RESEARCH-ARTICLE

Research on Regional Resource Optimal Allocation Based on Improved Ant Colony Algorithm

Published: 18 July 2025

GAITDI 2025: International Conference on Implementing Generative AI into Telecommunication and Digital Innovation
July 18 - 20, 2025
Beijing, China

GAITDI '25: Proceedings of the International Conference on Implementing Generative AI into Telecommunication and Digital Innovation 2025 (July 2025)
https://doi.org/10.1145/3771792.3773877
ISBN: 9798400714924

Research on Regional Resource Optimal Allocation Based on Improved Ant Colony Algorithm

Yiping Xu*
School of Economics
Wuhan Business University
Wuhan, Hubei Province, China
xuyiping816@126.com

Kaize Chen
School of Economics
Wuhan Business University
Wuhan, Hubei Province, China
1447491777@qq.com

Dingding Chang*
School of Economics and Management
North China University of Water Resources and Electric Power
Zhengzhou, Henan Province, China
Z20242071367@stu.ncwu.edu.cn

Abstract

In view of the current situation of regional resource allocation, this paper proposes a regional resource dynamic scheduling model based on the improved ant colony algorithm. This model takes the minimum cost and the least time as the optimization objectives and considers the constraint conditions such as the resource requirements and the sequence of tasks. At the same time, combined with the characteristics of the regional resource dynamic scheduling model, the traditional ant colony algorithm is improved, and an optimized encoding and decoding method is proposed. According to the results of computing power analysis, it shows that the improved ant colony algorithm has higher computational accuracy and faster convergence speed compared with the traditional ant colony algorithm.

CCS Concepts

• **Social and professional topics**; • **Professional topics**; • **Computing and business**; • **Socio-technical systems**;

Keywords

Improved ant colony algorithm, Regional resource allocation, Dynamic scheduling model

ACM Reference Format:
Yiping Xu, Kaize Chen, and Dingding Chang. 2025. Research on Regional Resource Optimal Allocation Based on Improved Ant Colony Algorithm. In *International Conference on Implementing Generative AI into Telecommunication and Digital Innovation (GAITDI 2025), July 18–20, 2025, Beijing, China.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3771792.3773877

1 Introduction

The logistics industry is an important industry that supports and promotes the economic and social development of a country. In 2023, the total social logistics volume in China was 352.4 trillion yuan, with a year-on-year growth of 5.2%, and the growth rate was 1.8 percentage points higher than that in 2022.[1, 2] The logistics industry in China is developing rapidly, and the overall momentum is good. In the process of the development of the logistics industry Baldacci, the degree of rational allocation of logistics resources will directly affect the efficiency of the logistics industry and thus affect the operational efficiency and development speed of the entire logistics industry.[3] In the logistics industry, to obtain profits, resources must be rationally allocated and arranged; otherwise, it will cause waste of resources, increased costs, and reduced economic benefits.

Therefore, this paper constructs a regional resource dynamic scheduling model for the logistics industry and uses the improved ant colony algorithm to solve it, realizing the scientific and rational allocation of logistics industry resources.

2 Regional Resource Dynamic Scheduling Model

2.1 Optimization Objective Function

The regional resource dynamic scheduling model of the logistics industry takes the minimization of the sum of the total cost and total time of logistics distribution completion as the optimization objective, and the objective function is expressed as follows.[4]

$$\begin{gathered} \min F = \min(\alpha F_c + (1-\alpha)F_t \\ \alpha \in [0,1] \end{gathered} \tag{1}$$

In the formula, F is the comprehensive optimization objective function; F_c is the total cost spent on completing the logistics distribution tasks; F_t is the total time spent on completing the logistics distribution tasks; α is the weight coefficient used to balance the importance of time and cost.

The calculation method of the total time F_t is:

$$F_t = \max_{j \in J} f_j \tag{2}$$

In this formula, J is the task set; f_j is the end time of task j. The calculation method of the total cost F_c is:

$$F_c = \sum_{j=1}^{nt} \sum_{h=1}^{n} d_j c_h \theta(jh) \tag{3}$$

In the above formula, d_j is the time required to complete task j, c_h is the personnel salary of team h, and θ(jh) is a binary variable indicating whether team h participates in task j. It satisfies the following relationship:

$$\begin{gathered} \theta(jh) = Q_{jht} = \begin{cases} 1, b_j \le t \le f_j \\ 0, t \notin \left[b_j, f_j\right] \end{cases} \\ \forall j \in J, \forall h \in H, \forall t \in T \end{gathered} \tag{4}$$

*Corresponding author

GAITDI 2025, Beijing, China

ACM ISBN 979-8-4007-1492-4/2025/07
https://doi.org/10.1145/3771792.3773877

In the above formula, H is the set of logistics distribution employees; T is the duration of all distribution tasks; θ(jh) is a binary variable indicating whether team h participates in distribution task j at time t. If it participates, θ(jh)=1; if it does not participate, θ(jh)=0.

2.2 Constraint Conditions

2.2.1 Constraints on the Logistics Distribution Sequence. There are requirements for the completion sequence between different distribution tasks, that is, the constraint conditions are satisfied:

$$f_p \leq f_j, \forall j \in J, \forall p \in P_j \tag{5}$$

2.2.2 Constraints on Employee Distribution Tasks. The same employee can only participate in the same logistics distribution task in the same time period. Therefore, θ(jh) also needs to satisfy the following constraint conditions:

$$\sum_{j=1}^{m} Q_{jht} \leq 1, \forall h \in H, \forall t \in T, \forall j \in J \tag{6}$$

3 Improved Ant Colony Algorithm

3.1 Basic Ant Colony Algorithm

In the basic ant colony algorithm, ants initially explore randomly with no pheromone trails.[5] Over time, shorter paths accumulate more pheromone as more ants traverse them, while longer paths' pheromone evaporates. The highest pheromone concentration ultimately identifies the shortest path. The advantages of the ant colony algorithm:

- The individuals in the ant colony algorithm do not interfere with each other. Whether some individuals complete the optimization or not will not affect the optimization ability of the algorithm, and the algorithm has a strong robustness effect.
- The ant colony algorithm is a global optimization algorithm, and the ant colony searches for the optimal result among all possible paths.
- The ant colony algorithm forms a solution set through dynamic optimization and gradual iteration. Compared with other algorithms, the ant colony algorithm is easy to combine with other algorithms to form a combined optimization algorithm.

The disadvantages of the ant colony algorithm: The construction time of the initial population is long. The ant colony lacks pheromone in the initial state, resulting in a long preparation time for effective search. Moreover, the ant colony has a certain randomness in individual actions, which will ultimately reduce the efficiency of the algorithm.

3.2 Improvement of the Ant Colony Algorithm

The ant colony algorithm's strong positive feedback quickly finds solutions but risks local optima.[6] This paper introduces a pheromone evaporation mechanism as a counterbalance - gradually reducing trail influence to maintain search diversity. Combined with three key factors (heuristic information, positive feedback, and evaporation), the enhanced algorithm ensures optimal pathfinding for regional logistics resource allocation. Therefore, this paper determines the factor values of the number of iterations according to the process of the algorithm to seek the optimal solution. In order to adjust the time and accuracy of the ant colony searching for the optimal path, the heuristic information and positive feedback mechanism can be set.

Let the value of γ represent the strength of the two mechanisms. If it is necessary to inhibit the convergence of the algorithm, the value of γ is reduced, that is, $\gamma 0$ is preferred; otherwise, $\gamma 1$ is selected.

$$\gamma = \begin{cases} \gamma_0, 0 < M < M_0 \\ \gamma_1, M_0 < M < M_{\max} \end{cases} \tag{7}$$

After repeated tests, $M_{\max}$ refers to the maximum number of iterations, where:

$$20\% M_{\max} < M_0 < 50\% M_{\max} \text{ and } \gamma_0 < \gamma_1$$

Meanwhile, this paper designs the encoding and decoding method, the ant colony transfer mechanism, and the pheromone update mechanism.

3.2.1 Ant Colony Transfer Mechanism. In order to improve the quality of ant colony algorithm in the search process, pseudo-random transfer rules are introduced to optimize the selection process of the next task. This rule provides an effective balance between deterministic and random selection, thus opening up new perspectives in the field of research.

The mechanism for ant J to select the next task:

$$j = \begin{cases} \arg\max_{g \in G_k} \{\gamma(i,g)^{\mu} \chi(i,g) \kappa^{\nu}\}, q \leq q_0 \\ j_p, \text{else} \end{cases} \tag{8}$$

In the formula, q and q_0 are random numbers within the range of [0, 1]. q is generated when ant k is searching for the next task, and $q_0$is generated when ant k is starting a new iteration. G_k is the set of optional next tasks for ant k; υ and μ are the heuristic information influence coefficient and the pheromone influence coefficient respectively. j_p is the next task obtained according to the roulette wheel selection strategy, and its calculation formula is:

$$j_p = \arg\min_{j \in G_k} |p_k(i,j) - r| \tag{9}$$

Then the probability that j is the next task is:

$$p_k(i,j) = \frac{\gamma(i,j)^{\mu} \chi(i,j)^{\nu}}{\sum_{g \in G_k} \gamma(i,g)^{\mu} \chi(i,g)^{\nu}}, j \in G_k \tag{10}$$

The calculation method of the heuristic information is:

$$\eta(i,j) = \max_{g \in G_k} f_g - f_j + 1 \tag{11}$$

3.2.2 Pheromone Update Mechanism. The pheromone update mechanism mainly consists of two parts: local pheromone update and global pheromone update.

- Local pheromone update is carried out during the process of each ant individual generating a task scheduling scheme. Its purpose is to avoid more ants from choosing the same task with excessive pheromone, which may lead to blockages.

$$\tau^t(i,j) = (1-\beta)\tau^t(i,j) + \beta\tau_0 \tag{12}$$

In the formula, β is the pheromone evaporation coefficient; τ_0 is a constant, $\tau_0 = \frac{1}{MT}$. m is the summary of the number of tasks; T is the latest end time of all tasks.

- Global pheromone update is carried out after all ants complete one round of iteration. Its purpose is to enable the information of the current global optimal solution to be transmitted to other ants. Therefore, it is necessary to add extra pheromone to the globally optimal ant individual.

$$\tau^{t+1}(i,j) = (1-\beta)\tau^{t}(i,j) + \beta\Delta\tau^{t}(i,j) \tag{13}$$

In the formula, $\Delta\tau^{t}(i,j)$ is the additional amount of pheromone increment.

$$\Delta\tau^{t}(i,j) = \begin{cases} \frac{1}{T_{g_{best}}}, (i,j) \in g_{best} \\ 0, \text{else} \end{cases} \tag{14}$$

In the formula, T_{gbest} is the value of the global optimal objective function, and g_{best} is the scheduling scheme of the global optimal task.

3.3 Optimization of pheromone volatile factors

The basic ant colony algorithm is prone to fall into the local optimal due to the fixed pheromone volatile factor: when the volatile factor is too high, the pheromone dissipates rapidly, which promotes the exploration of new paths but slows down the convergence rate. When the volatile factor is too low, there are too many residual pheromones, which can easily lead to precocious astringency. To this end, this paper proposes a strategy to dynamically adjust the volatile factor to balance the exploration and convergence efficiency, and its formula is as follows:

$$\begin{array}{ll} 0.95, & N < 0.1N_{\max} \\ \rho \ \cos\left(\frac{\pi}{2} \times \frac{N}{N_{\max}}\right) 0.7 + 0.25, & others \\ 0.25, & N > 0.9N_{\max} \end{array} \tag{15}$$

Among them, the pheromone volatilization factor in the ant colony algorithm changes from a fixed value to a value that changes with the maximum number of iterations. When the iteration is less than 0.1 times the maximum number of iterations, the pheromone volatilization factor is set to 0.95, and the faster the pheromone volatilization, the pheromone concentration on the path will decrease, increasing the possibility of exploring new paths. When this iteration is greater than 0.9 times the maximum number of iterations, the pheromone volatilization factor is set to 0.25 to guide the ants to converge to a certain path. At other times, the parameters are reduced by the cosine waveform, which enhances the efficiency and quality of the algorithm in solving the optimization problem.

4 Algorithm test

In order to comprehensively evaluate the performance of the proposed improved ant colony algorithm, firstly, this section analyzes the optimization performance of the algorithm through several standard test functions, so as to evaluate the global search ability and convergence speed of the improved algorithm in this chapter in solving complex multimodal function optimization problems. Secondly, the influence of changing the number of ant colony and the heuristic information weight on the stability of the algorithm is considered to evaluate the robustness of the algorithm.

4.1 Convergence analysis of algorithm

In order to verify the convergence of the improved ant colony algorithm, pheromones can be gradually accumulated on the global optimal path, thus achieving the convergence of the global optimal solution. In the experiment, the parameters of the standard ant colony algorithm are set as follows: the number of ants is set to 50, the number of iterations is 100, the pheromone evaporation coefficient is 0.5, and the pheromone intensity is 1.0.

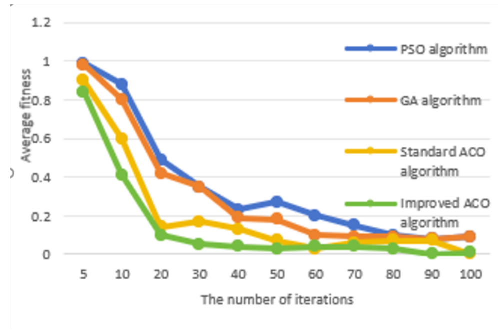

Figure 1: Sphere function optimization testing

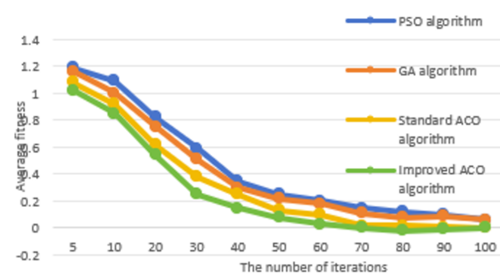

Figure 2: Ackley function optimization test

In order to visually demonstrate the performance of the improved ACO algorithm in the optimization of three functions, namely Rastrigin, Sphere and Ackley, the analysis results of the above three functions are drawn through experimental data, and the average fitness changes of the improved ACO, the standard ACO, the genetic algorithm (GA) and the particle swarm optimization algorithm (PSO) in the iterative process are compared.

Figure 1 shows that the improved ACO shows faster convergence speed and lower final solution deviation compared with the standard ACO and PSO, which verifies the effectiveness of dynamic pheromone update rules.

Figure 2 shows that in the Ackley function optimization problem, in the complex multi-peak Ackley function optimization problem, the improved ACO shows excellent global search ability, finds a solution closer to the global optimal solution, and highlights the advantages of the adaptive adjustment mechanism. The comprehensive results of three groups of experiments show that compared with the other three algorithms, the improved ACO converges to the better solution faster in the iterative process, and shows significant advantages in avoiding the local optimal solution. Therefore, the improved ant colony algorithm shows faster convergence speed and better search ability.

Table 1: Parameter setting required for the mold.

parameter	meaning	Parameter value
Qk	The maximum weight t that the distribution vehicle K can load the transported goods.	9
Tk	Maximum travel time h of the k th delivery vehicle	8
v	Average speed km/h of free running of distribution vehicles.	50
C22	The fixed use cost of each delivery vehicle is RMB.	50
C11	In-transit unit made in func/h	20
C12	Unloading unit cost yuan/h	25
C21	Distribution distance cost yuan/km	100

5 Case Analysis

In this chapter, the logistics situation of M enterprise in a certain area is taken as an example, and the example is analyzed according to the improved ant colony algorithm proposed above. The parameter settings are determined through the analysis of the results and parameters, and the performance of the improved algorithm is further verified by comparing the results of different algorithms. By comparing different distribution modes, suggestions and opinions are provided for logistics companies when choosing distribution modes.

In order to optimize the pharmaceutical logistics distribution routes of Company M, it is necessary to select some data information of Company M, including the locations of customer points, demand volumes, time windows, etc., as well as the number, capacity and cost of distribution vehicles.[7] Based on the historical distribution data of Company M and the relevant data of its distribution, this research object is determined.

5.1 Parameter settings

5.1.1 Multi-objective optimization module parameters. On the basis of establishing the optimization model of enterprise logistics distribution path, it is necessary to set up relevant parameters to solve and analyze the model. Because many customers are located close to each other in the distribution of M company's medical logistics, in order to reduce the cost, improve the efficiency and optimize the service quality, the mileage saving method is selected. To sum up, the relevant parameters need to include the parameters of the nodal mileage method, the parameters of the improved ant colony algorithm, and the special coefficient number of M company. According to the actual situation, these parameters are rationally set and adjusted, which is as follows (Table 1):

5.1.1.1 Parameters of nodal mileage method

The core of the nodal mileage method is to calculate the nodal quantity between the customer points, and then merge the distribution routes step by step according to the nodal quantity.[8] There are two main parameters in the nodal mileage method, which are the calculation formula of nodal quantity and the gauge I of the combined route. " In this paper, the most commonly used formula for calculating the amount of savings is adopted, Gen P:

$$S_{ij} = d_{io} + d_{0j} - d_{ij} \tag{16}$$

Among them, S_{ij}shows the amount of savings between the customer points i and j, the distance between the customer points and the delivery center, d_{io}shows the distance from the delivery center to the customer point, and d_{ij}shows the distance between the customer points I and j. If the customer points i and j are combined on the same route, then the distance saved is the difference between the distance from the original distribution center and the distance from i to j. The greater the amount of savings, the better the effect of combination. The rules of merging route refer to the sequence and formula of how to choose merging after calculating all the savings. In this paper, the rule that the maximum savings is the first is adopted, that is, the two customers with the largest savings are selected and merged at a time, until the customers who do not have enough pieces are low to choose. The condition of merging means that the merged route will not exceed the capacity of vehicles and the constraint of time windows, and the formula of merging means that two customer points are respectively taken as the starting point and the ending point of the route, or one customer point is inserted in front of the other customer point, or a part of the two routes is divided into lines to achieve the maximum.

5.1.1.2 Parameters of improved ant colony algorithm

There are four main parameters in the modified ant colony algorithm, which are the number of ants, the number of volatility coefficients of pheromones, the importance degree of pheromones and the importance degree of initial information.[9] According to the relevant facts, these parameters have been set and adjusted rationally, which is as follows.

- Number of ants: According to the information delivery results , the number of ants is selected as 29, which is the same as the number of customers, so as to ensure that each customer has an ant to visit and ask questions, and at the same time, it will not increase the calculation too much.
- The pheromone evaporation rate critically affects exploration-exploitation balance. If too low, pheromones accumulate excessively, trapping ants in known paths and reducing exploration. If too high, pheromones vanish too quickly, hindering effective use of historical data for convergence. This paper sets the evaporation rate at 0.5 (halving pheromones per iteration) to optimize this balance.
- Pheromone weight affects algorithm feedback. If too low, ants rely more on initial info, reducing adaptability. If too high, over-dependence increases premature convergence risk. Setting it to 1 balances influence with initial info for optimal path selection.

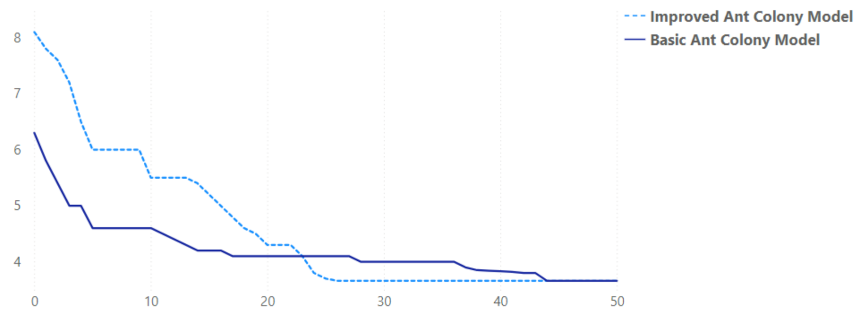

Figure 3: Convergence comparison curve

- Initial info's weight affects path calculation. If too low, ants overuse pheromones, ignoring problem specifics. If too high, they rely solely on initial data, neglecting learned experience. Optimal balance: set importance to 1, equal to pheromones, for unbiased path selection.
- According to the operation data of medical and pharmaceutical logistics distribution in S company, the special coefficient is determined to be 0.2, that is, the loss cost of goods accounts for 20% of the total distribution cost, so as to balance the cost and benefit of logistics distribution and ensure the quality and safety of goods.

5.2 Comparative Analysis of Algorithm Performance

To test the performance of the improved ant colony algorithm proposed in this paper, the logistics distribution data of a certain region are selected for verification. Meanwhile, the regional resource dynamic scheduling model of the improved ant colony algorithm is used to optimize the scheduling of the logistics distribution tasks in this region, thereby verifying the accuracy of the involved algorithm model.

Parameter Settings: Pheromone evaporation coefficient: β =0.5. Pheromone influence coefficient: μ =1. Heuristic information influence coefficient: ν =2.

A certain example is randomly selected from the data set. The computational iteration processes of the basic ant colony algorithm model and the improved ant colony algorithm model are shown in Figure5-1. It is found that the basic algorithm requires 44 iterations to reach the global optimal solution, while the improved ant colony algorithm can reach the global optimal solution with only 26 iteration operations. By comparison, the improved ant colony algorithm has enhanced the convergence speed and the ability to search for the global optimal solution.

A comprehensive performance comparison was conducted on the acquired data set. The comparison of the optimization results between the traditional ant colony model and the improved ant colony model is shown in Table 2. Looking at the data set as a whole, for any identical data set, the average deviation rate of the optimization results of the improved ant colony model algorithm is smaller than that of the traditional ant colony model. From the perspective of specific examples, when there is a deviation between the obtained optimal solution and the known optimal solution, the deviation rate of the optimization results of the improved ant colony model is almost less than 10%, and it is more concentrated in the range where the deviation does not exceed 2%. However, the basic ant colony model algorithm still has a certain proportion of deviation rates exceeding 10%. It can be seen from this that the improved ant colony model algorithm has higher computational accuracy.

5.3 Analysis of Dynamic Scheduling of Regional Logistics Resources

A simulation experiment was carried out by selecting the distribution data of a certain enterprise in a certain region. Data collection was conducted at 16 logistics distribution points. The results of logistics scheduling are shown in Table5-2. The total duration and total cost before and after the optimized scheduling are shown in Table5- 3.

Compared with before the optimized scheduling, the total time of the proposed algorithm is reduced by 24.78%, and the total cost is reduced by approximately 21.47%. Compared with the basic ant colony model algorithm, the total time of the improved ant colony model algorithm is reduced by about 15.79%, and the total cost is reduced by 7.7%. It can be seen that the improved ant colony model algorithm can reduce the total time for task completion and lower the resource costs incurred, providing effective informatization data support for cost reduction and efficiency improvement in logistics resource allocation.

6 Conclusion

Optimizing the allocation of regional resources through the improved ant colony algorithm is an effective optimization path, which requires a scientific procedure. In this paper, the dynamic optimization scheduling of regional resources in the logistics industry is achieved by using the improved ant colony algorithm model. The case analysis shows that the improved ant colony algorithm model in this paper has better computational speed and computational accuracy compared with the basic ant colony algorithm model. In the scheduling of logistics distribution operation tasks, the improved ant colony algorithm model can significantly reduce the total time and total cost for task completion compared with the basic ant colony algorithm model. The total time and total cost calculated are reduced by about 15.79% and 7.7% respectively compared with

Table 2: Performance comparison of the models

Model	Data Collection	Proportion of RD ≤ 2%	Proportion of RD ≤ 5%	Proportion of RD ≤ 10%	Average deviation rate
Basic Ant Colony Model	A	0.942	0.979	1	0.13
	B	0.823	0.921	0.953	0.65
	C	0.767	0.873	0.903	1.36
lmproved Ant Colony Model	A	0.978	1	1	0.07
	B	0.871	0.986	1	0.57
	C	0.812	0.892	0.995	1.01

Table 3: Results of Logistics Task Scheduling

No.	Duration(Minutes)	Resource 1	Resource 2	Resource 3
1	31	1	5	0
2	16	9	3	O
3	31	10	3	8
4	46	1	14	0
5	31	9	0	4
6	16	13	3	0
7	16	3	7	0
8	16	1	13	0
9	31	0	-1	0
10	46	4	-1	1
11	61	1	1	4
12	16	1	8	6
13	31	12	1	8
14	16	0	5	0
15	46	1	5	8
16	16	9	0	9

Table 4: Comparison Before and After Optimized Scheduling

Model	Algorithm Total Time(minutes)	Total Cost(RMB)
Before Optimized Scheduling	690	9 730
Basic Ant Colony Model	519	7 641
lmproved Ant Colony Model	437	7 052

the basic ant colony algorithm model. However, although the improved ant colony algorithm model in this paper can achieve the optimal scheduling of regional resources in the process of logistics distribution operations, it is still unable to evaluate the operation performance of logistics distribution at present, and this will be carried out in subsequent research.

Acknowledgments

This work was supported by the project fund: Wuhan Federation of Social Sciences “Research on the optimization and Upgrading of Wuhan’s Business Environment - from the perspective of market Players” (No. 2022KY-02).

References

[1] Karaoglan, Altiparmak, Kara, *et al.* The location-routing problem with simultaneous pickup and delivery[J]. Formulations and a heuristic approach Omega, 2012,40:465-477.
[2] Lopes, Souza, da Cunha, *et al.* A branch -and -price algorithm for the multi -vehicle covering tour problem[J]. Electronic Notes in Discrete Mathematics, 2013,44:61-66.
[3] Baldacci, Mingozzi, Roberti, *et al.* New route relaxation and pricing strategies for the vehicle routing problem[J]. Operations Research, 2011,59(5):1269-1283.
[4] Yu Y, Wang S H, Wang J W, *et al.* A branch-and-price algorithm for the heterogeneous fleet green vehicle routing problem with time windows[J]. Transportation Research— Part B: Methodological, 2019, 122: 511-527.
[5] Casazza M, Ceselli A, Wolfler C R. A route decomposition approach for the single commodity split pickup and split delivery vehicle routing problem[J]. European Journal of Operational Research, 2021, 289(3): 897-911.
[6] Demir E, Bekta T, Laporte G. A comparative analysis of several vehicle emission models for road freight transportation[J]. Transportation Research— Part D: Transport and Environment, 2011, 16(5): 347-357.
[7] Soriano A, Vidal T, Gansterer M, *et al.* The vehicle routing problem with arrival time diversification on a multigraph[J]. European Journal of Operational Research, 2020, 286(2): 564-575.
[8] Macrina G, Laporte G, Guerriero F, *et al.* An energy-efficient green-vehicle routing problem with mixed vehicle fleet, partial battery recharging and time windows[J]. European Journal of Operational Research, 2019, 276(3): 971-982.

[9] Anass E Y, Cherkaoui M, Fallahi A E. Tabu search and constraint programming-based approach for a real scheduling and routing problem[J]. International Journal of Applied Management Science, 2020, 12(1): 50.