

Automated Logistics Control Model Based on Improved Ant Colony Algorithm

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With the rapid development of modern logistics industry, traditional automated logistics control systems often lack transparency and visualization of the entire supply chain. It cannot comprehensively manage and optimize the entire supply chain. Therefore, an automated logistics control model is constructed based on ant colony algorithm and logistic chaotic mapping. By simulating the pheromone transmission process of ants, the optimal logistics transportation path is found. From the experimental results, the improved Ant Colony Algorithm (ACA) was tested on the DT100dataset, achieving an optimal solution within 200 iterations. Compared with traditional methods, the cost was reduced by 0.25 units. The distance solution image of the improved ACA was overall concave downwards, with a significant decrease after 20 iterations. The designed automated logistics control system used map APIs and sensor data to obtain real-time delivery routes. On average, each logistics node consumed 1.01% of electricity. Compared with traditional methods, it had the highest prediction accuracy, with an R2 of 0.98. In summary, the improved ant colony algorithm can optimize logistics delivery paths, reduce delivery time and cost, improve delivery efficiency, and reduce delivery energy consumption.

Povzetek: Razvit je avtomatiziran logistični nadzorni model za optimizacijo logističnih poti, ki zniža stroške ter izboljša dostavo. Temelji na izboljšanem algoritmu mravelj in kaotičnem logističnem preslikavanju.

1 Introduction

With the development of the global economy, the application of logistics industry in various fields is becoming increasingly widespread [1]. Traditional logistics control methods often exhibit certain limitations when dealing with complex and ever-changing environments [2]. In this context, improving the efficiency and accuracy of logistics control to adapt to complex and changing environments has become a research focus. Traditional automated logistics control systems mainly rely on precise sensors, actuators, and complex control algorithms. However, these systems often have some shortcomings in dealing with the uncertainty and complexity of actual production processes. For example, traditional control algorithms do not achieve ideal results in dealing with complex and nonlinear logistics problems. Logistic chaotic mapping can generate stochastic sequences. In addition, logistic chaotic mapping can also be used to optimize logistics path planning, improving the efficiency and accuracy of logistics transportation [3]. Ant Colony Algorithm (ACA) can quickly find the optimal solution by introducing some new rules. Each ant can prioritize the path with higher concentration of pheromones. Therefore, this algorithm has strong global search ability [4-5]. For this purpose,

the study combines logistic chaotic mapping with improved ACA to optimize automated logistics control. An automated logistics control model is proposed. This study explores how to apply the improved ACA to optimize logistics transportation by analyzing its principles and application methods. The innovation of this study combines logistic chaos mapping and improved ACA, utilizing the efficiency and accuracy advantages of automated logistics control model operation. Ultimately, it achieved device automation and intelligent control, while reducing system cost and maintenance difficulties. The study involves four parts. The first part is to analyze the current research status of improved ACA. The second part describes the application of improved ACA in automated logistics control and the process of model construction. The third part analyzes the performance of the improved ACA and the designed logistics model. The last part summarizes the entire text.

2 Related works

To solve the installation cost and environmental issues of renewable energy, Güven et al. introduced a powerful rule-based energy management scheme based on ACA to manage the power flow between the system components that make up the micro-grid. Experiments showed that this method had good performance and convergence, with

lower system cost [6]. To improve transient stability using continuous domain ant colony optimization algorithm, Moradi et al. solved the optimal power flow problem with transient stability constraints and extracted sensitivity coefficients. Compared with other traditional methods, the research method reduced the fuel cost of power system operation to 60928.36\$/h [7]. To solve the communication delay problem between controllers and switches caused by link failures in the network, Li et al. established a model based on task delay and dynamic constraints. A heuristic ACA was used to solve the adaptive allocation scheme of computing resources. Experimental showed that the proposed method optimized computational resources [8]. To solve the manual scheduling difficulties and delivery delays in the production process, He et al. proposed an improved ACA to establish a weaving production scheduling model. Experimental showed that this method optimized the actual weaving scheduling [9]. Pontes et al. proposed a new linear discriminant analysis variable selection algorithm based on ACA to increase the probability of discarding non informative variables. Experiments showed that this method could minimize generalization problems related to multi-collinearity to the greatest extent possible [10].

The application of green logistics in the offshore oil logistics industry is becoming increasingly urgent. Zhu et al. conducted empirical analysis from the basic concept of

green logistics. Then a series of measures for the development of green logistics in the offshore oil logistics industry were proposed [11]. To ensure the sustainability of drug distribution, Jin et al. proposed a hybrid replenishment model based on the multi-step traveling salesman problem model and the vehicle routing problem model. The results showed that the backfill route length under this model reduced by 32.18% [12]. To solve the problems that arise in the construction of logistics networks, Zhang et al. defined the network level, node functions, and connections between nodes based on the logistics network structure. Finally, the cost optimization in the logistics network was achieved through an improved urban agglomeration order gravity model [13]. Defalque et al. established a multi-objective, multi product, multi-level, and multi cycle mixed integer linear programming model to optimize the waste paper logistics process in the intermediate center. The model improved the efficiency of sustainable logistics processes [14]. Considering the time dependent effects caused by traffic congestion in logistics, Guo et al. established a time window green vehicle routing problem for cold chain logistics based on adaptive large neighborhood search technology. The research algorithm was effective and superior [15]. The summary table of the above research results is shown in Table 1.

Table 1: Summary table of research results

Study	Performance	Boundedness
Güven et al. [6]	Compared with the three methods of HOMER, ant colony optimizer, and Jaya, it has better performance and convergence	The complexity of algorithms is increased, resulting in lower computational efficiency
Moradi et al. [7]	The fuel cost for power system operation is reduced to 60928.36 \$/h	It requires a significant amount of computing resources and memory space, with high requirements for computer hardware
Li et al. [8]	It can optimize computing resources and reduce task completion delays	Its ability to handle complex nonlinear problems is limited
He et al. [9]	It can optimize the actual weaving scheduling	The complexity of algorithms has increased, resulting in lower computational efficiency
Pontes et al. [10]	The classification accuracy in datasets involving wide absorption bands in the ultraviolet region, low resolution, and strong spectral overlap is over 90%	It is sensitive to initial parameter settings and adjustment process
Zhu et al. [11]	It provides countermeasures and measures for the development of green logistics in the offshore oil logistics industry	There is no factual evidence to prove the effectiveness of the proposed measure
Jin et al. [12]	The length of the backfill route is reduced by 32.18%	Algorithm complexity increases and computational efficiency decreases
Zhang et al. [13]	It aims to optimize costs and achieve linkage of logistics network structure	There is no factual evidence to prove the effectiveness of the proposed method
Defalque et al. [14]	Effective solutions are proposed in the collected instance calculation tests	This study lacks comparative experiments
Guo et al. [15]	The proposed solution is 14.14% better than the CPLEX solution, with a shorter	Algorithm complexity increases

solution time

In summary, ACA has high sensitivity, which is widely used in machine automation collaboration. The current logistics control system needs further improvement in automation and intelligence. This study aims to improve the ACA and apply it to automated logistics control systems to improve logistics efficiency and reduce operating cost.

3 Application of improved ant colony algorithm in automated logistics control model

Traditional logistics control models are difficult to handle rich customer and order information data. Therefore, ACA is introduced into the logistics control model. Some improvement measures are taken to address the shortcomings of traditional ACA, which effectively solve problems such as path planning and resource scheduling in the logistics process.

3.1 Ant colony algorithm optimization strategy for automated logistics control

With the increasingly fierce market competition, various links in the production process are becoming more specialized [16]. This trend has led to the separation of logistics and commercial flow, gradually highlighting the importance of logistics. Traditional logistics control models lack automation and intelligent support. Many

operations and management require manual labor, which is inefficient and prone to errors. At the same time, the lack of intelligent support also makes it difficult for enterprises to predict and make decisions on logistics processes. This also prevents timely adjustment and optimization of logistics strategies [17]. On this basis, the automated logistics control model has emerged. The automated logistics control model is a comprehensive system that utilizes various automation technologies and equipment to control and optimize the logistics process. As an important component of logistics chain cost, managing and controlling logistics transportation cost can optimize logistics processes and improve logistics transportation efficiency. The logistics transportation cost is shown in equation (1).

$$C_1 = \sum_{k=1}^k S_k \sum_{i=1}^m f_i \quad (1)$$

In equation (1), S_k is the variable. k is the vehicle number. m represents the number of items that includes all transportation costs. f is the driving cost. The corresponding transportation cost is shown in equation (2).

$$C_2 = \sum_{i=1}^n \sum_{j=0}^n \sum_{k=1}^k C_{ijk} X_{ijk} \quad (2)$$

In equation (2), C_{ijk} represents the transportation cost between points i and j . C_{ijk} is the variable between transportation points. n is a constant. The automated logistics control system is shown in Figure 1.

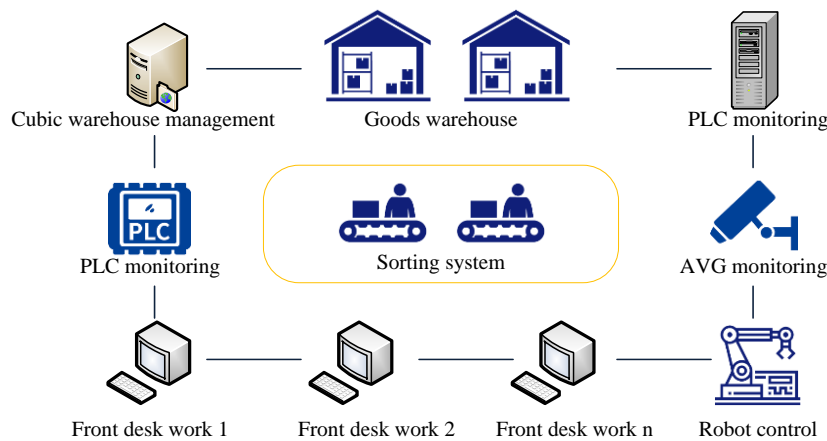


Figure 1: Automated logistics control system

The automatic logistics control system includes sorting system, goods warehouse, PLC monitoring, three-dimensional warehouse management, AGV monitoring, server, front-end work, mechanical arm, and other parts. The sorting system is mainly used to identify and classify goods. According to their destination or type,

they are distributed to different areas or modes of transportation. Goods warehouse is a facility used for storing goods, including automated warehouses and traditional warehouses. Logistics system monitoring mainly includes PLC monitoring and AGV monitoring. PLC monitoring can be used as a programmable logic

controller to monitor and control various parts of the logistics system. AGV monitoring is used to transport goods within or between warehouses, which is responsible for monitoring its operational status and position. The entire logistics system implements three-dimensional warehouse management, tracking and managing goods through computer systems to ensure accurate storage and retrieval of goods. The front-end work mainly includes processing orders, querying inventory, etc. To perform various tasks such as grabbing, moving, assembling, etc., the system uses a robotic arm for operation. With the increasing demand for logistics technology, the management level of traditional automatic logistics systems is relatively low. The ability to control the supply chain, plan transportation networks, and optimize warehouse management needs to be further improved. ACA is an optimization algorithm that simulates the process of ants searching for food in nature. It achieves information sharing and collaboration during the optimization process by simulating the pheromone transmission process of ants [18-19]. Therefore, introducing ACA into the logistics control model can effectively solve problems such as path planning and resource scheduling in the logistics process, improving the management level of automatic logistics control. The probability for node selection in ACA is displayed in equation (3).

$$P_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{is} [[\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta]}, & j \in \text{unpassed} \\ 0, & \text{else} \end{cases} \quad (3)$$

In equation (3), τ_{ij} is the information concentration. η_{ij} is the path visibility. α is the pheromone trade-off factor. β is the heuristic factor for expected values. The η_{ij} is shown in equation (4).

$$\eta_{ij} = \frac{1}{d_{ij}} \quad (4)$$

In equation (4), d_{ij} is the distance between point i and point j . After the ant colony completes the cycle, its pheromones will also be updated accordingly. The expression for pheromone update is shown in equation (5).

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \quad (5)$$

In equation (5), ρ is the pheromone evaporation coefficient. t is the time point. However, traditional ACA tends to randomly select the next node. Although random selection helps explore larger task spaces, applying positive feedback also takes a long time, resulting in slower convergence speed in the initial stage. Neglecting the coordination and optimization of the entire supply chain can result in low operational efficiency of the entire logistics chain, increasing time cost. To this end, the study introduces logistic chaotic mapping, aiming to utilize the characteristics of logistic chaotic mapping to improve the accuracy of knowledge accumulation. Then, some randomness is added to the paths in the basic ACA during the optimization process. The principle of logistic chaotic mapping is shown in Figure 2.

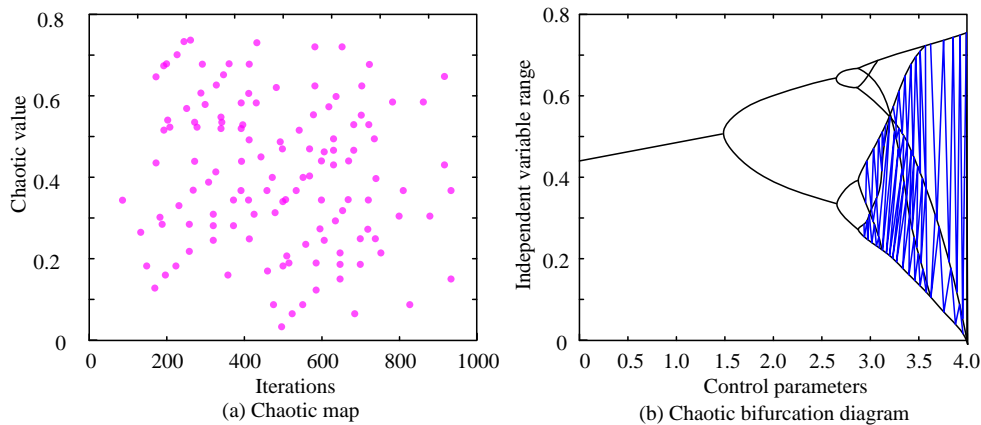


Figure 2: Logistic chaos mapping

Figure 2 (a) is a chaotic mapping diagram used to describe the evolution of the system's state over time under specific control parameters. It shows how the system state evolves over time given control parameters. In a chaotic state, the long-term behavior of the system is unpredictable. Even small initial condition changes can

lead to completely different results. Figure 2 (b) is used to visualize the system behavior when the control parameters change. It shows the pattern of system behavior changing with control parameters and reveals the transition process from order to chaos. The mapping function for logistic chaotic mapping is shown in

equation (6).

$$v_{i+1} = 4v_i(1-v_i) \tag{6}$$

In equation (6), v is the chaotic invariant set. The characteristics of logical chaotic mapping can enable ACA to have a larger search range and randomness in the initial stage, which helps to escape from local optima and accelerate the search for global optima. Optimizing the initial pheromone distribution through logical chaotic mapping can make ants more diverse and randomized in path selection, which is beneficial for accelerating convergence speed and improving the search efficiency of the algorithm. Based on ACA, an automated logistics control system hardware framework is used to initialize and optimize the ant colony population, as shown in equation (7).

$$v(o+1) = \mu v(o)(1-v(t)) \tag{7}$$

In equation (7), o is the number of iterations. μ is the control parameter. In ACA, the initial distribution of pheromones has a significant impact on the performance. After some iterations, if the concentration of pheromones on the current optimal path is too high, traditional ACA may experience local optima. Therefore, the study aims

to improve ACA by reducing excessive concentration of pheromones. The improved pheromone update mechanism is shown in equation (8).

$$\begin{cases} \tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij} \\ \Delta\tau_{ij} = \begin{cases} \sum_{k=1}^m \Delta\tau_{ij}^k, t \leq T \\ [1+a_1(T-t)] \cdot \Delta\tau_{ij}^k, t > T \end{cases} \\ \rho = \begin{cases} \rho_0, t \leq T \\ [1+a_2(t-T)] \cdot \rho_0, t > T \end{cases} \end{cases} \tag{8}$$

In equation (8), τ_{ij} represents the pheromone concentration along the path from node i to j , $\Delta\tau_{ij}^k$ represents the amount of pheromones released by ant k on path (i, j) . ρ represents the evaporation coefficient of pheromones. a_1 and a_2 are constants. Logistic chaotic mapping optimizes the initial pheromone distribution by randomly jumping the initial solution out of the local optimal solution domain, expanding the search range, and increasing the possibility of finding the global optimal solution. The improved algorithm flowchart is shown in Figure 3.

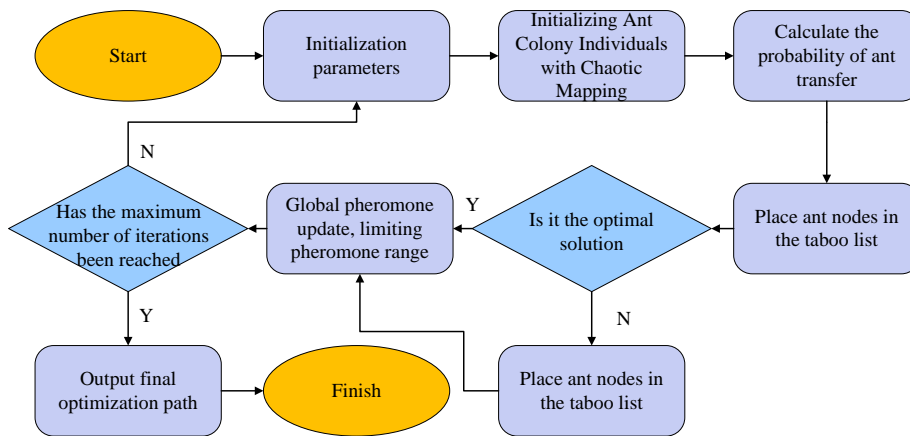


Figure 3: Improved ant colony algorithm process

Figure 3 showed the improved ACA process for this study. Firstly, the initial values of the chaotic map are set. Then the parameters of the ACA are set, including pheromone volatilization rate, pheromone intensity, ant population, etc. Next, logistic chaotic mapping is used to generate a set of new chaotic solutions. An improved ACA is used for searching. Then each ant updates its pheromones and selects the optimal solution based on the quality of the path during the search process. If the preset number of iterations is reached or a certain stopping criterion is met, the algorithm ends. Otherwise, the process returns to step 2 to continue iterating. In summary, this study introduces logistic chaotic mapping to improve the ACA, aiming to optimize the automated logistics system.

3.2 Design of an automated logistics system model based on improved ant colony algorithm

The automated logistics system model based on improved ACA mainly aims to achieve automation and optimization of the logistics process. Therefore, to improve the efficiency and accuracy of logistics systems, reduce cost, improve service quality, enhance scalability, and adapt to constantly changing market demands, an improved ACA is applied to design an automated logistics system model. In the model construction, the distribution path is first optimized. When the distribution source is 1 and the distribution task is one vehicle, the logistics optimization function is shown in equation (9).

$$\sum_{k=1}^m y_{ik} = 1, \forall i \in W \quad (9)$$

In equation (9), k is the refrigerated truck number. W is the set of target points. When the delivery source is 2, and the delivery task is one vehicle, the optimization function of the logistics path is shown in equation (10).

$$\sum_{i,j=0}^m x_{ijk} \leq 1, \forall k \in V \quad (10)$$

In equation (10), V represents the collection of refrigerated delivery vehicles. When the planned delivery route does not exceed the maximum travel distance of the delivery route, its expression is shown in equation (11).

$$\sum_{i,j=0}^m d_{ij} x_{ijn} \leq d_{\max} \forall n \in L \quad (11)$$

In equation (11), L is the delivery mileage. When the weight of the delivered goods does not exceed the maximum delivery capacity, the corresponding expression is shown in equation (12).

$$\sum_{i=0}^m q_i y_{ik} \leq Q, \forall k \in V \quad (12)$$

In equation (12), q_i represents the node demand. Q is the maximum load for logistics distribution. Automated logistics system refers to a system that achieves the automation and intelligence of logistics processes through advanced logistics technology and equipment, improving logistics efficiency and accuracy [20]. As an important equipment in automated logistics systems, stacker cranes are mainly used for the storage, retrieval, and sorting of goods. The picking operation is closely related to the automated logistics system. The operating trajectory of the stacker crane picking operation in this study is shown in Figure 4.

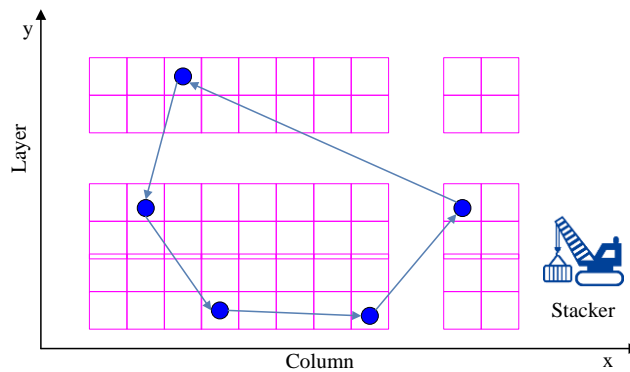


Figure 4: Stacker picking operation trajectory

The picking operation of the designed stacker crane is divided into two strategies. One strategy is to randomly select storage locations for storage and retrieval operations. Based on this strategy, the running path of the stacker crane is randomly generated. A different path is selected for each run. The advantage of this strategy is high flexibility, which can adjust the running path at any time. Another strategy is to first select the first inventory task. Then the nearest actionable storage location is selected in sequence for operation until all task storage locations are traversed. According to this strategy, the running path of the stacker crane is generated sequentially based on the order of tasks. Each run selects the next nearest available storage location. The advantage of this strategy is that it can ensure that each task is traversed. The operational model of the time spent on stacker crane operations at different cargo points is shown in equation (13).

$$T_{ij} = \max \left\{ |X_j - X_i| * W / V_x, |Y_j - Y_i| * H / V_y \right\} \quad (13)$$

In equation (13), X and Y are the coordinate points of goods transportation, respectively. The total time spent on stacker crane operations is shown in equation (14).

$$T = \sum_{i=0}^{n-1} T_{i,i} + 1 + T_{n,o} \quad (14)$$

In equation (14), n is the item number. Next, the path of the stacker crane is optimized to select the optimal sorting path to minimize the total time spent. The corresponding operating model is shown in equation (15).

$$T_{\min} = \min(T) = \min \left(\sum_{i=0}^{n-1} T_{i,i-1} + T_{n,o} \right) \quad (15)$$

The picking operation of the stacker crane optimizes path

planning, task allocation, operation sequence, and other aspects. This can make the operation of the stacker crane more efficient and stable, thereby improving the

performance of the entire automated logistics system. The final designed automation hardware composition system is shown in Figure 5.

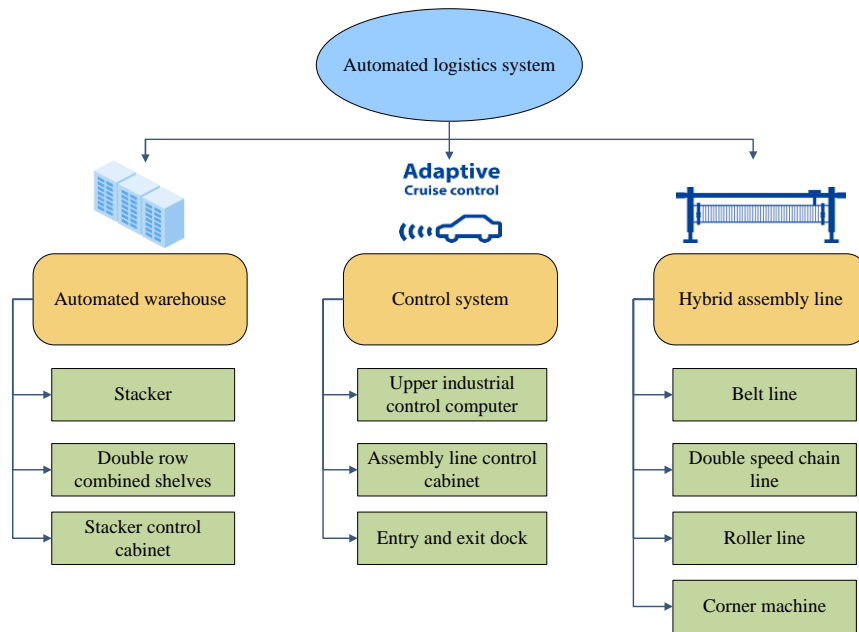


Figure 5: Automated logistics control system

Figure 5 shows the hardware framework of the automated logistics control system designed in this study. It mainly includes three parts: automated three-dimensional warehouse, control system, and hybrid assembly line. The improved ACA that integrates logistic chaotic mapping plays an important role in path planning and task scheduling. The main testing function used in system testing is shown in equation (16).

$$\max f(x_1, x_2) = 20(x_1^2 - x_2^2)^2 - (1 - x_2^2)^2 - 3(1 - x_2^2)^2 + 0.3 \quad (16)$$

By solving equation (16), the performance of the improved automatic logistics system can be tested. An automated three-dimensional warehouse is the core part of the automated logistics control system, consisting of high-rise shelves, stackers, handling robots, and inbound and outbound conveying systems. The control system is the core of the automated logistics control system, consisting of a control center, sensors, actuators, etc. Shelves are used to store goods. The stacker crane is responsible for storing and retrieving goods on the shelves. The handling robot is responsible for moving goods from one location to another. The inbound and outbound conveying system is used to deliver goods from the warehouse or from outside to the warehouse. The control center is responsible for receiving signals from sensors. According to the preset algorithm and program, the signal is processed and instructions are sent to the actuator. The actuator executes the corresponding actions. Hybrid assembly line is an efficient logistics

transportation method, composed of various conveying equipment, such as belt conveyor, roller conveyor, chain conveyor, etc. In summary, the study aims to design an automated logistics control system based on an improved ACA, providing more accurate and timely decision support for logistics control.

4 The application effect evaluation of improved ant colony algorithm in automated logistics control system

To further verify the superiority of the improved ACA in the automated control systems and the performance of the designed automated logistics control system, the designed method is compared with other algorithms.

4.1 Performance analysis of improved ant colony algorithm in automated logistics control model

Logistic chaotic mapping is used to improve the ACA, and then an automated logistics control system is constructed. Firstly, the performance verification is performed on the proposed LACO algorithm. The experiment is conducted in MATLAB/Simulink for system simulation. By setting corresponding parameters and constraints, the performance of the LACO algorithm is observed. The experimental model parameters are set in Table 2.

Table 2: Basic parameters of experimental model

Parameter	Parameter units	Parameter value
Unit fixed cost	Yuan	260
Unit transport costs	Yuan	3
Vehicle speed	km/h	55
Maximum vehicle mileage limit	km	12w
Rated heavy load	kg	4000
Pallet sizes	mm	460*450
Number of positions	2 rows	5 floors * 15 columns

The study is based on the Windows 11 platform, and the open-source MySQL software is used as the database. The number of projects is set to 50, the importance factor of the heuristic function is set to 5, the pheromone volatilization factor is set to 0.6, and the maximum number of iterations is set to 500. The DT100 dataset is used for testing. The classification results before and after the combination of LACO in this dataset are statistically analyzed. The DT100 dataset is a commonly used classification experiment dataset, consisting of a dataset

of 100 nodes. It is used to test the performance of algorithms in dealing with large-scale problems. The node distribution of this dataset is relatively uniform, with high connectivity and density. Next, the performance of the improved ACA in the automated logistics control system is analyzed. Basic ACA, PSO, and SAA before improvement are selected for comparison. The loss curves of these four algorithms are compared.

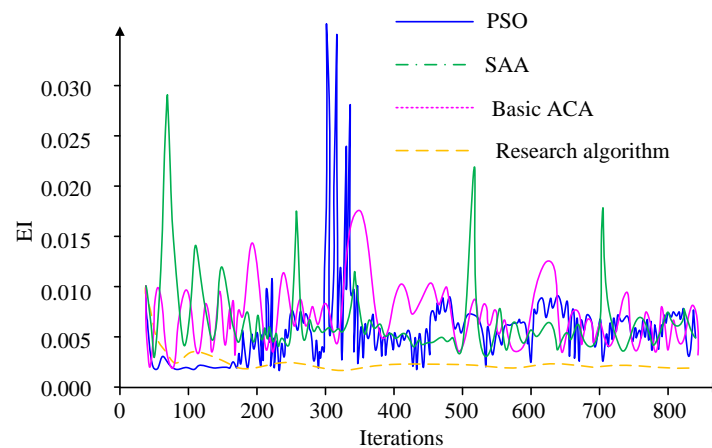


Figure 6: Comparison of loss curves of algorithms

Figure 6 showed the comparison results of the loss curves for four algorithms. Compared with the other three algorithms, the proposed LACO algorithm could find the optimal solution after 200 iterations. The PSO algorithm had significant losses when iterated around 300 times. The corresponding basic ACA and SAA algorithms had significant fluctuations in their loss functions, with loss values ranging from 0.003 to 0.026. From this, the LACO algorithm has better superiority in dealing with complex

problems. Because logistic chaotic mapping is used to generate initial solutions, it can guide ants to find the optimal solution faster. In addition, the LACO algorithm also utilized the advantages of ACA, such as swarm intelligence and distributed search, thereby improving search efficiency. Next, the cost solutions of the four algorithms are compared. The results are shown in Figure 7.

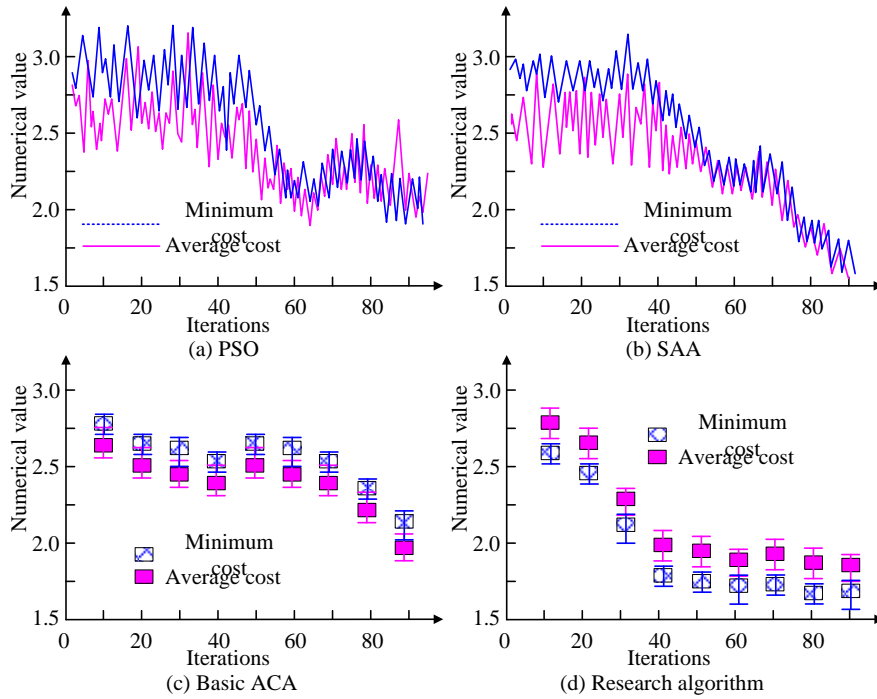


Figure 7: Comparison of algorithm cost solutions

Figure 7 showed a comparison of cost solutions for four algorithms in automated logistics systems. The minimum objective function value when solving optimization problems is compared. Figure 7 (d) shows the cost comparison. The results showed that the proposed algorithm was 0.25 units lower than the average cost. The cost solutions of PSO algorithm, SAA algorithm, and basic ACA were all higher than the average cost. The average minimum cost of the research algorithm was

about 0.51, 0.49, and 0.46 less than that of PSO, SAA, and basic ACA. From this, the LACO algorithm can continuously search and optimize the solution space by combining the advantages of logistic chaotic mapping and ACA, and quickly find cost solutions. Next, a comparative analysis is conducted on the distance solutions of the four algorithms. The analysis results are shown in Figure 8.

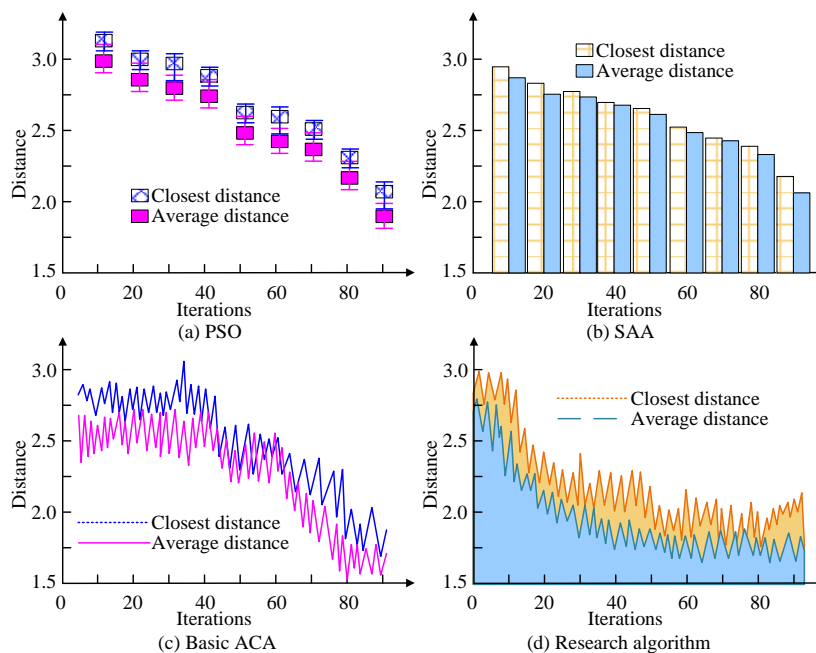


Figure 8: Comparison of algorithm distance solutions

Figure 8 shows a comparison of distance solutions for four algorithms. The distance solution calculates the distance between the current solution and the optimal solution, and updates the pheromone and transition probability based on this distance. Figure 8 (d) shows the distance solution results of the algorithm in this study. Compared with the distance solutions of the other three algorithms, the distance solution of the research algorithm was overall depressed. The decrease was significant after 20 iterations. The research distance cost was 0.64, 0.54, and 0.51 less than PSO, SAA, and basic ACA, respectively. In summary, the LACO algorithm combines the advantages of logistic chaos mapping and ACA. It has low loss in automated logistics systems, which can quickly obtain the optimal solution, with

strong global search ability.

4.2 The effectiveness analysis of an automated logistics control model based on improved ant colony algorithm

To verify the superiority of the designed automated logistics control system, real-time distribution paths are obtained through map APIs and sensor data in the experiment. The automated logistics control models based on PSO algorithm, SAA, basic ACA, and research algorithm are respectively used for comparing logistics distribution paths. The results are shown in Figure 9.

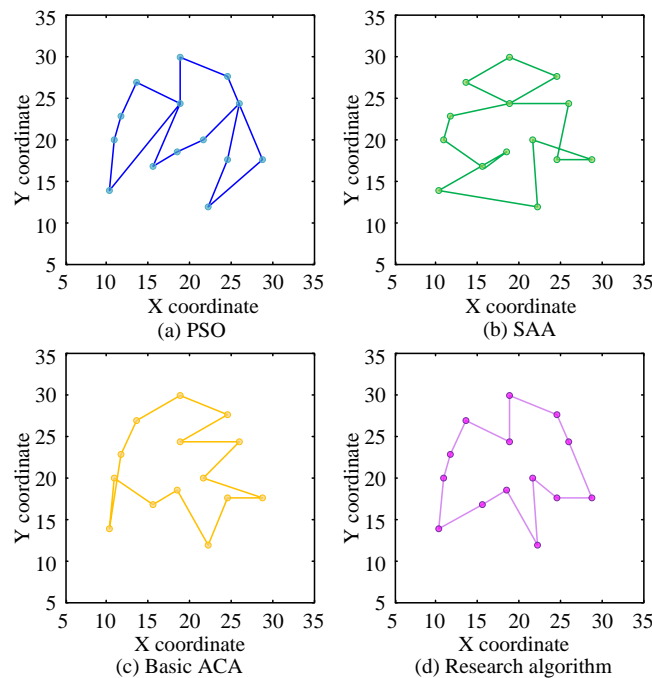


Figure 9: Comparison of logistics delivery path optimization models

Figure 9 shows the distribution path results of different models under the same 14 distribution points. Figure 9 (d) shows the distribution path optimization results of this research model. Compared with the other three models, the logistics distribution path of the designed model did not exhibit node conflicts or path duplication. The total delivery distance was 12 km, 15 km, and 34 km less than the PSO algorithm, SAA, and basic ACA, respectively.

From this, improving the ACA can optimize logistics distribution paths, reduce delivery time cost, and improve delivery efficiency. By simulating and optimizing the delivery process, the model can achieve faster and more accurate delivery services, meeting the timely needs of customers. Then, a comparison is made between the four models in terms of energy consumption. The comparison results are shown in Figure 10.

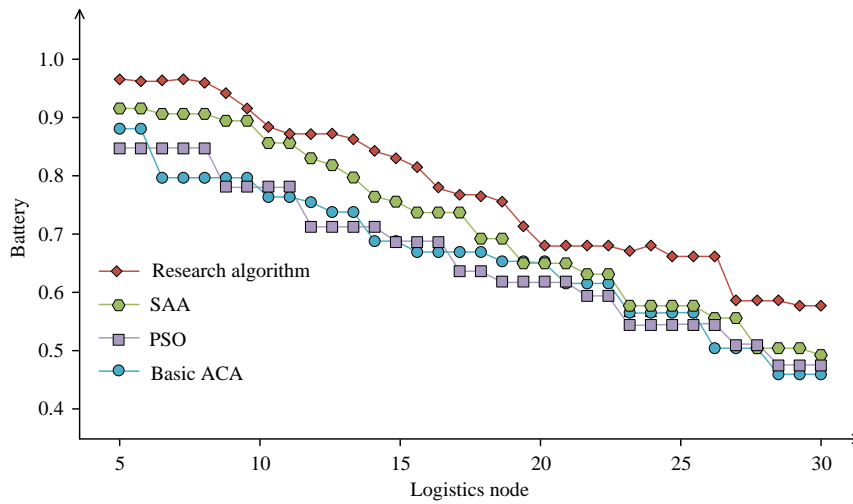


Figure 10: Comparison of model energy consumption

Figure 10 shows a comparison of model energy consumption. In the Figure, with the increase of time, the remaining electricity of the four logistics distribution models showed a decreasing trend. Compared with the other three models, the research model consumed less electricity. On average, each logistics node consumed

1.01%, which was 0.21%, 0.67%, and 1.02% less than the PSO, SAA, and basic ACA, respectively. The model used in this study can reduce energy consumption and environmental pollution. Finally, the operational accuracy of the research model is compared. The results are shown in Figure 11.

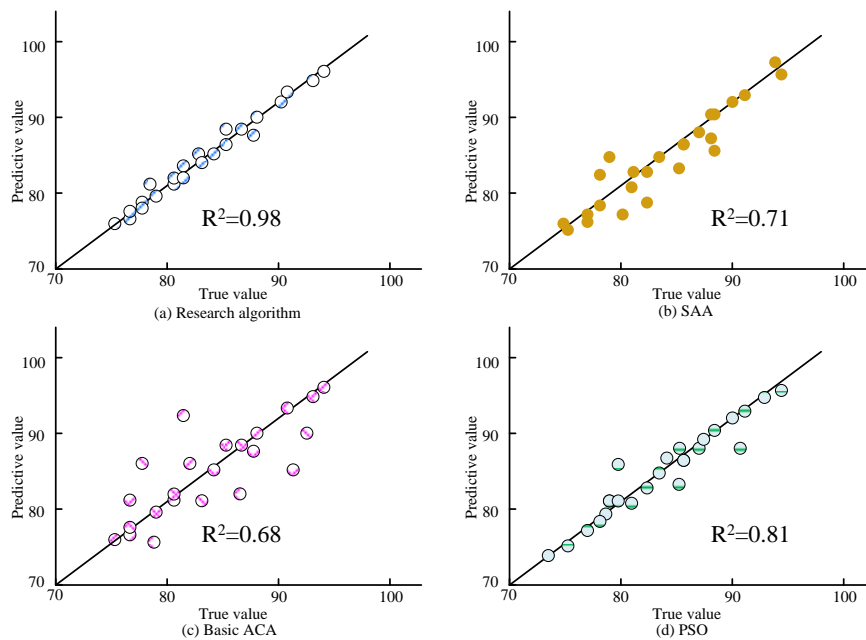


Figure 11: Comparison of model prediction accuracy

Figure 11 compares the prediction accuracy of four different logistics models. Figure 11 (a) shows the prediction accuracy results of the automated logistics control model designed in this study. The results showed that the designed model had the highest prediction accuracy, with R2 of 0.98, which was 0.27, 0.30, and 0.17 higher than the prediction accuracy of SAA, basic ACA, and PSO, respectively. In summary, the model can

optimize logistics routes, and reduce energy consumption in logistics distribution, with high prediction accuracy. The fitting effect is better than other models. To further validate the reliability and scalability of the proposed model, the ApolloScape real-world dataset published by Baidu is used for testing. The accuracy and solution time of the proposed model are compared with SAA, basic ACA, and PSO algorithms. The results are shown in

Figure 12.

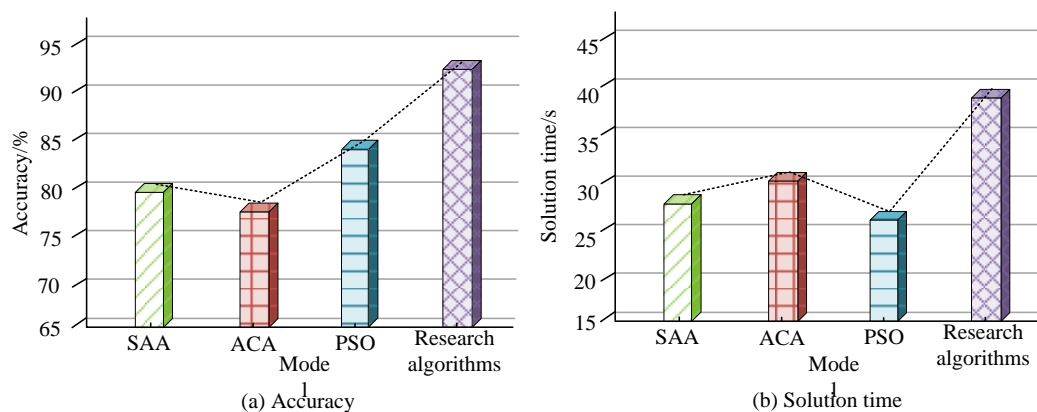


Figure 12: Comparison of accuracy and solution time of four models

Figure 12 compares the accuracy and solution time of four different logistics models. Figure 12 (a) shows the accuracy comparison results. The proposed model had the highest solution accuracy of 92.58%. Figure 12 (b) shows the comparison of solution times. The solution time of the proposed model was 38.64s, which was higher than the other three models, but still within an acceptable range.

5 Discussion

To improve logistics efficiency, ACA was introduced into the logistics control model. Then the LACO algorithm was proposed to address the shortcomings of traditional ACA. Finally, an automated logistics system model was designed based on the improved ACA. The test results on the DT100 dataset showed that the LACO algorithm had strong optimization ability, which could find the optimal solution at 200 iterations, minimizing the objective function value to be more than 0.25 units lower than the average cost. Introducing logical chaotic mapping allows the algorithm to have a larger search range and randomness in the initial stage, making it more likely to find the global optimal solution. This improvement measure also enhanced the algorithm performance and to some extent solved the problems faced in references [8] and [10]. In addition, compared with the PSO, SAA, and basic ACA, the delivery distance of the proposed model was shorter, the average power consumption per logistics node was lower, at 1.01%, and the prediction accuracy was higher, with an R2 of 0.98. This indicates that the proposed model has good optimization ability, which can effectively improve delivery efficiency and reduce energy consumption, and has certain practical application value. Unlike references [11] and [13], the study conducted tests on real-world datasets to validate the performance of the proposed model. In the ApolloScope dataset, the solution time of the proposed model was 38.64s, which was higher than traditional ACA. Although this study improved the algorithm performance, it also increased the complexity of the algorithm, resulting in a decrease in its

computational efficiency. This issue is similar to the problems in references [6], [9], [12], and [15]. Therefore, in future, it is necessary to further reduce the complexity of the algorithm as much as possible while ensuring performance.

6 Conclusion

With the continuous development of modern industrial automation technology, the logistics industry is undergoing tremendous changes. However, traditional automated logistics control systems often lack sufficient intelligence and adaptability. For this purpose, the study incorporated Logistic chaotic mapping into ACA to modify the logistics control system, verifying the superiority of the model through simulation experiments. Compared with the other three algorithms, the LACO algorithm could find the optimal solution at 200 iterations. The average minimum cost of research algorithms was about 0.51, 0.49, and 0.46 less than that of PSO, SAA, and basic ACA. The distance cost of research algorithm was 0.64, 0.54, and 0.51 less than that of PSO, SAA, and basic ACA, respectively. The total delivery distance of the research model was 12 km, 15 km, and 34 km less than that of the PSO, SAA, and basic ACA, respectively. The research model consumed less electricity, which was 0.21%, 0.67%, and 1.02% less than the PSO, SAA, and basic ACA respectively. The highest prediction accuracy of the designed model was highest, with R2 of 0.98, which was 0.27, 0.30, and 0.17 higher than the prediction accuracy of SAA, basic ACA, and PSO, respectively. In summary, the designed logistics model can effectively improve the overall performance and efficiency of the logistics system. There are shortcomings in this study. The real-time traffic and speed of logistics distribution have not been considered. Further consideration can be given to the impact of real-time and unexpected situations in logistics distribution on the logistics system.

References

- [1] Q. Han, Y. Sun, Q. Wu, and Z. Bai, "Research on optimization model of logistics transportation truck path considering environmental impact: experimental data from xiqing district, Tianjin," *Journal of Advanced Transportation*, vol. 2, no. 5, pp. 786-796, 2021. <https://doi.org/10.1155/2021/6665168>
- [2] A. Delgoshaei, H. Norozi, A. Mirzazadeh, M. Farhadi, G. H. Pakdel, and A. K. Aram, "A new model for logistics and transportation of fashion goods in the presence of stochastic market demands considering restricted retailers capacity," *RAIRO-Operations Research*, vol. 55, no. 9, pp. 523-547, 2021. <https://doi.org/10.1051/ro/2019061>
- [3] X. Wang, N. Guan, and J. Yang, "Image encryption algorithm with random scrambling based on one-dimensional logistic self-embedding chaotic map," *Chaos Solitons & Fractals*, vol. 150, no. 3, pp. 111-117, 2021. <https://doi.org/10.1016/j.chaos.2021.111117>
- [4] W. Hwang, D. Kang, and D. Kim. "Brain lateralisation feature extraction and ant colony optimisation-bidirectional LSTM network model for emotion recognition," *IET Signal Process*, vol. 16, pp. 45-61, 2021. <https://doi.org/10.1049/sil2.12076>
- [5] T. R. Brodetzki, G. Brodetzki, O. Feinerman, and A. Hefetz, "Worker demography and behavior in a supercolonial ant colony: The case of the desert ant *Cataglyphis niger*," *Ethology*, vol. 8, no. 3, pp. 876-889, 2020. <https://doi.org/10.1111/eth.12960>
- [6] A. F. Güven, N. Yrükere, and M. M. Samy, "Design optimization of a stand-alone green energy system of university campus based on jaya-harmony search and ant colony optimization algorithms approaches," *Energy*, vol. 253, no. 7, pp. 675-687, 2022. <https://doi.org/10.1016/j.energy.2022.124089>
- [7] B. Moradi, A. Kargar, and S. Abazari, "Transient stability constrained optimal power flow solution using ant colony optimization for continuous domains (ACO_R)," *IET Generation, Transmission & Distribution*, vol. 7, no. 9, pp. 786-798, 2022. <https://doi.org/10.1049/gtd2.12560>
- [8] C. Li, K. Jiang, and Y. Luo, "Dynamic placement of multiple controllers based on SDN and allocation of computational resources based on heuristic ant colony algorithm," *Knowledge-Based Systems*, vol. 241, no. 7, pp. 108-119, 2022. <https://doi.org/10.1016/j.knsys.2022.108330>
- [9] W. He, S. Meng, J. Wang, L. Wang, R. Pan, and W. Gao, "Weaving scheduling based on an improved ant colony algorithm," *Textile Research Journal*, vol. 91, no. 6, pp. 543-554, 2021. <https://doi.org/10.1177/0040517520948896>
- [10] A. S. D. Pontes, A. S. D. Araújo, and W. Marinho, "Ant colony optimization for variable selection in discriminant linear analysis," *Journal of Chemometrics*, vol. 77, no. 4, pp.897-903, 2020. <https://doi.org/10.1002/cem.3292>
- [11] Y. Zhu, and J. Suo, "The situation of offshore oil logistics industry and transportation scheme design of new concept of green logistics," *Journal of Coastal Research*, vol. 112, no. 12, pp. 112-123, 2020. <https://doi.org/10.2112/JCR-SI112-118.1>
- [12] H. Jin, Q. He, M. He, S. Lu, F. Hu, and D. Hao, "Optimization for medical logistics robot based on model of traveling salesman problems and vehicle routing problems," *International Journal of Advanced Robotic Systems*, vol. 18, no. 3, pp. 103-121, 2021. <https://doi.org/10.1177/17298814211022539>
- [13] X. Zhang, "B2C E-commerce logistics network optimization model," *Journal of Global Information Management*, vol. 6, no. 11, pp. 245-254, 2022. <https://doi.org/10.4018/JGIM.20220701.oa7>
- [14] C. M. Defalque, A. F. D. Silva, and F A S. Marins, "Goal programming model applied to waste paper logistics processes," *Applied Mathematical Modelling*, vol. 7, no. 3, pp. 786-792, 2021. <https://doi.org/10.1016/j.apm.2021.05.002>
- [15] X. Guo, W. Zhang, and B. Liu, "Low-carbon routing for cold-chain logistics considering the time-dependent effects of traffic congestion," *Transportation Research Part D: Transport and Environment*, vol. 6, no. 5, pp. 332-345, 2022. <https://doi.org/10.1016/j.trd.2022.103502>
- [16] S. Kumar, B. Sarkar, and A. Kumar, "Fuzzy reverse logistics inventory model of smart items with two warehouses of a retailer considering carbon emissions," *RAIRO - Operations Research*, vol. 55, no. 4, pp. 2285-2307, 2021. <https://doi.org/10.1051/ro/2021056>
- [17] S. Sharma, S. R. Singh, and M. Kumar, "A reverse logistics inventory model with multiple production and remanufacturing batches under fuzzy environment," *RAIRO - Operations Research*, vol. 55, no. 2, pp. 571-588, 2021. <https://doi.org/10.1051/ro/2021021>
- [18] Z. Wang, S. Gao, Y. Zhang, and L. Guo, "Symmetric uncertainty-incorporated probabilistic sequence-based ant colony optimization for feature selection in classification," *Knowledge-based Systems*, vol. 7, no. 4, pp. 78-86, 2022. <https://doi.org/10.1016/j.knsys.2022.109874>
- [19] D. Zhao, L. Liu, F. Yu, A. A. Heidari, and H. Chen, "Chaotic random spare ant colony optimization for multi-threshold image segmentation of 2D Kapur entropy," *Knowledge-Based Systems*, vol. 7, no. 5, pp. 234-245, 2020. <https://doi.org/10.1016/j.knsys.2020.106510>
- [20] P. P. Groumos, "A critical historic overview of artificial intelligence: issues, challenges, opportunities, and threats," *Artificial Intelligence and Applications*. Vol. 1, no. 4, pp. 197-213, 2023.

<https://doi.org/10.47852/bonviewAIA3202689>