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Application Research of Factor Constraint Algorithm in E-Commerce Logistics Route Optimization

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ABSTRACT

In modern society, e-commerce logistics services are replacing traditional manual transportation methods. However, fresh transportation challenges have emerged. This study proposes applying the factor constraint algorithm to the e-commerce logistics path transportation problem. The multi-objective constraints and optimization of node tasks, vehicle full load, route closure, and other issues in the process of logistics transportation are firstly carried out. The final target is the shortest path of logistics deliver. Then the genetic algorithm, particle swarm algorithm, and ant colony algorithm are integrated to obtain the HMOAC algorithm, and the logistics path transportation model is constructed. The research findings indicate that the HMOAC algorithm shows a high level of fit, with a 95% match compared to the ant colony algorithm. An example analysis of the algorithm can effectively optimize the target path and achieve the least expensive transportation cost.

1. Introduction

In the contemporary era, diverse sectors in China are experiencing rapid development and can be characterized as thriving. Among them, the logistics of the e-commerce industry is the main representative, which has become one of the important pillars supporting China's basic economy [1]. However, currently, the uneven logistics route has a significant impact on transportation costs during the logistics transportation process. This issue also impedes the growth of domestic e-commerce logistics industries and enterprises [2]. In the current development stage of e-commerce logistics, optimizing the selection of e-commerce logistics routes to enhance logistics efficiency and decrease transportation expenses presents a significant challenge [3]. To solve such problems, the study proposes to apply the factor constraint method to the selection and optimization of e-commerce logistics paths. This will facilitate improved and expedited service to customers in the fast-evolving information era [4, 5]. The factor-constrained algorithm proposed by the research is based on the genetic algorithm, particle swarm algorithm, and ant colony algorithm. The advantages of each algorithm are analyzed and summarized, before being incorporated into the multi-objective optimization algorithm. That is the hybrid multi-objective ant colony optimization algorithm (HMOAC), referred to as the factor constraint algorithm for short. The

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research is based on the research on the mutual combination and problem constraints of the logistics distribution center, target customers, distribution vehicles, and logistics routes. It has innovatively improved the efficiency, distribution accuracy, and transportation cost of my country's e-commerce logistics industry at this stage. To construct a set of path optimization models for the industry, it is urgent to reduce transportation costs effectively and simultaneously improve customer service, promoting the development of the logistics industry.

2. Related Works

The development and expansion of the e-commerce industry is undeniable. Among them, the issue of e-commerce logistics has always been a hot issue that scholars pay attention to. Specifically, scholars have investigated vehicle driving problems to better address e-commerce logistics. Dovgan et al. [6] proposed and developed a real-time multi-objective optimization algorithm for driving discovery (MODS-RT) for the driving problem of vehicles, and then carried out real-time selection and application of optimal control actions encountered in the process of vehicle driving. The MODS-RT algorithm is assessed on actual route data and compared to MODS and traditional single-objective algorithms to discover driving strategies. While MODS-RT uncovers inferior driving policies compared to MODS, it uncovers superior driving policies compared to single-objective algorithms, thus demonstrating the efficacy of multi-objective methods for real-time driving policy discovery [6]. To reduce logistics costs, Ghasemi et al. proposed a dual-objective mathematical positioning routing model. The successful distribution of logistics products is achieved through two parts: transportation level and road level. The model utilizes two approaches, Epsilon-constraint and NSGA-II, and is capable of resolving medium- to large-scale problems. The results show that the proposed model has the best overall performance [7]. Scholars such as Xames [8] analyzed the disruption of Bangladesh's food supply chain in the context of the COVID-19 epidemic. Collect evidence through various journal articles and conferences. Experiments have found that information sharing strategies such as contactless delivery, e-commerce, and user demand forecasts can effectively solve supply chain disruptions caused by epidemics. The experimental results provide realistic and feasible management measures for developing countries such as Bangladesh [8]. Yu et al. [9] initially analyzed the characteristics of the existing e-commerce system and addressed the identified issues. Then Java technology and the influence of cloud computing are utilized to examine the effects of e-commerce. Numerous theories, models, and structures within the system could be refined to identify the best logistics plan. The results suggest that the aforementioned method can circumvent the restrictions of conventional electronic trade, such as the incapability to promptly handle voluminous datasets, extract valuable data-mining insights, and execute successful electronic trade implementation. [9]. Boysen's team [10] proposed to use a hub-and-spoke approach to the problem of growing e-commerce logistics services for appropriate speed boosts and improvements. This approach helps to centralize parcel sorting as an automated process. And the process can enable multiple pallets to be loaded per cycle, thereby improving the sorting performance. According to the findings, the technique provides valuable insights into forecast errors, truckload variability, and the implications of increasing pit stops [10]. Yuan [11] analyzed the construction mechanism and algorithm of cross-border e-commerce export logistics mode using an artificial intelligence algorithm. They established a BP neural network model based on the location of the logistics distribution center to enhance the cross-border e-commerce export logistics model from the perspective of the value chain. The study focused on the mechanism of export logistics in cross-border e-commerce.

In addition, some scholars have conducted related research on e-commerce platforms and multi-objective algorithms. Two scholars, Taşkan and Karatop [12], conducted a new exploration into the way companies evaluate performance. The experiment used artificial intelligence to examine the path of organizational performance evaluation. The findings suggest that the field of organizational performance evaluation within enterprises is not currently keeping up with the Industry 4.0 era. This also shows from the side that enterprise development is inseparable from the support of e-commerce platforms [12]. Yazdani [13] research team took Iran's tourism e-commerce as the research object to analyze the factors that drive brand strengthening. In the process, Shannon entropy method was introduced to effectively sort the driving factors of brand strengthening. The results show that branding and advertising as communication methods can significantly promote the development of e-commerce brands [13]. Jia et al. proposed a dual-objective ant colony optimization algorithm to minimize the completion time and energy consumption of discrete problems in machines [14]. And an effective feasible solution construction method is proposed to quickly find feasible solutions in discrete optimization so that the ant colony value can pay attention to the promising areas in the search space. Through simulation experiments, the results demonstrate that the proposed algorithm obtains improved solutions to large-scale problems when compared to existing algorithms. To support research on dynamically constrained multi-objective optimization, Chen et al. introduced a series of challenging test problems. Subsequently, a dynamically constrained multi-objective optimization algorithm is designed to tackle the challenges posed by dynamics and constraints. The algorithm incorporates a non-dominated solution selection operator, a mating selection strategy, a population selection operator, a change detection method, and a change response strategy for enhanced optimization. Experimental results demonstrate that the test problem proposed can objectively distinguish algorithm performance. Compared to state-of-the-art algorithms, the proposed algorithm demonstrates great competitiveness in addressing dynamically constrained multi-objective optimization problems [15]. Zhu et al. [16] team proposed a new technique based on dynamic materialized views to efficiently handle queries for an emerging type of data present in modern e-commerce databases, namely progressive queries (PQs) or monotonic linear PQs. The fundamental concept is to construct a high-level relational graph for SQ based on historical PQs, which can be utilized to calculate the advantages of preserving the current SQ results as a materialized view. Experimental results indicate that the proposed technique can adeptly construct high-level relational graphs, manage materialized atlases, and strategically search for available views [16]. Hongmei [17] proposed an asymmetric encryption technology method and applied it to the current red copper of cross-border e-commerce to solve the inefficiency of document recording and the difficulty of identity verification, etc. Problem [17]. Simulation results show that compared with traditional cloud computing methods, the proposed solution has obvious advantages in data anti-theft, multi-party authentication, saving system overhead, etc. Taking advantage of the decentralization and the auditability of blockchain, it provides references for solving security problems in the process of data sharing, and for solving data sharing and cross-domain authentication problems.

Domestic and foreign scholars have done a lot of research on optimizing e-commerce logistics paths. At the same time, various multi-objective optimization algorithms such as ant colony algorithms and genetic algorithms are widely used in different fields. However, there are few studies that apply multi-factor optimization methods to the field of e-commerce logistics routes. To improve the level of e-commerce logistics and transportation while reducing associated costs, this experiment offered relevant information on vehicle routing. From the existing problems, a multi-constraint center vehicle routing model was proposed using a multi-factor objective optimization method. This model is expected to solve complex and dynamic transportation path problems for both domestic and foreign e-commerce logistics companies.

3. Construction of The Logistics Path Algorithm Model of E-Commerce under the Multi-Objective Optimization Algorithm

3.1 Multi-objective Optimization Algorithm Under the Factor Constraint Algorithm

The research on the constraint problem of multiple objectives in the selection of e-commerce logistics path is actually the problem of dispatching in logistics transportation, node tasks, full vehicle delivery, time of a single vehicle, vehicle model delivery problem, constrained optimization is performed on multiple objective problems such as route closure, and the final optimization objective is the shortest path of logistics dispatch [18]. The connection between the selection of e-commerce logistics routes and other components within the urban distribution system is displayed in Figure 1.

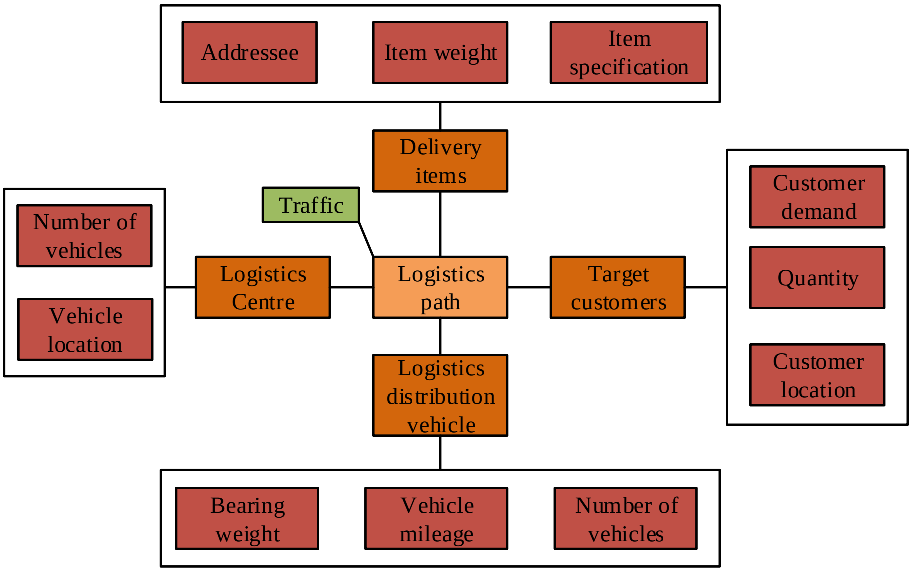

Fig. 1. Relationship between logistics route selection and logistics system elements

From Figure 1, the logistics distribution goods, the logistics center location, the problems encountered by the logistics vehicles and the requirements of the target customers jointly determine the choice of the logistics path. In the process, due to the different paths selected, the road conditions are also different. Therefore, road conditions will also have a certain impact on the optimization of logistics routes. Different factors have different influences. The number and location of vehicles are significant factors that impact the logistics distribution center. In addition, the delivery of goods is influenced by factors such as the receiver, weight, and specifications of the goods. The target customers are affected by the location, number, and needs of customers. Lastly, the load capacity, mileage, and number of vehicles are the main factors that influence the delivery vehicles. By analyzing the multi-constrained vehicle routing problem (MCVRP), a model can be established as shown in formula (1).

$$\begin{cases} \min Z_2 = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{q=0}^{Q} S_{ijq} \\ \sum_{i=1}^{n} p_i R_{iq} \le P, q = 1,2,\cdots,Q \\ \sum_{q=1}^{Q} R_{0q} = Q \\ \sum_{q=1}^{Q} R_{iq} = 1, i = 1,2,\cdots,n \\ \sum_{i=1}^{n} S_{i0q} = 1, i = 1,2,\cdots,Q \\ \sum_{i=1}^{n} S_{ijq} = R_{jq}, i = 1,2,\cdots,Q; q = 1,2,\cdots,Q \\ \sum_{j=1}^{n} S_{ijq} = R_{jq}, i = 1,2,\cdots,Q; q = 1,2,\cdots,Q \end{cases} \tag{1}$$

$$\begin{cases} t_i + w_i \ge Et_i \\ t_i + w_i \ge Lt_i \end{cases}, i = 1,2,\cdots,n \tag{2}$$

In Formula (1) and formula (2), $G = (V, E)$ represents an undirected graph; V represents the set of nodes; E represents the set of all boundaries in the model; $v_1, v_2, \cdots, v_n$ represent the node, corresponding to the target customer; v_0 is the logistics distribution center; Q represents the number of logistics distribution v_i vehicles p_i; P represents the maximum value; t_i represents the length of time that the logistics vehicle serves the customer; w_i represents the stay time of the logistics vehicle at the customer. Formula (3) demonstrates the explanation of other parameters.

$$\begin{cases} S_{ijq} = \begin{cases} 1, \text{Vehicle } q \text{ passing customer } v_i \text{ and driving to customer } v_j \\ 0, otherwise \end{cases} \\ R_{ijq} = \begin{cases} 1, \text{Vehicle } q \text{ completes the task of customer } v_i \\ 0, otherwise \end{cases} \end{cases} \tag{3}$$

It expands the parameters in formula (3). $[Et_i, Lt_i]$ represent the service time Et_i that logistics can provide customers; It represents the earliest time when customers can receive services; Lt_i represents the latest. When using multi-objectives to optimize research objects, it is often affected by different factors. To examine the association between these factors and the object under examination, a constraint algorithm was introduced in the experiment. This algorithm obtains the impact of multiple factors on the research object and produces an optimal solution for the object issue. In general factor constraint algorithms, multi-objective optimization algorithms are often used to constrain factors and select the optimal path for e-commerce logistics [19, 20]. For large-scale multi-objective optimization problems (LSMOPs), the specific definitions are shown in formulas (4) and (5).

$$\min F(x) = \left(f_1(x), f_2(x), \cdots, f_M(x) \right) \tag{4}$$

$$s,t, x = \left(x_1, x_2, x_3, \cdots, x_D\right) \in X \tag{5}$$

Formulas (4) and (5) represent the space to which the $X \in R^D$ decision variable belongs, the space to which F the target variable belongs, the $x = \left(x_1, x_2, \cdots, x_D\right)$ decision variable, and the $f_i\left(x\right) = \left(i = 1, 2, \cdots, M\right)$ target variable. And M and D represent the number of independent objective function parameters (dimension of objective function) and the scale of decision variables, respectively. In LSMOP, in general $M \geq 2$, $D \geq 100$. The objective function satisfies formula (6).

$$f_i\left(x\right), \forall i = \left\{1, 2, \cdots, M\right\} \tag{6}$$

Formula (6) actually expresses $X \in R^D$ the spatial refraction of a set of decision variables from the final target, that is to say $f_i : X \to R$. When solving the optimal solution among multiple objectives, the Pareto optimal solution set (Pareto Set, PS) is often intelligently obtained due to the conflict between the objective functions. The Pareto optimal solution set must satisfy formula (7).

$$PS = \left\{ x^* \middle| \neg \exists x \in X, x \prec x^* \right\} \tag{7}$$

Formula (7), PS represents the Pareto optimal solution set; x_1, x_2 represent any two solutions, and $x_1, x_2 \in X$, if at least one objective in the objective function is x_1 better or x_1 not worse than x_2 the solution x_2, it is called x_1 domination x_2 (represented as $x_1 \prec x_2$); x^* represents the Pareto optimal solution. optimal solution. The reason for the rapid growth of data in the solution lies in the reasonable grouping of decision variables, in which the decomposition of variables must satisfy formula (8).

$$f\left(x\right) < f\left(x'\right) \Rightarrow f\left(y\right) < f\left(y'\right) \tag{8}$$

Formula (8), $f\left(x\right)$ represents the separation function; and in the decision variables x_k, $\forall k \in \left\{1, \cdots, n\right\}, x, y, x', y' \in X$ at the same time $x = \left(x_1, \cdots, x_k, \cdots, x_n\right)$, $x' = \left(x_1, \cdots, x'_k, \cdots, x_n\right)$, $y = \left(y_1, \cdots, y_k, \cdots, y_n\right)$, $y' = \left(y_1, \cdots, y'_k, \cdots, y_n\right)$. When multiple variables call each other, $f\left(x\right)$ is an inseparable function. And the call interaction between variables satisfies formula (9) and formula (10).

$$\Delta_{\delta, x_p}\left[f\right]\left(x\right)\Big|_{x_p = a, x_q = b_1} \neq \Delta_{\delta, xp}\left[f\right]\left(x\right)\Big|_{x_p = a, x_q = b_2} \tag{9}$$

$$\Delta_{\delta, x_p}\left[f\right]\left(x\right) = f\left(\cdots, x_p + \delta, \cdots\right) - f\left(\cdots, x_p, \cdots\right) \tag{10}$$

In formula (9) and formula (10), $f\left(x\right)$ represents a separable and additive function; x_q, x_p represent the interaction between two variables; The parameters are satisfied $\forall a, b_1 \neq b_2, \delta \in R, \delta \neq 0$. When two different values are used to solve, the results of different values are obtained, which means that the variables x_q, x_p can call each other.

3.2 Construction of E-Commerce Logistics Path Selection Model under the Research Algorithm

When distributing e-commerce logistics, the problem can be regarded as a multi-objective multi-constrained multi-center vehicle routing problem (MCCVRP) for optimization purposes. The problems of using MCCVRP to constrain are: (1) multiple vehicles in the logistics distribution center; (2) selection of distribution routes; (3) vehicles can be customized to serve customers, and each customer can only be served once; (4) The delivery volume of all delivery vehicles is the same; (5) There is a specified time for logistics and distribution, and customers can only receive services within the time range. The main objectives are: (1) the shortest delivery route distance; (2) the least number of vehicles used; (3) the first priority target is the route, and the second priority target is the number of vehicles used [6, 21]. After comprehensively considering the issues that need to be constrained by the model, the influence of penalty factors is eliminated, and multiple constraints and objective functions are added to give a path selection model. Combining the obtained multi-constraint path and multi-objective optimization algorithm, the obtained MCCVRP problem model is shown in formula (11).

$$\begin{cases} \min Z_1 = N \\ \min Z_2 = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{q=0}^{Q} S_{ijq} \\ \sum_{ng=1}^{NG}\sum_{q=1}^{Q} R_{0q} = NG \\ \sum_{i=1}^{n} p_i R_{iq} \le P, q = 1,2,\cdots,Q \\ \sum_{q=1}^{Q} R_{0q} = Q \\ \sum_{q=1}^{Q} R_{iq} = 1, i = 1,2,\cdots,n \\ \sum_{i=1}^{n} S_{i0q} = 1, i = 1,2,\cdots,Q \\ \sum_{i=1}^{n} S_{ijq} = R_{jq}, i = 1,2,\cdots,Q; q = 1,2,\cdots,Q \\ \sum_{j=1}^{n} S_{ijq} = R_{jq}, i = 1,2,\cdots,Q; q = 1,2,\cdots,Q \end{cases} \tag{11}$$

$$\begin{cases} t_i + w_i Et_i \\ t_i + w_i Lt_i \end{cases}, i = 1,2,\cdots,n \tag{12}$$

For the explanation of all parameters in formula (11) and formula (12), please refer to formula (1). Formula (13) integrates the first two formulas in formula (11) to improve computational simplicity of subsequent experiments.

$$\min Z = 1000N + \frac{\sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{q=0}^{n} S_{ijq}}{1000} \tag{13}$$

Formula (13) selects transformation parameter values of 1000 and 1/1000 based on research to determine the test set for selection testing. MCCVRP has several constraints, including distribution costs that are related not only to route decisions, but also to factors like vehicle transportation volume and acceptable customer node service time intervals. In order to solve the multi-constraint vehicle constraint problem more quickly, a HMOAC is proposed based on various algorithms such as genetic algorithm, particle swarm algorithm and ant colony algorithm. First, the particle swarm algorithm is used to optimize the information data of the ant colony algorithm, as shown in formula (14).

$$\tau_{ij}(t0) = \tau_{ij}^{C} + \tau_{ij}^{P} \tag{14}$$

Formula (14), τ represents the value of the initial pheromone in the particle swarm i, j represents the coding code of the pheromone, and τ_{ij}^{P} represents the growth amount of the initial pheromone. The particle population optimization is performed on the logistics vehicle, and the maximum number of cycles of the population and the initial position and initial speed of the particles are set in the process. The obtained current number of cycles is then compared to the maximum number of cycles per formula (15).

$$T > T_{\max} \tag{15}$$

Formula (15), T represents the number of cycles of the particle population; $T_{\max}$ represents the optimal number of cycles. If not, it continues to return to the program operation, otherwise ends the operation and outputs the optimal path. And according to formula (10), the value of the final initial pheromone under the ant colony algorithm is obtained. Figure 2 illustrates the process of optimizing population pheromone with particle swarm optimization.

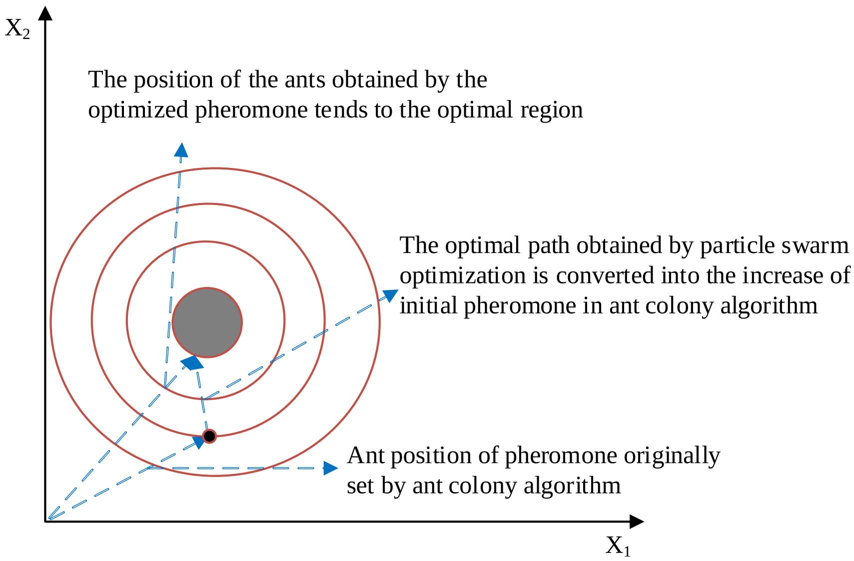

Fig. 2. Optimization process of pheromone by particle swarm optimization algorithm

In Figure 2, the innermost dark graphic circle represents the global optimal solution region. The particle swarm algorithm calculates the optimal path, which is then transformed into the initial pheromone for the ant colony algorithm's implementation. The resulting offspring generated by the ant colony algorithm significantly approach the global optimal solution region. Then it uses the particle swarm algorithm to α, β to optimize the heuristic factor in the ant colony algorithm. The process is shown in Figure 3.

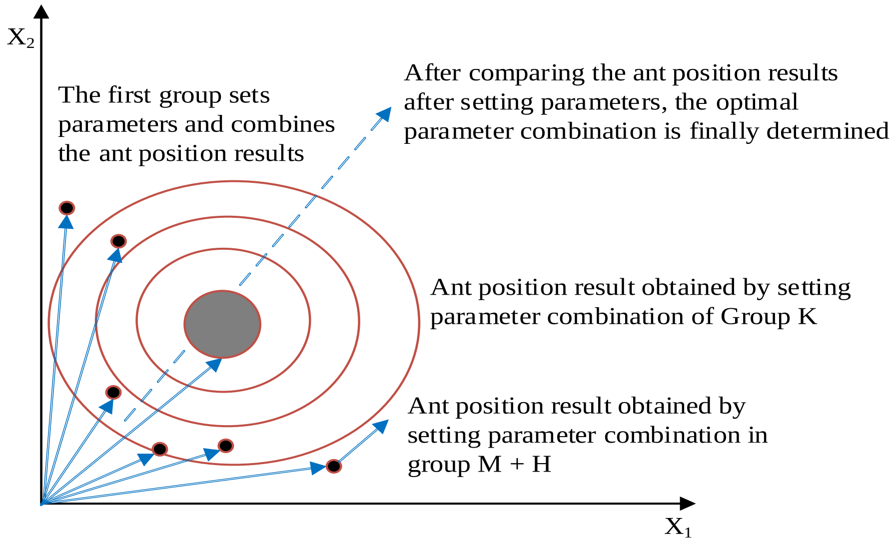

Fig. 3. Optimization process of heuristic factors by particle swarm optimization

In Figure 3, similar to the pheromone optimization process, the dark circle area represents the area of the global best solution. The algorithm is operated to display $M+H$ the complete test after the setting of the group parameters, and the obtained data are compared with each other to obtain the global optimal parameters (α_k, β_k). Then the genetic algorithm and the ant colony algorithm are combined to optimize the algorithm.

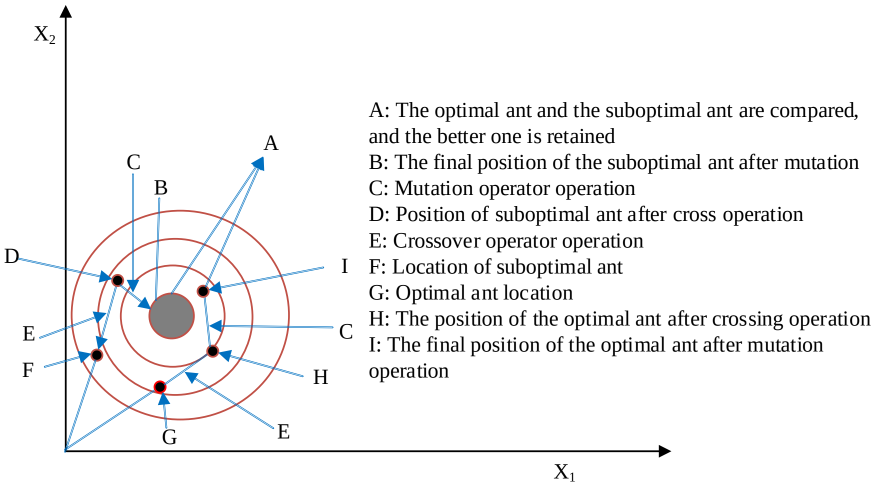

Fig. 4. Optimization process of genetic algorithm to ant colony algorithm

In Figure 4, the innermost inner layer of the dark area is still the area that represents the global optimal solution. In the figure, the optimal solution and the suboptimal solution in the ant colony algorithm are subjected to the mutation crossover operator operation of the genetic algorithm, and the result is obtained. It is shown that both of them are obviously close to the region of the global optimal solution. Then the algorithmic results are compared to natural selection, to achieve the optimal solution.

4. Implementation and Testing of Model Construction under HMOAC Algorithm

4.1 Perform a Simulation Test on The Constructed Model

To prove that the proposed HMOAC has a good selection effect on the optimization of e-commerce logistics path. The research compares the performance improvement of the proposed HMOAC with the genetic algorithm, particle swarm algorithm and ant colony algorithm with the horizontal and vertical motion trajectories as the starting point and other algorithms. Figure 5 displays the specific comparative results.

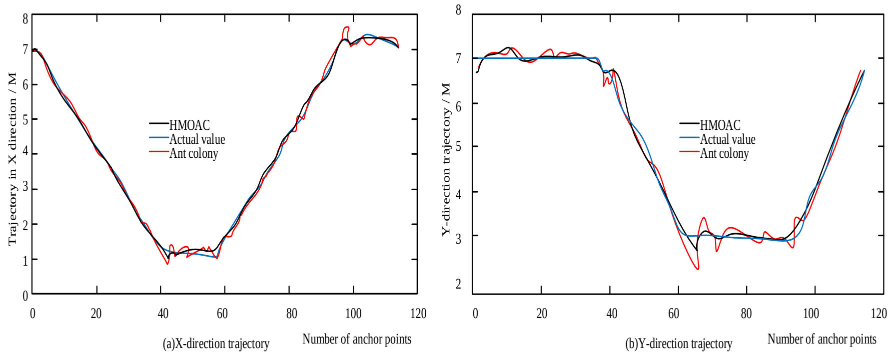

Fig. 5. Track diagram of vehicle path direction

In Figure 5, x and y are the true value abscissa and ordinate of the anchor point. In the figure, the ant colony algorithm serves as a comparison tool for the path direction against the proposed HMOAC algorithm. It can be found that whether it is the X-direction trajectory or the Y-direction trajectory, the obtained value of the HMOAC algorithm is more consistent with the actual value, and the fitting degree can be as high as 95%. In contrast, the ant colony algorithm's trajectory map significantly deviated from actual values. In the process of optimizing the logistics path of e-commerce, real-time monitoring is required for the direction and path of the delivery vehicles, which is convenient to provide customers with fast services, and ensure that the logistics vehicles are accurately positioned during the service process and are relatively close to the customer's location. The precision and recall rates of the algorithm are determined through comparison of PR curves, depicted in Figure 6.

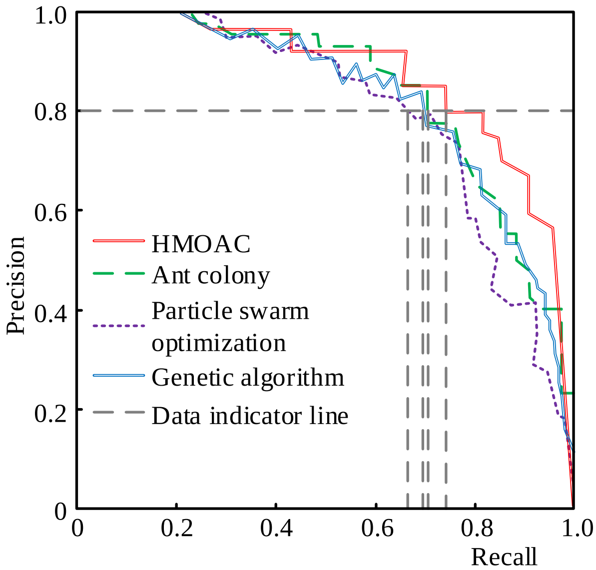

Fig. 6. PR curve comparison of algorithms

From Figure 6, in the comparison of the PR curve changes of the four algorithms, when the precision rate of the ant colony algorithm is 0.800, the recall rate of the algorithm under this precision rate is 0.712. When comparing the results with those of the genetic and particle swarm algorithms, the precision and recall rates are lower for the ant colony algorithm when under the same conditions. For instance, at a precision rate of 0.800, the genetic algorithm and particle swarm algorithm exhibit recall rates of 0.695 and 0.668, correspondingly. In contrast to the HMOAC algorithm proposed by the research, when the precision rate is 0.800 under the HMOAC algorithm, the recall rate can reach 0.778. Through the comparison of parameters under the same conditions, it can be known that the HMOAC algorithm adopted in this study has higher precision and recall than genetic algorithm, ant colony algorithm and particle swarm algorithm. These results demonstrate that the HMOAC algorithm has a higher accuracy rate when selecting optimal e-commerce logistics paths and is capable of serving customers without errors. Meanwhile, a higher recall rate can also improve the market position in e-commerce logistics. After that, the uniform convergence of each algorithm in different data sets is analyzed, and the results are shown in Figure 7.

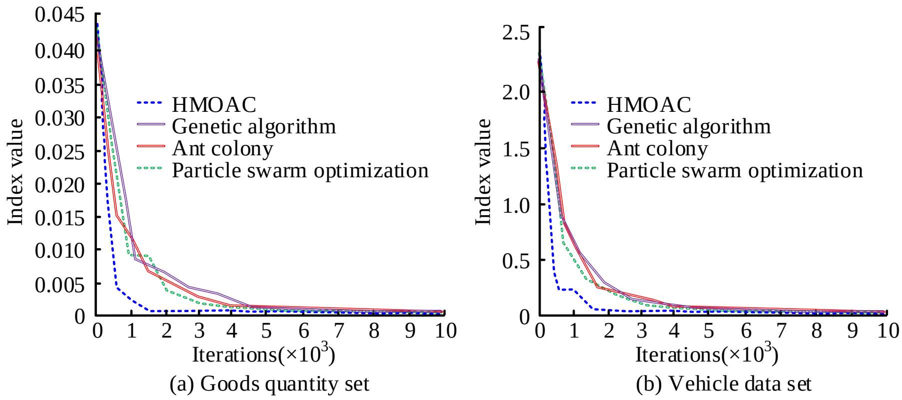

Fig. 7. Comparison of convergence of different algorithms

From Figure 7, the ant colony algorithm, the particle swarm algorithm and the genetic algorithm are selected as the comparison algorithms in the research to compare the convergence between the above three algorithms and the HMOAC algorithm. Figure 7 (a) is the test result in the logistics distribution cargo dataset. The results show that the HMOAC can obtain a small exponent value at the fastest time of 1000 times; while the other three algorithms can obtain the lowest exponent value when the number of iterations is higher than 4000 times. The test results for the transportation vehicle dataset are displayed in Figure 7b. The results show that when the HMOAC algorithm obtains the smallest index value, the number of iterations is still 1000 times; while other algorithms obtain the smallest index value, the number of iterations is still significantly higher than 4000 times. The study concludes that the HMOAC algorithm exhibits high convergence, leading to efficient computations in logistics route optimization and selection. Moreover, this algorithm can be applied to various data sets with high universality.

4.2 Simulation Analysis of E-Commerce Logistics Distribution Path Instance

The research uses Matlab2018A and Windows10 system to carry out statistical analysis of simulation experiment data images. The internationally recognized VRP problem library served as the experimental foundation, and data from the simulation process was utilized to validate the efficacy of the logistics path optimization and selection. The system parameters are set as follows: the population size is 1000; the number of algorithm computations is 10; the dimension D is equal to the sum of the number of customers and the number of delivery vehicles -1; the learning cycle of the proposed algorithm is set to 50; it runs 10 times independently. To accurately assess the performance of the proposed VRP algorithm, the optimal selection and distribution of the e-commerce logistics path is studied with a town as the object. The basic data settings in the simulation example are as follows: a distribution station (starting from serial number 0) and 16 customer points (serial number from 1 to 16) form an urban e-commerce logistics distribution system. The different demand scale statistics for each customer are shown in Table 1.

Table 1
Test data of VRP problems of eight customers

Customer number:	0	1	2	3	4	5	6	7	8
Abscissa (km)	42	45	36	20	23	5	29	35	51
Ordinate (km)	51	68	70	77	53	45	31	5	31
Delivery volume (T)	0	10	10	20	10	10	10	20	10
Customer number:	9	10	11	12	13	14	15	16	
Abscissa (km)	45	54	88	68	60	65	60	55	/
Ordinate (km)	36	35	33	60	55	85	81	85	
Delivery volume (T)	10	55	10	30	10	40	10	20	

In Table 1, the distribution center supplies customers with goods via three vehicles, each with a maximum capacity of 100. The needs of customers are met through the reasonable planning of the route, and the cost is minimized under the condition of the capacity constraints of the vehicle. Through experiments and comparisons, the best simulation path is obtained: 15->14->16->1->0->2->3->4->5->6->7->8->9- >1->10->11->12->13-, the obtained average minimum distance is 250.568 km. The optimal logistics distribution path diagram obtained by the proposed algorithm in solving the customer's VRP problem is given below, as shown in Figure 8.

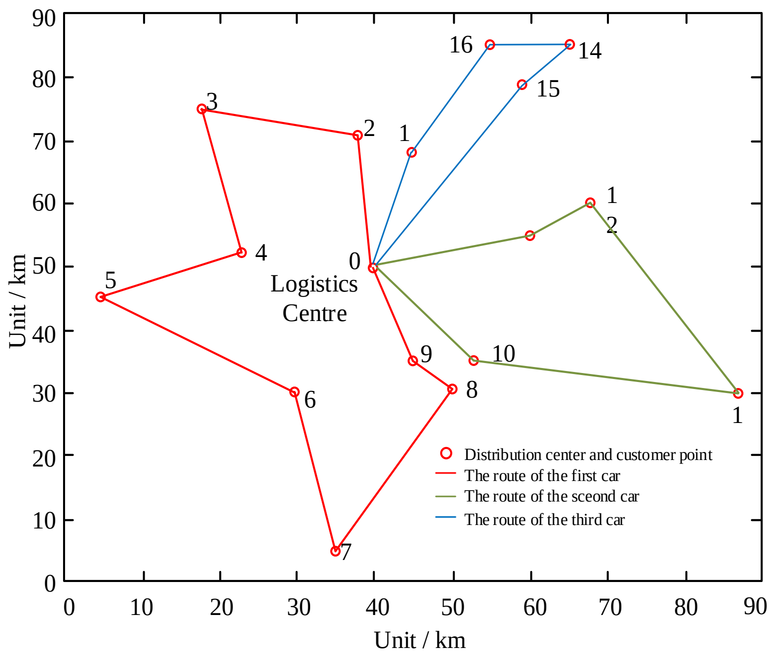

Fig. 8. Logistics distribution path diagram under HMOAC algorithm

Figure 8 presents the experiment on optimal route selection using 3 delivery vehicles. There are corresponding distribution routes under the HMOAC algorithm : (1) Vehicle No. 1: Logistics Center→Customer Point 2→Customer Point 3→Customer Point 4→Customer Point 5→Customer Point 6→Customer Point 7→Customer Point 8→Customer Point 9→Logistics Center; (2) Vehicle No.2: Logistics Center→Customer Point 10→Customer Point 11→Customer Point 12→Customer Point 13→Logistics Center; (3) Vehicle No.3: Logistics Center→Customer Point 15→Customer Point 14→Customer Point 16→Customer Point 1→Logistics Center. The total cost for each item is 7989.47 yuan based on this plan. The HMOAC algorithm utilized in the study was compared to the genetic algorithm, ant colony algorithm, and particle swarm algorithm. This comparison was performed to identify the most suitable solution for optimizing logistics route selection and to obtain the optimal solution. The optimal solution is obtained and its cost is predicted and calculated. Table 2 displays the results.

Table 2
Cost of the optimal solution of the example under each algorithm

Cost	Genetic algorithm	Ant Colony algorithm	Particle Swarm algorithm	HMOAC
Fixed cost	500	500	500	500
Transportation cost	125.8	121.57	128.99	108.24
Refrigeration cost	5110	5000.49	5359.31	5028.27
Damage cost	341.98	315.63	118.84	117.94
Carbon emission cost	44.55	41.46	40.59	36.19
Penalty cost	228.92	216.01	182.06	178.65
Total cost	6351.25	6195.16	6329.79	5969.29

From Table 2, the total cost of running the HMOAC algorithm proposed in this study is only 5969.29 yuan, with the lowest carbon emissions. It outperforms other algorithms in terms of cost and consumption, and it optimizes the target path effectively. This also means that solving the e-commerce logistics distribution path through the HMOAC algorithm can take into account both economic and environmental benefits.

5. Conclusion

The choice of the route in the logistics transportation and distribution has a particularly obvious impact on the transportation cost. To optimize the logistics route, a factor-constrained algorithm is utilized and a transportation model for the logistics route is established. The research algorithm is compared with genetic algorithm, particle swarm algorithm and ant colony algorithm. In the direction of the vehicle's path trajectory, the values obtained by the HMOAC algorithm for the X and Y direction trajectories are more in line with the actual values, with a 95% degree of accuracy. When comparing PR curves, the HMOAC algorithm outperforms other algorithms with a recall rate of 0.778 and a precision rate of 0.800. The outcome suggests that the HMOAC algorithm yields a higher precision rate when optimizing the selection of e-commerce logistics routes. It can provide customers with better service without mistakes, and it is also beneficial for enterprises to occupy a better market position in the logistics and transportation market of the e-commerce industry. For the comparison of convergence between the logistics distribution cargo data set and the vehicle data set, the HMOAC algorithm can obtain a smaller index value with 1000 iterations. Under the same conditions, the number of iterations of other algorithms is 4000, which means that the algorithm has high computational efficiency and universality in the optimal selection of logistics paths. The algorithm is performed in the case analysis, and the parameters are set to 1000, 10, 50, and 10 times, respectively, as the population size, the number of calculations, the learning cycle, and the number of runs. The use of this algorithm significantly lowered the transportation cost of the logistics path for waste disposal compared to other methods, while also producing the lowest carbon emissions. But the experiment only studied the situation where one distribution center is responsible for logistics and distribution activities in one area. Future investigations could explore integrating e-commerce logistics in multiple distribution centers within a city to attain several distribution centers.

Author Contributions

Conceptualization, C.L. and J.K.; methodology, C.L.; software, J.K.; validation, C.L., L.C.; formal analysis, L.C.; investigation, C.L.; resources, J.K.; data curation, C.L.; writing—original draft preparation, J.K.; writing—review and editing, L.C.; visualization, J.K.; supervision, C.L.; project administration, C.L.; funding acquisition, L.C. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data will be obtained from the author upon reasonable request.

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Conflicts of 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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