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Original article

Analysis of distribution path optimization algorithm based on big data technology

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A B S T R A C T

The traditional e-commerce logistics distribution path optimization algorithm has the problem of a long time to find the optimal path. To solve this problem, this paper designs an e-commerce logistics distribution path optimization algorithm in the context of big data, introduces NSGA-II evolutionary algorithm for solving multi-objective optimization problems, combines improved genetic algorithm to solve multi-objective terminal distribution path optimization model in new retail mode to obtain the Pareto optimal solution set of the research problem in this paper, and then establishes a multi-objective function for logistics distribution path optimization through five aspects: weight index, time efficiency index, customer importance index. In this paper, in the process of using the ant colony algorithm to solve the optimization of the end-delivery path of e-commerce logistics, global pheromone update rules such as the ant-perimeter model will be used for the pheromone update in the ant pathfinding process. Then, the multi-objective function of logistics distribution path optimization is established by five aspects: weight index, timeliness index, customer importance index, time window index, total path index, and finally, the distribution target weights are set to find the better distribution path in the objective function according to the different demands of e-commerce logistics, to complete the e-commerce logistics distribution path optimization. We were able to save 6.6% on the route optimized by the ant colony algorithm over the empirical route under the condition of path optimization with the ant colony algorithm. The experimental comparison results show that the designed e-commerce logistics distribution path optimization algorithm in the context of big data is shorter than the traditional algorithm to find the optimal path, which can reduce the e-commerce logistics distribution time and has certain practical application significance.

1. Introduction

With the development and progress of society, today's society has entered the Internet era, Tmall, Jingdong, and other large B2C e-commerce platforms are becoming more and more perfect, Tmall double eleven double twelve and other shopping festivals are exceptionally hot, people in the process of daily consumption, can feel the convenience and benefits brought by online shopping at any time and anywhere, the more and more trust in online shopping. In the context of big data, e-commerce enterprises can accurately predict the future needs of customers and realize personalized services for them. However, most enterprises fail to effectively use these data for route planning, and traditional logistics end distribution routes cannot cope with today's complex urban road traffic conditions and are no longer applicable to the actual needs of consumers. To meet the development requirements of e-commerce and improve customer satisfaction, the e-logistics distribution path is optimized to solve the problem of a long time for traditional e-commerce logistics distribution path optimization algorithm to find the optimal path. Currently, there are many e-commerce logistics distribution path optimization methods, the more classical methods are Pareto-based e-commerce logistics distribution path optimization and information exchange-based e-commerce logistics distribution path optimization methods, but there are certain shortcomings, such as e-commerce logistics distribution path optimization efficiency is low, it is difficult to find the real optimal e-commerce logistics distribution path optimization path. The distribution path optimization problem is a common problem in the subject of operations research. To study the e-

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commerce terminal distribution path optimization problem, we integrate consumers' requirements for product freshness and delivery time satisfaction, define the customer satisfaction metric function, construct a mathematical model for e-commerce terminal distribution path optimization that is closer to reality, and choose a suitable heuristic algorithm to solve it. The whole research process can use and improve the knowledge system of operations research, cross-fertilize management, mathematics, operations research, computer technology, and other disciplines, and can be regarded as an example of comprehensive research, which enriches the research content and research system of fresh e-commerce terminal delivery path optimization problem. To meet the development of e-commerce development requirements and improve customer satisfaction, the e-logistics distribution path is optimized To meet the requirements of e-commerce development, the e-logistics distribution path is optimized to solve the problem of a long time for the traditional e-commerce logistics To meet the requirements of e-commerce development and improve customer satisfaction, the e-logistics distribution path is optimized to solve the problem of finding the optimal path by traditional e-commerce logistics distribution path optimization algorithm.

This paper is based on big data technology, based on the analysis of previous research, explore the problem of e-commerce terminal distribution path optimization, build a mathematical model that meets the actual situation, and according to the model select and design a suitable algorithm to solve, to achieve the optimization of the current terminal distribution path driving scheme, improve the efficiency of e-commerce terminal distribution, reduce the cost of distribution, to provide a more reasonable and scientific terminal distribution for e-commerce, Therefore, the problem studied in this paper has certain theoretical significance and practical significance.

2. Related work

At present, scholars at home and abroad mainly focus on the traditional cold chain logistics distribution system, and less on the traditional logistics distribution path. And the cold chain logistics distribution system has major differences with the traditional distribution system, including the distribution target, the distribution path, and the demand of the distribution target.

In the literature (Zheng et al., 2020), a mathematical model of a simple logistics distribution vehicle optimization problem was studied, in which only the vehicle distribution distance and the maximum vehicle load constraint were considered. The problem can be regarded as an application of the simple traveler's problem (TSP) in the field of logistics. The global optimal solution can be obtained when the amount of data studied is small. An optimization algorithm for solving the wide time window vehicle path assignment problem is proposed in the literature (Chu and Yu, 2019), which incorporates a shortest path priority strategy by analyzing the relationship between the variables in the mathematical model. To solve the problem of poor initial solution quality and long computation time, the basic neighborhood algorithm is improved in the "remove process". The improved neighborhood algorithm converges faster than the basic neighborhood algorithm and can obtain a reasonable logistics distribution route plan. In the paper (Hu, 2019), an improved genetic algorithm is proposed to solve the logistics distribution vehicle scheduling problem. The objective function of this problem includes the shortest distance traveled by distribution vehicles, the largest vehicle loading capacity, and the highest customer satisfaction. Each customer point that needs to be delivered has a certain requirement for the delivery time and the delivery time follows a normal distribution. The improved genetic algorithm is ranked by the size of the population fitness value, and the individuals with low fitness value are eliminated, and the elite retention strategy is adopted among the selected outstanding individuals, and finally, the effectiveness of the improved genetic algorithm is verified by MATLAB simulation software. The literature (Massaro et al., 2019) mainly studied the logistics distribution service problem and analyzed the influence of delivery time on customer satisfaction. Meanwhile, the influence of service quality on the logistics industry is explained. Distribution staff usually need several different individuals to make subjective judgments in the process of serving customers, and deviations often occur in the process of conveying information, which affects the service quality in the logistics distribution process. The literature (Liu et al., 2020) has improved the traditional genetic algorithm in various aspects, using a greedy algorithm to initialize the population to improve the quality of the initial population. To reduce the complexity of binary coding, they used direct coding of natural numbers instead of traditional genetic algorithm binary coding and simplified the calculation of fitness values. The screening of the offspring of the traditional genetic algorithm was optimized by screening the optimal genetic individuals through the roulette selection method and elite retention strategy. The experimental results show that the improved genetic algorithm performs better than the standard genetic algorithm in the selection of offspring individuals. However, the improved genetic algorithm suffers from the problem of long computation time.

Foreign literature (Duan and Fu, 2019) proposed a hybrid genetic algorithm for solving vehicle path planning problems with time windows, which was combined with a genetic algorithm by hill-climbing algorithm, and the proposed hybrid genetic algorithm was applied to 56 instances, and the results confirmed the effectiveness of the algorithm. The literature (Hu et al., 2020) proposed the D-Ants algorithm based on the characteristics of the ant colony system for solving large-scale VRP, and the results showed that the algorithm not only improved the solution efficiency but also improved the effectiveness of the algorithm. The literature (Lorenc and Burinskiene, 2021) proposed a hybrid simulated annealing algorithm based on the nearest neighbor domain to solve the linear integer model of VRP with the objectives of minimum cost and maximum volume; the experimental results showed that the algorithm achieved good results in solving vehicle path problems of different sizes. In the literature (Liu et al., 2019), an improved particle swarm algorithm is proposed to solve the VRP problem with time windows, and the effectiveness of the algorithm is verified by examples. The literature (He et al., 2021) proposed a modular and hierarchical IRIC algorithm based on modularity for solving the vehicle path problem with soft time windows and applied the algorithm to 30 instances, and the simulation results showed that the IRIC algorithm has a short computation time and high quality of the solved set. In the literature (Guo, 2020), the parallel-based simulated annealing algorithm MT-PSA is used to solve VRPTW and the algorithm is applied to examples; the experimental results show that the MT-PSA algorithm greatly reduces the running time of the algorithm while the quality of the solved set is better than that of SPEA2. A new hybrid variable neighborhood has a forbidden search algorithm is proposed in the literature (Shao, et al., 2021) for solving vehicle path problems with multiple time windows.

3. Analysis of e-commerce logistics distribution path optimization algorithm based on big data technology

3.1. Distribution path optimization problem study

The distribution path problem was first proposed by Dantzig and Ramser in 1959. Since its introduction, the problem has received a lot of attention from experts in operations research, computer science, and network optimization. Its research results are now widely used in many fields of logistics management. As the core optimization problem of the logistics distribution process, the vehicle path problem refers to the planning of vehicles' driving routes and service stations to achieve the established logistics distribution goals under the premise of satisfying certain constraints (Barenji et al., 2019). However, with the diversification of customer needs, the distribution path problem has developed to date with increasingly complex models and more and more optimization objectives and constraints. For example, while satisfying the amount of customer demand and the delivery time specified by the customer, considering the carrying capacity of the vehicle and the traffic road condition restrictions, etc., to achieve the shortest transportation distance, the least time, the lowest cost, and other distribution goals.

Long years later and decades of research development, a large number of research results have been achieved in the vehicle path problem. The existing vehicle path problems can be classified according to different classification criteria, as shown in Fig. 1.

Under the constraints of the farthest distribution distance and load capacity of the vehicle, the distribution center develops a reasonable vehicle distribution plan, and the distribution staff carries out the distribution in an orderly manner according to the distribution plan (Sun et al., 2019). The model of the standard vehicle path optimization problem is represented mathematically as follows.

$$x_{\mathrm{ijk}} = \sigma_i^2 + \sigma_j^2 + \sigma_k^2 \tag{1}$$

$$C_{ij} = \sum_{i=1}^{n} x_i^2 \sigma_i + x_j^2 \sigma_j + x_k^2 \sigma_k \tag{2}$$

In this case, when i = 0, it is the distribution center. When i = 1,2,..., N, it denotes the customer point. C_{ij} denotes the transportation cost from customer i to customer j, and Q_k denotes the maximum load capacity of vehicle k.

$$Q_k = \frac{\sum g_i y_{ik}^2}{Cx} \tag{3}$$

$$R_k = \sum_{i=1}^{k} f_k(w_k) \tag{4}$$

$$L_k = \sum_{i=1}^{k} h_k(v_k) \tag{5}$$

$$E(k) = R_k * L_k^2 + \int Q_k x dx \tag{6}$$

Objective equation (3) indicates the lowest total cost of the logistics system; equation (4) indicates that the weight of each vehicle loaded with materials cannot exceed the maximum vehicle capacity; equation (5) ensures that there is only one vehicle for distribution at each customer point, and a total of K vehicles complete the distribution task; equation (6) ensure that the vehicles finally return to the departure point and the customer's distribution requirements are satisfied.

3.2. Research on ant colony algorithm based on big data technology

The colony can always find the optimal path from the anthill to the food source, which is more intelligent than a single ant. For each ant in the whole colony when it starts to look for food, it randomly chooses the path and releases pheromones in the path to look for food, this pheromone will keep volatilizing over time, for the path closer to the food, more ants may pass through this path in a certain time, thus for the path closer to food, more ants may pass this path in a certain time, thus forming a positive feedback parallel mechanism. On this basis, the logistics distribution path is established and the multi-objective function is optimized, mainly including weight index, time efficiency index, customer importance index, time window index, and total path index. The artificial ants in the ant colony algorithm will add a heuristic factor to this path and bring in a "visual" effect. The path length is added as an influencing factor for the path selection so that the ants can find the optimal path faster, as shown in Fig. 2. Ant colony algorithm for e-commerce logistics distribution path optimization has the following advantages.

3.2.1. Ant colony algorithm has strong searchability

Before ants enter the whole system, the pheromone concentration on the path is zero. Each ant is randomly scattered among the environment, and the ants then search for food in multiple search directions, thus expanding the understood search range (Viu-Roig and Alvarez-Palau, 2020). Ants select the set of paths they will take next by pheromone concentration among themselves, and randomly choose a path in the set of paths by roulette. All paths in the path set have a chance to be selected, which improves the search range of ants for the optimal path to some extent. Finally, with the volatility of pheromones as well as guidance, all ants converge on a path to carry food.

3.2.2. Ant colony algorithm is parallel

In the process of searching for food, ants are independent of each other and do not interfere with each other, and multiple ants work together to find the shortest path in the process of carrying food, which improves the efficiency of ants in the process of finding the shortest path.

3.2.3. Ant colony algorithm is a self-organizing algorithm

Self-organization refers to the process of changing the state of a system from disorder to order without the interference of the external environment. In the initial stage of the ant colony algorithm, ants are randomly distributed in the environment, and finally, through the guidance of pheromones, all ants gather on the shortest path, which reflects a process from a disorderly state to an orderly state.

3.2.4. Ant colony algorithm has positive feedback

Each and searches for the optimal path under the guidance of high pheromone concentration, and the process of pheromone concentration accumulation is a positive feedback process (Wang and Zhu, 2020). In the initial stage of ant search, the pheromone concentrations on the paths are the same. After several iterations, a large number of ants will gather on the shorter path, and the presence of a large number of ants will lead to higher and higher pheromone concentration on this path, which reflects a positive promotion between the number of ants and the pheromone concentration, and therefore, the ant colony algorithm has positive feedback.

The traveler's problem is the most basic distribution optimal path solution problem, which takes the minimum transportation cost as the primary factor, without considering the capacity of the vehicle and the time window constraint, the traveler starts from the starting point, visits all the destination points one by one, and returns to the original starting point. Of course, the traveler problem has a strong similarity with the e-commerce logistics distribution studied in this paper, so the problem can be solved by borrowing the idea of solving the traveler problem with full consideration of the specific requirements of the e-commerce logistics ends distribution path optimization problem.

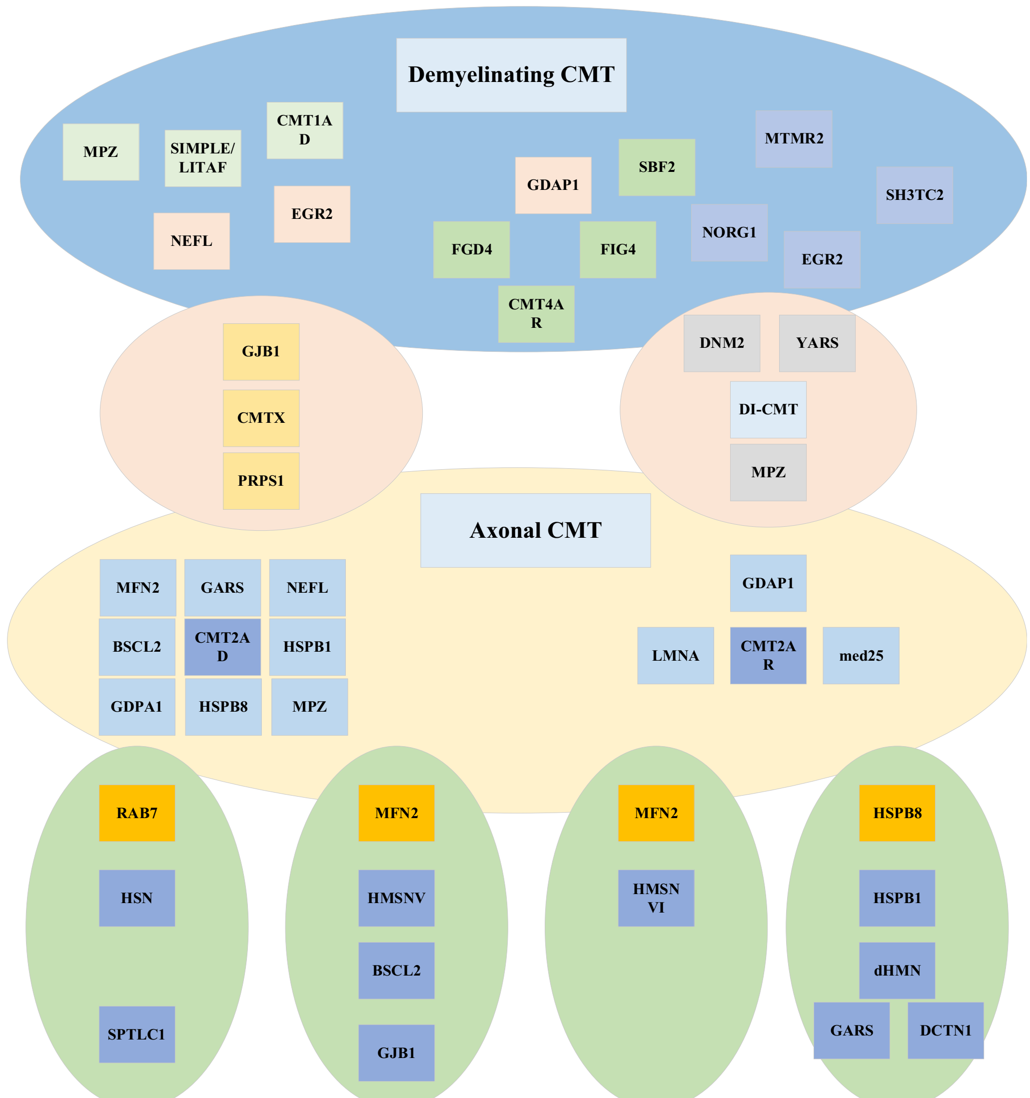

Fig. 1. Distribution path problem classification.

A simple description of the TSP problem is that there is a traveler who has to travel through n cities, and each city is visited once and only once and returns to the city of departure again at the end of the visit. The key to the problem is the pathfinding process, how to choose the path to allow the traveler to travel the shortest distance to visit all the cities (Tsang et al., 2021). At the beginning of the TSP problem, m ants are placed randomly in different cities, and m initial cities are placed in the search tabu_k table, and the probability P(t) of this ant moving from the current city to all cities in the non-search tabu table is calculated. $P_k(t)$ represents the probability of the kth ant moving from node i to node j at time t. The specific expression is shown in equation (7).

$$P_{i,j}^{k}(t) = \frac{[t_{i,j}(k)]^2 [\eta_{i,j}(t)]^{\beta}}{\sum [t_{i,j}(k)]^2 [\eta_{i,j}(t)]^{\beta}} \tag{7}$$

Nowadays, there are three main computational methods for pheromone update: the ant density model, the ant volume model, and the ant perimeter model. The three models are the same in terms of updating methods, but the main difference lies in the pheromone updating method. The ant-density model and the ant-volume model update the pheromone continuously in the process of finding the optimal path, which has a temporal continuity, i.e., when the ants finish walking an edge, i.e., after they reach another node from one node, they synchronize the pheromone updating process according to the ant-density model and the ant-volume model. Customers as a prerequisite for the survival of e-commerce logistics companies, in order to ensure the volume of customers, priority is given to the goods of important customers. The update process, which uses a local update approach, and the ant-perimeter model, which performs an overall pheromone update for each edge after all ants have walked all cities, is a pheromone global update approach. In the study of the ant colony algorithm, it is more common to use the ant-perimeter model to update the pheromone, and its operation process is simpler and the computation is further simplified during the operation of the program, which is more effective. To sum up, in this paper, we use the global pheromone update rule of the ant perimeter model to update the pheromone in the process of ant pathfinding when using the ant colony algorithm to solve the optimization process of the e-commerce logistics ends delivery path.

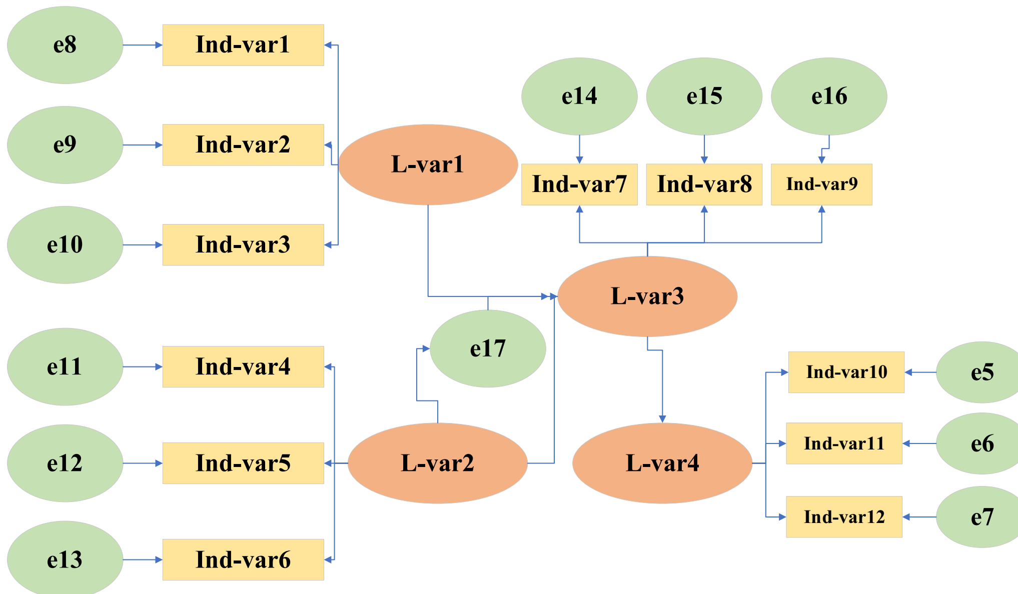

Fig. 2. Schematic diagram of path optimization.

4. Experimental validation and analysis of results

4.1. Experimental design

First, the logistics end distribution vehicle path optimization problem is used as a model to build the urban spatial network. In the urban spatial network logistics center is represented by the primary city point, the distribution center is represented by the secondary city point, and the end-customer point is represented by the tertiary point. Then, the urban spatial network is used as the basis to build the operation network containing logistics transportation, warehousing, and distribution processes. Finally, the parameters are initialized according to the scale of the problem under study. The working principle of logistics simulation is as follows: first, the goods start from the starting point (logistics center), then, they are transported to the nearest secondary point (logistics distribution center), and finally, they are transported to each tertiary point (end-customer point), and the whole logistics system distribution ends. Among them, the specific end-customer point which is distributed by the logistics distribution center is assigned according to the clustering idea.

In the process of parameter configuration of the logistics system, different parameters can be set for the experimental simulation according to the different needs of the actual problem. In the logistics simulation, Fig. 3 shows the customer location distribution (Sulova, 2021). From them, "x" indicates the logistics center, "y" indicates the logistics distribution center, and the points with numbers indicate the customer points, with 1–100 to distinguish the different customer points. The solid blue line indicates the distribution service between the logistics center and the distribution center. The red solid line is the line from one logistics center to another logistics center, which means that the logistics center and the logistics center are operational. There is no line between the logistics center and the end-customer point, which means it is not operational. The order quantity of one, two, or three points is configured in pieces, and the mass of each piece is generated randomly from 1 kg to 10 kg. The order quantity is converted to mass for city capacity calculation, which indicates the capacity of transporting goods between cities. When the city capacity is not able to transport all the goods, some of the goods will be stored in the logistics warehouse at random from all the goods, waiting for the

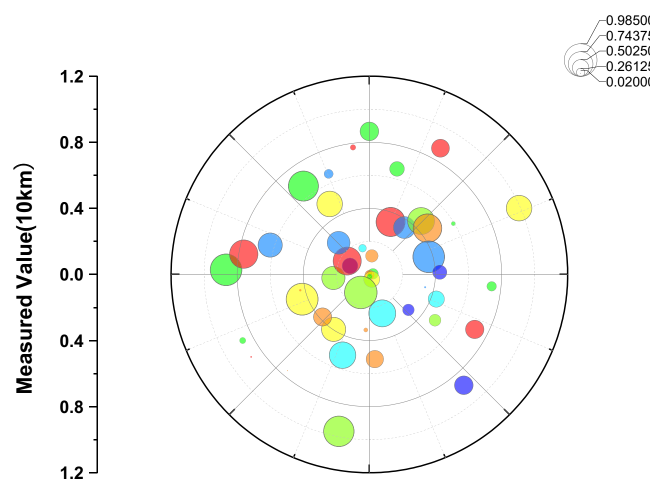

Fig. 3. Customer location distribution map.

next transport. Some parameters of terminal distribution: the rated load of the vehicle, the farthest driving distance of the vehicle, the running speed of the vehicle, the service time of the vehicle, etc. are the constraints of vehicle scheduling, which are configured according to the actual needs in the process of system initialization. The geographic coordinates of the logistics center, logistics distribution center, and terminal customer points are randomly generated between 0 and 1, which is more general in the process of studying the actual problem. In the column of system, the operation is some functional buttons of the logistics simulation model, which can terminate the system operation in time when the logistics system is abnormal.

In the process of e-commerce logistics distribution path optimization, the path (time) optimization principle is upheld, and the slope and congestion factors in the distribution path are taken into consideration because they will affect the progress of the whole distribution process, this paper mainly adopts the way of turning flat road to consider all kinds of influencing factors, to improve the fineness of the model calculation process and improve the path optimization effect, so that the whole logistics end distribution can deliver the goods in the consumer's expected or the courier company's expected time to deliver, and improve the user's satisfaction. In the travel business problem, the distance between distribution nodes is expressed using the Euclidean distance. Since the route of logistics end distribution is not simply a line between two points, but winding, the distance between two distribution points cannot be calculated simply by the absolute distance between coordinate points, and in the study of e-commerce, logistics end distribution, the coordinates of each distribution point in the two-dimensional plane only indicate the position between each distribution point The distance between distribution nodes in the process of logistics end distribution path optimization is expressed by the length of the route between distribution points (Mohammed et al., 2020). Because of the consideration of the influence factors in the distribution process, in the process of path optimization, the specific influence factors to flat road formula can be used to achieve the distribution process of the slope length to flat road length. And the transformed flat road length is added to the expectation factor in the ant colony optimized path process. Fig. 4 shows the optimal path analysis after optimization roar.

The scheduling arrangement module is to make reasonable arrangements for the implementation of specific distribution tasks based on the route planning results generated by the route planning module and consists of two functions: route arrangement and vehicle arrangement (Zhang et al., 2021). The route arrangement function generates a route list and identifies the sub route information formed after the route optimization with the route list number for the vehicle arrangement function to match the information of drivers and vehicles responsible for the implementation of logistics distribution tasks. The relationship between route arrangement and other module interfaces is: route arrangement realizes the data acquisition of path optimization results through the interface, completes the identification of the route and the route order, loading volume and distance display of a single-vehicle at a time, generates the route list information for vehicle arrangement class operation, and the status of customer orders involved in planning the formation of distribution routes is changed from pending to pending distribution (Kuo and Chen, 2020). Vehicle arrangement function generates dispatching order, implements the distribution tasks associated with the route list to specific distribution vehicles and personnel, generates dispatching plan, and can provide logistics distribution/pickup service to customer orders that have formed route list through route planning. The vehicle arrangement function calls customer orders, route orders, and vehicle information to carry out the arrangement of vehicle personnel, the association of orders and distribution orders, the results of vehicle arrangement are used to update the location of customer orders, generate dispatching tables for vehicle departure arrangements, and associate route tables with dispatching tables.

4.2. Analysis of results

To verify the feasibility of the algorithm and the validity of the model, the proposed model is solved using the ant colony algorithm and compared using the NSGA-II, and MOEA/D algorithms. To understand the distribution of the solution sets in the target space by NSGA-II, and MOEA/D, the Pareto fronts of the four algorithms on the VRPTW multi-objective model are shown in Fig. 5. From the Pareto frontier comparison, it can be seen that the solution set obtained by the MOEA/D-IRG algorithm is the closest to the Pareto frontier, followed by the ant colony algorithm and MOEA/D, while NSGA-II is the worst. In terms of the solution set distributivity, the solution sets obtained by the MOEA/D-IRG algorithm are more uniform compared to the three compared algorithms. The simulation experimental results show that the solution set obtained by the MOEA/D-IRG algorithm is better in terms of convergence and diversity when considering the shortest distribution distance and the least distribution time as the objectives, indicating that the decision variable interaction identification strategy can effectively identify the potential structures among decision variables and form subcomponents, reduce the consumption of the number of fitness evaluations in the grouping process of decision variables, and improve the convergence efficiency of the algorithm. S3-CMA-ES searches for solutions through a group of sub-populations and uses CMA-ES to optimize each sub-population to promote population convergence, but sacrifices the diversity of the algorithm to some extent. the decomposition strategy of MOEA/D transforms the multi-objective problem into a set of single-objective problems to solve, and the decomposition strategy can effectively maintain the diversity of the population, but with the expansion of the problem size, the convergence of the algorithm The worst quality of the solution set is obtained by NSGA-II because the adaptation of the search space becomes more complex as the problem size increases, and the search for non-dominated solutions becomes more difficult, and the use of non-dominated ranking strategy to select the population makes the algorithm easily fall into local optimum.

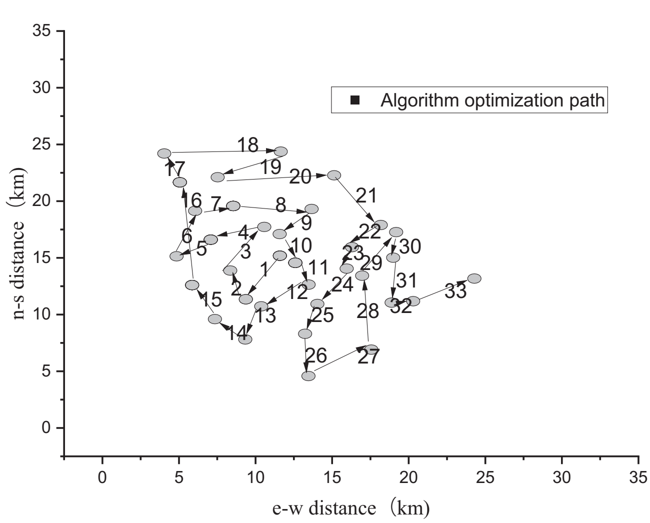

Fig. 4. Algorithm optimization path.

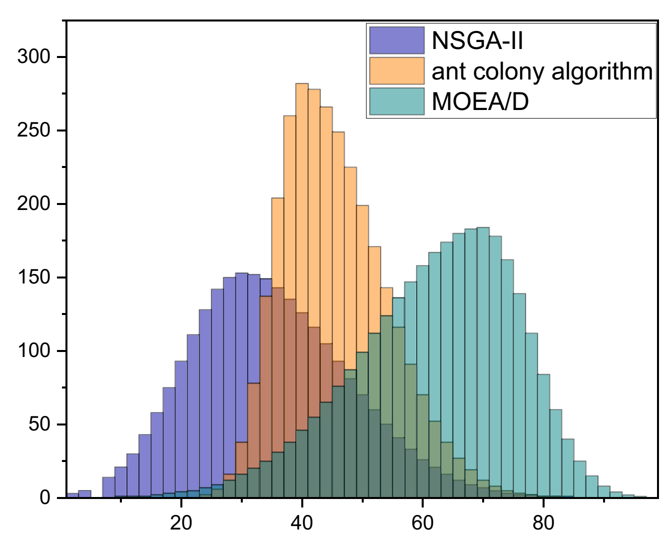

Fig. 5. Comparison of Pareto fronts of the three optimization algorithms.

From the distributivity of the solution sets in Fig. 5, the solution sets obtained by the MOEA/D-IRG algorithm are more uniform compared to the three compared algorithms. After obtaining the customer information, the proposed ant colony optimization algorithm and three comparison algorithms are used to calculate the urban logistics vehicle path planning model, and the calculation results are shown in Fig. 6.

We can see from Fig. 6 that the path calculated by the ant colony algorithm has the lowest cost and shortest time in the whole distribution process considering the slope and congestion, and Case 3 saves 34 m of dynamic path length than Case 2, indicating that we can save 34 m of dynamic length cost by considering the slope and congestion under the condition of path optimization with the ant colony algorithm, while Case 3 saves 5269–4923 = 346 m of dynamic path length compared with Case 1, indicating that the route optimized by the ACO algorithm can save 346 m of dynamic path length cost compared with the empirical path, which is a cost-saving ratio of 6.6%. The results show that the time required to find the optimal path by the designed optimization algorithm is less than 2 min, while the time required to find the optimal path by the traditional algorithm is more than 3 min, up to 4.6 min. The comparison shows that the time required by the traditional algorithm to find the optimal path 10 times is higher than that of the designed algorithm. Therefore, considering the waiting time, slope, and congestion, the path optimization process of e-commerce logistics end distribution process by ant colony algorithm can save more cost and improve the efficiency of distribution, and then we can use the ant colony algorithm for the informationization process of e-commerce logistics end distribution path optimization, and use informationization to serve the logistics end distribution, provide more high-quality and efficient distribution services for e-commerce customers, and increase customer satisfaction.

As can be seen from Fig. 7, the minimum total cost of convergence of the improved ACO is $3217.2, and the total cost obtained by MOEA/D optimization is $3490.6, with the former saving $273.4 over the latter. The quality of the solution obtained by the improved ant colony algorithm is better than the solution obtained by the other algorithms. In addition, the improved ant colony algorithm finds the global optimal solution faster than the traditional ant colony algorithm, and the convergence speed is better than that of the basic ant colony algorithm. The comparative analysis of the total cost convergence graphs of the four algorithms shows

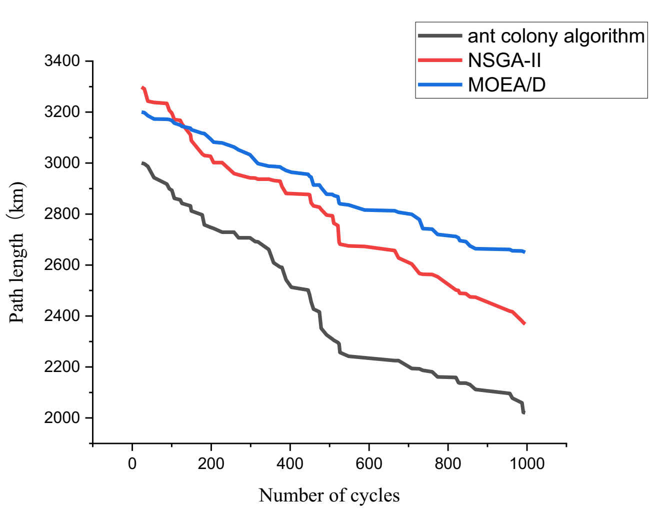

Fig. 6. Comparison of the path lengths of the three algorithms.

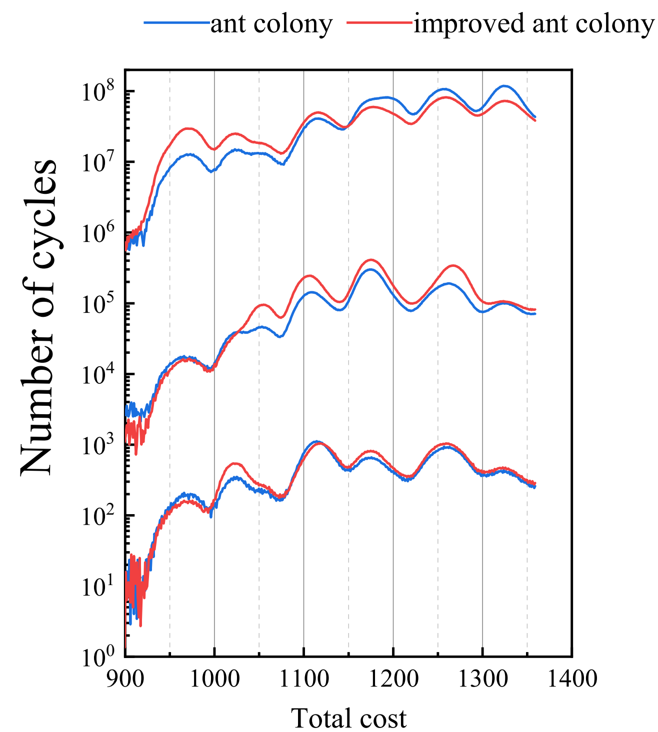

Fig. 7. Total cost convergence of the ant colony algorithms and improved ant colony algorithms.

that the improved ant colony algorithm has improved the accuracy and convergence speed, expanded the search range of the solution space, avoided the shortcomings of other algorithms that are easy to fall into local optimum, optimized the cold chain logistics distribution path effectively, saved the logistics cost for the enterprise, and improved the logistics efficiency of the enterprise.

From Fig. 7, it can be seen that the improved ant colony algorithm has improved the accuracy and convergence speed, expanded the search range of the solution space, and avoided the disadvantages of other algorithms that tend to fall into local optimum. The ant colony optimization algorithm can only have one population for optimizing two objectives in each independent experiment, and therefore its position update follows the integrated learning strategy commonly employed for the single population case to assist its update phase, rather than learning from an archive containing a large number of historical optimal solutions. As can be seen in Fig. 8, the non-dominated solution frontier derived from ant colony optimization shows a uniform distribution in the target space, while the non-dominated solution frontier derived from ant colony optimization is relatively trapped in a local optimum. Meanwhile, the size of each realistic dataset significantly affects the distribution of the frontier, i.e., narrower frontier distributions are easily found in large-scale realistic datasets. From this analysis, it can be concluded that the advantage of the archiving mechanism is that it can search for more new non-dominated solutions based on the historical optimal solutions retained by previous generations, which means that it is more capable of finding high-quality solutions in a wider search space than traditional methods.

This design of big data context of e-commerce logistics distribution path optimization algorithm compared with the traditional algorithm can save a lot of logistics distribution costs, which is in line with the e-commerce logistics distribution path optimization The economic utility of the optimization.

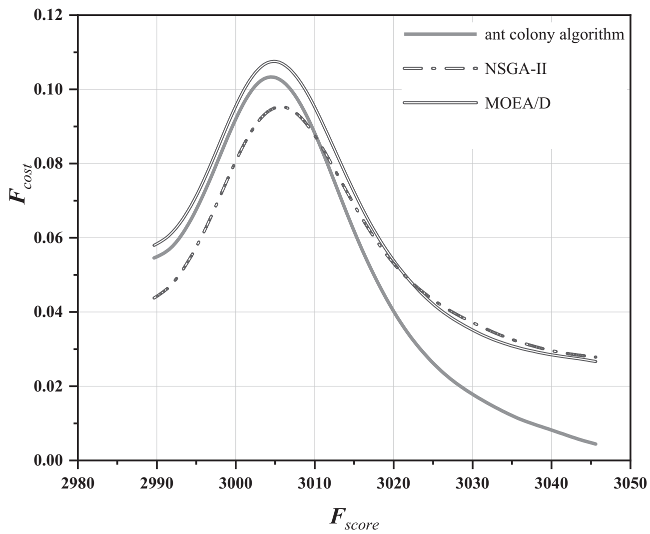

Fig. 8. Ant colony optimization results for different target points.

5. Conclusion

E-commerce is a product of the rapid development of information technology, and the rapid development of e-commerce makes e-commerce logistics end distribution problems become urgent problems, and the problems of slow efficiency and poor quality of e-commerce logistics end distribution affect the development of e-commerce enterprises. The research improves the ant colony optimization algorithm of e-commerce logistics distribution path optimization and uses simulation experiments to verify the effectiveness of this method to optimize the e-commerce logistics distribution path.

In this paper, the vehicle path problem with time windows is used to establish its mathematical model. The logistics distribution path optimization problem is optimized by an improved ant colony algorithm, which mainly includes the following aspects.

(1) To understand and grasp the review of research related to the logistics distribution vehicle path problem and ant colony algorithm. The current status of domestic and international research on VRP problems and ant colony algorithms is summarized and summarized.
(2) Modeling the logistics distribution problem. By analyzing the described problem, the constraints and optimization objectives of the logistics distribution model are listed and expressed by mathematical formulas, and a mathematical model of the logistics distribution optimization problem based on soft time windows is established. The basis is provided for solving the logistics distribution path optimization problem.
(3) Based on the maximum-minimum ant algorithm, an improved ant colony algorithm is proposed to solve the VRPTW problem. In this paper, the solution construction, path construction, pheromone setting, and pheromone updating are improved to improve the efficiency of the algorithm, and verified by some examples in the standard library of VRPTW designed by Solomon. etc. on the performance of the algorithm, and obtain the better range of the parameters.
(4) The improved ant colony algorithm was applied to the distribution path optimization of some branches of China Resources Vanguard in the Xi'an area, and the best distribution solution was obtained. The ant colony algorithm was realized to solve the multi-vehicle distribution logistics distribution path optimization problem with conditional constraints.

The e-commerce logistics distribution path optimization algorithm in the context of big data has a shorter time than the traditional algorithm to find the optimal path and can meet the demand of e-commerce logistics distribution. The algorithm should be continuously updated with the development of urban roads in the future practical application of the algorithm.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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