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Research Article

Expectation-Maximization Algorithm of Gaussian Mixture Model for Vehicle-Commodity Matching in Logistics Supply Chain

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A vehicle-commodity matching problem (VCMP) is presented for service providers to reduce the cost of the logistics system. The vehicle classification model is built as a Gaussian mixture model (GMM), and the expectation-maximization (EM) algorithm is designed to solve the parameter estimation of GMM. A nonlinear mixed-integer programming model is constructed to minimize the total cost of VCMP. The matching process between vehicle and commodity is realized by GMM-EM, as a preprocessing of the solution. The design of the vehicle-commodity matching platform for VCMP is designed to reduce and eliminate the information asymmetry between supply and demand so that the order allocation can work at the right time and the right place and use the optimal solution of vehicle-commodity matching. Furthermore, the numerical experiment of an e-commerce supply chain proves that a hybrid evolutionary algorithm (HEA) is superior to the traditional method, which provides a decision-making reference for e-commerce VCMP.

1. Introduction

With the development of Internet technology, a series of new solutions and adjustments are designed to the layout of the logistics industry. In the past, the distribution centers of producers nationwide have gradually evolved into personalized orders, which push up the update of logistics service and change the whole logistics system. The data of logistics system and customer transactions can track the execution process of order fulfillment from order allocation to order delivery on the Internet platform, so as to achieve collaborative management, service efficiency, and system cost control [1]. The firms need to synthetically balance the relationship of order service, logistics capacity, vehicle arrangement, inventory control, distribution cost, and so on, in order to form an orderly and uniform operation process [2]. For the mode of transportation, China's logistics can be divided into highway, railway, water transport, aviation, and pipeline. For e-commerce enterprises, there are limited physical resources to support offline services (e.g., vehicles and channels), so it is difficult to deal with abnormal situations in the transportation process [3], such as product deterioration caused by the mismatch between chilled/fresh products and refrigerated vehicles. Matching of vehicles and commodities promotes the whole logistics carriers' service, which is related to consumers' evaluation and feedback on the quality of commodities [4]. The importance of the vehicle-commodity matching problem (VCMP) is widely attracted to logistics companies and e-commerce enterprises.

Logistics system modeling and simulation technology are feasible and reliable to find optimal solutions for the order allocation and logistics distribution [5, 6]; Goswami et al. [7]. Yang et al. [5] formulated a cooperative rich vehicle routing problem (CoRVRP) for three typical logistics providers in the last-mile rural logistics system and it is solved by a new branch-price-and-cut algorithm. Patidar et al. [6] designed the vehicle routing for the collection of agrifood products from farmers to the market based on GA and PSO in India. Goswami et al. [7] developed a Bayesian game-

theoretic framework of product portfolio planning problem to find the right product portfolio set for the manufacturers, considering the duopolistic market and the product type. In the aspect of problems, the existing research has paid attention to the optimization of the logistics service process and the balance of interests of logistics service providers, but there is a gap in matching subprocess links in micrologistics service. Particularly, vehicles belong to the assets of enterprises, while goods belong to the needs of consumers, so the matching process is a way to improve service, which can make the connection of service links more efficient and personalized.

The plan of distribution resources (e.g., vehicles and commodity) using an intelligent algorithm and heuristic method has become a highly concerning challenge for scholars [8–11]. Regarding the evolutionary algorithm, in the research of Garg [9], particle swarm optimization (PSO) operates in the direction of improving the vector and the genetic algorithm (GA) for modifying the decision vectors using genetic operators. Garg [8] proposed the algorithm with the gravitational search method and genetic operators to upgrade solutions by selection, crossover, and mutation. Based on Garg's research, initializing the parameters can influence the design of the whole algorithm to a large extent. Therefore, our research structured the prearrangement model based on GMM and expectation-maximization (EM), so that the input parameters of the algorithm are stable.

Overall, our study makes three main contributions. First, VCMP is proposed to upgrade the service of logistics providers by matching vehicles and commodities. This is different from the global perspective of logistics system optimization; our research focuses on service details of matching. Second, our model is based on the standard GMM to optimize the input of the designed algorithm, forming a joint GMM-EM prearrangement model. Third, the GA algorithm is stable and can converge to the same solution repeatedly [8]. The convergence speed of the PSO algorithm is second, but the algorithm is not stable, and the final convergence result is easily affected by parameter size and initial population [9]. The convergence speed of the EA algorithm is relatively slow, but in dealing with the noise problem, EA can be a good solution, while the GA algorithm is difficult to deal with this kind of noise problem.

This research presents a novel expectation-maximization (EM) algorithm based on GMM for VCMP in the logistics supply chain. The remainder of this paper is organized as follows. The application scenarios of VCMP can be divided into two categories through literature review in Section 2. VCMP is described by a binary complete digraph in Section 3. On the basis of Section 3, a microoptimization model of VCMP is proposed in Section 4. In order to improve the delivery speed with stable service quality, the algorithm is designed for VCMP in Section 5. In Section 6, a numerical example is applied to the proposed models and algorithm. The conclusions and future research direction are presented in Section 7.

2. Literature Review

The application scenarios of VCMP can be divided into two categories in logistics industry.

Scenario I. Logistic companies and production enterprises have opened their own capacity pool system.

Learning from the research results of traditional industries is helpful to meet industry challenges in the era of networking. Ren et al. [3] optimized capacity allocation for cross-border e-commerce related 3PFL operations. Moghaddam [12] constructed a fuzzy multiobjective mathematical model to solve the uncertain customer order demand considering the supplier's ability and the proportion of returned products, in the reverse logistics system. Cont et al. [13] studied the order allocation model under stochastic dynamic constraints in the financial market and used matrix calculation and Laplace transform to calculate the probability of effective order allocation. Bayraktar and Ludkovski [14] based on Cont et al. considered a problem of solving the optimal clearing limit order and constructed the arrival of order as a price strength dependence. Mafakheri et al. [15] proposed a two-stage dynamic planning method for supply chain management to solve the problem of multisupplier ranking and then introduced the supplier parameters into an order allocation model to maximize the utility of the company. Kannan et al. [16] further expanded the research of Mafakheri to obtain a set of systematic methods. Azadnia et al. [17] proposed a comprehensive method based on rule weighted fuzzy algorithm, combined with multistage. The fuzzy analytic hierarchy process and multiobjective mathematical programming were used to solve the problem of multiproduct batch. The past research has mainly researched the optimization of different logistics services and the balance of interests of service providers, but there is a lack of matching subprocess of logistics service. Our research focuses on this gap to find a matching mechanism between vehicle service and commodity service so that a compact and personalized service process is designed and provided to consumers.

Scenario II. The public platform gathers the social capacity resources with the vehicle matching software.

The research on using intelligent algorithms to solve the integration problem of order and logistics distribution is becoming more and more obvious. Dávid and Krész [4] introduced the schedule assignment problem for public transit in the fleet of a transportation company. Torfi et al. [18] used FMCDM to determine the weight of multiple objectives in the location path problem and found the route from DCS to customers to minimize the total distribution network cost. For example, Marinakis [19] proposed an improved particle swarm optimization algorithm for the discrete optimization of the location path of random demand. The heuristic method can effectively deal with the problem of order allocation and location selection. Macedo et al. [20] proposed a metaheuristic algorithm for system exploration based on different neighborhood structures, which decomposes the integration problem into two subproblems, that is, vehicle routing problem and

location problem, so as to ensure shorter order processing time. The order allocation problem is more systematic and integrated with the downstream links such as path planning and inventory allocation. Foreman et al. [21] studied the supply optimization of Dell's transportation network based on order components. Yue et al. [22] found that enterprises' manufacturing can calculate all possible combinations of total cost and punctuality probability by order. Therefore, the portfolio method can not only ensure the low cost of the manufacturer's order purchase process but also meet the customer's requirements without failure activity. In recent years, [23–26] studied selecting suppliers for decision-maker, considering the price, the quality of purchased parts, the reliability of on-time delivery, and the risk factors of delayed delivery. According to Ren and Croson [27], different decision-makers often make suboptimal decisions in the face of changing supply chain and inventory allocation. Pan et al. [28] established a multiobjective linear order allocation model for information service enterprises with the objective of minimizing the discount cost, taking into account the influence of factors such as capacity and price. Hall et al. [29] found that, in a multiproduct supply chain, manufacturers receive orders from several distributors. If the available production capacity cannot meet all orders, distributors need to plan the distribution of capacity in advance before the order is reallocated. Garg [9] designed particle swarm optimization (PSO) for improving the vector and the genetic algorithm (GA) for modifying the decision vectors. Garg [8] proposed the gravitational search method and genetic operators to upgrade solutions by selection, crossover, and mutation. Based on existing research, the optimization of the algorithm depends on the model design and structure. Therefore, our research structured GMM-EM as the prearrangement so that the input parameters are suitable for the proposed hybrid evolutionary algorithm.

To sum up, the research so far shows that the research on order allocation of the logistics system is often combined with other classical service processes. There are three gaps in the existing research. Firstly, there are not enough integrated service factors to consider in the logistics system, such as order allocation, vehicle service, and personalized service. Secondly, most of the researches ignore the role of matching problem in the whole distribution process. Thirdly, the research and application of the heuristic method need to be improved to make it better combined with the model.

This paper aims at the cost optimization of the whole logistics operation process of e-commerce enterprises from order allocation to order delivery. VCMP is presented for commodity and vehicle to reduce the cost of the logistics system. GMM-EM is designed to solve the parameter estimation to optimize the algorithm. VCMP is designed to reduce and eliminate the information asymmetry between supply and demand, so that the order allocation can work at the right time and the right place and use the optimal solution of vehicle-commodity matching.

3. Vehicle-and-Commodity-Matching Problem (VCMP)

VCMP is described as a binary complete digraph, in which the node set is V. The vehicles with different service levels go back and forth between the warehouses and consumers to execute order fulfillments. Therefore, the vehicles must start from the assigned warehouse and choose the appropriate order distribution path. This process can be expressed as the arc set $E = \{(i, j): i, j \in V\} \backslash \{(i, j): i \in V_w, i \neq j\}$. The non-negative weight W_{ij} of each arc $(i, j) \in E$ is the transportation between the warehouses and the consumers. The variables' descriptions are shown in Table 1.

As shown in Figure 1, the matching process of VCMP is divided into four parts, including customers, orders, vehicles, and warehouses. Firstly, customers place orders on the Internet platform, and the e-commerce enterprise services the orders forming feedback information of order delivery. Customers' order information is divided into a sequential order flow from order 1 to N. Secondly, an order allocation process begins to form a commodity flew corresponding to order sequence. And then the matching step is started for commodities and vehicles. The matching process is required to invoke GMM-EM as a pretreatment. Thirdly, the path selection is computed for the initial location of the vehicle and the fixed location of the warehouse and supported by a new improved evolutionary algorithm. Fourthly, the selected warehouse is identified to generate the solution of order fulfillment for costumer.

The matching process of VCMP in Figure 1 is described by order allocation, matching, and path out. Finally, the logistics and delivery should be enabled for the Internet platform and the execution information is fed back.

4. Modeling

There are many factors to be considered in the integration of the logistics system for order allocation in multiple warehouses [30]. The logical relationship framework is shown in Figure 2. A system optimization model is proposed.

In Figure 2, the matching problem of VCMP is based on the data set of the enterprise. There are five kinds of data in the matching database, which is analyzed and mined to form a matching scheme. The model is built on the rationality of implementation in the sets of order, path, warehouse, and vehicle. In the process of modeling, capacity constraints are considered from two aspects, warehouse and vehicle. For costumer, the model considers the requirement of service time because logistics time is an important factor to measure service standards. Figure 2 summarizes the constraints that we need to consider during the modeling process.

Table 1: Variables' descriptions.

	Sets
V	The set of points i and j
P	The set of warehouse p
Q	The set of vehicle q
	Parameters
x_p	0-1 variable: 1 means that the warehouse p is selected; otherwise, it is 0
b_p	Unit fixed cost of warehouse
y_{ij}^q	0-1 variable: 1 means vehicle q from i to j; otherwise, it is 0
H_q	Unit fixed cost of freight vehicles
W_{ij}^q	The variable cost of transportation process from i to j
α_{ip}	0-1 variable: 1 means that the order i is assigned to warehouse p; otherwise, it is 0
β_{ij}^q	The load of vehicle q from node i to node j; $B_{ij} = \sum_Q \beta_{ij}^q$
t_i^q	The service start time for vehicle q from node i to j under time window constraint, $t_i \in t_i^q$
S_p	The upper limit load of warehouse

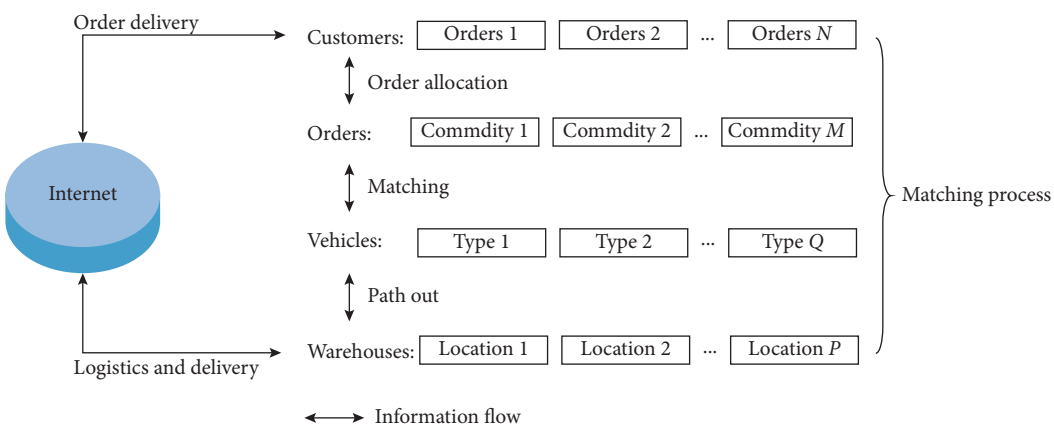


Figure 1: Schematic diagram of matching process.

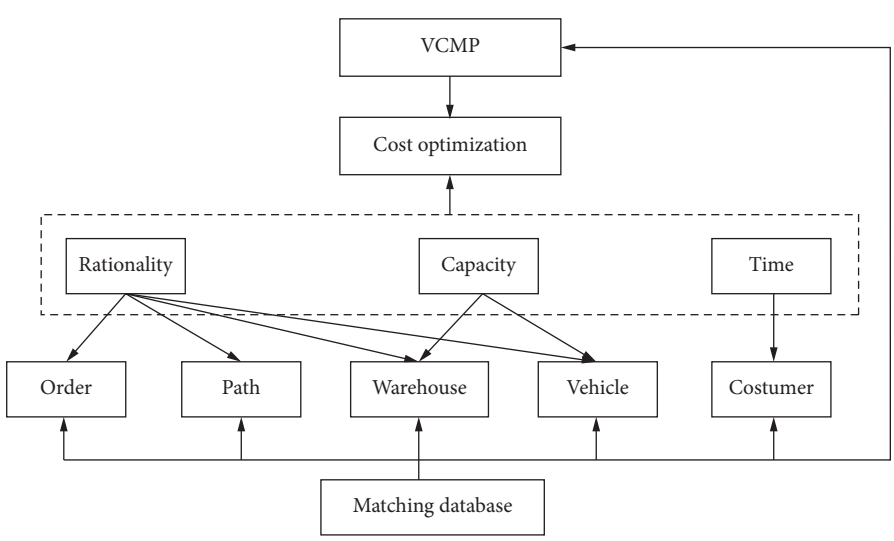


Figure 2: Logical block diagram of the model.

4.1. Objective Function. The total cost (TC) of the distribution process includes three parts: fixed cost of distribution warehouse, fixed cost of freight vehicles, and variable cost of transportation process. The objective function of the integration problem is as follows:

$$\min TC = \sum_P b_p x_p + \sum_Q \sum_V \sum_V H_q y_{ij}^q + \sum_Q \sum_V W_{ij}^q. \quad (1)$$

4.2. Constraints

4.2.1. Rationality Constraint. Although splitting the order will make commodities be delivered to consumers earlier, it will also increase the frequency of picking up and the cost of logistic time. At the same time, it also causes waste of resources in e-commerce distribution. Based on these two considerations, in order to avoid repeated distribution of orders, each order is processed by one vehicle only once.

$$\sum_Q \sum_V y_{ij}^q = 1. \quad (2)$$

The order distribution process is a closed loop, so it is necessary to ensure that the vehicles start from the warehouse and go back to the same one:

$$\sum_Q \sum_V y_{ji}^q = \sum_Q \sum_V y_{ij}^q. \quad (3)$$

Subloops removing constraints are as follows:

$$y_{ji}^q + y_{ij}^q \le 1. \quad (4)$$

The warehouse serving the customer's order is noted as the supply status:

$$x_p \ge \alpha_{ip}. \quad (5)$$

The allocation constraints of warehouse and vehicle are expressed as equations (6) and (7) for the order response, respectively. Both ensure that each order is allocated only once.

$$\sum_P \sum_V \alpha_{ip} = 1, \quad (6)$$

$$\sum_Q \sum_V y_{jj'}^{q'} + y_{ij}^q \le 1, \quad j \ne j', q \ne q'. \quad (7)$$

Avoid unreasonable routes $(v_p, v_1, v_2, \ldots, v_i, v_{p'}), p \ne p'$:

$$\sum_Q \sum_P \sum_V y_{ip}^q \le \alpha_{ip}, \quad (8)$$

$$\sum_Q \sum_P \sum_V y_{pi}^q \le \alpha_{ip}, \quad (9)$$

$$\sum_Q \sum_V \sum_V y_{ij}^q + \sum_V \sum_P \alpha_{ip'} + \alpha_{ip} \le 2, \quad p' \ne p,\ p \in P. \quad (10)$$

The carrying capacity of each node changes is described as d_i

$$d_i = \sum_Q \sum_V \beta_{i-1,i}^q - \sum_Q \sum_V \beta_{i,i+1}^q. \quad (11)$$

The order cannot be split, so each time when the vehicle returns to the warehouse means that a batch of orders have been processed. At this time, the vehicle load should be equal to 0; that is,

$$\sum_Q \sum_V \sum_V \beta_{ji}^q = 0. \quad (12)$$

4.2.2. Capacity Constraints. The total load of orders shall not exceed the transportation capacity of vehicles. N_q is the remaining load of the vehicle:

$$\beta_{ij}^q \le y_{ij}^q N_q. \quad (13)$$

The warehouse inventory configured by e-commerce enterprise is enough to meet the order allocation.

$$\sum_Q \sum_V \beta_{ij}^q \le \sum_P \sum_V \alpha_{jp} d_i. \quad (14)$$

For order allocation, it is necessary to consider the load capacity limit of the allocated freight vehicles and the load boundary constraint.

$$\beta_{ij}^q \le \left(N_q - d_i\right) y_{ij}^q, \quad (15)$$

$$\beta_{ij}^q \ge d_j y_{ij}^q. \quad (16)$$

The total supply of the configured warehouse cannot exceed its actual total capacity. S_i is the upper limit load of point i and then S_p is the upper limit load of warehouse point.

$$S_p x_p \ge \sum_V d_i \alpha_{ip}. \quad (17)$$

The open quantity of warehouse constraint is

$$\min x_p \le \sum_P x_p, \quad \min x_p \in \left\{ \sum_P S_p \ge \sum_V d_i \right\}. \quad (18)$$

4.2.3. Time Window Constraints. If the vehicle arrives at node $i \in V$ before time point l_i, it must wait until time point l_i to provide delivery service. h_i is the end of time window.

$$T_i + W_{ij} + t_i^q - t_j^q \le M\left(1 - y_{ij}^q\right). \quad (19)$$

M is an artificial variable.

$$l_i \le t_i^q \le h_i, i \in V, q \in Q. \quad (20)$$

4.3. Model Analysis and Function Transformation. Equation (1) is the objective function of the integration problem. Equations (1)–(20) are the constraint condition of the logistics service process model. The model is simplified as follows. The objective function is decomposed and the

relaxation constraint is tightened. Note that the total load weight of the vehicle q traversing from i to j is $B_{ij} = \sum_Q \beta_{ij}^q$. The variation equations (11)–(16) can get equations (21)–(26):

$$\sum_V \sum_V B_{ji} - \sum_V \sum_V B_{ij} = d_i, \tag{21}$$

$$B_{ij} \le \sum_Q \sum_V \sum_V N_q y_{ij}^q, \tag{22}$$

$$\sum_V \sum_V B_{ij} - \sum_V \sum_V \alpha_{ji} d_j = 0, \tag{23}$$

$$\sum_V \sum_V B_{ij} = 0, \tag{24}$$

$$B_{ij} \le \sum_Q \sum_V \sum_V \left(N_q - d_i\right) y_{ij}^q, \tag{25}$$

$$B_{ij} \ge d_j \sum_Q \sum_V \sum_V y_{ij}^q. \tag{26}$$

Let (μ, ν) be the solutions of (21)–(26) and (ω, ν) be the solutions of constraints (2) and (11)–(16). (μ, ν, ω) are the vectors of B_{ij}, β_{ij}, and y_{ij}^q, respectively. For the feasible solutions of (ω, ν), there is a feasible solution (μ, ν), and vice versa. By (2), there is $y_{ij}^{q*} = 1$, $q* \in Q$. At the same time, there is $\beta_{ij}^{q*} \ge 0$ by formula (15); namely,$\beta_{ij}^q = y_{ij}^q = 0$, $q \in Q - \{q*\}$.

The transformation of inequalities (19) and (20) are as follows.

Note that $B_{ij} = \sum_Q \beta_{ij}^q$, $T_{ij} = \sum_Q t_i^q$, and M is an artificial variable:

$$M\left(1 - \sum_Q y_{ij}^q\right) \ge S_i - S_j + T_i + W_{ij}, \tag{27}$$

$$l_i \le t_i^q \le h_i. \tag{28}$$

Constraints (3) and (7) are simplified. Let i, j, k be set as an effective equation representing the equivalent route $q_1, q_2 \in Q$, $y_{ij}^{q_1} = 1$, $y_{jk}^{q_2} = 1$. Constraint (3) and constraint (7) only allow the same vehicle; that is, $y_{ij}^{q_1} = 1$, $y_{jk}^{q_1} = 1$. From (3) and (7),

$$\sum_V y_{ji}^q = \sum_V y_{ij}^q. \tag{29}$$

5. Algorithm Design

In order to improve the delivery speed with the stability and continuity of service quality, the VCMP is realized by clustering the characteristics of related data (vehicles and commodities).

The basic idea of the algorithm is as follows.

Firstly, the parameters of the Gaussian model are estimated for each distribution vehicle by initializing the parameters and the results of the previous iteration. Secondly, the parameters of the Gaussian model are estimated again based on the estimated weight value. Finally, repeat the above steps until the fluctuation is very small and reaches the extreme value. The specific implementation steps are as follows.

Step 1. Initialize $\alpha_{q0}, \mu_{q0}, \sum_{q0}$.

Step 2. Set a posterior probability of α_q.

$$\beta_{q'q} = \frac{\alpha_q P_q\left(x_{q'}|\lambda\right)}{\sum_Q \alpha_l P_l\left(x_l|\lambda\right)}. \tag{30}$$

Step 3. Update the Gauss weight, mean value, and covariance matrix as follows:

$$\begin{aligned} \alpha_q' &= \frac{\sum_{q'}^Q \beta_{q'q}}{Q}, \\ \mu_q' &= \frac{\sum_{q'}^Q \beta_{q'q} x_{q'}}{\sum_{q'}^Q \beta_{q'q}}, \\ \sum{}_q' &= \frac{\sum_{q'}^Q \beta_{q'q}\left(x_{q'} - \mu_{q'}\right)\left(x_{q'} - \mu_{q'}\right)^T}{\sum_{q'}^Q \beta_{q'q}}. \end{aligned} \tag{31}$$

Step 4. Repeat Step 2 and Step 3 to update the three parameters until the algorithm converges, $|L(X|\lambda)^{(l)} - L(X|\lambda)^{(l+1)}| \le \varepsilon$.

The matching process of GMM-EM is shown in Figure 3. The first step is to train the sample of order data, path data, consumer data, warehouse data, and vehicle data, forming the initial data sets. The second step is to extract the eigenvalues for each data set for feature extraction. Make the results of the second step as input data into GMM-EM and then start step 4 to get the classification calculation of vehicle and commodity data. The final step is to get the matching classification value from 1 to H, which provides input for the path decision. The whole block diagram shows the basic logic of preprocessing.

Figure 4 gives an example of the pruning and inserting process in the self-adaptive neighborhood search algorithm. Figure 4(a) shows the initial location of warehouses (1, 2, and 3) and consumers (A, B, C, D, E, F, G, and H). We need to find the matching path of the three types of vehicles (oversize vehicles, medium-sized vehicles, and small vehicles) through the evolutionary algorithm to connect the consumer and the warehouse.

Figure 4(b) is the initial distribution scheme. The distribution area is radiated outward with the warehouse as the center. The discrete points scanned by the distribution area radius are recorded as the selected consumer points. The initial population size n is generated. The parent population obtains the offspring through the competitive selection strategy. The cross operation obtains the new offspring and then the partition operation divides the offspring nodes into the path selection. The adaptive neighborhood search algorithm learns to train the offspring and inserts them into the population. In the process of learning and training, the

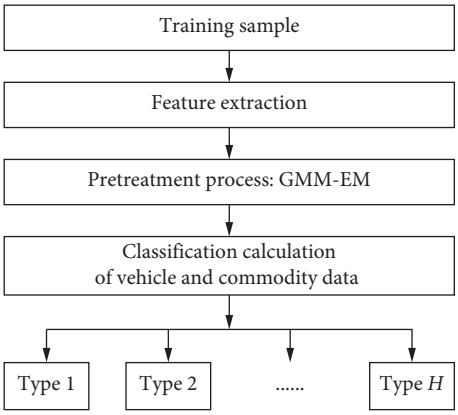


Figure 3: Schematic diagram of GMM-EM for VCMP.

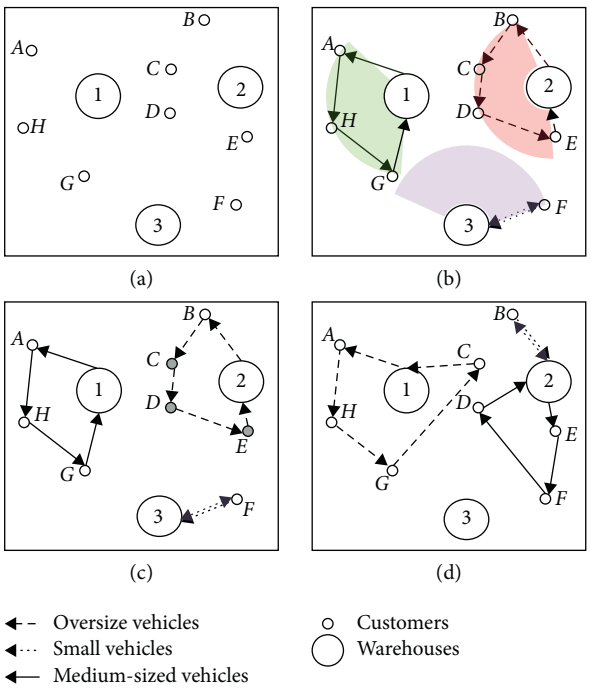


Figure 4: Adaptive neighborhood search process of evolutionary algorithm.

adaptive weight updates the probability associated with the adaptive neighborhood search.

Figure 4(c) shows the warehouse selection operation of the hybrid evolutionary algorithm. In terms of adaptability, the evolutionary algorithm focuses on the selection of excellent offspring and their behavior chain, which is suitable for solving integrated optimization problems. The initial solution is obtained by initializing the population data for the location path selection for VCMP. The adaptive neighborhood search algorithm is used as the learning and training stage of the solution process, and then a descendant partition is carried out to obtain the path solution for vehicle distribution that needs to traverse the warehouse to determine the route. Finally, we can get more solutions from the evolutionary stage.

Figure 4(d) is the result of the evolutionary algorithm. GMM-EM operator strengthens the evolutionary process to get the feasible solution after evolution. In the evolutionary process, new offspring are generated to join the population, and the number of offspring that can be further increased is m, and then the upper limit is $m+n$. If the number of iterations does not exceed the upper limit and the population size reaches the upper limit $m+n$ after training, the surviving offspring will be generated. Mutation stage is a feasible solution which can be generated by randomly selecting the evolved individuals from the population according to the size of probability.

6. Numerical Experiment

6.1. Experimental Data and Parameter Setting. The case data comes from Suning cloud store's plan to build an e-commerce shopping platform for a city. The goal is to integrate the O2O platform of commodities management, order information, logistics supply chain, and service delivery into one regional management. There are 6 open transfer warehouses in the city, with cost range of [36000, 50000], [80000, 120000], [16000, 25000], [85000, 100000], [16000, 28000], and [82000, 100000] separately. The operating costs of each warehouse are distributed within an interval. 100 samples of consumer orders are selected randomly, and the service capacity gradient of corresponding warehouse changes are shown in Table 2. Table 2 shows the changes in the number of consumer orders that the warehouse serves currently. The number of service consumers reflects the service capability of the warehouse. For example, when the service size is 10, the cost range of warehouse no. 1 is [90, 110], but when the service size is 20, the cost fluctuation range of warehouse no. 1 is [160, 220].

6.2. Experimental Results. According to the characteristics of load and fuel consumption, vehicles are divided into large vehicles, medium vehicles, and small vehicles. The service scheme of personalized matching consumer orders is designed to make full use of existing data resources and improve the accuracy of VCMP. GMM-EM algorithm is used to match vehicles and commodities according to time window, distribution distance, and path characteristics.

According to Table 3, the sample sets are tested in four situations. The hybrid evolutionary algorithm is tested in four cases. The differences of the total cost, error rate, and running time are calculated in the comparison sample set, with four situations based on three degrees of evolution (training, strengthen, and mutation) in Table 4. It can be seen that as the complexity of the algorithm increases from no evolution to complete evolution, the operation time increases, the error rate gradually decreases, and the planning cost also decreases with the increase of accuracy.

Table 4 selects 10 groups of customer nodes randomly to verify that situation 4 (in Table 3) of the algorithm is optimal to improve the calculation accuracy, with an average error of 1.53% (in Table 4). The accuracy in situation 4 is higher than that in the other three cases. In terms of the running time, it

Table 2: Gradient warehouse capacity and service scale.

Service scale	Cost ($/day)					
	Warehouse 1	Warehouse 2	Warehouse 3	Warehouse 4	Warehouse 5	Warehouse 6
10	90–110	100–120	80–90	95–100	140–160	160–190
20	160–220	160–210	110–160	120–180	110–160	230–250
30	190–230	220–230	140–170	150–290	140–170	270–320
40	220–310	230–330	170–220	180–350	170–270	350–630
50	530–620	320–410	280–350	290–540	350–650	390–700
60	650–800	500–630	280–550	310–620	480–790	500–820
70	810–900	520–630	350–530	370–680	550–870	580–850
80	815–900	660–730	510–710	520–810	610–900	620–890
90	750–950	780–930	550–900	600–920	660–980	750–920
100	780–1000	820–1080	700–1000	750–1100	790–1130	800–1300

Table 3: Test of hybrid evolutionary algorithm.

	Situation 1	Situation 2	Situation 3	Situation 4
Training	×	√	√	√
Strength	×	×	√	√
Mutation	×	×	×	√

Table 4: The operation results of hybrid evolutionary algorithm in four cases.

	Situation 1			Situation 2			Situation 3			Situation 4		
	Cost ($)	Error (%)	Time (s)	Cost ($)	Error (%)	Time (s)	Cost ($)	Error (%)	Time (s)	Cost ($)	Error (%)	Time (s)
1	392	4.25	271.16	330	2.55	330.19	305	2.04	363.21	379	**1.43**	381.37
2	401	3.33	283.54	801	2.00	337.85	481	1.60	371.63	321	**1.12**	390.21
3	492	4.87	290.39	472	2.92	348.47	103	2.34	383.31	310	**1.64**	402.48
4	556	4.97	265.88	603	2.98	314.26	494	2.39	345.68	506	**1.67**	362.97
5	803	5.61	277.56	430	3.37	335.47	529	2.69	369.02	181	**1.88**	387.47
6	537	4.26	283.17	235	2.56	336.20	678	2.04	369.82	627	**1.43**	388.32
Ave	**530**	**4.55**	**278.62**	**479**	**2.73**	**333.74**	**432**	**2.18**	**367.11**	**387**	**1.53**	**385.47**

becomes longer as the complexity of the algorithm increases. Thus, for VCMP, accuracy is the most important. Therefore, the proposed algorithm improves the matching accuracy through the cost of time.

6.3. Comparison and Sensitivity Analysis. The constraints are classified and solved according to the following four divisions based on the attribute analysis of logistics service for VCMP. As shown in Table 5, the Lagrangian relaxation degree of different divisions is obtained by relaxing the constraints of variable y_{ij}^{q}, among which four kinds of constraints (I, II, III, and IV) have similar solution space. For example, both formulas (2) and (3) express constraints related to the binary variables selected for the order in Table 5. Table 6 shows the comparison results between Lagrange relaxation and the algorithm in this paper.

The first two columns of Table 6 show the set size of customer quantity and warehouse quantity, respectively. From Table 6, it can be found that the HEA error fluctuation is below 8% and the error variation range of LP relaxation is below 16% in terms of accuracy, as the sample size of customer increases to 150 with the amplitude of 10 and 50. The whole operation time of LP relaxation is significantly larger than HEA with the increase of data volume.

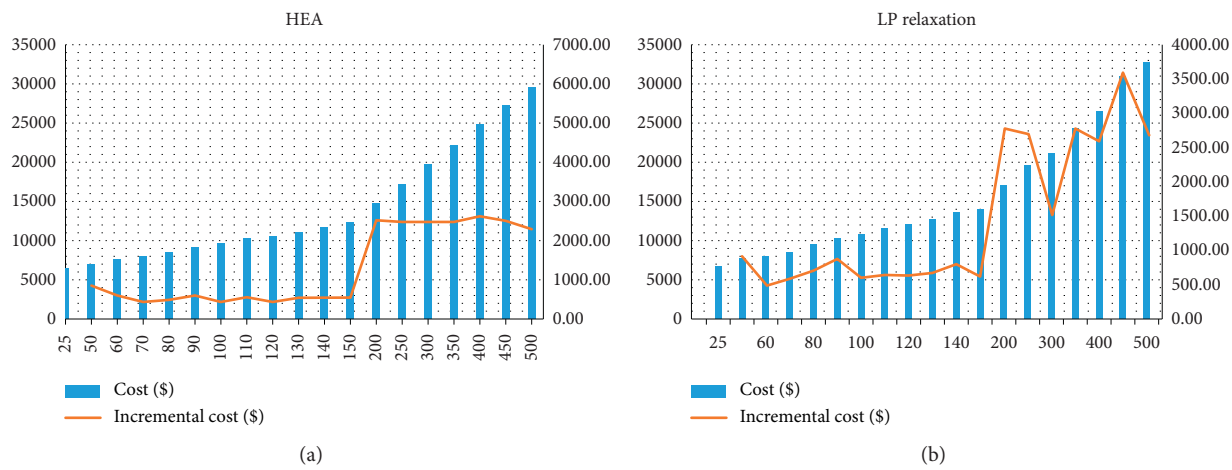
Table 5: Constraint classification.

Constraint	Inequality
I	(2)-(3), (6)–(10), (17), (19)-(20), (21)–(26)
II	(2)-(3), (6)–(10), (12)-(13), (15)–(17), (19)-(20)
III	(2)-(3), (6)–(10), (17), (21)–(26), (27)-(28)
IV	(2), (6), (8)–(10), (21)–(26), (17), (27)–(29)

The trend of target cost and cost increment can be seen from Figure 5. Figure 5(a) shows the cost situation of HEA, and the overall cost change range is [5000, 30000]. The cost increment jumps with the increase of sample point increment range from 1000 to 2800. After the sample size increment is stable, the cost increment is relatively stable and the fluctuation range is relatively convergent. Figure 5(b) shows the cost and sensitivity change of LP relaxation on cost. The range of cost change [5000, 33000] for LP relaxation is larger than that of HEA. Particularly in the aspect of cost increment, the increment fluctuates greatly with the increase of sample size. Therefore, with the increase of sample size, the results of HEA are more stable, convergent, and accurate. Compared with the traditional operational research methods, HEA can provide better decision-making reference for decision-makers in VCMP.

Table 6: Comparison results of HEA and LP relaxation.

		HEA				LP relaxation			
V_c	V_w	Error (%)	Running time	Number (optimal solution)	Total cost ($)	Error (%)	Running time	Number (optimal solution)	Total cost ($)
25	6	2.64	810.65	(22)	6196.82	2.49	837.03	(23)	6572.22
50	6	2.88	962.19	(22)	6970.50	2.97	1032.97	(25)	7476.40
60	6	3.26	1158.01	(25)	7529.81	4.05	1298.39	(26)	7939.58
70	6	3.79	1519.62	(25)	7963.28	5.23	1756.20	(29)	8505.23
80	6	4.33	1773.43	(29)	8472.29	5.91	1902.81	(29)	9210.07
90	6	4.57	2315.70	(30)	9102.06	6.39	2103.74	(29)	10093.35
100	6	4.82	2811.61	(33)	9536.72	6.72	2995.02	(29)	10678.97
110	6	5.12	3542.58	(38)	10098.68	7.99	3895.63	(30)	11323.63
120	6	5.96	3811.32	(38)	10527.84	8.61	4595.91	(30)	11950.85
130	6	6.39	4402.96	(43)	11081.25	10.95	5218.42	(30)	12608.10
140	6	7.01	5013.27	(43)	11623.91	12.03	5903.83	(30)	13416.35
150	6	7.97	5682.43	(45)	12170.74	15.81	6357.15	(30)	14025.41
200	6	12.64	7252.67	(51)	14724.82	19.22	7819.26	(32)	16816.95
250	6	14.30	8903.01	(51)	17201.50	23.36	9319.42	(40)	19536.32
300	6	15.91	10225.82	(51)	19673.86	26.92	11579.58	(42)	21004.87
350	6	18.35	11839.19	(53)	22172.33	30.40	14048.39	(49)	23793.24
400	6	20.96	13942.60	(57)	24798.50	36.27	16892.32	(49)	26351.78
450	6	24.80	15820.53	(62)	27309.72	43.05	19523.10	(49)	29972.15
500	6	27.32	17307.92	(62)	29625.46	52.81	22035.86	(49)	32661.58



(a) (b)

Figure 5: Sensitivity analysis of LP and HEA to objective function.

7. Conclusion

As the development of Internet technology, data resource from trading and logistics has been paid close attention on the costumers' service demand by scholars and managers. In order to upgrade the efficiency of the logistics industry and solve the predictive problem for Internet with logistics planning, a nonlinear mixed-integer programming model is proposed to reduce the total cost which considers the online orders allocation process in VCMP. Logistics system integration problem is broken into several subproblems in sequence, for example, order response, selection of warehouses, distribution of the vehicle, path planning, and order delivery. And then the complex problem is described as a directed graph so that all events and objects in the VCMP can be designed as points and vectors by mathematical method.

The detailed solution is summed up as follows. Firstly, vehicle classification is expressed as GMM-EM algorithm to solve the parameter estimation of VCMP, so that VCMP process is optimized by preprocessing. Secondly, in view of the features of the problems, a new HEA is designed, based on the idea of adaptive searching schemes to solve multistage integration problems. The warehouse and path planning with time window in the order allocation process are compared with the traditional logistic planning method. The results show that the performance of HEA is proved to be superior. Finally, experimental analysis validates the solution so that the rationality of the model and the feasibility of the algorithm can be obtained in the logistics integration

system. Research results indicate that intelligent algorithm can be applied to solve the new problems in the era of big data and logistics distribution system. In future research, the optimization of the heuristic algorithm and the research of the matching method are both valuable research directions.

Data Availability

All data generated or analyzed during this study are included in this paper.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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