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# Fast Logistics Facility-Distribution Optimization Based on IGOA

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**Abstract:** With the sustained prosperity of global e-commerce and the increasing demand for logistics timeliness, traditional distribution networks face challenges such as low efficiency, high costs, and poor resource allocation. To address these issues, this study proposes a fast logistics facility-distribution optimization method based on an Improved Grasshopper Optimization Algorithm. A multi-objective optimization model integrating facility location selection and vehicle routing planning is constructed, with the dual objectives of minimizing total cost and maximizing customer satisfaction. Customer satisfaction is quantified through a time penalty function and a service attenuation mechanism, incorporating soft time windows and service quality loss costs. The Improved Grasshopper Optimization Algorithm is enhanced via non-dominated sorting and crowding distance computation, along with a hybrid local search mechanism and a differentiated position update strategy to balance global and local exploitation. Experimental results demonstrate that after 30 days of operation, the proposed method achieves a vehicle load rate of 99.6%, an order consolidation ratio of 98.6%, an average delivery time of 5.8 hours, and a delivery cost of 2.1 dollars/order. These findings indicate that the method exhibits strong capabilities in path optimization, dynamic scheduling, real-time responsiveness, and system reliability, offering an intelligent and efficient solution for modern logistics distribution systems. It should be noted that these findings are derived from simulation experiments, and further validation in real-world logistics systems is necessary to confirm their practical applicability.

**Keywords:** Improved grasshopper optimization algorithm, fast logistics, multi-objective model for logistics facilities-distribution, local search mechanism, differentiated location update strategy.

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## 1. Introduction

As e-commerce rapidly develops and consumer demand for logistics timeliness increases, the logistics industry has become a key link connecting production and consumption (Mishra and Singh, 2022). The current logistics distribution network is facing multiple challenges, including insufficient delivery timeliness, high costs, uneven resource allocation, and high pressure on end-of-pipe distribution. These bottlenecks seriously restrict the overall efficiency and service quality of the supply chain and affect customer satisfaction (Gerçek, 2023). In addition, due to the single mode of transportation, limited logistics infrastructure, and a low level of digitalization, logistics costs are exceptionally high (Kadam and Kadam, 2024). The Grasshopper Optimization Algorithm (GOA) can search for the distribution center location combination that minimizes the total cost through optimization iterations, and it can efficiently search for a large path solution space and find better route combinations through global exploration and local development capabilities (Yildiz et al., 2022; Li and Jimenez, 2022). To optimize delivery routes, improve node layouts, enhance delivery efficiency, and effectively reduce operating costs, an innovative fast logistics distribution method using the Improved Grasshopper Optimization Algorithm (IGOA) is proposed. The facility activation cost is calculated through cost minimization and customer satisfaction maximization, achieving an optimal balance between total cost and customer satisfaction via synergistic trade-offs. It then screens superior individuals through non-domination ordering and congestion calculations, coordinating global exploration and local development capabilities. Ultimately, through iterative output of the Pareto frontier, generates an optimized site selection-distribution solution that balances multiple objectives. Although existing research has made progress in optimizing the layout of fast logistics facilities still has significant shortcomings in multi-objective collaborative optimization, dynamic real-time scheduling, and customer satisfaction. Therefore, this research aims to construct a fast logistics distribution optimization model that balances cost, efficiency, and satisfaction through an improved locust algorithm. Among them, the study raised two questions: 1) How to effectively balance the relationship between facility location, route planning, and customer satisfaction in a multi-objective fast logistics distribution optimization model? And in a dynamic logistics environment, can IGOA achieve real-time scheduling and route optimization while significantly reducing delivery costs and time? It is anticipated that this methodology will provide theoretical support for rapid logistics facility-distribution optimization studies.

## 2. Related Works

As the e-commerce worldwide continues to expand, the logistics system directly affects the overall efficiency of e-commerce transactions. Therefore, optimizing research on fast logistics facilities-distribution systems is of great significance. Koc et al. (2024) proposed using the Bayesian best worst method for multi-criteria decision-making in logistics village site selection. The findings denoted that the research method could accurately handle multi-criteria decision-making problems and provide a scientific basis for decision-makers. Liu et al. (2022) proposed an iterative optimization method that combines artificial neural network demand prediction with a mixed-integer programming model for demand response and facility location problems in the design of multi-level distribution networks for online retailers. The results showed that the research method demonstrated excellent capabilities for logistics cost optimization. Ye et al. (2022) proposed various models and algorithms, including precise, heuristic, and meta-heuristic algorithms, for optimizing the path of electric vehicles. During the research process, a classification summary and algorithm comparison were conducted. The results showed that the research method had excellent solving efficiency and application scalability. Rodríguez-Espíndola et al. (2025) designed a two-stage stochastic programming model that integrates multimodal transport and carbon reduction measures to address the issues of supply chain disruptions and carbon emissions in disaster relief. The findings indicated that the research method demonstrated good transportation flexibility, rescue satisfaction rates, and cost-effectiveness (Rodríguez-Espíndola et al., 2025). Tirkolaee et al. (2023) proposed grey wolf optimization and particle swarm optimization algorithms for the two-level multi-product position allocation path problem. The findings demonstrated that the research method had good computational efficiency and solution quality.

Many domestic and international scholars have conducted in-depth research and applied the IGOA algorithm. Wu et al. (2024) designed a GOA method that combines Cauchy mutation with a random weight mechanism to improve GOA performance. Results indicate that the research method demonstrated enhanced problem-solving performance and stability. Badr et al. (2023) proposed eight improved variants of the GOA that combine grouping and mutation mechanisms to address slow convergence and the tendency toward local optima. The results indicate that the research method significantly improves convergence speed, solution quality, and effectively reduces operating costs and peak loads. Deng and Liu (2023) proposed a hybrid GOA to balance the exploration and exploitation of metaheuristic algorithms, demonstrating strong competitiveness and efficiency across benchmarks and engineering optimization problems. Tamilarasan et al. (2024) proposed a random sorting improved teaching learning and adaptive GOA to address the issues of high energy consumption and short lifespan in wireless sensor network clustering protocols. The outcomes denoted that the research method had good throughput and stability. Chen et al. (2022) proposed an IGOA based on dynamic dual elite learning and sine mutation to address slow convergence and susceptibility to local optima in GOA. These findings denoted that this research method could effectively enhance convergence and accuracy.

In conclusion, existing research has a significant impact on the optimization of fast logistics facilities and distribution, but there are still problems such as low distribution efficiency, unreasonable storage facility locations and a high vehicle vacancy rate. The GOA simulates the foraging behavior of locusts, which can effectively avoid getting stuck in local optima too early when solving high-dimensional, multi-modal, multi-objective optimization problems. Its adaptive search mechanism gradually refines the search range during iterations, thereby approaching the true Pareto front more accurately. Therefore, a fast logistics facilities-distribution optimization method based on the IGOA is developed, aiming to meet the design requirements of fast logistics facilities-distribution optimization and improve the rationality of logistics facility location selection and delivery efficiency.

## 3. Optimization Method for Fast Logistics Facilities and Delivery based on IGOA

### 3.1. Construction of a Multi-Objective Model for Fast Logistics Facilities-Distribution based on Customer Satisfaction

The traditional fast logistics facilities-distribution method has shortcomings such as focusing on single goals, minimizing costs or maximizing efficiency, and overly relying on historical experience and fixed patterns (Alzoubi et al., 2025; Dash and Dixit, 2024). The multi-objective model for fast logistics facility delivery based on customer satisfaction treats customer satisfaction as a core optimization objective and balances it with cost, efficiency, and other objectives to improve user experience and market competitiveness while reducing operating costs (Hebbi and Mamatha, 2023). Therefore, to achieve more accurate delivery planning, a multi-objective model for fast logistics facility delivery based on customer satisfaction is developed. The logistics facility location distribution path problem can be divided into various types of models types based on application scenarios and constraints, and its specific framework is shown in Fig. 1.

In Fig. 1, the logistics facility location distribution path model systematically classifies the logistics facility location distribution path problem into five dimensions: capacity, time window, number of centers, cargo flow, and objectives. To reflect the economic cost of facility activation and resource occupation, the cost of facility activation is studied and calculated, and its expression is shown in Eq. (1).

$$F_1 = S_0 \sum_{m\in M}\sum_{n\in N}\sum_{k\in K} X_{mnk} \tag{1}$$

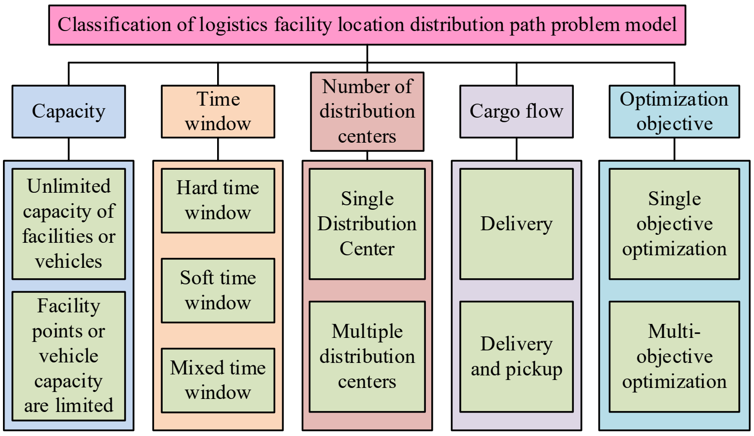


**Fig. 1.** Logistics facility location distribution path model framework
Notes: Capacity: vehicle load $Q_v$, facility capacity $C_f$, Time window: $[e_i, l_i]$, Objectives: minimize cost Min $Z_1$, maximize satisfaction max $Z_2$

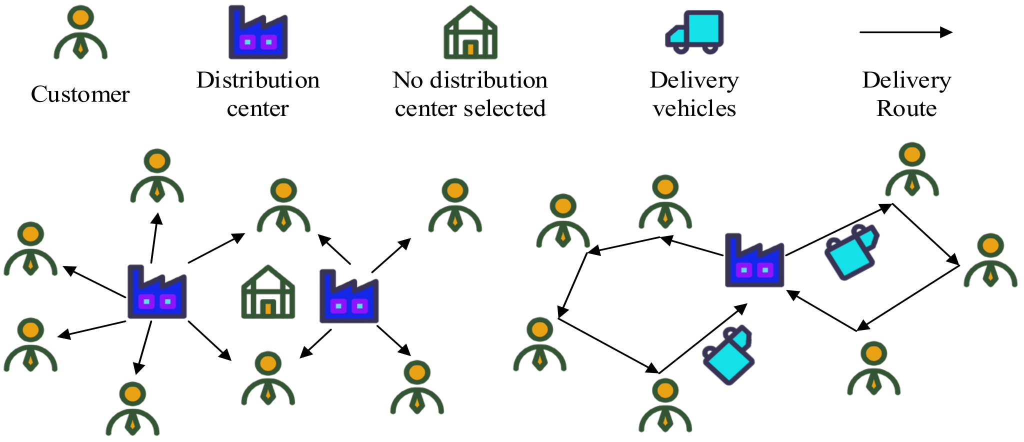
In Eq. (1), $F_1$ is the facility activation cost, $S_0$ is the unit time activation cost of a single facility, $M$ is the candidate facility set, $N$ is the distribution node set, $K$ is the available transportation tool set, and $X_{mnk}$ is the decision variable. Subsequently, the energy consumption cost of total transportation is studied and calculated, and its expression is shown in Eq. (2).

$$\begin{cases} F_2 = S_1 \sum_{m\in M}\sum_{n\in N}\sum_{k\in K} d_{mn}\gamma(D_{mn})X_{mnk} \\ \gamma(D_{mn}) = \gamma_0 + \dfrac{\gamma_{\max}-\gamma_0}{D_{\text{cap}}} D_{mn} \end{cases} \tag{2}$$

In Eq. (2), $F_2$ is the total transportation energy consumption cost, $S_1$ is the unit energy price, $d_{mn}$ is the Euclidean distance from facility $m$ to service node $n$, $\gamma(D_{mn})$ is the dynamic energy consumption coefficient per unit distance, $\gamma_0$ denotes the basic energy consumption rate when the transportation vehicle is unloaded, $\gamma_{\max}$ denotes the maximum energy consumption rate when the transportation vehicle is fully loaded, $D_{\text{cap}}$ is the rated load capacity of the transportation vehicle, and $D_{mn}$ denotes the actual load capacity of the facility $m$ to node $n$. Subsequently, the facility activation cost is calculated as the total time penalty cost, providing computable constraints for maximizing satisfaction in multi-objective optimization, as expressed in Eq. (3).

$$\begin{cases} F_3 = \sum_{n\in N} \Psi(\tau_n) \\ \Psi(\tau_n) = \begin{cases} \mu_1(\theta_n^{\min} - \tau_n) & \text{if}\tau_n < \theta_n^{\min} \\ 0 & \text{if}\theta_n^{\min} \le \tau_n \le \theta_n^{\text{opt}} \\ \mu_2(\tau_n - \theta_n^{\text{opt}}) & \text{if}\theta_n^{\text{opt}} < \tau_n \le \theta_n^{\max} \\ L_m & \text{if}\tau_n > \theta_n^{\max} \end{cases} \end{cases} \tag{3}$$

In Eq. (3), $F_3$ denotes the total time penalty cost, $\tau_n$ denotes the actual arrival time at node $n$, $\Psi(\tau_n)$ is the time penalty function, $\theta_n^{\min}$ is the earliest time the node can serve, $\theta_n^{\text{opt}}$ is the upper limit of the customer's most satisfactory time window, $\theta_n^{\max}$ is the absolutely unacceptable time, $\mu_1$ and $\mu_2$ are penalty coefficients and $L_m$ is the maximum value. The time penalty function is a piecewise linear function of the actual arrival time relative to the customer's preferred time window. Penalty coefficients are set to reflect different levels of dissatisfaction: early arrival penalty is 0.5, late arrival penalty is 2.0, and unacceptable time penalty is 10.0. The logical transformation of total penalty cost is used to normalize satisfaction between 0 and 1. In summary, the main problems in the fast logistics facilities-distribution model are facility location and vehicle delivery routing, as shown in Fig. 2.



(a) Site selection issue

(b) Vehicle routing problem

**Fig. 2.** Facility site selection and vehicle delivery path problems

(Notes: Key decision variables: Candidate facility coordinates $\left(x_f, y_f\right)$, Customer coordinates $\left(x_c, y_c\right)$, Routing variable $x_{ij}^v = 1$ if vehicle $v$ travels from $i$ i to $j$, Facility selection variable $y_f = 1$ if facility $f$ is activated)

In Fig. 2(a), the core of the facility location problem is how to select the optimal site from candidate centers to efficiently serve surrounding customers and form a distribution network. The core of the vehicle delivery routing problem is how to optimize the driving routes of multiple vehicles from the distribution center to efficiently serve all customers. The facility activation cost is calculated as the cost of service quality loss through a loss grading quantification mechanism, and its expression is shown in Eq. (4).

$$F_4 = \Pi \sum_{m \in M} \sum_{n \in N} \sum_{k \in K} q_n X_{mnk} \cdot \max\left\{ \frac{\xi_1 - \rho_n}{\xi_2 - \xi_1}, 0 \right\} \tag{4}$$

In Eq. (4), $F_4$ is the cost of service quality loss, $\Pi$ is the unit order opportunity loss coefficient, $q_n$ is the order value of node $n$, $\xi_1$ is the acceptable service attenuation threshold for customers, $\xi_2$ is the service complete failure threshold, and $\rho_n$ is the service timeliness attenuation rate. Continuing to study the economic cost of quantifying facility layout, its expression is shown in Eq. (5).

$$\begin{cases} F_5 = \sum\limits_{l \in L} \Phi_l Y_l \\ \sum\limits_{l \in L} Y_l \cdot A_l \geq \theta_{\mathrm{cov}} \end{cases} \tag{5}$$

In Eq. (5), $F_5$ is the total cost of facility network construction, $L$ denotes the set of candidate facility types, $\Phi_l$ is the daily average construction cost of facility type $l$, $Y_l$ is the decision variable, $A_l$ is the coverage radius of a single facility, and $\theta_{\mathrm{cov}}$ is the lowest coverage rate in the region. Finally, the facility activation cost is calculated as the total cost of facility providers, which is expressed as Eq. (6).

$$\min F_{facility} = F_{carbon} + F_{cool} + F_{construction} \tag{6}$$

In Eq. (6), $F_{facility}$ represents the total cost of facility providers, $F_{carbon}$ denotes the cost of facility carbon reduction, $F_{cool}$ denotes the cost of intelligent environmental control, and $F_{construction}$ represents the amortized cost of facility construction. In summary, the multi-objective model of fast logistics-distribution based on customer satisfaction is shown in Fig. 3.

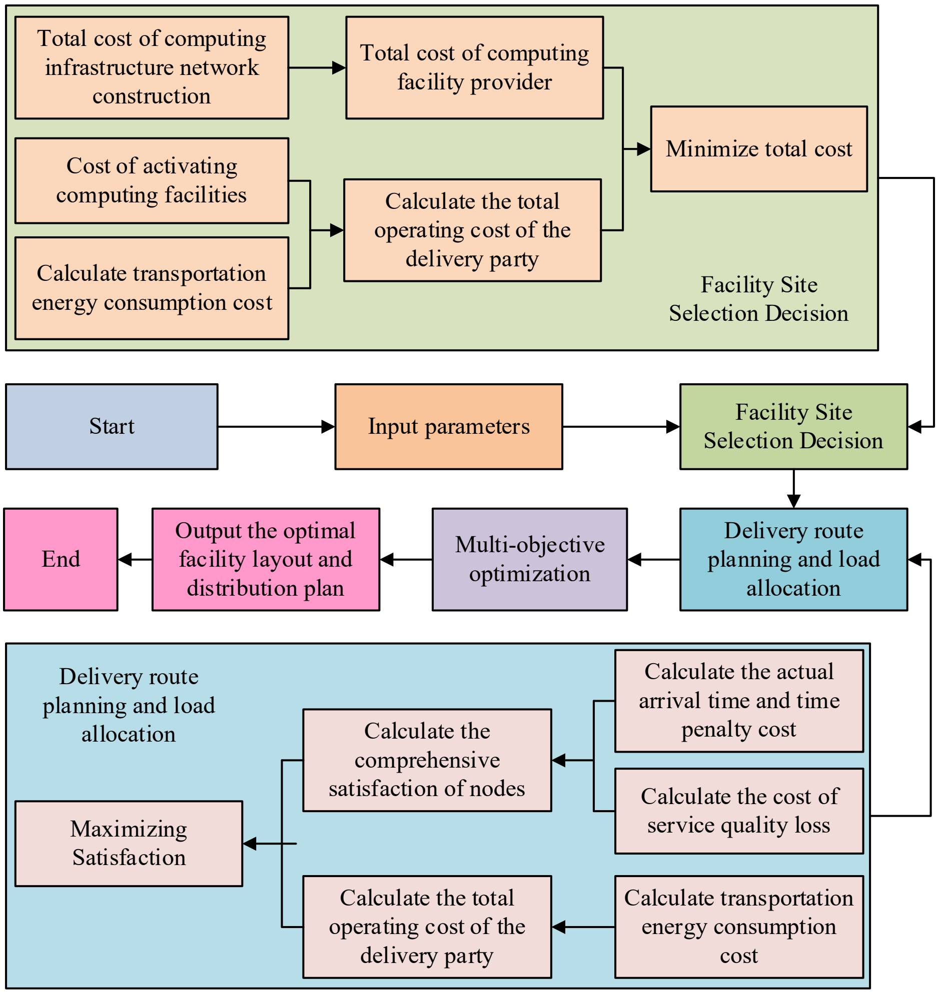


**Fig. 3.** Multi-objective model of fast logistics facility-distribution based on customer satisfaction

(Notes: Facility activation cost: Eq. (1), Transportation energy cost: Eq. (2), Time penalty cost: Eq. (3), Service quality loss: Eq. (4), Facility network cost: Eq. (5), Total provider cost: Eq. (6))

In Fig. 3, the model integrates facility location and path planning. It minimizes costs by quantifying the total costs of facility construction, operations, and transportation energy consumption. At the same time, the maximum satisfaction is achieved by calculating the time penalty and node satisfaction based on the actual arrival time. Since sharing cost data, the two modules have collaborated and contributed to the central multi-objective optimizer, ultimately yielding a facility layout and distribution plan that achieves the optimal balance between total cost and customer satisfaction.

### 3.2. Design of IGOA based on Rapid Logistics Facility-Distribution Multi-Objective Model

Combining the multi-objective model of fast logistics facilities distribution with the improvement of a metaheuristic algorithm can effectively explore the Pareto optimal solution set of multiple objectives, such as cost, time, customer satisfaction, and resource utilization in the logistics distribution system (Haruna et al., 2022; Sultanov and Hasanov, 2024). The GOA has strong global exploration capabilities and an enhanced balance between convergence speed and solution accuracy (Bao and Zhang, 2024). Targeted improvements to the GOA that address the multi-objective and multi-constraint characteristics of logistics distribution provide a more efficient and reliable computational tool for solving complex optimization problems in fast logistics facility distribution systems (Bhushan and Sahoo, 2022; Huiyong et al., 2023). Therefore, a multi-objective model based on fast logistics facility distribution is developed to design an IGOA, and its location update is formulated in Eq. (7).

$$X_i^{t+1} = c_1\left(\sum_{j=1 j\neq i}^{N} w_{ij}\cdot s\left(\| x_j^t - x_i^t \|\right)\frac{x_j^t - x_i^t}{d_{ij}}\right) + c_2\cdot \hat{F}_d \tag{7}$$

In Eq. (7), $X_i^{t+1}$ is the position vector of the $i$ th grasshopper individual at iteration $t+1$, $c_1$ and $c_2$ are nonlinear decay coefficients, $w_{ij}$ is the facility customer association weight, $s(\cdot)$ is the social interaction intensity function, and $\hat{F}_d$ is the elite solution in the non-dominated solution set. Subsequently, the study uses a dynamic leader-ratio adjustment factor to adaptively balance dual-objective optimization, as shown in Eq. (8).

$$\lambda = \lambda_{\text{init}} - (\lambda_{\text{init}} - \lambda_{\text{final}}) \times \tan\left(\frac{\pi}{4} \cdot \frac{t}{T_{\max}}\right) \tag{8}$$

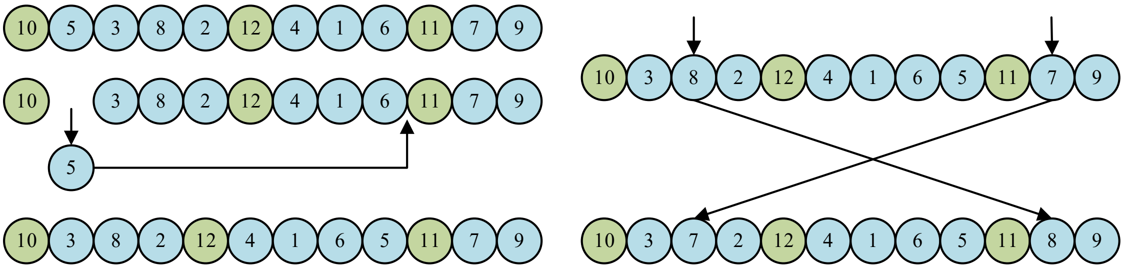
In Eq. (8), $\lambda$ is the leader follower dynamic scaling factor, $\lambda_{\text{init}}$ is the initial leader ratio, $\lambda_{\text{final}}$ is the termination leader ratio, and $T_{\max}$ is the maximum iteration count. The study also introduces a leader position update strategy, whose expression is shown in Eq. (9).

$$\mathsf{L}_i^{t+1} = \begin{cases} \text{LOX}(\mathsf{L}_i^t, \mathsf{P}_1^t) & \text{if } \xi < 1/3 \\ \text{LOX}(\mathsf{L}_i^t, \mathsf{P}_2^t) & \text{if } 1/3 \le \xi < 2/3 \\ \text{LOX}(\mathsf{L}_i^t, \mathsf{P}_3^t) & \text{otherwise} \end{cases} \tag{9}$$

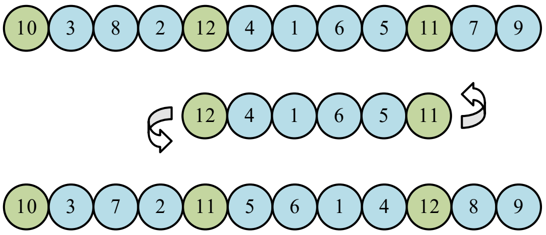
In Eq. (9), $\mathsf{L}_i^t$ denotes the position vector of the $i$ th leader in the $t$ th generation, $\mathsf{P}_k^t$ is the elite solution ranked $k$ th in terms of crowding in the $t$ th generation Pareto frontier, $\text{LOX}(\cdot)$ is a linear sequential crossover operator, and $\xi$ denotes a uniformly distributed random number in $[0,1]$. Next, it will investigate the introduction of local search mechanisms to optimize delivery routes and collaborate with facility location decisions, as expressed in Eq. (10).

$$\mathsf{R}_i^{t+1} = \begin{cases} \text{Insertion}(\mathsf{R}_i^t) & \text{if } \xi < 1/3 \\ \text{Swap}(\mathsf{R}_i^t) & \text{if } 1/3 \le \xi < 2/3 \\ \text{Reversion}(\mathsf{R}_i^t) & \text{otherwise} \end{cases} \tag{10}$$

In Eq. (10), $\mathsf{R}_i^{t+1}$ denotes the position vector of the $i$ th follower individual in the $t$ th generation, $\text{Insertion}(\cdot)$ is a randomly selected client node inserted into another position in the path, $\text{Swap}(\cdot)$ is the position of two client nodes in the swapping path, and $\text{Reversion}(\cdot)$ is the order of nodes in the reverse path segment. The schematic diagram of the neighborhood operation of the local search mechanism is denoted in Fig. 4.



(a) Schematic diagram of node single point insertion (b) Schematic diagram of node single point exchange



(c) Node reversion diagram

**Fig. 4.** Schematic diagram of node insertion, exchange, and reversion in local search mechanism

In Fig. 4, the three core neighborhood operations of single point insertion, single point exchange, and node reversion in the local search mechanism help the algorithm escape from local optima by finely adjusting the solution sequence structure. This mechanism can effectively solve problems such as path optimization. To support multi-objective decision-making, a multi-objective optimization framework is developed, and its expression is shown in Eq. (11).

$$\begin{cases} \min \Psi(\mathbf{z}) = [\psi_1(\mathbf{z}), \psi_2(\mathbf{z}), \cdots, \psi_k(\mathbf{z})] \\ \text{s.t.} \quad \begin{array}{l} \mathbf{z} \in \mathsf{Z} \\ \mathsf{Z} \subseteq R^d \end{array} \end{cases} \tag{11}$$

In Eq. (11), $\Psi(\mathbf{z})$ is the multi-objective optimization function vector, $\mathbf{z}$ is the decision variable vector, $Z$ denotes the feasible solution space, and $R^d$ is the $d$ dimensional real number space. Finally, the facility activation cost is calculated as the crowding distance to drive the algorithm's global search, as expressed in Eq. (12).

$$\delta_i = \sum_{k=1}^{2} \left( \frac{F_k(i+1) - F_k(i-1)}{F_k^{\max} - F_k^{\min}} \right) \tag{12}$$

In Eq. (12), $\delta_i$ is the crowding distance of individual $i$, $F_k(i)$ denotes the value of individual $i$ on the $k$ th objective function, $F_k^{\max}$ and $F_k^{\min}$ indicate the maximum and minimum values of the current population on the $k$ th objective function, respectively. Overall, the operation process of the fast logistics facilities-distribution optimization method based on the IGOA is shown in Fig. 5.

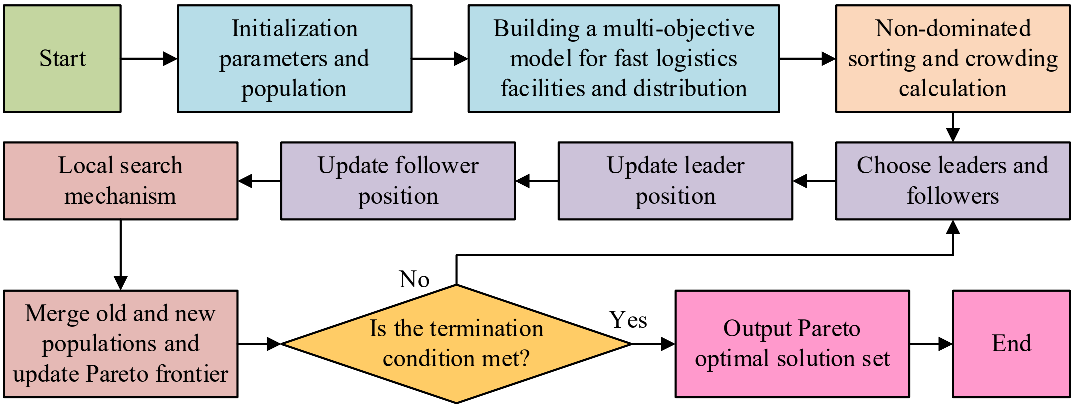


**Fig. 5.** Rapid logistics facilities-distribution optimization method based on IGOA

(Notes: Enhanced with step-wise details: Non-dominated sorting, Crowding distance calculation (Eq. (12); Local search, Node insertion/exchange/reversion (Fig. 4), Position update, Leader-follower strategy (Eqs. (7)-(9))

In Fig. 5, the research method involves constructing a multi-objective model after initializing the population. Next, non-dominated sorting and crowding degree calculation are performed to screen outstanding individuals, and a fusion of local search and differentiated position update strategy that distinguishes leaders and followers is adopted to effectively coordinate global exploration and local development capabilities. The iterative process continues until the conditions are met and outputs the Pareto front, providing a set of optimized location-distribution solutions that balance multiple objectives such as cost and timeliness for logistics network planning. The key parameters of IGOA are set as follows: group size = 100, maximum iteration times = 500, the nonlinear attenuation coefficient is the absolute value of the coefficient, and the facility customer association weight is the absolute value of the weight. The initial lead ratio is 0.3, and the final lead ratio is 0.1. The stopping criterion is either reaching the maximum number of iterations or achieving an improvement in the Pareto front of less than 1% over 50 consecutive iterations.

## 4. Effectiveness Analysis of Fast Logistics Facilities-Distribution Optimization Method based on IGOA

All performance evaluations presented in this study are based on simulation models under controlled experimental conditions. The results reflect the algorithm’s potential in theoretical and simulated scenarios, yet real-world deployment and field trials are required to assess its actual performance in dynamic operational environments.

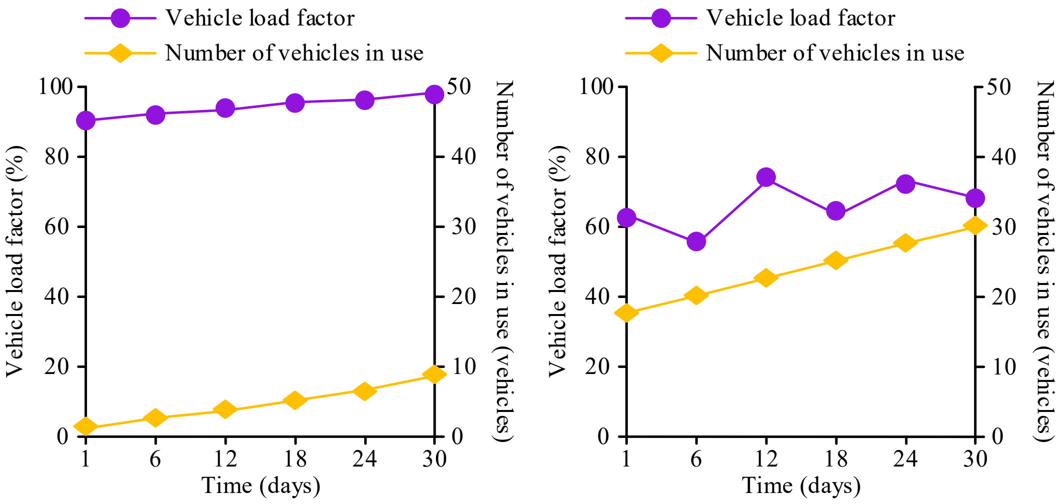
### 4.1. Performance Testing of Fast Logistics Facilities-Distribution Optimization Methods

To verify the performance of the fast logistics facilities-distribution optimization method based on the IGOA, a simulation model was constructed, and its experimental environment and specific configuration are shown in Table 1.

In Table 1, the configurations listed were used for performance testing on the Homberger and Gehring dataset. The dataset used in experiments included instances with 100 to 1000 customer nodes, time windows following uniform and clustered distributions, and variable demand ranges. The proposed method demonstrated consistent performance across different scales. Parameter tuning for larger instances included increasing population size to 200 and iteration counting to 800 to maintain solution quality. The research method was compared with the Ant Colony Optimization Algorithm (ACOA) and the Tabu Search Algorithm (TSA). Comparing the changes in vehicle load factor and vehicle usage over time using the three methods, the results are shown in Fig. 6.

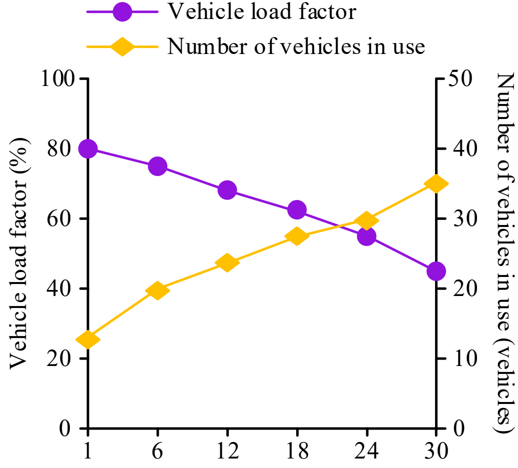
**Table 1.** Test environment and specific configuration

| Test environment | Specific configuration |
|---|---|
| CPU | Intel Xeon Gold 5317 |
| Memory | 512GB DDR4 ECC memory |
| Storage | 2TB SSD (system disk, RAID 1) |
| Network | Intel i350 dual-port Gigabit network card |
| VR device | HTC Vive Pro 2 headset |
| Basic environment | Ubuntu Server 22.04 LTS |



(a) Research method

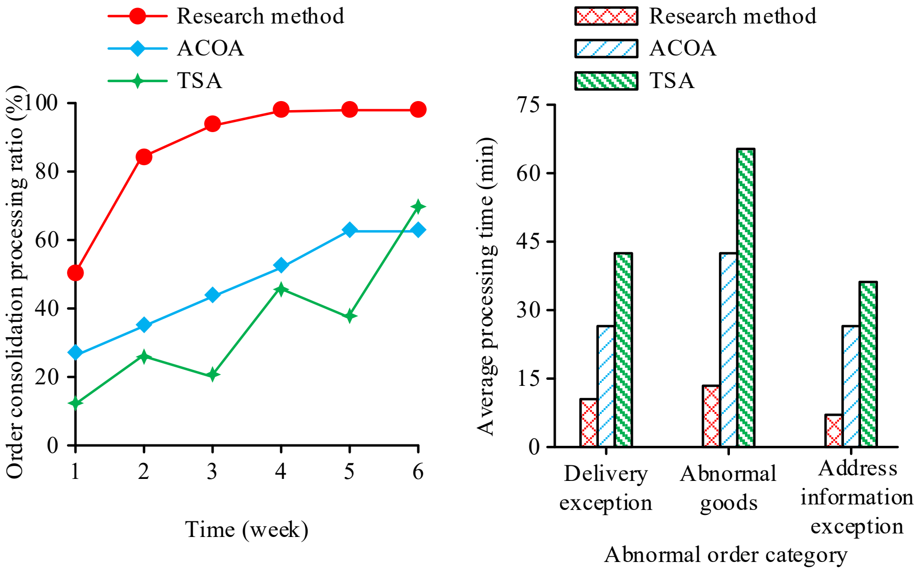
(b) ACOA



(c) TSA

**Fig. 6.** Changes in vehicle load rate and vehicle usage

In Fig. 6(a), as usage time increased, both the vehicle load rate and the number of vehicles used in the research method gradually increased. However, the overall vehicle load rate was greater than 90%, and the overall vehicle usage rate was less than 10 vehicles. When the usage time increased from 1 day to 30 days, the vehicle load rate increased from 90.2% to 99.6%, and the number of vehicles used increased from 1 to 9. In Fig. 6(b), when the usage time was 30 days, the ACOA method used 30 vehicles, and the overall vehicle load factor fluctuated. As shown in Fig. 6(c), with the increase of usage time, the vehicle load factor of the TSA method decreased slowly. Overall, comparative methods as a research method offer better resource utilization, intelligence, and efficiency. Regarding improvements in vehicle load rate and vehicle usage, it can be theoretically attributed to the convergence guarantee mechanism of IGOA, which incorporates adaptive parameter tuning and elitism preservation. These features enable the algorithm to converge stably to high-quality solutions, thereby improving resource utilization efficiency. Comparing the dynamic merging processing capabilities of the three methods with the changes in usage time and the average processing time of different abnormal orders, the results are shown in Fig. 7.



(a) Changes in the ability to dynamically merge orders over time

(b) The average processing time for different abnormal orders

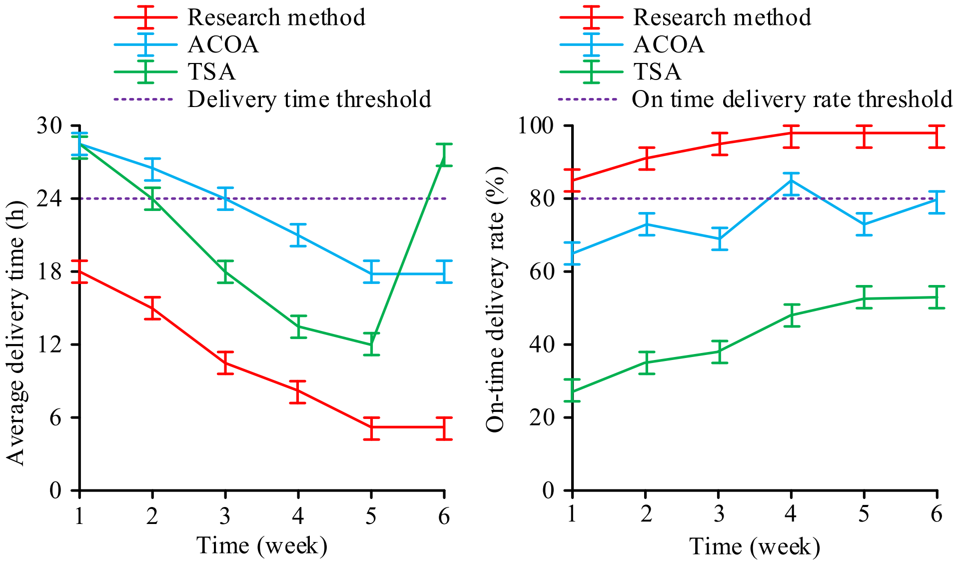
**Fig. 7.** Ability to dynamically merge orders and average processing time for various abnormal orders

In Fig. 7(a), the order consolidation processing ratio of the research method rapidly increased when the usage time was less than two weeks, then the upward trend slowed down, and finally stabilized at a usage time of four weeks, with a stable value of 98.6%. Among the other two methods, the ACOA method reached a stable 62.4% order consolidation processing ratio after 5 weeks. The order consolidation processing ratio for the TSA method fluctuated and increased over the course of the process. In Fig. 7(b), the three methods had significant differences in processing time for different types of abnormal orders. The abnormal order processing time for the research method was 11.9 minutes for delivery abnormalities, 13.2 minutes for goods abnormalities, and 9.8 minutes for address information abnormalities. The other two methods had significantly longer processing times for different abnormal orders compared to the research method. Compared to ACOA and TSA, the proposed method had better intelligence and learning ability. Regarding the reduced processing time for abnormal orders and the enhanced dynamic order consolidation capability, the robustness and learning ability were theoretically supported by the hybrid local search mechanism and the diversified position update strategies embedded in IGOA. These mechanisms allow the algorithm to quickly adapt to dynamic changes in order profiles, maintaining efficient operation under uncertainties. Overall, the fast logistics facilities-distribution optimization method proposed by the research based on the IGOA shows enhanced resource utilization, intelligence, efficiency, robustness, and learning ability.

### 4.2. Practical Application Effect of Fast Logistics Facilities Delivery Optimization Method

Based on the performance verification of the fast logistics facilities-distribution optimization method based on the IGOA, further research was conducted to evaluate the practical application of the method. The research adopted a capacity-constrained vehicle routing problem dataset, which includes multiple types of instances, such as small-scale, extremely small-scale, and Set F, and built a big data analysis platform. The research method was compared with ACOA and TSA. The Average Delivery Time (ADT) of the three methods was compared with the on-time delivery rate over time. The results are shown in Fig. 8.

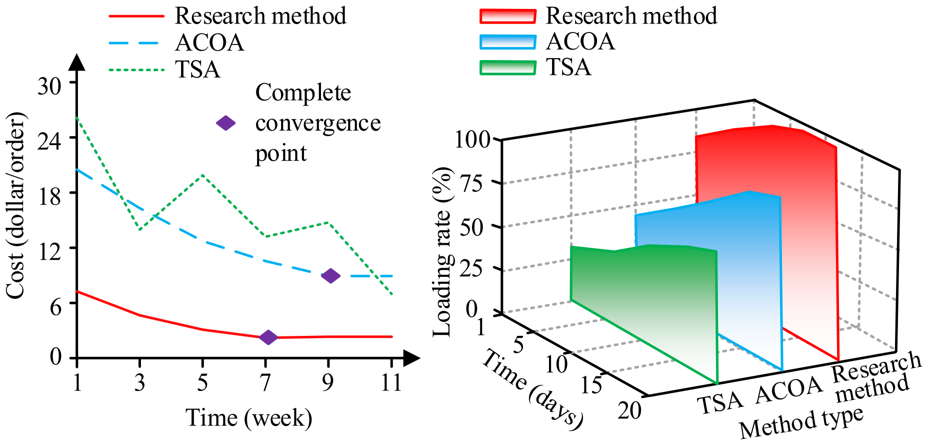
In Fig. 8(a), the ADT threshold of the system was 18 hours. The ADT of the research method was below the threshold. When the usage time was 1 week, the ADT of the research method was 18.0 hours; when the usage time was 5 weeks, the ADT dropped to a stable 5.8 hours. However, the ADT of the other two methods was higher than that of the research method. The ADT of the ACOA method dropped below the threshold only at 3 weeks, whereas the ADT of the TSA method showed an abnormal increase at 5 weeks. In Fig. 8(b), the on-time delivery rate threshold of the system was 80%. The on-time delivery rate of the research method was above the threshold. When the usage time was one week, the on-time delivery rate was 85.2%. When the usage time reached four weeks, the on-time delivery rate reached a stable value of 98.6%. The on-time delivery rates of the other two methods were lower than that of the research method, with the ACOA method's on-time delivery rate fluctuating throughout the process, and the TSA method's on-time delivery rate overall below the threshold. Therefore, when used as a research method, the comparative approach provides better customer orientation and adaptability. Regarding the reduction in ADT and improvement in the on-time delivery rate, the theoretical foundation lies in the multi-objective optimization framework of IGOA, which employs crowding distance computation and Pareto front maintenance. This ensures an effective trade-off between delivery timeliness and customer satisfaction, thereby improving scheduling reliability. Comparing the distribution costs of the three methods over time and the loading rates at different usage times, the results are shown in Fig. 9.



(a) Average delivery time under different running times

(b) On-time delivery rate at different operating times

**Fig. 8.** Changes in ADT and on-time delivery rate



(a) Changes in delivery costs with running time

(b) Loading rate at different operating times

**Fig. 9.** Changes in delivery costs and loading rates under different usage times

In Fig. 9(a), the delivery cost of the research method was 6.2 dollars per order over a one-week period. When the usage time was seven weeks, the delivery cost was fully converged and stabilized at 2.1 dollars per order. Among the other two methods, the ACOA method fully converged after nine weeks, but its stable value reached 9.6 dollars per order. The delivery cost for the TSA method fluctuated during the decline. In Fig. 9(b), the overall loading rate of the research method exceeded 75%. When the usage time was increased from one to fifteen days, the loading rate increased from 82.5% to a stable value of 98.2%. The loading rate of the other two methods was significantly lower than that of the research method. Compared with ACOA and TSA, the proposed method demonstrated greater robustness and stability. Regarding the decrease in delivery cost and increase in loading rate, the stability in cost optimization was theoretically explained by IGOA's balanced global exploration and local exploitation mechanisms. These prevent premature convergence to local optima, enabling sustained cost reduction and operational efficiency. Overall, the fast logistics facilities-distribution optimization method based on the IGOA proposed by the research has strong path optimization capabilities, dynamic scheduling, real-time response, reliability, timeliness, intelligence, economy, and stability.

## 5. Conclusion

At the theoretical level, this study provides a new methodological framework for optimizing complex logistics systems by integrating multi-objective modeling with improved meta-heuristic algorithms, thereby enriching the algorithmic toolbox for logistics network optimization. To address the problems of low logistics efficiency, slow response speed, high system operating costs and poor user experience and service quality in traditional fast logistics facilities-distribution systems, an innovative fast logistics facilities-distribution optimization method based on the IGOA was proposed. The study developed a rapid logistics facility-distribution multi-objective model based on customer satisfaction to achieve more precise distribution planning. An IGOA was designed based on this model to address complex optimization problems. The research findings indicated that, with a usage time of 1 week, the ADT for the research method was 18.0 hours. After 5 weeks of use, it dropped to a stable value of 5.8 hours. The abnormal order processing time was 11.9 minutes when facing delivery abnormalities, 13.2 minutes when facing goods abnormalities, and 9.8 minutes when facing address information abnormalities. When the usage time was 7 weeks, the delivery cost dropped to a stable value of 2.1 dollars per order. The results indicate that the multi-objective model constructed in the study effectively achieves the optimal balance between minimizing total cost and maximizing customer satisfaction through the collaborative trade-off mechanism and the Pareto front output of IGOA. It has better advantages in resource utilization, intelligence, and response efficiency. Moreover, it has strong dynamic scheduling and real-time response capabilities, which can robustly handle abnormal situations and effectively reduce costs and time when adapting to dynamic logistics scenarios. The proposed method demonstrates promising capabilities in simulation-based assessments. Its real-time responsiveness and practical effectiveness should be further examined through real-world implementations and field studies. However, research focuses on static or periodic evaluations. In the future, more challenging dynamic simulation scenarios can be introduced to assess the algorithm's performance in multi-objective trade-offs and to enhance its adaptability and decision-making capabilities in uncertain environments.

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## Institutional Review Board Statement

Not applicable.

## Declaration of Artificial Intelligence (AI) Tools

The author used DeepSeek solely for language editing and readability improvement. The author reviewed and verified all content and takes full responsibility for the accuracy and integrity of the manuscript.

## References

Alzoubi, K., Theeb, N. A., and Al-Khalailah, T. (2025). Selecting the best network design for COVID-19 healthcare waste disposal using fuzzy analytic hierarchy process. *International Journal of Logistics Systems and Management*, 50(3), 319-333. doi.org/10.1504/IJLSM.2025.144674

Badr, A. A., Saafan, M. M., Abdelsalam, M. M., and Haikal, A. Y. (2023). Novel variants of grasshopper optimization algorithm to solve numerical problems and demand side management in smart grids. *Artificial Intelligence Review,* 56(10), 10679-10732. doi.org/10.1007/s10462-023-10431-5

Bao, X. and Zhang, J. (2024). Multi-objective decision optimization design for building energy-saving retrofitting design based on improved grasshopper optimization algorithm. *International Journal of Renewable Energy Development*, 13(6), 1058-1067. doi.org/10.61435/ijred.2024.60483

Bhushan, B. and Sahoo, G. (2022). FLEAC: Fuzzy logic-based energy adequate clustering protocol for wireless sensor networks using improved grasshopper optimization algorithm. *Wireless Personal Communications*, 124(1), 573–606. doi.org/10.1007/s11277-021-09373-4

Chen, L., Tian, Y., and Ma, Y. (2022). An improved grasshopper optimization algorithm based on dynamic dual elite learning and sinusoidal mutation. *Computing*, 104(5), 981-1015. doi.org/10.1007/s00607-021-00991-1

Dash, B. P., and Dixit, V. (2024). Disaster supply chain with information and digital technology integrated in its institutional framework. *International Journal of Production Research*, 62(8), 3003-3022. doi.org/10.1080/00207543.2022.2042612

Deng, L., and Liu, S. (2023). A novel hybrid grasshopper optimization algorithm for numerical and engineering optimization problems. *Neural Processing Letters*, 55(7), 9851-9905. doi.org/10.1007/s11063-023-11230-3

Gerçek, D. (2023). Assessment of spatial clustering of socioeconomic variables and facilities at district level: The case of Körfez-Derince-İzmit. *Resilience*, 7(2), 209-220. doi.org/10.32569/resilience.1352951

Haruna, A. A., Muhammad, L. J., and Abubakar, M. (2022). Novel thermal-aware green scheduling in grid environment. *Artificial Intelligence and Applications*, 1(4), 244-251. doi.org/10.47852/bonviewAIA2202332

Hebbi, C. and Mamatha, H. R. (2023). Comprehensive dataset building and recognition of isolated handwritten Kannada characters using machine learning models. *Artificial Intelligence and Applications*, 1(3), 179-190. doi.org/10.47852/bonviewAIA3202624

Huiyong, W., Shuchun, J., and Zhu, J. (2023). Simulation model and fault analysis of air circulation system of the aircraft based on grasshopper optimization algorithm: support vector machine. *Soft Computing*, 27(18), 13269-13284. doi.org/10.1007/s00500-022-07403-2

Kadam, A. A. and Kadam, S. A. (2024). Theoretical foundations and practical implementation of supply chain optimization: A metal fabrication business model. *World Journal of Advanced Engineering Technology and Sciences*, 13(1), 831-844. doi.org/10.30574/wjaets.2024.13.1.0480

Koc, S., Erden, C., Ateş, Ç., and Ceviz, E. (2024). Evaluation of potential logistics village alternatives using Bayesian best-worst method. *Optimality*, 1(1), 100-120. doi.org/10.22105/opt.v1i1.35

Li, G. and Jimenez, G. (2022). Optimal diagnosis of the skin cancer using a hybrid deep neural network and grasshopper optimization algorithm. *Open Medicine*, 17(1), 508-517. doi.org/10.1515/med-2022-0439

Liu, J., Chen, W., Yang, J., Xiong, H., and Chen, C. (2022). Iterative prediction-and-optimization for E-logistics distribution network design. *INFORMS Journal on Computing*, 34(2), 769-789. doi.org/10.1287/ijoc.2021.1107

Mishra, S. and Singh, S. P. (2022). Designing dynamic reverse logistics network for post-sale service. *Annals of Operations Research*, 310(1), 89-118. doi.org/10.1007/s10479-020-03710-9

Rodríguez-Espíndola, O., Dey, P., Albores, P., and Chowdhury, S. (2025). Sustainability and intermodality in humanitarian logistics: A two-stage multi-objective programming formulation. *Annals of Operations Research*, 346(2), 1687-1716. doi.org/10.1007/s10479-023-05459-3

Sultanov, F. and Hasanov, P. (2024). Integrated multi-product, multi-level supply chain inventory model with joint replenishment and loss sharing. *International Journal of Integrated Supply Management*, 17(2), 176-208. doi.org/10.1504/IJISM.2024.138820

Tamilarasan, N., Lenin, S. B., Mukunthan, P., and Sendhilkumar, N. C. (2024). Stochastic ranking improved teaching-learning and adaptive grasshopper optimization algorithm-based clustering scheme for augmenting network lifetime in WSNs. *China Communications*, 21(9), 159-178. doi.org/10.23919/JCC.ja.2022-0505

Tirkolaee, E. B., Goli, A., and Mardani, A. (2023). A novel two-echelon hierarchical location-allocation-routing optimization for green energy-efficient logistics systems. *Annals of Operations Research*, 324(1), 795-823. doi.org/10.1007/s10479-021-04363-y

Wu, L., Wu, J., and Wang, T. (2024). The improved grasshopper optimization algorithm with Cauchy mutation strategy and random weight operator for solving optimization problems. *Evolutionary Intelligence*, 17(3), 1751-1781. doi.org/10.1007/s12065-023-00861-z

Ye, C., He, W., and Chen, H. (2022). Electric vehicle routing models and solution algorithms in logistics distribution: A systematic review. *Environmental Science and Pollution Research*, 29(38), 57067-57090. doi.org/10.1007/s11356-022-21559-2

Yildiz, B. S., Pholdee, N., Bureerat, S., Yildiz, A. R., and Sait, S. M. (2022). Enhanced grasshopper optimization algorithm using elite opposition-based learning for solving real-world engineering problems. *Engineering with Computers*, 38(5), 4207-4219. doi.org/10.1007/s00366-021-01368-w

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