application scope. The main conclusions of this paper are as follows:

(1) Fully considering demand urgency in food emergency logistics facility location is crucial. The method proposed for determining demand urgency can identify both the numerical value and the urgency level of demand. The results are straightforward and practical. By observing that demand points or foods with the same urgency level share common attributes, decision-making in the location and configuration of emergency logistics facilities can be made more rational.

(2) The model extensively addresses the decision-making environment involving facility disruptions. Case studies highlight the importance of creating distinct location models and factoring in facility disruptions. The model's solution algorithm can generate comprehensive objective values for different scenarios and determine the optimal decision plan, encompassing the type, number, location, and capacity of emergency logistics facilities, along with material supply. This capability aids decision-makers in promptly devising effective strategies.

(3) Analyzing variations in comprehensive objective values under different parameter settings and comparing results across various decision-making scenarios reveal distinct trends and frequencies of change for specific parameters within different intervals. Some parameters exhibit clear thresholds, and their changes vary across decision-making contexts. This insight can guide decision-makers in identifying relevant parameters effectively before making informed decisions.

The methods and models presented in this paper effectively tackle the location problem of emergency logistics facilities for food. However, there are areas that can be improved. The method for assessing demand urgency relied solely on objective weighting, overlooking subjective factors that could enhance future research. Furthermore, the model was constructed on specific assumptions without considering real-world factors such as cargo damage costs and model dynamics. Subsequent research could explore these dimensions to further improve the analysis.

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