Investigation of Vehicle Logistics Cost Control Model Based on Internet of Things Mode Based on E-commerce Platform

Fengjuan Zhang, M.Sc
Fengjuan Zhang, Lecturer, School of Foreign Language, Zhengzhou University of Industrial Technology, Zhengzhou, Henan, 450000, China
Correspondence LecZhang;nrogut@163.com

Objectives: The rise of the Internet of Things and e-commerce platform has enabled logistics companies to embark on a fast-growing road. How to effectively control the cost of vehicle transportation under the condition of continuous increase in the total volume of logistics business is the key to influencing the sustainable development of logistics enterprises. Methods: In order to reduce the cost of vehicle transportation, the use of artificial intelligence ant colony algorithm to build intelligent deployment model is explored. Results:After analyzing the principle and implementation flow of the traditional ant colony algorithm, the ant colony algorithm is updated and optimized from the perspective of many dynamic factors and large changes in the logistics vehicle.Conclusion: A combination of optimal algorithm parameters is constructed to help logistics companies find the most cost-effective vehicle scheduling plan. Simulation tests show that the optimized ant colony algorithm can quickly find the optimal cost-effective route and effectively control the vehicle logistics costs.

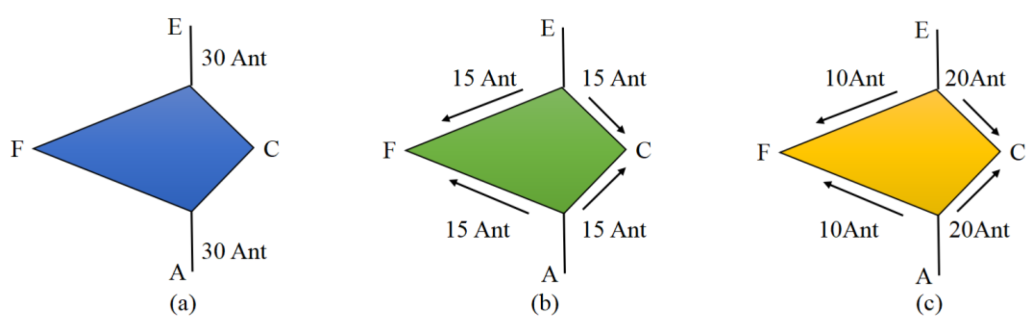
Keywords:E-commerce; Internet of Things; Logistics Cost; Research
Tob Regul Sci.™ 2021;7(5-2): 4763-4774
DOI: doi.org/10.18001/TRS.7.5.2.41

If the dispatch management of logistics vehicles can achieve scientific research and precise operation, it will certainly promote logistics companies to win more market orders in the Internet of Things business[1]. The vehicle transportation time, the number of vehicles, the capacity of the vehicle, the mission of the vehicle, the driving route of the vehicle, etc. are collected and the constraints affecting cost efficiency are found [2]. According to the mathematical model, the constraints are analyzed, and the most reasonable route of the vehicle is found with the aim of minimizing the most cost-effectiveness and time and cost, thereby effectively controlling the direct and indirect costs of vehicle operation [3.] The mathematical model of the vehicle scheduling problem mainly involves the parameters of the objective function and constraint functions of the vehicles, goods and parking lots[4]. Dynamic vehicle scheduling problem is the main direction of research today. As a problem of the extension of the vehicle scheduling problem in the stationary state, the main feature of the dynamic vehicle scheduling problem is that only a small part of the relevant information is mastered before the vehicle scheduling. Most of the information is dynamic or unknown, such as customer conditions, vehicle conditions, weather conditions during transportation, road conditions, etc. [5]. From the above, it can be seen that there are many factors of information change. If all the factors are introduced for analysis, the best results cannot be obtained. From the characteristics of rapid changes in logistics information under the Internet of Things and e-commerce customers' orders changing at any time, artificial intelligence algorithms are used to comprehensively study the multi-objective optimization model [6].

Learning ant behavior is to learn how the ant colony conducts the best search behavior without external guidance. This is the process of solving complex combinatorial optimization problems using mathematical equations [7]. Huge ant colonies are relatively mysterious in their communication channels and information prompts. In the absence of an ant for unified scheduling, ant colonies can adjust their search direction to form the shortest route between nests and food even if they encounter various environmental changes [8]. The intelligent behavior of ant populations is mainly due to the fact that ants have effectively used their own body fluids—pheromones. When passing by, this type of substance characterized by concentration information is left[9]. Afterwards, the ants who passed through can judge the high concentration route by judging the intensity and content of pheromones. The ants will randomly choose the direction of the walk from the nest. The more ants walk through, the more pheromones will be left. Pheromones will gradually decrease over time until they disappear. In general, shorter paths will attract more ants to choose. The ant colony uses this analysis to determine the pheromone and finds the shortest return path[10].

The ant colony algorithm is in the state of randomly selecting a route when the path search is first performed. After becoming familiar with the space route, the ant colony can adaptively find the selection rule of the shortest route in the search. The best search route which is found is the global optimal solution [11]. In the path traveled by different ants, the pheromone will become more and more as the number of ants. The probability that this route will be selected will be greater. This is the probabilistic advantage of a route. The shorter the path chosen, the faster the pheromone contained will grow. This is the main principle of pheromone updating. By judging the pheromone concentration and other information, the ant colony achieves indirect communication, and thus the ant colony can achieve coordinated communication within the population without external organization guidance [12]. Figure 1 is a schematic diagram of the principle of an ant colony algorithm. Ants are set to search for food A from nest E, and each unit will crawl for distance d. In each unit time, 30 ants search for food from the lair. In Figure b, when the pheromone is not found, the random probability guides the ant to choose a different path to go. It is assumed that there is a certain time condition T=1, if the 30-scale ant colony on path C has passed and the other path has only passed 15 scale ant colonies, the pheromone left by the large-scale ant colony will be more. After the ant selection path to choose BCD this pheromone the most concentrated route will be more and more. After that, the ant that selects the route chooses BCD more and more of this pheromone's thickest route. After the whole ant colony adopts this biologically inherited route selection principle, the BCD route will be the route with the best pheromone concentration that best meets the search needs [13]. This is the search process of ant colony from random selection to adaptive optimal selection.

Figure 1
Ant Colony Algorithm Schematic Diagram

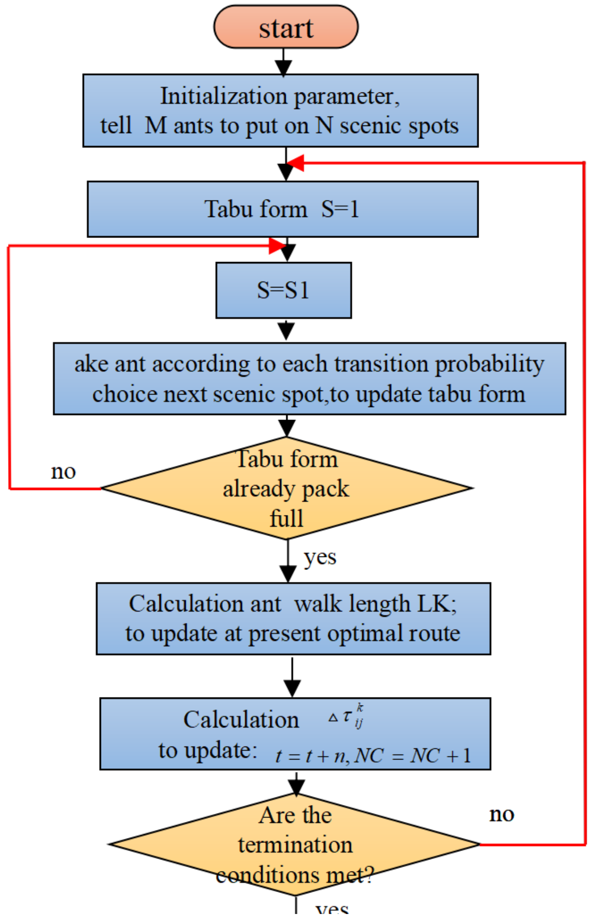


The construction process of the ant colony algorithm model is the process of the ant colony foraging the search path. First, the total number of ants is set to 0. The variable N is the number of places. The N locations in the route selection are numbered 1-N, and then a formula is selected according to the given probability to obtain the selection probability of each location. According to the corresponding rules, the location with transfer value is selected. Ant K calculates the probability of the next location to be traveled according to formula (1) at the current location i. $\tau_{ij}(t)$ is the concentration of pheromone on the line (i,j) composed of sites i and j. At t=0, $\tau_i(0)=\tau_0$. $\eta_{ij}(t)=1/d_{ij}$ is the ant colony departure point information. α shows the influence of pheromone concentration on the result. β denotes the state of influence on the ant colony route selection. When the value of α increases, the path chosen by the subsequent ants must be the path that the more intelligent ants have chosen in the previous path. When β is large, ants increase the probability of choosing the current shorter path under greedy selection. $allowed_k$ is the ant colony of ant k in the current moment condition. The sites where the previous ant colonies have been gathered are placed in the corresponding exclusion table $tabu_k$, and the subsequent selection of $tabu_k$ by the ant colony will change dynamically and follow the path selection of the ants differently [14].

$$P_{ij}^k(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{r\in allowed_k}\tau_{ir}^{\alpha}(t)\eta_{ir}^{\beta}(t)}, & j\in allowed_k\\ 0, & j\notin allowed_k\end{cases} \quad (1)$$

The steps of implementing the logistics vehicle scheduling by using the ant colony algorithm are as follows. First, the initial algorithm with the parameters such as the number of vehicles collected, the starting point, the departure time, the vehicle's stay in the parking lot, the user's situation, the user's address, and the user's demand are provided. Second, it is assumed that in the absence of pheromone, the equation is used to calculate the initial data of the path distance. The number of times that an ant iterates at the initial starting point is 1. The third is to let the time ant ant and cost ant adaptively choose the next location j. The fourth is to determine whether the time to reach location j is the shortest. If the ant representing the vehicle is running longer than expected, the algorithm must return to the previous steps 1-3 to reselect. If the arrival time of the vehicle is within the planned time, the next location will be selected after completing the mission. The fifth is to calculate the vehicle transit time Tt and the cost parameter Tc. Time ants and cost ants are compared to find out the lines and the local pheromone on these routes is updated. Finally, according to the concentration of pheromone, the current global optimal route Rbest is found. The sixth is to let the ants in the entire ant group go through the path selection process[15]. The value of the global optimal pheromone is calculated and the global pheromone is updated. The seventh is to judge the current iteration number g>G. If the value exceeds G, the loop is stopped and the optimal result is output. If the value of >G is increased, the number of iterations is increased by one and the algorithm returns to step three. The above process iteration is repeated [16]. Figure 1 shows the basic principle of the ant colony algorithm.

Figure 2
Flow Principle Of Basic Ant Colony Algorithm

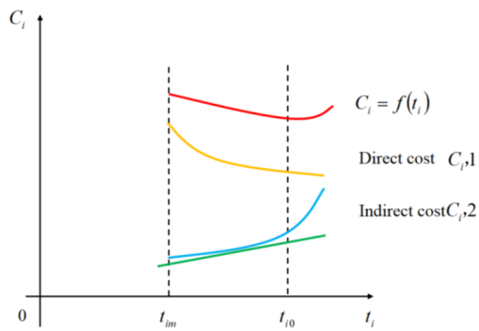


The effect of ant colony algorithm on the intelligent planning of vehicle logistics circuits mainly depends on the path selection, pheromone update principle and parameter indexes. Starting from this principle, the vehicle logistics intelligence model is also a multi-objective optimization problem. If decisions are to be made in daily life, the indicators of influence will often not be single. If multiple choices must be made to make a choice, it will be a question of whether the choice of decision-making scheme is the best choice, that is, the process of making the optimal decision-making process, which is also often difficult to choose [17]. Therefore, the solution to the multi-objective optimization problem is often to find the optimal solution or the optimal solution set in some range. The optimal solution here is called the Pareto optimal solution. It is a method of comprehensive and coordinated post-processing. The problem of using mathematical principles to optimize multi-objective decision-making is to establish a process of matching function expressions around these goals [18]. By building the function model for each objective's objective function and its constraints, it is possible to provide a solution model that can be followed for similar problems. The function model of the multi-objective optimization problem (MOP) under general conditions is shown in equation (1). $X=(x_1,x_2,\cdots,x_n)^T$, and here the space vector is represented by n dimensions. $f_i(X)(i=1,2,\cdots,m)$ stands for different sub-goals. There is an m-dimensional vector $(f_1(X), f_2(X),\cdots, f_m(X))$ in the target space of the problem. $gi(X)\le 0, i=1,2,\cdots,p$ is a model-constrained constraint function [19].

$$\begin{aligned} &\min_{X\in\Omega} F(X)=(f_1(X), f_2(X),\cdots, f_m(X)) \\ &X\in\Omega\subset R^n \\ &s.t. \quad gi(X)\leq 0, i=1,2\cdots, p \end{aligned} \quad (2)$$

The control of the operating costs of logistics vehicles is a comprehensive and balanced system that cannot influence only one goal but other goals. In order to achieve multi-objective vehicle scheduling optimization, the main purpose is that the vehicle's direct and indirect costs must be most effectively controlled [20]. The two indicators of the overall cost of logistics vehicles P and vehicle safety S can be used to represent the quantitative under multi-objectives in Figure 3.

Figure 3
Logistics Vehicle Cost-Safety Relationship Model



METHODS

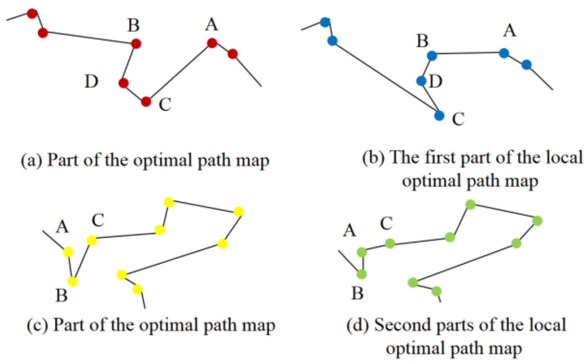
In the later stage of the algorithm, the ant colony algorithm adds random factors to help the ant colony do not go into the local optimal misunderstanding and find the global optimal solution. The principle of random factors is that when the ant colony enters the next node, there are three directions to choose from. It is assumed that the probabilities of these three directions are calculated to be 0.3, 0.4, and 0.6, respectively. Traditional ant colony algorithm will inevitably choose the direction of probability 0.6 as the next node to move. At this time, random factors are introduced and a random node is selected to participate in the ant selection in the segmented region of (0, 0.3) (0.3, 0.4) (0.4, 0.6). This allows most of the ants to choose randomly with probability in the path selection. It is also possible to let some ants choose another new path under the new probability, which can reduce the probability of going to a relatively short route. The improved transfer rules are shown in equations (4) and (5). Among them, the time of the algorithm is t, and $allowed_k(i)$ is the combination of the aggregation points that may be selected at the starting point of the K-th ant i-path.

$$v=\begin{cases} \arg\max_{j\in allowed_k(i)}\left\{\left[\tau_{i,j}(t)^{a}\right]\left[\eta_{i,j}(t)^{\beta}\right]\right\} \\ j \quad other \end{cases} \quad (4)$$

$$\eta_{ij}(t)=\frac{1}{d_{ij}(t)}*\left(s_{i,j}(t)=\frac{1}{d_{ij}(t)}*\left(d_{pi}+d_{pj}-d_{ij}\right)\right) \quad (5)$$

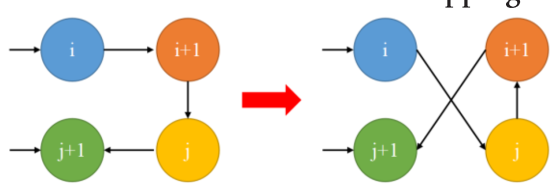
Entering a local search is one of the most likely to occur in an ant colony algorithm that affects the best solution. Here, 2-opt can be used to optimize the computational solution for each local search, allowing the optimal solution and the nearest neighbors to be interchanged, thus obtaining a new solution. After the new solution is used for loop search, if the result is due to the originally calculated optimal solution, the new solution is used to improve the quality of the best solution of the ant colony algorithm. Figure 4 is a comparison of the area decomposition of the optimal path map and the local optimal path. It can be seen from c and d in the figure that the best route at this time is ABC, and the local best route is BAC. Actually, the length of BC is greater than AC, which is to avoid that all ants at point C choose A as the next node, so that it can avoid going out of the best case of local search.

Figure 4
Comparison of the Optimal Path Graph and the Regional Decomposition Map of the Local Optimal Path



The principle of 2-opt of the diverse heuristic local optimization method is that it is a method of exchanging the vectors of the best solutions generated each time, and the guidance scope can internally perform the interactive position of such a child. The strategy for optimization and improvement is: If the path weights after ant interaction decrease and satisfy condition $d_{ij}+d_{i+1,j+1}<d_{i,i+1}+d_{j,j+1}$, (i,j)(i+1,j+1) is used to replace (i,i+1)(j,j+1). Figure 5 shows the optimization principle of ant colony switching.

Figure 5
2-OPT Schematic View of Swapping

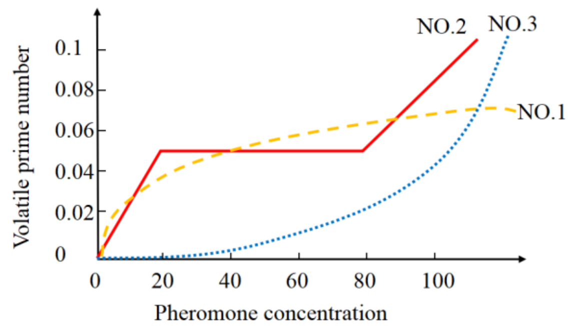


The optimization constant's volatility factor is set as a variable function and the algorithm is updated. In the commonly used ant colony algorithm, the volatilization factor will choose a fixed constant, which does not actually meet the needs of practical applications. Volatilization factors will increase with the increase in pheromone concentrations and decrease with less. So, the actual volatility function is a variable function. As shown in formula (6). Here t+1 represents the pheromone concentration at the time path ij. $\Delta\tau_{ij}(t)$ is the increase in pheromones, where volatile factors are represented by the norma l ρ. In the real state, the volatile factor becomes a function $\mu(\tau_{ij}(t))$ related to the pheromone concentration at the time.

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\rho_1\Delta\tau_{ij}(t) \quad (6)$$

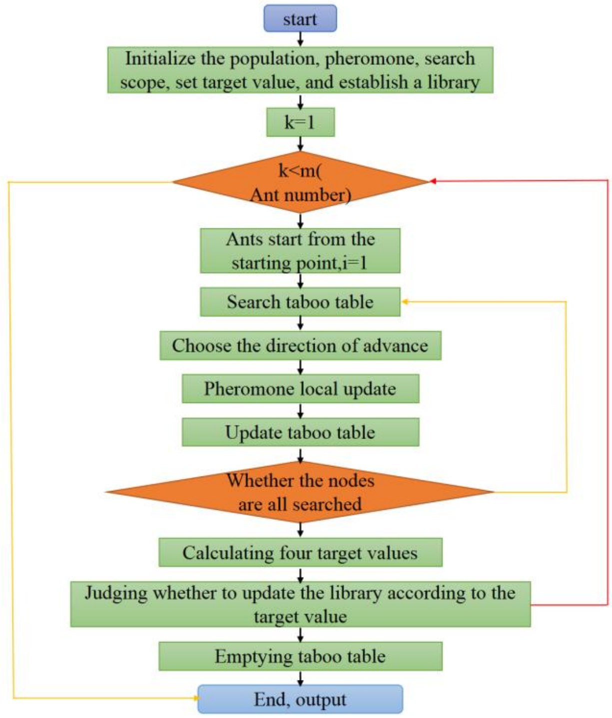
In order to further determine the specific relationship of the functions, experimental studies have found that there is a certain linear relationship between volatile factors and information concentration, as shown in Figure 5. One of the relationships is the increase in the concentration of pheromone, and the volatilization factor will appear as a concave increase in the curvature. The other is that sudden changes in information concentration do not occur, but merely the convex lines increase state is shown. However, when the concentration of single information exceeds a certain limit, the volatilization factor will increase the state of the concave line with increased curvature. The last change in the function is that the volatility factor increases following the pheromone and the concave line increases.

Figure 6
Relation Diagram of Volatilization Factor and Pheromone Concentration



In smart dispatching, which aims to reduce the cost of logistics vehicles, some constraints will appear to restrict each other. In order to prevent the path searched by ants from being inconsistent with the actual situation, a search forbidden area needs to be established during the operation of the algorithm, so that the ants can only search for nodes meeting the transportation needs of the vehicle. The area that ants forbid to search will be updated according to the logistics location needs. The process of multi-population ant colony algorithm is to initially process population size and pheromones of four ant colonies. Four target values are set for the four targets and four populations are independently searched. After an ant search in one of the populations is completed, the search results are substituted into the objective function for comparative analysis of the target, and co-evolutionary system operations are performed on the information, so that the evolution direction between the four populations is consistent. The process of multi-population ant colony algorithm is shown in Figure 7.

Figure 7
The Flow of Multi Group Ant Colony Algorithm



RESULTS

Simulation experiments are used to test the performance of the optimized ant colony algorithm. First, the environment and parameters are set for the experiment. It is assumed that logistics vehicles deliver goods to many delivery points. Each delivery point has a time limit. It is necessary to choose the appropriate distribution vehicle to pass the appropriate route. After finishing all the delivery points in an orderly manner, it needs to return to the distribution center. The overall goal is to minimize shipping costs. Under this constraint, the distribution center choose a truck with a suitable load. The vehicle must meet the following conditions. First, trucks start from the distribution center and must return to the distribution center after completing the task. The supply of delivery points on each distribution route cannot exceed the maximum load of the vehicle. The total length of each delivery route must not exceed the number of miles traveled by the truck. The demand at each delivery point can be met and can only be completed in one truck at a time. The delivery time of each delivery point must be guaranteed, and the total wage time of the vehicle cannot exceed its longest working time. Parameters such as the actual delivery point and delivery amount must be returned to the distribution center before the vehicle departs. The latest delivery time cannot be less than the time from the delivery center to the delivery point at the specified speed. After the construction of the constraint condition is completed, the experiment is first carried out to solve the vehicle scheduling problem in an ideal state.

Figure 8
Two Algorithms for Vehicle Scheduling Under Ideal Road Conditions

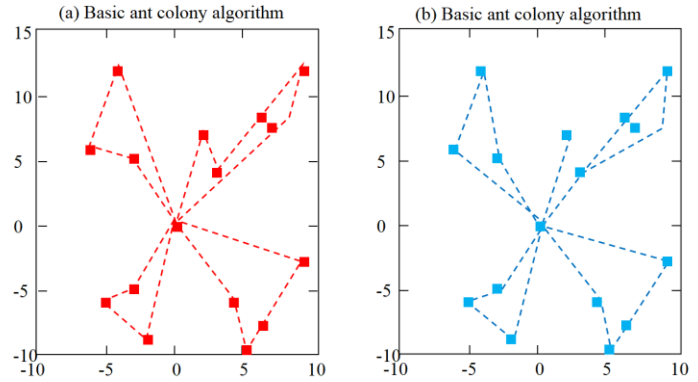
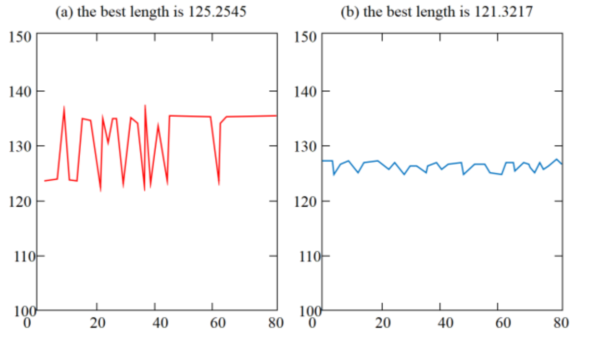


Figure 9 shows the relationship between the number of iterations of the two algorithms and the optimal function, which also identifys the length of the optimal path. It can be seen from the figure that the relationship between the optimal route length and the number of iterations tends to find the optimal solution in a straight line state, as shown in the optimized ant colony algorithm in Figure 7b.

Figure 9
The Relationship Between the Number of Iterations and the Optimal Function Of The Two Algorithms



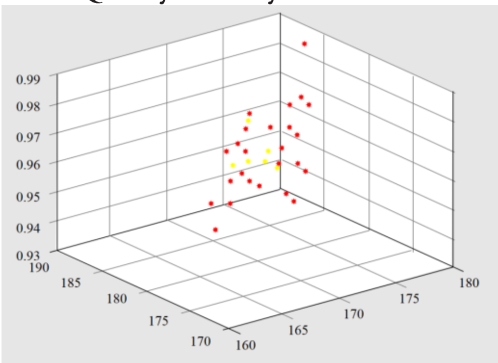
In order to verify the performance of the multi-objective optimization under the ant colony algorithm-based logistics vehicle cost constraint, the duration m of each work unit in the raw data is used to represent the time required under normal working conditions, and t represents the time required under the limit working state. m and b in the direct cost of each subsystem represent the direct costs under normal conditions and the direct costs under limit conditions. After solving the direct costs of subsystems by using unit cost and logistics workload, the cost-effectiveness and safety-reliability values of the unit can be obtained, thereby establishing a relational model. The cost function model is shown in Table 1.

Table 1
Cost Time Function Relation Model

Work unit	Maximum number of compressed days	β_i	Cost time function relation
X1	6	40231	C1=1100921+40413(21-ti)+2500ti
X2	2	831	C1=1000001+8721(15-ti)+2500ti
X3	12	13241	C1=4300000+14211(45-ti)+2500ti
X4	7	23089	C1=87600+5471(12-ti)+2500ti
X5	5	5498	C1=973156+15012(11-ti)+2500ti
X6	4	15028	C1=50656+3278(7-ti)+2500ti
X7	2	3209	C1=10231+518(8-ti)+2500ti
X8	2	9572	C1=312301+9561(17-ti)+2500ti
X9	1	18	C1=3218+17(11-ti)+2500ti
X10	0	0	C1=4680+2500ti

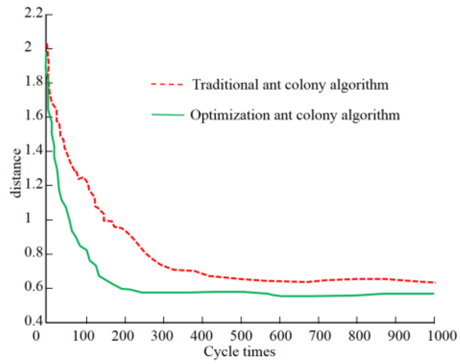
The above calculation data matrix is run into the multi-population ant colony algorithm proposed in this paper. Running in a matlab environment on a computer-aided platform, ans a three-dimensional scatter plot of the time, cost, quality, and safety of the experiment can be obtained, as shown in Figure 10. From the scatter plot, it can be seen that the optimal solution searched by the ant colony algorithm is not a single entity but an optimal solution set. At this time, the decision makers can make more prominent choices for the different targets according to actual needs. However, it can be seen from the experiment that with the shortest running time, it is impossible to achieve the lowest cost and highest quality. Therefore, the choice of the final optimal plan needs to be determined after combining the actual comprehensive balance.

Figure 10
Time Period - Cost - Quality - Safety Three Dimensional Scatter Plot



Finally, the basic ant colony algorithm and the optimized ant colony optimal convergence curve proposed in this paper are compared. The results are shown in Figure 11. The optimized ant colony algorithm has better solution quality than the traditional ant colony algorithm and the minimum number of loops required for the showing that the optimized ant colony algorithm has greatly improved the search accuracy and convergence speed.

Figure 11
Two Algorithm Convergence Curve Contrast Diagram



DISCUSSION

The logistics vehicle scheduling problem is a multi-NP complexity problem. The ant colony algorithm originates from the bionic evolution process of ants searching for the optimal path, and has unique advantages in solving path optimization problems. On the basis of expounding the implementation process, principle and mathematical model structure of ant colony algorithm, the structural optimization and equations of the algorithm are updated from the characteristics of increasing logistics network e-commerce traffic and the constraints of dynamic changes in logistics vehicle operations. First, function updating is performed on transition probabilities to optimize path selection. The volatile constants in the optimization constant are studied. Volatilization factor variable functions are proposed to improve the accuracy of the ant colony algorithm. The heuristic local optimization method 2-opt is used to avoid the ant colony algorithm from entering local search. A multi-objective model such as cost-time-security is established to achieve safe operation of the vehicle under optimal control of costs. Finally, simulation tests are conducted to prove that the accuracy and convergence of the optimized ant colony algorithm are outstanding. The best route searched out can effectively control the running cost of logistics vehicles. There are still some areas that can be improved in this study. The next step can be further studied from the optimization of ant colony algorithm process.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

Reference

1. Chávez J J S, Escobar J W, Echeverri M G. A multi-objective Pareto ant colony algorithm for the Multi-Depot Vehicle Routing problem with Backhauls. *International Journal of Industrial Engineering Computations,* 2016, 7(1):35-48.
2. Chen Y, An A. Application of ant colony algorithm to geochemical anomaly detection. *Journal of Geochemical Exploration,* 2016, 164:75-85.
3. Fathian M, Shiran G R, Jafarian-Moghaddam A R. Erratum to: Two New Clustering Algorithms for Vehicular Ad-Hoc Network Based on Ant Colony System. *Wireless Personal Communications,* 2016, 87(4):1435-1435.
4. Gandibleux X, Delorme X, T'Kindt V. An Ant Colony Optimisation Algorithm for the Set Packing Problem. *Lecture Notes in Computer Science,* 2017, 3172:49-60.
5. Jovanovic R, Tuba M, Voß S. An ant colony

optimization algorithm for partitioning graphs with supply and demand. *Applied Soft Computing*, 2016, 41(3):317-330.
6. Kucukkoc I, Zhang D Z. Integrating ant colony and genetic algorithms in the balancing and scheduling of complex assembly lines. *International Journal of Advanced Manufacturing Technology*, 2016, 82(1-4):265-285.
7. Liu M, Zhang F, Ma Y, et al. Evacuation path optimization based on quantum ant colony algorithm. *Advanced Engineering Informatics*, 2016, 30(3):259-267.
8. M.D. Toksari. A hybrid algorithm of Ant Colony Optimization (ACO) and Iterated Local Search (ILS) for estimating electricity domestic consumption: Case of Turkey. *International Journal of Electrical Power & Energy Systems*, 2016, 78:776-782.
9. Otero F E B, Freitas A A. Improving the interpretability of classification rules discovered by an ant colony algorithm. *Evolutionary Computation*, 2016, 24(3):385-409.
10. Şaban Gülcü, Mahi M, Ömer Kaan Baykan, et al. A parallel cooperative hybrid method based on ant colony optimization and 3-Opt algorithm for solving traveling salesman problem. *Soft Computing*, 2016(2):1-17.
11. Saghatforoush A, Monjezi M, Faradonbeh R S, et al. Combination of neural network and ant colony optimization algorithms for prediction and optimization of flyrock and back-break induced by blasting. *Engineering with Computers*, 2016, 32(2):255-266.
12. Tian J, Gao M, Ge G. Wireless sensor network node optimal coverage based on improved genetic algorithm and binary ant colony algorithm. *Eurasip Journal on Wireless Communications & Networking*, 2016, 2016(1):104.
13. Wan Y, Wang M, Ye Z, et al. A feature selection method based on modified binary coded ant colony optimization algorithm. *Applied Soft Computing*, 2016, 49:248-258.
14. Wang P, Lin H T, Wang T S. An improved ant colony system algorithm for solving the IP traceback problem. *Information Sciences*, 2016, 326(C):172-187.
15. Wang Y, Zhang L Y, Fei T, et al. Chaotic-simulated annealing ant colony algorithm for TSP. *Computer Engineering & Design*, 2016., 6:23-27.
16. Xu B, Min H. Solving minimum constraint removal (MCR) problem using a social-force-model-based ant colony algorithm. *Applied Soft Computing*, 2016, 43:553-560.
17. Xu B. An efficient Ant Colony algorithm based on wake-vortex modeling method for aircraft scheduling problem. *Journal of Computational & Applied Mathematics*, 2017, 317:157-170.
18. Zhang J T, Song Y J, Chun-Ming Y E. Hybrid Ant Colony Algorithm for Multi-Depot Container Truck Transportation Problems. *Industrial Engineering & Management*, 2017, 38：221.
19. Zhou D, Wang L, Zhang Q. Obstacle avoidance planning of space manipulator end-effector based on improved ant colony algorithm. *Springerplus*, 2016, 5(1):509.
20. Zhu H, Zhen S, Di W U, et al. Path planning for mobile robot based on improved ant colony algorithm. *Journal of Chongqing University of Posts & Telecommunications*, 2016, 385-386:717-720.