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A Two-Stage Stochastic Programming Model for Emergency Supplies Pre-Position under the Background of Civil-Military Integration

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Abstract: The pre-positioning of emergency supplies is of great significance for a timely and effective rescue after a disaster. Using the background of civil-military integration in China, this paper puts the military storage facilities into the layout scheme of emergency supplies reserve and builds a two-stage stochastic programming model of emergency supplies location–allocation optimization, the aim of which is to effectively use the reserve resources of both military and civilian sides to reduce the reserve cost. Then, an improved whale optimization algorithm (IWOA) with more strategies is designed to solve the model. The applicability of the model is proved via a real-world case study in Tangshan, China. The case study shows that when the unit storage cost of military storage facilities is less than 1.5 times of that of civilian emergency storage, the military and civilian joint reserve mode can reduce the reserve cost-effectively; decision-makers can set different maximum rescue times according to different preferences to adapt to different emergency decision-making needs.

Keywords: civil-military integration; pre-positioning of emergency supplies; two-stage stochastic programming; improved whale optimization algorithm

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1. Introduction

In recent years, natural disasters such as earthquakes and floods have occurred frequently across the whole world, seriously threatening the lives and safety of people [1]. These natural disasters are sudden, urgent and highly uncertain, so a common strategy for dealing with natural disasters is to pre-position emergency supplies so that they can be delivered to the affected area in the first place [2]. Pre-positioning of emergency supplies involves a preparation stage and response stage. The core of the preparation stage is to determine the location of emergency reserve facilities and the type and quantity of supplies to be stored. The core of the response stage is to deliver the materials present in emergency facilities to the disaster site in time and at the lowest cost when a disaster occurs. Therefore, it is important to get global optimization of facility location and resource allocation problems under limited resources and costs.

In times of disaster, the military reserve system plays a key role in emergency response. However, when the military and the government participate in the rescue, they often face problems such as resource waste and low efficiency caused by multiple leaderships and repetitive construction of facilities. This is because the core idea of military–civilian integration is the mutual transformation of military and civilian technology and sharing between military resources and civilian resources. Emergency logistics under the background of civil–military integration emphasizes the sharing of emergency logistics resources, such as the joint reserve of emergency supplies and joint construction of emergency facilities, the aim of which is to increase emergency efficiency and reduce logistics costs. Inevitably, this integration makes pre-positioning more difficult.

In this paper, we put the military storage facilities into the layout scheme of emergency in order to build a civil-military emergency pre-position model, which is to determine the locations of military storage facilities and national civilian emergency facilities and the allocations of emergency supplies, such that the pre-positioning cost is decreased. Then, an improved whale optimization algorithm (IWOA) is designed to solve the model. In order to give full play to the good search performance of the whale optimization algorithm, logistic chaos mapping, nonlinear convergence factor and the Cauchy-Gaussian variation are introduced to adjust the global search ability and local search ability of the algorithm. The main contributions of the paper can be summarized as follows:

- Put the military storage facilities into the layout scheme of the national emergency reserve; the surplus military warehouse is used to store emergency supplies in order to save reserve resources and improve emergency efficiency.
- Build a two-stage stochastic programming model of emergency supplies pre-position; both the facility location of pre-disaster and supply allocation post-disaster are simultaneously considered to solve the suboptimal problem caused by separate optimization.
- Design the IWOA to cope with the proposed model; compared with other classical algorithms, experiments show that IWOA has better optimization performance.

The remainder of this paper is organized as follows. Section 2 reviews the closely relevant literature on emergency facilities' location and resource allocation operations management. Section 3 presents the problem description and formulates a two-stage stochastic programming model to optimize the emergency operations. Section 4 designs the IWOA with more strategies to solve the model. Section 5 implements the model to carry out a case study in Tangshan, China with the illustrations of collected data and computational results. Finally, we conclude the paper in Section 6.

2. Literature Review

At present, the emergency supply pre-positioning literature is mainly divided into two stages: the preparation stage (pre-disaster) and the response stage (post-disaster). The research related to our problem can be categorized into three streams: pre-disaster emergency decision-making [3–9], post-disaster emergency decision-making [10–14] and the combination of pre-and-post disaster emergency decision-making [15–19].

The pre-disaster emergency decision-making has focused mainly on the location of emergency facilities, the determination of reserves and the inventory problem. It was first used by the U.S. military to study logistics in a potential war using a pre-position model of emergency supplies [3]. Grass et al. [4] proposed a mixed integer linear programming to determine the facilities' locations considering the uncertainty of disaster occurrence. Paul and MacDonald [5] considered the location and reserve capacity of the emergency distribution centers to prevent facility damage and casualties. Yang et al. [6] formulated a multi-period dynamic distributionally robust pre-positioning model of emergency supplies under uncertainty of demand. For rapid-onset predictable disasters, Jon and Subodha [7] considered the influence of incorporating returns into pre-disaster deployments. Shu et al. [8] proposed a design model for the humanitarian relief supply network under large-scale natural disasters such as floods and hurricanes. Turkes et al. [9] assumed uncertainties in demand, transportation network availability and inventory depletion, and utilized iterative local search techniques to find good locations and inventory allocation.

The post-disaster emergency decision-making includes the location of emergency shelters, the allocation of emergency supplies and the optimization of vehicle routes. Sheu [10] developed a hybrid fuzzy clustering-optimization method for the operation of emergency logistics co-distribution responding to urgent relief demands during the crucial rescue period. Najafi et al. [11] studied the transport of supplies and casualties in emergency response after an earthquake when resource shortages occur. Zhang et al. [12] proposed a collaborative truck-and-drone system to perform the post-disaster assessment task in the humanitarian relief networks. Lu et al. [13] developed a rolling horizon-based prediction and optimization framework for real-time relief distribution after disasters. The objective of the proposed model is to minimize the total time needed to deliver relief supplies to beneficiaries while considering the risk-averse attitude of the decision-makers.

Hu et al. [14] established a bi-objective robust model for emergency resource allocation under uncertainty and developed a heuristic particle swarm optimization algorithm to solve the Pareto frontier.

Facility location of pre-disaster and supply allocation post-disaster are two key factors affecting rescue efficiency, which are interrelated and mutually restricted. Therefore, considering operations of pre-disaster and post-disaster, simultaneously, is conducive to realizing the overall coordination and rational layout of emergency supplies, and meeting the maximization of emergency supplies fill rate in the early stage of the disaster. Rawls and Turnquist [15] presented a two-stage stochastic mixed integer programming model under natural disaster scenarios to solve the problems of location and quantity of pre-disaster storage and the distribution of post-disaster materials. Wang et al. [16] explored how mobile phone location data were applied to capture accurate disaster information rapidly and proposed a preparedness-response two-stage scenario-based stochastic programming model with mobile phone location data for integrated pre-positioning and real-time response operation optimization. Aslan and Celik [17] considered the influence of the demand uncertainty for disaster relief items and the vulnerability of roads and facilities on the pre-disaster decision-making of warehouse location and item reservation; moreover, a two-stage stochastic programming model is established. Chen et al. [18] presented a two-stage delivery process model to represent the delivery of post-disaster relief materials through the combination of social donation and on-site emergency procurement and proposed a risk-sharing scheme in which the state and suppliers jointly reserve relief materials. Davis [19] proposed a stochastic programming model to acquire the amount of supply and the cooperative reallocation scheme of reserve network inventory by using the forecast information. An overview of studies on emergency decision-making is shown in Table 1. Whether it is a pre-disaster or post-disaster emergency, there are few quantitative studies on the introduction of the idea of "civil–military integration" into emergency decision-making.

Table 1. Overview of studies on emergency decision-making.

Type	Author	Year	Method	Topic
Pre-disaster emergency decision-making	[3]	2004	Integer programming	Position and configure pre-positioned assets
	[4]	2018	Two-stage stochastic programs	Disaster management
	[5]	2016	Stochastic programs	Location and capacity allocations
	[6]	2021	Multi-period dynamic distributionally robust optimization	Pre-positioning of emergency supplies
	[7]	2020	Stochastic programs	Pre-Disaster Deployments
	[8]	2021	Nonlinear integer programming	Emergency facility location and relief supply pre-positioning
	[9]	2021	Linear programming	Facility location
	[10]	2007	Hybrid fuzzy clustering-optimization approach	The operation of emergency logistics co-distribution
Post-disaster emergency decision-making	[11]	2013	Multi-objective robust optimization	Logistics planning in the earthquake response phase
	[12]	2021	Mixed-integer linear programming	Humanitarian relief network assessment
	[13]	2016	Rolling horizon-based framework	Relief distribution in the aftermath of disasters
	[14]	2016	Bi-objective robust optimization	Emergency resource allocation under uncertainty

Table 1. *Cont.*

Type	Author	Year	Method	Topic
Combination of pre-and-post disaster emergency decision-making	[15]	2010	Two-stage stochastic mixed integer program	Pre-positioning of emergency supplies
	[16]	2021	Two-stage scenario-based stochastic programming model	Integrated pre-positioning and real-time response operation optimization
	[17]	2019	Two-stage stochastic programming	Pre-disaster decisions of warehouse location and item pre-positioning
	[18]	2017	Newsvendor approach	Pre-positioning of relief inventories
	[19]	2013	Stochastic programming	Inventory planning and coordination in disaster relief efforts

The last important stream related to our work is the methodologies of dealing with large-scale optimization models. For the recent large-scale optimization models, the solving speed and accuracy of the traditional optimal method cannot perform well. Nature provides great inspiration to solve complex optimization problems. Scholars design some optimization algorithms to deal with large-scale optimization problems by simulating the foraging or evolution behavior of organisms in nature. Some widely used heuristic algorithms are particle swarm optimization algorithm, sparrow algorithm, ant colony optimization algorithm and so on [20–22]. Australian researchers Mirjalili and Lewis designed a novel swarm intelligence optimization algorithm, namely the whale optimization algorithm (WOA), which is inspired by the hunting mechanism of humpback whales in nature in 2016 [23]. This algorithm simulates the shrinking encircling, spiral updating position and random hunting mechanisms of humpback whale pods. Nowadays, WOA has been widely applied in engineering, clustering, classification, robot path, image processing, network, task scheduling and other fields. Liu and Zhang [24] proposed a differential evolution chaotic whale optimization algorithm and applied the algorithm to the distribution network fault location of IEEE-33 nodes, which improved the effectiveness and accuracy of the distribution network fault location. Yan et al. [25] improved the whale optimization algorithm to solve the 3D path planning of autonomous underwater vehicles based on forward-looking sonar. Bo et al. [26] proposed a multi-stage mine reuse scheduling method based on an improved whale optimization algorithm. Qian et al. [27] testified the efficiency of the improved multi-objective whale optimization algorithm in the field of vehicle crashworthiness. Tair et al. [28] applied a chaotic oppositional WOA with a firefly search to medical diagnostics. Zhang et al. [29] proposed an energy minimization whale optimization algorithm for workflow scheduling in clouds. In terms of facility location and supply allocation, Yan et al. [30] used the improved WOA to solve the multi-objective optimization problem of water resource allocation in Handan, China. Javid et al. [31] used WOA to solve the robust fuzzy mathematical programming model of a closed-loop supply chain network. Jiang et al. [32] combined WOA and particle-swarm optimization algorithms to cope with the site selection problem of municipal solid waste incineration plants based on certain rules. An overview of studies on optimization algorithms is shown in Table 2.

Table 2. Overview of studies on optimization algorithm.

Algorithm	Author	Year	Topic	Improvement Strategy
Genetic algorithm	[20]	2021	Review of Genetic algorithm	-
Grey wolf optimizer	[21]	2014	The first study of GWO	-
Bat algorithm	[22]	2012	Global engineering optimization	-

Table 2. *Cont.*

Algorithm	Author	Year	Topic	Improvement Strategy
Whale optimization algorithm	[23]	2016	The first study of WOA	-
	[24]	2022	Layer recognition	Chaotic logistic map, Exploitation and exploration, Lévy flight mechanism, Evolutionary population dynamics
	[25]	2022	Three-dimensional path planning of autonomous underwater vehicles.	-
	[26]	2022	Mine water reuse	Opposition-based learning strategy, Lévy flight strategy, Nonlinear convergence factor
	[27]	2022	Deterministic optimization of vehicle structural crashworthiness	Evolution operators
	[28]	2022	Medical diagnostics	-
	[29]	2022	Workflow scheduling in clouds	-
	[30]	2018	Allocation of water resources	Logistic mapping, Inertia weighting
	[31]	2019	The closed-loop supply chain management	-
	[32]	2019	Constrained engineering design problems	Levy flight, Chaotic local search

At present, most of the research on civil-military integration is qualitative. Scholars pay more attention to the construction of a national emergency reserve strategy from the perspective of national policy and industrial planning. There are few quantitative studies on civil-military integration and, as far as we know, there is no report on the location–allocation optimization of emergency rescue in the civilian and military joint reserve. Our work is also the first to propose the IWOA for this kind of combinatorial optimization problem. The results indicate that the IWOA yields higher convergence precision and rates.

3. Model Formulation

3.1. Problem Description

The basic idea of the military and civilian joint reserve is that the local government should make overall planning for the layout of the military and civilian joint reserve, and optimize the reserve scale and structure according to the characteristics of public emergencies in different regions. The military uses its idle storage capacity and specialized storage function to reserve, manage and maintain the stored national emergency and disaster relief materials, which can also be applied to war supplies.

There are local civilian emergency storage facility candidates set I, military storage facility candidates set D and affected areas set J. Scenario set S is used to describe the potential disaster scenario, and the demand for supplies is generated according to the scenario. Considering distributive fairness, if the minimum demand in the affected area is not met, there will be a higher penalty cost due to the lack of stock or the transfer of goods from outside. Maximum rescue time is set according to the urgency of disaster relief. This emergency pre-position decision has obvious two-stage characteristics. When determining the location and reserve capacity of civilian emergency facilities and military storage facilities, future disasters are unknown, so the demand of each affected area is random. Therefore, a two-stage stochastic programming model is established. The objective of the first stage is to minimize the sum of costs for facility location and inventory pre-positioning as well as the expected value of the objective function of the second stage in regard to disaster scenarios, so as to determine the location and capacity of local emergency storage facilities and military storage facilities. After the occurrence of random variables, the objective of the second stage is to minimize the sum of total travel costs and penalty cost of unsatisfied demands for deciding the optimal allocation scheme of emergency supplies in the corresponding scenario after the occurrence of an emergency. The decision of the first stage needs to consider the expected loss of the second stage, and the decision of the second stage depends on the facility's location and capacity decision of the first stage.

To simplify the problem, we consider that the following assumptions are satisfied:

1. The locations and numbers of civilian emergency facility candidates and military storage facility candidates are known.
2. Use the same mode of transportation and the same type of vehicle to transport emergency supplies from the storage facilities to the affected area, and the unit material transport cost depends on the transport time between the two places.
3. Considering the emergency rescue of the early stage of disaster, the supply needs of the affected areas can only be met by emergency storage and military storage facilities, and social donations are not considered.
4. The objects of the reserve are general emergency supplies with low confidentiality, such as supplies, bedding, medicinal materials and general parts.

3.2. Two-Stage Stochastic Programming Model

A two-stage stochastic programming model for the pre-position of emergency supplies considering military storage facilities is established in this section to minimize the total cost of the system. The first stage: when the demand is unknown, determine the facility location and capacity of the civilian emergency facility and the military storage facility. The second stage: when the location and capacity of each storage depot are known, the disaster situation and the demand of the affected area are also known, and the emergency supplies allocation plan of emergency supplies under the corresponding scenario is determined.

$$\min f = \sum_{m\in M}\sum_{i\in I} c^m x_i^m + \sum_{i\in I}\sum_{k\in K} b_{ik}y_{ik} + \sum_{d\in D}\sum_{k\in K} b_{dk}y_{dk} + E_S[Q(x,y,s)] \tag{1}$$

The objective function of the first stage (1) includes the fixed cost of locating and operating facilities, storage cost of emergency supplies pre-positioned at civilian emergency facilities and military storage facilities and the expected value of the second stage solution in regard to disaster scenarios $E_S[Q(x,y,s)]$.

$$\sum_{k\in K} y_{ik}v_k \le \sum_{m\in M} x_i^m \overline{V^m},\ \sum_{k\in K} y_{dk}v_k \le V_d, \quad \forall i\in I, d\in D, m\in M \tag{2}$$

Constraint (2) indicates that the sum of the volume of supplies stored in the civilian emergency facilities and the military storage facilities does not exceed its maximum reserve capacity.

$$\sum_{m\in M} x_i^m \le 1 \quad \forall i\in I,\ m\in M \tag{3}$$

Constraint (3) ensures each potentially affected area can only be equipped with a maximum of one emergency storage.

$$\sum_{m\in M}\sum_{i\in I} x_i^m \le h,\ \sum_{d\in D} x_d \le g, \quad \forall i\in I,\ d\in D,\ m\in M \tag{4}$$

Constraint (4) indicates that the number of the selected civilian emergency facilities is at most h, and the number of the selected military storage facilities is at most g.

$$x_i \in \{0,1\}, x_d \in \{0,1\}, \quad \forall i\in I, d\in D \tag{5}$$

Constraints (5) indicates that the x_i and x_d are binary variable.

$$y_{ik} \geq 0, y_{dk} \geq 0, \quad \forall i \in I, d \in D, k \in K \tag{6}$$

Constraint (6) ensures y_{ik} and y_{dk} are non-negative.

$$Q(x,y,s) = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\mu_k t_{ij} z_{ijk(s)} + \sum_{d\in D}\sum_{j\in J}\sum_{k\in K}\mu_k t_{dj} z_{djk(s)} + \sum_{j\in J}\sum_{k\in K}\omega_k\left(l_{jk(s)} - \left(\sum_{i\in I} z_{ijk(s)} + \sum_{d\in D} z_{djk(s)}\right)\right) \tag{7}$$

The objective function of the second stage problem (7) incorporates the total travel time cost (includes the time of distributing emergency supplies from civilian emergency facilities to affected areas and from military storage facilities to affected areas) and the penalty cost of unsatisfied demand.

$$\sum_{j\in J} z_{ijk}(s) \leq y_{ik}, \ \sum_{j\in J} z_{djk}(s) \leq y_{dk}, \ i \in I, d \in D, k \in K \tag{8}$$

Constraint (8) limits the total amount of emergency supplies sent from depots to the affected area by the number of emergency supplies pre-positioned at the storage facilities.

$$sign(z_{ijk(s)})t_{ij} \leq T, \ sign(z_{djk(s)})\, t_{dj} \leq T, \ i \in I, d \in D, j \in J \tag{9}$$

Constraint (9) indicates that the travel time should meet the requirements of emergency distribution.

$$\sum_{i\in I} z_{ijk(s)} + \sum_{d\in D} z_{djk(s)} \leq l_{jk(s)}, \quad j \in J, k \in K \tag{10}$$

Constraint (10) shows that the unmet quantity of material demand is nonnegative

$$z_{ijk(s)} \geq 0, z_{djk(s)} \geq 0, \ i \in I, d \in D, j \in J, k \in K \tag{11}$$

Constraint (11) ensures $z_{ijk(s)}$ and $z_{djk(s)}$ are nonnegative.

3.3. Assessment of Demand in Affected Areas

In different disaster scenarios, there is usually a disaster center with the highest disaster level, and the disaster level of other affected areas decreases according to the distance from the disaster center. The disaster level includes four levels: extremely major (Level I), major (Level II), general (Level III) and no disaster (Level V). It is assumed that other disaster-affected points decrease by one level every 50 km from the disaster center. If the disaster center is located at point j_1, the disaster level of j_2 can be approximated by the following formula:

$$\omega_{j_2}(s) = \min\left\{4, round(\omega_{j_1}(s) + \frac{o_{j_1 j_2}}{50})\right\} \tag{12}$$

In Formula (12), $o_{j_1 j_2}$ is the straight-line distance between the two affected areas, and $round(\ )$ is the rounded whole function.

Assume that half of the population at each Level I affected area needs emergency supplies. Based on the demand quantity of Level I disasters, the demand quantity decreases with the decrease in disaster grade. With each decrease in disaster grade, the affected population decreases by half. The demand for the first emergency supplies in the disaster scenario is as follows:

$$l_{jk}(s) = \begin{cases} \frac{n_j}{2^{\omega(s)}} \cdot l_k^{\max}, \ \omega(s) \leq 3 \\ 0, \ \omega(s) > 3 \end{cases} \tag{13}$$

In Formula (13), n_j represents the population in the affected areas, and $l_k^{\max}$ represents the demand of each person for the kth emergency supplies when a Level I disaster occurs.

4. Materials and Methods

Due to the large scale and many other variables of the two-stage stochastic programming problem, traditional precise solutions such as the branch and bound method and the cut plane method are difficult to obtain better results quickly. In order to solve the optimization model quickly, the IWOA is considered as the algorithm in this paper. WOA is a new swarm intelligence bionic optimization algorithm proposed by Australian scholars Mirjalili and Lewis in 2016 [23]. As a novel heuristic optimization algorithm, WOA has a simple updating mechanism, few adjustment parameters and certain randomness. Compared with other heuristic optimization algorithms, WOA has higher search ability and search speed, and shows good performance in facility location and allocation problems [30,31,33,34]. In order to prevent the algorithm from falling into local optimum, logistic chaos mapping, nonlinear convergence factor and the Cauchy-Gaussian variation are introduced to adjust the global and local searching ability of the algorithm, and give full play to the good searching performance of WOA.

4.1. Whale Optimization Algorithm

This algorithm is inspired by the hunting mechanism of humpback whales in nature and simulates the shrinking encircling, spiral updating position and random hunting mechanisms of humpback whale pods. This model consists of the following three stages: encircling prey, bubbling-net attacking and search for prey.

1. Encircling Prey

WOA simulates that humpback whales hunt by surrounding the contracted prey. Assuming that the current candidate solution is the target prey, other whales update their positions towards the target location, and their behaviors can be expressed as follows:

$$\widetilde{\boldsymbol{D}} = \left|\boldsymbol{C} \cdot \boldsymbol{X}_{\bar{t}}^{*} - \boldsymbol{X}_{\bar{t}}\right| \tag{14}$$

$$\boldsymbol{X}_{\bar{t}+1} = \boldsymbol{X}_{\bar{t}}^{*} - \boldsymbol{A} \cdot \widetilde{\boldsymbol{D}} \tag{15}$$

$$\boldsymbol{A} = 2\boldsymbol{a} \times \boldsymbol{r} - \boldsymbol{a} \tag{16}$$

$$\boldsymbol{C} = 2\boldsymbol{r} \tag{17}$$

where $\bar{t}$ represents the current iteration, $\boldsymbol{X}_{\bar{t}}$ is the position vector of the individual whale at iteration $\bar{t}$, $\boldsymbol{X}_{\bar{t}}^{*}$ is the position vector of the optimal solution at iteration $\bar{t}$, $\widetilde{\boldsymbol{D}}$ represents the distance between the above two, $\boldsymbol{A}$ and $\boldsymbol{C}$ are coefficient vectors, $\boldsymbol{r}$ is a random vector in [0, 1] and $\boldsymbol{a}$ is a control parameter that is linearly decreased from 2 to 0 over the course of iterations.

2. Bubbling-Net Attacking

As whales catch their prey, they shrink, encircle and spiral updating position. The shrinking encircling mechanism is mainly achieved by decreasing the value of control parameter $\boldsymbol{a}$. For the spiral updating position, a logarithmic spiral equation is created between the position of the whales and the current best solution to simulate the spiral movement of humpback whales. Assume that the shrinking encircling mechanism and the spiral position mechanism have the same renewal probability during optimization ($P = 0.5$). The model can be expressed as

$$\boldsymbol{X}_{\bar{t}+1} = \begin{cases} \boldsymbol{X}_{\bar{t}}^{*} - \boldsymbol{A} \cdot \widetilde{\boldsymbol{D}} & P < 0.5 \\ \boldsymbol{D}' e^{\dot{b}l} \cos(2\pi l) + \boldsymbol{X}_{\bar{t}}^{*} & P \geq 0.5 \end{cases} \tag{18}$$

where $\boldsymbol{D}' = \left|\boldsymbol{X}_{\bar{t}}^{*} - \boldsymbol{X}_{\bar{t}}\right|$, p is a random probability in [0, 1], l is a random number in $[-1, 1]$ and $\dot{b}$ is a constant for defining the shape of the logarithmic spiral.

When $|\boldsymbol{A}| < 1$, the whale's next position can be anywhere between its restricted position and the position of its prey.

3. Search for Prey

In the search for prey, when $|\boldsymbol{A}| \geq 1$ is set, the WOA selects random whale individuals instead of the current optimal individuals as target prey, so that they can search in the global scope. The mathematical model is as follows:

$$\widetilde{\boldsymbol{D}} = |\boldsymbol{C}\boldsymbol{X}_{rand} - \boldsymbol{X}_{\bar{t}}| \tag{19}$$

$$\boldsymbol{X}_{\bar{t}+1} = \boldsymbol{X}_{rand} - \boldsymbol{A} \cdot \widetilde{\boldsymbol{D}} \tag{20}$$

where $\boldsymbol{X}_{rand}$ is a position vector randomly selected from the current whale population.

4.2. Improved Whale Optimization Algorithm

In order to give full play to the good search performance of WOA, an IWOA is proposed in this section. Logistic chaos mapping, nonlinear convergence factor and the Cauchy-Gaussian variation are introduced to adjust the global search ability and local search ability of the algorithm. The detailed steps are as follows:

1. Logistic Chaos Mapping

The initial position of the individual population is very important to the optimization performance of the swarm intelligence algorithm, so the logistic chaotic mapping is introduced to initialize the population, so that the population is evenly distributed, and the convergence speed and optimization accuracy of the algorithm are improved [35]. The formula is as follows:

$$\boldsymbol{X}_{\bar{t}+1} = \alpha \boldsymbol{X}_{\bar{t}}(1 - \boldsymbol{X}_{\bar{t}}) \tag{21}$$

where α is a control parameter, $\alpha = 4$.

2. Nonlinear Convergence Factor

The exploration and development capability of WOA largely depends on the change of convergence factor $\boldsymbol{a}$. Since the original convergence factor decreases linearly from 2 to 0, the convergence accuracy of the algorithm will be seriously affected in the late iteration and the algorithm will easily fall into local optimal. In order to balance the relationship between global search and local search of the algorithm, the nonlinear improved convergence factor method is introduced to IWOA [36]. The improved convergence factor is:

$$\boldsymbol{a} = \left(\boldsymbol{a}_{initial} - \boldsymbol{a}_{final}\right) + \frac{1 - \bar{t}/T_{\max}}{1 - \mu\bar{t}/T_{\max}} \tag{22}$$

where $\boldsymbol{a}_{initial}$ and $\boldsymbol{a}_{final}$ are the start value and end value of $\boldsymbol{a}$, respectively, μ is the linear weight factor, μ = 25.

3. The Cauchy-Gaussian Variation

At the late iterate stage of WOA, local optimal stagnation tends to occur. In order to solve this problem, the Cauchy-Gauss mutation strategy is adopted to select the individual with the best fitness at present for mutation, and then compare the position before and after mutation to select the better position for the next iteration [37]. The formula is as follows:

$$\boldsymbol{X}^t_{newbest} = \boldsymbol{X}^t_{\text{best}}\left[1 + \lambda_1 Cauchy\left(0, \sigma^2\right) + \lambda_2 Gauss\left(0, \sigma^2\right)\right] \tag{23}$$

$$\sigma = \begin{cases} 1, f(\boldsymbol{X}_{best}) < f(\boldsymbol{X}_{\text{i}}) \\ \exp\left(\frac{f(\boldsymbol{X}_{best}) - f(\boldsymbol{X}_{\text{i}})}{|f(\boldsymbol{X}_{best})|}\right), otherwise \end{cases} \tag{24}$$

where $\boldsymbol{X}^t_{\text{newbest}}$ represents the position of the optimal individual after mutation, σ^2 represents the standard deviation of the Cauchy-Gaussian variation strategy, $Cauchy\left(0, \sigma^2\right)$ is a random variable that satisfies a Cauchy distribution, $Gauss\left(0, \sigma^2\right)$ is a random variable that satisfies a Gaussian distribution, $\lambda_1 = 1 - t^2/T^2_{\max}$, $\lambda_2 = t^2/T^2_{\max}$, in the optimization process, λ_1 gradually decrease, λ_2 gradually increase, so that the algorithm can jump out of the current stagnation, and coordinate its local development and global exploration ability.

4.3. Solving Steps

Pseudocode of IWOA solution step is as Algorithm 1.

Algorithm 1. Pseudocode of IWOA solution.

Begin
  Set the maximum iteration number and population size, then initialize the population based on logistic chaos mapping according to Equation (21);
  Calculate the fitness value of individual whale and obtain the current optimal solution;
  $while\ (t \leq t_{\max})$
  $for\ i = 1 : N$
    Calculate the value of the nonlinear convergence factor a according to Equation (22), update parameter $\boldsymbol{A}, \boldsymbol{C}, P, l$;
    $if(p < 0.5)$
      $if(|\boldsymbol{A}| < 1)$
        Get a new individual by encircling the prey according to Equation (15);
      $else\ if\ (|\boldsymbol{A}| \geq 1)$
        Get a new individual by searching for prey according to Equation (20);
      end if
    $else\ if\ (p \geq 0.5)$
        Get a new individual by bubbling-net attacking according to Equation (18);
    end if
  end if
    The Cauchy-Gaussian variation is performed according to Equation (23);
    Update the current optimal individual and fitness location;
$t = t + 1$;
end while
end

As shown in Figure 1, the solving process of IWOA is as follows.

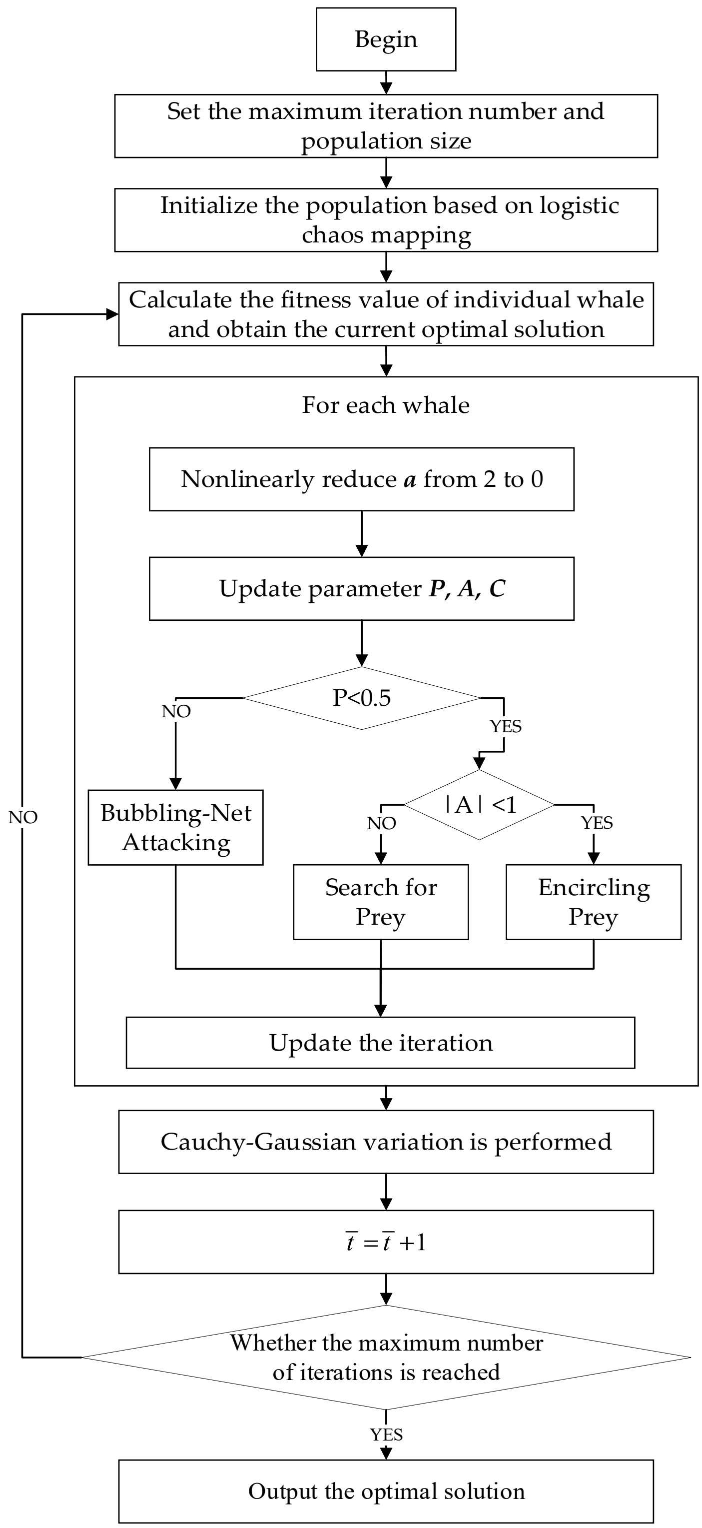

Figure 1. Solving Steps of IWOA.

5. Case Study

5.1. Background of Study Area

An earthquake is one of the major disasters in China, which is also regarded as one of the most recurrent and harmful events that could cause massive damages and severe economic losses. The eastern Hebei region is located in the seismic belt around the Bohai Sea, which is not only a place where earthquakes and other natural disasters happen frequently but also an important military strategic location. Tangshan city in the east of Hebei Province is selected to conduct the case study. Earthquakes caused by the compression of tectonic plates in these areas may occur unpredictably, which makes the case study more meaningful as it may serve as a decision-supporting tool for such events.

5.2. Model Parameter Determination

This subsection includes two parts: the data and parameters related to (i) potential civilian emergency facilities and military storage facilities, (ii) seismic scenario generation and (iii) affected area needs. These are designed closely to follow the realistic situation, yet should be used for illustration only.

5.2.1. Potential Civilian Emergency Facilities and Military Storage Facilities

We set the central point of each district as the civil emergency facility candidates, which are also the potential affected areas. Therefore, the time distance between the civilian emergency facilities and the locally affected areas is 0 for each region. Four military storage facility candidates were assumed because of confidentiality reasons. Figure 2 shows the locations of potential affected areas and storage facility candidates.

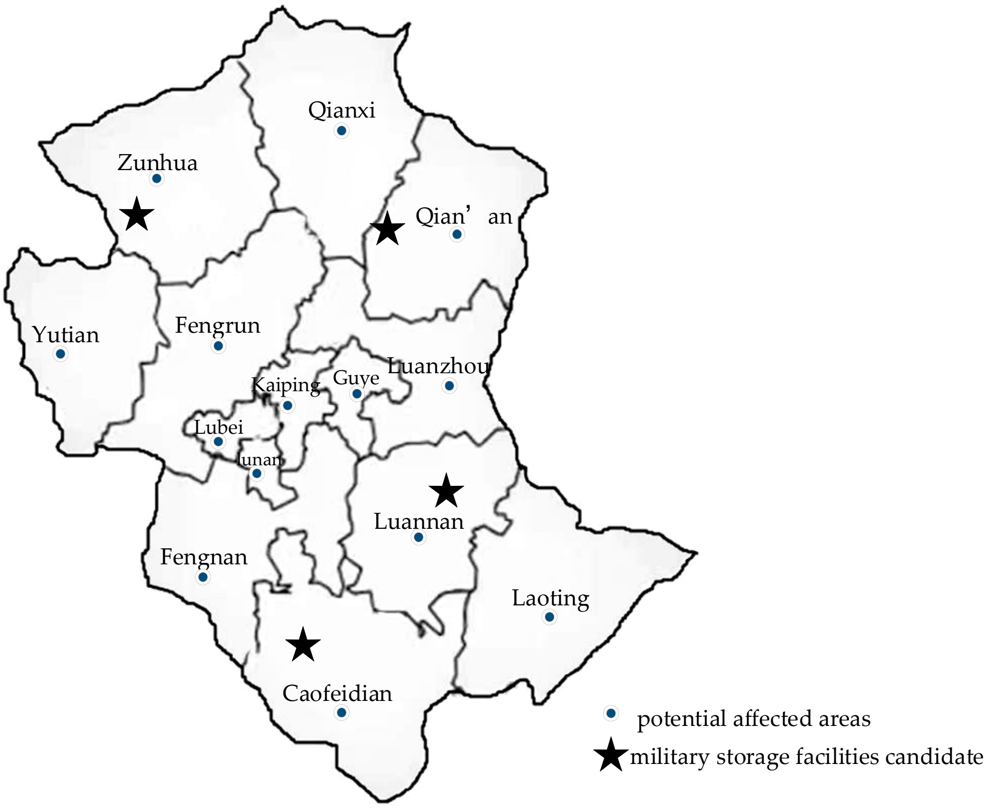

Figure 2. Location map of potentially affected areas and reserve facility options in Tangshan.

In response to a possible earthquake, a number of civilian emergency facilities will be set up among 14 potential affected areas, and several military storage facilities will be selected from the four local options for military storage facilities of common material. Drinking water and food are considered as two kinds of emergency supplies. It is assumed that the reserve cost of military storage facilities is 10% higher than that of civilian emergency storage, and the related costs are shown in Table 3. The construction costs and capacity of different types of facilities are shown in Table 4 below.

Table 3. Unit volume and associated costs of emergency supplies.

Emergency Supplies	Unit Volume (m^3)	Unit Storage Cost in Civilian Emergency Facility (CNY)	Unit Storage Cost in Military Storage Facility (CNY)	Unit Travel Time (CNY/h)	Unit Penalty Cost (CNY)
Drinking water (L)	0.015	1.12	1.23	1.5	25.4
Food (KG)	0.019	1.78	1.96	1.1	35.6

Table 4. The construction costs and capacity of storage facilities.

Storage Facilities	Quantitative	Construction Cost (10^4 CNY)	Reserve Capacity (10^4 m^3)
Large civilian emergency facilities		500	15
Medium civilian emergency facilities	≤6	300	10
Small civilian emergency facilities		200	5
Military storage facilities	≤2	0	5

5.2.2. Scene Collection Generation

According to the Hebei Seismological Bureau, from the beginning of historical records to 2021, 44 earthquakes with a magnitude of 5 or above occurred within 100 km of Tangshan. Among them, 37 with a magnitude of 5.0–5.9, 5 with a magnitude of 6.0–6.9, and two with a magnitude of 7.0–7.9. Disasters are classified into three levels according to earthquake magnitude: Level III (7.0–7.9), Level II (6.0–6.9) and Level I (5.0–5.9) (Table 5).

Table 5. Frequency of earthquakes occurring within 100 km of Tangshan city.

Magnitude	Level	Frequency	Probability
7.0–7.9	III	2	0.045
6.0–6.9	II	5	0.114
5.0–5.9	I	37	0.841
Total		44	1

According to the probability of earthquake occurrence of different levels in historical data, several typical disaster scenarios of each level are selected to construct a scenario set of 8 scenarios, as shown in Table 6.

Table 6. Definition of disaster scenario.

Scenario	Disaster Center	Level	Probability
1	Luanzhou	I	0.022
2	Fengnan	I	0.023
3	Guye	II	0.061
4	Luannan	II	0.053
5	Kaiping	III	0.232
6	Yutian	III	0.361
7	Luanzhou	III	0.248

5.2.3. Affected Areas Needs

According to The Statistical Yearbook of Hebei Province 2020, the total population of 14 potential disaster sites at the end of 2020 is shown in Table 7. The actual road network data from Baidu Map was used to calculate the travel distance between 14 potential affected areas. The average transport speed of military and civilian relief vehicles is 80 km/h and 50 km/h respectively, and the maximum rescue time is 2 h because the initial stage of rescue is considered only.

Table 7. Population at each potentially affected area.

Potential Affected Area	Fengrun	Lubei	Qian'an	Zunhua	Yutian	Fengnan	Luanzhou
Population (10^4)	80.07	78.46	77.68	70.7	66.49	55.25	52.01
Potential Affected Area	**Luannan**	**Laoting**	**Qianxi**	**Caofeidian**	**Lunan**	**Guye**	**Kaiping**
Population (10^4)	50.85	38.92	36.56	35.21	33.42	31.79	27.94

The disaster level and demand of affected areas is determined according to Formulas (12) and (13). The per capita demand in the affected areas is calculated according to the standard that 1.5 L of drinking water and 0.5 kg of food are provided per person per day. The demand in the affected areas under various scenarios is shown in Table 8 below.

Table 8. Drinking water and food requirements in different situations (10^4 L, 10^4 KG).

Scene	1		2		3		4		5		6		7	
Supplies	**Water**	**Food**	**Water**	**Food**	**Water**	**Food**	**Water**	**Food**	**Water**	**Food**	**Water**	**Food**	**Water**	**Food**
Fengrun	420.37	140.12	210.18	70.06	210.18	70.06	105.09	35.03	105.09	35.03	105.09	35.03	105.09	35.03
Lubei	205.96	68.65	411.92	137.31	205.96	68.65	102.98	34.33	102.98	34.33	102.98	34.33	0	0
Qian'an	407.82	135.94	203.91	67.97	203.91	67.97	101.96	33.99	101.96	33.99	0	0	101.96	33.99
Zunhua	185.59	61.86	185.59	61.86	92.79	30.93	92.79	30.93	0	0	92.79	30.93	0	0
Yutian	174.54	58.18	174.54	58.18	87.27	29.09	87.27	29.09	0	0	0	0	0	0
Fengnan	145.03	48.34	290.06	96.69	72.52	24.17	72.52	24.17	72.52	24.17	0	0	0	0
Luanzhou	136.53	45.51	136.53	45.51	136.53	45.51	136.53	45.51	68.26	22.75	0	0	68.26	22.75
Luannan	266.96	88.99	133.48	44.49	133.48	44.49	133.48	44.49	66.74	22.25	0	0	66.74	22.25
Laoting	204.33	68.11	102.17	34.06	51.08	17.03	102.17	34.06	0	0	0	0	51.08	17.03
Qianxi	95.97	31.99	95.97	31.99	95.97	31.99	47.99	16	47.99	16	0	0	0	0
Caofeidian	92.43	30.81	184.85	61.62	46.21	15.4	92.43	30.81	0	0	0	0	0	0
Lunan	175.46	58.49	175.46	58.49	87.73	29.24	87.73	29.24	43.86	14.62	0	0	43.86	14.62
Guye	166.9	55.63	83.45	27.82	83.45	27.82	83.45	27.82	41.72	13.91	0	0	41.72	13.91
Kaiping	146.69	48.9	146.69	48.9	73.34	24.45	73.34	24.45	36.67	12.22	0	0	36.67	12.22

5.3. Results Analysis

5.3.1. Model Results Analysis

With MATLAB2018a as the operating platform, the algorithm is executed on Intel(R), Core(TM)i7-6500ucpu, 2.50 GHz, 16.00 GB memory, Windows10 operating system PC. We set the population size as 100 and the maximum number of iterations as 100. By solving the pre-position model of emergency supplies considering the military storage facilities, the optimal site selection and storage sites are obtained, respectively, Qian'an (medium), Zunhua (small), Lunan (medium), Guye (small), 2nd military storage facility and 3rd military storage facility. As shown in Table 9, these six facilities reserve 16.1523 million liters of drinking water and 5.2689 million kilograms of food, with the average utilization rate of the warehouse reaching 84.53%.

Table 9. Facilities location and optimal amount of reserve.

Location	Supplies	Drinking Water (10^4 L)	Food (10^4 KG)	Warehouse Utilization
Qian'an	Medium civilian emergency facilities	371.47	115.46	77.66%
Zunhua	Small civilian emergency facilities	194.3	41.64	74.11%
Lunan	Medium civilian emergency facilities	447.47	172.63	99.92%
Guye	Small civilian emergency facilities	253.35	3.16	77.21%
	Military storage facilities 2	208.11	85.32	94.85%
	Military storage facilities 3	140.51	108.68	83.45%

When the disaster reaches Levels I and II, drinking water and food can basically meet all the needs for seven days after the disaster. When the disaster reaches Level III, the actual total demand for drinking water and food in Tangshan is 28.24 million liters and 9.41 million kilograms. According to the method in this paper, the optimal reserves of drinking water and food can meet 61% and 64% of the initial demand of disaster respectively. Due to the magnitude of the earthquake, the optimal food storage plan could not meet all the needs of the first seven days of the disaster, but it could still meet all the needs of the first four days of the earthquake. Within four days, emergency supplies can be sent to the affected area through inter-provincial allocation to meet follow-up needs.

Due to space limitations, only the allocation scheme of scenario 5 is shown, as shown in Figure 3 below.

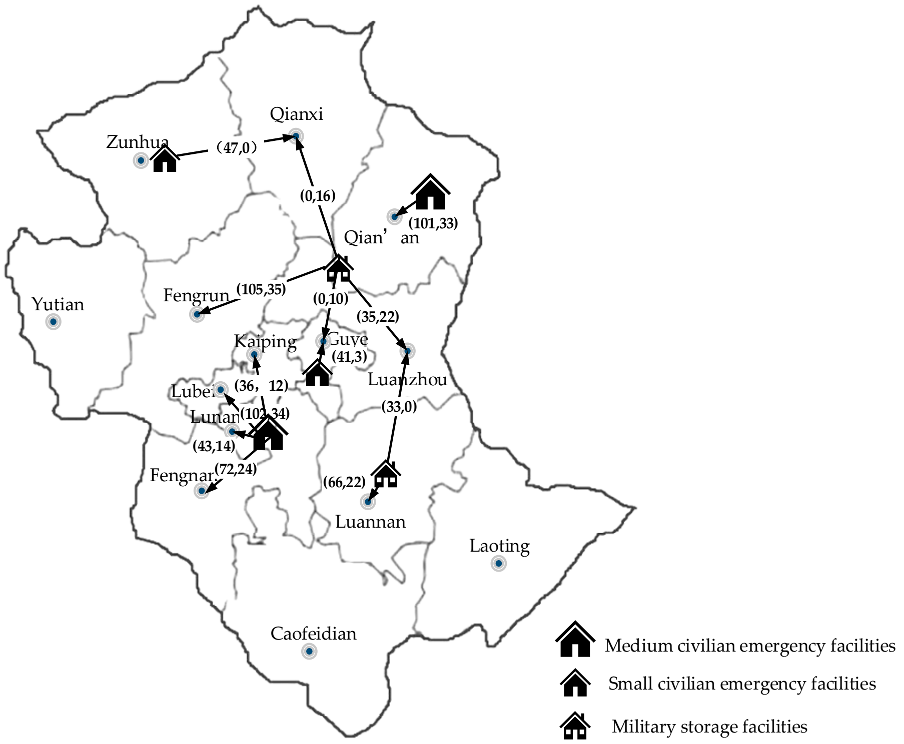

Figure 3. Supplies distribution options in scenario 5. (The numbers in parentheses indicate the allocation amount of drinking water and food, respectively, and the arrows indicate the distribution relationship rather than the transportation route).

In order to verify the influence of military storage facilities on the results, IWOA with the same parameters is used to acquire the facility location scheme, reserve scheme and distribution scheme when local emergency supplies are stored independently. As shown in Table 10, compared with the local independent reserve mode, the military and civilian joint reserve mode reduce the total cost of the system by 5.02% and the weighted transportation time by 37.45%, and the material satisfaction rate under major disaster scenarios (level III) has little change on the whole. The results show that the plan of military and civilian joint reserve can greatly improve the economy of supplies reserve and the timeliness of supplies distribution, and improve the emergency ability to deal with major emergencies in this region.

Table 10. Schemes comparison of local independent reserve and joint reserve.

The Reserve Type	The Number of Location Facilities	Supplies Satisfaction Rate in Level III		Weighted Transit Time (h)	The Total Cost (10^4 CNY)
		Drinking Water	Food		
Independent reserves	4	64.65%	59.17%	358.80	6247.01
Joint reserves	6	61.08%	64.31%	224.42	5933.49
Rate of change		−5.52%	+8.69%	−37.45%	−5.02%

5.3.2. Parameter Sensitivity Analysis

1. Maximum rescue time

In the emergency reserve decision-making, if the emergency rescue time is too long, the restriction on the transportation distance will not play a role of constraint; if the emergency rescue time is too small, emergency facilities can only cover a small number of affected areas, which may lead to high reserve cost. In order to analyze the impact of the maximum rescue time limit on the total system cost and weighted transport time, the maximum rescue time was increased from 0.5 to 3. The experimental results are shown in Figure 4. The results show that there is a clear inflection point in the curve when the maximum rescue time is 1 h or 2 h and the total cost of the system changes obviously.

2. Unit reserve cost of military storage facilities

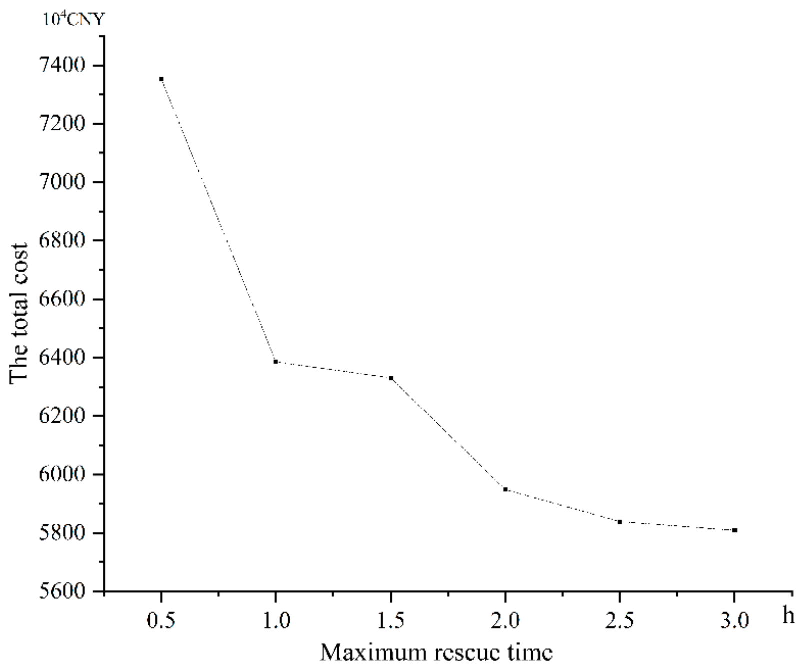

Figure 4. Maximum rescue time sensitivity.

The military storage facilities can greatly save the construction cost of the national reserve by using the idle storage capacity of the army to reserve emergency supplies. However, due to the high degree of specialization and strong management ability of the military reserve, the unit reserve cost of the military agent storage point is higher than that of the ordinary civilian emergency reserve. The change in unit reserve cost of military storage facilities will directly affect the total cost and total reserve of the system. Analyzing the change of unit reserve costs of the military storage facilities will affect the total costs and total reserve capacity of the system, The reserve cost of the civilian emergency facilities remains unchanged, and the ratio of unit storage cost of military storage facilities to civilian emergency facilities gradually changes from 1 to 2 for testing, The experimental results are shown in Figure 5. The results show that when the unit reserve cost of military storage facilities is less than 1.5 times that of civilian emergency facilities, the optimal result of the model will contain the maximum number of military storage facilities; when the unit reserve cost of military storage facilities is 1.65 times higher than that of civilian emergency facilities, the optimal results of the model will not include military storage facilities.

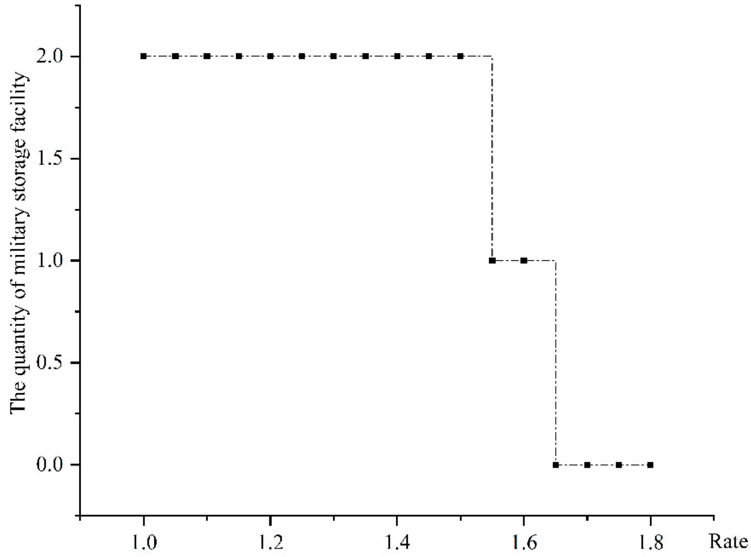

Figure 5. Unit reserve cost sensitivity of military storage facilities.

5.4. Comparison with WOA and Other Algorithms

In order to verify the performance of the IWOA, the genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA) and WOA are employed to solve the model by using the same parameters. The convergence curve in Figure 6 shows that GA, PSO and SA tend to fall into local optimum prematurely for the pre-position model proposed in this paper. IWOA integrates logistic chaotic population initialization, nonlinear convergence factor and improved points of the Cauchy-Gaussian variation, which improves the global search ability of the algorithm and shows better convergence speed and accuracy.

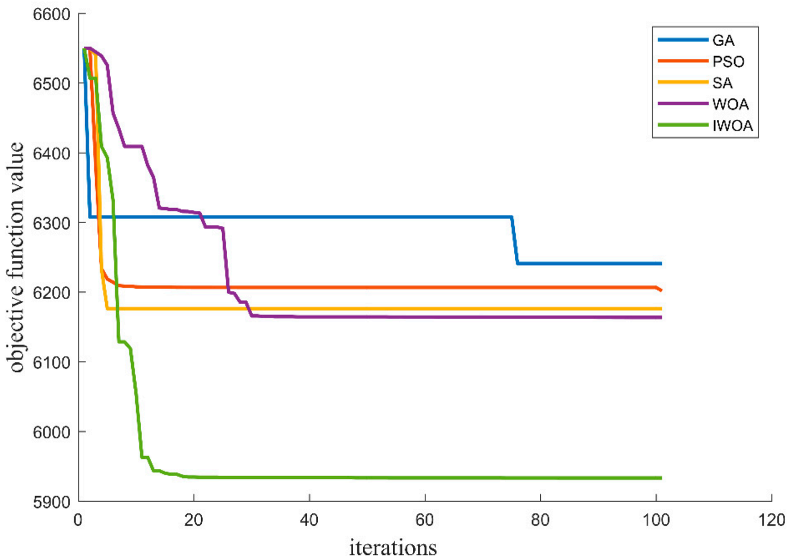

Figure 6. Convergence curve.

Compared with the results of the five algorithms, the minimum cost is 59.3349 million yuan, 62.4123 million yuan, 620.17 million yuan, 61.7649 million yuan and 61.6366 million yuan, respectively. As shown in Figure 7, compared with other algorithms, IWOA can not only calculate the minimum total cost of the system, but also obtain a better value in the emergency rescue time of the obtained allocation scheme and the emergency supplies satisfaction rate in the case of level III disasters.

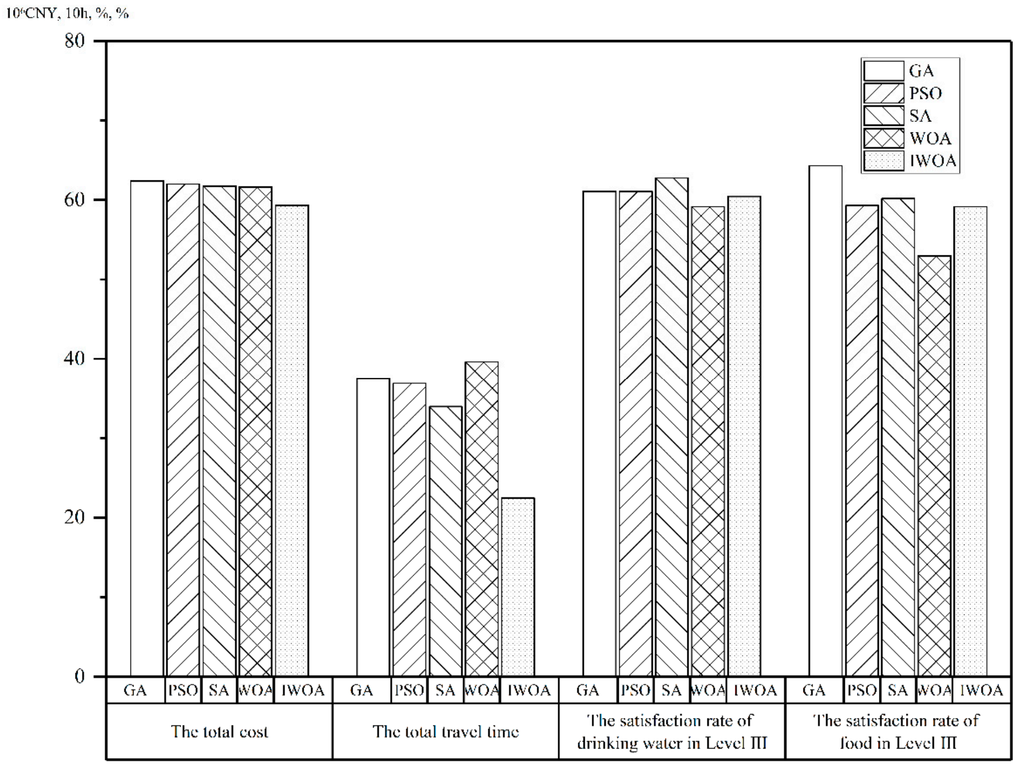

Figure 7. Comparison results of different algorithms.

6. Managerial Implications

In this section, we will discuss and summarize some interesting managerial insights that emerged from our model formulation and case study analytical results.

(I) We studied the pre-positioning of emergency supplies problem from the perspective of civil-military integration, the aim of which is to effectively make use of the logistics resources of both military and civilian sides to reduce emergency reserve costs. The model of using idle resources of the military to provide storage support for national emergency reserve activities provides a thinking point for managers. In our case study of Tangshan, we first compared the joint reserves model with the independent reserves model. The experimental results show that the joint reserves model obtains a relatively optimal solution under the same parameters. Through the model, it can be verified that the joint reserves model proposed in this paper has practical significance in management practice.

(II) We studied the influence of parameters T on the model results. In order to analyze the impact of the maximum rescue time limit on the total system cost and weighted transport time, the maximum rescue time was increased from 0.5 to 3. The results show that the total cost of the system changes obviously when the maximum rescue time is 1 h and 2 h. If decision-makers are inclined to consider the total cost of pre-disaster storage and response, the maximum rescue time can be 2 h. If decision-makers prefer to consider the timeliness of post-disaster distribution, they can choose the maximum rescue time of 1 h.

(III) Finally, we adjusted the cost of the military storage facilities. The results indicate that when the unit reserve cost of military storage facilities is less than 1.5 times that of civilian emergency facilities, selecting the largest number of military storage facilities can effectively reduce the reserve cost. When the unit reserve cost of military storage facilities is 1.65 times higher than that of civilian emergency facilities, it is more economical to reserve all civilian emergency storage facilities for managers.

7. Discussion

The military has always been the backbone of emergency relief, and the implementation of the military and civilian joint reserve is an important way to effectively solve the problem of emergency relief supplies reserve and improve the ability of the country and the military to deal with natural disasters and emergencies. For the military and civilian general emergency supplies, the military and civilian joint reserve can effectively share the idle storage capacity resources of the army, improve the utilization rate of resource elements and avoid repeated construction. Based on this, this paper proposes a pre-position problem of emergency supplies considering the military storage facilities and builds a two-stage stochastic programming model based on the scenario: the model in the first stage determines the optimal location and the optimal amount of storage, the model in the second stage determines the optimal supply distribution scheme. Aimed at the problem that the initial WOA solution is random and the late iteration is easy to fall into local optimum, the logistic chaotic mapping is introduced to initialize the population and the non-linear convergence factor method and the Cauchy-Gauss mutation strategy are introduced to balance the relationship between global search and local search of the algorithm. To sum up, we developed the IWOA with multi-strategies when searching for solutions to the problem. Based on the case analysis of the Tangshan earthquake disaster scenario, the optimal decision of location selection, supplies storage and post-disaster distribution of military and civilian storage was obtained. The results show that: (1) the total cost of the system can be slightly reduced and the post-disaster transportation time can be effectively optimized by using the military and civilian joint reserve mode for the general emergency supplies. (2) Decision-makers can choose the maximum rescue time according to different emergency decision-making needs. (3) When the unit storage cost of military storage facilities is less than 1.5 times that of civilian emergency storage, the military and civilian joint reserve mode can reduce the reserve cost. (4) For the model in this paper, compared with WOA, the IWOA based on chaotic initialization, nonlinear convergence factor and the Cauchy-Gaussian variation shows better convergence accuracy and convergence speed. In terms of calculation results of the model, IWOA can not only obtain the minimum total cost of the system, but also get a better value in the emergency rescue time of the obtained allocation scheme and the emergency supplies satisfaction rate in the case of level III disasters.

However, the location–allocation model in this paper only considers the civilian emergency relief scenarios and does not consider the military response scenarios. In subsequent studies, both civilian emergency and military response efficiencies can be considered as the objectives of the model to conduct joint optimization. In the optimization of resource deployment under the background of civil–military integration, there are still many new problems that have not been deeply explored, such as the unified scheduling and route planning of military–civilian vehicles in emergency rescue, and the design of military–civilian logistics integration network. These problems can be studied systematically in the future to provide decision support for military and civilian managers.

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Glossary

Sets:

I	Set of local civilian emergency facility candidates i
D	Set of military storage facility candidates d
J	Set of affected areas j
S	Set of scenarios s
K	Set of the types of emergency supplies k
M	Set of the level of civilian emergency facility m

Parameters:

p_s	The probability of the scenario s occurring
h	The maximum number of civilian emergency facility
g	The maximum number of military storage facility
t_{ij}	Unit travel time from civilian emergency facilities i to affected area j
t_{dj}	Unit travel time from military storage facilities i to affected area j
c^m	Fixed cost of locating and operating a level m civilian emergency facility
b_{ik}	Unit storage cost of emergency supplies k in civilian emergency facility i
b_{dk}	Unit storage cost of emergency supplies k in military storage facilities d
μ_k	Unit time cost of distribution vehicles of emergency supplies k
ω_k	Unit penalty cost of unsatisfied demands for emergency supply k
$l_{jk}(s)$	Demand for emergency supplies k for each affected areas j in scenario s
v_k	Unit volume of emergency supplies k
$\overline{V^m}$	Spatial capacity of level m civilian emergency facility i
$\overline{V_d}$	Spatial capacity of military storage facilities d
T	Maximum emergency rescue time

Decision variables:

x_i^m	1, if a level m civilian emergency facility is selected at location i; 0, otherwise
x_d	1, if a military storage facility is selected at location d; 0, otherwise
y_{ik}	The quantity of the emergency supplies k pre-positioned at civilian emergency facilities i
y_{dk}	The quantity of the emergency supplies k pre-positioned at military storage facilities d
$z_{ijk}(s)$	The quantity of emergency supplies k delivered from civilian emergency facilities i to affected area j in scenario s
$z_{djk}(s)$	The quantity of emergency supplies k delivered from military storage facilities i to affected area j in scenario s

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