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Optimization of Emergency Logistics Transport Scheduling in Multi-DC Supply Chains Based on SA-GOA

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Abstract: Given the challenges of climate change in the world today and constant health scares among the population, it is essential to have an optimal emergency logistics transport scheduling process that will help in minimizing losses during disasters. However, current methods lack dynamic adaptability and effective multi-objective coordination. This study introduces a logistics transport scheduling optimization model that combines the Simulated Annealing (SA) algorithm with the Grasshopper Optimization Algorithm (GOA). By leveraging the strengths of Simulated Annealing, Grasshopper Optimization, Hybrid Particle Swarm Optimization (HPSO), and NSGA-II, the model achieves efficient global exploration and multi-objective optimization. Experimental results demonstrate that the model reaches 99% accuracy in cost prediction, 98% on-time delivery rate and goods integrity rates, and 95% demand satisfaction, significantly outperforming comparison models. These results demonstrate the significant adaptability and relevance of the model to the emergency logistics scheduling problem under multiple distribution centers, offering a flexible approach towards future transportation solutions.

Keywords: SA-GOA, Multi-Distribution center, HPSO, NSGA-II, Logistics scheduling, Supply Chains.

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1. Introduction

As there are various irregular climatic conditions and health issues globally, the importance of emergency logistics and transportation cannot be ignored, since they are essential in providing necessary support during disasters and preventing further damage. A multi-distribution center supply chain is one of such effective logistics systems, which helps to diversify risk and scheduling activities. However, real-world emergency transportation planning often encounters complex challenges such as sudden demand fluctuations, highly unpredictable transportation conditions, and conflicts between multiple objectives (Modica et al. 2023; Tsolaki et al. 2023). In case the schedule is poorly planned, it may result in resource wastage, delays in rescuing operations, and secondary dangers. Numerous studies have been carried out over the years in the field of logistics and transportation scheduling. Such areas include digital and smart revolution, machine learning techniques, sustainable development, intelligence optimization methods, and multi-objective optimization techniques (Fernandes et al. 2023; Lin et al. 2023). These studies have offered valuable insights for emergency logistics, yet gaps remain in dynamic adaptability, multi-objective coordination, and efficient resource use, making it hard to fully address complex emergency scenarios (Ma et al. 2023). Achieving multi-objective optimization and dynamic, adaptive scheduling in emergency logistics within a multi-distribution center supply chain is thus critically important. To tackle this issue, the study introduces an intelligent scheduling optimization model that combines the Simulated Annealing (SA) algorithm and the Grasshopper Optimization Algorithm (GOA). Additionally, this model incorporates Hybrid Particle Swarm Optimization (HPSO) and an improved Non-dominated Sorting Genetic Algorithm II (NSGA-II), forming a multi-algorithm collaborative framework (SGHPN).

This study's innovations and contributions are as follows: First, for the dynamic and complex environment of emergency logistics across multiple distribution centers, a multi-objective optimization scheduling problem model is explicitly developed, including key metrics such as cost, time, service quality, and resource utilization. This study integrates SA and GOA while combining the parameter optimization capabilities of HPSO with the multi-objective solution mechanism of the improved NSGA-II and proposes a multi-algorithm collaborative framework that balances global search and local optimization. Additionally, by clearly defining the problem and constructing a multi-algorithm fusion optimization framework, this approach not only addresses a gap in multi-objective dynamic optimization for emergency logistics scheduling but also offers practical new ideas and solutions for efficient scheduling of emergency supplies.

2. Related Works

The SA algorithm is well-established, effectively avoiding local optima and adapting to various optimization challenges. The GOA, inspired by biological behavior, provides strong global search capabilities, has few parameters, and is easy to implement, making both algorithms widely studied around the world. For instance, Gangadevi et al. (2024) developed a multi-objective hybrid fruit fly optimization algorithm enhanced by SA for timely tomato disease detection. He et al. (2023) combined artificial neural networks with SA to design broadband patch antennas. Gülbaş and Çetin (2023) applied SA to extend the lifespan of wireless sensor networks through energy and distance-based clustering. Badr et al. (2023) improved GOA with grouping and mutation techniques for smart grid demand-side management. Janabi and Kurnaz (2024) used GOA for Internet of Things positioning, which reduced localization errors.

Logistics transport scheduling has advanced significantly, with extensive global research. For example, Zhang and Pan (2023) proposed a multi-agent reinforcement learning-based hierarchical optimal scheduling algorithm to address component and multi-vehicle layered planning issues. To optimize prefabricated component production and transport integration planning, balancing delivery timeliness with transportation economics, Dan and Liu (2024) introduced a comprehensive scheduling optimization model based on delivery time windows. Lin et al. (2023) developed a layered coordination optimization framework for logistics scheduling, utilizing a graph search algorithm to ensure service quality while reducing operational costs. Zhao and Wang (2023) presented a path optimization framework to enhance resource scheduling systems for public health emergencies. To address the problem of coordinated scheduling in cloud manufacturing for process and logistics services, Liu et al. (2023) proposed a cooperative scheduling solution based on game theory. The authors designed a two-level scheduling solution that was optimized using the decision tree technique and achieved successful objective optimization.

Existing research in emergency logistics and transportation scheduling has made notable progress, including exploring traditional planning models for path and resource allocation, enhancing global optimization and convergence speed with single intelligent algorithms, and applying multi-objective optimization methods to balance efficiency, cost, and service levels. However, there are still notable disadvantages to these research efforts. The first problem is that they fail to incorporate flexibility, as most of these techniques cannot cope with the challenges posed by dynamic environments and emergencies involving multiple distribution centers. The second challenge is that they tend to focus narrowly on optimization, failing to achieve an effective compromise among factors such as costs, time, resource management, and quality. To fill these gaps, this study proposes a multi-algorithm fusion optimization model based on SA-GOA. This approach utilizes both the advantages of SA and GOA concerning their global and local searching ability, makes full use of the ability of HPSO in parameter adaptation, and takes into account the multi-objective optimization characteristics of an improved NSGA-II approach. This study not only enlarges the applicability scope of collaborative optimization based on multiple algorithms within the emergency logistics scheduling system but also provides a better way to solve the problem of distributing emergency materials.

3. SA-GOA-based Optimization of Emergency Logistics Transport Scheduling

3.1. SA-GOA Fusion Mechanism

In emergency logistics scheduling involving more than one distribution center, the transport environment may be highly uncertain and complicated. The scheduling strategy may be stuck in local optima, resulting in poor performance. Conventional single optimization techniques lack robustness and convergence rate in complicated conditions. It is therefore essential to design an approach that maintains a balance between global search and local optimization. The SA algorithm helps avoid local optima, while the GOA effectively explores the solution space. Combining these two approaches allows for broad initial exploration through the random search of simulated annealing and deep search by mimicking the collective behavior of grasshoppers in GOA (Ghannadi et al. 2023). Based on this, the two are integrated to form the SA-GOA algorithm to enhance the ability to solve emergency logistics scheduling problems. In multi-center emergency logistics scheduling, SA-GOA explores and refines solutions iteratively to improve transportation efficiency and resource utilization, as shown in Fig. 1.

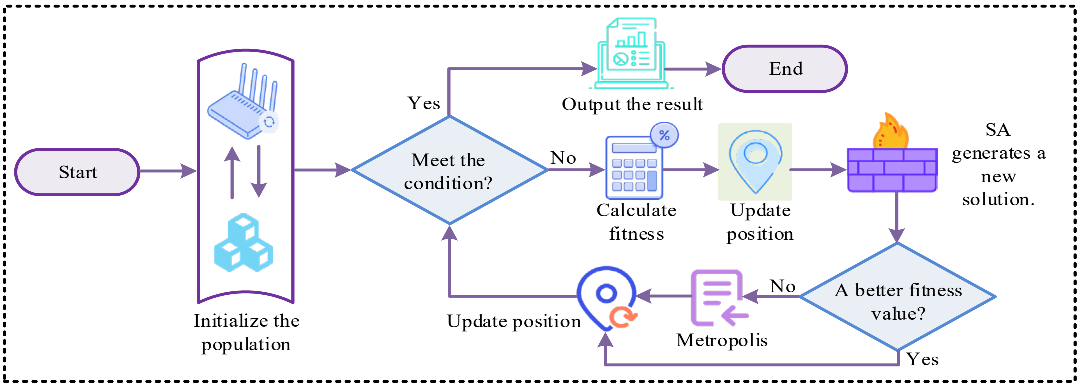


Fig. 1. SA-GOA-based logistics scheduling optimization flowchart

As shown in Fig. 1, the method first initializes GOA and SA parameters, along with the distribution center and demand data. GOA searches the solution space, updating positions based on transportation fitness values. The best GOA solutions are then refined by SA using the Metropolis criterion, accepting better solutions and probabilistically worse ones. Iteration continues until convergence, and the optimal transport plan is obtained. The position update process in GOA is calculated as shown in Eq. (1).

$$X_i^d = c(\sum_{j=1}^{N} c\frac{ub_d - lb_d}{2} s(|x_j^d - x_i^d|)\frac{x_j - x_i}{d_{ij}}) + \hat{T}_a \tag{1}$$

In Eq. (1), X_i^d represents the position of the i-th grasshopper in d-dimensional space, l denotes the current iteration. ub_d and lb_d are the upper and lower bounds. d_{ij} is the distance between the i-th and j-th grasshoppers. $\hat{T}_a$ is the optimal solution of the current grasshopper in the d-dimensional space. In the update process, the inter-individual force is key, as shown in Eq. (2).

$$\begin{cases} S_i = \sum_{j=1}^{N} s(d_{ij})\hat{d}_{ij} \\ \hat{d}_{ij} = \dfrac{x_j - x_i}{d_{ij}} \end{cases} \tag{2}$$

In Eq. (2), S_i denotes the force between individuals in the population, $\hat{d}_{ij}$ indicates the unit vector pointing from the j-th grasshopper to the i-th one. N represents the total number of individuals in the grasshopper population, and $s(d_{ij})$ is the social interaction function. The SA algorithm iterates through the Metropolis criterion, and its calculation is shown in Eq. (3).

$$P = \begin{cases} 1, \Delta E \le 0 \\ e^{-\frac{\Delta E}{T}}, \Delta E > 0 \end{cases} \tag{3}$$

In Eq. (3), P represents the probability, ΔE is the difference in the objective function values between the new and current solutions, and T represents the current temperature. After applying the Metropolis criterion to decide whether to accept the solution, the SA algorithm performs the cooling operation, as shown in Eq. (4).

$$T_{k+1} = \alpha T_k \tag{4}$$

In Eq. (4), T_k represents the temperature in the k-th iteration, and α denotes the cooling factor, typically ranging from $0 < \alpha < 1$.

3.2. HPSO Parameter Optimization

The SA-GOA algorithm leverages GOA's global search and SA's Metropolis criterion to escape local optima, balancing exploration and exploitation. However, parameter tuning remains time-consuming in complex transport scheduling. To address this, the HPSO algorithm integrates PSO with a Genetic Algorithm (GA) by introducing genetic operators into PSO, combining their strengths to efficiently handle multi-constraint, high-dimensional optimization (Nachaoui et al. 2024; Polamuri et al. 2023). Thus, HPSO is incorporated into SA-GOA to enhance emergency logistics scheduling performance, as shown in Fig. 2.

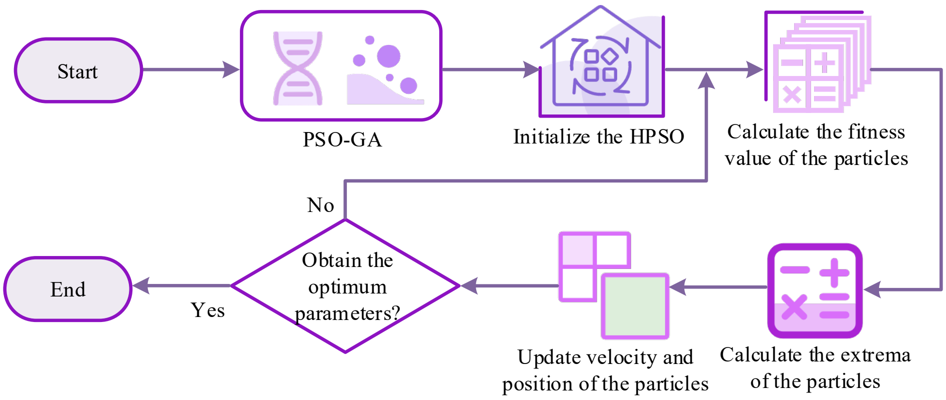


Fig. 2. HPSO algorithm flowchart (Source: https://icon.sucai999.com/ and author self-drawn)

As shown in Fig. 2, the algorithm embeds GA's fitness evaluation, selection, crossover, and mutation into PSO initialization, setting particle positions, velocities, and parameters. It then computes fitness, updates individual and global bests, and iteratively adjusts velocities and positions until optimal parameters are found, after which the algorithm outputs the results. The velocity update is given in Eq. (5).

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot (pBest_i - x_i(t)) + c_2 \cdot r_2 \cdot (gBest - x_i(t)) \tag{5}$$

In Eq. (5), $v_i(t+1)$ represents the velocity vector of the i-th particle in the $t+1$-th iteration, r_1 and r_2 are random numbers uniformly distributed within the $(0,1)$ range, $pBest_i$ denotes the optimal position searched by the i-th particle, and $gBest$ represents the global optimal position found by the entire particle swarm. While updating the particle velocity, the calculation for position update is shown in Eq. (6).

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{6}$$

In Eq. (6), $x_i(t+1)$ represents the position vector of the i-th particle in the $t+1$-th iteration. $x_i(t)$ denotes the position vector of the i-th particle in the t-th iteration. The hybrid SA-GOA and HPSO algorithm, termed SGHP, is shown in Fig. 3.

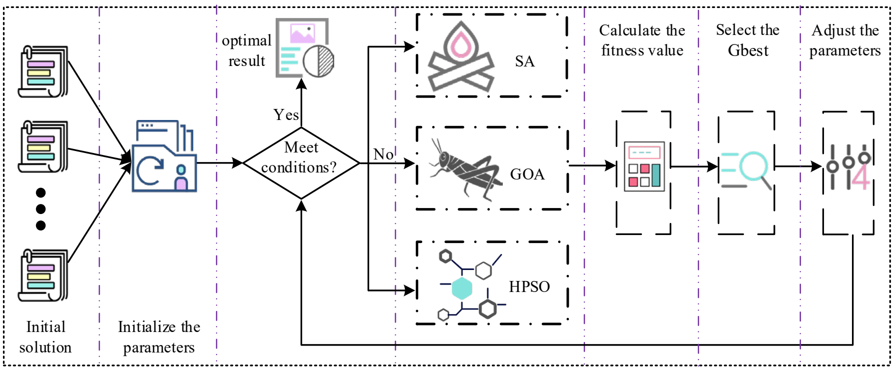


Fig. 3. SGHP model flowchart

As shown in Fig. 3, the hybrid model generates 3N initial solutions and sets SA, GOA, and HPSO parameters. It then iteratively executes GOA, SA, and HPSO on grouped solutions, evaluates fitness, updates parameters, and selects the global optimum until the termination condition is met, completing the optimization process.

3.3. Improved NSGA-II Multi-Objective Optimization

Although the SGHP model enhances global and local search for efficient emergency logistics scheduling, real-world scenarios often require balancing multiple objectives, such as minimizing cost and delivery time. However, parameter tuning and local optima remain challenges. The NSGA-II, using fast non-dominated sorting and crowding distance comparison, effectively handles multi-objective optimization and avoids local optima (Jafari and Rezvani 2023). Its process is illustrated in Fig. 4.

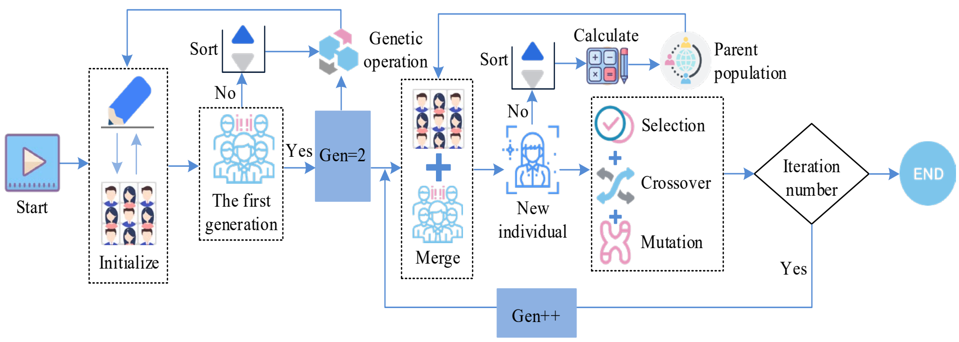


Fig. 4. NSGA-II operation flowchart

As shown in Fig. 4, NSGA-II begins with random population initialization, followed by fast non-dominated sorting, after which selection, crossover, and mutation operations are performed to produce the offspring population. The parent and offspring populations are then merged, sorted, and updated. Iteration continues until the preset generation limit is reached. The crowding distance is calculated using Eq. (7).

$$C_i = \sum_{j=1}^{M} (f_{j_{i+1}} - f_{j_{i-1}}) \tag{7}$$

In Eq. (7), i represents the i-th individual, M is the number of objective functions, and $f_{j_{i+1}}$ and $f_{j_{i-1}}$ represent the function values. The crowding distance guides individual retention to maintain diversity, followed by genetic operations. The mutation is computed in Eq. (8).

$$V_j^{'} = V_j + \Delta(V_j, \xi) = V_j + \sigma'(\cos(\frac{\pi}{2}\sin((2\xi - 1)(m+1))))^{\frac{1}{m+1}} - \sin(\frac{\pi}{2}\sin((2\xi - 1)m))^{\frac{1}{m}} \tag{8}$$

In Eq. (8), V_j represents the value of the j-th gene of the individual before mutation, $V_j^{'}$ is the value of the j-th gene after mutation, m is the distribution index, σ' is the scaling factor, and ξ is a random number uniformly distributed. Although NSGA-II effectively handles multi-objective problems, it may fall into local optima in high-dimensional cases. To improve this, matrix real-number encoding and neighborhood search operators are introduced to enhance representation and local optimization. The improved NSGA-II process is shown in Fig. 5.

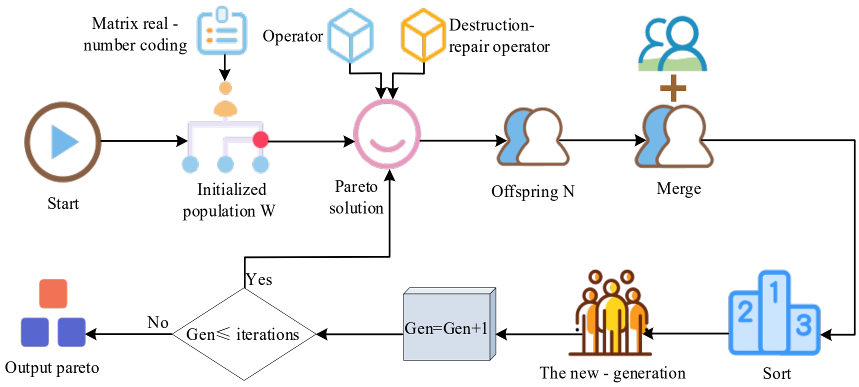


Fig. 5. Improved NSGA-II operation flowchart

As shown in Fig. 5, the improved NSGA-II generates the initial population via matrix real-number encoding and applies insertion and destruction-repair operators to each Pareto solution. Offspring are created and merged with parents for non-dominated sorting and dynamic crowding distance adjustment. The process repeats until the maximum generation is reached, after which the Pareto optimal solution is output. Based on the improved NSGA-II mentioned above, the emergency logistics scheduling problem for multiple distribution centers is encoded. Specifically, the matrix real number encoding method is used to encode each scheduling scheme as a genotype individual. The rows of the matrix correspond to distribution centers or vehicles, the columns to demand points or task sequences, and the matrix elements to distribution orders, transportation volumes, or vehicle allocation relationships. The genotype is directly mapped to the phenotype, which is the actual executable transportation scheduling plan, including the driving path, access sequence, loading capacity, and arrival time of each vehicle at each demand point. In the process of evolution, algorithms perform crossover, mutation, and neighborhood search operations on genotypes to generate new individuals and use constraint repair mechanisms to ensure that their corresponding phenotypes meet practical constraints such as vehicle load, time window, and vehicle quantity. A clear mapping relationship between genotype and phenotype is maintained to ensure consistency between individual evaluation and scheduling execution in the multi-objective optimization process. The dynamic crowding calculation is shown in Eq. (9).

$$D(i) = \sum_{m=1}^{M} \frac{f_m(i+1) - f_m(i-1)}{f_m^{\max} - f_m^{\min}} \tag{9}$$

In Eq. (9), $f_m(i+1)$ is the value of the $i+1$-th individual in the m-th objective function, $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum value of the objective function m in the current population. To clarify the representation of solutions in the model and improve reproducibility, this study employs matrix real-number encoding to represent candidate solutions. Each individual (genotype) is represented as a real-number matrix $M \times N$, where rows correspond to distribution centers or vehicles, columns correspond to demand points, and element x_{ij} represents the service priority or allocation relationship between distribution center i and demand point j. This encoding is mapped to the actual scheduling scheme (phenotype) through a decoding process. A schematic diagram of the chromosome structure and genotype-phenotype mapping is shown in Fig. 6.

As shown in Fig. 6, the model uses matrix real-number encoding to represent candidate solutions, where rows correspond to distribution centers or vehicles, columns correspond to demand points, and elements are used to characterize service priorities or allocation relationships. The encoding is decoded through sorting and constraint allocation to generate vehicle routes and service sequences that satisfy load and time window constraints, thus realizing the mapping from genotype to actual scheduling scheme.

3.4. SGHPN Fusion Framework

While the improved NSGA-II enhances global optimization capabilities and preserves solution diversity in multi-objective optimization scenarios, a single algorithm still faces limitations in handling the dynamic and complex nature of emergency logistics scheduling across multiple distribution centers. To address this issue, this study integrates SA-GOA, HPSO, and improved NSGA-II to propose a unified SGHPN framework that combines dynamic adaptability with multi-objective optimization. The model combining the SGHP model with the improved NSGA-II is named SGHPN, and its operation flowchart is shown in Fig. 7.

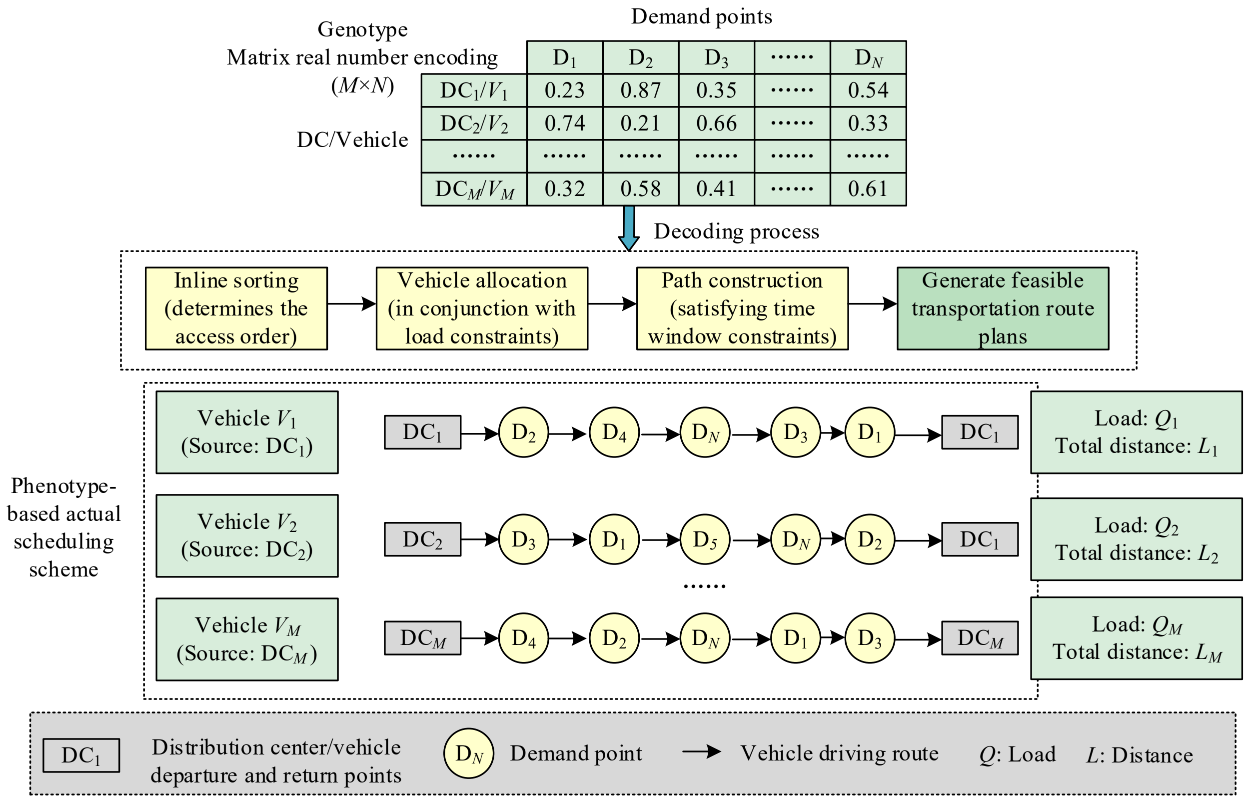


Fig. 6. Chromosome encoding and genotype–phenotype mapping structure

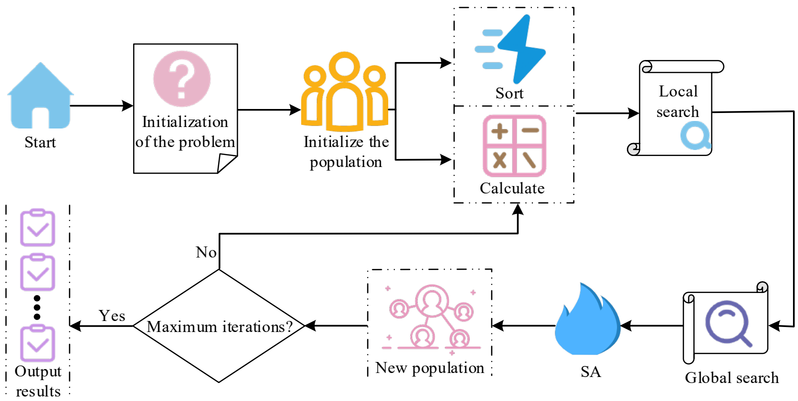


Fig. 7. SGHPN model operation flowchart

As shown in Fig. 7, the SGHPN model initializes the multi-center emergency logistics problem, defines objectives and parameters, and sets NSGA-II configurations. The population is encoded and sorted using NSGA-II, with crowding distance calculated. GOA performs local search, HPSO conducts global search, and SA perturbs and updates individuals. NSGA-II then generates new populations until the iteration limit is reached, after which the non-dominated solution set is output and analyzed. The optimization objectives include minimizing total transportation costs, minimizing total delivery time, and maximizing demand fulfillment rate. The total transportation cost is represented by the sum of the product of the transportation unit price and the transportation volume from each distribution center to each demand point. The total delivery time is defined as the accumulation of transportation time for each route. The satisfaction rate of demand is quantified by a binary variable of whether each demand point has been successfully met. Based on this, a multi-objective optimization objective function is constructed to achieve collaborative optimization of cost, time, and service level while satisfying vehicle load and quantity constraints. The initialization and modeling calculation are shown in Eq. (10).

$$C = \sum_{i=1}^{n} \sum_{j=1}^{b} c_{ij} x_{ij} \tag{10}$$

In Eq. (10), n is the number of distribution centers, b is the number of demand points, c_{ij} is the transportation cost, and x_{ij} is the transportation volume from the distribution center i to demand point j. The transport process aims to minimize delivery time and maximize service level, as defined in Eq. (11).

$$\begin{cases} T = \max_{j=1}^{b} \left\{ \sum_{i=1}^{n} t_{ij} x_{ij} \right\} \\ S = \sum_{j=1}^{b} d_j y_j \end{cases} \tag{11}$$

In Eq. (11), t_{ij} represents the transportation time from the distribution center i to demand point j, d_j represents the demand satisfaction level for demand point j, and y_j is a variable indicating whether demand point j is satisfied. If satisfied, it is 1. If not, it is 0. During delivery, the calculation process for vehicle number and load capacity constraints is shown in Eq. (12).

$$\sum_{i=1}^{n} \sum_{j=1}^{b} w_{ij} x_{ij} \le W_k, \forall k = 1, 2, ..., K \tag{12}$$

In Eq. (12), w_{ij} represents the unit weight of goods. W_k represents the vehicle load capacity limit. K represents the total number of vehicles. This model integrates multiple algorithms to address multi-objective problems, enhancing local optimization and global exploration for more efficient scheduling. Based on the above, the pseudocode of the SGHP algorithm is shown in Table 1.

3.5. Indicator and Measurement Definitions

The performance of the proposed model is verified using metrics such as memory usage, utilization, delivery rate, and cost prediction accuracy. The cost prediction accuracy refers to the classification accuracy of transportation, inventory, emergency response, and environmental costs. The specific calculation formula is shown in Eq. (13).

$$\begin{cases} Acc_{micro} = \dfrac{1}{K} \sum_{i=1}^{K} Acc_k \\ Acc_k = \dfrac{\sum_{i=1}^{N} 1[y_i = k] \cdot 1[\hat{y}_i = k]}{\sum_{i=1}^{N} 1[y_i = k]} \times 100\% \end{cases} \tag{13}$$

In Eq. (13), K represents the number of categories, which equals 4. Acc_{micro} represents the cost prediction accuracy. N represents the total number of samples. i represents the sample index. y_i represents the true category of the i th sample. $\hat{y}_i$ represents the predicted category of the i th sample. k represents the category index. Acc_k represents the class-by-class accuracy of the k th sample, and $1[\square]$ represents the indicator function, which takes the value 1 if the condition is true and 0 otherwise. The calculation formulas for delivery on-time rate and safety violation rate are shown in Eq. (14).

$$\begin{cases} PR = \dfrac{1}{M} \sum_{i=1}^{M} 1[e_i \le a_i \le l_i] \times 100\% \\ SVR = \dfrac{1}{M} \sum_{i=1}^{M} 1[w_i \ge s_{without}] \times 100\% \end{cases} \tag{14}$$

In Eq. (14), PR represents the on-time delivery rate. SVR represents the safety violation rate. M represents the number of orders delivered during the statistical period. a_i represents the arrival time of the i th order. $[e_i, l_i]$ represents the time window of the i th order. $1[e_i \le a_i \le l_i]$ represents that the arrival is recorded as “on time” if it is within the time window. w_i represents the i th task or vehicle delivery, and $s_{without}$ represents the number of safety violations.

4. Performance Analysis of SA-GOA-based Optimization Model

4.1. Effective Validation of SGHP Algorithm

To evaluate the SGHP algorithm's performance in emergency logistics scheduling, it was compared with Monte Carlo Simulation–Genetic Algorithm (MCS-GA), Ant Colony Optimization–Local Search (ACO-LS), and Adaptive Fruit Fly Optimization Algorithm (AFOA). Experiments were run on an AMD EPYC processor with 64 GB RAM, NVIDIA A6000 GPU, and Linux OS. This study uses the classic Solomon VRPTW dataset as an algorithm benchmark. Its capacity constraints correspond to emergency vehicle loading restrictions, hard/soft time windows, and service times characterize task urgency and on-site operation duration, and three types of spatial distribution (C/R/RC) cover the "clustered/random/mixed" demand patterns in disaster situations. This facilitates systematic evaluation of the multi-objective trade-off between cost, timeliness, and accessibility, maintaining comparability with existing research. The performance of SGHP, MCS-GA, ACO-LS, and AFOA was compared, with their memory usage and response times shown in Fig. 8.

Table 1. SGHP algorithm pseudo code

```
Algorithm: SGHPN (Hybrid SA–GOA–HPSO–improved NSGA-II)
Input:
Data & constraints:
Distribution centers D, customers C, vehicles V
Cost matrix c_ij, travel-time matrix t_ij, service/handling times
Feasibility constraints (vehicle capacities, time windows, max duty time, fleet size, etc.)
Objectives (multi-objective):
Minimize total transportation cost, total travel/late penalties, route complexity;
Maximize service level / demand satisfaction
Key parameters:
SA (Simulated Annealing):
T0          # initial temperature
α∈(0,1)    # geometric cooling factor
Tmin        # minimum temperature (stopping threshold)
L           # chain length (neighborhood trials per temperature)
Metropolis acceptance: if Δ≤0 accept; else accept with prob exp(−Δ/T)
GOA (Grasshopper Optimization Algorithm):
N_GOA       # population size
I_GOA       # max iterations
c(t)        # shrinking factor, linearly decreasing: c ← c_max − (c_max−c_min)·(t/I_GOA)
s(r)        # social interaction function: s(r) = f·exp(−r/l) − exp(−r)    (typical f≈0.5, l≈1.5)
Bounds & projection/repair to feasible region
HPSO (Hybrid PSO with GA operators):
N_PSO       # particles
w_max→w_min    # inertia weight linearly decreasing per generation
c1, c2      # cognitive/social learning factors
v_max       # max velocity (per-dimension cap)
pc_PSO      # crossover rate (GA operator on particle encodings)
pm_PSO      # mutation rate (GA operator on particle encodings)
stop_PSO    # stop by max iterations or consecutive no-improvement generations
Improved NSGA-II:
N_NSGA      # population size
G           # max generations
pc_NSGA     # crossover rate (e.g., SBX / uniform)
pm_NSGA     # mutation rate (≈ 1/decision-dimension)
```

k_tour # tournament size (2 or 3)

Enc # matrix real-valued encoding (multi-DC, multi-vehicle, time windows)

NeighOps # neighborhood operators: insertion, destroy–repair

Common stopping:

time_limit # optional wall-clock cap

stall_gen # consecutive no-improvement generations

seed # RNG seed for reproducibility

Output:

Pareto set P and representative schedules (balanced in cost/time/service)

Procedure:

1 Initialize:

- Generate N_NSGA feasible individuals with Enc ⇒ P0; repair any infeasible solutions (capacity/time windows/vehicle count).

- Non-dominated sort + crowding distance on P0 ⇒ Pareto front P; set T ← T0.

2 For gen = 1..G:

Global exploration via GOA around current population P

2.1 Build candidate set G_cand with GOA:

For t = 1..I_GOA:

For each grasshopper i:

Compute pairwise distances r_ij and unit directions ê_ij

Social force S_i ← Σ_j s(r_ij)·ê_ij

Update position: x_i ← c(t)·((ub−lb)/2 · S_i) + g_best

Project/repair x_i to feasible region

End

End

Local refinement via SA on each candidate

2.2 For each x ∈ G_cand:

Repeat L times:

Propose neighbor x’ via Enc-preserving perturbations (swap/insert/2-opt), then repair constraints

If x’ dominates x then x ← x’

Else compute scalarized gap Δ = φ(x’) − φ(x) (e.g., reference-point Tchebycheff)

Accept x’ with probability exp(−Δ/T)

End

Update temperature: T ← max(alpha·T, Tmin)

Optional hyperparameter adaptation via HPSO

2.3 Optimize Θ = {c_max,c_min, alpha, L, v_max, …} with HPSO:

Initialize particle positions (parameters) and velocities

While not stop_PSO:

For each particle θ:

Run a short evaluation of steps 2.1–2.2 using θ; score quality (e.g., hypervolume HV↑ or IGD↓ of P)

Update velocities: v ← w·v + c1·rand()·(pbest−x) + c2·rand()·(gbest−x); clip to ±v_max

Update positions x ← x + v; clip to parameter bounds

Apply GA operators with rates pc_PSO, pm_PSO to elite particles

End

Apply best θ* to subsequent generation(s)

Evolutionary update with improved NSGA-II + neighborhood intensification

2.4 Generate offspring Q from P:

Selection: k_tour tournament using rank + crowding distance

Crossover with rate pc_NSGA (SBX/uniform), repair feasibility if needed

Mutation with rate pm_NSGA (polynomial/Gaussian), maintain Enc consistency

Intensify elites with NeighOps (insertion, destroy–repair)

Merge & truncate to form next generation

2.5 R ← P ∪ Q ∪ G_cand(SA-refined); non-dominated sort + crowding; truncate by rank+crowding ⇒ P

Stopping check

2.6 If gen=G or time_limit reached or no HV improvement for stall_gen generations: break

3 Return final Pareto set P; report several representative trade-off solutions.

Constraint handling (unified):

Prefer repair for hard constraints (capacity, time windows, max duty, fleet size). If repair fails, apply strong penalties so infeasible solutions are dominated.

Reference: :contentReference[oaicite:0]{index=0}

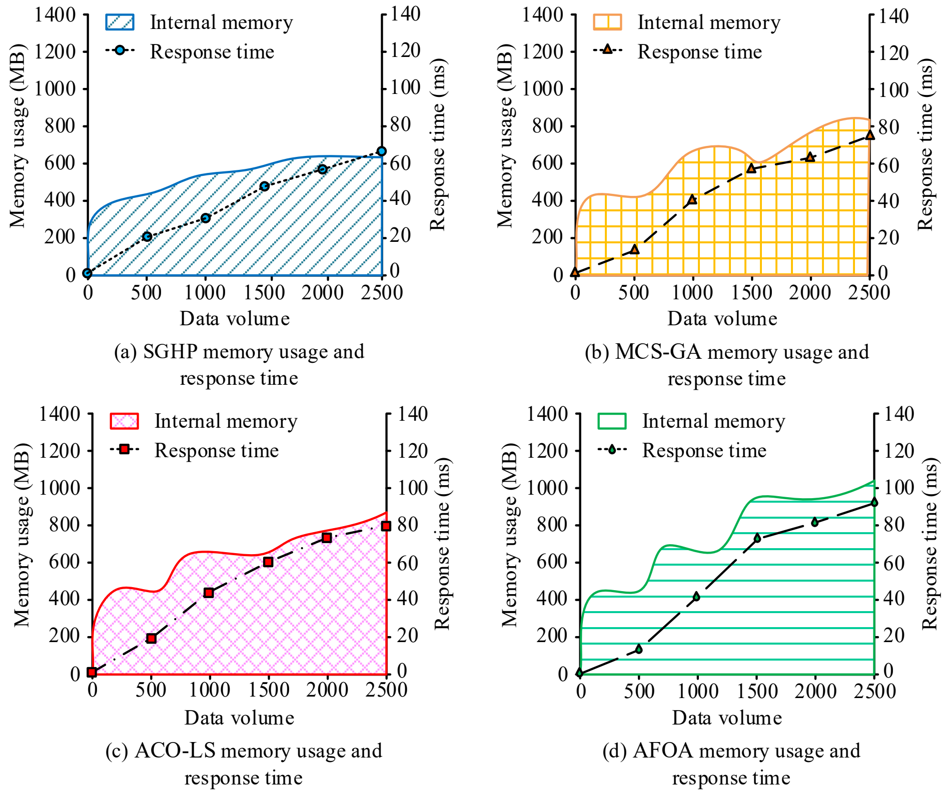


Fig. 8. Comparison of system memory usage and response time

In Fig. 8, as data volume increased, SGHP's memory usage rose slowly (max 620 MB, 68ms), while MCS-GA, ACO-LS, and AFOA reached 850 MB/76ms, 880 MB/80ms, and 1050 MB/92ms, respectively. Overall, SGHP demonstrated superior computational efficiency. Fig. 9 compares vehicle and distribution center utilization across the four algorithms.

In Fig. 9, vehicle utilization for all algorithms increased and then stabilized with more iterations. SGHP reached a maximum of 93%, while MCS-GA ranged between 82% and 97%. The maximum distribution center utilization for other algorithms was 94%, 92%, and 84%, respectively. Overall, SGHP demonstrated strong resource utilization performance. To further verify service quality, this study compared the delivery accuracy and demand satisfaction rates, as shown in Fig.

9.

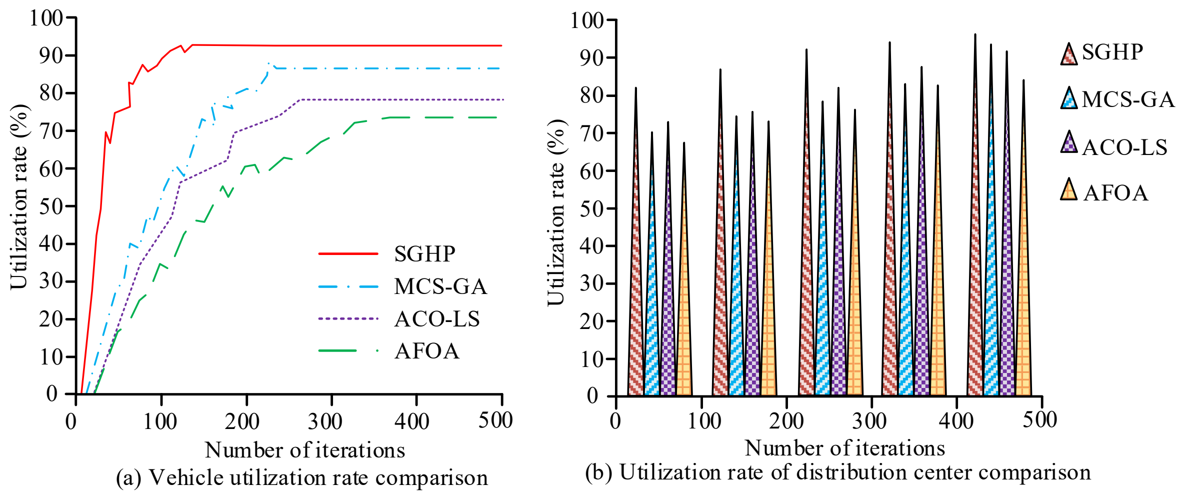


Fig. 9 Comparison of vehicle utilization and demand satisfaction rates

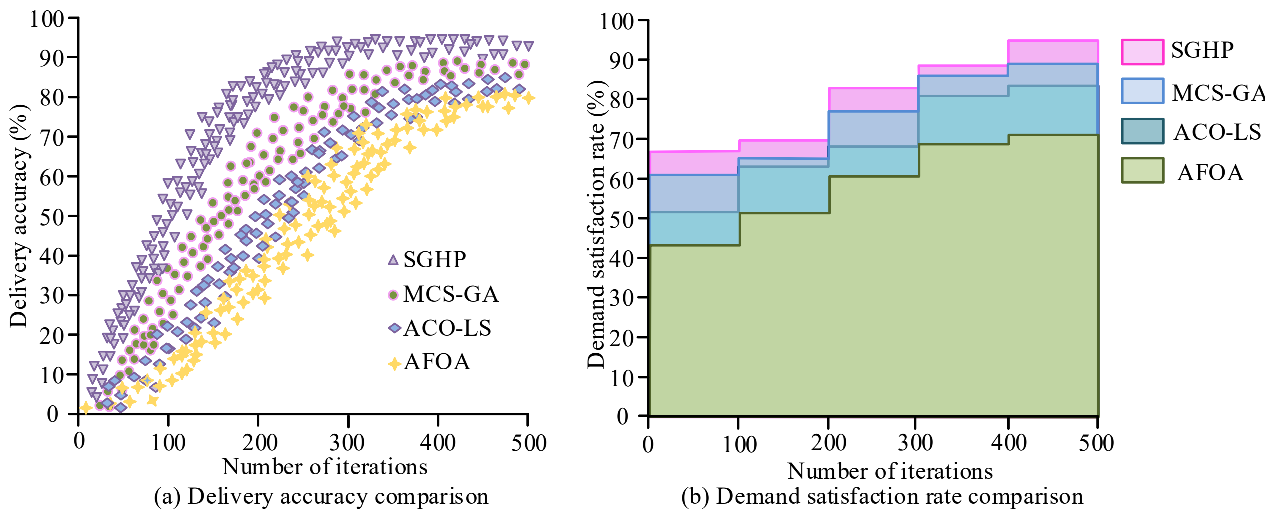


Fig. 10. Comparison of delivery accuracy and demand satisfaction rates (Source: author self-drawn)

In Fig. 10(a), all algorithms improved and then converged in delivery accuracy, with SGHP converging fastest and reaching 93%. In Fig. 10(b), SGHP achieved the highest demand satisfaction rate of 95%, followed by MCS-GA at 90%, ACO-LS at 83%, and AFOA at 71%. Overall, SGHP demonstrated superior delivery accuracy and service quality.

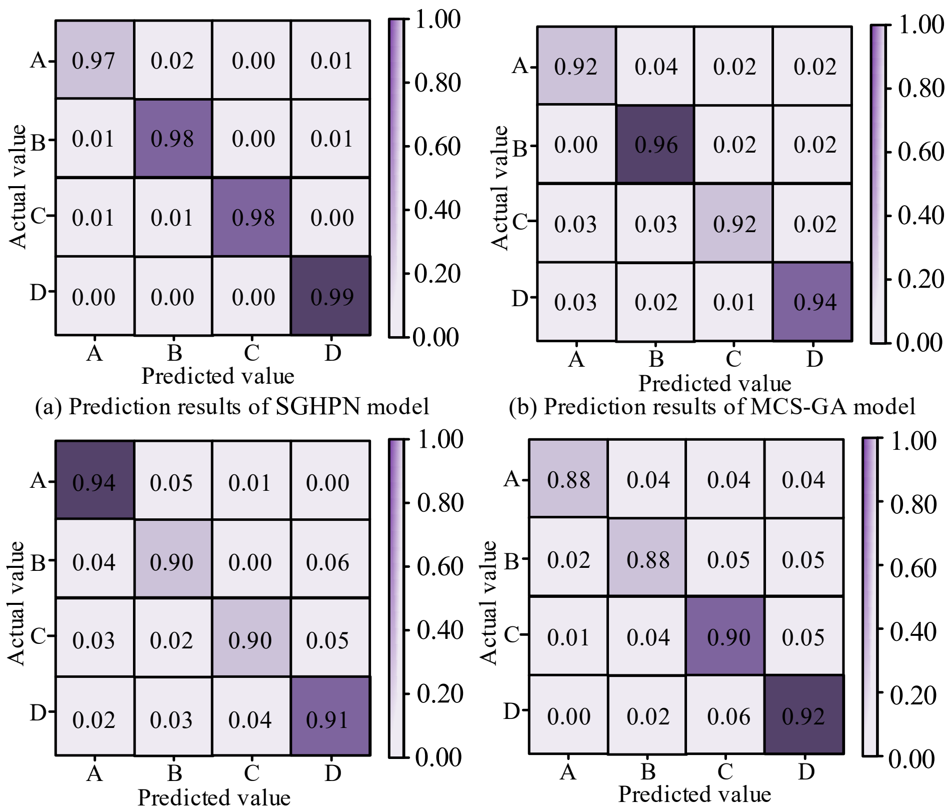
3.2. SGHPN Model Evaluation and Analysis

After validating the SA-GOA algorithm, this study further assessed the SGHPN model by comparing it with MCS-GA, ACO-LS, and AFOA. Data from 120 logistics companies in 10 major hub cities from 2014 to 2024, including orders, vehicle operations, distribution centers, and costs, were analyzed. Results are shown in Fig. 11.

In Fig. 11(a), SGHPN demonstrated prediction accuracy of 97% to 99% for these four types of costs and performed the best among all the comparison models. This indicates that the SGHPN model can more accurately identify the distribution patterns of different cost components in each link of the supply chain, thereby providing a reliable cost basis for managers to make decisions on transportation routes and inventory allocation. Fig. 11(b) shows that the prediction accuracy rates of MCS-GA, ACO-LS, and AFOA range from 92% to 96%, 90% to 94%, and 88% to 92% respectively, all of which are lower than those of the SGHPN model. This indicates that in the complex cost structure of a multi-distribution center supply chain, the SGHPN model effectively improves the overall accuracy of cost estimation through a multi-algorithm collaborative mechanism. Fig. 12 compares delivery punctuality and route complexity to further assess scheduling performance.

In Fig. 12(a), as order volume increases, the on-time delivery rates of all models show an upward trend. Among them, the SGHPN model maintains the highest rate at all order volume levels, reaching 98%. This indicates that the SGHPN model can more effectively meet the time window constraints and reduce the risk of delays when handling large-scale and high-density supply chain delivery tasks. As shown in Fig. 12(b), the path complexity of the SGHPN model is 25%, significantly lower than the 38% of MCS-GA, 47% of ACO-LS, and 58% of AFOA. In actual supply chain operations, a lower path complexity means fewer cross-paths and repeated driving, which helps to reduce fuel consumption, shorten the total driving distance, and improve vehicle turnover efficiency. The SGHPN model achieves the lowest path complexity while maintaining a high on-time delivery rate, indicating that it can achieve a better balance between time efficiency and path economy, which is of practical significance for the sustainable operation of multi-distribution center supply chains in large-scale emergency dispatching. For a thorough assessment of the model's performance, four different models have been used for solving the problem of emergency scheduling of a multiple distribution centers' supply chain in a logistic hub city. These optimized results, such as material status rates, have been compared against their non-optimized values. This test was conducted ten times. The results are shown in Table 2.

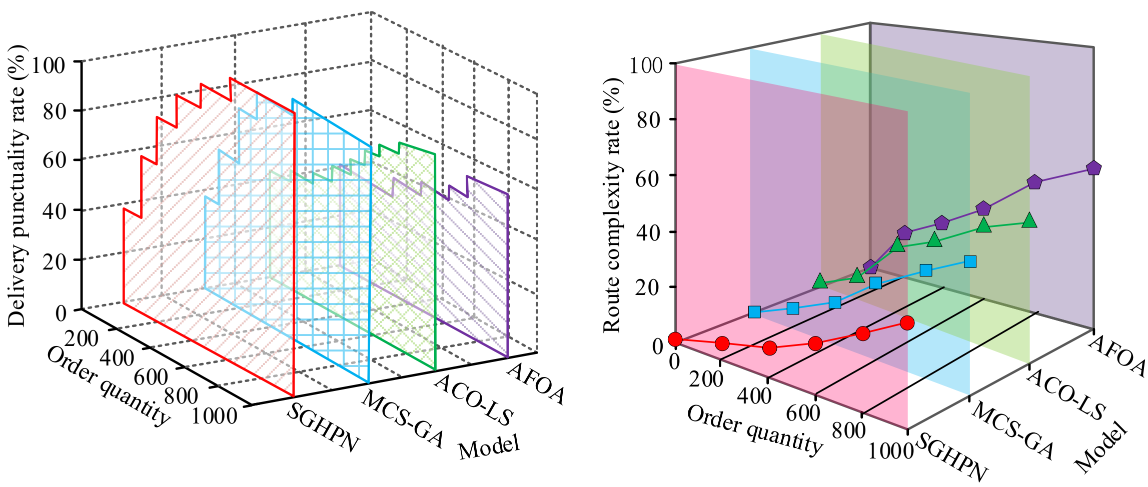
A: Transportation cost B: Inventory cost C: Emergency cost D: Environmental cost



(a) Prediction results of SGHPN model (b) Prediction results of MCS-GA model

(c) Prediction results of ACO-LS model (d) Prediction results of AFOA model

Fig. 11. Cost classification prediction accuracy experiment results



(a) Delivery punctuality rate comparison (b) Route complexity rate comparison

Fig. 12. Comparison of delivery punctuality and route complexity rate

Table 2. Comparison of results before and after algorithm optimization

Feedback indicator	Before the renovation	SGHPN	MCS-GA	ACO-LS	AFOA
Rate of the goods in good condition (%)	58.3 ± 1.1	98.1 ± 0.6	85.4 ± 1.3	74.2 ± 1.6	67.9 ± 1.4
Vehicle load rate (%)	50.8 ± 0.9	93.2 ± 0.8	78.7 ± 1.2	57.5 ± 1.5	50.9 ± 1.3
Safety violation rate (%)	63.7 ± 1.3	8.4 ± 0.5	20.6 ± 0.9	31.8 ± 1.1	39.4 ± 1.2
Demand satisfaction rate (%)	38.9 ± 1.2	95.1 ± 0.7	76.3 ± 1.4	58.7 ± 1.6	56.2 ± 1.5

As shown in Table 2, in terms of the goods integrity rate, the SGHPN model achieved 98.1%, which was an increase of 68.3% compared to the baseline model and 14.9% higher than the best-performing comparison model MCS-GA. This indicator reflects the quality guarantee capability of emergency supplies in the supply chain processes such as storage, loading, and transportation. A high integrity rate means less material loss and more reliable emergency response. In terms of vehicle loading rate, the SGHPN model reached 93.2%, which was an increase of 83.5% compared to the optimized model, indicating that this model can make better use of the transportation capacity resources of each distribution center and reduce empty trips and low-load transportation. In terms of safety violation rate, the SGHPN model dropped to 8.4%, significantly lower than the 63.7% of the optimized model and other comparison models, indicating that this model can effectively avoid high-risk operations in route selection and time window arrangement. In terms of demand fulfillment rate, the SGHPN model reached 95.1%, which increased by 144.5% compared to the baseline model, This indicates that the model can more accurately respond to the urgency and material type requirements of each demand point in the supply-demand matching process of multiple distribution centers and multiple demand points. To further demonstrate the application effect of the model in actual supply chain scheduling, a set of typical examples were selected based on Table 2. Taking a simplified supply chain system containing 2 distribution centers (DC_1, DC_2) and 5 demand points (D_1-D_5) as an example, the optimized scheduling results of the SGHPN model are shown in Fig. 13.

Fig. 13 illustrates a supply chain scenario where the SGHPN model rationally allocates delivery tasks to different distribution centers and generates executable paths. Vehicle V_1 departs from DC_1, completes delivery tasks D_2, D_4, and D_1 sequentially, and then returns. Vehicle V_2 departs from DC_2, completing delivery tasks D_3 and D5. Both paths effectively control delivery distance and time costs while satisfying vehicle load and time window constraints. This demonstrates that the model can achieve collaborative processing of task decomposition and path optimization in a multi-distribution-center environment, exhibiting strong practical application capabilities.

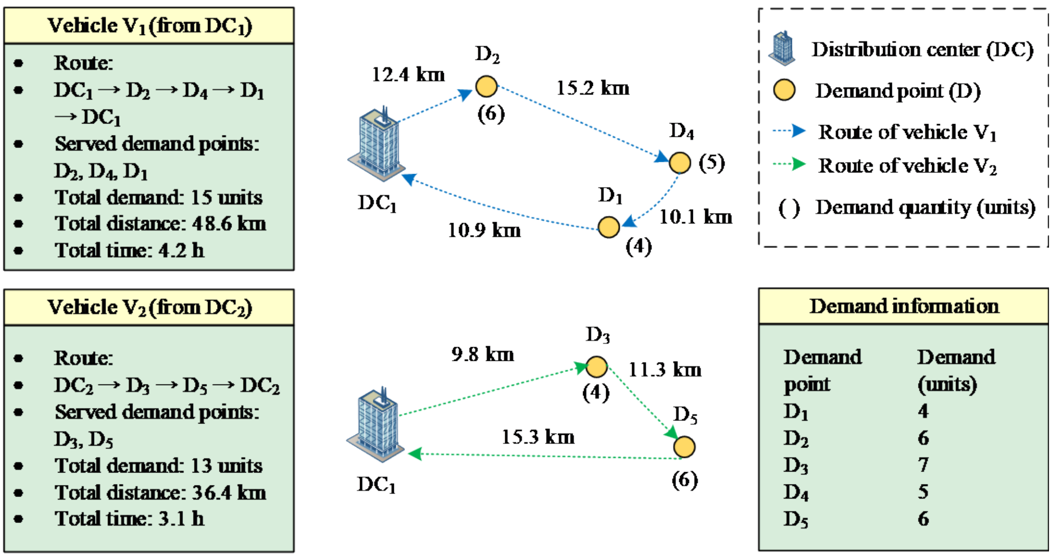


Fig. 13. Optimal scheduling result of the SGHPN model in the example supply chain system

5. Conclusion

This study introduces and validates an SGHPN framework that combines SA–GOA, HPSO, and an improved NSGA-II for dynamic, uncertain, and conflicting multi-objective emergency logistics scheduling across multiple distribution centers. The framework significantly enhances overall performance compared to baseline models on the Solomon VRPTW benchmark and real-world multi-DC data. Cost classification prediction accuracy reaches up to 99%, on-time delivery performance reaches 98%, path complexity is reduced to 25%, cargo integrity rate increases to 98%, and safety violation rate drops to about 8%. Additionally, the proposed method shows reduced volatility and improved robustness in repeated tests, demonstrating its practical engineering value and potential for widespread application. Based on the above results, supply chain managers can make the following adjustments to the existing decision-making process. In terms of cost prediction, managers should introduce a multi-algorithm collaborative prediction mechanism to replace the traditional single cost estimation method, to improve the classification prediction accuracy of transportation costs, inventory costs, emergency response costs and environmental costs. During the formulation of distribution plans, managers can dynamically adjust the vehicle allocation and route selection strategies of each distribution center based on the on-time delivery rate and path complexity indicators provided by the model and preferentially adopt the scheduling schemes that can simultaneously increase vehicle utilization and meet demand. In terms of safety and quality management, managers need to incorporate the safety violation rate into the daily scheduling assessment system and use the violation rate prediction results provided by the model to intervene in advance in high-risk transportation tasks.

Future work will focus on the following: first, introducing constraints and perturbations more relevant to the field and conducting cross-city field pilots for verification; second, enhancing online and adaptive learning, along with hyperparameter self-scheduling, to boost adaptability and convergence efficiency during long-term operations; also, considering the inclusion of interpretability and compliance analysis, as well as expanding sustainability metrics like carbon footprint and social cost, to offer more reliable decision support for real emergency command situations.

Author Contributions

Mingmin Yan contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. Chaoran Xu contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection and draft preparation. Yangyang Feng contributed to manuscript editing, visualization, supervision, project administration, and funding acquisition. All authors have read and agreed with the manuscript before its submission and publication.

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Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

During manuscript preparation, the authors used artificial intelligence (AI) tools (such as ChatGPT) to polish and optimize the language of some texts, solely to improve readability and grammatical accuracy. The AI tools were not involved in key academic work such as research design, data analysis, results interpretation, or conclusion formation. All academic viewpoints and research findings were independently completed by the authors, who are responsible for the authenticity and completeness of the paper's content.

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