RESEARCH ARTICLE

Multi-Objective Optimization for Emergency Material Dispatch with Backup Centers in Earthquake-Induced Distribution Failures Using Improved NSGA-II

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Abstract

Earthquakes pose significant risks to infrastructure and supply chains, making the timely and fair distribution of emergency relief materials crucial for reducing casualties and economic losses. This study addresses the challenge of optimizing emergency material dispatch under scenarios where distribution centers fail due to earthquake damage, with the aim of improving both the timeliness and fairness of resource allocation during post-disaster recovery. A multi-objective optimization model is developed, which integrates distribution center failures and the activation of backup centers. The model minimizes total dispatch time, maximizes fairness in supply distribution, and reduces unmet demand. The solution is based on a second-generation non-dominated sorting genetic algorithm (NSGA-II), which is tailored to solve the proposed scheduling problem. Case studies, including simulations based on the 2008 Wenchuan earthquake, demonstrate that activating alternative distribution centers when primary centers fail can significantly improve delivery efficiency, fairness in material distribution, and reduce unmet demand. The improved NSGA-II algorithm outperforms the basic NSGA-II in terms of both solution quality and diversity. The findings underscore the importance of optimizing emergency logistics under failure scenarios to improve rescue efficiency and fairness. The model offers a scientifically-grounded approach for decision-making bodies to enhance post-disaster logistics operations, ensuring timely and equitable distribution of resources.

Keywords: emergency material dispatch, distribution center failure, material distribution fairness, non-dominated sorting genetic algorithm.

1 Introduction

Among the various forms of natural disasters, earthquakes are notorious for their suddenness and destructive power, causing profound impacts on human society within a short timeframe. Therefore, the rapid delivery of humanitarian relief supplies after an earthquake is particularly urgent. How to reduce casualties and economic losses caused by natural disasters is an issue that requires urgent

Academic Editor:
Feng Ding

Submitted: 07 December 2025
Accepted: 10 January 2026
Published: 21 April 2026

Vol. 3, **No.** 2, 2026.
10.62762/TIS.2025.202079

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Citation
Li, F., & Lv, J. (2026). Multi-Objective Optimization for Emergency Material Dispatch with Backup Centers in Earthquake-Induced Distribution Failures Using Improved NSGA-II. *ICCK Transactions on Intelligent Systematics*, 3(2), 108–125.

research and resolution. However, the intense destructive force of earthquakes inflicts significant damage on geospatial infrastructure. Earthquakes not only directly destroy transportation networks like roads but also damage critical material storage centers, rendering core distribution hubs within post-earthquake emergency response systems inoperable. This not only significantly increases material transportation time and delivery complexity but also compromises the fairness of material supply, thereby negatively impacting rescue efficiency and effectiveness. Therefore, researching how to optimize emergency logistics scheduling under scenarios where emergency relief material storage and transportation infrastructure fails becomes particularly important. This ensures rapid material dispatch after an earthquake, thereby reducing loss of life and property.

Research on the theoretical framework of emergency logistics can be traced back to the 1970s, pioneered by foreign scholars [1]. In recent years, with the increasing frequency of emergencies, research trends in the field of emergency logistics have also grown rapidly. Scholars have conducted systematic studies on emergency material dispatch issues from various perspectives, including demand urgency and material satisfaction [2], multi-stage emergency material scheduling [3], and post-disaster fuzzy demand [4]. Emergency material dispatch constitutes a critical component of post-disaster relief efforts. Faster delivery of supplies to affected areas significantly enhances the effectiveness of emergency rescue operations. The primary focus of emergency material dispatch research lies in coordinating the distribution of various materials required at disaster sites based on post-disaster needs.

Against the backdrop of natural disasters and public health emergencies, emergency material dispatch faces significant variations in demand distribution, transportation conditions, and supply chain structures across different scenarios. Ergün et al. [5] developed a game-theoretic model for emergency logistics planning tailored to earthquake scenarios. Wang [6] proposed a two-stage stochastic mixed-integer programming model that balances cost considerations with penalties for unmet demand while accounting for demand randomness, demonstrating strong practical applicability. Pan et al. [7] employed robust optimization methods, integrating multimodal transportation and collaborative platforms, to develop a multi-objective optimization model. This model aims to enhance the efficiency of post-disaster material distribution, reduce costs, and strengthen the system's adaptability to uncertainty. Chen [8] compared multi-material disaster relief optimization models focused on cost minimization versus demand satisfaction maximization. The study prioritized demand satisfaction as the primary objective, emphasizing the necessity of improving fairness and efficiency in post-disaster relief efforts.

As disaster scenarios become increasingly uncertain, traditional deterministic optimization models struggle to handle complex environments. Consequently, scholars have introduced various optimization techniques to establish different models. Yu et al. [9] proposed a multi-objective, multi-period mixed-integer nonlinear programming model for resource allocation in humanitarian logistics, incorporating three key metrics: efficiency, effectiveness, and equity. Wang et al. [10] developed a multi-objective location-allocation model that simultaneously considers timeliness and fairness, employing the MOHH optimization framework to solve this complex model. Sun et al. [11] proposed a two-stage distributed robust optimization model incorporating 3D printing technology to enhance the flexibility and robustness of post-disaster material production and distribution through facility siting and resource pre-positioning. Sentia et al. [12] conducted a systematic review of diverse methodologies in emergency logistics over recent years, noting the rapid increase in the use of mixed-integer programming, genetic algorithms, multi-objective optimization, and simulation methods for complex scheduling problems. They emphasized that future research must integrate real-time data to enhance model practicality. Carnero Quispe et al. [13] found that utilizing temporary facilities for flexible scheduling in emergency scenarios can effectively improve system responsiveness, representing a key direction for future facility planning.

For emergency supply dispatch models, researchers have designed various algorithms to solve them. Sun and Liu [14] employed an improved artificial bee colony algorithm to locate emergency logistics centers during sudden disasters. Ke and Bookbinder [15] employed a two-stage robust approach to evaluate the balance between emergency logistics risks and costs. Yin and Lu [16] utilized a CA "cluster-head-path-quadratic" heuristic algorithm to optimize the "one-to-many" dispatch problem under emergency conditions. Wang et al. [17] designed particle swarm optimization and variable neighborhood search algorithms to solve a time-cost-based mixed-integer programming model. For the multi-objective scheduling model in this study, a second-generation non-dominated genetic algorithm was selected to solve the emergency material multi-objective scheduling model. Building upon the genetic algorithm, introducing a metric termed "congestion level" to maintain population diversity and employing a hierarchical sorting strategy to ensure solution convergence and diversity [18] enhances the flexibility of model solution and increases the model's scalability.

Research on facility failure scenarios can be traced back to Drezner [20], whose p-center and p-median models were the first to incorporate facility failure factors. Snyder and Daskin [19] developed a reliability p-median facility location model accounting for failures to address supply chain location problems considering facility failures. Berman et al. [21] developed a mixed-integer programming model demonstrating that optimal location strategies strongly depend on facility failure probability. Zhang et al. [22] established location models under failure scenarios with varying failure probabilities, separately addressing cost minimization and coverage maximization objectives.

The location of emergency facilities directly impacts the stability, response speed, and coverage breadth of emergency supply chain structures. Wang et al. [23] reviewed the evolution of facility location problems in emergency logistics, systematically organizing research findings and application scenarios across different models. Zhang et al. [24] proposed a multi-objective stochastic programming model that accounts for facility and road reliability while integrating inventory and transportation decisions. This model aims to optimize facility location, inventory allocation, and transportation routes in disaster relief logistics, thereby enhancing the overall system's reliability and resilience. Wang et al. [25] proposed a distributed robust optimization model to optimize the location allocation of backup warehouses and the planning of disaster relief material distribution networks under uncertainty in demand and facility locations. Sheikholeslami and Zarrinpoor [26] constructed a three-tier emergency supply chain model for perishable goods during epidemics, simultaneously considering multiple factors to demonstrate how to design operational emergency supply chains during public health emergencies. Sun and Liao [27] pointed out that supply chain network structure, supply base diversity, and transportation flexibility are key factors in mitigating risks and enhancing supply chain reliability during public health events.

In summary, to address the issues and shortcomings identified in the literature review on emergency supply scheduling while aligning with practical requirements, this study constructs a material dispatch model aimed at minimizing total delivery time, maximizing distribution fairness, and minimizing unmet demand at disaster sites under the scenario of distribution center failure. An NSGA-II algorithm tailored for this model is designed to solve the problem, yielding constraint-satisfying Pareto frontier solutions. The model's effectiveness is validated through case studies, providing valuable insights for government emergency decision-making bodies to enhance rescue efficiency and fairness.

The rest of this paper is organized as follows: Section 2 describes the problem and establishes the mathematical model. Section 3 introduces the improved NSGA-II algorithm. Section 4 presents a case study based on the Wenchuan earthquake. Finally, Section 5 concludes the paper and suggests future research directions.

2 Problem Description and Model Development

2.1 Problem Description

Following an earthquake disaster, emergency relief supplies at distribution centers near the affected area are limited. During this period, if a distribution center becomes inoperable and cannot be repaired in time due to factors such as aftershocks, an alternate distribution center must be activated to provide services to disaster sites.

Against this backdrop, an emergency supply scheduling model is developed to activate alternative distribution points when primary distribution centers fail. First, under post-disaster conditions of supply shortages, the model addresses the anxiety of affected populations while actively responding to disaster-stricken areas' needs. It maximizes the timeliness and fairness of emergency supply distribution while minimizing the unmet demand at affected locations. Based on this, a multi-objective emergency supply scheduling model grounded in mixed-integer programming is established. This model accounts for distribution center failures and the activation of backup centers, capacity

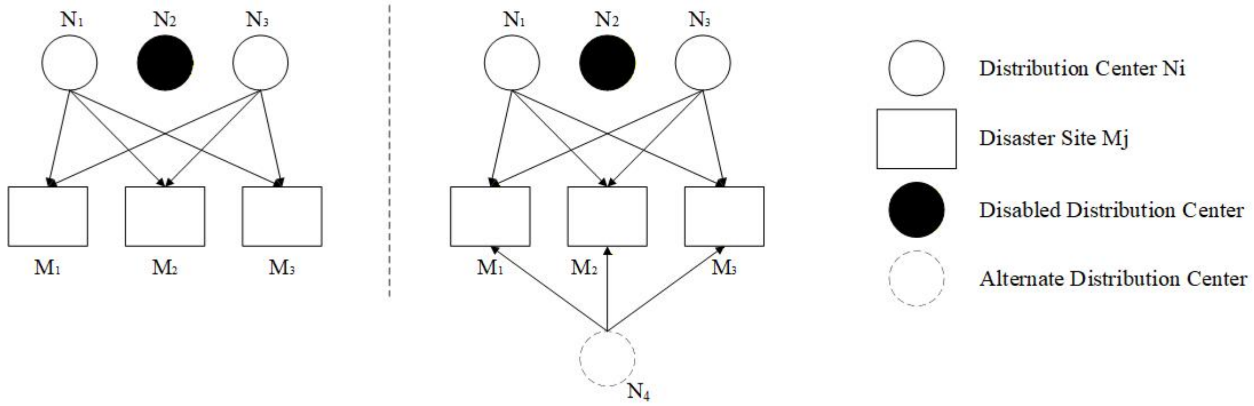

Figure 1. Scheduling diagram for adding alternative distribution centers in failure scenarios.

constraints at both primary and backup centers, and the interdependent relationships between supply and demand at each node. The goal is to minimize losses caused by disasters. The multi-objective emergency supply allocation problem under distribution center failures, incorporating the activation of backup centers, is illustrated in Figure 1.

2.2 Model Assumptions

The following assumptions are made regarding the research questions addressed in this paper:

(1) The demand volume at each demand point is known and fixed; the total supply of emergency materials at the onset of the disaster is less than the total demand at the affected points;

(2) Distribution centers are homogeneous, differing only in capacity; distribution centers may become inoperable due to earthquake damage, and the failure of each distribution center is independent; when a distribution center fails and cannot be repaired in time, it cannot serve any affected point, at which point an alternative distribution center is activated to serve the affected point;

(3) This study considers only vehicle-based material transportation; roads connect distribution centers, backup distribution centers, and affected locations, with known distances between each distribution center and affected location; the number of dispatchable vehicles is sufficient;

(4) It is assumed that the logistics dispatch system can obtain real-time information when distribution centers fail, allowing decisions to be made based on the latest available data.

Based on the above problem description and assumptions, a mathematical model is formulated in the next subsection. To clearly present the model, the main symbols used throughout this paper are first defined as Table 1.

2.3 Model Development

Once an emergency distribution center is damaged by an earthquake, it will temporarily lose its ability to fulfill distribution tasks and remain inoperable for an extended period. Therefore, researching rational material allocation schemes under distribution center failure scenarios better aligns with practical realities. The primary consideration is the timeliness of distributed supplies: shorter delivery times yield greater benefits for disaster relief efforts. Thus, minimizing the total emergency distribution time is established as the first decision objective.

$$\min Z_1 = \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{p_{rs} \in P_{rs}} x_{ij}^{p_{rs}} y_i^{p_{rs}} t_{ij} \tag{1}$$

The meaning of variables in the formula is shown in Table 1, and so do the subsequent formulas.

Considering the loss of satisfaction at disaster sites due to distribution center failures and initial shortages of supplies, the quantity of emergency resources may not simultaneously meet the demands of all sites. Therefore, ensuring fairness across each demand site becomes paramount. This paper employs the variance in satisfaction across all disaster sites to measure the fairness of supply distribution. A smaller variance indicates a fairer distribution plan. Thus, minimizing the variance in supply satisfaction across all disaster sites is established as the second decision objective.

$$\min Z_2 = \frac{\sum_{j=1}^{m} (\mu_j - \overline{\mu})^2}{m-1} \tag{2}$$

Table 1. Description of model symbols.

Symbol	Description
$N = \{i \mid i = 1, 2, 3 \ldots, n\}$	Emergency distribution center cluster
$M = \{j \mid j = 1, 2, 3 \ldots, m\}$	Disaster site cluster
$L = \{i^* \mid i^* = 1, 2, 3 \ldots, l\}$	Alternative distribution center cluster
p	Probability of a single distribution center failure
p_s	Probability of simultaneous failure of s distribution centers
S	Maximum possible number of failures at the distribution center
W_i	Capacity of distribution center i
W_{i^*}	Capacity of alternative distribution center i^*
Q_j	Supply requirements for disaster site j
d_{ij}	Distance from distribution center i to disaster site j
d_{i^*j}	Distance from alternative distribution center i^* to disaster site j
α_{ij}	Road condition coefficient from distribution center i to disaster site j
α_{i^*j}	Road condition coefficient from alternative distribution center i^* to disaster site j
v	Vehicle speed
n_{ij}	The amount of supplies delivered from distribution center i to disaster site j
n_{i^*j}	The amount of supplies delivered from alternative distribution center i^* to disaster site j
μ_j	Satisfaction level at disaster site j
$\overline{\mu}$	Average satisfaction across all disaster sites
λ	Lowest level of satisfaction with relief supplies at disaster sites
U_j	Unmet demand at disaster site j
p_{rs}	A failure scenario consisting of s failed distribution centers
P_{rs}	The set of all failure scenarios p_{rs}
$y_i^{p_{rs}}$	0-1 variable, in scenario p_{rs}, distribution center i is 0 if it fails and 1 if it remains operational.
$x_{ij}^{p_{rs}}$	0-1 variable, indicating 1 when the distribution center i supplies materials to the disaster site j under the scenario p_{rs}, and 0 otherwise.
$h_{i^*}^{p_{rs}}$	0-1 variable, in scenario p_{rs}, alternative distribution center i^* is 0 if it fails and 1 if it remains operational.
$x_{i^*j}^{p_{rs}}$	0-1 variable, indicating 1 when the alternative distribution center i^* supplies materials to the disaster site j under the scenario p_{rs}, and 0 otherwise.

To ensure maximum coverage of disaster-affected locations under scenarios with limited resources and distribution center failures, a new objective function is introduced to minimize the unmet demand ratio across all affected points. This enhances the robustness and effectiveness of the entire emergency logistics system. To this end, drawing inspiration from Rath and Gutjahr [28], this study introduces the concept of the unmet demand ratio, defined as the percentage of unmet demand across all demand points relative to the total demand. This objective function aims to minimize the unmet demand ratio, with the specific formula as follows.

$$\min Z_3 = \frac{1}{\sum_{j=1}^{M} Q_j} \sum_{p_{rz} \in P_{rz}} \sum_{j=1}^{m} \Big(Q_j - \sum_{i=1}^{n} n_{ij} x_{ij}^{P_{rz}} y_i^{P_{rz}} - \sum_{i^*=1}^{l} n_{i^*j} x_{i^*j}^{P_{rz}} h_{i^*}^{P_{rz}} \Big) \tag{3}$$

The model constraints are as follows:

$$t_{ij} = \frac{d_{ij}}{v}, i \in N, j \in M \tag{4}$$

$$t_{i^*j} = \frac{d_{i^*j}}{\alpha_{i^*j} \nu}, i^* \in L, j \in M \tag{5}$$

$$p_0 = (1-p)^n \tag{6}$$

$$p_s = C_n^s p^s (1-p)^{n-s} \tag{7}$$

$$U_j \geq Q_j - \sum_{i=1}^{n} n_{ij} - \sum_{i^*=1}^{l} n_{i^*j}, j \in M \tag{8}$$

$$\mu_j = \frac{\sum_{i=1}^{n} n_{ij}}{Q_j}, j \in M \tag{9}$$

$$\overline{\mu} = \frac{\sum_{j=1}^{m} \mu_j}{m} \tag{10}$$

$$\sum_{j=1}^{m} n_{ij} \le M \cdot y_i^{p_{rs}}, i \in N \tag{11}$$

$$\begin{cases} \sum_{i^*=1}^{l} h_{i^*}^{p_{rs}} > 0, \sum_{i=1}^{n} y_i^{p_{rs}} < n \\ \sum_{i^*=1}^{l} h_{i^*}^{p_{rs}} = 0, \sum_{i=1}^{n} y_i^{p_{rs}} = n \end{cases}, p_{rs} \in P_{rs} \tag{12}$$

$$\sum_{j=1}^{m} \sum_{p_{rs} \in P_{rs}} x_{ij}^{p_{rs}} \cdot n_{ij} \le W_i \cdot y_i^{p_{rs}}, i \in N \tag{13}$$

$$\sum_{j=1}^{m} \sum_{p_{rs} \in P_{rs}} x_{i^*j}^{p_{rs}} \cdot n_{i^*j} \le W_{i^*} \cdot y_{i^*}^{p_{rs}}, i^* \in L \tag{14}$$

$$\sum_{i=1}^{n} \sum_{p_{rs} \in P_{rs}} x_{ij}^{p_{rs}} \cdot n_{ij} + \sum_{i^*=1}^{l} \sum_{p_{rs} \in P_{rs}} x_{i^*j}^{p_{rs}} \cdot n_{i^*j} \le Q_j, j \in M \tag{15}$$

$$n_{ij} \ge 0, n_{i^*j} \ge 0 \tag{16}$$

$$\forall \mu_j \ge \lambda, j \in M \tag{17}$$

$$x_{ij}^{p_{rs}} \in \{0,1\}, x_{i^*}^{p_{rs}} \in \{0,1\}, h_{i^*}^{p_{rs}} \in \{0,1\} \tag{18}$$

Equations (1), (2), and (3) represent the objective functions for minimizing the total emergency dispatch time, maximizing the fairness of resource allocation, and minimizing the unmet demand at disaster sites, respectively. Equation (4) represents the transportation time from distribution center i to disaster site j. Equation (5) represents the transportation time from distribution center i^* to disaster site j. Equation (6) represents the probability that all distribution centers are in a normal state. Equation (7) represents the probability of simultaneous failure of s distribution centers. Equation (8) calculates the degree of unmet demand at disaster site j. Equation (9) calculates the material satisfaction level at disaster site j. Equation (10) calculates the average material satisfaction level across all disaster sites. Equation (11) indicates that if a distribution center fails, it ceases to supply materials to demand points. Equation (12) indicates that when a distribution center fails, an alternative distribution center is activated. Equation (13) indicates that distribution center i, when operational, can allocate supplies to multiple disaster sites, but the total allocation cannot exceed inventory. Equation (14) indicates that an alternative distribution center i^*, when activated, can allocate supplies to multiple disaster sites, but the total allocation cannot exceed inventory. Equation (15) indicates that the supplies received by each disaster site cannot exceed its actual demand. Equation (16) indicates that the allocated supply quantity must be non-negative. Equation (17) represents the material satisfaction constraint for disaster sites. Equation (18) is the 0-1 decision variable constraint.

3 Algorithm Design

For solving multi-objective problems, most scholars employ heuristic algorithms, primarily including Tabu Search, Simulated Annealing, and Particle Swarm Optimization. The NSGA-II algorithm combines non-dominated solution ranking, density-based ranking, and genetic cross-mutation operators to achieve superior Pareto optimality. The emergency supply scheduling model investigated in this paper is a typical multi-objective planning model requiring the comprehensive consideration of three objective functions. However, the three objective functions in this study possess different dimensions and exhibit small variance values, making it challenging to uniformly convert them into a single-objective formulation for solution. The non-dominated sorting genetic algorithm NSGA-II can perform simultaneous operations on two objective functions. Therefore, this paper employs the NSGA-II algorithm for solution and introduces improvements.

3.1 Encoding and Decoding

This model features two types of decision variables: binary decision variables $x_{ij}^{p_{rs}}$ and $x_{i^*j}^{p_{rs}}$, and real-valued decision variables n_{ij} and n_{i^*j}. The chromosome structure comprises $n + l$ rows and $2m$ columns, where n represents the total number of distribution centers, l denotes the total number of candidate distribution centers, and m indicates the total number of disaster-stricken locations.

As shown in Figure 2, the chromosome encodes $n + 1$ rows, where the first n rows contain s rows of zeros, with s representing the number of inactive distribution centers, here set to 1. The entire structure is divided into two parts by a dashed line: the first m columns indicate whether a distribution center or backup center transports supplies to a disaster site, while the subsequent m columns specify the quantity transported. The decoding of the first chromosome row in Figure 2 indicates that Distribution Center 1 transports supplies to disaster sites 1, 3, and 5 with quantities of 80, 90, and 70 respectively. The decoding of the second row shows Distribution

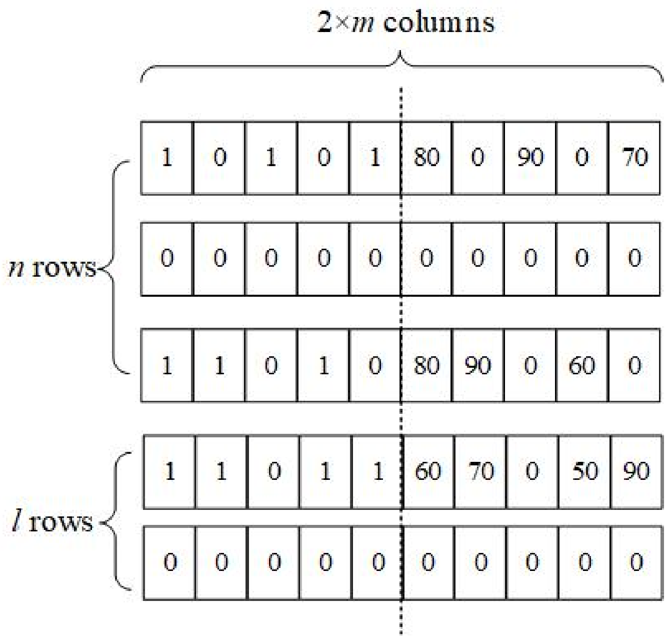

Figure 2. Schematic Diagram of Chromosome Coding.

Center 2 is inactive. The third row decodes that Distribution Center 3 transports supplies to disaster sites 1, 2, and 4 with quantities of 80, 90, and 60 respectively. The fourth chromosome decodes as: Alternative Distribution Center 1 is activated, transporting supplies to disaster sites 1, 2, 4, and 5 with quantities of 60, 70, 50, and 90 respectively. The fifth chromosome decodes as: Alternative Distribution Center 2 is not activated.

3.2 Crossover and Mutation

The crossover and mutation operations in NSGA-II are similar to those in genetic algorithms. The purpose of employing these operations is to generate the next generation from the parent population, thereby increasing the diversity of the population.

3.2.1 *Crossover*

For binary decision variables (0-1), a two-point crossover method is employed. For real-valued variables, Simulated Binary Crossover (SBX) is used. This is because real-valued variables represent actual delivery quantities—continuous real-valued variables requiring optimization within the real number range. SBX effectively handles such continuous optimization problems. Assuming the two parent generations are $P1$ and $P2$, the offspring $C1$ and $C2$ obtained through SBX crossbreeding can be calculated using the following formula:

$$\begin{cases} C_1 = 0.5\left[(1+\beta_q)P_1 + (1-\beta_q)P_2\right] \\ C_2 = 0.5\left[(1-\beta_q)P_1 + (1+\beta_q)P_2\right] \end{cases} \tag{19}$$

The formula for calculating $beta_q$ is as follows:

$$\beta_q = \begin{cases} (2u)^{\frac{1}{\eta_c+1}}, & u \leq 0.5 \\ \left(\frac{1}{2(1-u)}\right)^{\frac{1}{\eta_c+1}}, & u > 0.5 \end{cases} \tag{20}$$

where u is a uniform random number between [0,1], and η_c is the distribution exponent, typically ranging from 5 to 20. In this case, η_c is set to 5. Since a chromosome row includes both binary decision variables and real-valued variables, the two types of crossover are performed sequentially during processing, as shown in Figures 3 and 4.

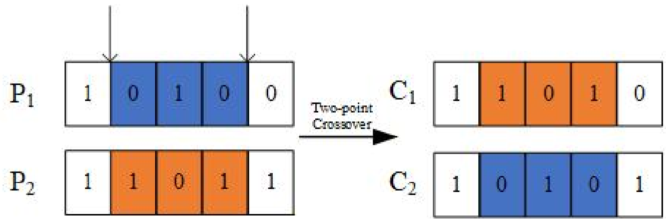

Figure 3. Schematic Diagram of Two-Point Crossover.

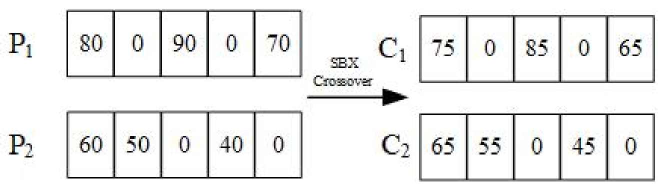

Figure 4. Schematic Diagram of SBX Crossover.

To enhance population diversity, dynamically adjusting crossover probabilities—such as based on individual fitness values—is beneficial. Individuals with high fitness should have low crossover probabilities to prevent disrupting optimal solutions, while those with low fitness should have high crossover probabilities to increase diversity. Therefore, an adaptive crossover operator is employed to dynamically adjust crossover probabilities. For individual i, its crossover probability p_c^i can be defined as:

$$p_c^i = \begin{cases} p_{c,\max} - \frac{(p_{c,\max}-p_{c,\min})(f_i - f_{avg})}{f_{\max}-f_{avg}}, \text{if } f_i \geq f_{avg} \\ p_{c,\max}, \text{if } f_i < f_{avg} \end{cases} \tag{21}$$

where $p_{c,\max}$ represents the upper limit of the crossover probability, set here to 0.9, denoting the maximum crossover probability for individuals with low fitness; $p_{c,\min}$ represents the lower limit of the crossover probability, set here to 0.5, denoting the minimum crossover probability for individuals with high fitness; f_i denotes the fitness value of the current individual i; $f_{a\nu g}$ denotes the average fitness value of the current population; $f_{\max}$ denotes the maximum fitness value of the current population.

This approach ensures that when an individual is already performing well, crossover operations are minimized to avoid disrupting its favorable traits. Conversely, when an individual is performing poorly, more frequent crossover operations are required to introduce diversity and prevent it from becoming trapped in a local optimum.

3.2.2 Mutation

For binary decision variables (0-1), mutation is achieved by flipping certain genes (i.e., changing 0 to 1 or 1 to 0). For real-valued variables, Polynomial Mutation (PM) is employed. Its core principle involves generating a perturbation value based on a polynomial distribution, adding it to the current gene value, and thereby producing a new gene value. This method is suitable for continuous variables. Assuming the upper and lower bounds of a real variable are $[n_{\min}, n_{\max}]$, for a specific real variable , its variation formula is as follows:

$$n^{'} = n + \beta_q(n_{\max} - n_{\min}) \tag{22}$$

where $beta_q$ is the parameter in equation (20), and the same operation is applied here.

Chromosomal mutation is another mechanism for enhancing population diversity. Its adaptive adjustment operates in opposition to adaptive crossover: individuals with high fitness exhibit low mutation probability to preserve superior solutions, while those with low fitness exhibit high mutation probability to increase diversity. Therefore, an adaptive mutation operator is employed to dynamically adjust mutation probabilities. For individual i, the mutation probability p_m^i can be defined as:

$$p_m^i = \begin{cases} p_{m,\max} - \dfrac{(p_{m,\max} - p_{m,\min})(f_i - f_{avg})}{f_{\max} - f_{avg}}, & \text{if } f_i \geq f_{avg} \\ p_{m,\max}, & \text{if } f_i < f_{avg} \end{cases} \tag{23}$$

where $p_{c,\max}$ represents the upper limit of the probability of mutation, set here to 0.1, denoting the maximum mutation probability for individuals with low fitness; $p_{c,\min}$ represents the lower limit of the mutation probability, set here to 0.01, denoting the minimum crossover probability for individuals with high fitness; f_i denotes the fitness value of the current individual i; $f_{a\nu g}$ denotes the average fitness value of the current population; $f_{\max}$ denotes the maximum fitness value of the current population.

When individuals are already relatively strong, reduce mutation operations to avoid disrupting their favorable traits; when individuals perform poorly, increase mutation operations to introduce diversity and prevent getting stuck in local optima.

3.3 Local Search Operator

The primary function of the domain search operator is to perform local optimization on individuals after they undergo crossover and mutation operations, thereby enhancing solution quality. Its core mechanism involves generating a set of neighboring solutions around the current solution, obtained by fine-tuning specific variables of the current solution. This chapter introduces this operator to improve the algorithm.

First, generate the domain. For solutions with high fitness, introduce a perturbation component defined as follows:

$$p^{'} = p + \Delta p \tag{24}$$

where $p^{'}$ represents the generated domain solution, and Δp denotes the perturbation vector. A normal distribution perturbation is employed, where $\Delta p \sim N\left(0, \sigma^2\right)$.

Considering the application of domain search for individuals with high fitness, the domain search operator is introduced for the top 20% of individuals in each population. A greedy search strategy is employed to identify individuals superior to the current ones. The specific steps are as follows:

Step 1: Generate k domain solutions $p_1^{'}, p_2^{'}, \ldots p_k^{'}$ using the method described in Equation (24).

Step 2: Calculate the fitness of all domain solutions;

Step 3: Select the domain solution $p_{best}^{'}$ with the highest fitness;

Step 4: Compare the fitness of the highest-fitness domain solution with that of the selected individual. If $f\left(p_{best}^{'}\right) > f(p)$, replace the original individual with $p_{best}^{'}$; otherwise, do not replace.

The introduction of domain search operators enhances the quality of local optimal solutions, enabling rapid convergence toward exact solutions when approaching the global optimum. This significantly strengthens the algorithm's local search capabilities.

3.4 Repair Operator

For the crossover and mutation of the aforementioned chromosomes, considering that each chromosome row comprises both 0-1 decision variables and real-number variables, different crossover and mutation methods are applied to these two types of variables. Consequently, there is a probability of generating chromosomes with inconsistent meanings before and after processing. In such cases, a repair operator is introduced to fix the chromosomes, ensuring that solutions resulting from crossover and mutation remain feasible and maintaining consistency between 0-1 variables and real-number variables.

The specific operational steps are as follows:

Step 1: Iterate through each row of the chromosome to check whether the 0-1 variables match the real-number variables;

Step 2: If inconsistencies exist, proceed with two distinct repair scenarios. Scenario 1: When the 0-1 variable is 0 but the real-number variable is non-zero, force the real-number variable to 0. Scenario 2: When the 0-1 variable is 1 but the real-number variable is 0, randomly assign the real-number variable a reasonable non-zero value within the range less than the capacity of the distribution center and the demand of the affected location;

Step 3: If consistent, do not repair.

By introducing the repair operator, solutions that violate constraints due to crossover or mutation can be repaired, ensuring chromosomes remain valid.

3.5 Termination Conditions

This paper considers three objectives under the scenario of enabling alternative distribution centers: total delivery time Z_1, satisfaction variance Z_2, and proportion of unmet demand Z_3. All three objective functions require minimization, so the fitness function of the NSGA-II algorithm is defined as $F_1 = 1/Z_1$, $F_2 = 1/Z_2$, and $F_3 = 1/Z_3$. By calculating these three objectives, the fitness value of each solution is obtained, followed by decoding to derive the final objective values.

Through NSGA-II's non-dominated sorting, the Pareto front solution set for each generation is obtained. Iteration is performed cyclically until the maximum iteration limit is reached, at which point the algorithm terminates and outputs the final complete solution set.

The algorithm flowchart for this paper is shown in Figure 5.

4 Case Study Analysis

4.1 Improved Algorithm Verification

The improvements described above were incorporated into the NSGA-II algorithm. To validate the effectiveness of these enhancements, the modified NSGA-II algorithm was compared with the baseline NSGA-II algorithm using classical test functions. To mitigate solution randomness, both algorithms were applied to the classical test functions ZDT1–4, conducting evaluations across four dimensions.

Both the improved NSGA-II and the basic NSGA-II algorithms were configured with a population size of 300, 500 iterations, a crossover probability of 0.9, a mutation probability of 0.1, an adaptive crossover lower bound of 0.5, and an adaptive mutation lower bound of 0.01. The test results are shown in Figure 6.

This chapter employs the Hypervolume (HV) metric to evaluate the NSGA-II algorithm. The metric quantifies the size of the solution set's coverage area within the objective space, comprehensively reflecting how closely the solution set approaches the true Pareto frontier. A higher HV value indicates greater proximity to the true Pareto frontier and simultaneously signifies better convergence.

As shown in Figure 6, the improved NSGA-II algorithm outperforms the original NSGA-II algorithm on all four test functions, validating its superior performance across all four dimensions.

To evaluate the algorithm's diversity performance, this chapter employs the Spacing Metric (SP) indicator. This metric calculates the distance distribution among individuals to assess the diversity and uniformity of the solution set. A smaller SP value indicates a more uniform distance distribution among individuals in the solution set, signifying better diversity.

The improved NSGA-II algorithm and the original NSGA-II algorithm were run with the same parameter settings as described above. After 10 runs, the average results are shown in Table 2.

Table 2. SP indicator results.

Algorithm	SP
NSGA-II	6.510^{-24}
Improved NSGA-II	2.410^{-26}

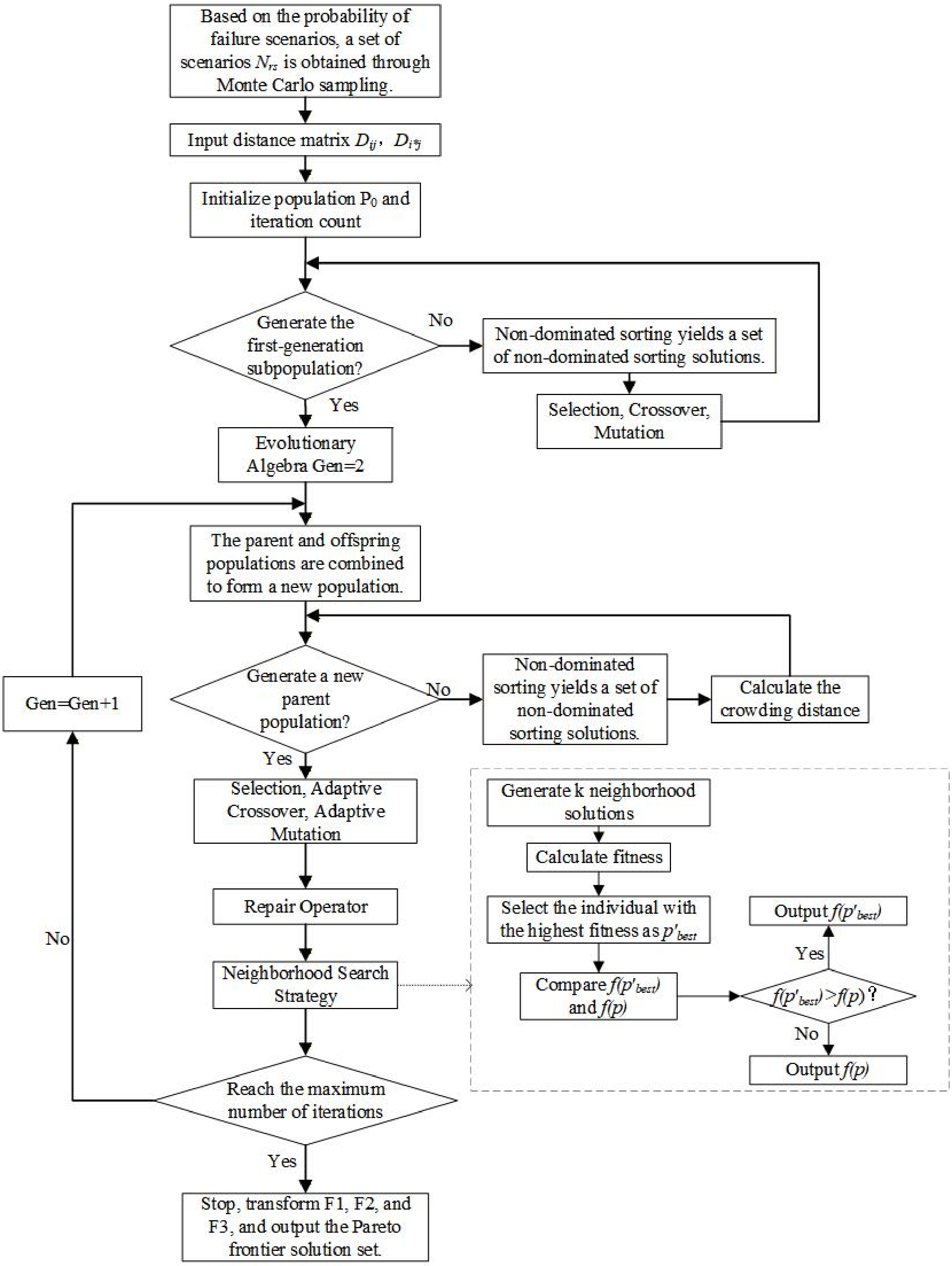

Figure 5. Algorithm flowchart.

As shown in the Table 2, the improved algorithm demonstrates superior distribution compared to the initial algorithm. Combined with the test results across the four dimensions discussed earlier, this confirms that the algorithmic improvements introduced in this chapter are effective, yielding better performance in

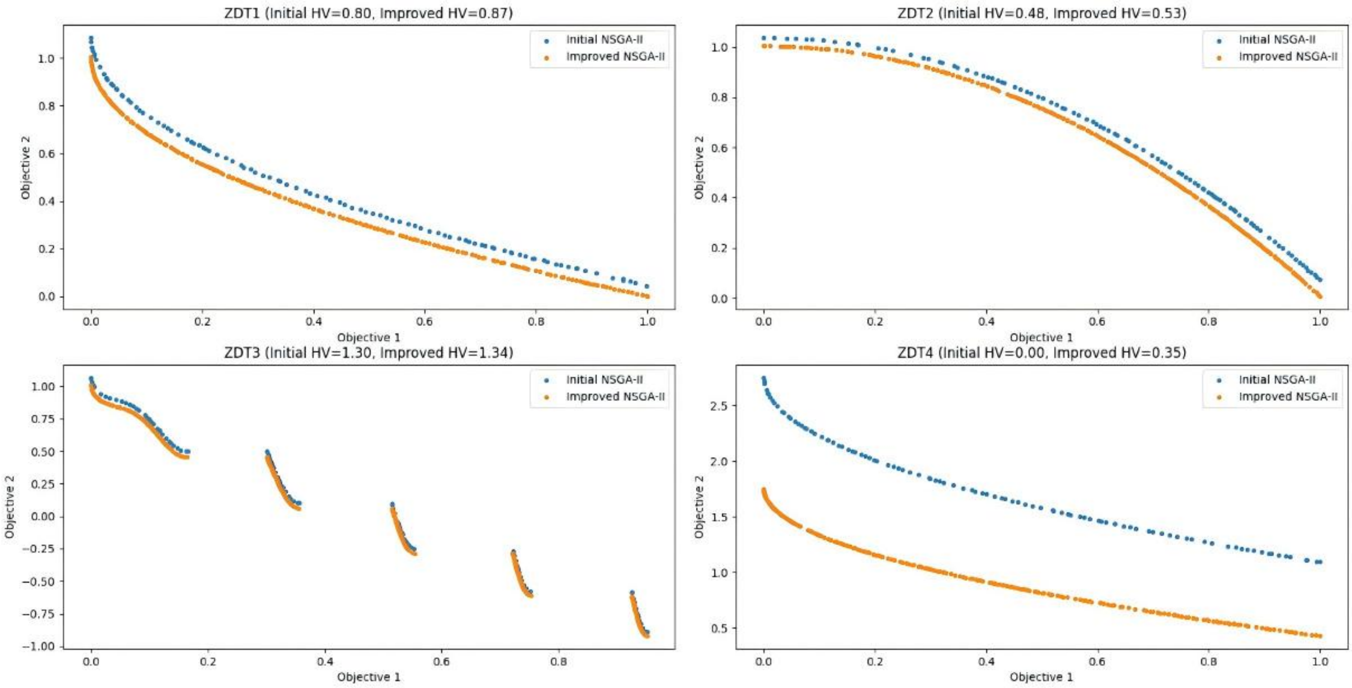

Figure 6. Comparison of Algorithm performance before and after improvement.

Table 3. Data for case study locations.

Location	Type	Capacity/Demand (tons)
Wenchuan County	Distribution Center	42
Pingwu County	Distribution Center	32
Mianzhu City	Distribution Center	30
Shifang City	Distribution Center	27
Qingchuan County	Distribution Center	32
Beichuan County	Alternative Distribution Center	27
Zitong County	Alternative Distribution Center	26
Anxian County	Alternative Distribution Center	29
Mao County	Disaster Site	32
Dujiangyan City	Disaster Site	22
Pengzhou City	Disaster Site	19
Xiaojin County	Disaster Site	29
Songpan County	Disaster Site	26
Jiuzhaigou County	Disaster Site	32
Lizhou County	Disaster Site	11
Cangxi County	Disaster Site	10
Yanting County	Disaster Site	14
Wangcang County	Disaster Site	14
Jiangyou City	Disaster Site	18
Santai County	Disaster Site	16

both diversity and diversity. Therefore, the improved NSGA-II algorithm will be employed to solve the model in all subsequent case studies.

Table 4. Road condition coefficients between distribution centers and disaster sites.

Node	Wenchuan County	Pingwu County	Mianzhu City	Shifang City	Qingchuan County
Mao County	0.75	0.5	1	0.75	0.5
Dujiangyan City	0.5	0.75	0.5	1	0.75
Pengzhou City	0.75	1	0.75	0.5	1
Xiaojin County	1	0.75	0.5	0.75	0.5
Songpan County	0.75	0.5	1	0.5	0.75
Jiuzhaigou County	0.5	0.75	0.5	1	0.5
Lizhou County	1	0.5	0.75	0.5	1
Cangxi County	0.5	0.75	0.5	0.75	0.25
Yanting County	0.25	0.5	0.25	0.5	0.5
Wangcang County	1	0.75	0.5	1	0.75
Jiangyou City	0.75	1	0.75	0.5	1
Santai County	0.5	0.5	1	0.75	0.5

4.2 Case Data

The 2008 Wenchuan earthquake disaster caused immense losses to people's lives, health, and socioeconomic development. To validate the effectiveness of the models and algorithms presented in this chapter, a simulation case study was designed using the Wenchuan earthquake as the backdrop. This study analyzed scenarios involving distribution center failures and considered alternative distribution centers. Based on the distribution of earthquake intensity, 20 affected areas within Wenchuan County were selected to construct the disaster zone.

Five of these areas were designated as distribution centers, three as alternative distribution centers, and the remainder as disaster points. Specific details are shown in Table 3.

The maximum number of failures for the distribution center is set to 2, with a minimum delivery satisfaction rate of 60% for affected points. Assuming a vehicle speed of 60 km/h, the road condition coefficients between the distribution center, alternative distribution centers, and affected points are shown in Table 4 and Table 5.

4.3 Case Solution

Based on the above data, we first consider the most ideal scenario where none of the distribution centers fail. Under this condition, the NSGA-II algorithm is parameterized with a population size of 300, a crossover probability of 0.9, a mutation probability of 0.01, and 1000 iterations. The distribution results obtained through Python programming are visualized in the Pareto frontier diagram shown in Figure 7.

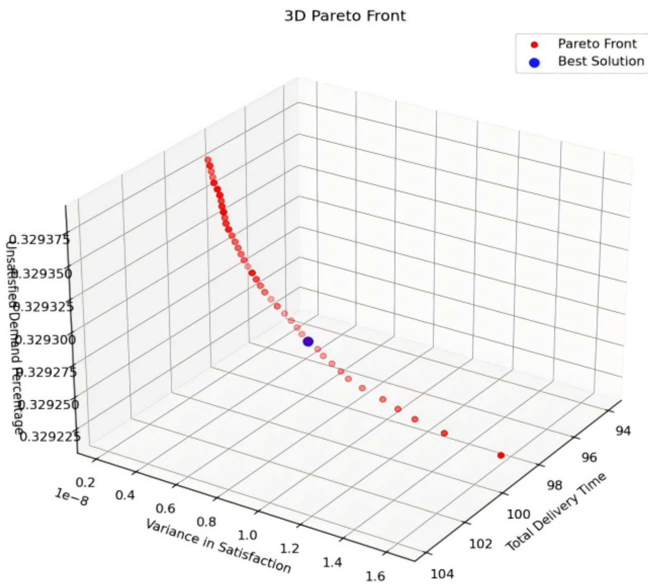

Figure 7. Pareto Frontier Diagram for All Distribution Centers Operating Normally.

Based on the Pareto frontier solution set diagram, the optimal solution is selected from the Pareto solution set using the ideal point method for analysis. First, the theoretical optimal value for each objective is determined. Then, the Euclidean distance from each frontier solution to the ideal point is calculated, and the solution with the smallest distance is selected, as indicated by the blue point in the figure. Its allocation matrix is shown in Table 6.

As shown in Figure 7 and Table 6, the optimal solution achieves a total delivery time of 163.94 hours, with a satisfaction variance of 0.00001 and an unmet demand

Table 5. Road condition coefficients between alternative distribution centers and disaster sites.

Node	Beichuan County	Anxian County	Pengzhou City
Mao County	1	0.75	0.5
Dujiangyan City	0.75	0.5	0.75
Pengzhou City	0.5	1	0.5
Xiaojin County	0.75	0.5	1
Songpan County	0.5	0.75	0.75
Jiuzhaigou County	0.75	1	0.5
Lizhou County	0.5	0.75	1
Cangxi County	0.25	0.5	0.75
Yanting County	0.5	0.25	0.5
Wangcang County	0.75	0.5	1
Jiangyou City	0.5	0.75	0.5
Santai County	0.75	1	0.25

Table 6. Optimal solution distribution matrix for the ideal point method.

Node	Wenchuan County	Pingwu County	Mianzhu City	Shifang City	Qingchuan County
Mao County	5346	2633	7104	2992	3368
Dujiangyan City	6255	2599	1731	761	3376
Pengzhou City	3537	2378	1257	891	4666
Xiaojin County	5155	4280	2185	3594	4216
Songpan County	6516	5687	3190	2022	0
Jiuzhaigou County	4494	971	8420	3247	4318
Lizhou County	616	2713	2133	0	1908
Cangxi County	234	301	1310	1193	3661
Yanting County	1113	3960	0	1768	2543
Wangcang County	603	1797	1659	5112	213
Jiangyou City	1323	4141	947	3776	1872
Santai County	6741	505	0	1611	1833

ratio of 33.01%. Given the initial assumption of existing material shortages in the post-earthquake period, the original total unmet demand rate was 32.92% based on the example data. Comparing this with the unmet demand rate of the optimal solution demonstrates that the optimal solution maximizes the material delivery volume to each disaster-affected point. Therefore, further example experiments are conducted for the distribution center failure scenario.

For the distribution center failure scenario, the Monte Carlo sampling method was employed to generate scenarios. The specific steps are as follows:

(1) Define Parameters Define the probability p of failure for five distribution centers (N1, N2, N3, N4, N5) as 0.1, with failures being independent of each other. The maximum number of simultaneous failures is 2.

(2) Generate Random Failure Scenarios Generate an independent Bernoulli random variable for each distribution center, where 1 indicates failure and 0 indicates normal operation. The variables are as follows:

$$y_i^{p_r} = \begin{cases} 1, Distribution\,Center\,Failure \\ 0, Distribution\,Center\,Operating\,Normally \end{cases} \tag{25}$$

If the number of invalid instances in a generated scenario exceeds 2, discard that scene. Repeat sampling until a sufficient number of valid scenes are generated. (3) Calculate scene probability For each valid scenario (failure count $\mathrm{k} \in \{0,1,2\}$), its original probability is:

$$P_{\text{primitive}} = (0.1)^{\mathrm{k}} \cdot (0.9)^{5-\mathrm{k}} \tag{26}$$

Since scenarios with failure counts $\mathrm{k} > 2$ have been discarded, the probabilities of the remaining valid scenarios must be normalized:

$$P_{\text{normalization}} = \frac{P_{\text{primitive}}}{\sum_{k=0}^{2}(0.1)^{\mathrm{k}} \cdot (0.9)^{5-k}} \tag{27}$$

The normalized probability is 0.99144. The resulting scenarios and probabilities are shown in Table 7.

A stratified sampling approach was employed, utilizing a random number method to select two scenarios for analysis, one with a failure count of 1 and another with a failure count of 2, as detailed below.

(1)Scenario with 1 failure

The scenario selected is the failed scenario for Qingchuan County (Scene Number 6). Using the same NSGA-II algorithm settings as above, the model was solved for the failure of Qingchuan County and the activation of three alternative distribution centers. The results are shown in Table 8.

As shown in the Table 8, when Qingchuan County becomes inoperable, the delivery times for all alternative distribution centers exceed those of a single inoperable center. This is because Qingchuan's failure—likely caused by aftershocks—leads to secondary disasters such as road damage, bridge collapses, and landslides, further deteriorating road conditions.

Furthermore, the alternative distribution centers (such as Beichuan County, Zitong County, and An County) are located farther from the disaster site. Particularly in mountainous areas with complex terrain, the increased transportation distance directly leads to longer delivery times.

As shown in the Table 9, activating alternative distribution centers reduces both the variance in satisfaction levels and the proportion of unmet material demands. This demonstrates the model's effectiveness. For the entire emergency logistics system, the failure of a distribution center incurs losses across the entire network. Activating backup distribution centers mitigates these losses, thereby improving rescue operations during the initial post-disaster phase.

Among the three alternative distribution centers, Anxian County emerged as the optimal choice. It not only achieved the shortest delivery times and the lowest proportion of unmet demand but also demonstrated the highest fairness in resource allocation. Therefore, comparing scenarios where only Qingchuan County is unavailable versus activating Anxian County reveals that Anxian's geographical location is closer to the disaster site than Qingchuan County. This conclusion holds true when compared to the other two alternative distribution centers as well. The reason lies in Anxian's advantageous location, which is adjacent to railways, highways, and airports, enabling rapid response to the disaster site's needs.

The activation of alternative distribution centers can significantly improve the fairness of material allocation and reduce unmet demand, though the effectiveness varies across different centers. In actual emergency material dispatch, the optimal alternative distribution center should be selected based on specific circumstances to maximize the fulfillment of affected locations' needs. This also demonstrates the model's effectiveness in activating backup distribution centers when primary centers fail, thereby minimizing losses.

(2)Scenario with 2 Failed Facilities

Considering the scenario with 2 failed facilities, this indicates more severe post-earthquake impacts. The selected scenarios are those with failures in Pingwu County and Shifang City (Scene Number 12). The same NSGA-II algorithm settings are applied. For this failure scenario, the model is solved by activating two facilities from each of the three alternative distribution centers.

As shown in the Table 9, the failure of Pingwu County and Shifang City necessitated route re-planning for the distribution system, resulting in significantly increased delivery times compared to scenarios where all distribution centers operated normally. The failed distribution centers originally handled substantial delivery tasks. Their failure increased the load on the remaining distribution centers, further prolonging delivery times. Additionally, considering that the failures in Pingwu County and Shifang City were caused by factors such as aftershocks, secondary disasters like road damage, bridge collapses, and landslides further deteriorated road conditions. Meanwhile, the variance in customer satisfaction also increased compared to the scenario where all distribution centers were operational, with the proportion of unmet demand reaching 57.20%. This indicates that the failure of distribution centers significantly impacts overall demand fulfillment. The outages in Pingwu County and Shifang City directly resulted in a large volume of unmet demand. Particularly in post-earthquake emergency situations, demand may become more concentrated and urgent, making the activation of alternative distribution centers critically important.

Based on the satisfaction variance results and the proportion of unmet demand across scenarios in

Table 7. Monte carlo sampling results.

Scene Number	Failed Distribution Center Combination	Number of Failures k	Original Probability	Normalized Probability
1	No failure	0	0.59049	0.5956
2	Wenchuan County	1	0.06561	0.0662
3	Pingwu County	1	0.06561	0.0662
4	Mianzhu City	1	0.06561	0.0662
5	Shifang City	1	0.06561	0.0662
6	Qingchuan County	1	0.06561	0.0662
7	Wenchuan County, Pingwu County	2	0.00729	0.0074
8	Wenchuan County, Mianzhu City	2	0.00729	0.0074
9	Wenchuan County, Shifang City	2	0.00729	0.0074
10	Wenchuan County, Qingchuan County	2	0.00729	0.0074
11	Pingwu County, Mianzhu City	2	0.00729	0.0074
12	Pingwu County, Shifang City	2	0.00729	0.0074
13	Pingwu County, Qingchuan County	2	0.00729	0.0074
14	Mianzhu City, Shifang City	2	0.00729	0.0074
15	Mianzhu City, Qingchuan County	2	0.00729	0.0074
16	Shifang City, Qingchuan County	2	0.00729	0.0074

Table 8. Results of the failure scenarios in Qingchuan County.

Specific Conditions	Delivery Time (hours)	Satisfaction Variance	Percentage of Unmet Demand
Qingchuan County becomes unavailable, no alternative locations will be activated	128.9	0.001	46.10%
Qingchuan County becomes unavailable, activate Beichuan County	160.7	0.00026	35.00%
Qingchuan County becomes unavailable, activate Zitong County	149.8	0.00043	35.52%
Qingchuan County becomes unavailable, activate An County	148.2	0.00001	34.17%

Table 9, activating the backup distribution center significantly reduces satisfaction variance while also markedly lowering the proportion of unmet demand for supplies. This indicates that activating the backup distribution center effectively mitigates demand gaps caused by failure, thereby enhancing the overall efficiency of the distribution system. When a distribution center fails, the system incurs certain losses. Activating the backup distribution center can significantly reduce these losses, thereby better supporting rescue operations in the early post-disaster phase and ensuring timely supply of materials and balanced fulfillment of demand.

Regarding the three outcomes of activating alternative distribution centers, it is evident that Beichuan County and An County perform optimally as backup distribution centers. Not only do they achieve the shortest delivery times with an unsatisfied demand ratio of 34.32%, but they also deliver the highest fairness in resource allocation. Therefore, comparing scenarios where only Pingwu County and Shifang City fail with scenarios where Beichuan County and An County are activated reveals that activating these two alternative distribution centers effectively alleviates pressure on the remaining operational distribution centers while filling the gap caused by the failure of the original alternative distribution centers.

In summary, activating backup distribution centers proves effective following failures. Even when the number of failures is uncertain, the model consistently generates constraint-satisfying scheduling solutions. This approach effectively minimizes losses caused by distribution center failures while underscoring the critical importance of ensuring their operational continuity post-disaster.

5 Conclusion

This study investigates emergency supply dispatch under scenarios where distribution centers fail post-earthquake, drawing the following conclusions.

Distribution center failures significantly impact overall dispatch strategies. Research indicates that the failure of critical distribution centers post-earthquake

Table 9. Results of deactivated cases in Pingwu County and Shifang City.

Specific Conditions	Delivery Time (hours)	Satisfaction Variance	Percentage of Unmet Demand
Pingwu County and Shifang City are deactivated, no alternative locations will be activated	138.2	0.19	57.20%
Activate Beichuan County and Zitong County	155.9	0.0003	35.40%
Activate Beichuan County and An County	151.3	0.0002	34.32%
Activate Zitong County and An County	161.6	0.0008	34.57%

markedly affects both the efficiency of emergency supply dispatch and the fairness of resource allocation. Prioritizing the restoration of these distribution centers is crucial for enhancing rescue efficiency. Simulations of post-earthquake distribution center failure scenarios reveal that the failure of critical distribution centers increases the total delivery time for emergency supplies and reduces the fairness of resource allocation. This finding underscores the importance of ensuring the rapid restoration of key logistics nodes in post-disaster relief efforts to improve rescue efficiency and mitigate disaster impacts.

Raising the minimum satisfaction threshold for resource allocation can effectively enhance distribution fairness and improve satisfaction in disaster-affected areas. By appropriately increasing the minimum satisfaction threshold for resource allocation, both the fairness of distribution and the satisfaction levels in affected regions can be significantly elevated. Sensitivity analysis indicates that as the minimum resource satisfaction threshold increases, delivery times correspondingly lengthen, yet the variance in resource allocation satisfaction decreases markedly. This implies that during emergency relief distribution, establishing a reasonable minimum satisfaction threshold can balance rescue efficiency and distribution fairness to a certain extent. It ensures that the basic needs of more disaster-affected locations are met, thereby enhancing overall rescue effectiveness and satisfaction in affected areas. The above conclusions provide government emergency decision-making departments with a scientific and efficient material dispatch plan during disasters. This approach helps improve rescue efficiency and fairness, ensuring that the basic needs of affected areas are met promptly.

Although this paper introduces novel perspectives on emergency supply dispatch, certain limitations remain. For instance, the model's assumptions are relatively idealized—such as the initial supply volume being less than the total demand at affected locations and the independent failure of distribution centers—which may deviate from real-world scenarios. Additionally, exploring the integration of machine learning and deep learning technologies to enhance computational efficiency and solution quality represents a crucial direction for future research.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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