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Optimization of Unmanned Vehicle Delivery Routes Considering Charging and Time Windows

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Abstract: With the increasing application of unmanned vehicles in logistics delivery, more and more researchers are paying attention to improving delivery efficiency, improving delivery service levels and reducing costs. This research considers the unmanned vehicle delivery problem with time windows, where the delivery must be completed within the required time window, otherwise there will be a penalty and a penalty cost will be incurred. And considering the limited range of the unmanned vehicle's battery, whether it needs to enter the charging station for charging or not, the model is established based on the minimum running cost and penalty cost. And a genetic algorithm is designed. Finally, the effectiveness of the model and algorithm is verified by examples.

Keywords: Unmanned Vehicle; Time Windows; Charging Station; Genetic Algorithm.

1. Introduction

In recent years, the logistics industry has developed rapidly and played an important role in economy. Vehicle route problem is a key aspect of logistics delivery, often determining the cost, delivery time, and customer satisfaction of the delivery process. Therefore, it is of great significance to reasonably schedule and scientifically plan delivery routes for delivery vehicles in logistics delivery.

The VRP (Vehicle Routing Problem, VRP) has been widely studied since it was proposed by Dantzig and Ramser[1] in 1959. Yong Wang et al. [2] studied the Time-dependent multi-central coordinated delivery vehicle routing problem in urban logistics delivery and traffic congestion relationship, and constructed a vehicle travel time calculation model based on path space-time decomposition. They clarified the relationship between vehicle travel time and path space-time decomposition under road traffic congestion conditions, designed a fuel consumption and carbon dioxide emission calculation method based on vehicle travel time, and constructed a Time-dependent Multi-Central Logistics Delivery Network Multi-Objective Optimization Mathematical Model. They proposed a hybrid intelligent heuristic algorithm. Experts and scholars have studied specific VRP problems with different constraints and related parameters based on actual conditions. For example, Bai et al.[3]considered the impact of real-world transportation on the environment when building the model and took carbon emissions into account in the optimization objective function, with the goal of minimizing carbon emission costs. Qi Jinhong et al.[4]established a green vehicle routing model with multiple optimization objectives that consider revenue. Ganji et al.[5]considered the impact of speed, load, and driving distance on carbon emissions levels. He Qi et al.[6]studied a VRPHTW problem based on hard time window constraints and designed an algorithm to seek a high-quality approximate solution. Zhang et al. [7] considered the time constraints of multiple departure points and visited nodes from a single vehicle depot in the multi-trip vehicle routing problem with time windows. Chen Xiqiong et al. [8] studied the same-structure VRP problem with the constraint of maximum vehicle capacity to achieve the minimum cost and minimum vehicle workload difference. Shang Zhengyang et al. [9]considered the constraint of loading capacity and maximum loading volume to maximize vehicle utilization. Wang Yong et al. [10] elevated the loading constraint path optimization problem to a three-dimensional angle and planned the number of rows, columns, and layers when loading. The above studies consider real-world delivery scenarios and constraints, making the VRP increasingly applicable to real-world scenarios.

With the rapid development of unmanned vehicle technology, more and more delivery companies are considering using unmanned vehicle instead of human drivers for delivery services, which can save labor costs and reduce operational costs caused by fuel consumption. The optimization of unmanned vehicle routing has attracted widespread attention from scholars. Xu Junxiang et al.[11]studied the routing problem of unmanned vehicle considering dynamic driving times, proposing that dynamic driving times are related to time-varying speeds. They comprehensively analyzed actual vehicle speeds, time, remaining mileage, and charging time to establish a mathematical model aimed at minimizing total delivery time. Wang Lei et al.[12]researched the optimization of delivery routes for unmanned vehicle from the perspective of environmental perception and collaborative decision-making, constructing a model aimed at minimizing total costs while considering delivery and soft time window constraints, and designed a multi-population genetic algorithm. Wang Yuqin et al. [13]studied the optimization of delivery routes for unmanned vehicle by incorporating the characteristics of real-time information sharing and path selection in intelligent connected environments, developing a two-stage model based on real-time traffic information for vehicle routing problems, and designed a genetic algorithm. Zhao et al. [14] proposed a path planning method for unmanned vehicle based on an adaptive particle swarm optimization algorithm, considering the obstacle avoidance capabilities of unmanned vehicle and enabling the rapid generation of high-quality global paths. Nayak et al. [15]researched the task planning applications of unmanned vehicle and ground robots, which essentially relate to the traveling salesman problem, and obtained feasible solutions through a variable neighborhood search algorithm.

In summary, there has been limited research on the optimization of delivery routes for unmanned vehicle that considers both charging and time windows constraints. Therefore, this paper constructs an optimization model for the delivery routes of unmanned vehicle addressing the issues of charging and time windows constraints. Additionally, developing a genetic algorithm to solve the NP-hard problem associated with this model has significant theoretical implications and practical application value.

2. Problem Modeling

2.1. Problem Description

The delivery problem based on unmanned vehicle can be described as follows: Due to the rapid development of unmanned vehicle technology, a logistics distribution center utilizes unmanned vehicle to deliver a certain amount of goods to each customer point nearby. Given the differing needs of each customer point, there are time windows constraints for deliveries, exceeding these time windows incurs a penalty cost. During this process, unmanned vehicle has energy limitations, meaning their range is finite, and they may need to visit charging stations for recharging along the way. The delivery schematic is shown in Figure 1 below. The goal is to plan the paths of the unmanned vehicle in such a way that minimizes both the driving costs and the penalty costs.

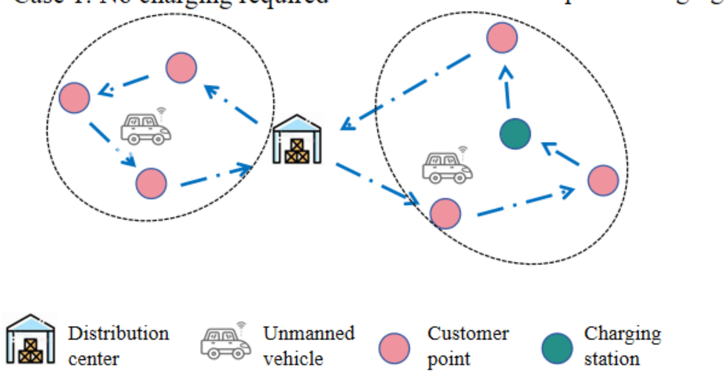

Figure 1. Schematic diagram of distribution path

The assumptions are as follows:

(1) During the delivery process, each unmanned vehicle can only enter a charging station a maximum of once;

(2)When an unmanned vehicle leaves the charging station, its battery is fully charged;

(3)The demand of each customer point is known and does not exceed the rated carrying capacity of the unmanned vehicle;

(4)The speed of each unmanned vehicle during the delivery process is constant and the same;

(5)The coordinates of the distribution center, customer points, and charging stations are all known;

(6)Each customer point can only be served by one specific unmanned vehicle;

(7)The service time and time windows for each customer point are known, as well as the charging time and range of the unmanned vehicle;

(8)The departure time of the unmanned vehicle from the distribution center is 0;

(9)Vehicle breakdowns, road obstacles, and other issues during the delivery process are not considered;

(10)All unmanned vehicle return to the distribution center after completing their delivery tasks;

(11)There is only one distribution center in the area.

2.2. Mathematical Model

The model parameters and variable descriptions in this research are presented in Table 1 below:

The objective of this model is to minimize the total cost, which consists of the transportation cost of the unmanned vehicle and the penalty cost. The total transportation cost of the unmanned vehicle from the distribution center can be expressed as follows:

$$C_R = C\sum_{s\in S}\sum_{i\in N}\sum_{j\in N, i\neq j} x_{ijs} d_{ij} \tag{1}$$

If the unmanned vehicle arrives outside the time window specified by the customer, it will produce certain punishment, and the punishment cost can be expressed as:

$$C_{pu} = C_\alpha \times \max(\alpha_i - t_i, 0) + C_\beta \times \max(t_i - \beta_i, 0) \tag{2}$$

The objective function of unmanned vehicle distribution problem is:

$$C_Z = C_R + C_{pu} \tag{3}$$

The constraints are as follows:

$$w_{ns}^e \geq 0 \qquad \forall n \in N, \forall s \in S \tag{4}$$

$$\sum_{i\in L} y_{si} b_i \leq B \qquad \forall s \in S \tag{5}$$

$$\sum_{s\in S}\sum_{i\in L} x_{zis} - \sum_{s\in S}\sum_{j\in L} x_{jzs} = 0 \tag{6}$$

$$\sum_{s=1}^{S} y_{is} = 1 \qquad i \in L \tag{7}$$

$$\sum_{j=0}^{L}\sum_{s=1}^{S} x_{ijs} = 1 \qquad i \in L \tag{8}$$

Table 1. Model parameters and variables

Parameter	Description
L	Customer Point Collection
S	Set of unmanned vehicles, subscript denoted as s
U	Charging station collection
Z	Distribution center, subscript denoted as z
N	Set of all points, subscript denoted as n , $N = L \cup U \cup Z$
C	The cost of unmanned vehicle delivery per unit distance
d_{ij}	Distance from point i to point j ,$i, j \in N$
b_i	Customer i 's demand for goods, $i \in L$
B	Maximum load capacity of unmanned vehicle
w_{ns}^e	Remaining power when unmanned vehicle s reaches point n
w_{ns}^l	The remaining power when the unmanned vehicle s leaves point n
W	Battery capacity of unmanned vehicle
α_i	Earliest service time of customer i time window, $i \in L$
β_i	Latest service time of customer i time window, $i \in L$
C_α	Waiting costs incurred by early arrival of unmanned vehicles
C_β	Penalty costs incurred by unmanned vehicles arriving later than the time window
t_i^e	Time when the unmanned vehicle arrives at point i , $i \in N$
t_i^l	The time when the unmanned vehicle leaves point i , $i \in N$
th_i	Waiting time of unmanned vehicle at point i , $i \in L$
tf_i	Service time or charging time of unmanned vehicle at point i , $i \in L \cup U$
t_{ij}	The travel time of the unmanned vehicle from point i to point j , $i, j \in N$
$x_{ijs} = \begin{cases} 1 \\ 0 \end{cases} \quad s \in S, i, j \in N$	1 if the unmanned vehicle s travels from i to j, and 0 otherwise
$y_{si} = \begin{cases} 1 \\ 0 \end{cases} \quad s \in S, i \in N$	1 if the customer is delivered by an unmanned vehicle, otherwise 0

$$\sum_{i=1}^{L} x_{ijs} = 1 \qquad \forall j \in L, \forall s \in S \tag{9}$$

$$\sum_{i=1}^{L}\sum_{s=1}^{L} x_{ijs} = \sum_{k=1}^{L}\sum_{s=1}^{S} x_{jks} \qquad \forall k \in L \tag{10}$$

$$\sum_{i \in L}\sum_{j \in L} x_{ijs} \le |L| \qquad \forall s \in S \tag{11}$$

$$t_z^l = 0 \tag{12}$$

$$t_i^l = t_i^e + th_i + tf_i \qquad i \in L \cup U \tag{13}$$

$$t_j^e = \sum_{i \in N}\sum_{j \in N} x_{ijs}(t_i^l + t_{ij}) \qquad i \ne j, \forall s \in S \tag{14}$$

$$th_i = \begin{cases} 0 & t_i^e \ge \alpha_i \\ \alpha_i - t_i^e & t_i^e < \alpha_i \end{cases} \qquad \forall i \in L \tag{15}$$

$$w_{is}^e = w_{is}^l \qquad \forall i \in L, \forall s \in S \tag{16}$$

$$w_{ns}^e \ge 0 \qquad \forall n \in N, \forall s \in S \tag{17}$$

$$w_{is}^l = W \qquad \forall i \in Z \cup U, \forall s \in S \tag{18}$$

Equation (4) ensures that the travel distance of the unmanned vehicle is within the capacity constraints, meaning that the battery level of the vehicle must be greater than zero when it reaches each delivery point; equation (5) indicates that the total amount of goods carried by the unmanned vehicle must be within the rated carrying capacity; equation (6) represents the constraint that the unmanned vehicle departs from the distribution center and ultimately returns to it.; equations (7) to (10) ensure that each customer can only be served by one specific unmanned vehicle; equation (11) states that the number of customers served by each unmanned vehicle must be less than or equal to the total number of customers; equation (12) indicates that the departure time of the unmanned vehicle from the distribution center is zero; equation (13) shows that the time when the unmanned vehicle leaves a point is the sum of the time it arrives at that point, the service time at that point, and the waiting time at that point; equation (14) states that the time the unmanned vehicle arrives at a point is equal to the time it leaves the previous customer point plus the travel time from the previous point to the current point; equation (15) indicates that if the time the unmanned vehicle arrives at a customer point is earlier than the earliest service time in the time window, it must wait until the earliest service time required by the customer to begin service; otherwise, no waiting is required, and the waiting time is zero; equation (16) states that the battery level of the unmanned vehicle is the same when it arrives at and leaves a customer point, meaning that no battery is consumed during the service process; equation (17) ensures that the remaining battery level of the unmanned vehicle is sufficient to reach the planned customer points or charging stations or to return to the distribution center; equation (18) indicates that the battery level of the unmanned vehicle is fully charged when it departs from the distribution center or charging station.

3. Algorithm Design

For the NP-hard problem addressed in this paper, the genetic algorithm is suitable for solving large-scale optimization problems because it accelerates the search process by simultaneously handling multiple individuals. Therefore, this research employs a genetic algorithm for the solution.

3.1. Coding Design

Considering the characteristics of the problem addressed in this paper, the encoding method used is integer encoding[16]. The chromosome length is the sum of the number of customers, charging stations and unmanned vehicle plus 1— $l+u+s+1$. The encoding for the distribution center is represented by 0; the real-number index of the assigned customer points is indicated by $1,2,3,\ldots,l$; and the real-number index of the charging stations is also indicated by $l+1,l+2,\ldots,l+u$.

For example, if a distribution center has 3 unmanned vehicles available for delivery services, needs to serve 10 customers, and there are 2 charging stations in the area, a chromosome may look as follows: 0,7,5,12,8,0,2,9,6,11,3, 0,1,4,10,0. The delivery paths represented by this chromosome are as follows:

The delivery path for the first unmanned vehicle is 0-7-5-12-8-0. This means the vehicle starts from the distribution center, serves customers 7 and 5 consecutively, then due to battery constraints, enters charging station number 12 to recharge. After recharging, it continues to serve customer 8 before returning to the distribution center. Similarly, the delivery path for the second unmanned vehicle is 0-2-9-6-11-3-0. This indicates that the vehicle departs from the distribution center, serves customers 2, 9, and 6 in succession, then enters charging station number 11 to recharge due to battery limitations. After recharging, it continues to serve customer 3 before returning to the distribution center.

The delivery path for the third vehicle is 0-1-4-10-0. This means that the unmanned vehicle leaves the distribution center, serving customers 1, 4, and 10 in succession, and then returns directly to the distribution center, indicating that the third unmanned vehicle has enough battery to complete the entire route without needing to recharge along the way.

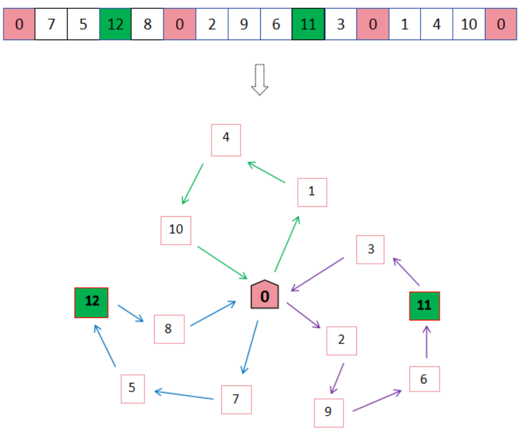

Figure 2. Schematic diagram of coding mode and path

3.2. Initializing Population

First, a random sequence of real numbers is formed using the existing customer points and the numbered representation of the charging stations, where the demand for goods at the first customer point in the chromosome is denoted by b_i . If $\sum_{i=1}^{k} b_i \le B$ and $\sum_{i=1}^{k+1} b_i \ge B$,the cargo load of the unmanned vehicle reaches its maximum capacity upon arrival at point i, the vehicle has completed its service to that customer and needs to return to the distribution center. In this case, the 0 indicates the distribution center was then inserted behind the chromosome position; the above calculation was then repeated until s-1 zeros had been inserted in the chromosome. Since the unmanned vehicle starts from the distribution center and ultimately returns there, an additional 0 is also added at the beginning and the end of the chromosome, forming an initial chromosome. This process is repeated multiple times to generate L individuals, which together constitute an initial population.

3.3. Constraint Treatment

Common methods for handling constraints include the following three approaches:

Firstly, repair operator method, in this method, repair operators are incorporated into crossover, mutation, and other operations to ensure that the generated offspring meet the constraint conditions. For example, this can be achieved by correcting the properties of individuals that do not satisfy the constraints. However, this approach may require the design of complex repair operators to handle different types of constraints, and the repair operations could introduce new uncertainties, potentially affecting the performance of the algorithm. Secondly, constraint handling techniques: This involves designing specific genetic operations, such as constraint handling crossover and constraint handling mutation, to guarantee that mutation and crossover operations do not produce individuals that violate the constraints. However, this requires a deep understanding of the characteristics of the constraints and the design of corresponding constraint-handling techniques, which may increase the complexity and computational cost of the algorithm.

Third, the penalty function method: based on the practical circumstances of the problem studied in this paper, the third method—the penalty function method—is employed. In this approach, penalty terms are added to the fitness function to impose penalties on individuals that violate the constraint conditions, thus suppressing them during the genetic evolution process. The constraints related to the unmanned vehicle's range and maximum load are handled using the penalty function method, resulting in the objective function:

$$\min G = C_R + \sum_{s\in S}\sum_{i\in L} C_{pu} + \omega_1 \max\Big(\sum_{i\in L} b_i - B, 0\Big) + \omega_2 \max(-w_{ns}^{e}, 0)$$

Both constraints must be satisfied simultaneously. If the sum of the ω_1 and ω_2 are large, that can result in an extremely high objective function value for individuals that do not meet the constraints.

Since a higher fitness value increases the probability of subsequent selection, the reciprocal of the aforementioned objective function is taken as the fitness function, which is defined as: $f(i)=\dfrac{1}{G}$.

3.4. Genetic Operation

(1) Selection

Based on the fitness values of individuals, a portion of individuals is selected from the current population to participate in the reproduction of the next generation. The goal is to retain the excellent individuals, eliminate inferior ones, and maintain diversity within the population to aid the algorithm in effective search and evolution. This research uses Roulette Wheel Selection: each individual is assigned a probability proportional to its fitness value, so individuals with higher fitness have a greater chance of being selected when individuals are chosen randomly. The process involves calculating the fitness values of individuals in the population. The selection probability of an individual is given by $P(i)=\dfrac{f(i)}{\sum_{i\in L} f(i)}$, and the cumulative probability of an individual being selected in the current population is $Pa(i)=\sum_{i\in L} P(i)$. A random real number is $R\in[0,1]$, and if $Pa(i)>R$, the first individual is selected; otherwise, individual i are selected according to the $Pa(i-1)<R<Pa(i)$.

(2) Crossover

There are many crossover operations for real-valued encoding, including single-point crossover, two-point crossover, uniform crossover, and simulated binary crossover. However, these methods are challenging to apply to optimization problems involving multiple vehicles and multiple sub-paths. To improve the optimization capability in later stages, a crossover operator suitable for solving the problem addressed in this paper is designed, maximizing the retention of optimal sub-paths. The operation is as follows:

1) As shown in the figure, randomly generate two parent chromosomes A: 0-7-5-12-8-0-2-9-6-11-3-0-1-4-10-0 and B: 0-1-3-10-0-8-7-12-2-6-0-4-9-11-5-0. Then, randomly select a segment from these two chromosomes as sub-path 1: 0-2-9-6-11-3-0 and sub-path 2: 0-4-9-11-5-0;

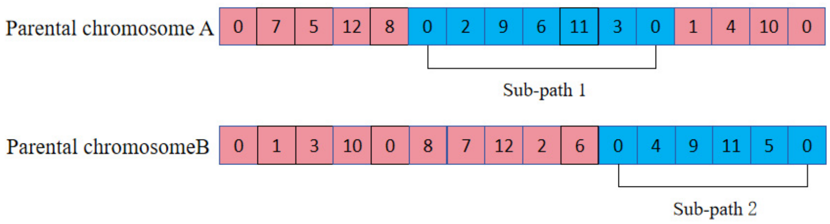

Figure 3. Selecting subpaths

2)The selected sub-paths 1 and 2 are placed at the front;

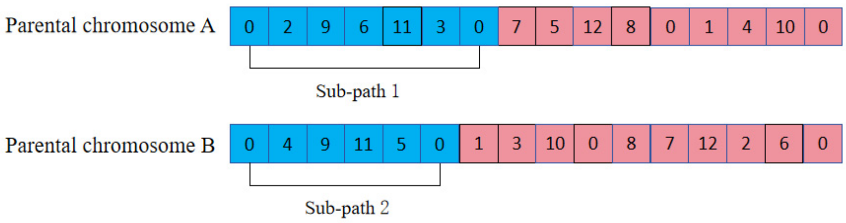

Figure 4. Subpath Prefix

3)The sub-path 1 from parent chromosome A obtained in step 2 is used as a segment of the offspring chromosome, while the encoding from parent chromosome B that does not include sub-path 1 is sequentially added to the end of sub-path 1 according to the encoding order in parent chromosome B. Finally, the encoding 0 is added at the end, resulting in offspring chromosome A*: 0-2-9-6-11-3-0-4-5-1-10-8-7-12-0. Similarly, offspring chromosome B* is obtained as: 0-4-9-11-5-0-2-6-3-7-12-8-1-10-0. This process is illustrated in the figure below:

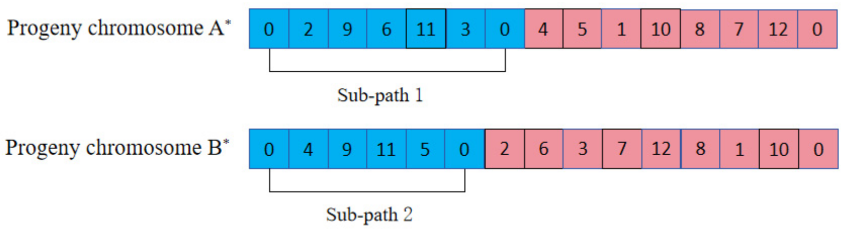

Figure 5. Preliminary formation of progeny chromosomes

4)Taking offspring chromosome, A* as an example, the encoding 0 can be added to any of the 8 positions following sub-path 1, resulting in 8 possible scenarios. The fitness value for each scenario is calculated, and the one with the maximum fitness value is selected as offspring chromosome A. Offspring chromosome B* has 9 possible scenarios, and similarly, offspring chromosome B is derived. The figure below shows one of the generated offspring chromosomes: Offspring chromosome A is 0-2-9-6-11-3-0-4-5-1-0-10-8-7-

12-0; offspring chromosome B is 0-4-9-11-5-0-2-6-3-7-12-0-8-1-10-0.

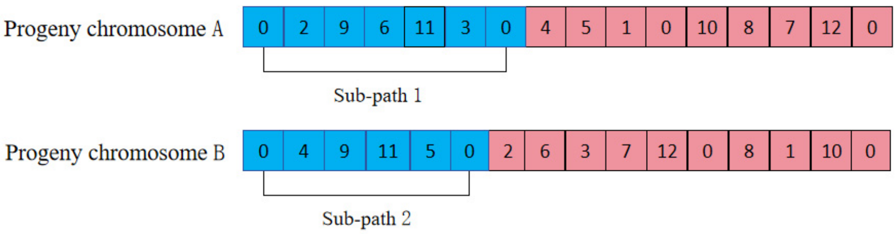

Figure 6. Progeny chromosomes

(3) Mutation

Swap Mutation: A segment of gene sequence is selected from the chromosome, and then this segment undergoes swap mutation to produce multiple offspring chromosomes. The fitness value of each chromosome is calculated, and the one with the highest fitness value is selected to enter the offspring population.

4. Example Analysis

4.1. Introduction of an Example

Table 2. Customer Distribution Information Table

number	X	Y	earliest time(h)	Latest time(h)	demand(t)	service time(h)
1	56	56	0	100	0	0
2	92	76	0	1	0.3	0.2
3	66	78	0	1	0.1	0.2
4	56	27	1	2	0.4	0.3
5	88	72	2	4	0.2	0.3
6	88	32	7	8	0.2	0.3
7	24	48	5	6	0.4	0.3
8	40	48	3	5	0.6	0.5
9	32	80	0	2	0.7	0.8
10	16	69	7	8	0.2	0.3
11	88	96	1	3	0.6	0.4
12	56	70	4	5	0.3	0.5
13	48	96	1	2	0.5	0.7
14	32	104	3	8	0.6	0.7
15	80	56	3	4	0.8	0.6
16	48	40	0	1	0.3	0.2
17	23	16	2	4	0.4	0.2
18	48	8	2	3	0.3	0.4
19	16	32	7	8	0.1	0.1
20	8	48	6	8	0.1	0.1
21	32	64	7	9	0.2	0.2
22	24	96	1	3	0.4	0.5
23	72	104	1	3	0.3	0.2
24	72	32	8	10	0.6	0.7
25	72	16	6	10	0.2	0.2
26	88	8	7	8	0.7	0.7
27	104	56	6	7	0.3	0.1
28	104	32	4	6	0.5	0.5
29	83	45	0	100	0.4	0.4
30	32	40	0	100	0.4	0.4

A certain unmanned vehicle delivery center provides delivery services to 27 nearby customer points. The delivery center has three unmanned vehicles of the same type, each with a maximum load capacity of 5 and a range of 200. Each customer has different cargo demands and specific time windows for service. The time window for the delivery center and charging station is [0, 100]. If an unmanned vehicle enters the charging station for recharging, the charging time is 0.5 hours. The unmanned vehicles maintain a constant speed during delivery, with a speed of $40km/h$. In terms of costs, the operating cost for each unmanned vehicle is 5 yuan per kilometer, with a waiting cost C_α of 20 yuan per hour for arriving early and a penalty cost C_β of 30 yuan per hour for arriving late outside the time window. Other delivery information can be found in Table 2.

The location distribution of customer points, the delivery center and the charging station is shown in the figure below. Since the coordinates of all points are distributed within a 120 × 120 matrix range, in order to better reflect actual delivery conditions, the scale is defined as 10:1, meaning that all points are distributed within a 12 km × 12 km matrix range.

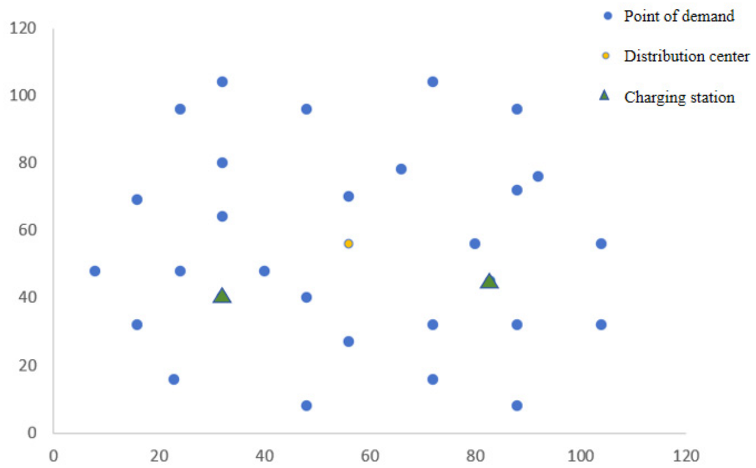

Figure 7. Distribution of coordinate points

4.2. Results and Analysis

This paper uses Python (Python-3.11.0) software for the programming operations of the genetic algorithm mentioned above and verifies the solutions for the examples in this paper. The relevant parameter settings are as follows: population size geneNum = 100, number of iterations generationNum = 1000, and the crossover and mutation probabilities are respectively set to $Pc = 0.9$ and $Pm = 0.1$.

The program was run, and fifteen random solutions were generated. The results indicate that all 3 unmanned vehicles are providing delivery services, with both situations present (requiring charging midway and not requiring charging midway). The results are shown in Table 3 below.

Table 3. Results of Fifteen Examples

number	Total distance(km)	total cost(yuan)
1	774.7016	3889.5078
2	750.0700	3763.3502
3	755.4280	3788.1402
4	763.3460	3828.7298
5	770.1160	3867.5802
6	766.4983	3848.4914
7	754.7241	3783.6203
8	739.5927	3712.9633
9	724.4964	3632.4818
10	719.3525	3608.5630
11	726.6734	3645.3671
12	747.7140	3752.5702
13	745.5648	3740.8238
14	726.6734	3643.3671
15	735.7967	3688.9834
Average	746.7272	3746.3026

As shown in Table 3, all fifteen random solutions resulted in feasible solutions, with the delivery distances maintained between 710 km and 780 km, and the total costs ranging from 3600 to 3900 yuan. This indicates that the solutions are quite similar, with an average distance of 746.7272 km and an average cost of 3746.3026 yuan.

Among the fifteen solutions, the tenth solution exhibited the highest quality. The specific delivery details for each unmanned vehicle generated in this solution are presented in Table 4 and Figure 8. The optimization process of the solution is illustrated in Figure 9. From the figure, it can be seen that the algorithm consistently converges towards a better direction throughout the computation, reaching an optimal solution around the 520th generation. Furthermore, the optimal solution is relatively stable, with an optimal cost of 3608.5629 yuan and a corresponding total distance of 719.5126 km. This demonstrates that the algorithm's solving process is relatively stable and performs well. The genetic algorithm designed in this paper shows a certain degree of feasibility and reliability for solving unmanned vehicle delivery problems with charging and time windows.

Table 4. Distribution of each unmanned vehicle

Unmanned vehicle	path	distance(km)	cost(yuan)	necessary to charge Yes or No
1	0-2-12-8-21-13-22-10-0	179.8782	902.1407	No
2	0-23-24-25-5-27-26-28-4-1-0	224.6875	1127.6760	Yes
3	0-15-3-17-16-18-19-9-20-6-29-7-11-14-0	314.7868	1578.7463	Yes
total	—	719.5126	3608.5630	—

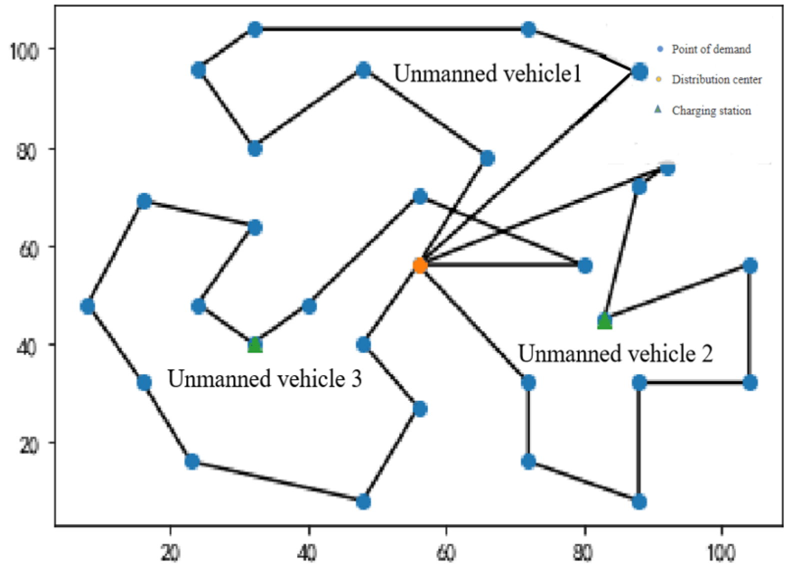

Figure 8. Distribution of coordinate points

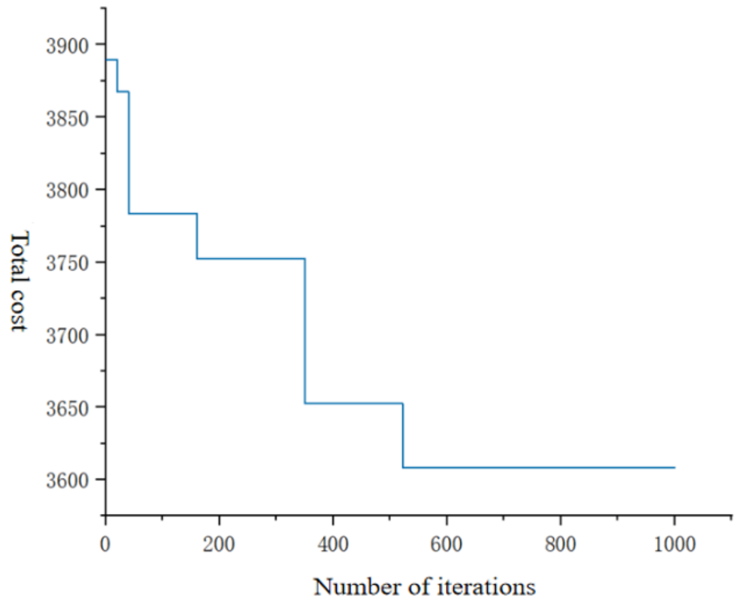

Figure 9. Optimization process diagram

5. Conclusion

Unmanned vehicle delivery is a hot research topic at present, and both its theoretical study and practical applications are still in the early stages. This paper proposes an optimization method for unmanned vehicle delivery routes that includes charging and time windows. It first describes the delivery scenario of this study, where a delivery center provides unmanned vehicle services to surrounding customers. If an unmanned vehicle does not arrive at a customer point within the designated time window, it incurs a penalty. Additionally, unmanned vehicles have a limited battery capacity and range; if the entire delivery service cannot be completed within the range, the vehicle needs to stop at a charging station to recharge. Therefore, to minimize the total cost, which includes both operational and penalty costs during the delivery process, it is necessary to scientifically plan the delivery routes for the unmanned vehicles. Based on this issue, this study makes relevant assumptions and constructs a mathematical model that fits the problem. It also designs suitable coding and improved crossover operators to develop an enhanced genetic algorithm for this problem. Finally, through example cases, the effectiveness and feasibility of the algorithm are analyzed, providing decision support for future unmanned vehicle delivery operations management. Currently, the research only considers a single delivery center and a single type of delivery vehicle, which differs from practical situations. Moreover, the actual delivery process is unlikely to maintain a constant speed. Therefore, future work could focus on optimizing delivery routes under varying conditions with multiple delivery centers and multiple vehicle types.

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