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Research on location-routing optimization of distribution center for emergency supplies based on IMOCS-LNS hybrid algorithm

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A B S T R A C T

This paper establishes a location-routing optimization model of the distribution center for emergency supplies with the goals of system reaction time, total cost of consumption, psychological fear of the populace in disaster-affected locations, and material usage rate. Where the excess time, demand, and penalty coefficient are the components of the penalty cost in the total consumption cost, and where the psychological panic of those in the affected area is represented by the psychological perception function of panic developed in accordance with the prospect theory. An improved hybrid multi-objective cuckoo-large-neighborhood search algorithm was then designed to introduce tent mapping, nonlinear inertia weights, elite strategies, congestion operators, and dynamically adjusted discovery probabilities into the standard multi-objective cuckoo optimization algorithm, which generates a new solution using a large-neighborhood search algorithm after discarding part of the solution with the discovery probability, and then accepts the current nondominated solution with dynamic probabilities. The paper uses the improved algorithm to solve Christofides69, an arithmetic example from the standard dataset of the LRP problem, and the results show that the solution provided by the improved algorithm outperforms the solutions provided by the standard multi-objective cuckoo search algorithm and the NSGA-II algorithm in terms of the total cost of dissipation, the level of psychological panic of the people in the affected area, the rate of utilization of the supplies, and the number of distribution centers open. Finally, the improved algorithm was used to analyze cases of different sizes separately, and it was found that the algorithm yielded better results and was therefore able to demonstrate its effectiveness.

1. Introduction

Emergencies, such as natural disasters and public health emergencies, seriously infringe on the safety of people's lives and further socio-economic development in all countries. The outbreak of a new coronavirus (COVID-19) in 2019 caused billions of infections worldwide, triggering problems such as plunging crude oil prices and flash meltdowns in stock markets, leading to global losses of hundreds of billions of dollars per month, sharply increasing the risk of triggering a global economic crisis and having a major impact on international politics and economies, constantly affecting human life and the development of societies (McVernon et al., 2023; Ponboon et al., 2016). In the aftermath of major emergencies, victims experience significant physical and psychological trauma, necessitating the rapid transportation of large quantities of emergency supplies to the areas in need of relief assistance. Failing to deliver emergency supplies promptly and in sufficient quantities can lead to widespread panic among affected populations, with potentially catastrophic consequences. However, prior to the deployment of emergency supplies, it is imperative to establish an efficient and effective emergency supply network (Caunhye et al., 2016). The strategic placement of distribution centers and the optimization of supply delivery routes are critical components of such

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a network, capable of enhancing disaster relief efforts (Feng et al., 2019). Consequently, the swift determination of distribution center locations and the selection of optimal delivery routes to ensure timely supply delivery to affected areas, while minimizing panic among victims, represent pivotal challenges within the domain of emergency logistics networks.

In addressing challenges like optimizing the location and routing of emergency supply distribution centers, scholars have primarily focused on data analysis and research. This analytical approach has laid the groundwork for informed decision-making by both businesses and governmental bodies (Lin et al., 2004). Numerous studies have demonstrated that the utilization of data has greatly enhanced scholars' capabilities in tackling such issues. Specifically, harnessing data not only facilitates the practical application of theoretical models and algorithms in real-world scenarios, thereby validating these models and algorithms (Wang et al., 2023), but it also equips governments and businesses with post-disaster solutions that encompass multiple objectives, offering valuable insights for managing similar events in the future (Qin et al., 2019). Furthermore, it provides real-time decision support in disaster-prone regions, such as those affected by droughts and floods (Wu et al., 2020; Elluru et al., 2019).

In summary, the focus of this paper is to delve into the challenges surrounding the location and routing of distribution centers for emergency supplies following disaster events. Our goal is to ensure the swift and efficient delivery of emergency provisions to disaster-stricken areas, ultimately providing decision-makers with enhanced solutions by means of mathematical modeling.

2. Review of the literature

The Location Routing Problem (LRP) was initially introduced by Maranzana F.E (1965). and Webb (1968), among others. It gained further attention from researchers like Watson-Grandy et al. (1973), among others, who proposed a location routing problem tailored for logistics distribution involving multiple affected sites. Building upon this foundation, scholars have made substantial progress and refinements to the original LRP model over time. These advancements in location routing for logistics systems involved the incorporation of realistic constraints, including limitations on the number of vehicles (Dukkanci et al., 2019), vehicle capacity (Perl et al., 1984), and time windows (Beiki et al., 2021). Moreover, scholars expanded the scope of objectives to encompass factors such as cost (Leng et al., 2020), carbon emissions (Zhou et al., 2023), and time (Schmidt et al., 2019) within the objective function. The evolution of LRP models extended from single-stage to multi-stage formulations (Wang & Nie, 2023) and beyond.

In the context of emergency logistics systems, researchers have focused on optimizing the location and distribution routing of distribution centers while considering multiple constraints and objectives. For instance, Santoso et al. (2005) formulated the objective function for the entire emergency logistics system as the minimization of total costs, while ensuring that the capacity constraints of distribution centers and the demand at delivery points were met realistically. Özdamar et al. (2004) emphasized the role of dynamic time considerations in addressing traffic issues and advocated for comprehensive integration of factors like time window constraints, distribution routes, and truck sequencing in emergency logistics planning. Building on this prior work, scholars delved deeper into LRP models with time window constraints. Sahitya et al. (2019) proposed both active and passive LRP models with time windows for post-disaster emergency logistics systems. The active model aimed at minimizing fixed, transport, and risk costs, considering pre-disaster risk factors associated with each facility. The passive model aimed at minimizing changes in route costs, non-delivery penalties, delay penalties, and lost waiting time costs while incorporating disruptions caused by disasters into the model. Examples showcased that a combination of active and passive approaches in designing emergency logistics distribution systems could enhance overall system resilience. In a different context, Hassanpour et al. (2023) developed a mixed-integer linear programming model with time window constraints to address the location routing problem in the context of an epidemic. They defined three scenarios with varying severity levels and devised algorithms to solve the model. Their algorithm demonstrated superior performance in handling large-scale problems and exhibited a high degree of robustness.

In the realm of emergency LRP, initial studies primarily concentrated on optimizing the total system response time, focusing on the single-objective problem. Díaz et al. (2018) constructed a post-earthquake LRP model with a time window and designed a memory algorithm (MA) for solving it with the objective of minimizing the total response time during evacuation to determine the location of emergency shelters and evacuation routes that meet the time constraints for the post-earthquake situation. The validity of the model and the algorithm was verified with an example. As the field of emergency LRP continued to evolve, scholars began to integrate cost and carbon emissions as additional objective functions within the model framework, tailoring them to distinct scenarios such as earthquake and epidemic situations. For instance, in their investigation of emergency LRP systems for post-earthquake relief efforts, Nedjati A et al. (2017) introduced a constraint on the number of vehicles available in the yard, with the primary goal of minimizing weighted waiting times and overall demand loss. They also developed two enhanced versions of the NSGA-II algorithm to address this challenge. Furthermore, Vahdani et al. (2018) formulated a nonlinear integer multi-objective LRP model for post-earthquake emergency scenarios. Their objectives included minimizing total cost, total path time, maximizing path reliability, accommodating multiple cycles, and handling multiple commodities. This complex problem was also considered post-earthquake road rehabilitation. To tackle this challenge, the researchers proposed two meta-heuristic algorithms. Zhang et al. (2018) introduced uncertainty theory into the field and established an emergency location-path model with time, cost, and carbon emissions as objectives. They converted the multi-objective problem into a single-objective one using the principal objective method and designed a hybrid intelligent algorithm to resolve it. The robustness of their algorithm was demonstrated through numerical examples, although it's worth noting that it solely considers fixed distribution center costs and vehicle travel expenses, omitting other costs like distribution center operation expenses. Shen et al. (2019) proposed a multi-objective emergency logistics location-path model that aimed to minimize delivery time, total cost, and carbon emissions. Their approach also accounted for supply point construction costs and operational expenses. Moreover, the uncertainty in demand was addressed by incorporating a triangular fuzzy function. To solve this comprehensive model, a hybrid two-stage algorithm was developed and successfully validated using classical databases and practical examples.

In addition to the mentioned variations in the emergency LRP models, some researchers have incorporated humanitarian considerations, specifically addressing the psychological well-being of individuals in crisis-stricken areas. However, there are fewer studies on this. Sheu et al. (2014), for instance, devised an integrated and seamless centralized emergency supply network comprising three sub-networks: a shelter network, a medical network, and a distribution network. They developed a three-stage multi-objective mixed-integer linear programming model with the aims of minimizing distance, cost, and psychological distress experienced by those on the receiving end of aid. This innovative approach was rigorously tested and validated. In the context of emergency materials supply, Wang and Sun (2023) introduced three humanitarian-oriented objectives: efficiency, equity, and effectiveness. They crafted a multi-stage emergency supply distribution model that accommodated these principles. Experimental results indicated that this model could effectively scale up for large-scale emergency supply distribution scenarios. Based on the cumulative prospect theory, Zhu et al. (2021) comprehensively considered the nature of the path and the attitude of the decision maker as well as the selection behavior to establish an emergency material distribution network model, and finally conducted a sensitivity analysis of the parameters to derive the path selection strategy under different conditions.

In the realm of solving LRP models, both exact and heuristic algorithms find widespread application. For instance, when addressing LRP models with time windows, Sattrawut et al. (2023) employed a branch-and-bound algorithm. While this approach efficiently computed numerous cases, it was noted to be labor-intensive and computationally demanding. Consequently, an increasing number of scholars turn to heuristic algorithms for tackling such models. These algorithms offer the advantage of swiftly generating multiple sets of Pareto optimal solutions. Raeisi and Jafarzadeh Ghoushchi (2023) for example, devised six algorithms, including the multi-objective invasive weed optimization algorithm, for solving LRP problems. Zhong et al. (2022) developed a hybrid algorithm that combined ant colony optimization with forbidden search techniques to address the maritime emergency material distribution location-path problem. After conducting extensive analysis using practical examples, they concluded that this model facilitated more informed decision-making at different levels, ultimately enhancing service capabilities in emergency scenarios.

In summary, for the emergency LRP problem, scholars have studied the time, cost terms and environmental factors in great depth and applied them to specific scenarios such as earthquakes and public health emergencies. The results obtained by bringing data into the models and algorithms show that these models can effectively solve the distribution problem of emergency supplies. However, most of the previous literature have modeled the objectives of total cost spent, total response time, and carbon emission, and few studies have considered the total system response time, cost, panic level of the people in the disaster area, and material utilization rate of the distribution center at the same time. However, these objective items directly affect the efficiency of the emergency response system. Therefore, this paper takes the above four points as the research objectives and establishes a location-routing optimization model of the distribution center for emergency supplies to ensure the rapid and efficient delivery of supplies and at the same time alleviate the psychological panic of the people in the disaster-stricken areas, which in turn provides a basis for post-disaster management. In addition, this paper also designs an improved hybrid cuckoo-large neighborhood search algorithm based on the standard multi-objective cuckoo search algorithm to solve the model.

The content framework of this paper is as follows: section 3 describes the location-routing optimization model for distribution centers of emergency supplies. Section 4 describes the IMOCS-LNS algorithm in detail. Section 5 compares the performance of the IMOCS-LNS algorithm with MOCS algorithm and NSGA-II through examples. Solution 6 draws the corresponding conclusions.

3. Emergency supplies distribution center location - routing optimization model

This paper mainly studies the issue of location-routing optimization of distribution centers for emergency supplies in the context of emergency events. A number of distribution centers are selected from the alternative distribution centers, and a number of vehicles are sent from these distribution centers to deliver supplies to all the affected sites. With the objectives of minimizing the system response time, total cost of consumption, the degree of psychological panic of the people in the disaster-stricken places, and material utilization rate of the emergency logistics system, a model is established for the location of emergency supply points and the optimization of distribution routes.

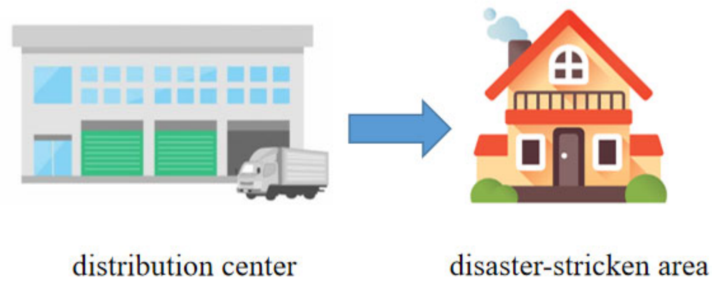

Fig. 1. Diagram of the Emergency Material Distribution Network

3.1 Model assumptions

(1) The location, maximum capacity, and construction cost of the candidate distribution center are known.
(2) The location and demand of the affected site are known.
(3) The transport cost per unit load per unit distance travelled by the vehicle, the maximum vehicle load, and the fixed cost are known.
(4) Vehicles must depart from and return to a certain supply point and return to that distribution center.
(5) Each vehicle is activated only once.
(6) The alternative distribution centers are all built and stocked with supplies.

3.2 Description of symbols

M indicates the full set of alternative distribution centers, $M = \{1,2,3,\dots,m\}$
N indicates the full set of affected sites, $N = \{1,2,3,\dots,n\}$
J denotes a collection of alternative distribution centers and disaster sites， $J = M \cup N$
O indicates a collection of transport vehicles， $O = \{1,2,3,\dots,o\}$
AC_mdenotes the cost of operating distribution center m
V_o indicates the speed at which vehicle o is travelling
Q_m denotes the capacity of the distribution center m
d_n denotes requirement for the affected site n
Q_o indicates the maximum load capacity allowed for the vehicle o
K_{mo} denotes the number of transport vehicles owned by distribution center m
B_o indicates the maximum mileage of the vehicle
d_{ij} denotes the distance between point i and point j
S indicates the speed of loading and unloading of demanded supplies
LT_n denotes the latest time of delivery of supplies to the affected site n
C_o indicates the cost per unit distance travelled by the transport vehicle
G_o represents the fixed cost required to use a transport vehicle
h indicates the penalty factor for supplies not arriving at the affected site in the required time
SF_n denotes the penalty cost incurred by the affected site n for service in excess of psychological expectations of time
R indicates the level of public risk perception when $T_n = T_n^{'}$
R_n denotes the perceived level of risk for people at the affected site n
$T_n^{'}$ indicates the time at which the public believes the supplies should reach the affected site n
T_n denotes the actual time for the supplies to reach the affected site n
β indicates the risk aversion factor
λ is the aversion coefficient, which indicates the degree of aversion people feel when faced with a loss, with aversion increasing with λ
X_{mno} is a decision variable, whether vehicle o transports materials from distribution center m to the affected site n
U_{no} is a decision variable, whether vehicle o serves the affected site n
M_m is a decision variable, whether the alternate distribution center m is selected.

3.3 Objective function analysis

In order to better describe the location-routing optimization model of the distribution center for emergency supplies studied in this paper, the individual objective functions in the model are analytically described as follows:

(1) Timeliness function for emergency distribution response

The total response time of the emergency supply network is the most important factor to be considered in the emergency relief process, only when emergency supplies are in place on time can they be used to maximum effect. In this paper, we mainly consider the transportation time as well as the supply handling time during the distribution of emergency supplies, and the expressions are shown below:

$$T=\sum_{o\in O}\sum_{m\in J}\sum_{n\in J}\frac{d_{mn}}{V_o}X_{mno}+2\frac{\sum_{n\in N}d_n}{S}$$

(2) The economic function of emergency distribution

The costs involved in this model include location costs and transportation costs. Location selection costs generally include construction costs and operating costs, i.e., the cost of human and material resources used in the construction process and the operating costs of utilities, maintenance, etc. required after completion. However, as it has been assumed in the model assumptions that the alternative distribution centers have been built, the construction costs are not considered, and only the operational costs are considered. Route costs generally include the transport costs of the transport vehicle, which are related to the distance traveled, and the fixed costs, which are the fixed costs incurred in using the vehicle. In addition to this, penalty costs are incurred if supplies do not reach the affected site in the required time. Therefore, the economic function established in this paper includes the following three aspects: (i) the transportation and fixed costs of the vehicles used to transport emergency supplies from the distribution center to the point of demand; (ii) the operating costs of the distribution center once it is opened; and (iii) the penalty costs arising from the arrival time of supplies exceeding the public expectation time at the point of demand.

$$C=\sum_{m\in m}AC_mM_m+\sum_{o\in O}\sum_{m\in J}\sum_{n\in J}C_o\,d_{mn}X_{mno}+\sum_{n\in N}SF_n+\sum_{o\in O}\sum_{m\in M}\sum_{n\in N}G_o\,X_{mno}$$

where the penalty costs arising from the arrival of supplies in excess of the public expectation of arrival times at the point of demand are as follows:

$$SF_n=\begin{cases}hd_n(T_n-T_n'),T_n'<T_n\le LT_n\\0,T_n\le T_n'\end{cases}$$

When the actual time of arrival of emergency supplies at the affected site does not exceed the public's psychological expectation of the arrival of supplies, the penalty cost is 0. If the actual time of arrival of emergency supplies at the affected site exceeds the public's psychological expectation of the arrival of supplies, the penalty cost is related to the product of the excess time and the amount of supplies required at the affected site.

(3) The perception function of people's panic at the point of demand

This paper considers the psychology of the public at the point of need and proposes a psychological risk perception function based on prospect theory to quantify the risk perception of disaster victims regarding the arrival time of supplies after an emergency event. The public will be informed through various sources of the time it takes for emergency supplies to reach each point of need, i.e., the time taken to deliver supplies from the nearest distribution center to the point of need, by the following formula:

$$T_n'=min\left(\frac{d_{mn}}{V_o}\right),\forall m\in M,n\in N$$

Using the public's psychological expectation of when supplies will arrive at the point of need as a reference point, the degree of perceived psychological risk is greater than 0. The reason for this is that when an emergency occurs, disaster victims at the point of need will immediately become psychologically upset. According to prospect theory, the public's psychological risk perception is relatively small when $T_n<T_n'$. That means the time for emergency supplies to arrive at the point of need is small compared to the public's psychologically expected time. When $T_0=T_n'$, the degree of risk perception is R_0.It is a suitably large number. And when$T_n>T_n^{'}$, the degree of public psychological risk perception is large (Wang et al., 2013). However, in this thesis, the time for emergency supplies to arrive at the point of demand is necessarily greater than or equal to the public's psychological expectation because the time for supplies to arrive at the point of demand is not less than the time for supplies to be delivered from the nearest alternative distribution center to the point of demand. The public perception of risk at the point of need is therefore as follows:

$$R_n=\lambda(T_n-T_n')^{\beta}+R_0$$

(4) Material utilization rate of distribution centers

When delivery vehicles are loaded from distribution centers and delivered to affected sites, the volume delivered is the sum of the demand at each affected site. During this phase, not all the material in each distribution center may be used to support the affected site, so surplus material is created.

$$Y = \sum_{m\in M}\sum_{o\in O}\sum_{n\in N} d_n X_{mno} \Big/ \sum_{m\in M} Q_m M_m \,, \forall m \in M$$

3.4 Model construction

The objective functions of the model in this paper include the timeliness function of the emergency supply, the economy function, the psychological perception function of the code in the affected places, and the utilization rate of the materials, and the constraints that can be considered include the time-window constraints, the capacity constraints, the capacity constraints of the vehicle, and the mileage constraints of the vehicle. In summary, the site-path optimization model for the emergency supply distribution center established in this paper is shown below:

Objective function:

$$min\, T = \sum_{o\in O}\sum_{m\in J}\sum_{n\in J} \frac{d_{mn}}{V_o} X_{mno} + 2\frac{\sum_{n\in N} d_n}{S} \tag{1}$$

$$min\, C = \sum_{m\in m} AC_m M_m + \sum_{o\in O}\sum_{m\in J}\sum_{n\in J} C_o\, d_{mn} X_{mno} + \sum_{n\in N} SF_n + \sum_{o\in O}\sum_{m\in M}\sum_{n\in N} G_o\, X_{mno} \tag{2}$$

$$min\, R = \sum_{n\in N} R_n \tag{3}$$

$$min\, Y = \sum_{m\in M}\sum_{o\in O}\sum_{n\in N} d_n X_{mno} \Big/ \sum_{m\in M} Q_m M_m \,, \forall m \in M \tag{4}$$

Constraints:

$$\sum_{m\in M} Q_m \geq \sum_{n\in N} d_n \tag{5}$$

$$\sum_{o\in O}\sum_{n\in N} d_n\, X_{mno} \leq Q_m, \forall m \in M \tag{6}$$

$$\sum_{m\in J}\sum_{n\in N} d_n\, X_{mno} \leq Q_o, \forall o \in O \tag{7}$$

$$\sum_{o\in O} U_{no} = 1, \forall n \in N \tag{8}$$

$$\sum_{n\in N} X_{mno} = \sum_{n\in N} X_{nmo} \,, \forall m \in M, o \in O \tag{9}$$

$$\sum_{i\in J} X_{mio} = \sum_{i\in J} X_{imo} \,, \forall i \in J, o \in O \tag{10}$$

$$X_{mno} = 0, \forall m \in M, n \in N \tag{11}$$

$$\sum_{n\in N}\sum_{o\in O} X_{mno} \leq K_{mo}, \forall m \in M \tag{12}$$

$$\sum_{m\in J}\sum_{n\in J} d_{mn}\, X_{mno} \leq B_o, \forall o \in O \tag{13}$$

$$T_z = \frac{d_{mz}}{V_o} X_{mzo} \leq LT_z, \forall z \in N, o \in O, m \in M \tag{14}$$

$$T_n = \sum_{o\in O}\sum_{i\in N} \left(\frac{d_{in}}{V_o} + \frac{d_i}{s} + T_i\right) X_{ino}, +\forall n \in N \tag{15}$$

$$T_n \leq LT_n, \forall n \in N \tag{16}$$

$$SF_n = \begin{cases} hd_n(T_n - T_n^{'}), T_n^{'} < T_n \leq LT_n \\ 0, T_n \leq T_n^{'} \end{cases} \tag{17}$$

$$R_n = \lambda(T_n - T_n')^{\beta} + R_0 \tag{18}$$

$$T_n' = min\left(\frac{d_{mn}}{V_o}\right), \forall m \in M, n \in N \tag{19}$$

$$Y_m = Q_m - \sum_{o \in O} \sum_{n \in N} d_n X_{mno}, \forall m \in M \tag{20}$$

$$X_{mno} \le M_m, m \in M \tag{21}$$

$$X_{mno} \le U_{no}, \forall m \in J, n \in J \tag{22}$$

$$X_{mno}, U_{no}, M_m = \{0,1\} \tag{23}$$

Eqs. (1-4) are all objective functions; Eq (5) indicates that the storage of emergency supplies distribution center can meet the demand at the point of demand; Eq (6) indicates that the volume of supplies shipped from the distribution center to each affected site must not exceed its upper limit; Eq (7) represents the capacity constraint for distribution vehicles; Eq (8) indicates that a affected site is served by only one transport vehicle; Eq (9) indicates that each vehicle starts at the distribution center and returns to that distribution center when it has completed its task; Eq (10) expresses the guarantee of continuity and closure of distribution vehicle routes, i.e. the transport entering each node must leave from that node; Eq (11) indicates that a transport vehicle may not be transported from one distribution center to another; Eq (12) indicates that the number of transport vehicles issued from a distribution center must not exceed the number of transport vehicles owned by that distribution center; Eq (13) represents the transport vehicle mileage constraint; Eq (14) indicates the time of arrival of a transport vehicle from a distribution center at the first point of demand; Eq (15) indicates the time of arrival of the transported supplies at the point of demand; Eq (16) represents the time window constraint for the arrival of the transported supplies at the point of demand; Eq (17) represents the penalty cost of not delivering emergency supplies to the point of need in a timely manner; Eq (18) indicates the level of public psychological panic at the point of demand; Eq (19) indicates the time when the public learns through various channels that emergency supplies have arrived at each point of need, i.e. the public's psychological expectation time; Eq (20) indicates the quantity of supplies remaining in the distribution center; Eqs (21)-(22) represent the relationships between variables; Eq (23) represents the variables.

4. Solution of the emergency supplies distribution center location-routing optimization model

The multi-objective optimization problem studied in this paper is an NP-Hard problem that is commonly solved by heuristic algorithms (Mara et al., 2021). Among others, the multi-objective cuckoo search algorithm has the advantages of fewer parameters, less susceptibility to falling into local optima, better global search capability, and more satisfactory feasible solutions within an acceptable time frame (Peng et al., 2020, 2021). However, it has the disadvantage of slow convergence, and after the solution is discarded new solutions are generated randomly, and the quality of the new solutions is not well controlled. Therefore, in this paper, we improve the standard multi-objective cuckoo algorithm and use a large-scale neighborhood search algorithm when a new solution is generated after the solution is discarded, which is enough to help jump out of the local optimal solution and expand the search space. Therefore, this paper proposes a hybrid multi-objective cuckoo-large neighborhood search algorithm.

4.1 Standard Multi-objective cuckoo search algorithm

In 2009, Yang and Deb proposed the cuckoo search algorithm, a biomimetic meta-heuristic intelligent optimization algorithm that simulates the cuckoo's breeding behavior and flight patterns (Yang et al., 2009). The flight mode of the cuckoo search algorithm is the Lévy flight mode, which is quite common among other animals such as birds and insects. As shown in Fig. 2, the Lévy flight is a combination of high-frequency short-distance walks, low-frequency long-distance walks, and 90° turns. This is a randomized wandering mode, where the long-distance walk facilitates jumping out of the local optimum to improve the global search and the short-distance walk facilitates the local search, the combination of which enables the algorithm to traverse all solutions in the solution space better than other algorithms.

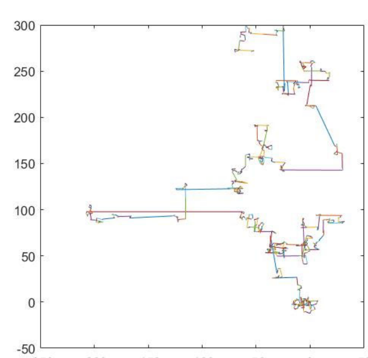

Fig. 2. Map of Lévy flight path

In practice, however, many problems cannot have a single objective; there are usually multiple objectives, which are often in conflict with each other, so that sometimes the true optimal solution may not exist. Compared to single-objective optimization problems, multi-objective optimization problems are more difficult and complex to solve, and their solutions form Pareto fronts, for which the better Pareto fronts should have uniformly distributed solutions.

In 2010, Yang and Deb (2013) extended the cuckoo search algorithm by proposing the multi-objective cuckoo search algorithm (MOCS) to solve multi-objective optimization problems. In the multi-objective cuckoo search algorithm, population size n, discard probability p_a, step size α and the parameters β in the Lévy flight are configurable parameters.

For optimization problems with multiple objectives, the multi-objective cuckoo search algorithm modifies the three ideal rules in the single-objective cuckoo algorithm, which are modified as follows (Nguyen et al., 2017):

(1) Each cuckoo lays K eggs at a time and places them in a randomly chosen nest, with the kth egg corresponding to the solution of the kth objective.

(2) Among randomly selected nests, the nest with the better egg quality is passed on to the next generation.

(3) Each nest has a probability of being discovered by the host bird based on the similarity or difference of the eggs, and a new nest containing K eggs is created, increasing the diversity of eggs by random mixing.

4.2 Large Neighborhood Search Algorithm

The Large Neighborhood Search (LNS) algorithm, first proposed by Shaw in 1998, embodies good applicability for solving LRP, and many modern heuristic algorithms refer to the idea of neighborhood search in their design (Shaw, 1998). In the process of neighborhood search, a variety of neighborhood search operators successfully extend the search range. The algorithm uses the destroy operator and the repair operator for the initial solution, searches its domain based on the neighborhood of the solution, determines whether there exists a neighborhood solution that is better than the current solution, if so, the neighborhood solution replaces the current solution, if not, the current solution is retained, and repeats the process until it obtains the optimal solution. There are many kinds of destroy operators and repair operators in the large neighborhood search algorithm, and different operators can be designed according to different problems, so according to the model of this paper, four kinds of destroy operators and one kind of repair operator are proposed.

4.3 Improved Multi-objective Cuckoo-Large Neighborhood Search Hybrid Algorithm

In order to be able to make the algorithm converge faster and improve the algorithm's search performance, this paper proposes an improved multi-objective cuckoo-large neighborhood search hybrid algorithm (IMOCS-LNS), which improves the original algorithm in the following five aspects:

(i) Chaotic initialization of populations helps to ensure the diversity and homogeneity of the initial population and provides a better basis for subsequent population iterations;
(ii) The introduction of non-linear inertia weights, which facilitate the global convergence of the algorithm;
(iii) Improved orientation of the bird's nest location when updating, where an elite strategy is introduced to move in the direction of the more optimal solution when updating;
(iv)The fixed discovery probability in the original algorithm is changed to a dynamically adjusted discovery probability, which facilitates traversing more solutions in the solution space;
(v) Optimized the way a bird's nest is generated when a new bird's nest is discovered by choosing a large neighborhood search algorithm to update the solution and produce a random solution.
(vi) An acceptance criterion for random solutions that cannot dominate the old solution is added, using the probability of accepting a poor solution in the simulated annealing algorithm as the acceptance probability.

4.3.1 Encoding and decoding of solutions

In this paper, we use natural number coding to represent the feasible solution individuals. Each individual contains one or more paths; each path consists of a set of affected sites and a distribution center, indicating that a distribution vehicle departs from that distribution center and completes emergency supplies distribution tasks in the order in which the affected sites are arranged. Assume that m affected sites are numbered as follows: $1,2,3,\ldots,m$; The first alternative distribution center has n_1 vehicles; the second alternative distribution center has n_2 vehicles; and the nth alternative distribution center has n_n vehicles. Then an individual feasible solution is represented by a sequence of m affected sites and $(n_1+n_2+\ldots+n_n)$ vehicle permutations. If there is no affected site number in front of a distribution center, it means that a vehicle will not be activated; if there are affected sites in front of a distribution center, it means that a vehicle will be activated to deliver emergency supplies to the previous affected sites in sequence. For example, given 9 affected sites and 3 alternative distribution centers, the labels 1-9 denote affected sites and 10-12 denote alternative distribution centers; alternative distribution center 10 has 2 vehicles;

alternative distribution center 11 has 1 vehicle; and alternative distribution center 12 has 2 vehicles. A feasible solution to the problem is given in Table 1. This feasible solution consists of three paths. Route 1 is followed by vehicle 1 from distribution center 10, which returns to distribution center 10 after completing the emergency supply distribution tasks for affected site 5, affected site 7, affected site 4, and affected site 1 in that order. Route 2 is a route from which the vehicle 1 of the distribution center 12 departs from the point and returns to the point after completing the distribution tasks of the emergency supplies for the disaster-stricken place 2, the disaster-stricken place 6, and the disaster-stricken place 8 in turn. Route 3 is followed by the vehicle 2 of distribution center 12 from this point to complete the task of distributing emergency supplies to affected site 3 and return to distribution center 12. From Table 1, we can also learn that ① no vehicle has been activated at distribution center 11, indicating that this distribution center is not open; ②only one of the two vehicles at distribution center 10 has been activated, and both vehicles at distribution center 12 have been activated.

Table 1
Coding table

Route 1：10-5-7-4-1-10					None	Route 2：12-2-6-8-12				Route 3：12-3-12			None
5	7	4	1	10	11	2	6	8	12	3	9	12	10

4.3.2 *Chaos initialization*

In the MOCS algorithm, the initial population is generated in a random way, which may lead to an uneven distribution of the population and may produce many inferior solutions, resulting in slow convergence and affecting the performance of the algorithm. Chaos is a state of motion with randomness obtained from deterministic equations, a non-linear phenomenon with the advantages of randomness, ergodicity, regularity, and sensitivity to initial conditions (Yu et al., 2022). Incorporating features of the chaos principle can effectively improve population diversity without losing individual randomness, providing a basis for further effective global search. In this paper, the Tent map function is used to initialize the population with chaos, and its function expression is as follows:

$$x_{t+1} = \begin{cases} 2x_t, & 0 \le x_t \le \frac{1}{2} \\ 2(1-x_t), & \frac{1}{2} < x_t \le 1 \end{cases} \tag{24}$$

According to the Tent map, the bird's nest i generates a column of chaotic points in the feasible domain according to the following steps:

Step1: Generate a random bird's nest x_n according to the above coding method (Lai et al., 2019).
Step2: Map each dimension $x_{nk}, k = 1,2,\dots,n$ on the location x_n of the nest to the interval [0,1] by the following formula (Shen et al., 2022):

$$cx_{nk} = \frac{x_{nk} - a_k}{b_k - a_k} \tag{25}$$

where$[a_k, b_k]$is the domain of definition of the kth dimensional variable x_{nk}.

Step3: Use the above equation to iterate M times to generate the chaotic sequence $cx_{nk}^1, cx_{nk}^2, \dots, cx_{nk}^M$ (Zhang et al., 2020a).
Step4: Map the points of the chaotic sequence back to the original space according to the following equation (Ai et al., 2023):

$$x_{nk}^s = a_k + cx_{nk}^s(b_k - a_k) \tag{26}$$

Step5: From these chaotic sequences we can obtain the column of chaotic points of x_n after the Tent mapping (Zhang et al., 2020b):

$$x_n^s = \left(x_{n,1}^s, x_{n,2}^s, \dots, x_{n,n}^s\right)^T, s = 1,2,\dots,M \tag{27}$$

4.3.3 *Non-linear inertia weights*

In the MOCS algorithm, the algorithm's optimization route is based on a combination of short-distance search and occasional long-distance exploitation in the search space by Lévy flights. Inertia weights can effectively balance the relationship between global exploration and local search so that the exploration ability in the first iteration of the algorithm and the development ability in the later iteration can be enhanced, thus improving the overall optimization-seeking ability of the algorithm. This paper invokes a non-linear inertia-decreasing strategy.

$$\omega^{(t)} = \omega_{min} + (\omega_{max} - \omega_{min})exp\left[-\frac{t^2}{(kT)^2}\right] \quad (28)$$

where t denotes the current number of iterations, k is the expansion constant used to adjust the curve, and T denotes the total number of iterations.

4.3.4 Undominated ordering

For multi-objective optimization problems, in general, the algorithm finds a Pareto optimal set of solutions rather than a single solution. No one solution in the Pareto optimal solution set can be said to be better than another, and the process is as follows:

(1) For each individual p set the following two parameters: the number of solutions n_p that dominate p and the set of solutions S_p that are dominated by p;
(2) Set $i = 1$ and find the individuals with $n_p = 0$, which are the individuals that are not currently dominated by any other solution, and classify them as the first level of non-dominated individuals in F_1;
(3) For each individual j in F_1, visit the set S_j where j is able to dominate individuals, and subtract n_k from 1 for each solution k in S_j, i.e., subtract n_k from 1 for the number of individuals dominating k;
(4) If $n_k - 1 = 0$, deposit k as the second level of non-dominating individuals in the set F_2;
(5) Repeat steps 3 and 4 until all the solutions in the solution set are grouped in some F_i.

4.3.5 Crowing distance calculation

After the non-possession sort, the allocation of crowding distances begins. Individuals in each tier are assigned to the crowding distances, which is calculated as follows (Yue et al., 2021):

(i) For the m-th objective function f_m on the i-th layer frontier, n is the number of individuals on that frontier. Initializing the distance of all individuals $d_m^j = 0$, where j denotes the j-th individual of the i-th frontier and d_m^j denotes the distances of the m-th objective function for the j-th individual in the i-th frontier (Sheikholeslami et al., 2017);

(ii) Sort all individuals in the i-th frontier by the value of the m-th objective function from the smallest to the largest (Zhao et al., 2022);

(iii) Assign the distance between the two individuals of the sorted boundary to infinity (Li et al., 2022), i.e., $d_m^1 = +\infty$ and $d_m^n = +\infty$;

(iv) For an individual from $j = 2$ to $j = n - 1$ its distance equation is as follows (Cui et al., 2023):

$$d_m^j = d_m^j + \frac{x_m^{j+1} - x_m^{j-1}}{f_m^{max} - f_m^{min}} \quad (29)$$

where x_m^{j+1} denotes the m-th objective function's value for the j+1st individual, x_m^{j-1} denotes the m-th objective function's value for the j-1st individual, f_m^{max} and f_m^{min} denote the maximum and minimum values in the m-th objective function, respectively.

(v)Sum the distance of the j-th individual in each objective function is the crowding degree of the j-th individual, as follows (Luo et al., 2023):

$$D_j = \sum_{m \in M} d_m^j \quad (30)$$

where M denotes the number of objective functions.

The meaning behind crowding distance is based on computing the Euclidean distance between individuals in each layer of the pareto frontier in an m-dimensional space of m objective functions, where two individuals at the boundary of each layer are assigned an infinite distance, so that the two solutions are always selected.

With the introduction of crowding distance, everyone in the set has two properties, one being the crowding distance D_i and the other being the non-dominance hierarchy F_i . Then there is the following definition: if the conditions $F_i < F_j$ or $F_i = F$ and $D_i > D_j$ are satisfied, then the i-th individual is better than the j-th individual (Meng et al., 2019). This means that when the levels are different, the solution at the lower level is preferred; if the levels are the same, the solution with the greater crowding is preferred. Since solutions with small crowding distances indicate a denser distribution of solutions, and conversely, solutions with large crowding distances indicate a more dispersed distribution of solutions, introducing this can eliminate the relatively dense set of solutions, increase the diversity of solutions and the uniformity of their distribution, and obtain a uniformly distributed set of pareto-optimal solutions.

4.3.6 Step control

In the MOCS algorithm, α denotes the step size, which is composed of a step control factor and the difference between a random solution in the solution space and the current solution. The aim is to accommodate the difference between the qualities of the solutions and to simulate the characteristic that similar solutions are not easily found, so that its step size is also proportional to the difference between the two solutions. In order to be able to bring the solution closer to the solution of good quality, the IMOCS-LNS algorithm designed in this paper uses an elite strategy in terms of step size, i.e., when randomly selecting a solution, the solution in the pareto frontier is selected for learning, and thus a good direction is obtained, so that the step size α can be expressed as:

$$\alpha = \alpha_0\left(x_i^{(t)} - x_m^{(t)}\right) \tag{31}$$

where $x_m^{(t)}$ denotes the solution with the largest crowding in the solution set of the t-th pareto frontier of the iteration t, and $x_i^{(t)}$ denotes the current solution at iteration t. Therefore, in the IMOCS-LNS algorithm, the search path of the algorithm and the nest location update strategy are as follows:

$$x_i^{(t+1)} = \omega^{(t)} x_i^{(t)} + \alpha \oplus Lévy(\beta), i = 1,2,3, \dots, n \tag{32}$$

$$\omega^{(t)} = \omega_{min} + (\omega_{max} - \omega_{min}) exp\left[-\frac{t^2}{(kT)^2}\right] \tag{33}$$

$$\alpha = \alpha_0\left(x_i^{(t)} - x_m^{(t)}\right) \tag{34}$$

where α_0 is the step control variable and $Lévy(\beta)$ is the random step size obeying the distribution of $Lévy$, i.e:

$$Lévy \sim u = t^{-1-\beta}, 0 \le \beta \le 2 \tag{35}$$

In the IMOCS-LNS algorithm, the complete Lévy flight formula is as follows (Sankararao & Yoo, 2011):

$$s = \alpha_0\left(x_i^{(t)} - x_m^{(t)}\right) \oplus Lévy(\beta) \sim 0.01 \frac{u}{v^{\frac{1}{\beta}}}\left(x_i^{(t)} - x_m^{(t)}\right) \tag{36}$$

where u and v follow a normal distribution and satisfy $u \sim N(0, \sigma_u^2)$,$v \sim N(0, \sigma_v^2)$, Γ is the standard cardinal distribution.

$$\sigma_u^2 = \left\{\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\right\}^{1/\beta}, \sigma_v^2 = 1 \tag{37}$$

4.3.7 Probability of discovery

In the MOCS algorithm, the discovery probability p_a is a very important parameter. An appropriate discovery probability is conducive to increasing the diversity of solutions and thus finding the global optimal solution quickly. However, in the MOCS algorithm, the value of p_a is often taken as a fixed value of 0.25, which is obviously not conducive to global search, so this paper replaces the fixed discovery probability with a dynamically adjusted probability, as in Eq. (38)：

$$p_a^t = p_a^{max} - \beta(p_a^{max} - p_a^{min}) \log_T t \tag{38}$$

where p_a^t is the probability that the i-th egg is found, and $p_{min}$and p_{max} are the lower and upper bounds of the probability of discovery, respectively. A random number $r \in [0,1]$ is generated and if $p_a^t \ge r$, the nest position is changed as in the next section, otherwise, the nest position is not changed.

4.3.8 Stochastic solution generation

In constituting the stochastic solution, this paper adopts the large neighborhood search algorithm to improve the current solution by expanding the search space through the destruction operator and the repair operator. The destruction operator is randomly selected when choosing the operator to destroy the current solution to form the destruction pool, and then the repair operator is subsequently selected to insert the nodes in the destruction pool into the current solution as it goes to form the new solution.

(1) Destroy operator

Remove φ nodes from the current solution and put them into the destruction pool. The size of φ affects the degree of brokenness of the solution; too big or too small will make the algorithm less efficient in finding the best. In general, φ is taken according to Eq. (39). The destroy operator used in this paper is as follows:

$$\varphi = \left[\frac{N}{8} : \frac{N}{4}\right] \tag{39}$$

① Distribution Center Shutdown

Among the selected distribution centers, one is randomly selected to be closed, and all demand points that are under the responsibility of this distribution center will be eliminated and put into the destruction pool.

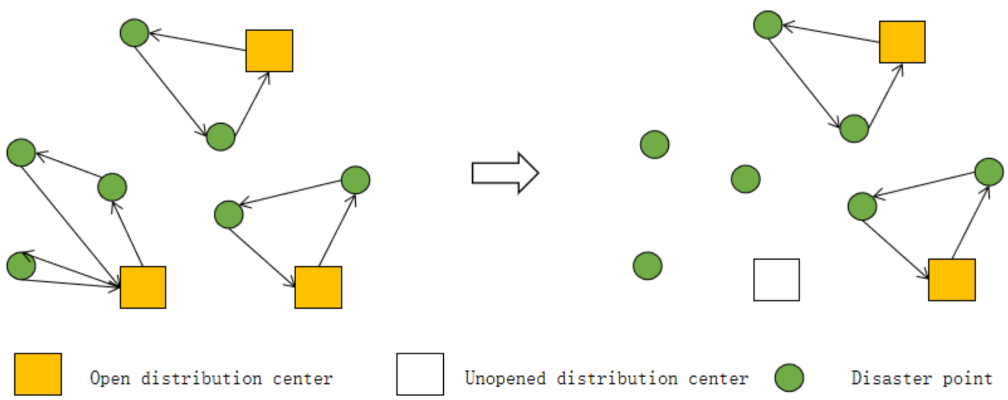

Fig. 3. Distribution Center Closure Schematic

② Distribution center open

Among the unselected distribution centers, one is randomly selected to be open and the φ nodes closest to that distribution center are selected to be removed from the solution and put into the destruction pool.

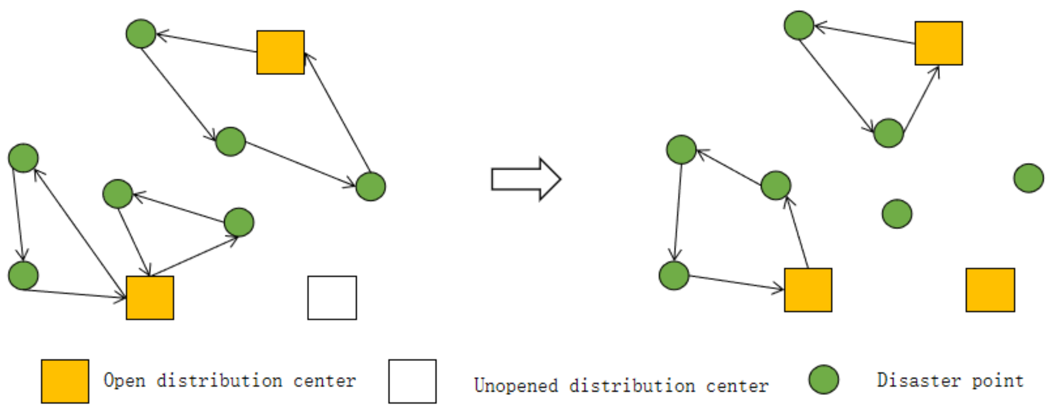

Fig. 4. Distribution Center Closure Schematic

③ Randomly eliminating the affected points

In the current solution, φ affected points are randomly selected to eliminate them into the destruction pool.

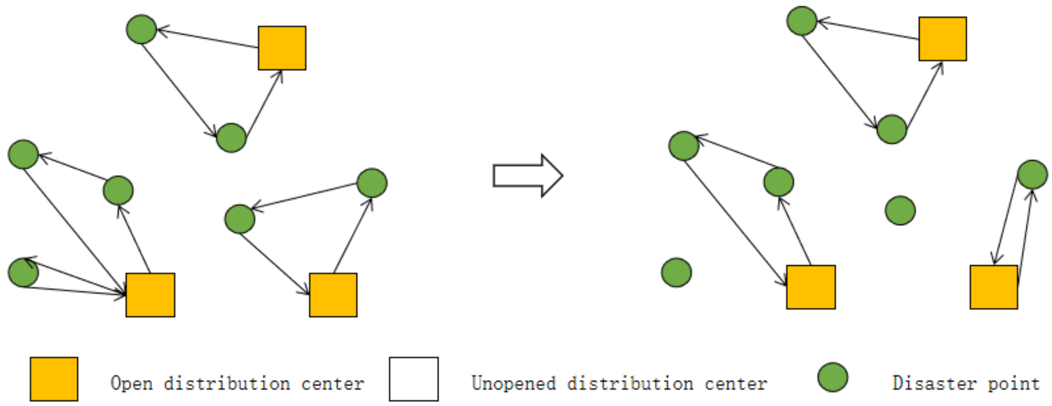

Fig. 5. Distribution Center Closure Schem

④ Randomly Remove Paths

In the current solution, a path is randomly selected, the route is removed, and the affected points on that route are put into the destruction pool.

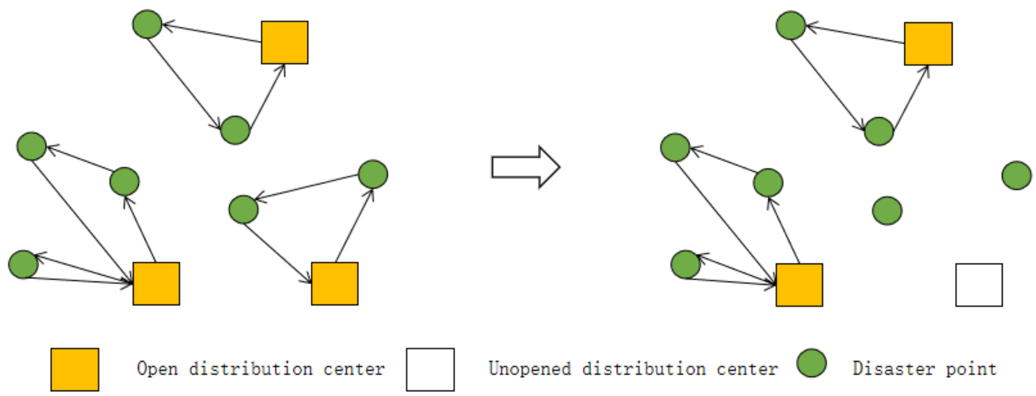

Fig. 6. Diagram of the immediate deletion path

(2) Repair operator

After the destroy operator removes some nodes from the current solution, the repair operator is needed to reinsert the nodes in the destroy pool into the current solution to form a new neighborhood solution.

① Random insertion

Randomly insert the affected points in the destruction pool into the feasible positions until the number of nodes in the destruction pool is 0. Although it may produce poorer solutions, it can increase the diversity and randomness of the solutions to avoid falling into the local optimum.

4.3.9. Solution acceptance criterion

If the random solution can dominate the current solution, then the random solution replaces the current solution, and if the random solution cannot dominate the current solution, then the random solution is accepted with the probability of accepting the poor solution based on the simulated annealing algorithm proposed by Sankarao and Yoo (2011) with the following formula:

$$p = \prod_{i=1}^{n} \exp\left[\frac{-\left(f_i^{new} - f_i^{old}\right)}{T}\right] \tag{40}$$

$$T^i = \alpha T^{i-1} \tag{41}$$

where T^i denotes the cooling temperature from iteration to generation i. Setting the initial temperature as T_0 and the cooling coefficient as α and i is the number of iterations. In summary, the flow of the hybrid IMOCS-LNS algorithm is as follows:

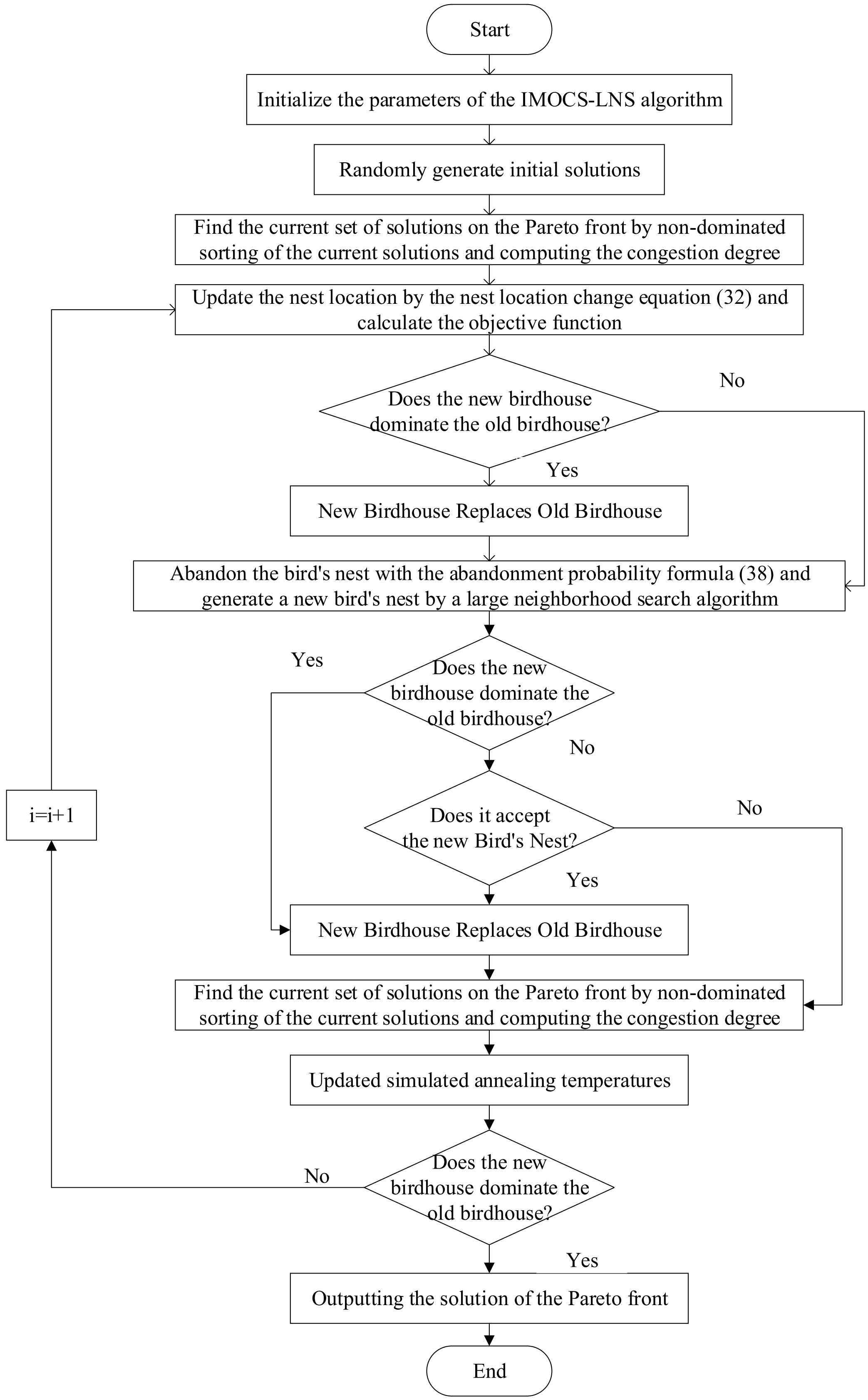

Fig. 7. Flowchart of the improved multi-objective cuckoo algorithm

5. Example analysis

In this paper, data from Christofides69 in the standard dataset of LRP problems proposed by Barreto et al. were chosen for testing (Barreto et al., 2007). This dataset contains a total of 75 groups of data on the affected sites and 10 groups of data on alternative distribution centers, including X and Y coordinates of the affected sites and alternative distribution centers, demand, and capacity of the distribution centers. The following table shows the information on the coordinates of the alternative distribution centers, some of the coordinates of the affected sites, and the information on the demand. Table 1 shows the data for the 10 groups of alternative distribution centers and Table 2 shows the data for the 10 groups of affected sites.

Table 1
Information on alternative distribution centers

No.	X	Y	Capacity
A1	44	41	300
A2	56	7	300
A3	40	72	300
A4	62	12	300
A5	46	5	300
A6	25	75	300
A7	69	22	300
A8	69	61	300
A9	51	67	300
A10	33	73	300

Table 2
Information on the affected site

No.	X	Y	Demand
B1	22	22	18
B2	36	26	26
B3	21	45	11
B4	45	35	30
B5	55	20	21
B6	33	34	19
B7	50	50	15
B8	55	45	16
B9	26	59	29
B10	40	66	26

5.1 Parameter setting

The algorithm was implemented using MATLAB 2017a programmed on a 64-bit machine on a Win10 system with 8G of memory, a population size of 200, and a maximum number of 300 iterations, with the specific parameters shown in Table 3 and Table 4.

Table 3
Algorithm parameter settings

Algorithms	Parameter settings
IMOCS	$P_a^{min} = 0.1$, $P_a^{max} = 0.9$, $\omega_{min} = 0.3$, $\omega_{max} = 0.9$
NSGA-II	$P_m = 0.5$, $P_c = 0.1$

Table 4
Setting of other parameters

Basic parameters	Value of parameters	Basic parameters	Value of parameters
m	10	S	5 units/min
n	75	C_o	RMB4/kilometre
AC_m	18000	G_o	RMB 1000/vehicle
V_o	45 km/h	h	1 RMB/minute/unit
Q_m	300 units	R	16
Q_o	60 units	α	0.88
K_{mo}	7	β	0.88
B_o	200 km	λ	2.25
LT_n	3 hours		

5.2 Analysis of calculation results

By comparing the results of the IMOCS-LNS, MOCS and NSGA-II algorithms for solving the model, the total system response time obtained by the IMOCS-LNS algorithm is somewhat longer, 1.41 hours and 3.57 hours longer than that obtained by the other two algorithms, respectively. However, the number of distribution centers being selected using this algorithm is less than that obtained by the other two algorithms, and the total cost is lower. In addition to these, the level of psychological panic of the people in the affected places obtained with the IMOCS-LNS algorithm is the lowest. This is very much in line with humanitarianism, as the level of people's psychological panic has a direct impact on the harmonious development of society, so from one point of view, the results obtained by this algorithm have a strong advantage. The IMOCS-LNS algorithm also yields the highest material utilization rate of the three algorithms, reducing material waste. In summary, although the IMOCS-LNS algorithm is at a disadvantage in terms of time compared to the other two algorithms, the results are better in terms of total cost of consumption, the number of distribution centers opened, the panic level of people in the affected areas, and the material utilization rate, so it is evident that the improved algorithm in this paper solves the model better.

Table 5
Algorithm comparison results

Algorithms	Number of distribution centers selected	Time	Cost	level of psychological panic	Utilization of materials
IMOCS-LN	6	95.71	160731.74	1246.36	75.78%
MOCS	6	94.3	161623.67	1250.14	75.78%
NSGA-II	8	92.14	199246.33	1250.42	56.83%

The results of the IMOCS-LNS algorithm to solve the model are shown in the table below. The distribution centers activated are 1, 2, 5, 6, 8 and 9, with 6 transporters, 4 transporters, 6 transporters, 5 transporters, 2 transporters and 6 transporters respectively. The total time spent on distribution is 95.71 hours, and the total cost is $160,731.74, the psychological risk perception of the people in the affected areas is 1,246.36, and the material utilization rate is 75.78%. The distribution roadmap is shown in Fig. 8.

Table 6
Model’s results

DC	Route of vehicle distribution	Time	Cost	level of psychological panic	Utilization of materials
A1	A1→B26→B7→B8→A1 A1→B17→B3→B6→A1 A1→B4→B2→A1 A1→B27→B30→B29→A1 A1→B16→B23→B1→A1 A1→B34→B13→B12→A1	95.71	160731.74	1246.36	75.78%
A2	A2→B71→B20→B37→B15→A2 A2→B5→B45→B57→A2 A2→B47→B48→B36→A2 A2→B70→B60→A2				
A5	A5→B61→B22→B64→A5 A5→B62→B73→B63→B68→A5 A5→B43→B56→A5 A5→B28→B69→A5 A5→B21→B33→A5 A5→B74→B41→B42→A5				
A6	A6→B39→B9→B25→A6 A6→B31→B55→B18→A6 A6→B50→B44→A6 A6→B40→A6 A6→B32→B24→B49→A6				
A8	A8→B59→B54→B52→A8 A8→B14→B19→A8				
A9	A9→B35→B46→A9 A9→B11→B53→A9 A9→B38→B10→B72→A9 A9→B66→B65→A9 A9→B58→B51→A9 A9→B67→B75→A9				

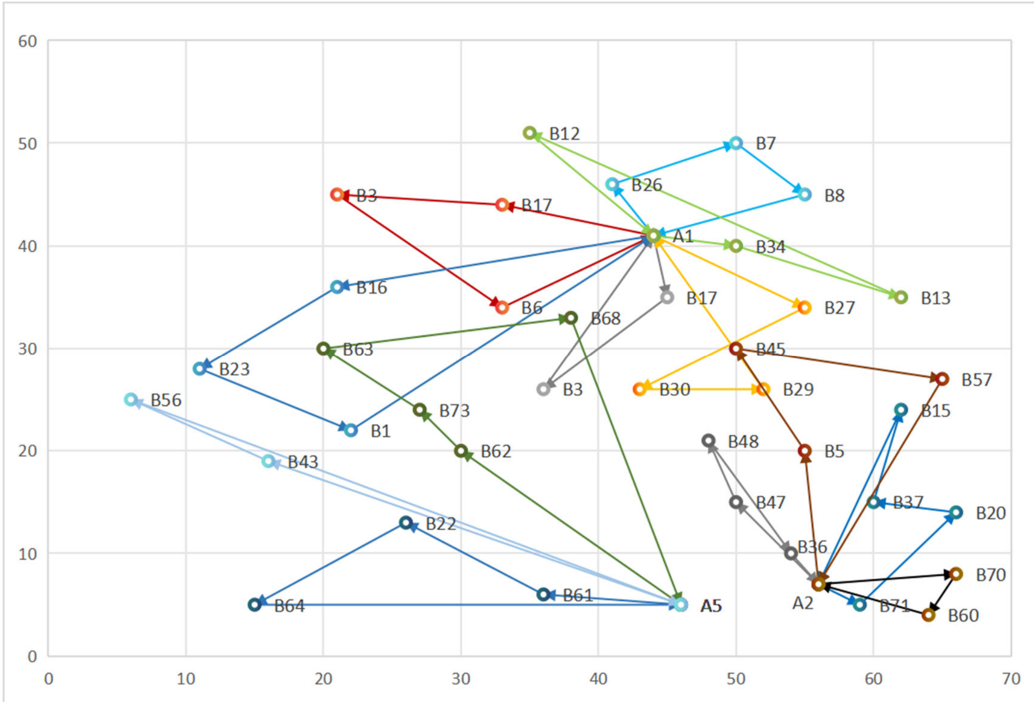

Fig. 8. Model's result

5.3 Case analysis of different scales

In the dataset, 4 groups of data with less than 30 nodes are randomly selected as small scale cases, 5 groups of data with less than 70 nodes and more than 30 nodes are selected as medium scale cases, and 6 groups of data with more than 70 nodes are selected as large scale cases to be analyzed, and the results are shown in the table below:

Table 7
Analysis of small-scale examples

Case name	MOCS-LNS		MOCS		NSGA-II	
	panic level	cost	panic level	cost	panic level	cost
Srivastava86（8×2）	**130.5**	**34015.72**	137.9	45161.93	135.68	47004.45
Perl83（12×2）	**199.2**	**45076.77**	199.6	45336.36	199.6	45318.95
Gaskell67（21×5）	**340.6**	**147663.3**	363.9	921584	356.3	754198.8
Gaskell67（22×5）	**374.3**	**241711.3**	405.2	364499.1	390.2	308818.5

Table 8
Analysis of medium-sized examples

Case name	MOCS-LNS		MOCS		NSGA-II	
	panic level	cost	panic level	cost	panic level	cost
Min92（27×5）	**460.98**	**395360.3**	490.99	622697.5	475.11	570625.7
Gaskell67（29×5）	**514.04**	**994944.7**	574.95	1177484	566.37	1052492
Gaskell67（32×5）	**556.57**	**940534**	567.65	995770	570.37	1305185
Gaskell67（36×5）	**652.23**	**169553**	655.49	171775.9	655.25	171884.9
Christofides69（50×5）	**932.19**	**190291.5**	955.27	200728.7	932.74	205477.2
Perl83（55×15）	**956.65**	**257969**	962.17	269042.1	958.11	294496.9

Table 9
Analysis of large-scale examples

Case name	MOCS-LNS		MOCS		NSGA-II	
	panic level	cost	panic level	cost	panic level	cost
Perl83（85×7）	**1475.29**	**293878**	1476.89	294759.5	1477.34	294909.2
Christofides69（100×10）	**1951.36**	**300978.2**	2265.37	402013.6	2009.34	319150.8
Or76（117×14）	**2445.06**	**443228.7**	2519.9	452887.8	2550.88	457439.6
Min92（134×8）	**2501.09**	**868607.5**	2566.62	894726.7	2544.66	900639.7
Daskin95（150×10）	**3214.41**	**1407175**	3261.2	1483080	3240.68	1567094
Perl83（318×4）	**5916.81**	**1225582**	6012.79	1231179	5994.96	1235916

In the four objective functions chosen in this paper, after an emergency, the decision maker should firstly take the panic of the people in the affected area as the primary consideration from the humanitarian point of view, and the panic degree of the people in the affected area is determined by the delivery time of the materials, in order to let the table show the results more clearly, only the panic degree of the people in the affected area is presented in the two objectives; the material utilization rate can reflect the warehouse's status, a high material utilization rate indicates that the number of open warehouses is appropriate, and vice versa, it indicates that the number of open warehouses is inappropriate, resulting in a waste of costs, however, in the total consumed costs, there are not only the costs related to warehouses, but also the delivery costs and the penalty costs, therefore, in order to be able to more intuitively see the cost of costs, the cost is selected as the second evaluation index in these two objectives. From Tables 6, 7 and 8, it can be concluded that the IMOCS-LNS algorithm produces significantly better results than the MOCS algorithm and the NSGA-II algorithm in solving cases of different sizes and can generate solutions with less panic and cost. Therefore, the IMOCS-LNS algorithm has a better optimal search in solving the site selection-path problem and is suitable for this problem.

6. Conclusions and future research

Firstly, in this paper, a model is developed for distribution centers for emergency supplies location - routing optimization with the objectives of system response time, total cost of consumption, psychological panic of people in the disaster-stricken area, and material utilization rate. The total response time of the system includes distribution time and loading and unloading time. Total consumption costs include distribution costs, distribution center operating costs and penalty costs. And psychological the panic level of people at the demand point is expressed by the psychological risk perception function based on the prospect theory, which can better quantify the panic psychology of disaster victims.

Subsequently, an improved hybrid multi-objective cuckoo-large neighborhood search algorithm was designed, introducing Tent mapping, nonlinear inertia weights, dynamically adjusted discovery probabilities and congestion distances into the algorithm. After the solution is discarded, a new solution is generated using a large-scale neighborhood search algorithm. When the generated new solution fails to dominate the old one, the probability of accepting a poor solution based on the simulated annealing algorithm is used as an acceptance criterion.

Finally, the LRP standard example is selected as the model data and solved by the IMOCS-LNS algorithm, which shows that the results of this algorithm are only slightly worse than the other two algorithms in terms of the system response time and better than the other two algorithms in terms of the total cost, the psychological panic of the people in the affected area, the material utilization rate, and the number of distribution centers selected. The results of this algorithm are able to minimize the total cost and the psychological fear of the people in the affected area, as well as maximize material utilization. In addition to this, cases of different sizes were brought into the model and solved by the algorithm, and it was found that the results obtained were also better than the other two algorithms. This shows that the algorithm is effective in solving the model and can provide decision-makers with a basis for decision-making. However, the paper only investigates the location-routing optimization model for emergency supply distribution centers under certain parameters, but in the actual post-disaster relief process, the demand and road capacity vary randomly, so future research can explore the location-routing optimization of emergency supply distribution centers under uncertain information on this basis.

Conflicts of interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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Data availability statement

All data generated or analyzed during this study are included in this paper.

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