Hindawi
Journal of Function Spaces
Volume 2023, Article ID 9892364, 1 page
https://doi.org/10.1155/2023/9892364

Retraction

Retracted: Construction of Mathematical Model of Logistics Delivering Based on Intelligent Mobilization

Journal of Function Spaces

Received 17 October 2023; Accepted 17 October 2023; Published 18 October 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] H. Liang and J. Guo, "Construction of Mathematical Model of Logistics Delivering Based on Intelligent Mobilization," *Journal of Function Spaces*, vol. 2022, Article ID 7386227, 11 pages, 2022.

Hindawi
Journal of Function Spaces
Volume 2022, Article ID 7386227, 11 pages
https://doi.org/10.1155/2022/7386227

Research Article

Construction of Mathematical Model of Logistics Delivering Based on Intelligent Mobilization

Haijun Liang and Jing Guo

Hebei Vocational University of Industry and Technology, Shijiazhuang 050081, China

Correspondence should be addressed to Jing Guo; guojing@hbcit.edu.cn

Received 27 June 2022; Revised 6 August 2022; Accepted 26 August 2022; Published 12 September 2022

Academic Editor: Miaochao Chen

Distribution process is the core of logistics enterprise system. Efficient distribution process is the key for enterprises to improve logistics service level, gain competitive advantage, and win customers. In order to reduce the design error of the system and ensure the effective operation of the system, this paper establishes the system model and analyzes the properties of the model through the evaluation and analysis of various resources of the distribution system. The future development of intelligent logistics system is not only the key for logistics enterprises to win competition, but also a new measure to promote China's economic development. This is not only a typical NP hard problem, but also a major challenge for the rational and scientific development of the intelligent logistics industry. Based on the previous theoretical research results, this paper intends to explore the intelligent logistics distribution route selection scheme by using mathematical modeling methods such as particle swarm optimization, so as to provide new technologies and methods for logistics distribution operation and management decision-making. The results show that compared with the traditional genetic algorithm, the accuracy of the improved particle swarm optimization algorithm is improved by 10.36%. This method effectively improves the operation cycle and link efficiency and achieves the purpose of optimization. The improved particle swarm optimization algorithm proposed in this paper is not only more suitable and effective for enterprise decision makers to deal with subjective judgments in an imprecise environment. It is also based on the evaluation sequence of each indicator of the alternative obtained from the evaluation and the comprehensive evaluation of all indicators. By weighting and considering the results, the best solution for enterprise logistics and distribution is selected.

1. Introduction

As one of the basic industries and development arteries for the development of the national economy, it has received extensive attention from all walks of life. With the increasing application of automation technology and information technology in manufacturing and other entity enterprises, the competitiveness of manufacturing technology to improve products has become less and less, so enterprises focus on improving competitiveness in logistics, focusing on transportation. The functions of storage, loading and unloading, packaging, distribution, and information processing are organically combined, and it is hoped that professional and perfect supply chain services can enhance its core competitiveness and industrial-added value [1]. How to integrate the logistics delivering system and improve the efficiency of logistics delivering has become a key problem to be considered in the study of logistics theory and the actual operation of logistics enterprises. The development of modern logistics information technology and control technology has created conditions for solving this problem. The integration of logistics system is to provide efficient and high-quality comprehensive services for logistics system. Coordinate and reorganize internal elements at different levels in physical and soft environments. Logistics integration service can not only generally reduce the operation cost of logistics system, but also provide efficient and high-quality comprehensive services to meet various flexible logistics needs. Logically speaking, logistics system integration services will create a broader range of large enterprises. In this emerging integrated service field, there are traditional operators, such as express delivery, collect freight, and road transportation companies. There are also new entrants, such as state-owned railways, private railways, and postal companies. This integrated system provides unlimited development space for all these participants.

Combined with mathematical models, this paper realizes the optimization of logistics intelligent distribution path and realizes the modeling of the impact of intelligent distribution mode selection technology on logistics economic development. Finally, empirical analysis is carried out to draw validity conclusions. With the continuous development of the logistics industry, more and more attention has been paid to the research in this area. Vehicle logistics is a very important part of the logistics field. It is different from other logistics categories and has extremely high comprehensiveness and complexity. Jathe et al. propose a positioning technology based on WiFi round trip time (RTT), which will help to obtain robust positioning results. The proposed positioning technology is based on geometric method, using trilateral measurement and probability method based on the possibility of vehicle position, which strengthens the logistics planning of the whole vehicle [2]. At present, most of the research to solve this problem focuses on the following aspects: first, analyze the possible related factors and quantify these factors. When the general solution method is no longer applicable, a new method needs to be used for research. In order to achieve the goal of the enterprise, it is necessary to study the optimization problem of the enterprise logistics delivering network system. This paper makes full use of the idea of mathematical modeling to transform the complex practical problems such as vehicle stowage, commodity transportation, and transportation capacity constraints in the process of vehicle logistics operation. It has become a mathematical language, and a scientific and reasonable mathematical model has been constructed. Each model is interlocked, and the output data of each module will be directly used as the input data of the next module, which increases the operability of the model and basically realizes the intelligent logistics and distribution of the enterprise's own status quo. The location routing problem (LRP) is one of the most concerned problems in the enterprise logistics delivering system [3]. It is now widely accepted that the success of many businesses depends primarily on location-distribution network decisions. Because of the complexity of this problem and the integrity of the logistics delivering system [4], managers of many enterprises tend to make decisions based on the experience gained. The research goal of this paper is to consider the basic loading constraints of car carriers on the basis of batch orders and take the minimum cost and the minimum number of cars as the objective function to realize the optimal route and intelligent service vehicle distribution problem.

The innovative contribution of this paper is to analyze the location of logistics distribution center combined with machine learning method. The path planning problem of multiple distribution centers is studied. The structural framework of enterprise logistics system network considers the modeling of nodes and processes. The mathematical model of distribution center location path planning is established, and a new particle swarm optimization algorithm is proposed. It is applied to the optimization of distribution center location and road. Compared with genetic algorithm, the performance of particle swarm optimization algorithm is better than genetic algorithm. The improved particle swarm optimization algorithm proposed in this paper is not only more suitable and effective to deal with the subjective judgments of enterprise decision makers in an imprecise environment, but it is also based on the evaluation sequence of each indicator of the alternative obtained from the evaluation and the comprehensive evaluation of all indicators. By weighting and considering the results, choose the best solution for enterprise logistics and distribution.

This paper studies the construction of the mathematical model of intelligent mobilization logistics delivering. The structure is as follows: The first chapter is the introduction part, which mainly expounds the research background and research significance of intelligent mobilization logistics delivering, and puts forward the research purpose, method, and innovation of this paper. The second chapter mainly summarizes the relevant literature, summarizes the advantages and disadvantages, and puts forward the research ideas of this paper. The third chapter is the method part, which focuses on the location-path method combining particle swarm algorithm and logistics delivering. The fourth chapter is the experimental analysis part. This part is experimentally verified on the dataset, and the performance of the model is analyzed. This part mainly reviews the main content and results of this study, summarizes the research conclusions, and points out further research.

2. Related Work

The whole vehicle path optimization problem aims at using the minimum number of cars and at the same time making full use of the loading capacity of the cars to achieve reasonable stowage and transportation, so as to achieve the goals of the lowest transportation cost or the shortest route. Scholars have long pointed out that facility positioning is closely related to transportation routes, and the positioning of factories, warehouses, and supply points is generally affected by transportation costs [5].

Delgoshaei et al. systematically studied the model and optimization algorithm of logistics distribution vehicle scheduling problem [6]. Ransikarbum et al. have done fruitful work on the problem of knowledge representation and intelligent modeling [7]. Yong et al. conducted researches from different perspectives, mainly focusing on the fields of mathematical modeling and optimization algorithms [8]. Konstantakopoulos et al. propose a method to classify multiple VRP variables related to freight transportation faced by most logistics and distribution companies in their daily operations and an algorithm to solve various problems. [9]. Qin et al. propose a comprehensive cold chain vehicle routing optimization model with the objective function of minimizing the cost per satisfied customer. For customer satisfaction, this paper uses the punctuality of delivery as the evaluation standard. [10]. Li et al. proposed a scanning algorithm to solve large- and medium-sized vehicles with load constraints and distance constraints, using the polar coordinate angle of each customer point to determine the direction of each route and then using an iterative calculation process to continuously optimize the total travel distance [11]. On this basis, Amaruchkul et al. innovated the uniparental genetic algorithm, which uses the gene conversion position to recombine chromosomes [12]. Wang et al. proposed a mixed-vehicle multivehicle VRP model by introducing the fleet model and designed a hybrid algorithm combining tabu search heuristic and genetic algorithm [13]. Liu et al. applied the evolution reversal operator to enhance the local search ability of the genetic algorithm [14]. Kayvanfar et al. discussed a dynamic vehicle routing system based on online traffic information, where the system completes delivery tasks within a given time window according to customer requirements [15]. In order to use the dynamic time information, the system needs to establish the shortest path meter. The algorithm for the stochastic logistics problem is proposed. The algorithm is based on the decision-making process model, and the approximate optimal solution method is given. The algorithm has good practicability. Aiming at the increasing demand for flexibility in logistics delivering, a dynamic vehicle scheduling system is constructed that randomly arrives according to user orders during the planning period [16].

Since vehicle routing optimization problems often have many objectives and constraints, in order to simplify the solution process of such problems, some techniques and mathematical models can be applied to decompose or transform the problem into one or more existing research results based on the research results of previous scholars. This paper analyzes the results of the basic problems. Then the corresponding theory and algorithm are applied to solve each subproblem, and the optimal solution closest to the optimal solution of the original problem is obtained. The obtained optimal solution can also play a guiding role in practical problems.

3. Methodology

3.1. Using Mathematical Modeling to Complete the Optimization of Logistics Distribution Route. Mixed distribution means that the enterprise establishes a distribution system for small-scale distribution, while large-scale distribution can be outsourced and undertaken by a third-party distribution company [17]. Anderluh et al. assigns some customers ("gray areas") to echelons and the impact of three different urban layouts on the solution for free. The potential Pareto optimal solutions of two and three objectives are illustrated to effectively support the decision makers of sustainable urban logistics [18]. Virtual logistics refers to a logistics mode that uses computer network technology to carry out logistics operation and management and realize the sharing and optimal allocation of logistics resources among enterprises. That is, multiple member enterprises with complementary resources and technologies, in order to achieve the strategic objectives of resource sharing, risk sharing, complementary advantages, and other characteristics. Under the condition of maintaining its own independence, it has established a relatively stable partnership. Virtual logistics is the virtual integration of enterprise warehouses distributed all over the world into a large logistics support system by using increasingly perfect communication network technology and means. By completing rapid, accurate and stable material support tasks, we can meet the demand of multi frequency and small batch orders in the logistics market. The virtual logistics delivering mode is a new type of distribution concept that has appeared in recent years. It refers to the logistics delivering mode carried out by the dynamic alliance formed by the idea of virtual enterprises. The specific process is shown in Figure 1.

The positioning-routing problem of the logistics system generally considers two principles: customer service level and the total cost of the logistics system [19]. Customer service level is a relatively vague concept, which can be refined into some operational goals in actual systems, such as customer response time, product diversity, and product acquisition capabilities.

The optimization angle includes the following aspects: (1) maximum loading principle. In order to reduce the logistics cost as much as possible, it is necessary to minimize the situation that the car carrier is not fully loaded or empty. Therefore, during stowage, the maximum load capacity and space constraints of the car carrier should be calculated in detail according to the order details and customer needs so as to minimize the waste of space and ensure the maximum loading efficiency of the car carrier. (2) Principle of weight limit. The principle of weight limit refers to the fact that the maximum load should be considered when loading the car, but at the same time, the car cannot be overweight. If the total weight of the car carrier exceeds the carrying capacity of the road, on the one hand, it violates the "Road Traffic Safety Law," and on the other hand, it will also affect the service life of the car carrier. (3) Loading and unloading principle. After the route scheduling plan is formulated, the logistics stowage should make a stowage plan according to the car route, so as to shorten the entire distribution cycle and improve the logistics delivering efficiency.

In the process of cargo transportation, it is extremely important to choose a reasonable delivery route. It can not only speed up distribution and improve service quality, but also effectively reduce distribution costs. Increase economic benefits. This paper constructs a planning model of delivery routes, which transforms the delivery problem into a theoretical optimal solution problem and a travel promotion problem in operations research. It is solved by programming, and the area is divided by ray rotation method according to the group method in the transportation route optimization strategy. The maximum bearing capacity of the deliveryman is 50 kg, and the volume of the goods is not more than 1 cubic meter. Use integer programming to plan the route in each area, so as to get the optimal route. This model can reasonably arrange the delivery route for logistics enterprises and improve the delivery efficiency. Saving delivery costs has a strong theoretical guiding role, so it has great practical value. In the process of cargo transportation, it is extremely important to choose a reasonable delivery route. It can not only speed up distribution and improve service quality, but also effectively reduce distribution costs and increase economic benefits.

Modeling perspective. (1) Type of input data: it may be deterministic or random. Many literatures started to study deterministic because it is relatively easy, but now, more research focuses on random data, especially the randomness of customer needs. (2) Objective function: The common objective function for the positioning-routing problem is to minimize the total cost, which is the sum of the positioning cost and the transportation cost. There are also some literatures that

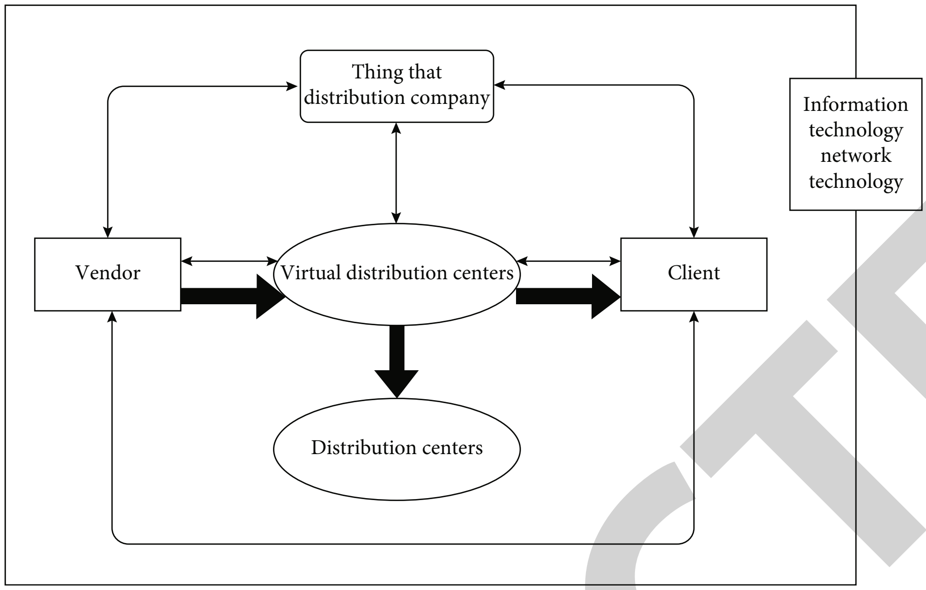

Figure 1: Virtual logistics delivering mode.

use different cost measurement methods, such as multiobjective methods and objective-dominant methods. (3) Solution space: The solution space can be discrete, network, or continuous. Considering the actual situation, most of these problems are discrete. But there is also a lot of work considering the positioning problem around transportation and the positioning problem of the traveling salesman. (4) Solving methods: There are mainly precise methods and heuristic methods. More and more literature uses heuristic methods, but precise methods are also very successful for some specific problems [19].

3.2. Iterative Update of Logistics Delivering Route Based on Particle Swarm Optimization and Genetic Algorithm. In order to further solve the problems of particle swarm optimization algorithm in the process of logistics distribution path, we can analyze here according to the characteristics of multiobjective constraint optimization in the logistics distribution path notebook. Then, the inertia weight of particle swarm optimization algorithm is improved, and a nonlinear variable particle swarm optimization algorithm is proposed. The vehicle number in logistics distribution can obtain the vehicles assigned by the distribution center to customers through the operational analysis of particles. Then, analyze the sequence of vehicles' driving paths in the logistics path. Then, determine the value size of the particles. Find the value analysis of the customer point where the logistics distribution vehicle J completes the distribution. The order analysis can be carried out according to the order from small to large value range, and then, the formal path order problem of distribution can be determined. Particle swarm optimization is to simulate the predation behavior of birds. The principle of the algorithm is as follows: POS first initialize a group of random particles, and each particle is a bird in the search space, representing a solution in the n dimensional space, where the position of the i th particle is $Xi = (x_{i1}, x_{i2}, \cdots, x_{\text{in}})$, and the velocity vector of each particle is $V_i = (v_{i1}, v_{i2}, \cdots, v_{\text{in}})$. The individual extremum is the optimal solution found by the particle itself, that is, pBest, and the global extremum is the optimal solution currently found by the entire population, that is, gBest. But at the same time, because of its obvious shortcomings, such as dealing with discrete optimization problems, it is easy to fall into local optimum and so on. Figure 2 is a flowchart of the particle swarm algorithm.

In each iteration, the particle updates its position and flight speed by tracking the individual extremum and the global extremum to search for the optimal particle in the solution space. The state update equation is as follows:

$$Vi_{t+1}P = wVi_t + c_1 * \text{rand}\,() * (P_{i,t} - Xi_t) + c_2 * \text{rand}\,() * \left(P_{g,t} - Xi_t\right),$$
$$Xi_{t+1} = Xi_t + Vi_{t+1}. \tag{1}$$

Among them, the above formula represents the speed update of the particle, and the following formula represents the position update of the particle, which is the inertia weight, which represents the dependence of the particle on the current self-information; c_1, c_2 is the acceleration coefficient, c_1 express reliance on own experience, and c_2 represents the particle's dependence on the group experience. Compared with the genetic algorithm, the particle swarm algorithm has simpler rules [19]. The following is a flowchart of the particle swarm algorithm: the problem of localization and path change is considered, that is, to minimize the total cost and average waiting time or total loop length, and shows how to adopt heuristic ideas to deal with these goals. Their general idea is as follows: Let $G\_(V, E)$ be an undirected transport network with a set of V nodes and E edges, $|V| = n$, $|E| = m$. G represents the set of all points in the transportation network. For any node $v \in V$, two positive numbers w_v^-, w_v^+ are given, and the value of $w_v^- \leq w_v^+, w_v^-, w_v^+$ is the upper and lower bounds on the weighted w_v of node $v \in V$. And weight w_v can take any value on interval $[w_v^-, w_v^+]$. Let S be the Cartesian product over the interval $[w_v^-, w_v^+]$, and then, any $W \in S$ is called a weighted set

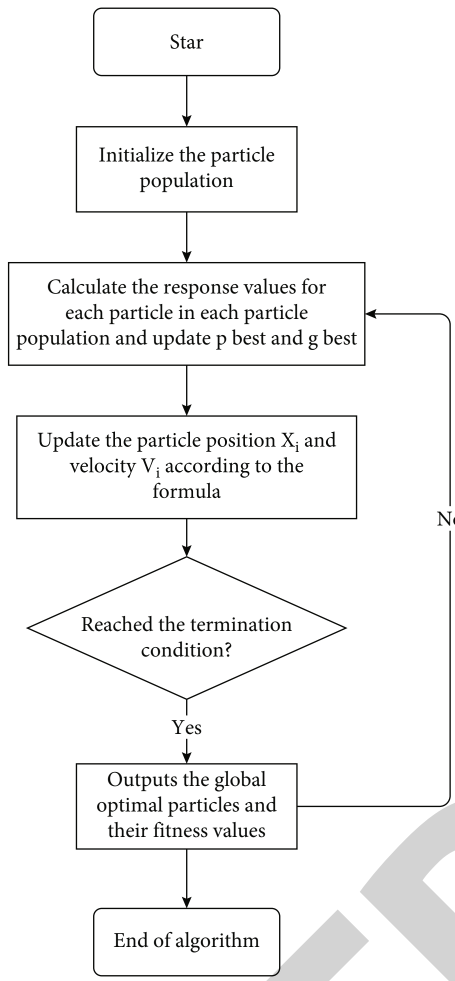

Figure 2: Flowchart of particle swarm optimization.

and denotes that a feasible weight is assigned to the network nodes. For any point a, b in network G, let $d(a, b)$ denote the shortest path between a, b, assuming that the matrix of shortest paths between nodes on G can be given (takes $O(n^3)$ time). Assuming that p identical facilities in network G need to be located, x_i represents the anchor point of the i facility, set $X = \{x_1, \cdots, x_p\} \in G^p$ is called the positioning variable, and G_P takes the set of all p pairs in network G. For locating variable X and node $v \in V$, define the distance between nodes $v \in V$ and X as

$$d(v, X) = \min_{x \in X} d(v, x). \tag{2}$$

For positioning variable X and weighted set $W = \{w_v, v \in V\} \in S$, define

$$F(W, X) = \max_{v \in V} w_v d(v, X). \tag{3}$$

where $F(W, X)$ is the maximum weighted distance between location variable X and weighted set $W = \{w_v, v \in V\} \in S$. For any two location variables, $X, Y \in G^P$, define $REGR(X, Y) = \max_{W \subset S}(F(W, Y) - F(W, Y))$.

In common algorithms, an implicit selection mechanism is embedded in the process of determining the optimal location for each particle. Therefore, the idea of genetic algorithm can be used, and how to introduce the selection mechanism to form a new hybrid algorithm is the focus of current research. At the beginning of the iteration, each particle initializes its speed and position in space in a random way. Then, in the iteration process, the particle tracks the two extreme values to determine its position and velocity in the solution space. An extreme value is the optimal position of a single particle itself in the iterative process (that is, the spatial solution corresponding to the optimal fitness value). This is called the individual extremum of particles. The other extreme value is the optimal position found by all particles in the population during the iteration process, which becomes the global extreme value. If particles only track an extreme value, the algorithm is called local particle swarm optimization or global particle swarm optimization [20]. In evolutionary algorithms, the selection mechanism is usually used for the survival of the fittest areas, that is, selecting good areas and eliminating poor areas, which is conducive to more reasonable allocation of limited resources. The simulation results show that the algorithm has certain advantages in some test functions. The selection mechanism of hybrid particle swarm optimization and genetic algorithm is very similar. The hybrid particle swarm optimization algorithm uses the fitness value of each individual particle's current position, and assigns these particles a suitable order according to the fitness value of each particle, and then assigns good positions and velocities to the group with poor fitness values. Individuals, where the second half of the whole ranking with low fitness value is defined as the individual with poor fitness value, maintain the best position of each individual [21]. Therefore, the group can concentrate on the space with relatively good fitness value, and at the same time, it is also affected by the individual's own memory of retaining the best previous position. Through the research on the related algorithms of the logistics delivering path problem, the particle swarm algorithm is selected as the tool to solve the logistics delivering path problem in this paper. The limitations of particle swarm optimization are analyzed, and the ideas are summarized according to the existing improvement methods of particle swarm optimization (Figure 3).

4. Result Analysis and Discussion

A complete logistics network system, considering all its costs, including the cost of all transportation and positioning facilities per unit time, is used to compare the cost of enterprise operations under various network system structures, and guide enterprises to choose the appropriate logistics delivering network system.

When LRP considers multiple objectives such as customer service and cost, the objectives are generally divided into two: The first objective is to deliver goods on time according to the requirements of customers to improve the quality of logistics services, which is called the objective of completing delivery tasks on time. That is, when customers place an order, they often specify the arrival time of the goods and how to arrange distribution to meet the customer's time requirements [22]. This is one of the main goals of the enterprise logistics system;

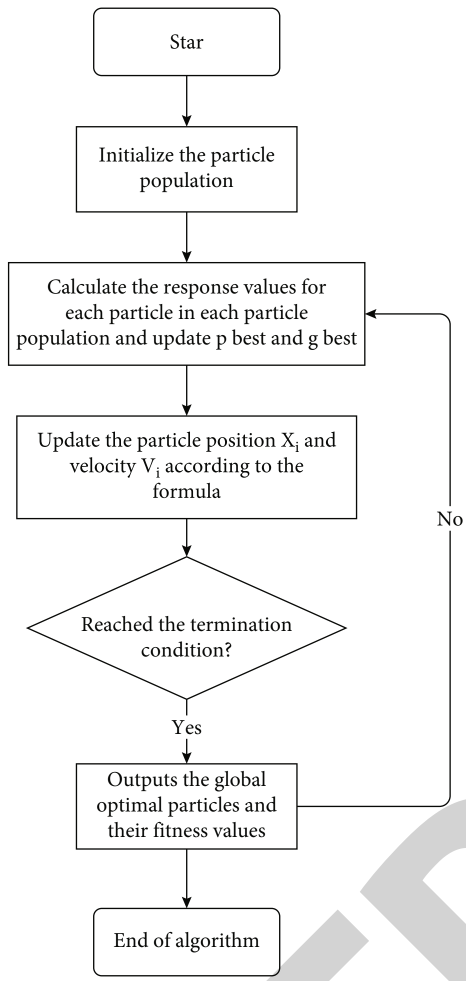

FIGURE 3: Flowchart of the improved particle swarm algorithm.

the second goal is to rationally optimize the logistics positioning location and distribution route to achieve the lowest total operating cost, which is called the lowest cost [23]. This is a requirement for enterprises to reduce the total cost of the logistics delivering system, including the cost of positioning facilities, the total operating cost, and the total cost of transportation routes. For the multiobjective enterprise logistics delivering system positioning-path problem, the relevant models established are as follows:

Variable parameters are as follows:

(i) $P = \{1, 2, \cdots, n\}$ means n feasible location facility

(ii) $C = \{i | i = 1, 2, \cdots, m\}$ refers to m customer in need of service

(iii) $S = P \cup C$ refers to the sum of all facility positioning points and demand customer points (including distribution centers and warehouses)

(iv) $V = \{v_k | k = 1, 2, \cdots, s\}$ means s means of transport

(v) $\mathrm{uc}_{\mathrm{ijk}}$ refers to the average unit distance transportation cost of the k vehicle from customer i to customer j

(vi) TC_k means the average unit cost of acquiring the k means of transport

(vii) d_{ij} refers to the distance from customer i to customer j

(viii) w_1, w_2, respectively, refer to the weight coefficients of the two objectives

(ix) q_j refers to the average number of customer $j \in C$ needs

(x) Q_k refers to the capacity of the k-th transport vehicle

(xi) F_t refers to the average unit time penalty cost of delaying the delivery of the goods as required by the customer

(xii) t_{ijk} refers to the time it takes for the k-th vehicle to travel from customer i to customer j

(xiii) T_K refers to the departure time of the k th car

(xiv) T_i, T_j, respectively, refer to the time from customer i to customer j

(xv) $\mathrm{ET}_{\mathrm{ij}}$, $\mathrm{LT}_{\mathrm{ij}}$, respectively, refer to the lower limit and upper limit of the time period from customer i to customer j

(xvi) T_{ijf} refers to the time it takes to deliver the goods on time from customer i to customer j as required, and it can be the arrival time period specified by a customer in advance $\mathrm{ET}_{\mathrm{ij}} \le T_{\mathrm{ij}} \le \mathrm{LT}_{\mathrm{ij}}$, $T_{\mathrm{ij}} = T_k + t_{\mathrm{ijk}}$

(xvii) T_{ijf} refers to the delay from customer i to customer j when the goods are not delivered as required

The multiobjective LRP model to build the model is

$$f_1 = \min \left\{ \left[w_1 \sum_{i,j \in C} \sum_{k \in V} \left(\mathrm{LT}_{\mathrm{ij}} - T_{\mathrm{ij}}\right)^2 + w_2 \sum_{i,j \in C} \sum_{k \in V} \left(T_{\mathrm{ij}} - \mathrm{ET}_{\mathrm{ij}}\right)^2 \right] + \sum_{i,j \in C} F_t T_{\mathrm{ijf}} \right\}, \tag{4}$$

$$f_2 = \sum_{i=1}^{s} \mathrm{TC}_k \sum_{i=1}^{m} \sum_{j=1}^{m} x_{\mathrm{ijk}} q_j + \sum_{i=1}^{n} G_i Z_i + \sum_{k=1}^{s} C_k \sum_{i=1}^{m} \sum_{j=1}^{m} x_{\mathrm{ijk}} \mathrm{uc}_{\mathrm{ijk}} q_j d_{\mathrm{ij}}. \tag{5}$$

Locate a transportation route arrangement problem location—routing problem; LR refers to a given number of potential facilities. Among these potential facilities, a group of facility locations should be determined. At the same time, a set of transportation routes from each facility point to each customer point is determined based on meeting the goal of the problem (usually the minimum total cost). The location of customer points and customer demand is known or estimable. The location of one or more facilities of the goods is known, and

Table 1: Simulation results.

Algorithm	Number of vehicles	Number of particles	Number of particles	Mean algebra	Experimental optimal average distance
Optimized particle swarm optimization	7	50	57	522.3	594.325
		100	59	433.2	594.246
		120	62	360.1	594.233
Traditional particle swarm algorithm	7	50	40	554.3	594.665
		100	45	459.6	594.364
		120	49	370.6	594.365

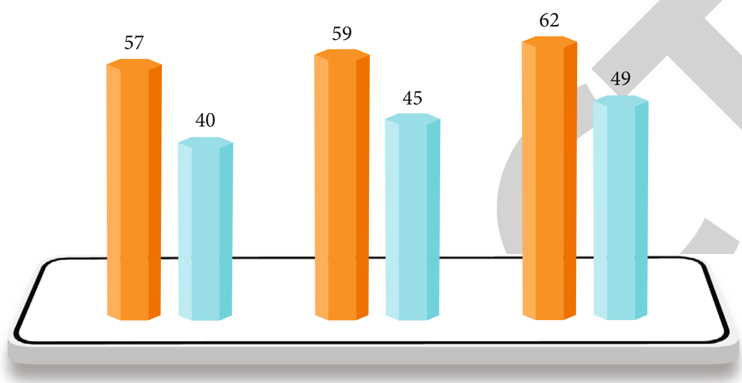

Figure 4: Comparison of the times of reaching the optimal path.

the goal of the problem is to establish those potential facilities to minimize the total cost. People have made a long-term and in-depth study on its model and algorithm. At present, there are few relevant papers in China, and the existing papers usually adopt the two-stage method to solve this problem. That is, the original problem is divided into two small problems: La and VRP. First, solve the LA, and then, solve the VRP problem on this basis. In fact, for LRP models including time windows, there are still some limitations in solving practical problems in some specific cases. For example, the requirement for just-in-time production is very high, and manufacturing enterprises that implement zero-inventory production need a more real-time positioning-path problem method, that is, to realize the path selection and location decision under uncertain factors, which is the dynamic positioning-path problem. For example, a logistics delivering system has multiple production locations, multiple distribution centers, and multiple vehicles, and the decision is to optimize the entire logistics system through facility positioning and route selection decisions. The demand is not generated randomly and disorderly as in the traditional research method, but occurs according to a demand queue with a certain probability. Although there may be some unexpected events that lead to large changes in demand, usually the change in customer demand should be a deviation from the production plan within a certain limit. According to the previous introduction, the following compares the optimization algorithm with the traditional particle swarm algorithm to prove the superiority of the optimization algorithm. In this paper, the number of particles is simulated, and the advantages and disadvantages of the optimization algorithm and the traditional algorithm are compared. Compared with traditional methods, the optimized particle swarm optimization algorithm has better results in the selection of the optimal distance than before, which proves that the optimized algorithm is more conducive to finding the optimal distance. The optimal solution improves the practicability of the algorithm in finding the optimal allocation scheme, and the optimal solution is more optimized. The simulation results are analyzed, and the results are shown in Table 1:

It can be seen from Figure 4 that whether the number of particles is 50, the number of particles is 100 or the number of particles is 120, the number of times the particle swarm algorithm has reached, and the optimal path is more than that before the optimization.

It can be seen from Figure 5 that whether the number of particles is 50, the number of particles is 100 or the number of particles is 120, and the average algebra of the optimized particle swarm algorithm is reduced, which is convenient for the realization of the algorithm, simple operation, and time saving.

It can be seen from Figure 6 that whether the number of particles is 50, the number of particles is 100, or the number of particles is 120, and the optimized particle swarm algorithm obtains better results in the optimal distance selection than before the optimization, which proves that the optimized algorithm is more conducive to finding the optimal distance. The optimal solution improves the practicability of the algorithm in finding the optimal distribution plan, and the optimal solution found is more optimized. It can be seen from the

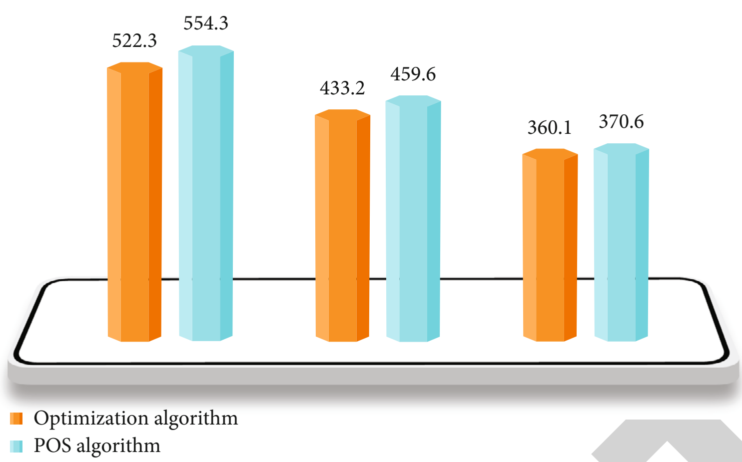

Figure 5: Average algebra comparison chart.

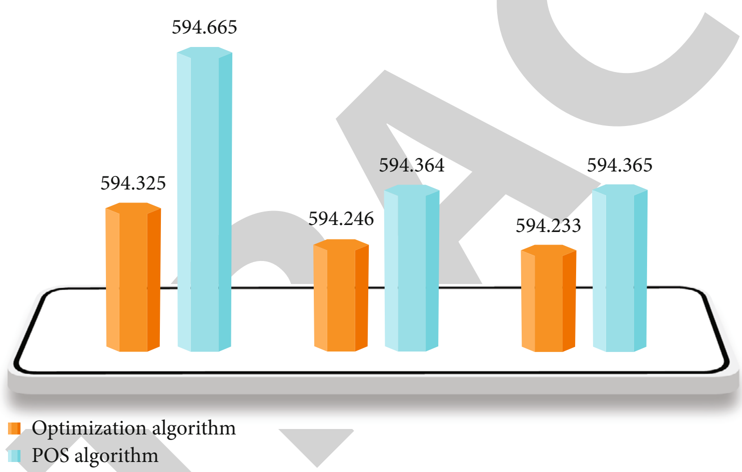

Figure 6: Comparison of optimal distances.

simulation results that the optimized particle swarm algorithm is effective and achievable in logistics delivering, and it is significantly better than the traditional particle swarm algorithm in reaching the optimal number of paths, average algebra, and optimal average distance.

The application scenario of this paper is the vehicle distribution scheduling optimization problem of multifreight center, multivehicle type, and multicommodity model. The calculation example in this section is intended to use 6 paths and 10 positioning data to solve the vehicle logistics solution Table 2.

The case uses Matlab2015b to program the calculation example, and performs the operation experiment on an Intel i5 2.30 GHz computer, and the preset number of iterations is 500. After ten running experiments, the best experimental results are as follows: the total transportation cost is 16547.298 yuan, the algorithm running time is 256.4985 s, and the required car transporter is 7.

The algorithm iteration diagram is shown in Figure 7. By observing and querying the Matlab workspace, it can be seen that the optimal solution of the experiment is obtained in the 65th generation of GA-PSO, and the population gradually converges to the optimal solution in the 80th generation, that is, about 20 s after the algorithm runs. The algorithm can converge to the global optimal solution.

Table 2: The location and demand of each customer point.

Position	Abscissa/km	y-axis/km	Order
1	380	70	2*A +3*B +2*F
2	350	100	2*C +3*D
3	250	120	2*C +4*E
4	225	139	3*C +2*F
5	275	219	5*A
6	255	175	2*D +2*F
7	325	275	3*A +2*D
8	425	155	2*B +3*F
9	455	290	4*A +2*C
10	475	155	2*B +3*C

In order to verify the effectiveness of the algorithm and compare and analyze the performance of the algorithm, this

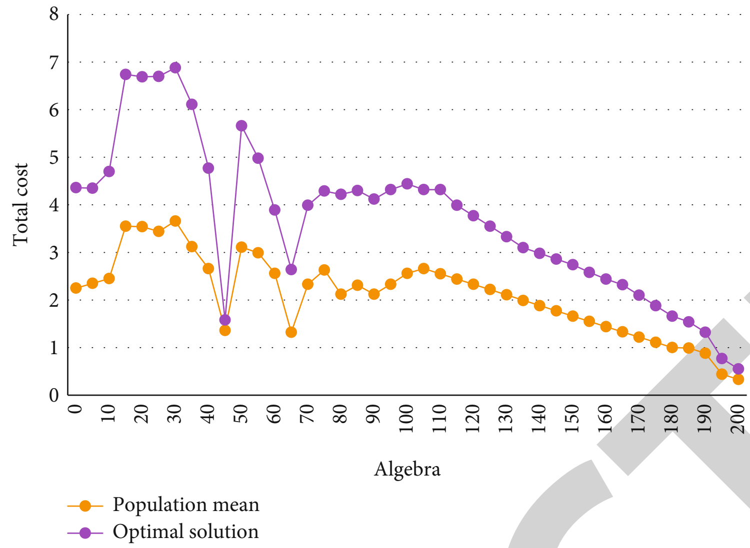

Figure 7: Iterative diagram of the hybrid algorithm.

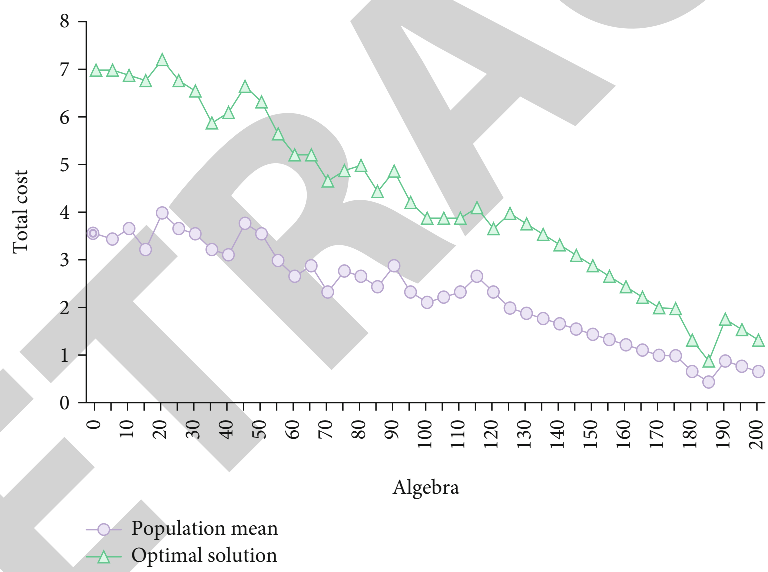

Figure 8: Iterative diagram of genetic algorithm.

paper uses the genetic algorithm to perform programming simulation experiments on the case. The randomization technique is used to guide the efficient search of a coded parameter space. Among them, selection, crossover, and mutation constitute the genetic operation of genetic algorithm. The core content of genetic algorithm is composed of five elements: parameter coding, initial population setting, fitness function design, genetic operation design, and control parameter setting. The coding method and population initialization in the genetic algorithm are the same as the GA-PSO hybrid algorithm. The convergence diagram of the genetic algorithm is shown in Figure 8:

The two algorithms have been simulated for ten times, respectively. Table 3 lists the comparison of the experimental results of the algorithms, and gives the maximum and average value of the ten operation costs of each algorithm, the convergence algebra when the cost is the lowest and the results of each algorithm.

By comparing the simulation results of the two algorithms, it can be seen that the particle swarm hybrid algorithm has faster convergence and better optimization results. This shows that in a large-scale practical application, the conventional genetic algorithm takes too long to search for optimization, and once it falls into a local optimum, it cannot easily jump out, and cannot meet the timeliness of actual operation. The improved particle swarm algorithm has relatively better performance and better global search ability, which can meet the actual needs of logistics delivering scheduling.

The multivehicle logistics delivering model based on the shortest path designed in this paper can be solved by the optimized particle swarm algorithm; that is, the optimized particle

Table 3: Algorithm results comparison.

Algorithm	Total number of cars	Optimal cost	Convergent algebra	Highest cost/RMB	Average cost/RMB	CPU(s)
Particle swarm algorithm	7	16543.52	65	16853.43	16654.32	233.6579
Genetic algorithm	7	17889.12	70	17999.23	17165.43	325.5643

swarm algorithm can solve the logistics delivering problem. Compared with the traditional particle swarm algorithm, the particle swarm optimization algorithm designed in this paper introducing fuzzy classification and self-adaptive mutation mechanism has its own advantages and is an effective optimization algorithm, which can be used in practical operation. The two models based on the shortest vehicle travel path with the fewest vehicles and the two models based on customer satisfaction have different logistics delivering schemes; that is, for different optimal distribution targets, the resulting distribution schemes are also different.

5. Conclusions

In this paper, facility location and transportation combination optimization are studied as a whole. The influence of the two different factors on each other shall be taken into account. In the actual planning of logistics system, it is necessary to unify the location selection of logistics facilities and the decision-making of transportation routes. It is not advisable to ignore one of them and consider only one of them. The constituent factors of problem research and the main content of current research are given. This paper briefly describes the dynamic models of two common location routing problems in logistics distribution systems. From the perspective of analysis and comparison, firstly, the common location problems, routing problems, and the research status of location routing problems are described in detail. The path calculated by the data model improves the logistics distribution, improves the operation cycle and link efficiency, and achieves the purpose of optimization. Compared with the traditional genetic algorithm, the accuracy of the improved particle swarm optimization algorithm is improved by 10.36%. However, intelligent optimization itself is rich in content, and logistics system is a highly applicable field. Therefore, the research still has some limitations. The follow-up research directions mainly include as follows: when studying the logistics distribution path problem, this paper only studies the core optimization algorithm. In the future, GIS technology can be integrated into the core algorithm of this paper, so as to develop a more practical logistics distribution path system. Particle swarm optimization algorithm itself means a certain degree of parallelism, and a particle is independent of other particles in a cycle. Therefore, in essence, particle swarm optimization should be a distributed collaborative optimization method.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

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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