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IoT-Enabled Intelligent Warehousing Optimization for Cross-Border E-Commerce

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Abstract: To address the limitations of traditional warehousing systems in coping with order fluctuations and unexpected events, resulting in an imbalance between inventory and cost control, this study proposes an intelligent warehousing management system that integrates the Ant Colony Genetic Algorithm (ACGA) and the Internet of Things (IoT). To enhance the intelligence of warehouse management, this study selected Ant Colony Optimization for path planning and Genetic Algorithm (GA) to enhance global search capability. The combination of the two forms ACGA to improve convergence performance. The system simultaneously integrates IoT to enable real-time data collection and dynamic feedback, compensating for the algorithm's shortcomings in sensing unexpected events. By deeply integrating ACGA with IoT, this study constructs an intelligent warehouse management system that enables integrated, closed-loop operation of perception and scheduling. Experimental results show that the root mean square error of path planning in scheduling tasks is 62.3m. In terms of accuracy, the proposed system improves from 36.9% to 96.7%, and the F1-score stabilizes at 0.97 by the end of iterations. In a simulated cross-border e-commerce warehousing management environment, the system availability increases to 94.2% after 100 iterations. Regarding overall performance, the response delay is 25ms, and the computational load rate reaches 68%, helping to avoid resource idleness and system overload. At the same time, the energy consumption is only 18 W·h, the task completion rate reaches 98.5%, and the system stability is 99.2%. These results indicate that the proposed system significantly outperforms the comparison system in comprehensive performance and meets the optimization needs in complex cross-border e-commerce task environments, offering a feasible technical solution for intelligent warehousing management.

Keywords: Internet of things, genetic algorithms, ant colony optimization, cross-border, E-commerce, intelligent warehousing, management system, optimization design.

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1. Introduction

In recent years, the swift expansion of the global economy has spurred the rapid rise of cross-border e-commerce, generating fresh avenues for growth in China's economy. Efficient management of overseas warehouses has become a key factor in reducing operational costs and maximizing profits (Chen et al., 2023a). Traditional warehousing management systems struggle to respond to sudden situations (e.g., warehouse overflow and stock shortages) and cannot balance soaring sales with cost control (Chen et al., 2023b). To address this problem, some researchers have introduced computer vision technology into warehousing management. By deploying depth cameras to identify goods, this approach has shown some improvement in operational efficiency. However, it fails to function under low-light conditions, revealing its limitations (Iqbal et al., 2023; Dhanya et al., 2022). To enhance the intelligence in warehousing management, studies have found that the Ant Colony Optimization (ACO) algorithm possesses self-organizing and positive feedback capabilities for path-planning tasks (Awadallah et al., 2025). Meanwhile, the GA, known for its global search, can further optimize the ACO's search process. By combining the two, the ACGA forms to enhance the global convergence performance of the algorithm. However, this algorithm lacks the ability to perceive and respond to emergencies. The Internet of Things (IoT), through the deployment of various sensors, enables the real-time collection of information on goods and equipment operating parameters. Based on this, this study integrates ACGA with IoT to construct an intelligent warehousing management system designed for cross-border e-commerce, named ACGA-IoT. By building a sensing layer and feedback structure within the IoT environment, the system realizes a scheduling mechanism that combines intelligent optimization with real-time perception. This system is expected to dynamically adjust inventory and regulate goods circulation in cross-border warehousing, providing a novel approach to intelligent warehousing management.

2. Related Works

Scholars both in China and abroad have widely applied IoT by deploying sensor devices to collect real-time data from environments and equipment. For example, Wang (2023) integrated IoT with a multi-objective optimization algorithm to build a cross-border e-commerce framework and combined it with an adaptive neuro-fuzzy inference system to improve supply chain performance. Experimental results showed that the average absolute error in demand forecasting was 2.54, which was 8.58% lower than that in traditional methods. Wei et al. (2022) applied IoT to agricultural management and environmental monitoring by combining mathematical models collected through IoT with unmanned aerial vehicles and implementing a joint path planning strategy. The results showed that this method effectively collected data and achieved a scientific management process. The ACGA, which combines the advantages of both ACO and GA, has been shown to be effective in path planning and multi-objective optimization. For instance, Uslu et al. (2022) used the ACGA hybrid algorithm to solve problems in process planning and scheduling by adjusting local optimum parameters and integrating hybrid optimization techniques. The experiments demonstrated that the hybrid algorithm performed significantly better than non-hybrid algorithms and could be applied to various complex scenarios. Khashan et al. (2023) compared the performance of GA and ACO in determining the optimal thrust coefficient of a propeller by combining thrust and power coefficients to obtain the optimal value. The results showed that GA outperformed ACO in accuracy when determining the thrust coefficient. Mingyue et al. (2023) used the ACGA to analyze patrol points in urban areas, where ACO was used to generate precise patrol routes that GA was used to optimize. The experiment confirmed that integrating both algorithms produced accurate patrol routes and contributed to crime prevention.

The rapid expansion of cross-border e-commerce has been accompanied by the emergence of various challenges. To improve operational efficiency and control costs, many scholars have extensively studied this field. For example, Xiao (2023) analyzed the supply chain management model for cross-border e-commerce by refining key processes, including production, transportation, inventory, and sales. The research showed that this method improved overall supply chain efficiency, reduced costs, and expanded management approaches. Qiu (2024) developed three types of e-commerce decision-making models: decentralized, centralized, and hybrid, and used simulations to analyze contract sensitivity. Results revealed that the centralized model improved collaboration among members, enhanced production capacity, and increased the level of logistics services. Jin (2024) designed a personalized and targeted sales path to better understand consumer demand in cross-border e-commerce. By promoting local brands, the study developed an intelligent, demand-oriented marketing model. The results indicated that this model effectively improved logistics efficiency and provided an innovative direction for e-commerce development. Feng (2025) proposed a model that combined convolutional neural networks with bidirectional gated recurrent units to optimize product selection strategies in e-commerce. Through the application of a multi-channel convolutional neural network to capture features at multiple granular levels, this approach enabled precise analysis of customer reviews. He (2024) applied analytical methods to examine policy content in the e-commerce sector, identifying key elements in policy updates and optimization directions. The findings showed that this approach had practical applications in policy response and could offer standardized guidance.

In summary, previous studies on cross-border e-commerce often focused on individual segments and did not establish a complete operational chain. Additionally, a lack of intelligent management models remains a key issue. To address these problems, this study proposes a cross-border e-commerce intelligent warehousing management system based on ACGA-IoT. By utilizing IoT to build an intelligent sensing layer and achieve dynamic optimization in scheduling, this study aims to enable effective warehouse management, balance inventory levels and operational costs, and provide an innovative approach to intelligent warehousing management.

3. Construction of Cross-Border E-Commerce Intelligent Warehousing Management System based on ACGA-IoT

3.1. Improved Design based on ACO Algorithm

ACO, a distributed, intelligent algorithm that simulates the foraging behavior of ants, is suitable for solving combinatorial optimization, path planning, and scheduling problems (Arranz, 2023). Because of these features, scholars apply ACO in intelligent warehousing systems for cross-border e-commerce to address multi-task scheduling and real-time dynamic optimization issues (Morin et al., 2023). The path selection probability in ACO is shown in Fig. 1.

$$P_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}{}^{\alpha}(t)*\eta_{ij}{}^{\beta}(t)}{\sum\limits_{k\in N_k}\tau_{ik}{}^{\alpha}(t)*\eta_{ik}{}^{\beta}(t)}, k\in N_k\\ 0, k\notin N_k\end{cases}\tag{1}$$

In Eq. (1), $P_{ij}{}^{k}(t)$ represents the probability that individual k moves from node i to node j at time t. N_k denotes the set of unvisited nodes of individual k. τ_{ij} indicates the pheromone intensity on the path between node i and node j. η_{ij} is the heuristic function. α controls the importance of pheromone, while β controls the influence of heuristic information. The heuristic function in ACO is expressed in Eq. (2).

$$\eta_{ij}=\frac{Q}{d_{ij}}\tag{2}$$

In Eq. (2), Q denotes the pheromone intensity, and d_{ij} refers to the total travel distance of the path. The pheromone updating process in ACO is shown in Eq. (3).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}{}^{k} \tag{3}$$

In Eq. (3), ρ denotes the pheromone evaporation coefficient. $\Delta\tau_{ij}{}^{k}$ denotes the pheromone increment that individual k adds to the path ij, and m is the number of individuals. However, ACO has relatively low convergence efficiency over multiple iterations, is easily affected by the initial path, and exhibits low search performance. GA, on the other hand, has a strong global search ability and ensures population diversity. Therefore, the study utilizes GA to optimize ACO, and the specific optimization mechanism is shown in Fig. 1.

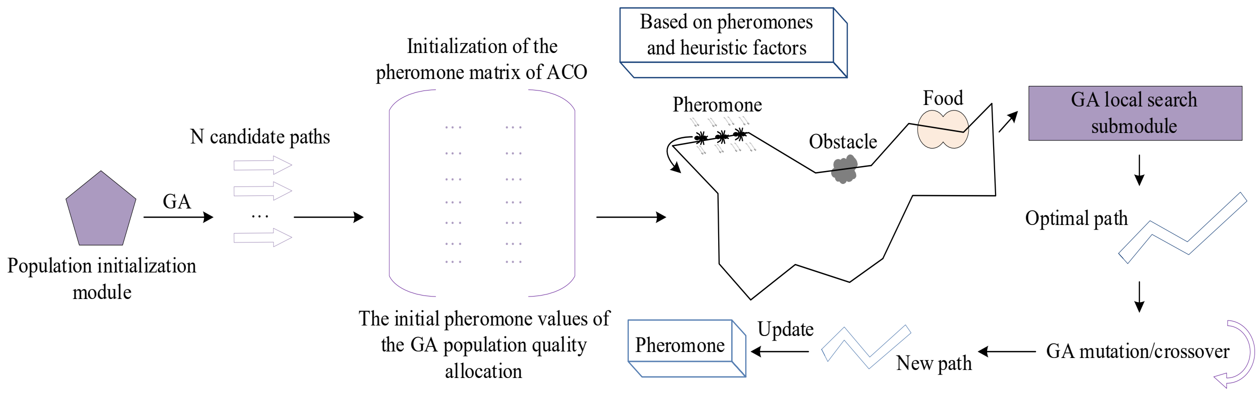


Fig. 1. The specific optimization mechanism of GA for ACO

As shown in Fig. 1, GA first randomly generates N candidate paths based on a preset path encoding rule. Then, it assigns initial values to these candidate paths in the pheromone matrix of ACO. Guided by pheromone and heuristic factors, ants select the next node step by step from the starting point until reaching the endpoint and update the pheromone after each iteration. After multiple iterations of ACO, the current optimal solution is selected and passed to GA for crossover or mutation operations to generate new candidate paths. In this way, GA helps ACO escape local optima and find a global optimal path. Therefore, the study introduces GA to optimize ACO and builds the ACGA hybrid algorithm. This algorithm defines a fitness function to guide the selection strategy during crossover and mutation. Its expression is shown in Eq. (4).

$$F(k) = \omega_1 * L_k + \omega_2 * T_k + \omega_3 * E_k \tag{4}$$

In Eq. (4), F is the fitness value. L_k denotes the total path length, T_k is the total time required to complete tasks, E_k is the energy consumption. ω_1, ω_2, and ω_3 are the weights of path length, completion time, and energy consumption, respectively. The operating principle of the fitness function in ACGA is shown in Fig. 2.

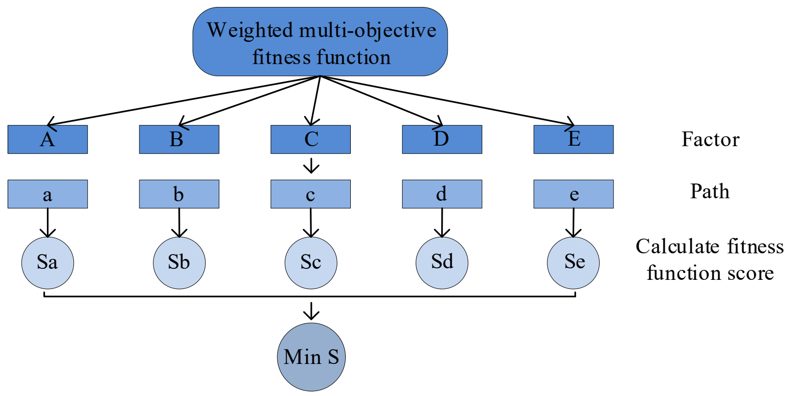


Fig. 2. Operating principle of fitness function in ACGA

As shown in Fig. 2, in real applications, path selection in ACGA is affected by various factors, including path length, execution time, energy consumption, and task urgency. Therefore, ACGA constructs a weighted multi-objective fitness function to evaluate multiple objectives comprehensively. The function scores all candidate paths and minimizes the overall score to determine the optimal balanced solution and output the optimal path. However, relying solely on multi-objective fitness scoring cannot guarantee global optimality. To enhance path optimization performance, the study introduces a pheromone-adjusted path updating strategy. The pheromone updating expression in ACGA is shown in Eq. (5).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{\ k} + \gamma \frac{1}{F(i)} \tag{5}$$

In Eq. (5), γ is the fitness feedback weight from the GA. The pheromone increment updating process is expressed in Eq. (6).

$$\Delta\tau_{ij}(t) = (\frac{A}{D_g} + \frac{B}{D_n}) * \frac{1}{N_c} \tag{6}$$

In Eq. (6), D_g represents the length of the local optimal path, D_n denotes the length of the global optimal path. A and B are the pheromone weight factors for the local and historical global optimal paths, respectively. The ACGA process with pheromone adjustment mechanism is shown in Fig. 3.

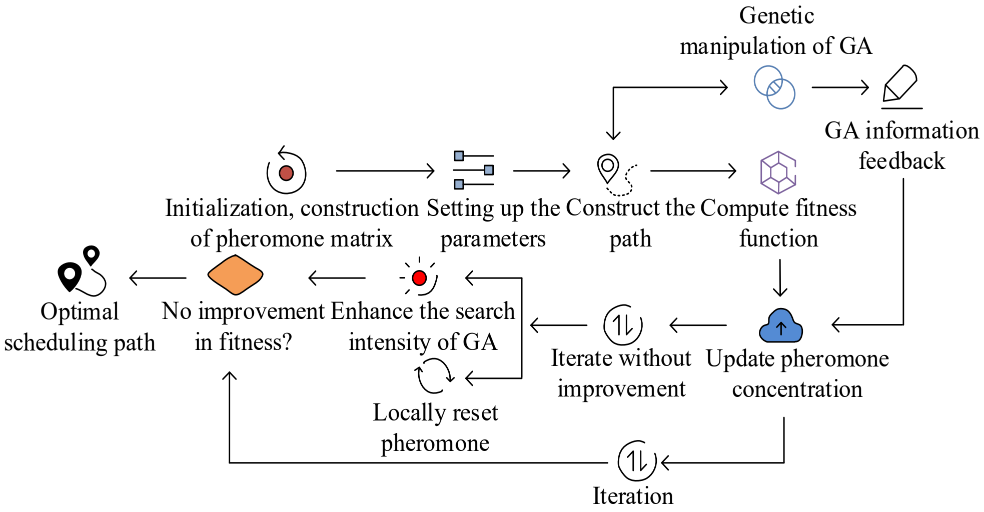


Fig. 3. Operation process of the ACGA hybrid algorithm

As shown in Fig. 3, the algorithm first initializes the pheromone matrix, sets the initial guiding weights between nodes, and defines parameters. Then, it constructs paths based on pheromone and heuristic information, calculates fitness values, and performs GA operations on the paths. The optimal solutions from GA are fed back to ACO to adjust the pheromone distribution. Next, pheromone intensity is updated based on the fitness value. If there is no significant improvement after consecutive iterations, the algorithm introduces a local disturbance mechanism and resets part of the pheromone matrix to escape local optima. If the termination condition is satisfied, the algorithm outputs the optimal scheduling path.

3.2. Construction of an Intelligent Cross-Border E-Commerce Warehouse Management System

The study proposes integrating GA to optimize ACO. This approach provides heuristic decomposition ability while ensuring global optimization, population diversity, and achieving efficient convergence performance. With these features, the method can be applied to cross-border e-commerce warehouse management systems to meet the needs of multi-warehouse collaboration and flexible scheduling. Therefore, the study introduces the ACGA hybrid algorithm to build a warehouse management system to satisfy the requirements of cross-border e-commerce. It first analyzes the existing problems in warehouse management. The key issues are shown in Fig. 4.

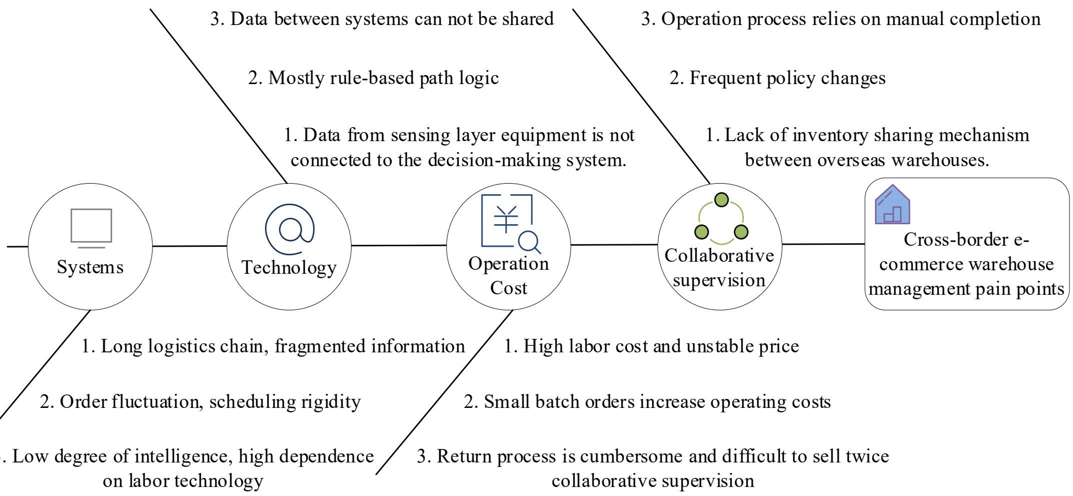


Fig. 4. Schematic diagram of problems in cross-border e-commerce warehouse management

In Fig. 4, on the system level, the cross-border logistics chain is long, and warehouse information is highly fragmented. The order volume fluctuates greatly, while warehouse resource scheduling is rigid. On the technical level, data from sensing devices are not connected to the decision-making system. On the cost level, labor costs in overseas warehouses are high, and warehouse prices are unstable. Based on these problems, the study defines optimization factors for path planning. According to the conditions, ACGA generates multiple paths. The study then evaluates whether the path planning in the scheduling system is reasonable, as shown in Eq. (7).

$$L_{total} = \sum_{k=1}^{K} \sum_{(i,j)\in N_k} d_{ij} \tag{7}$$

In Eq. (7), L_{total} represents the total length of all task paths, and K is the number of scheduled tasks. The study also applies execution units to calculate the standard deviation of task loads, which measures whether there is overload among execution resources. This is shown in Eq. (8).

$$\sigma = \sqrt{\frac{1}{M}\sum_{i'}^{M}(x_{i'} - \bar{x})^2} \tag{8}$$

In Eq. (8), M denotes the total number of devices, $x_{i'}$ denotes the number of tasks assigned to the i'-th execution device, and $\overline{x}$ is the average number of tasks. However, the current ACGA-based warehouse management system for cross-border e-commerce has limitations, such as information delay and the inability to dynamically avoid resource conflicts. To address these problems, the study introduces IoT to design an intelligent management system. This allows real-time sensing data to act as adjustment factors for path nodes, as shown in Eq. (9) (Bandewad et al., 2023).

$$S_z(t) = \frac{\lambda_1}{C_z(t)} + \lambda_2 \cdot A_z(t) + \lambda_3 \cdot (1 - \frac{E_z(t)}{E_{max}} \tag{9}$$

In Eq. (9), $S_z(t)$ is the IoT status evaluation factor of node z at time t. $C_z(t)$ is the current channel congestion level of node z. $A_z(t)$ is the device availability of node z at time t. $E_z(t)$ is the current energy consumption of the node. E_{max} is the maximum allowed energy consumption of the system. λ_1, λ_2, and λ_3 are the weight factors for channel congestion, device availability, and energy consumption, respectively. During the data collection process, the system uses ETL to process multi-source data and obtains input values for intelligent scheduling, as shown in Eq. (10).

$$D' = ETL(S_t, R_t, I_t) \rightarrow \Psi_t \tag{10}$$

In Eq. (10), S_t represents the system status information. R_t is the real-time IoT sensing data. I_t is the scheduling optimization data. ETL is data extraction. Ψ_t is the output result at the current time t. With the IoT operation process clarified, the study builds a cross-border e-commerce intelligent warehouse management system based on ACGA and IoT. The system architecture is shown in Fig. 5.

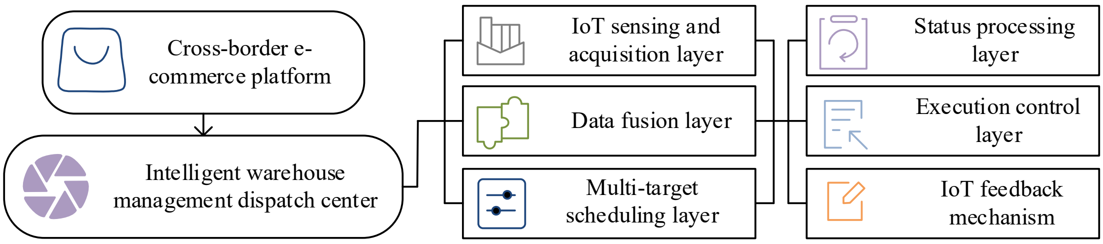


Fig. 5. Architecture of the intelligent warehouse management system for cross-border e-commerce

Fig. 5 shows the operational architecture of the cross-border e-commerce intelligent warehouse management system integrating the IoT-ACGA scheduling mechanism. The system is jointly driven by the e-commerce platform and the intelligent scheduling platform, forming a closed-loop process, which includes perception, fusion, scheduling, execution, feedback. The system includes an IoT sensing layer, a data fusion layer, a multi-objective scheduling layer, a status processing layer, an execution control layer, and an IoT feedback mechanism. The IoT feedback mechanism designed in the study adjusts the warehouse management system through forward optimization, as shown in Fig. 11.

$$R_{IoT} = \frac{N_{triggered}}{N_{total}} \tag{11}$$

In Eq. (11), $N_{triggered}$ is the number of times IoT exception feedback is triggered, and N_{total} is the total number of scheduling rounds. With the IoT process clarified, the study evaluates the transport tasks in the cross-border e-commerce intelligent warehouse system and analyzes the energy consumption, as shown in Eq. (12) (Liu et al., 2023; Rock et al., 2024).

$$E_{total} = \sum_{k=1}^{l'} (\alpha_1 \cdot L_k + \alpha_2 \cdot W_k + \alpha_3 \cdot R_k) \tag{12}$$

In Eq. (12), E_{total} is the total energy consumption. L_k is the path length. W_k is the load weight. R_k is the number of turns. α_1, α_2, and α_3 are the weight coefficients for path length, load weight, and number of turns, respectively. l' is the number of individual paths. By integrating IoT into the cross-border e-commerce intelligent warehouse management system, the system can improve the dynamic feedback process and adjust the warehouse scheduling model in real time. The detailed operation process of the ACGA-IoT-based system is shown in Fig. 6.

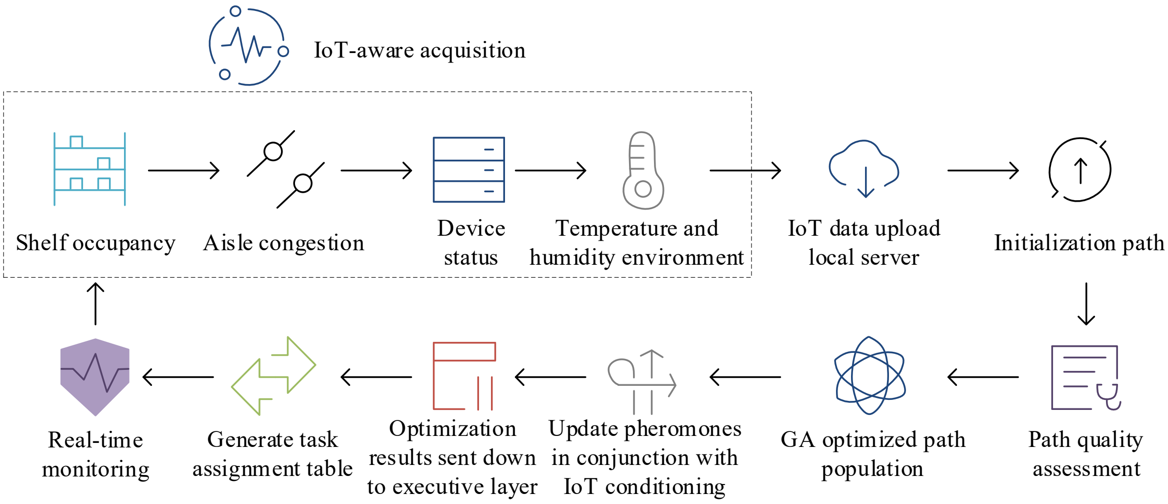


Fig. 6. Operation process of the ACGA-IoT cross-border e-commerce intelligent warehouse management system

As shown in Fig. 6, the system first builds an IoT sensing and data collection structure to monitor warehouse status in real time, including shelf usage, channel congestion, equipment status, and environmental parameters such as temperature and humidity. Then, it uploads the data collected by IoT to the edge gateway and applies ACGA for optimization and scheduling, which includes path initialization and quality evaluation. During the optimization process, GA optimizes the population of paths and adjusts the path weights using IoT status factors. After multiple rounds of iterative optimization, the final optimized result is delivered to the execution layer. The scheduling system then generates the final task allocation table, while IoT continues to monitor the execution status in real time, thus maintaining the closed-loop operation of the warehouse system.

4. Performance Comparison of ACGA-IoT-based Intelligent Cross-Border E-Commerce Warehousing System

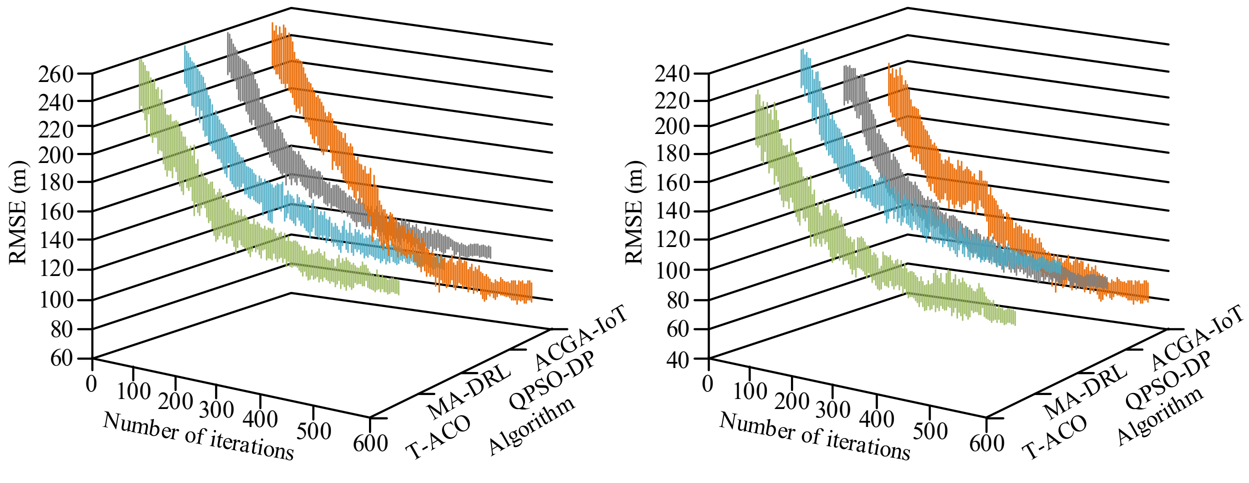
4.1. Performance Analysis of the ACGA-IoT Hybrid Algorithm

To validate the effectiveness of the ACGA-IoT hybrid algorithm, this study selected three algorithms as benchmarks: Transformer-enhanced Ant Colony Optimization (T-ACO), Multi-agent Deep Reinforcement Learning for Logistics Optimization (MA-DRL), and Quantum-behaved Particle Swarm Optimization with Dynamic Perception (QPSO-DP). The study used a real-world dataset, the Large-scale Last-mile Delivery dataset (LaDe), released by Alibaba Cainiao Network in 2022, which contained delivery records of 10,671,702 packages by 21,000 couriers between March and August 2020. The experimental platform was constructed with the following hardware configuration: AMD EPYC 7763 CPU, NVIDIA A100 80GB GPU, 512GB DDR4 ECC memory, a 4TB NVMe SSD, and a 16TB 7200RPM HDD. The software environment included Ubuntu Server 22.04 LTS as the operating system, along with components such as Pandas, NumPy, and Apache Spark. The study first compared the predicted and actual values of the path planning task using Root Mean Square Error (RMSE). The results are shown in Fig. 7.

In Fig. 7(a), the RMSE value of MA-DRL increased after 190 iterations. In contrast, ACGA-IoT reached a stable RMSE of 82.3m at the end of 330 iterations. In Fig. 7(b), the initial RMSE of MA-DRL was 223.1m, the highest among all four algorithms. ACGA-IoT started at 190.5 m and showed no significant decline between 180 and 230 iterations, but eventually dropped to 62.3m. The above results indicate that the path prediction accuracy of the research method is higher than that of the benchmark algorithms and can effectively reduce the walking distance in actual operations. To further verify the performance of each algorithm, the study compared their accuracy and F1-score. The comparison results are shown in Fig. 8.

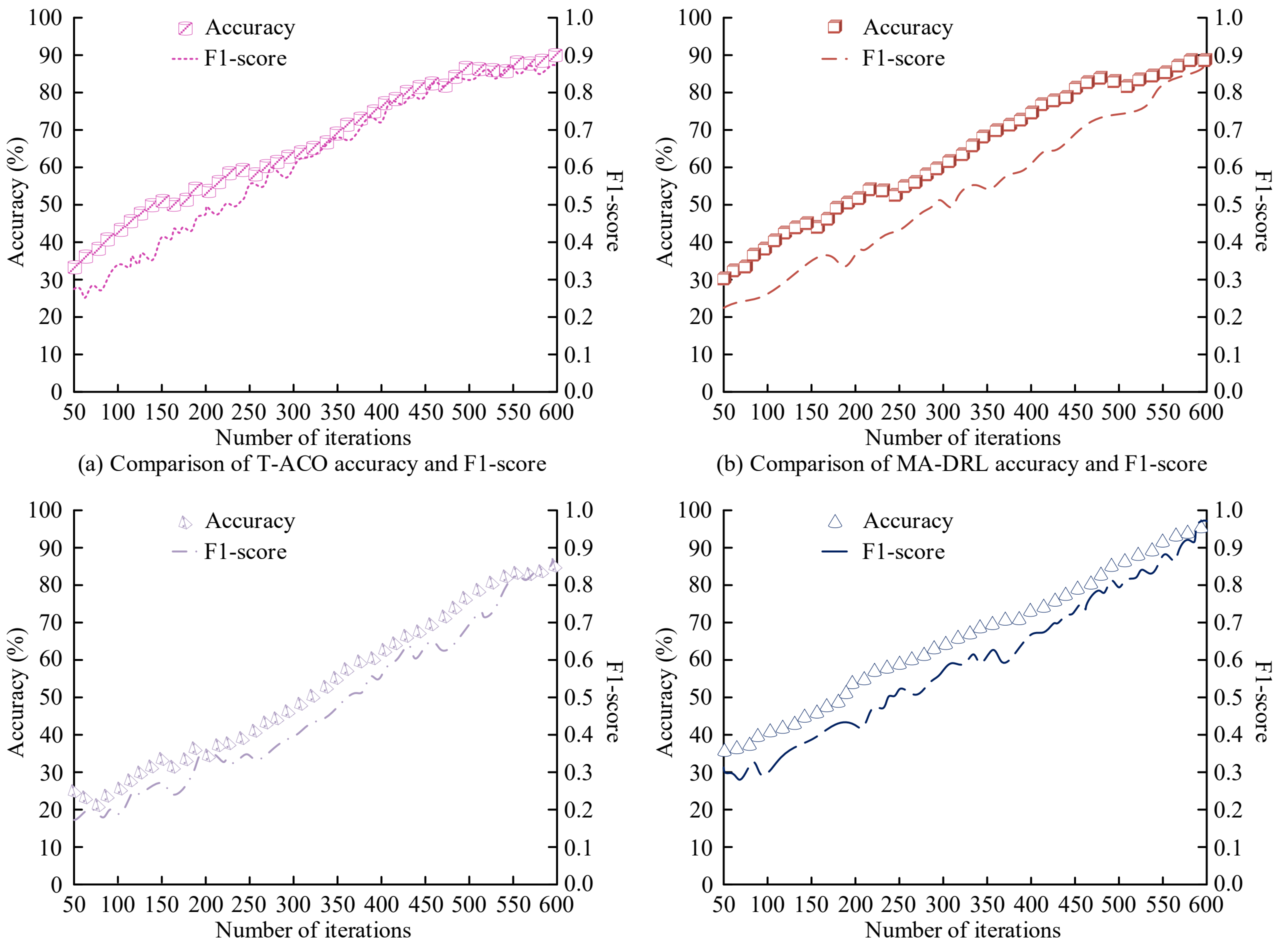
In Fig. 8(a), the accuracy of T-ACO increased slowly between 160 and 250 iterations. In Fig. 8(b), the accuracy of MA-DRL stabilized at 89.9% after 600 iterations. Fig. 8(c) shows that QPSO-DP started with an accuracy of 26.1% and an F1-score of 0.18. In Fig. 8(d), the accuracy of ACGA-IoT rose from 36.9% to 96.7%, and the F1-score improved from 0.30 to 0.97. This indicates that the system is highly reliable in task classification and anomaly recognition, which can significantly reduce reliance on manual judgment. To evaluate the fitness values of each algorithm, the study compared their predicted and actual fitness values, as shown in Fig. 9.

As shown in Fig. 9(a), ACGA-IoT achieved the highest prediction accuracy and the best fitting performance, with a final fitness value of 0.9881. In Fig. 9(b), MA-DRL showed relatively poor prediction accuracy with noticeable deviations in the middle stage and a final fitness value of 0.9675. Fig. 9(c) shows that QPSO-DP had a stable fitting curve with some deviations and a final fitness value of 0.9786. In Fig. 9(d), most of the test points of T-ACO fell on the curve, indicating good overall prediction, with a final fitness value of 0.9798. This indicates that the research method has the best performance in balancing multiple objectives, such as path length, time, and energy consumption, and can achieve a comprehensive evaluation of intelligent warehousing systems.



(a) Comparison of RMSE of four algorithms in training set (b) Comparison of RMSE of four algorithms in verification set

Fig. 7. RMSE comparison of four algorithms



(a) Comparison of T-ACO accuracy and F1-score (b) Comparison of MA-DRL accuracy and F1-score

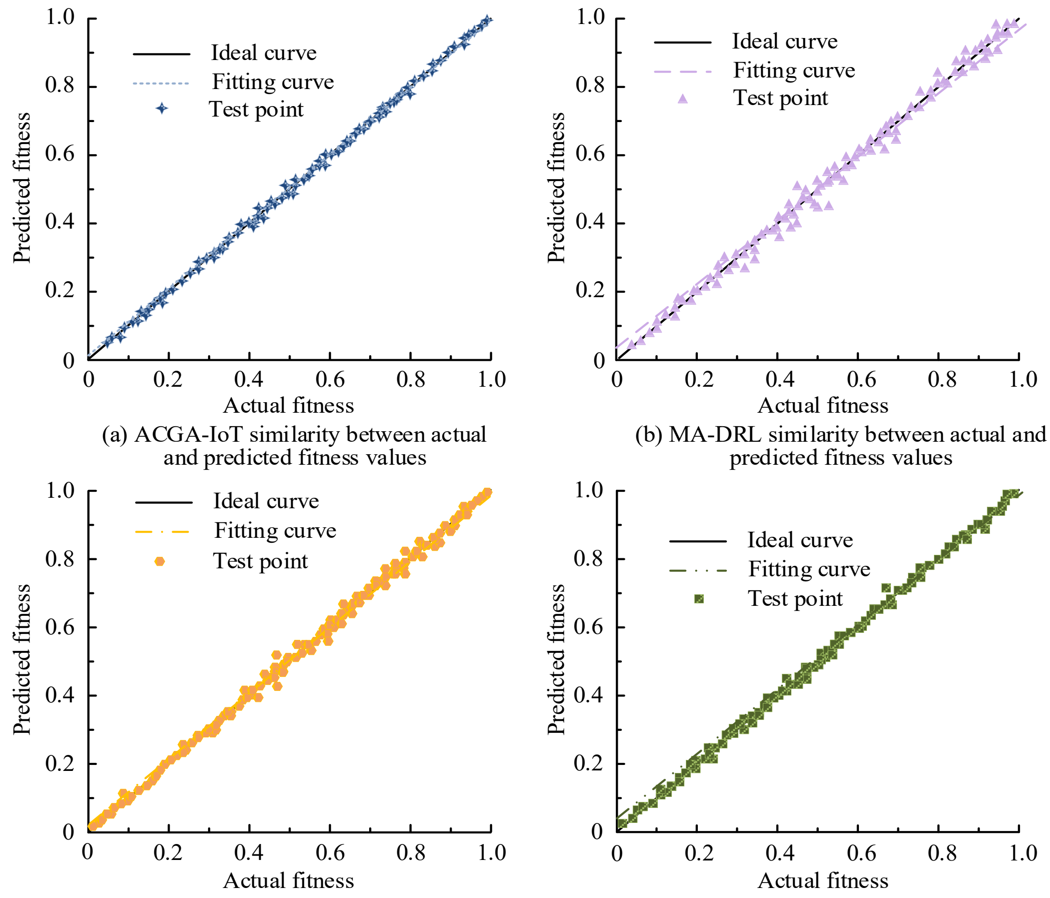
(c) Comparison of QPSO-DP accuracy and F1-score (d) Comparison of ACGA-IoT accuracy and F1-score

Fig. 8. Accuracy and F1-score comparison of four algorithms

4.2. Performance Verification of the Intelligent Warehousing Management System

After verifying the effectiveness of the ACGA-IoT algorithm, the study further evaluated the ACGA-IoT-based intelligent warehouse management system for cross-border e-commerce. A lightweight warehouse simulation environment was built using Python 3.9, Matplotlib 3.5, and SimPy 4.0.1. The hardware configuration included an Intel i5 processor, 8GB of memory, 5GB of available disk space, and a 1080p resolution display. The study selected the following systems as benchmarks: Mobile Network Version 2 (MobileNetv2)-based intelligent warehouse management system, Cross-platform

Warehouse Frontend System Based on HTML5 and PWA (HTML5-PWA), and AutoEncoder-based Anomaly Detection (AE-AD). A multidimensional scheduling dataset simulating cross-border e-commerce warehousing scenarios was constructed. The dataset included order data, warehouse environment sensing data, layout data, and various cross-border attribute data. The data collection period spanned from January 2024 to January 2025, covering seasonal fluctuations and promotional peaks. In total, 2 million real-time data points were collected, simulating destinations in regions such as Europe, North America, and Southeast Asia. The study first analyzed accuracy and system availability. The comparison results of the four systems are shown in Fig. 10.



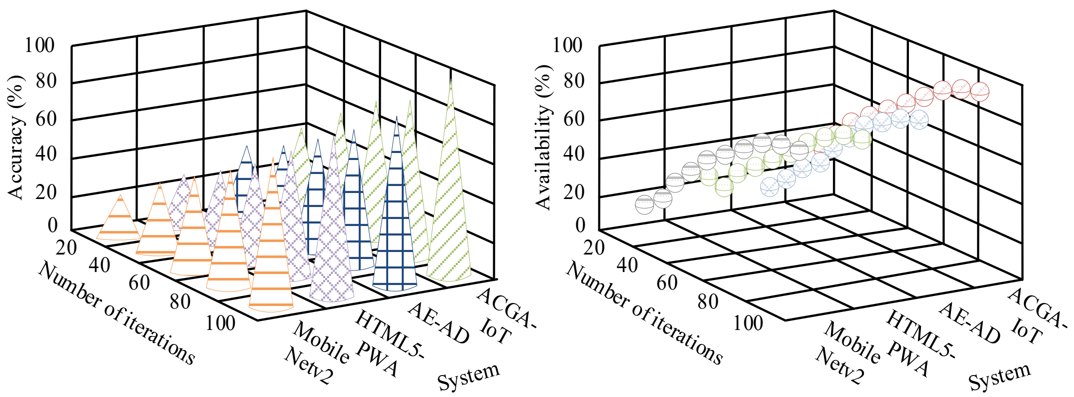
(a) ACGA-IoT similarity between actual and predicted fitness values

(b) MA-DRL similarity between actual and predicted fitness values

(c) QPSO-DP similarity between actual and predicted fitness values

(d) T-ACO similarity between actual and predicted fitness values

Fig. 9. Fitness value comparison of four algorithms



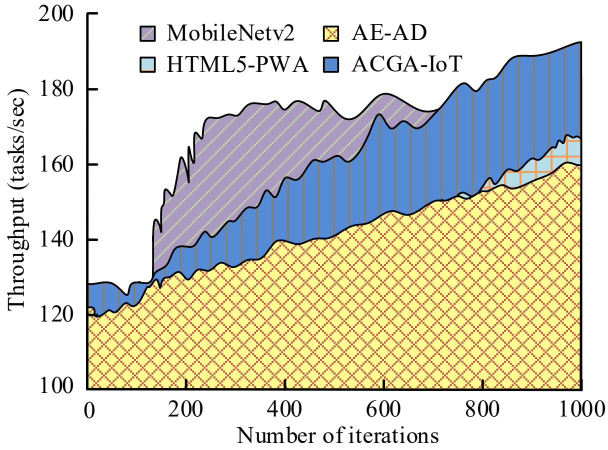
(a) Comparison of the accuracy of the four systems

(b) Comparison of the availability of the four systems

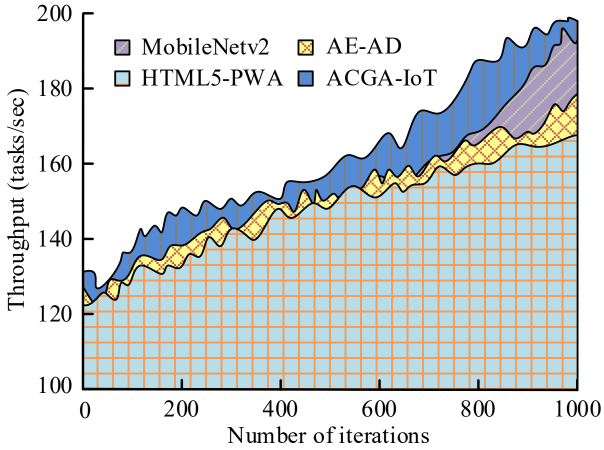
Fig. 10. Accuracy and system availability comparison

As shown in Fig. 10(a), the ACGA-IoT system achieved significantly higher accuracy than the other systems between 60 and 100 iterations. Between 80 and 100 iterations, its accuracy surged and eventually stabilized at 97.1%. In contrast, the MobileNetv2 system started with a relatively low accuracy of 19.4%. In Fig. 10(b), the system availability of ACGA-

IoT showed a continuous upward trend throughout the iterations, increasing from 25.1% to 94.2%. The other three systems reached a plateau in availability at around 80 iterations. This means that the system can remain stable even under long-term high-load operation, significantly reducing the risk of interruption. To further assess system performance, throughput was selected as the evaluation metric. The comparison results are shown in Fig. 11.



(a) Comparison of throughput in training set



(b) Comparison of throughput in verification set

Fig. 11. Throughput comparison of four systems

As shown in Fig. 11(a), the throughput of the MobileNetv2 system fluctuated around 176 tasks per second between 240 and 1000 iterations. In contrast, the ACGA-IoT system achieved stable throughput at 960 iterations, ending at 192 tasks per second. In Fig. 11(b), the MobileNetv2 system showed an increase to 193 tasks per second after 1000 iterations. In contrast, the ACGA-IoT system maintained a stable value of 198 throughput per second at the end of the iteration, which is higher than the typical industry benchmark, indicating that the system has the processing capability to cope with peak orders during major promotional periods Overall, the ACGA-IoT system demonstrated better throughput stability and significantly outperformed the benchmark systems on both training and validation sets. To analyze the practical warehouse management effectiveness of the four systems, the study compared their performance using comprehensive indicators, including system response delay, inventory turnover rate, and inventory accuracy. The results are presented in Table 1.

Table 1. Comparison of comprehensive performance metrics across four systems

Name	MobileNetv2	HTML5-PWA	AE-AD	ACGA-IoT
System response delay (ms)	42	38	48	25
Calculated load ratio (%)	85	45	78	68
Energy consumption (W·h)	24	20	22	18
Task completion rate (%)	89.3	92.1	85.7	98.5
Stability (%)	91.7	93.5	88.9	99.2
Inventory accuracy (%)	94.2	93.7	92.1	98.4
Inventory turnover ratio (times/year)	4.1	3.8	4.5	6.2

As shown in Table 1, the ACGA-IoT system achieved the lowest response delay at 25ms, outperforming the other systems in terms of latency. Its computational load rate was 68%, indicating a moderate level that avoided resource idleness while effectively preventing system overload. The HTML5-PWA system, in comparison, showed a response delay of 38ms and performed slightly worse in terms of stability and task completion rate. This system helps reduce order fulfillment delays, improve inventory accuracy, and lower energy consumption in large-scale cross-border logistics operations.

5. Conclusion

To address the inability of traditional warehouse management systems to balance sales and costs under unexpected conditions, this study proposed an intelligent warehouse management system that integrated ACGA with the IoT. The system leveraged the global search capability of GA and integrated it with an IoT-enabled sensing layer and real-time feedback mechanisms to optimize inventory levels and reduce operational costs. The study tested the ACGA-IoT algorithm using the public LaDe dataset. The results demonstrate that the RMSE on the validation set was 62.3m, and the accuracy stabilized at 96.7% after 600 iterations. In terms of fitness, the algorithm achieved a value of 0.9881. In the simulated cross-border e-commerce warehouse scenario, the ACGA-IoT system reached an accuracy of 97.1%, while its system availability increased from 25.1% to 94.2%, with throughput stabilizing at 192 tasks per second. Regarding comprehensive metrics, the system achieved a response delay of only 25ms, a stability rate of 99.2%, and a task completion rate of 98.5%, which outperformed the HTML5-PWA system's 92.1%. These results indicate that the ACGA-IoT system performed well in key metrics such as accuracy, stability, and resource utilization efficiency, showing strong potential for application in intelligent warehouse management for cross-border e-commerce. However, the study did not include real-world deployment or validation in complex warehouse environments. Future work focuses on expanding dataset coverage and improving the system's practicality.

Author Contributions

All Authors made substantial contributions to the conceptualization and design of this study, the acquisition, interpretation, and validation of the data; the drafting and critical revision of the manuscript, and the final approval of the version to be published.

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Declaration of AI Tools

The authors confirmed that no Artificial Intelligence (AI) tools were used in the preparation of this manuscript.

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