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Research Article

Inventory Path Optimization of VMI Large Logistics Enterprises Based on Ant Colony Algorithm

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In order to better manage the supplier's inventory and formulate a reasonable distribution plan, based on the existing research, taking the two-level supply chain system composed of one supplier and multiple retailers as the research object and VMI mode as the background, this paper studies the inventory path optimization problem with the goal of minimizing the total cost in the planning period. Taking the retailer's inventory capacity and vehicle capacity constraints as constraints, this method constructs a mixed integer programming model with random demand in multiple cycles and the goal of minimizing the total cost in the planning period. When building the model, the distribution cost is refined. In addition to identifying shipping-related start-up costs and travel costs, processing costs are associated with additional delivery time, which is close to reality. In the algorithm design, the genetic algorithm is combined with the C–W algorithm, a similar hybrid genetic algorithm is used to solve the model, and the sample model is used for estimation; that is, the expected value of the random sample is taken, which is used as the target value for each chromosome. In addition, when optimizing roads, the C–W algorithm is used to divide vehicle capacity according to truck capacity as much as possible, thereby reducing the number of vehicles used and saving the overall total cost of preparation time for certain projects. Facts have proved that the optimized and improved inventory path is more conducive to help enterprises reduce logistics costs and provide theoretical support for enterprise management decisions.

1. Introduction

In today's society, with the progress of science and technology and the continuous development of social economy, enterprises are facing more and more fierce market competition in the environment of economic globalization. In such an external market environment, the competition among enterprises is not only the competition of product quality and performance or service quality, but also the competition between upstream and downstream supply chains. If enterprises simply rely on their own strength to resist other competitors and ignore the advantages of upstream and downstream supply chains, they are bound to be at the bottom of the market competition [1]. The content and analysis of market research industry research are not only the management of independent market products, but also the participation of upper and lower markets in all logistics and the management of logistics data by sharing the stored data, as shown in Figure 1. VMI's customer management concept enables companies in the product market to no longer manage their own products individually but to adopt strategic and collaborative strategies to conveniently manage inventory on the product chain to ensure the synchronous operation of the entire chain. It can not only improve market competitiveness, but also solve the bullwhip effect in products [2]. In this context, this paper proposes a VMI large-scale product development industry product development method based on swarm algorithm.

2. Literature Review

In view of the application of VMI, Cong T. et al. discussed the optimal strategies in the case of decentralized and centralized VMI supply chain through Game Analysis on the premise of considering the loss avoidance behavior of suppliers and the impact of market demand on retailers' promotion behavior. On this basis, they constructed the VMI supply chain coordination contract model under the

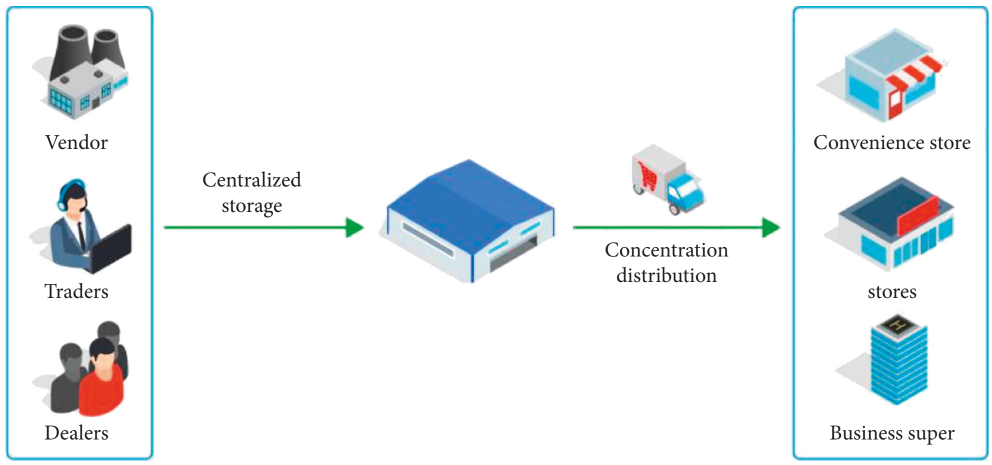

Figure 1: Supply chain of logistics enterprises.

wholesale price promotion cost sharing contract [3]. Lv et al. established a Nash negotiation revenue sharing contract model starting from the price subsidy income under the premise that the product price is affected by the demand; under the constraints of onboard capacity and mixing time window, the simultaneous optimization of single-cycle inventory and routing is studied [4]. Syah et al. put forward the corresponding control strategy for the bullwhip effect and control problem under VMI mode through the construction of the model and the comparative analysis of the total cost before and after the implementation of supplier managed inventory strategy [5]. Salviano et al. studied the application of VMI in lithium battery manufacturers. Firstly, it analyzes the problems existing in the company's existing inventory management mode. Secondly, it prepares for the implementation of VMI from the aspects of implementation team, technical support, selection of materials and warehouses, operation mode, and replenishment mode of VMI; then it shows the implementation process of VMI strategy, analyzes the implementation effect, and finally summarizes the advantages and disadvantages in the implementation process of VMI, puts forward improvement measures, designs VMI implementation scheme for autoparts enterprises, and solves the problem of cost waste [6]. In terms of model construction, Ulusam Seçkiner et al. proposed the inventory control system of inventory/distribution plan and further determined the optimal inventory strategy and vehicle route by establishing a mixed integer linear programming model [7]. Al amyal et al. studied the inventory routing problem in which suppliers have production capacity constraints and the purchased transportation services can meet the needs of retailers [8]. Kanso et al. embed the desired outcome into the decision-making process and see the benefits by introducing the development of stochastic dynamic programming problems, finding a good idea in small cases and finally creating a solution math, solutions to mixed linear programming models [9]. Xue et al. established a mixed integer linear programming model for a supply chain system composed of a single manufacturer and multiple retailers based on the VMI strategy and proposed a genetic algorithm to solve the inventory path problem, replenishment times, quantities, and vehicle routing are determined [10]. Xing et al. study IRPs from the perspective of business interests and apply a variety of objective stochastic models to determine benefits, service levels, and green standards [11]. For the IRP of liquefied natural gas under destructive weather conditions, X. M. et al. proposed a two-stage stochastic mixed integer programming and the preference model of decision-makers to deal with potential damage [12].

3. Product Optimization Method Model of Large-Scale Logistics Business Based on VMI

3.1. Problem Description. This paper studies the supply chain system composed of a single supplier (a distribution center is set at the supplier) and multiple retailers with known geographical locations and uses the supplier managed inventory model for inventory management. The supplier monitors the inventory in real time, decides whether to replenish it according to its historical sales data and inventory situation after the end of each cycle, that is, before the actual demand faced by the retailer arrives, and completes the distribution before the beginning of the second cycle [13]. Among them, the retailer adopts the (t, R, S) strategy. This paper sets the replenishment point RI corresponding to R and the maximum inventory level Mi corresponding to s; that is, when the retailer's inventory level is lower than the replenishment point ri, the supplier distributes goods for the retailer to make its inventory level reach the maximum inventory level Mi; otherwise, there is no delivery.

Determine the inventor-related parameters of suppliers and the number and distribution of suppliers in time planning by combining methods of optimizing inventors and a two-stage supply chain system, which not only requires retailers to reach a certain level, but also fully utilizes the capabilities of vehicles, reduces the number of vehicles to one level, and finally achieves the goal of reducing the overall cost in planning. The costs considered include inventory cost (inventory holding cost and shortage cost) and distribution cost (vehicle start-up cost, vehicle driving cost, and labor cost) [14]. Among them, the article considers the distribution service of a single product. There are inventory restrictions at retailers. The scale of retailers is small; the demand follows normal distribution and the demand is moderate; that is, one vehicle can distribute goods to multiple retailers at the same time, and a single retailer can only be distributed by one vehicle in the same cycle. During the delivery process, the vehicle leaves the distribution center, asks the seller about the delivery method, and returns to the seller. The vehicle models are the same, regardless of the restrictions of vehicle travel time and travel distance [15].

3.2. Model Assumptions. Considering the complexity of the actual situation and the feasibility of model construction, the following assumptions are made for the model:

(1) The planning period includes m distribution cycles, which are continuous and positive integers.

(2) It is assumed that, in the determined planning period, the random demand faced by retailers follows the normal distribution with mean μ and variance 2σ, the demand is moderate, and the demand among different retailers is independent of each other.

(3) The retailer adopts the (t, R, S) strategy. The supplier checks the retailer's storage surplus every T cycle. If the inventory is lower than the replenishment point R, replenish the retailer to make its storage level reach s; otherwise, the retailer will not be replenished. This paper sets the replenishment point r_{i} corresponding to R and the maximum inventory level M_{i} corresponding to s for retailer i. Due to the limitation of retail mall location, according to the actual situation, it is assumed that MI is known [16].

(4) Retailers are allowed to be out of stock without replenishment, but there will be a certain out of stock cost. It is assumed that the out of stock cost is positively related to the out of stock volume.

(5) The supplier's lead time is 0, which is a kind of goods supplied by the retailer.

(6) The coordinates of suppliers and retailers are known, and the distance d_{ij} is expressed by Euclidean straight-line distance. The transportation between any two points is in good condition.

(7) A distribution route has only one car service.

(8) The dealership has an unlimited number of cars of the same model and carrying capacity.

(9) In each cycle, the same retailer completes the distribution task by one vehicle, and the vehicle can distribute to multiple retailers at one time.

(10) Each vehicle is only shipped once a week, from and back to the delivery point.

(11) After the vehicle is delivered to one retailer, leave immediately and go to the next retailer for delivery.

(12) The models are the same, and the restrictions of vehicle driving time and distance are not considered.

(13) The cost in the model includes inventory cost (retailer inventory holding cost and shortage cost) and distribution cost (vehicle start-up cost, vehicle driving cost, and labor cost). The goal is to reduce the total cost during the planning period. Among them, the inventory holding price is proportional to the final product, the exit price of the product is proportional to the output, and the starting price is proportional to the number of vehicles to be delivered and the transportation cost. Proportional to the distance to the truck, the reward is proportional to the delivery time [17].

3.3. Model Construction

3.3.1. Retailer Inventory Holding Cost. Shipping costs refer to the cost of keeping existing goods and the cost of storing food, including storage costs, taxes, insurance, damage costs, theft costs, and, most importantly, affordable prices. Its level is related to the inventory level. The higher the inventory, the more the holding cost [18].

It is assumed that the seller's daily carrying cost is proportional to the inventory cost (final inventory) for the day. The ending inventory of the t-th cycle of retail point i is related to the opening inventory, the distribution volume arriving on that day, and the random demand faced by the retailer in this cycle. The ending inventory at the spot is equal to the opening (before distribution) inventory of the retailer on that day plus the distribution volume arriving on that day minus the random demand faced by the retailer on that day [19]. Specifically, it can be expressed as

$$E_{ti} = \max\{I_{ti} + q_{ti} - D_{ti}, 0\}. \tag{1}$$

The ending inventory of the retailer is the opening inventory of the next cycle, so the beginning inventory of the retailer in the i-th $(t+1)$ cycle is shown in

$$I_{(t+1)i} = E_{ti} = \max\{I_{ti} + q_{ti} - D_{ti}, 0\}. \tag{2}$$

When the retailer's inventory reaches the maximum at the beginning of the delivery cycle, it determines whether the retailer needs to replenish its inventory at the beginning of the delivery cycle according to the retailer's inventory at the beginning of the delivery cycle. When the retailer's opening inventory in the current cycle is greater than the replenishment point r_{i}, replenishment is not required. Then, the delivery volume of the supplier to the retailer in the t-th cycle can be expressed as

$$q_{ti} = \begin{cases} M_i - I_{ti}, & I_{ti} < r_i, \\ 0, & I_{ti} \geq r_i. \end{cases}, \forall_i \in N, t \in T. \tag{3}$$

To sum up, the inventory holding cost of retailer i in cycle t is shown in

$$HC_{ti} = H_i \times E_{ti} = \max\{I_{ti} + q_{ti} - D_{ti}, 0\}. \tag{4}$$

The inventory holding cost of all retailers in cycle t can be expressed as

$$HC_t = H_i E_{ti} = H_i \sum_{i\in N} \max\{I_{ti} + q_{ti} - D_{ti}, 0\}. \quad (5)$$

Shortage cost refers to the cost caused by supply interruption caused by insufficient inventory. When the sum of the retailer's opening inventory and distribution volume in a cycle is less than the random demand faced by the retailer in that cycle, there will be a shortage. Assuming that the shortage is not replenished and the retailer's shortage cost is directly proportional to the shortage volume in this cycle, the shortage cost of retailer i in cycle t can be expressed as

$$s_{ti} = \max\{D_{ti} - (I_{ti} + q_{ti}), 0\}. \quad (6)$$

Therefore, the out of stock cost of all retailers in cycle t can be expressed as

$$PC_{ti} = P_i \sum_{i\in N} s_{ti} = P_i \sum_{i\in N} \max\{D_{ti} - (I_{ti} + q_{ti}), 0\}. \quad (7)$$

3.3.2. Distribution Cost Analysis. Distribution cost is the cost incurred by suppliers when distributing goods to retailers. When most scholars study the inventory route optimization problem, the distribution cost only considers the vehicle start-up cost and the vehicle driving cost related to the driving distance. This paper further refines the distribution cost and increases the labor cost related to the distribution time [20]. That is, the distribution cost includes vehicle start-up cost, vehicle driving cost, and labor cost (calculated by man hours), so the distribution cost incurred by the supplier when distributing goods to the retailer in cycle T can be expressed as

$$\begin{aligned} DC_t = {} & S_c \sum_{t\in T}\sum_{v\in K} y_{0t}^{y} + C_{ij} \sum_{v\in K}\sum_{j\in N^2}\sum_{i\in N^2} d_{ij} x_{ijt}^{y} \\ & + R_c \sum_{v\in K}\sum_{j\in N^2}\sum_{i\in N^2} \frac{d_{ij}}{V} y_{ijt}^{y}. \end{aligned} \quad (8)$$

3.3.3. Objective Function and Constraints. According to the above analysis and the transformation between the corresponding formulas, the inventory path optimization model based on VMI is established, which belongs to the mixed integer programming model.

$$\begin{aligned} \min TC = {} & H_i \sum_{t\in T}\sum_{i\in N} (I_n + q_{ti} - D_{ti} + s_{ti}) + P_i \sum_{t\in T}\sum_{i\in N} s_{ti} \\ & + S_c \sum_{t\in T}\sum_{v\in K} y_{0t}^{y} \\ & + C_{ij} \sum_{t\in T}\sum_{v\in K}\sum_{j\in N^2}\sum_{i\in N^2} d_{ij} x_{ijt}^{y} \\ & + R_c \sum_{t\in T}\sum_{v\in K}\sum_{j\in N^2}\sum_{i\in N^2} \frac{d_{ij}}{V} x_{ijt}^{y}, \end{aligned} \quad (9)$$

$$I_{(t+1)i} = I_{ti} + q_{ti} - D_{ti} + s_{ti}, \quad \forall_i \in N, t \in T, \quad (10)$$

$$s_{ti} = \max\{D_{ti} - (I_{ti} + q_{ti}), 0\}, \quad \forall_i \in N, t \in T, \quad (11)$$

$$q_{ti} = \begin{cases} M_i - I_{ti}, & I_{ti} < r_i, \\ 0, & I_{ti} \geq r_i, \end{cases} \quad \forall_i \in N, t \in T, \quad (12)$$

$$\sum_{v\in K} y_{it}^{y} \leq 1, \forall_i \in N, \quad t \in T, \quad (13)$$

$$\sum_{j\in N} x_{0jt}^{y} = \sum_{j\in N} x_{j0t}^{y}, \forall_v \in K, \quad t \in T, \quad (14)$$

$$\sum_{j\in N, j\neq 1} x_{ijt}^{y} + \sum_{j\in N, j\neq 1} x_{jit}^{y} = 2y_{it}^{y}, \quad \forall_i \in N, \quad v \in K, \quad t \in T, \quad (15)$$

$$\sum_{i\in N} q_{ti} y_{it}^{y} \leq W, \quad \forall_v \in K, \quad t \in T, \quad (16)$$

$$y_{it}^{y} \in \{0, 1\}, \quad \forall_i \in N, \quad t \in T. \quad (17)$$

Among them, (9) represents the total cost during the planning period, including inventory cost and distribution cost. The first two are commodity prices, including retail price holding prices and commodity exit prices caused by demand. The latter three items are distribution costs, including vehicle start-up costs, vehicle driving costs, and labor costs. Equation (10) represents the relationship between the opening inventory of retailer I in cycle $(t + 1)$ and the opening inventory, distribution volume, demand, and shortage volume in cycle t; (11) represents the shortage of retailer i in cycle t; (12) represents the distribution volume of retailer I in cycle $(t + 1)$. When the retailer's opening inventory is lower than the replenishment point r_i, the supplier distributes for the retailer, and the distribution volume is the difference between the maximum inventory level M_i and the opening inventory level I_{ti}; otherwise, no delivery will be made. Equation (13) indicates that each retailer can only be delivered once at most in the cycle; (14) indicates that all vehicles in each cycle can only leave the distribution center and return to the sender after completing the delivery service; (15) indicates that the vehicle leaves after visiting the retailer and its service, that is, to ensure that there is no loop in the distribution line of each vehicle; (16) indicates that the distribution volume of each vehicle in any cycle does not exceed its maximum load capacity; (17) shows value constraint of decision variable [21].

4. Model Solution of VMI Inventory Path Problem

4.1. Solution Idea of Ant Colony Algorithm. While bug culture has always been a heuristic for development, it still has many limitations compared to some familiar heuristics, such as the computational cost of constructing the solution which is too high. The efficiency of algorithm exploration is low; the algorithm runs slowly or even stagnates; it can only be used to solve the performance improvement problem, not to do anything about the performance problem (continuous performance improvement). In response to the problems existing in traditional ant colony algorithms, scientists have proposed a variety of solutions, that is, improvements on the basis of traditional ant colony algorithms, such as ant colony system algorithm, polymorphic ant colony algorithm, pheromone diffusion ant colony algorithm, and deinterleaving local optimization slave colony algorithm[22]. Figure 2 is the evolution curve of the traditional ant colony algorithm, and Figure 3 is the evolution curve of the ant colony algorithm. Experimental results show that the latter method can be used to solve the global integration problem.

The key to the ant colony system algorithm is to modify the algorithm's local data and international data separately and use both to solve patterns. Local pheromone update means that Manu adjusts the pheromone concentration on the way to the local pheromone while looking for the ideal method; global update refers to adjusting the pheromone concentration to the optimal one during the search process after all ants complete the optimal search [23]. The choice of colony system algorithm is a combination of randomness and certainty. The advantage of the slave group system over the traditional slave culture is that it solves the problem of rapid changes in the slave algorithm slowing down or even drowning in the process of developing a solution. The main reason for the stagnation is that the algorithm accepts the idea of random selection when creating a solution, and the selection strategy of the ant colony system algorithm is a combination of deterministic selection and random selection, which effectively solves the above problems. When the ant colony algorithm is easy to choose the method, the result in the transition state, the preference only affects the influence of the transportation rate and the pheromone concentration, and the influence of the market loss and the commodity holding price will be considered.

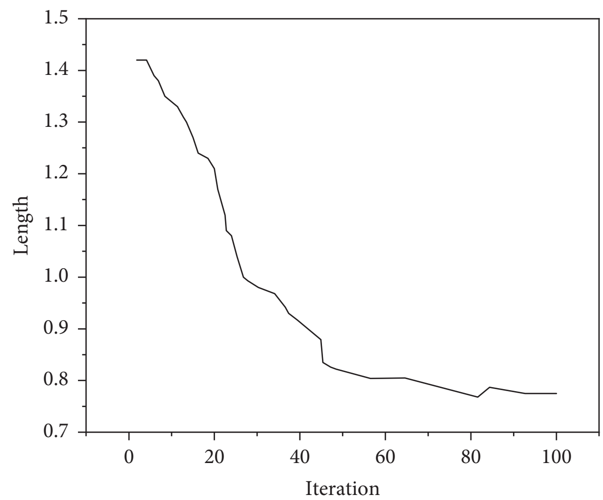

Figure 2: Evolution curve of traditional ant colony algorithm.

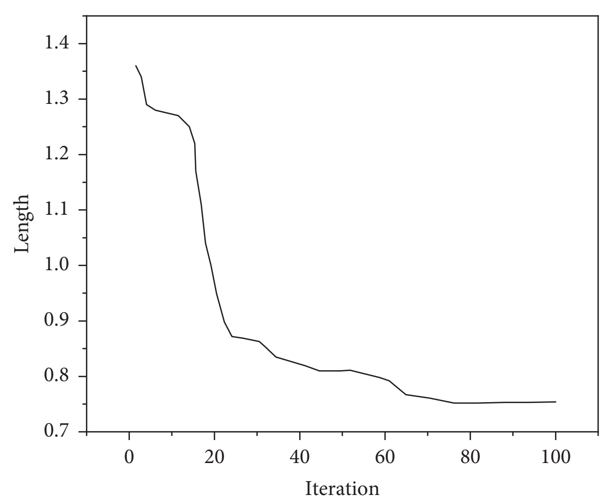

Figure 3: Evolution curve of improved ant colony algorithm.

4.2. Design of Ant Colony System Algorithm. First, randomly place all the ants of the prepared Atlas. Once all the ants have formed their own drive, they will absorb the pheromone of the process. When a new ant arrives on a path, it determines the path based on the number of pheromones left by the ants crossing the path. If a method has a low pheromone concentration, new ants will arrive at a method-selecting node with little ability of selecting a method. While cultural errors have traditionally been used to develop solutions, it has shifted very quickly and even erratically. The main reason for this is that it uses a random selection strategy when running the solution [24]. To prevent this from happening, we need to improve the ant colony algorithm to dynamically modify the build results during the creation process and accept the option of combining algorithms, fully and randomly choosing the creation method.

4.3. Selection of Volatilization Coefficient ρ. The pheromone released to the passing edge during ant movement will gradually weaken with the passage of time until it disappears. Generally, ρ-pheromone volatilization coefficient is used to represent the disappearance degree of pheromone, and, accordingly, 1-ρ represents the residue coefficient of pheromone. The value of ρ has an impact on the global exploration ability of the algorithm and the rotation speed of the algorithm. Particularly, when solving large problems, a major ρ can reduce the impossible amount of pheromone to zero, affecting the global research ability of the algorithm. [25]. A smaller ρ means that the pheromone volatilizes slowly and the residual information dominates the algorithm. The randomness and global search ability of the algorithm will be improved, but the rotation speed will be affected. The appropriate choice of the value of ρ is an important issue.

The effect of volatility coefficient ρ on the performance of ant colony algorithm is analyzed through experiments. Using ant week system, choose Oliver 30 urban problem experiment. Relevant parameter settings: number of ants $M = 30$, $Q = 50$, expected heuristic factor $\beta = 1$, and pheromone heuristic factor $\alpha = 1$. The cut-off cycle is the difference between the results obtained from two probe-adjacent cycles of less than 0.001, and the change in volatilization coefficient is $\rho \in \{0.9, 0.7, 0.5, 0.3\}$. 10 experiments are carried out for each ρ value, and the average value is the average of the path

Table 1: Effect of volatilization coefficient ρ on the performance of ant colony algorithm.

Pheromone volatilization coefficient ρ	Average value	Optimal path length	Worst path length	Optimal and worst path length difference	Number of cycles
0.3	430.92	426.53	434.26	7.73	24
0.5	430.65	424.94	432.20	7.26	32
0.7	428.53	424.69	431.31	6.62	46
0.9	431.05	428.63	436.01	7.32	120

length obtained 10 times. The shortest method from 10 trials is the length of the best method, and the longest is probably the worst method. The experimental results are shown in Table 1.

The experimental results show that the integral of the colony algorithm is greatly affected by the variance ρ, while the others are unchanged. As shown in Figure 4, when ρ is small, the pheromone volatilizes slowly, and the residual information (corresponding to 1-ρ which is large) plays a dominant role. The randomness and global search ability of the algorithm will increase, but it will take more time to assemble. When ρ is large, good data input is important, and the integration speed is fast, but the research is weak and easily falls into the category of local improvement.

The relationship between residual coefficient 1-ρ and path length L is shown in Figure 5.

In the ant colony algorithm, when choosing the pheromone volatilization coefficient ρ, it is necessary to comprehensively determine the global detection ability and convergence speed. We need to choose a suitable one according to the actual needs of the specific problem in order to quickly achieve a balance of international research and integration. In general, the security and global research capabilities of an algorithm should be determined in advance, followed by rapid competition. Experiments show that, in general, when the value range of ρ is 0.5–0.7, the performance of the algorithm is stable and can obtain better convergence speed and search efficiency.

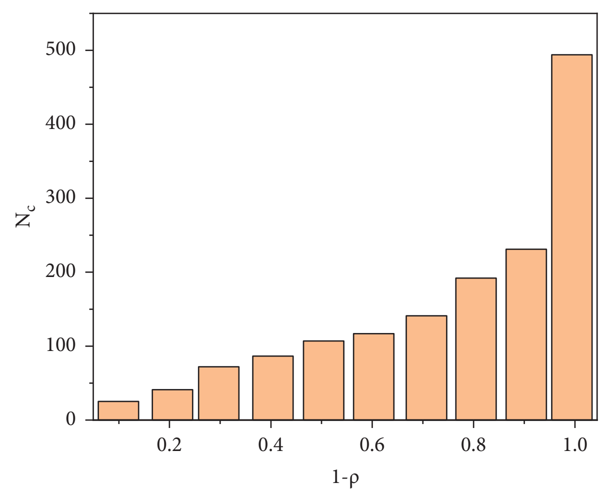

Figure 4: Relationship between 1-ρ and convergence algebra NC.

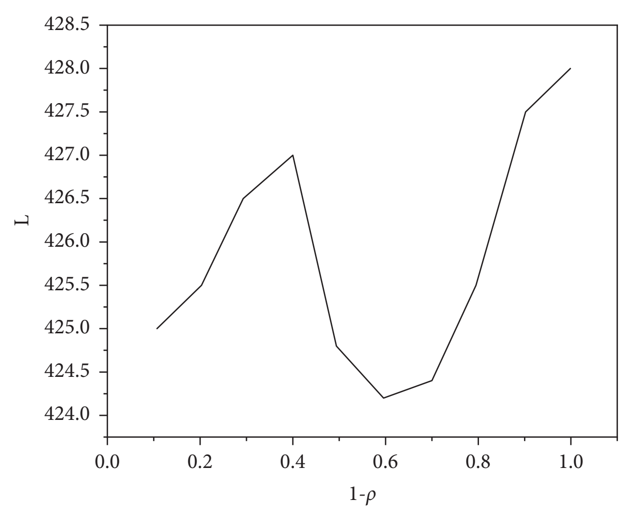

Figure 5: Relationship between 1-ρ and path length L.

4.4. Definition and Characteristics of Ant Colony Algorithm

4.4.1. Definition. Ant colony optimization algorithm is a classic swarm intelligence algorithm for solving combinatorial optimization problems. The optimization mechanism of the ant colony algorithm can be divided into two stages as follows. Adaptation stage: the model of the candidate solution is continuously adjusted according to the data written in the method. Cooperation stage: in order to produce better solutions, information exchange should be carried out between candidate solutions.

As shown in Figure 6, the process of ants differs from the most commonly used data in the world, while other regional data are designed to use local files. Experiments show that the calculation effect of the ant week system is better than the latter two. Therefore, the semicircle is usually chosen as the basic model of the ant colony algorithm [26]. The experiment chose a 20-node problem to go to the retail market. The number of iterations is 1000, the number of cochlear ants is $m = 20$, and other default values are as follows:

$$\alpha = 1, \beta = 2, \rho = 0.3, Q = 100. \quad (18)$$

Take 5 better results, as shown in Table 2.

4.4.2. Characteristics. The main features of ant colony algorithm include the following: distributed computing without central control and self-organization. Ant colony realizes complex and orderly group behavior through information interaction among individuals; Compared with other algorithms, parallelism is an obvious advantage of ant colony algorithm. Its search process does not start from one

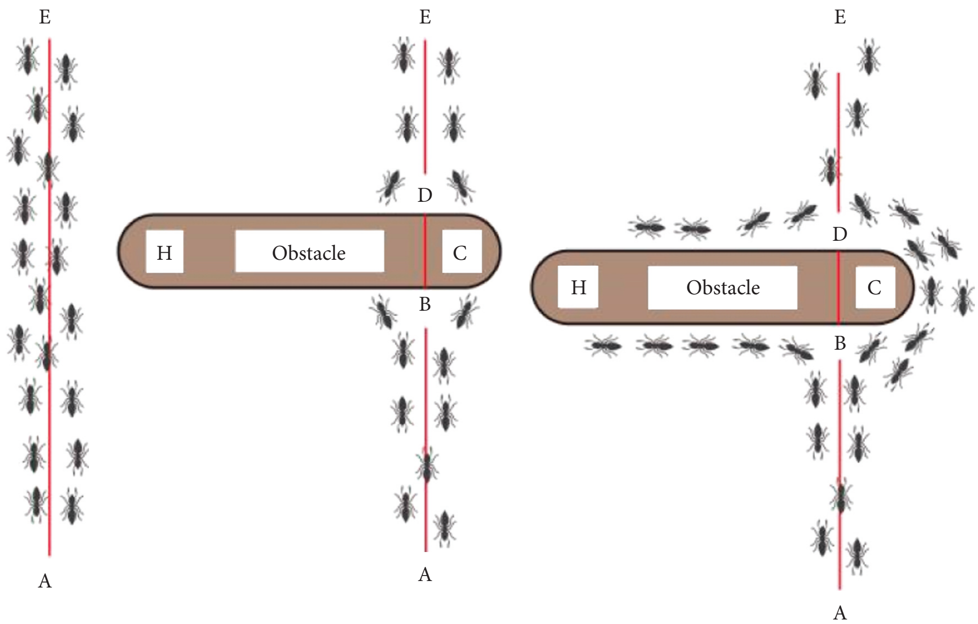

Figure 6: Diagram of the shortest path found by real cochlear ant.

Table 2: Experimental results of three basic mother ant system models.

Number of experiments	Ant-density system	Ant-quantity system	Ant-cycle system
1	33.154824	28.543268	24.268741
2	27.365182	27.216583	27.226584
3	29.265716	27.112642	25.954268
4	27.351954	30.268841	27.335894
5	30.255871	32.164482	25.365498
Average length	29.4787094	29.0611632	26.030197

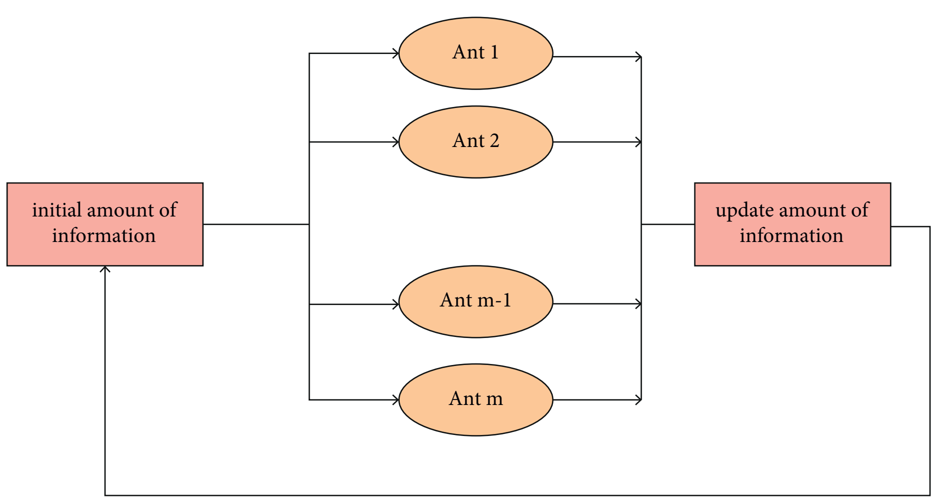

Figure 7: Schematic diagram of ant colony system parallelism.

point, but from multiple points at the same time. In the ant colony model for solving VRP, m cochlea ants are independent of each other; that is, each mother ant selects an independent path, and there is no mutual interference with each other (as shown in Figure 7). The results produced by the M mother ants at time t affect the mother ants starting after time T. Therefore, the M mother ants can be regarded as m parallel behavior residents, and the operation efficiency and response ability of the whole algorithm will be greatly improved due to the adoption of distributed parallel mode.

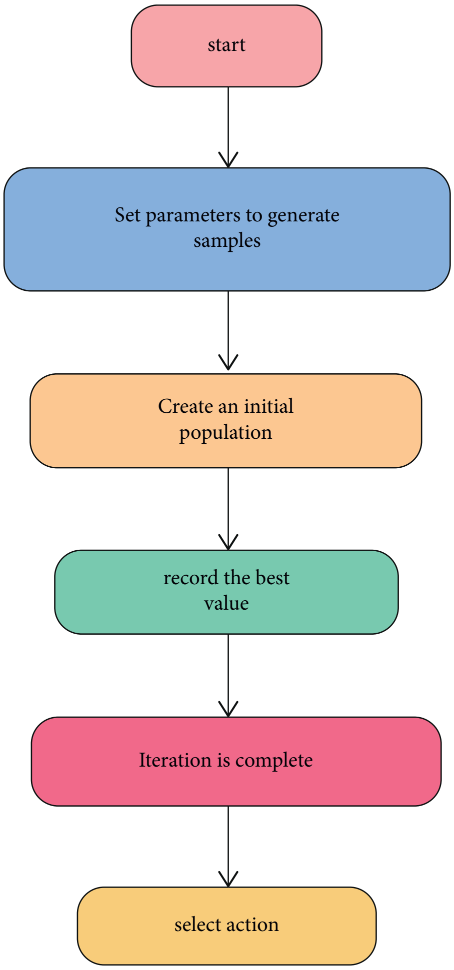

Figure 8: Design flow chart of hybrid genetic algorithm.

It is a probabilistic global search algorithm. Uncertainty provides algorithms with multiple ways to find global solutions; intelligent algorithms, as multiple agents, need to cooperate with each other to adapt to better environments. The lack of some knowledge to solve the problem will not have a serious impact on the algorithm optimization.

4.5. Hybrid Genetic Algorithm Design. The main flow of hybrid genetic algorithm design is shown in Figure 8.

4.5.1. Generate Sample Data. According to the sample mean approximation method, the data needs to be processed before designing the main program; that is, a certain number of sample data are generated as sample values, which are independent of each other and obey the same distribution. In this paper, a sample corresponds to the demand of each cycle in the retailer's planning period. Firstly, the demand mean of each retailer is generated, and then the standard deviation is obtained according to the mean and the relationship between the preset mean and standard deviation, and then the demand subject to a certain distribution can be generated.

Table 3: Ranking of saved mileage.

Serial number	$s\ (i,\ j)$	$(i,\ j)$
1	91.2377	(3, 5)
2	46.2647	(2, 8)
3	29.3426	(2, 4)
4	27.1356	(6, 7)
5	11.2647	(2, 3)
6	4.0064	(4, 5)
7	0.8425	(2, 6)
8	0.2336	(5, 8)

4.5.2. Design Coding Scheme. According to the relevant parameters of inventory strategy set in the research of inventory path optimization based on VMI, this paper uses integer coding to encode the chromosome. Suppose that the supplier distributes goods to n retailers with vehicles with the same model.

4.5.3. Population Initialization. When the population is initialized, a certain number of chromosomes are randomly generated as the initial population of genetic evolution. Due to the parallel search ability of genetic algorithm, the amount of data to be processed in each iterative evolution process is very large. Therefore, the setting of population size will inevitably affect the optimization results and operation efficiency of genetic algorithm. So far, the optimal population size has not been determined, which is generally selected between 10 and 200. This paper sets the population size as 20 according to the actual needs. During population initialization, 20 individuals are randomly generated as the first generation chromosomes according to the coding scheme; that is, the replenishment points are coded according to the coding method set in the coding scheme to generate the initial population.

4.5.4. Chromosome Decoding. After the initialization of the population, the initial solution needs to be generated by decoding; that is, the distribution volume is calculated and output according to the randomly generated 8 individuals. Secondly, the C–W algorithm is called to divide the paths of these retailers based on the vehicle capacity. When dividing the route, first find the retailer to be delivered and the corresponding location coordinates; secondly, the distance between two points is calculated, and, on this basis, the saved mileage value is calculated to form a saved odometer. Then, the saved mileage values in the saved odometer are arranged in descending order; finally, according to the vehicle constraints, the retailer combination in the energy-saving odometer is reasonably arranged to form an effective distribution line. The sequence number of each point pair in the table is the renumbered sequence number, which can be restored after completing the path division. Finally, check the corresponding points i and j item by item according to the sequence of saved mileage values s (i, j) shown in Table 3 and generate effective lines according to onboard constraints.

After the division is completed, the objective function is calculated. Each person has f fitness models; that is, calculate f times for each person and take the average value as the target value. At this time, the generation process of the initial solution ends, find out the optimal value (i.e., the minimum value of the total cost in the planning period), and record it. The next step is to enter the main cycle of genetic algorithm, through the process of allocating fitness value, selection, crossover, and mutation, decode according to the above decoding method, find the optimal value and record it, and continue to iterate in this way until the termination condition is reached, so as to complete the improvement process of the initial solution and finally find the optimal solution.

4.5.5. Genetic Operator Design. Selection operation, also known as chromosome replication, selects individuals with good genes in the process of population evolution by simulating the phenomenon of natural selection in the biological world. Among them, the selection operator is the operation of survival of the fittest for individuals in the population. In this paper, the roulette wheel option is used for career selection, and the proportion of each person entering the next generation is expressed as the proportion of the individual body value to the number of individual body values of the entire population. The greater the fitness value, the greater the probability that an individual will be selected.

Crossover, also known as recombination, is an important set of genetic algorithms that distinguish it from other algorithms. This is the first way to create new people. In this paper, two-point crossover is adopted; that is, two natural numbers r_1 and r_2 are randomly generated in two paired individual coding strings as two intersections, and then the parts of chromosomes between the two intersections in the two individuals are exchanged. When pairing individuals, the random pairing method is adopted; that is, n individuals in the population form $[N/2]$ pairs of paired individuals in a random way, where $[X]$ represents the largest integer not greater than X. Variation is the change of one or some gene values on the chromosome with a relatively small probability. Changing the workflow with options and crossover operators can avoid some data loss due to optional and crossover operations. Reengineering is a way to help create new humans that maximize the effectiveness of genetic algorithms.

4.6. Case Analysis and Result Analysis. To identify the performance of models and algorithms, a special example was created. The research data for this list is a two-stage comprehensive data, including 10 manufacturers. Distributors set up distribution centers, which arrange the distribution of goods to retailers. The supplier monitors the retailer's inventory level in real time through the POS system. Assuming that one day is a cycle, the supplier delivers goods after the retailer closes the door every day and before the next day; that is, the order lead time is 0. The location coordinates of the distribution center are (0, 0), and the location coordinates of retailers are randomly generated and evenly distributed between (–200, 200). See Tables 4 and 5, for details.

Table 4: Distribution center and retailer coordinates.

Number	Coordinate	Number	Coordinate
1	(0, 0)	6	(−33, −120)
2	(120, −11)	7	(97, 164)
3	(−90, 102)	8	(188, 26)
4	(−44, −50)	9	(−190, 153)
5	(74, −75)	10	(37, 174)

In order to solve the model, the MATLAB calculation program is compiled. In addition, in order to avoid generating the same initial population in multiple calculations, a dynamic random number generator is defined combined with the internal time of the computer. After debugging, set the parameters of genetic algorithm, as shown in Table 6.

4.6.1. Results and Effectiveness. In order to verify the effectiveness of the joint optimization of inventory and path, under the same environment, the total cost of the planning period calculated under the decentralized decision-making is compared with the total cost of the planning period calculated under the joint optimization. The calculation method of the total cost in the planning period under decentralized decision-making is as follows: firstly, the power exponential approximation method is used to determine the replenishment point of each retailer. Then, combined with the sample mean approximation method, according to the known parameters such as the demand, opening inventory level, and maximum inventory level of each retailer, the distribution volume of suppliers as retailers in each cycle is calculated. The supplier adopts the direct distribution strategy when delivering for each retailer; that is, each vehicle can only serve one retailer in the same cycle. Thus, the total cost in the planning period including inventory cost and distribution cost can be obtained. Among them, inventory cost includes inventory holding cost and shortage loss cost, and distribution cost includes vehicle start-up cost, vehicle driving cost, and labor cost. When the power exponent approximation method is used to determine the replenishment point, the fixed cost is determined by averaging the number of vehicles required in each cycle of 15 cycles in the planning period obtained from the above joint optimization results; that is, the average number of vehicles required in each cycle is 3, and the vehicle start-up cost of 3 vehicles is taken as the fixed cost. The significance of using the sample mean approximation is that the result is the sample mean of the random model; that is, for each group of retailer replenishment points, the average of multiple samples is calculated many times and taken as the objective function value. Table 7 shows the results of five operations. It can be seen from the data in the table that, compared with decentralized decision-making, the total cost savings in the planning period are more than 20%. On the one hand, it shows that it is very necessary to jointly optimize inventory and path; on the other hand, it verifies that the hybrid

Table 5: Mean and standard deviation of retailer demand.

Retailer number	Average demand	Standard deviation	Retailer number	Average demand	Standard deviation
1	117	11.7	6	97	9.7
2	81	8.1	7	105	10.5
3	93	9.3	8	91	9.1
4	119	11.9	9	81	8.1
5	98	9.8	10	110	11.0

Table 6: Parameters of genetic algorithm.

Parameter	Meaning	Value
popsize	Population number	20
maxgen	Maximum number of iterations	1000
pc	Crossover probability	0.7
pm	Variation probability	0.1

Table 7: Comparison of operation results.

Operation order	Total cost in planning period			
	Decentralized decision—making	Joint optimization	ΔC	Gap (%)
1	86206.65	68230.35	17976.30	20.85
2	86354.94	67894.50	18460.44	21.38
3	87853.75	68931.17	18922.58	21.54
4	86008.20	66861.42	19146.78	22.26
5	86686.68	68285.00	18401.68	21.23

genetic algorithm is effective in solving the model to a certain extent and also reflects the feasibility of the model.

5. Conclusion

Vendor managed inventory breaks the traditional inventory management mode, manages inventory through systematic and integrated ideas, and then solves the bullwhip effect. The core problem of implementing VMI strategy is the joint optimization of inventory and path. At present, VMI strategy has been successfully applied in chain supermarkets, automobile manufacturing, petrochemical, and other industries. Effectively solving this problem can reasonably save costs for enterprises and improve their economic benefits. The research on inventory path optimization based on VMI provides decision support for the core problems in the effective implementation of supplier managed inventory strategy and has strong research significance. Taking the vehicle routing optimization problem in the process of logistics distribution as the research object, this paper focuses on several representative vehicle routing optimization problems: vehicle routing problem with capacity constraint, vehicle routing problem with time window constraint, vehicle routing problem with simultaneous delivery and pickup, and multiobjective vehicle routing problem and establishes various mathematical models. Based on the in-depth analysis of the internal operation mechanism and influencing factors of ant colony algorithm, this paper proposes two improved ant colony algorithms and analyzes the performance of the algorithm through experimental simulation. The simulation results show that the hybrid ant colony algorithm has strong global and local search ability. When the algorithm falls into local extreme points, the crossover operator designed in this paper can generate a new search area and continue the search, so as to expand the search space and avoid the stagnation of the algorithm. Mutation operation can significantly strengthen the local search ability of the algorithm and help to improve the quality of the solution. Combined with the structural characteristics of vehicle routing optimization problem, the hybrid algorithm adopts real number coding scheme, and the chromosome (solution) directly reflects the actual path, which is more intuitive. At the same time, it also ensures the feasibility of the solution generated by the current solution after algorithm operations such as crossover and mutation. In the hybrid algorithm, the adoption of dynamic local update strategy increases the opportunity to explore unused edges and avoids the “premature” of the algorithm to a certain extent.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this article.

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