

## *Retraction*

# **Retracted: Multipoint Distribution Vehicle Routing Optimization Problem considering Random Demand and Changing Load**

## **Security and Communication Networks**

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] X. Pan, Y. Wu, and G. Chong, "Multipoint Distribution Vehicle Routing Optimization Problem considering Random Demand and Changing Load," *Security and Communication Networks*, vol. 2022, Article ID 8199991, 10 pages, 2022.

## Research Article

# Multipoint Distribution Vehicle Routing Optimization Problem considering Random Demand and Changing Load

Xiaoming Pan,<sup>1</sup> Yong Wu ,<sup>2</sup> and Gao Chong<sup>1</sup>

<sup>1</sup>Business School, Hohai University, Nanjing 210098, Jiangsu, China

<sup>2</sup>College of Business, Nanjing Xiaozhuang University, Nanjing 211171, China

Correspondence should be addressed to Yong Wu; [wuyong71@njxzc.edu.cn](mailto:wuyong71@njxzc.edu.cn)

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In the distribution scenario, the using cost of vehicles is closely related to energy consumption, and the energy consumption rate of a vehicle is closely related to the size of its load. The traditional vehicle routing optimization model takes the shortest distance as the optimization goal when the customer demand is determined, while the influence of the random demand and the changing load on the energy consumption and cost of vehicles in the process of distribution is ignored. Therefore, in this paper, load varying vehicle routing problem with stochastic demands (LVGVRPSD) model is proposed with the goal of minimizing transportation energy consumption and considering the load variability and the randomness of customer demand. K-means clustering algorithm is combined with ant colony optimization (ACO) to solve the problem, and the constraint of risk probability is introduced to describe the vehicle overload problem. Examples in the standard vehicle routing problem test data set are provided and analyzed. LVGVRPSD is also compared with the traditional capacitated vehicle routing problem (CVRP) model. The case study results show that the vehicle energy consumption can be reduced by 2% in the model that considers changing load compared to the model that does not consider changing load. The results illustrate that the method of path optimization is more advantageous and reasonable in the pursuit of reducing energy consumption, when the changing load and the random demand of customer are considered.

## 1. Introduction

Distribution business is one of the most important businesses of logistics enterprises, and its vehicle routing optimization research is of great significance to reduce vehicle energy waste, lower distribution costs, diminish exhaust emissions, and realize green logistics and sustainable development of economy [1–4].

Vehicle routing problem (VRP) was first proposed by Danting and Ramser [5] in 1959; it can be generally described as follows: the vehicle departs from the distribution center, and then the forward route of the vehicle is optimized under certain constraints, including the amount of customer demand, the specific location of the customer point, the number of vehicles, the maximum capacity of the vehicle and time constraints, etc.

Over the past few decades, with the extensive practical application of VRP and the in-depth development of theory, achievements in this area have been continuously enriched.

In [6], the vehicle routing problem of simultaneous pickup and delivery and time window was proposed, and the particle swarm optimization (PSO) algorithm was used to solve this complex combinatorial optimization problem. In [7], a vehicle routing problem to be solved through heuristic procedures was proposed. In [8], the satisfiability model theory was successfully used to solve the vehicle routing problem with time window constraints. The quality of the solution proved to be competitive compared to other optimization techniques because the solution time significantly reduced and opened the door to larger problems. In [9], a vehicle routing problem with generalized fuzzy travel time, multiple stops, split delivery, and alternative fuel-powered vehicles was proposed. A hybrid genetic algorithm was developed to solve the problem. In [10], a new ACO algorithm (called AMR) was proposed to solve VRP. The proposed algorithm allows ants to enter and exit the warehouse multiple times until they have visited all customers, which simplifies the process of constructing feasible solutions. In

[11], a practical variant of VRP was proposed in the logistics industry, called VRP with simultaneous delivery and pickup and time windows. In [12], a generalized variant of VRPOD by considering vehicle capacity heterogeneity and time window was proposed, which has heterogeneous capacity, time window, and occasional vehicle routing problem of driver. In [13], a multiobjective multisite vehicle routing problem with time windows was proposed, and a two-stage multiobjective evolutionary algorithm was developed to deal with this problem. There have been some results considering the vehicle routing problem, while there are few studies on the lowest using cost and least energy consumption of multipoint distribution vehicles that consider random demand and changing load.

The traditional vehicle routing optimization model only considers the shortest transportation distance, ignoring the impact of vehicle load on energy consumption, and the resulting optimal route is not the smallest in terms of energy consumption. At the same time, existing research generally only considers certain customer needs, while ignoring its randomness. However, in real delivery scenarios, the demand for each customer point is often random. Moreover, the using cost of a vehicle is closely related to fuel consumption, and fuel consumption is closely related to the total weight of the vehicle [14]. During the delivery process, a customer point is passed, whether it is unloading or loading, the load on the vehicle will change, and the corresponding energy consumption will also change accordingly.

Therefore, on the basis of the capacitated vehicle routing problem (CVRP), load varying vehicle routing problem with Stochastic Demands (LVGVRPSD) model that considers both random demand and changing load is proposed to study the energy consumption of distribution vehicles according to the difference between vehicle energy consumption and load. The model also introduces risk probability which is used to restrict the overloading of vehicles; at the same time, ant colony optimization (ACO) and k-means clustering algorithm are combined to solve the model. The simulation experiment results show that the LVGVRPSD model is more superior and reasonable in terms of saving energy, reducing costs, and meeting customer needs.

## 2. Methodologies

**2.1. Principle of Ant Colony Optimization.** ACO is a new simulation evolution algorithm proposed by Italian scholar DORIGO et al. [15–17] in the 1990s. The researchers observed that ants in nature do not seek out food sources on their own, but this is a group behavior. In their search for food, ants leave a pheromone on the path they travel. At the same time, they can also sense pheromones released by other ants. The concentration of this pheromone gradually decreases over time. The basic idea of applying ant colony algorithm to solve optimization problems is to use the walking paths of ants to represent the feasible solutions of the problem to be optimized, and all paths of the entire ant colony constitute the problem to be optimized in the solution space. Ants with shorter paths release more pheromones. Over time, the concentration of pheromone

accumulated on the shorter path gradually increased, and so did the number of ants choosing this path. In the end, the whole ant will focus on the optimal path under the action of positive feedback, which corresponds to the optimal solution of the problem to be optimized at this time [18–20].

The basic idea of the above ant colony algorithm is described in mathematical language in an abstract way. Without loss of generality, the number of ants in the whole ant colony is set as  $m$ , the number of cities is set as  $n$ , the distance between city  $i$  and city  $j$  is set as  $d_{ij}$  ( $i, j = 1, 2, \dots, n$ ), and the pheromone concentration on the path connecting city  $i$  and city  $j$  at moment  $t$  is set as  $\tau_{ij}(t)$ .

The next city that ant  $k$  ( $k = 1, 2, \dots, m$ ) prepares to visit is based on the concentration of pheromones on each intercity connecting road. The probability of ant  $k$  moving from city  $i$  to city  $j$  at moment  $t$  is denoted as  $P_{ij}^k(t)$ , which is calculated as

$$P_{ij}^k = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha * [\eta_{ij}(t)]^\beta}{\sum_{s \in \text{allow}_k} [\tau_{ij}(t)]^\alpha * [\eta_{ij}(t)]^\beta}, & s \in \text{allow}_k, \\ 0, & s \notin \text{allow}_k, \end{cases} \quad (1)$$

where  $\eta_{ij}(t)$  is the heuristic function that denotes the desired degree of transfer of ants from city  $i$  to city  $j$ .  $\text{allow}_k$  ( $k = 1, 2, \dots, m$ ) is the set of cities to be visited by ant  $k$ .  $\alpha$  is the pheromone importance factor, whose larger value indicates that the concentration of pheromone plays a greater role in the transfer.  $\beta$  is the heuristic function importance factor, whose larger value indicates that the heuristic function plays a greater role in the transfer.

At the same time, the pheromone on each intercity connection path is gradually disappearing as the ants release it, setting the parameter  $\rho$  ( $0 < \rho < 1$ ) to indicate the degree of pheromone volatilization. Therefore, when all ants have completed a cycle, the pheromone concentration on each intercity connection path needs to be updated in real time,

$$\begin{cases} \tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}, \\ \Delta\tau_{ij} = \sum_{k=1}^n \Delta\tau_{ij}^k, \end{cases} \quad 0 < \rho < 1, \quad (2)$$

where  $\Delta\tau_{ij}^k$  denotes the concentration of pheromone released by the  $k$ th ant on the path connecting city  $i$  to city  $j$ .  $\Delta\tau_{ij}$  denotes the sum of the concentration of information released by all ants on the path connecting city  $i$  to city  $j$ .

Three different models have been given for the ant pheromone problem by M. Dorigo et al. The ant cycle system model is generally chosen, which means that the overall information about the ant's pathway is used to calculate the concentration of pheromone released

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L_k}, & \text{the } k\text{th ant visits city } j \text{ from city } i, \\ 0, & \text{other,} \end{cases} \quad (3)$$

where  $Q$  is a constant, which represents the total amount of pheromone released by the ants in one cycle, and  $L_k$  is the length of the path that the  $k$ th ant passes.

**2.2. K-Means Clustering Algorithm.** The k-means clustering algorithm was first proposed by MacQueen in 1967 [21–23]. As a typical partition-based clustering algorithm, it is the most widely used clustering algorithm due to its simplicity and efficiency. The k-means clustering algorithm needs to specify the number  $k$  of clusters in advance. The solution idea is to randomly select  $k$  data objects from  $n$  data objects as the center point of the class and then divide the remaining  $n-k$  data objects into the class with the smallest difference from each center point. The center of the class is optimized and adjusted according to the division result until the position of the new cluster center does not change or changes a little compared to the original cluster center [24].

The k-means algorithm can be described in mathematical language as follows: given a set of  $n$  data objects  $V = \{v_1, v_2, \dots, v_n\}$ , the attribute value of the data object is  $x_i (i = 1, 2, \dots, n)$ , constructing  $k$  cluster subsets  $\{c_1, c_2, \dots, c_k\}$  to minimize the difference of various data objects in the  $k$  cluster subsets. The objective function of the k-means algorithm is

$$F = \text{Min} \sum_{j=1}^k \sum_{v_i \in c_j} |x_i - \bar{c}_j|^2 c_j, \quad (4)$$

where  $\bar{c}_j$  is the cluster center of cluster  $c_j (j = 1, 2, \dots, k)$  in cluster subset  $\{c_1, c_2, \dots, c_k\}$ , and  $v_i$  represents all data objects in cluster  $c_j$ . The method of selecting cluster centers is shown as

$$\bar{c}_j = \frac{1}{|c_j|} \sum_{v_i \in c_j} x_i, j = 1, 2, \dots, k, \quad (5)$$

where  $|c_j|$  is the number of data objects in the cluster center, and  $x_i$  represents the attribute value of the  $c_j$  data object in the cluster.

In the clustering problem of path planning, the data object is the customer node, and the attribute value of the data object is the geographic location of the customer node, and a certain distance is selected as the similarity between the customer nodes. Euclidean distance is generally selected as the similarity between customer nodes for the k-means algorithm, so the Euclidean distance between any two customer nodes  $x_i$  and  $x_j$  can be expressed as

$$d(x_i, x_j) = \sqrt{\left( \sum_{i=1}^n \sum_{j=1}^n (x_i - x_j)^2 \right)}. \quad (6)$$

The minimization of the sum of squares of the errors in the objective function clusters in the above equation can be described as minimizing the sum of squares of the distances between the customer node positions  $x_i$  and their nearest cluster centers  $c_j$ .

Combining k-means clustering algorithm and ant colony algorithm in vehicle routing optimization can effectively decompose large-scale vehicle routing problems into several small-scale subproblems and then use ant colony algorithm to optimize each subproblem. The ant colony algorithm itself has strong robustness, and at the same time it is a positive feedback algorithm, which can guide the problem to the

direction of the optimal solution with higher reliability and finally integrate all the subproblems to obtain the optimal solution to the problem. In this way, not only the scale of solving the vehicle path optimization problem is reduced, but also the optimization performance of the algorithm for the path problem is improved.

### 3. LVGVRPSD Model

**3.1. Problem Description.** Based on a graph-theoretic formulation, the LVGVRPSD problem can be specifically described as follows: in an undirected graph  $G = (V, U, T, )$   $V = \{v_0, v_1, \dots, v_N\}$  is the set of all nodes in the graph,  $v_0$  denotes the distribution center,  $V' = \{v_1, v_2, \dots, v_N\}$  is the set of customer nodes, the matrix  $U = [u_{i,j}]_{N \times N}$  denotes the set of edges in the graph, the matrix  $T = [t_{i,j}]_{N \times N}$  denotes the weights of the edges, the weights  $t_{i,j}$  denote the distribution transport energy consumption of the vehicle from the customer point  $v_i$  to  $v_j$  without load, and the problem has the following assumptions.

- (1) With only one distribution center  $v_0$ , all customer nodes  $V'$  in the customer node set are divided into a complete and mutually independent subpath, and the set of customer nodes after the division is  $V'' = \{V_1, V_2, \dots, V_K\}$ , where,  $V_b, V_l \subseteq V''$ ,  $V_b \cap V_l = \emptyset$ , and  $V_1 \cup V_2 \cup \dots \cup V_K = V''$ . This corresponds to the set of subpaths  $R = \{r_1, r_2, \dots, r_k\}$ .
- (2) The locations of the customer nodes are known, and the demand of the middle  $N$  customer nodes is expressed as  $c_1, c_2, \dots, c_n$ , the demand of the customer nodes is random, and the customer demand is assumed to follow a continuous Gaussian distribution, whose mean and variance, etc. can be obtained from historical information. The demand of each customer node must be satisfied and can only be served once by a vehicle.
- (3) The vehicle does not consider other factors that affect changes in the vehicle's energy consumption during the distribution process such as driving speed and road conditions.

Based on the graphical description of the LVGVRPSD problem, the corresponding mathematical model is constructed and parameters and related notation involved in the model are defined in Table 1.

The mathematical optimization model of the LVGVRPSD problem is as follows [25]:

$$\min F = \sum_{i \in V_K} \sum_{j \in V_K} \sum_{k \in W} (1 + \gamma) u_{ijk} t_{ij}, \quad (7)$$

$$p \left( \sum_{i \in V_k} c_{ki} > \bar{c}_{th} \right) \leq \bar{P}_{th}, \quad k \in W, \quad (8)$$

$$\sum_{i \in V_k} u_{k0i} = 1, k \in W, \quad (9)$$



TABLE 1: The definition of set and parameter symbol.

Symbol	Definition
$V = \{v_0, v_1, \dots, v_N\}$	Node collection.
$V_l = \{v_1, v_2, \dots, v_N\}$	Customer node set.
$V'' = \{V_1, V_2, \dots, V_K\}$	Customer node set after partition.
$U = [u_{i,j}]_{N \times N}$	Edge set in the graph.
$R = \{r_1, r_2, r_3, r_4, r_5\}$	Subpath collection.
$W = \{1, \dots, M\}$	Vehicle collection.
$t_{i,j}$	Energy consumption of transportation from customer point $v_i$ to $v_j$ without loads.
$c_{ki}$	The load that vehicle $k$ carries when it leaves from customer node $v_i$ , $k \in W$ .
$c_{r_k}$	The total demand of customers in the subroute $r_k$ served by vehicle $k$ .
$\gamma$	$\gamma = c_{ki}/M$ , $M$ is the vehicle's own weight.
$c_{th}$	Maximum load of the vehicle.
$\bar{c}_{th}$	Maximum planned load of the vehicle.
$P_{th}$	The risk probability corresponding to the maximum load of the vehicle.
$\bar{P}_{th}$	Preset target risk probability.
$u_{ijk} = \begin{cases} 1, & \text{Vehicle } k \text{ travels from } v_i \text{ to } v_j, \\ 0, & \text{other.} \end{cases}$	Decision variables.

$$\sum_{i \in V_k} u_{kih} = \sum_{i \in V_k} u_{khj}, \forall h \in V_K, k \in W, \quad (10)$$

$$\sum_{i \in V_k} u_{kjo} = 1, k \in W \quad (11)$$

$$\sum_{k \in W} \sum_{i \in V_K, j \neq i} u_{kij} = 1, \forall j \in V_K, \quad (12)$$

$$\sum_{k \in W} \sum_{j \in V_K, j \neq i} u_{kji} = 1, \forall i \in V_K, \quad (13)$$

$$\sum_{i \in S} \sum_{j \in S} u_{ijk} \leq |S| - 1, \forall S \in V_K, k \in W, \quad (14)$$

$$u_{ijk} \in \{0, 1\}, \forall i, j \in V_K, k \in W, \quad (15)$$

where (7) is the objective function, which indicates the minimization of the total energy consumption of distribution transport. Equation (8) indicates that the probability of a vehicle's actual load being greater than its maximum planned load should be less than the predetermined target risk probability. Equations (9)–(11) ensure that each vehicle departs from the center of distribution, serves the customer, and then leaves and eventually returns to the distribution center. Equations (12) and (13) ensure that each customer can only be served once by one vehicle. Equation (14) is the set of customers served by the vehicle for the branch route elimination constraint. Equation (15) is the attribute of decision variable.

In fact, if the LVGVRPSD model transforms random customer demand into deterministic customer demand, then the LVGVRPSD problem becomes the corresponding load varying vehicle routing problem (LVGVRP). If the load variation is not considered in the process of finding the optimum and the customer demand is random, then the LVGVRPSD problem becomes a vehicle routing problem with stochastic demands (VRPSD).

**3.2. The Constraint of Risk Probability.** In the problem of LVGVRPSD, there is a risk that the vehicle capacity constraint will not be satisfied due to the randomness of the customer node's demand. To avoid overloading situations, a risk probability constraint is used to cope with the effect of stochastic customer demand on the actual vehicle load. The actual maximum planned vehicle load  $\bar{c}_{th}$  in each subpath is determined by calculating a predetermined target risk probability  $\bar{P}_{th}$  to ensure that the vehicle load in each subpath satisfies the vehicle capacity constraint of the LVGVRPSD problem, and this risk probability threshold can be set according to actual demand.

Based on the historical demand information of the customer nodes, the corresponding probability distribution functions can be obtained. In this paper, the complementary function of the cumulative distribution is used to calculate the target risk probability  $P_{th}$  corresponding to the maximum vehicle load  $c_{th}$ . The specific target risk probability is defined as

$$P(c_{r_k} > c_{th}) = \int_{c_{th}}^{+\infty} p(c_{r_k}) dc_{r_k}, \quad (16)$$

where  $c_{r_k} = \sum_{i \in V_K} c_{ki}$ ,  $k \in W$ , is the total demand of customers in the subpath  $r_k$  served by vehicle  $k$ , and  $p(c_{r_k})$  is the probability density function of  $c_{r_k}$ . In this paper, we assume that the probability distribution function of customer demand obeys a Gaussian distribution, specifically,  $c_{r_k} \sim N(\mu_{r_k}, \sigma_{r_k}^2)$ , where  $\mu_{r_k}$  is the mean and  $\sigma_{r_k}^2$  is variance. At this point, the probability of risk can be further defined as

$$\begin{aligned} P(c_{r_k} > c_{th}) &= \int_{c_{th}}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma_{r_k}} \exp\left(-\frac{(c_{th} - \mu_{r_k})^2}{2\sigma_{r_k}^2}\right) dc_{r_k} \\ &= Q\left(\frac{c_{th} - \mu_{r_k}}{\sigma_{r_k}}\right). \end{aligned} \quad (17)$$

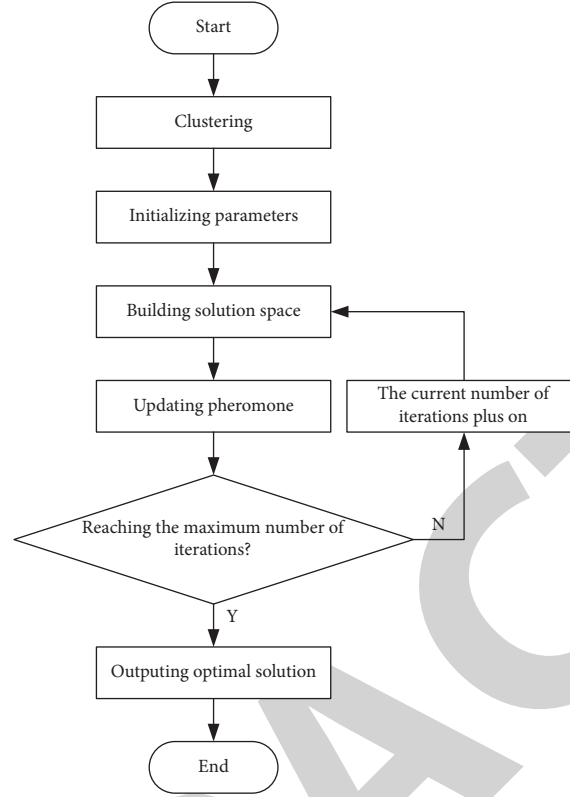


FIGURE 1: The solving flowchart of LVGVRPSD model.

It follows from the above equations that the corresponding risk probability  $P_{th}$  can be calculated for a given maximum vehicle load  $c_{th}$ , but in practice it is more desirable to determine the actual maximum planned vehicle load  $\bar{c}_{th}$  in each subpath by means of a predetermined target risk probability  $\bar{P}_{th}$

$$Q\left(\frac{\bar{c}_{th} - \mu_{r_k}}{\sigma_{r_k}}\right) \leq \bar{P}_{th}. \quad (18)$$

A further inverse extrapolation gives the maximum planned loading  $\bar{c}_{th}$  of vehicle  $k$

$$\bar{c}_{th} \leq \sigma_{r_k} \left( Q^{-1}(\bar{P}_{th}) \right) + \mu_{r_k}. \quad (19)$$

It follows from (19) that different risk probabilities  $P_{th}$  correspond to different maximum planned loading volumes  $c_{th}$ . In practical application, the value of target risk probability should be set reasonably to ensure the quality of delivery service and balance the contradiction between the reliability of the route and the risk of overload.

The solving flowchart of LVGVRPSD model is shown in Figure 1.

In actual transportation scenarios, vehicle load has a proportional relationship with its energy consumption rate. The vehicle routing optimization model proposed in this paper not only considers the shortest transportation distance, but also takes into account the impact of vehicle load on energy consumption. At the same time, both the determined customer needs and the randomness are considered.

#### 4. Case Studies

The parameters related to the ant colony algorithm used in this experiment were set as follows. The pheromone importance factor  $\alpha$  was 20, the heuristic function importance factor  $\beta$  was 5, and the total amount of pheromone released was 100. The pheromone volatility factor was dynamically adjusted [26], and the specific rules for the values are as follows:

$$\rho = \begin{cases} 0.9, & \text{iter} \in [0, 0.25 * \text{iter\_max}), \\ 0.5, & \text{iter} \in [0.25 * \text{iter\_max}, 0.75 * \text{iter\_max}), \\ 0.1, & \text{iter} \in [0.75 * \text{iter\_max}, \text{iter\_max}], \end{cases} \quad (20)$$

where iter is the current number of iterations and iter\_max is the maximum number of iterations.

In the initial stage of the algorithm, the value of  $\rho$  is set to a relatively large value to enhance the global search ability of the algorithm. In the middle and later stages, the value of  $\rho$  is appropriately reduced to converge to the optimal solution faster. The segmentation value not only enhances the global search ability of the algorithm, but also accelerates the convergence of the algorithm to a certain extent.

The experimental object chosen is the A-n32-k5 arithmetic example of Set A in the standard test dataset Augerat considering CVRP problem.  $\gamma$  indicates the change of load on the vehicle after leaving the node  $v_i$  ( $i = 0, 1, \dots, N$ ) in the data table, and it also reflects the size of the demand of each customer node. And the value of energy consumption that each  $\gamma$  corresponds to represents the energy consumed by

TABLE 2: Comparison of energy consumption between CVRP and LVGVRP.

Subpath	CVRP			LVGVRP		
	Route	$\gamma$	Energy consumption	Route	$\gamma$	Energy consumption
$r_1$	0	0.80	115.26	0	0.80	91.87
	21	0.68	15.12	13	0.64	39.43
	31	0.59	8.56	17	0.45	3.24
	19	0.35	3.02	19	0.21	6.52
	17	0.16	27.89	31	0.12	10.08
	13	0.00	51.04	21	0.00	64.03
The energy consumption of $r_1$	—	—	<b>220.88</b>	—	—	<b>215.17</b>
$r_2$	0	0.94	31.58	0	0.94	31.58
	30	0.80	27.48	30	0.80	27.48
	12	0.59	13.11	12	0.59	13.11
	1	0.40	14.88	1	0.40	14.88
	16	0.22	10.91	16	0.22	10.91
	26	0.20	32.31	26	0.20	32.31
27	0.00	25.96	27	0.00	25.96	
The energy consumption of $r_2$	—	—	<b>156.23</b>	—	—	<b>156.23</b>
$r_3$	0	0.90	47.95	0	0.90	47.95
	24	0.66	4.98	24	0.66	4.98
	14	0.63	47.52	14	0.63	47.52
	6	0.51	39.87	6	0.51	39.87
	23	0.43	10.11	23	0.43	10.11
	3	0.37	4.33	3	0.37	4.33
2	0.16	55.78	2	0.16	55.78	
7	0.00	37.05	7	0.00	37.05	
The energy consumption of $r_3$	—	—	<b>247.60</b>	—	—	<b>247.60</b>
$R_4$	0	0.71	106.52	0	0.71	61.96
	29	0.69	33.20	20	0.63	34.85
	15	0.47	25.16	5	0.56	33.60
	10	0.39	22.46	25	0.32	21.33
	25	0.15	24.77	10	0.24	21.23
	5	0.08	23.09	15	0.02	20.04
20	0.00	36.24	29	0.00	62.29	
The energy consumption of $r_4$	—	—	<b>271.43</b>	—	—	<b>255.29</b>
$r_5$	0	0.75	134.48	0	0.75	148.51
	18	0.74	16.42	28	0.60	20.49
	8	0.68	21.38	4	0.41	12.05
	28	0.53	19.59	11	0.27	21.14
	4	0.34	11.45	8	0.21	11.42
	11	0.20	34.99	18	0.20	22.06
9	0.04	4.41	9	0.04	4.41	
22	0.00	84.17	22	0.00	84.17	
The energy consumption of $r_5$	—	—	<b>326.89</b>	—	—	<b>324.25</b>
Total energy consumption	—	—	<b>1223.03</b>	—	—	<b>1198.54</b>

the vehicle in the process of leaving from the current node to the next node. The location and demand of all customer nodes are fixed and known. In addition, 0 denotes the starting point and all vehicles eventually return to the starting point 0. The set of subpaths  $R = \{r_1, r_2, r_3, r_4, r_5\}$ .

**4.1. Comparison of CVRP and LVGVRP.** In Table 2, CVRP model is the shortest path as the optimization objective without considering the load variation, while the energy consumption (7) is introduced to calculate the energy consumption value corresponding to the shortest path. The LVGVRP model, on the other hand, is an algorithmic

optimization search with the lowest energy consumption as the objective and the energy consumption (7) as the objective function.

From Table 2, it can be concluded that the vehicle path optimization method considering load variation can achieve lower energy consumption compared to the optimization method that does not consider load variation.

Specifically, by observing subpath 5( $r_5$ ) in Figures 2 and 3, it can be found that the number and location of customer nodes in both are exactly the same, but the access order is very different. The shortest path in Figure 2 is the optimization goal, while the goal of the optimization in Figure 3 is the lowest energy consumption, and by observing the data in

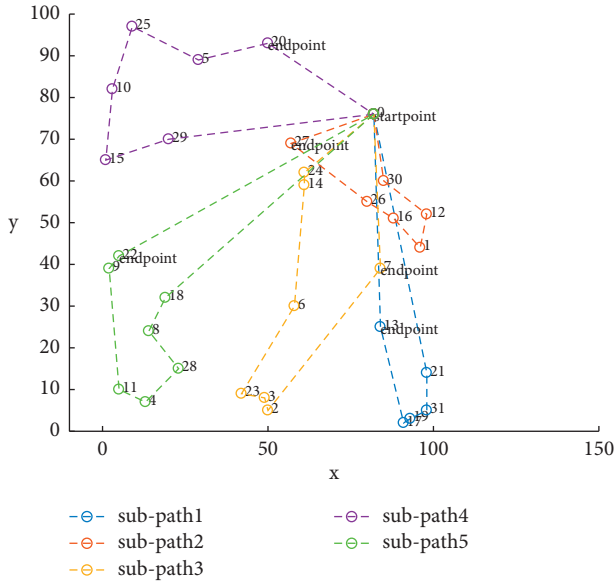


FIGURE 2: Optimal path diagram under the CVRP model.

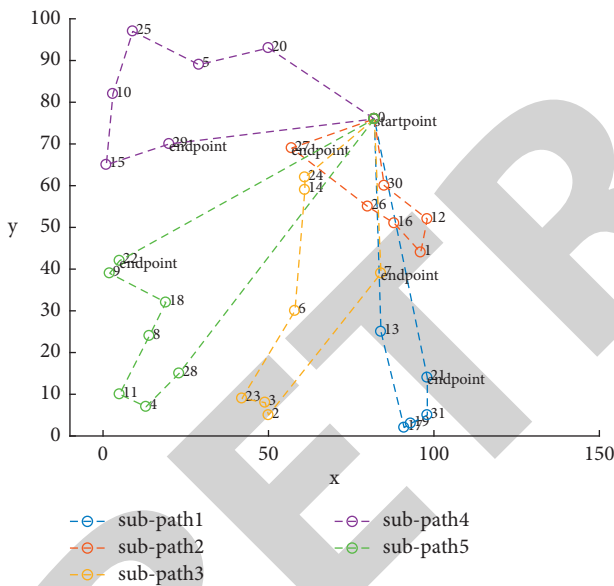


FIGURE 3: The optimal path diagram under the LVGVRP model.

Table 2, we can see that the energy consumed  $r_5$  in Figure 3 is lower than that in Figure 2, which indicates that the shortest path is not the lowest energy path.

Then, comparing subpath 3( $r_3$ ) in Figures 2 and 3, it can be seen that the number and location of customer nodes in both subpaths are exactly the same, and the order of visits is exactly the same, and this is also the case for subpath 2( $r_2$ ). Looking at the data in columns of  $r_2$  and  $r_3$  in Table 2, respectively, it can be found that the changes of  $\gamma$  and the final energy consumption value in subpath 2 and subpath 3 are also the same, which indicates that the route with the shortest distance in  $r_2$  and  $r_3$  is exactly the route with the lowest energy consumption. This conclusion complements the analysis of subpath 5. It can be concluded that when

considering the load variation, it is possible that the shortest route in the vehicle path problem is the lowest energy consumption route, but it is also possible that it is not the lowest energy consumption route. And the shortest distance and the lowest energy consumption are not equivalent.

Finally, the subpaths 4 ( $r_4$ ) in Figures 2 and 3 are compared, and it can be found that the number and location of customer nodes in the two diagrams are exactly the same, and the access order is completely opposite, and similarly, the subpaths 1 ( $r_1$ ) in the two diagrams are also the same. In the subpath 4 of Figure 2, excluding the starting point 0, the access route is  $29 \rightarrow 15 \rightarrow 10 \rightarrow 25 \rightarrow 5 \rightarrow 20$ , and the corresponding customer node demand is  $2 \rightarrow 22 \rightarrow 8 \rightarrow 24 \rightarrow 7 \rightarrow 8$ . In the subpath 4 of Figure 3, excluding the starting point, the access route is  $20 \rightarrow 5 \rightarrow 25 \rightarrow 10 \rightarrow 15 \rightarrow 29$ , and the corresponding customer node demand is  $8 \rightarrow 7 \rightarrow 24 \rightarrow 8 \rightarrow 22 \rightarrow 2$ . No matter the order of access is  $0 \rightarrow 29 \rightarrow 15 \rightarrow 10 \rightarrow 25 \rightarrow 5 \rightarrow 20 \rightarrow 0$  or  $0 \rightarrow 20 \rightarrow 5 \rightarrow 25 \rightarrow 10 \rightarrow 15 \rightarrow 29 \rightarrow 0$ , the distance traveled by the vehicle is the same, but for energy consumption, such a change in the access order is of great impact. In Figure 3, customer node “20” is visited first, because the demand at node “20” is a little higher compared to customer node “29”, and the vehicle can unload more cargo at this node. In addition, node “20” is closer to the starting point “0”, so that the vehicle can avoid carrying large quantities of goods for long distance transportation and reduce the energy consumption of distribution. Comparing the energy consumption values in the columns of Table 2, we can find that subpath 1 and subpath 4 in Figure 3 can achieve lower energy consumption compared with subpath 1 and subpath 4 in Figure 2.

4.2. Comparison of VRPSD and LVGVRPSD. This experiment was conducted to compare the difference in energy consumption between the LVGVRPSD model with considering load factors and the VRPSD model without considering load factors under the condition of random customer demand. Moreover, VRPSD model is the shortest path as the optimization objective without considering the load variation, while the energy consumption (7) is introduced to calculate the energy consumption value corresponding to the shortest path. The LVGVRPSD model, on the other hand, is an algorithmic optimization search with the lowest energy consumption as the objective and the energy consumption (7) as the objective function. The target risk probability of the subpath with the highest total customer demand is set to 0.1.

The test case is to improve the A-n32-k5 case in the standard test data set of the selected CVRP problem to obtain an experimental data set suitable for random problems. The specific improvement procedure is as follows.

- (1) Assume that the demand of the customer nodes in the case obeys a Gaussian distribution.



TABLE 3: Comparison of energy consumption between VRPSD and LVGVRPSD.

Subpath	VRPSD			LVGVRPSD		
	Route	$\gamma$	Energy consumption	Route	$\gamma$	Energy consumption
$r_1$	0	0.99	167.94	0	0.99	185.46
	18	0.98	20.58	28	0.89	26.64
	8	0.93	27.09	4	0.74	16.33
	28	0.84	25.91	11	0.65	30.12
	4	0.69	15.84	8	0.60	16.57
	11	0.59	51.09	18	0.59	32.22
	9	0.48	6.90	9	0.48	6.90
	22	0.45	134.05	22	0.45	134.05
The energy consumption of $r_1$	—	—	<b>449.38</b>	—	—	<b>448.28</b>
$r_2$	0	0.99	35.58	0	0.99	35.58
	30	0.89	14.71	30	0.89	14.71
	26	0.88	40.21	26	0.88	40.21
	14	0.85	6.10	14	0.85	6.10
	24	0.68	14.92	24	0.68	14.92
	27	0.56	42.83	27	0.56	42.83
	20	0.50	59.95	20	0.50	59.95
The energy consumption of $r_2$	—	—	<b>214.30</b>	—	—	<b>214.30</b>
$r_3$	0	0.99	136.13	0	0.99	119.26
	29	0.97	42.55	5	0.94	46.07
	15	0.83	34.49	25	0.79	31.73
	10	0.78	31.57	10	0.73	32.56
	25	0.62	38.32	15	0.59	34.42
	5	0.57	94.53	29	0.57	107.90
The energy consumption of $r_3$	—	—	<b>377.58</b>	—	—	<b>371.94</b>
$r_4$	0	0.99	113.39	0	0.99	111.54
	6	0.91	55.58	13	0.87	81.04
	23	0.86	14.46	2	0.72	5.99
	3	0.80	6.26	3	0.66	12.94
	2	0.65	71.78	23	0.61	46.70
	13	0.54	86.19	6	0.54	87.62
The energy consumption of $r_4$	—	—	<b>347.66</b>	—	—	<b>345.83</b>
$r_5$	0	0.99	63.04	0	0.99	56.19
	12	0.83	16.61	16	0.88	20.77
	1	0.71	56.57	12	0.72	15.63
	21	0.62	16.05	1	0.60	53.00
	31	0.56	9.26	21	0.51	14.98
	19	0.40	3.44	31	0.46	8.62
	17	0.29	53.42	19	0.29	3.17
	7	0.19	16.50	17	0.18	48.95
	16	0.08	30.48	7	0.08	43.93
The energy consumption of $r_5$	—	—	<b>265.36</b>	—	—	<b>265.23</b>
Total energy consumption	—	—	<b>1654.28</b>	—	—	<b>1645.57</b>

- (2) The average of the random demand of the customer nodes in the example is the same as the demand of the customer nodes corresponding to the deterministic CVRP example.
- (3) Except for the randomness of the demand of each customer node, other information including the distance and location to the distribution center is constant.

From the data in Table 3, it can be concluded that, under the condition of random customer demand, the vehicle path optimization method that considers load variation can

achieve lower energy consumption compared to the method that does not consider load variation.

Specifically, from Figures 4 and 5, compared to Experiment 4.1, the same three types of subpaths emerge from the experiment under customer demand uncertainty: the exact same order of vehicle visits under both models, such as subpath 2( $r_2$ ), the exact opposite order of vehicle visits under both models, such as subpaths 3( $r_3$ ) and subpaths 4( $r_4$ ), and the partial order of vehicle visits under both models, such as subpaths 1( $r_1$ ) and subpaths 5( $r_5$ ). The data in Table 3 show that all the paths except subpath 2 achieve lower energy consumption under the LVGVRPSD model compared to under the VRPSD model. The results for subpaths 1, 2, and 5

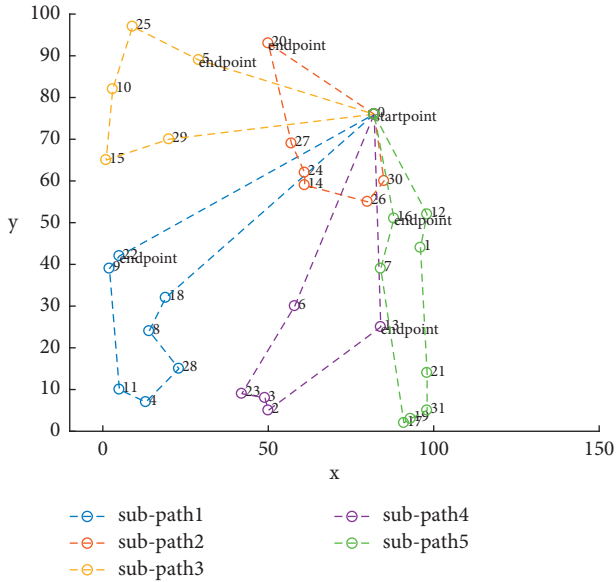


FIGURE 4: Optimal path diagram under the VRPSD model.

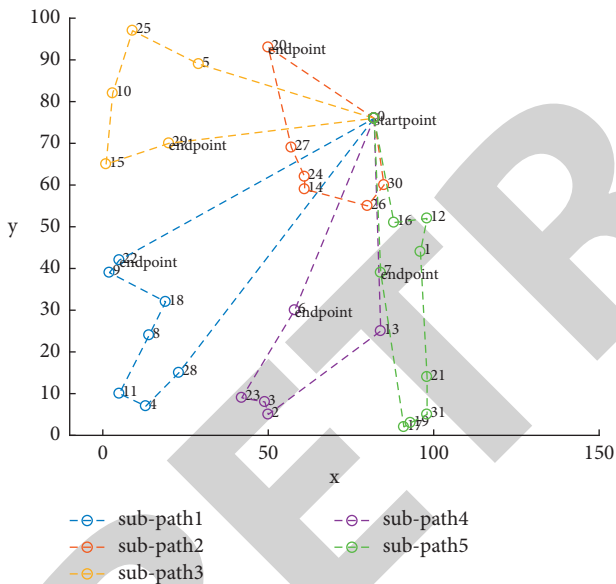


FIGURE 5: The optimal path diagram under the LVGVRPSD model.

show that the shortest path and the lowest energy consumption path are equally inequivalent in the case of random customer demand, while subpaths 3 and subpaths 4 illustrate that when energy consumption is the optimization objective, vehicle path planning integrates load and distance to avoid vehicles carrying large quantities of goods over long distances and reduce energy consumption.

It is also worth noting that the experimental data under the determination of customer demand is shown in Table 2. In each subpath, after the vehicle leaves the last customer node, the goods on the vehicle are just delivered. At this time, the load is 0, and the corresponding value of  $\gamma$  is also 0, while in the experimental data under the uncertainty of customer demand, in Table 3, the value of  $\gamma$

corresponding to the vehicle in subpath 1 after leaving the last customer node is 0.45, and in subpath 2 corresponds to 0.50, subpath 3 corresponds to 0.57, subpath 4 corresponds to 0.54, and subpath 5 corresponds to 0.08. This shows that after the vehicle has delivered all customer nodes, there are still surplus goods on the vehicle. From the value of  $\gamma$ , it can be seen that subpath 5 has a higher fit with the maximum planned loading capacity compared to the other subpaths, and the maximum planned loading capacity calculated based on the subpath with the largest customer demand may cause energy waste for other subpaths with less demand.

### 5. Conclusion

Considering the randomness of customer demand in actual distribution scenarios and the linear relationship between distribution energy consumption and vehicle load, in this paper, a multipoint distribution vehicle routing problem that considers both load changes and customer random demand was discussed. By combination of  $k$ -means clustering algorithm and ant colony algorithm, the model can be solved. Based on the experimental data, the following conclusions can be drawn:

- (1) When the customer demand is known for sure, the vehicle route optimization method that considers the load variation can achieve lower energy consumption than the method that does not consider the load variation, and the vehicle using cost can be relatively smaller. And the shortest route does not equate to the lowest energy consumption.
- (2) When the customer demand is uncertain, similarly, the vehicle path optimization method that considers the load change can achieve lower energy consumption than when the load change is not considered, and the corresponding vehicle using cost is relatively smaller.
- (3) Compared with the determination of customer demand, the energy consumption of delivery vehicles under random customer demand is higher.

In this paper, we can conclude that, considering the load change in the vehicle routing problem, the distribution energy consumption of the vehicle can be reduced by 2%. However, in the actual transportation process, there are many factors that affect the energy consumption of vehicles, including driving speed and road congestion. In future research, factors such as driving speed and road congestion can be taken into account.

### Data Availability

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

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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## References

- [1] Z. Li and M. Yang, "Research on vehicle route optimization based on low carbon emissions," *Mathematics in Practice and Knowledge*, vol. 47, no. 11, pp. 44–49, 2017.
- [2] S. Biswas, S. G. Anavatti, and M. A. Garratt, "Multiobjective mission route planning problem: a neural network-based forecasting model for mission planning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 1, pp. 430–442, 2021.
- [3] J. Xie, S. Xiao, Y. C. Liang, L. Wang, and J. Fang, "A throughput-aware joint vehicle route and access network selection approach based on SMDP," *China Communications*, vol. 17, no. 5, pp. 243–265, May. 2020.
- [4] Z. Wang, J. Yu, W. Hao, and J. Xiang, "Joint optimization of running route and scheduling for the mixed demand responsive feeder transit with time-dependent travel times," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 4, pp. 2498–2509, 2021.
- [5] J. Mandziuk, "New shades of the vehicle routing problem: emerging problem formulations and computational intelligence solution methods," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 3, no. 3, pp. 230–244, Jun. 2019.
- [6] C. Lagos, G. Guerrero, E. Cabrera, A. Moltedo, F. Johnson, and F. Paredes, "An improved particle swarm optimization algorithm for the VRP with simultaneous pickup and delivery and time windows," *IEEE Latin America Transactions*, vol. 16, no. 6, pp. 1732–1740, 2018.
- [7] T. Mansur Fantazzini and M. T. Arns Steiner, "Vehicle routing problem solved through heuristics procedures: a case study," *IEEE Latin America Transactions*, vol. 17, no. 05, pp. 858–864, May. 2019.
- [8] L. W. Rizkallah, M. F. Ahmed, N. M. Darwish, and N. Alechina, "SMT-LH: a new satisfiability modulo theory-based technique for solving vehicle routing problem with time window constraints," *The Computer Journal*, vol. 63, no. 1, pp. 91–104, Jan. 2020.
- [9] M. K. Mehlawat, P. Gupta, A. Khaitan, and W. Pedrycz, "A hybrid intelligent approach to integrated fuzzy multiple depot capacitated green vehicle routing problem with split delivery and vehicle selection," *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 6, pp. 1155–1166, 2020.
- [10] X. Wang, T. M. Choi, H. Liu, and X. Yue, "Novel ant colony optimization methods for simplifying solution construction in vehicle routing problems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 11, pp. 3132–3141, 2016.
- [11] J. Wang, Y. Zhou, Y. Wang, J. Zhang, C. L. P. Chen, and Z. Zheng, "Multiobjective vehicle routing problems with simultaneous delivery and pickup and time windows: formulation, instances, and algorithms," *IEEE Transactions on Cybernetics*, vol. 46, no. 3, pp. 582–594, Mar. 2016.
- [12] L. Feng and L. A. J. Z. K.-C. K. Zhou, "Solving generalized vehicle routing problem with occasional drivers via evolutionary multitasking," *IEEE Transactions on Cybernetics*, vol. 51, no. 6, pp. 3171–3184, 2021.
- [13] J. Wang, T. Weng, and Q. Zhang, "A two-stage multiobjective evolutionary algorithm for multiobjective multidepot vehicle routing problem with time windows," *IEEE Transactions on Cybernetics*, vol. 49, no. 7, pp. 2467–2478, 2019.
- [14] P. Typaldos, I. Papamichail, and M. Papageorgiou, "Minimization of fuel consumption for vehicle trajectories," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 4, pp. 1716–1727, 2020.
- [15] D. Liang, Z.-H. Zhan, Y. Zhang, and J. Zhang, "An efficient ant colony system approach for new energy vehicle dispatch problem," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 11, pp. 4784–4797, 2020.
- [16] F. Goudarzi, H. Asgari, and H. S. Al-Raweshidy, "Traffic-Aware VANET routing for city environments-A protocol based on ant colony optimization," *IEEE Systems Journal*, vol. 13, no. 1, pp. 571–581, Mar. 2019.
- [17] G. Han and Z. T. H. L. Y. M. Zhou, "Ant-colony-based complete-coverage path-planning algorithm for underwater gliders in ocean areas with thermoclines," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 8, pp. 8959–8971, 2020.
- [18] H. Yang, J. Qi, Y. Miao, H. Sun, and J. Li, "A new robot navigation algorithm based on a double-layer ant algorithm and trajectory optimization," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 11, pp. 8557–8566, 2019.
- [19] Y. Xiao, J. Jiao, D. Qiao, J. Du, and K. Zhou, "Summary of the basic principles and applications of ant colony algorithm," *Light Industry Science and Technology*, vol. 34, no. 3, pp. 69–72, Mar. 2018.
- [20] M. Li and Y. Wu, "Dynamic decision model of real estate investment portfolio based on wireless network communication and ant colony algorithm," *Wireless Communications and Mobile Computing*, vol. 2021, pp. 1–14, Article ID 9261312, 2021.
- [21] I. Khan, Z. Luo, J. Z. Huang, and W. Shahzad, "Variable weighting in fuzzy k-means clustering to determine the number of clusters," *IEEE Transactions on Knowledge and Data Engineering*, vol. 32, no. 9, pp. 1838–1853, 2020.
- [22] X. Li and H. Liu, "Greedy optimization for K-means-based consensus clustering," *Tsinghua Science and Technology*, vol. 23, no. 2, pp. 184–194, Apr. 2018.
- [23] S. Soor, A. Challa, S. Danda, B. S. D. Sagar, and L. Najman, "Iterated watersheds, A connected variation of K-means for clustering gis data," *IEEE Transactions on Emerging Topics in Computing*, vol. 9, no. 2, pp. 626–636, Jun. 2021.
- [24] Y. Yang, G. He, and Y. Li, "K-means algorithm for optimizing the selection of initial clustering center," *Computer Knowledge and Technology*, vol. 17, no. 5, pp. 252–255, 2021.
- [25] F. Gao, *Research on Distribution Route Optimization under Uncertain Factors*, Beijing Jiao tong University, Beijing, China, Jun. 2019.
- [26] D. Qin and C. Wang, "A hybrid ant colony algorithm based on 2-opt algorithm," *Industrial Control Computer*, vol. 31, no. 1, pp. 98–100, 2018.