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Original scientific paper

OPTIMIZATION OF UNMANNED VEHICLE SCHEDULING AND ORDER ALLOCATION

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Abstract
With the development of unmanned vehicles from laboratories to commercial logistics distribution, unmanned vehicles are facing prominent problems, such as order allocation, reasonable setting of appointment time windows, and vehicle route optimization. With the campus distribution of Cainiao unmanned vehicles as an example, an appointment order allocation and route planning problem model of unmanned vehicles was constructed to realize efficient order picking and optimize the operating cost. The operation and distribution efficiency of unmanned vehicles before and after planning was compared using the improved genetic algorithm with limits of load and soft time windows as model constraint conditions. Results of the calculation example reflect that the parcel distribution amount under the planned 1 h appointment mode more than doubled that under the current unplanned 1 h appointment mode. Moreover, the operating cost and parcel picking scheme of Cainiao unmanned vehicles under the planned 1 h and 30 min appointment modes are given, providing decision-making reference for enterprises to balance customer satisfaction and unmanned vehicle scheduling.
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Key Words: Unmanned Vehicle, Vehicle Scheduling, Order Allocation, Improved Genetic Algorithm

1. INTRODUCTION

Prevailing in the globe in recent years, especially since the outbreak of COVID-19, unmanned vehicles play an important role in cargo dispatching, and researchers have deeply investigated them from a technical angle continuously toward product layout and commercial application. In 2014, Starship launched the trial operation of unmanned vehicles in university campuses. Leading enterprises within the industry, such as JD, Meituan, and Cainiao in China, have made breakthroughs in the commercial distribution of unmanned vehicles.

Despite the qualitative leaps in solving the "last one kilometre" campus express delivery of unmanned vehicles and saving time and labour for users, weaknesses remain in the commercial distribution field of unmanned vehicles (e.g., a long appointment time span and low customer satisfaction). The route optimization of unmanned vehicles is more complicated because of the lack of drivers' decision-making link. In previous studies, the route planning of unmanned vehicles has been explored mainly in the experimental stage (for example, Rojas Viloria et al. [1] reviewed research literatures regarding the route optimization of unmanned vehicles). However, they have not been commercially applied yet. In this study, the practical application scenes of unmanned vehicles in China are combined to investigate the route optimization and order allocation problems of unmanned vehicles under the dispatching mode of orders randomly selected at each integral point of time. Specifically, the following problems are mainly solved in this study:

(1) A route planning algorithm of unmanned vehicles based on the improved GA is proposed, and the optimal distribution schemes in different customer appointment time lengths are presented.

(2) Given the current situation of manual order picking by Cainiao unmanned vehicles, orders are automatically allocated and distributed by the system to unmanned vehicles through algorithm optimization, thereby reducing the wrong picking rate.

2. STATE OF THE ART

The research related to this study involves the route planning and operation of unmanned vehicles. Next, a literature review is presented from two aspects.

In the aspect of route planning for unmanned vehicles, Cai and Du [2], Gul et al. [3], Nazarahari et al. [4] and Scholar et al. [5] solved multi-objective multi-mobile-robot route planning models using the balanced whale optimization algorithm, grey wolf optimizer-particle swarm optimization algorithm, artificial potential field algorithm, and A* algorithm, respectively. They also determined the route optimization scheme for mobile robots on a collision-free route, but they only considered the route optimization for mobile robots in environments with static obstacles. Gao et al. [6] selected the firework algorithm to solve the route planning problem of unmanned vehicles under a three-dimensional map with a simulated practical environment, which was closer to the real environment, but the influence of the dynamic changes in obstacles was ignored. Das et al. [7] and Connell and La [8] thought that the operating environment of mobile robots was rarely static, so the improved gravitational search algorithm and the RRT* algorithm were introduced to solve the route optimization scheme for mobile robots in a dynamic environment. Fatin et al. [9] adopted the hybrid particle swarm optimization-improved frequency bat algorithm to compare the optimization schemes for the route planning problem of mobile robots under static and dynamic environments. All of the aforementioned studies have been restricted to the exploration of route planning methods for unmanned vehicles in the experimental stage, but the problems faced by unmanned vehicles when applied to the field of commercial logistics distribution have not been considered.

When it comes to the operation of unmanned vehicles, Nils et al. [10] developed the scheduling program for the last kilometre home delivery of mobile robots to substitute the traditional home delivery concept of trucks, but the test was performed only through a small-scale calculation example. Malus et al. [11] presented a multi-agent reinforcement learning method to schedule unmanned vehicles, which improved the order allocation efficiency; however, this method remained at the test stage in simulated environments. Bae and Chung [12] deemed that the min–max objective multi-depot heterogeneous travelling salesman problem was an important content in the potential application of unmanned vehicles. And thus high-quality feasible solutions were generated by the proposed algorithm within a short calculation time. Zheng et al. [13] and Zhang et al. [14] presented Dijkstra-Dinic fusion algorithm and global-local route planning combined algorithm, respectively, thereby meeting multi-unmanned-vehicle collaborative planning task requirements under complex urban environments. Hu et al. [15] constructed an optimization model for the unmanned vehicle-based distribution of medical protective supplies considering the priority level of hospitals and solved it using the genetic simulated annealing algorithm. Jiang [16] and Zhao et al. [17] proposed the multi robot scheduling problem of unmanned warehouse, but it was only limited to the warehouse without considering the actual road conditions. According to the above study results, the practical application of unmanned vehicles in the field of logistics distribution has been explored by scholars from different angles but with a shortage of pertinent solutions to problems generated in the practical operation of logistics enterprises.

Given the above research results and limitations, the terminal delivery problem of Cainiao unmanned vehicles put into operation for a certain period of time was explored in this study. Subsequently, an optimization model specifically for the scheduling and order allocation of unmanned vehicles was proposed. The main contributions of this study were described as follows: First, since the appointment time span of Cainiao unmanned vehicles is 1 h and orders are randomly picked at each integral point of time to dispatch vehicles, this problem was solved using the improved GA, and the parcel distribution amount after the optimization more than doubled that under the current situation; second, to balance customer satisfaction and economic benefits, the distribution cost, vehicle input quantity, and cargo loading rate under two modes – 1 h and 30 min of appointment time span – were compared; third, the intelligent allocation schemes for appointment orders at Cainiao stations with the optimal cost under each mode were given, thereby saving the random order picking work.

The remainder of this study is organized as follows: Section 3 models the scheduling and order allocation problem of Cainiao unmanned vehicles, seeking for the balance between customer satisfaction and comprehensive cost. Section 4 establishes the algorithm rules of the improved GA for the research problem. Section 5 compares the optimization schemes for unmanned vehicle scheduling and order allocation under different appointment time spans using the practical operation data of Cainiao stations in East China Jiaotong University. In the final section, the whole paper is summarized.

3. METHODOLOGY

3.1 Problem description

In this study, an appointment order allocation and route planning model of Cainiao unmanned vehicles was constructed with the minimum operating cost as the objective and soft time windows, limits of load, and closed type vehicle routes as the constraint conditions. Moreover, the changes in the parcel distribution amount of Cainiao unmanned vehicles within the appointment time span of 1 h before and after planning were compared. To enhance customer satisfaction, the appointment time span was shortened to 30 min to compare the operating cost and cargo loading rate of Cainiao unmanned vehicles within the appointment time span of 1 h and 30 min, thereby rendering decision-making references for enterprises to balance customer satisfaction and economic benefits.

3.2 Symbol definition

(1) Parameter definitions

Table I: Parameter definitions.

Parameter	Definition	Parameter	Definition
C	Total operating cost	i	Penalty coefficient for unit surplus loading capacity
FC	Fixed cost	D_{ij}	Distance between the distribution sites i and j
N	Set of distribution sites	T_i	Time point for an unmanned vehicle to arrive at the distribution site i
L	Maximum loading capacity of unmanned vehicles	s_i	Stopping time at the distribution site i
u	Distribution cost within unit distance	G_i	Number of parcels at the distribution site i
K	Set of unmanned vehicles	E_i	Starting point of time window at the distribution site i
e	Penalty coefficient for arrival earlier than the starting time window of distribution sites	F_i	Ending point of time window at the distribution site i
f	Penalty coefficient for arrival later than the ending time window of distribution sites	t_{ij}	Running time of an unmanned vehicle from the distribution site i to the distribution site j

(2) Decision variables

When the unmanned vehicle k runs from the point i to the point j, $x_{ijk} = 1$. Otherwise, $x_{ijk} = 0$.
When the unmanned vehicle k serves the user i, $y_{ik} = 1$. Otherwise, $y_{ik} = 0$.

3.3 Problem hypotheses

(1) The starting and ending points of each unmanned vehicle are the same and unique.
(2) The loading capacity of each unmanned vehicle is the same, and each order is only distributed by one vehicle.
(3) After completing the distribution, unmanned vehicles need to return to the Cainiao distribution centre, with each unmanned vehicle only responsible for one distribution loop.
(4) The stop points for each unmanned vehicle are limited, but each distribution site may contain orders of multiple customers.
(5) The quantity demanded of each order, the total quantity demanded of distribution sites, time window constraints, and location information are all known.
(6) Unmanned vehicles are subjected to an upper load limit, and only the limitation in the number of parcels is considered.

3.4 Model construction

(1) Operating cost analysis

Given the above problems and model assumptions, the minimization of operating costs (including the transportation and distribution cost, the penal cost for the deviation from the time window constraint, the penalty cost for the surplus loading capacity, and the fixed cost, as follows) was taken as the objective.

Transportation cost C_1:

$$C_1 = u\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=0}^{N} D_{ij} x_{ijk} \tag{1}$$

Penalty cost for time window deviation C_2:

$$C_2 = e\sum_{i=1}^{N}\max(E_i - T_i, 0) + f\sum_{i=1}^{N}\max(T_i - F_i, 0) \tag{2}$$

Penalty cost for the surplus loading capacity C_3:

$$C_3 = r(KL - \sum_{i=1}^{N} G_i) \tag{3}$$

Fixed cost C_4:

$$C_4 = FC \tag{4}$$

(2) Establishment of mathematical model

The objective function is expressed as follows:

$$\min C = C_1 + C_2 + C_3 + C_4 \tag{5}$$

The constraint condition is presented as follows:

$$\sum_{i=1}^{N} G_i y_{ik} \le L,\ \forall\ k \in \ \{1, 2, \ldots,\ K\} \tag{6}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{K} y_{ik} = 1 \tag{7}$$

$$\sum_{i=0}^{N} x_{ijk} = y_{jk},\quad \forall j \in \{1, 2, \ldots,\ N\},\quad \forall k \in \{1, 2, \ldots,\ K\} \tag{8}$$

$$\sum_{j=0}^{N} x_{ijk} = y_{ik}, \forall i \in \{1, 2, \ldots,\ N\},\quad \forall k \in \{1, 2, \ldots,\ K\} \tag{9}$$

$$\sum_{j=1}^{N} x_{0jk} = \sum_{i=1}^{N} x_{i0k} \le 1, \forall k \in \{1, 2, \ldots,\ K\} \tag{10}$$

$$E_i < F_i, i \in \{1, 2, \ \ldots, N\} \tag{11}$$

$$T_j = T_i + s_i + t_{ij}, i, j \in \{0, 1, 2, \ldots, N\}, i \neq j \tag{12}$$

Eq. (5) denotes the minimum objective function, that is, the minimum distribution cost, including the transportation and distribution cost, the penal cost for the deviation from the time window constraint, the penalty cost for the surplus loading capacity, and the fixed cost. Eq. (6) indicates that the total number of parcels loaded on each vehicle does not exceed the maximum loading capacity of the unmanned vehicle. Eq. (7) means that each order is only served by one vehicle. Eq. (8) ensures that only one adjacent node exists before the distribution site *j*. Eq. (9) ensures that only one adjacent node exists after the distribution site *i*. Eq. (10) stipulates that the vehicle departing from the distribution centre needs to return to the distribution centre after completing the distribution task. Eqs. (7)–(10) co-ensure a feasible loop. Eq. (11) displays the relationship between the upper and lower limits of the time window, and Eqs. (11) and (12) stand for the distribution time window constraints.

3.5 Algorithm design

In this study, the improved GA with a strong search ability and good adaptability was selected to handle the appointment order allocation and route planning problem of Cainiao unmanned vehicles. Moreover, local search and optimization guidance factors were added into the algorithm to strengthen the algorithm climbing ability and prevent the local optimal solution. The concrete solving steps are detailed as follows:

(1) Chromosome coding rules

A fixed-length string of natural numbers was used to represent the chromosome, *cusnum* denotes the total number of distribution sites, *vnum* stands for the maximum number of vehicles allowed to allocate, and the chromosome length was expressed as $N = cusnum + vnum – 1$, where 1-*cusnum* is the serial number of distribution sites, and *cusnum*+1–*N* represents the route separation number. Each chromosome separated several substrings, each of which represents the route of one vehicle. Numbering was performed on a premise that three routes were allowed at most to complete the distribution at six distribution sites, where 1–6 represents the serial number of distribution sites, and 7–8 denotes the route separation number. A chromosome was randomly selected from the chromosome set in the example, as shown in Fig. 1.

2	5	3	7	4	6	1	8

Figure 1: Calculation example of coding rules.

This coding routes were expressed as:
Route 1: 0->2->5->3->0.
Route 2: 0->4->6->1->0.

(2) Generation of initial population

Punctuality is an important condition in the distribution of unmanned vehicles. In this study, whether the time window condition was violated served as an important basis for generating the initial population. Meanwhile, nodes were inserted following the principle of the least number of vehicles used, with the main steps described as follows:

Step 1: Randomly generate a set of distribution sites $N\{1, 2, 3, \ldots, N\}$.

Step 2: Randomly select a distribution site as a newly added distribution site.

Step 3: Judge whether any distribution site is in the current sub-route memory *(route*); if *route* is empty, then the newly added distribution site is added into *route* and deleted from *N*, and then return to Step 2; or otherwise, proceed to Step 4.

Step 4: The newly added distribution site is used to test whether the time window requirement among all distribution sites in *route* is satisfied. If the time window and capacity requirements are satisfied, the newly added distribution site is inserted between distribution sites and deleted from *N*. If no appropriate insertion point exists and the capacity requirement is satisfied, then the newly added distribution site is inserted at the end of the sub-route and deleted from *N*. If the capacity requirement is not satisfied, then proceed to Step 5.

Step 5: Save the sub-route in route as VC_i, clear route, and capacity memorizer *load*, and return to Step 2.

Step 6: Insert route separation number between sub-routes to form chromosomes after all distribution sites are inserted.

Step 7: Repeat the previous steps until an initial population with enough number of distribution sites is generated.

(3) Fitness calculation

Considering the constraint of vehicle loading capacity, the fitness function in this study was expressed by the objective and penalty functions. The vehicle loading capacity was exceeded, served as a penalty term, and was added into the penalty function to construct a fitness function. The reciprocal of the objective and penalty functions was taken as the fitness value. *C* is the objective function, *P* is set as the penalty function, and *M* is the penalty coefficient.

$$fitness(x) = \frac{1}{C + MP} \tag{13}$$

$$P = \max(L - \sum_{i=1}^{N} G_i y_{ik}, 0), \forall k \in \{1, 2, \dots, K\} \tag{14}$$

(4) Selection

In this study, the optimization guidance factor and roulette selection method were combined.

(5) Crossover

Crossover points were randomly selected from two parent chromosomes according to the crossover probability *Pc*, followed by the crossover operation using the OX crossover strategy. The crossover process was demonstrated in Fig. 2 along with the example of chromosome coding rules.

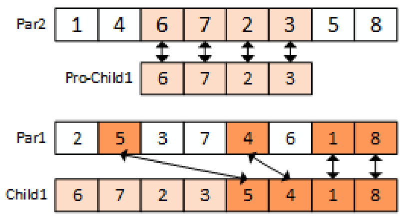

Figure 2: Chromosome Crossover.

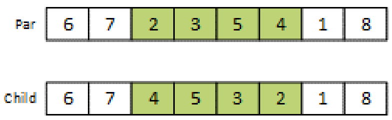

Figure 3: Chromosome Mutation.

(6) Mutation

A chromosome was selected according to the mutation probability *Pm*. A segment of the distribution site sequence was re-ranked repeatedly through 2-Opt transformation. The above chromosome mutation after crossover was taken as an example (Fig. 3).

(7) Local search

After the genetic operation, the population chromosome was locally searched using the concrete steps as follows:

Step 1: A distribution site is randomly selected from the set of distribution sites as the shifted distribution site.

Step 2: A distribution site is set from the set of shifted distribution sites. According to Eq. (15), the correlation between the shifted distribution site *i* and all non-shifted distribution sites is calculated individually. In Eq. (15), V is used to judge whether the shifted distribution site i is on the same route as the non-shifted distribution site j. If not, then $V = 1$, or otherwise $V = 0$. md stands for the maximum distance between the shifted distribution site i and all distribution sites. D_{ij} represents the distance between the shifted distribution site i and the non-shifted distribution site j.

$$R_{ij} = \frac{1}{V + \frac{D_{ij}}{md}} \tag{15}$$

Step 3: The correlations of the shifted distribution site i and all non-shifted ones are ranked in descending order. A distribution site was randomly selected from the non-shifted ones and shifted out, as per Eq. (16). In Eq. (16), *rand* denotes a random number within (0, 1), *remove* stands for the number of to-be-shifted distribution sites, and *nip* represents the number of rest non-shifted distribution sites. Steps 2 and 3 are repeated until all the to-be-shifted distribution sites are shifted.

$$\lceil nip \cdot rand^{remove} \rceil \tag{16}$$

Step 4: All shifted distribution sites are inserted into the rest routes node by node to find the insertion point that meets the time window and capacity constraints with the minimum distance increment. If no such node exists, then a new sub-route will be added. This step is repeated until the best insertion position for all shifted distribution sites is found.

Step 5: The farthest heuristic insertion method is used. Specifically, the distribution site with the maximum increment of the minimum insertion object distance is first inserted into the loop, and the already inserted distribution sites are deleted from the set of shifted distribution sites. Steps 4 and 5 are repeated until all shifted distribution sites are inserted into the loop.

Step 6: The fitness of each chromosome is calculated. The old chromosome will be replaced if the fitness is higher than that on the original route.

(8) Insertion of new offspring population

In the genetic operation, each generation will reserve excellent individuals in the parent at a proportion of *ratio* as the optimal guidance factors. The remaining chromosomes are selected from the parent individuals for the genetic operation. After crossover, mutation, and local search, the optimization guidance factors are blended with the new offspring population for the next round of genetic operation.

(9) Termination

The maximum number of iterations is set reasonably according to the population size, and the algorithm is terminated when the number of iterations reaches the maximum value.

4. EMPIRICAL RESEARCH ON A CALCULATION EXAMPLE

4.1 Data acquisition

In this study, the input quantity, appointment mode, and distribution mode of Cainiao unmanned vehicles were investigated using the distribution of Cainiao unmanned vehicles in East China Jiaotong University as the study object. Given the large appointment time window (1 h) at present, the appointment time window span was adjusted into two modes (e.g., 1 h and 30 min) to simulate the distribution of customer orders within one period of time. In this way, the comprehensive operating cost and vehicle loading rate of Cainiao unmanned vehicles under different appointment time window spans were compared.

(1) Selection of location information

Through the survey on Cainiao data, the stop points and running routes of unmanned vehicles in East China Jiaotong University were obtained, as shown in Fig. 4.

Figure 4: Running routes of unmanned vehicles in East China Jiaotong University.

Since the rectangular coordinate system was required in the algorithm design, the 20 stop points were converted into rectangular coordinates via Excel. The distance matrix (unit: m) between the starting point and the 19 stop points (1 represents the Cainiao distribution centre) was obtained through map ranging to prevent curved road between actual point locations.

(2) Generation of distribution information

According to the distribution data survey of unmanned vehicles at Cainiao stations in East China Jiaotong University, unmanned vehicles distribute parcels 12 times for 12 h per day, with each constituting one period of appointment time. According to the research objectives in this study, the comprehensive operating costs of Cainiao unmanned vehicles in two periods of appointment time – 1 h and 30 min – were compared. The appointed distribution order data of unmanned vehicles after desensitization were acquired from Cainiao stations in East China Jiaotong University. On this basis, three groups of evenly distributed order data were generated and explained (specific order data were not placed in this study because of length restrictions) for the sake of algorithm comparisons (Table II):

Table II: Description of order data.

Appointment time span	**Selection of continuous intervals for orders**	**Upper limit of number of appointed parcels (piece)**
1 h	One interval	168
30 min	One interval	84
	Two intervals	168

Note: The continuous interval of orders refers to the fact that Cainiao unmanned vehicles distribute appointment orders in multiple continuous intervals simultaneously each time. For example, 8:00–8:30 and 8:30–9:00 are two continuous intervals under the 30 min mode.

(3) Parameter setting

According to investigation and analysis, Cainiao unmanned vehicles are only charged once per day. The unit distribution cost coefficient was calculated by combining the cost spent in charging each time and battery loss. Based on the unit cost coefficient, the time window penalty function and capacity penalty coefficient were set (see Table III) on the premise of ensuring the punctuality and capacity constraints.

4.2 Results analysis of calculation example

In this study, an improved GA model was established on the simulation experimental platform MATLAB R2018a for repeated data iterations, and the following results were acquired.

Table III: Model parameters.

Parameter	Definition	Value
u	Transportation cost within unit time (RMB¥/min)	0.1
alpha	Penalty coefficient for the violation against the capacity constraint (RMB¥/piece)	5
e	Penalty coefficient for arrival earlier than the starting time window of distribution sites (RMB¥/piece)	5
f	Penalty coefficient for arrival later than the ending time window of distribution sites (RMB¥/piece)	10
L	Maximum loading capacity of unmanned vehicles (piece)	45
NIND	Population size	100
MAXGEN	Number of iterations	500
P_c	Crossover probability	0.9
P_m	Mutation probability	0.05
ratio	Optimization guidance factor	0.9
remove	Number of shifted distribution sites in local search	0.2×N

(1) Appointment time span of 1 h

The order data within the appointment time span of 1 h generated in Section 5.1 were operated to obtain the optimized cost convergence curve and distribution route map of unmanned vehicles (Fig. 5). The related results of the distribution schemes are listed in Table IV.

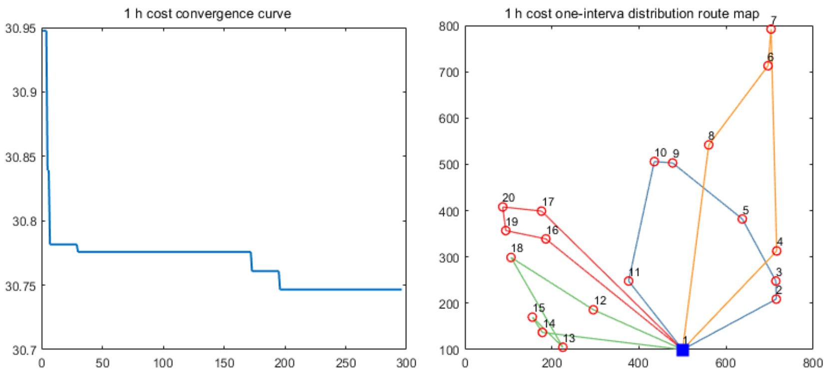

Figure 5: 1 h cost convergence curve and distribution route map.

Table IV: 1 h distribution scheme.

Total operating cost (RMB¥)	30.8
Unit parcel operating cost (RMB¥/piece)	0.183
Total capacity utilization rate of vehicles	93.3 %
Route 1	1->2->3->5->9->10->11->1 (Completion time of distribution: 23.4 min)
Order allocation	0101-0112, 0201-0206, 0401-0406, 0701-0705, 1501-1504, 0801-0809
Route 2	1->16->19->20->17->1 (Completion time of distribution: 22.7 min)
Order allocation	1001-1015, 1801-1806, 1901-1908, 1101-1112
Route 3	1->14->15->13->18->12->1 (Completion time of distribution: 25.3 min)
Order allocation	1601-1609, 1701-1706, 1301-1308, 1201-1211, 0901-0907
Route 4	1->8->6->7->4->1 (Completion time of distribution: 30.0 min)
Order allocation	1401-1404, 0501-0515, 0601-0613, 0301-0312

(2) Appointment time span of 30 min

The current appointment time span at Cainiao stations is 1 h, which is large. Thus, the parcels were loaded only in one appointment interval (e.g., the appointment orders from 8:00 to 9:00 are initially distributed at 8:00) each time. When the appointment time span was reduced, the appointment orders of multiple continuous intervals could be loaded each time. According to the 30 min, one-interval and two-interval (appointment time span) order data in Section 5.1, the results of two optimization schemes were obtained, the distribution schemes of unmanned vehicles are presented in Tables V and VI, and the cost convergence curve and route map are exhibited in Fig. 6.

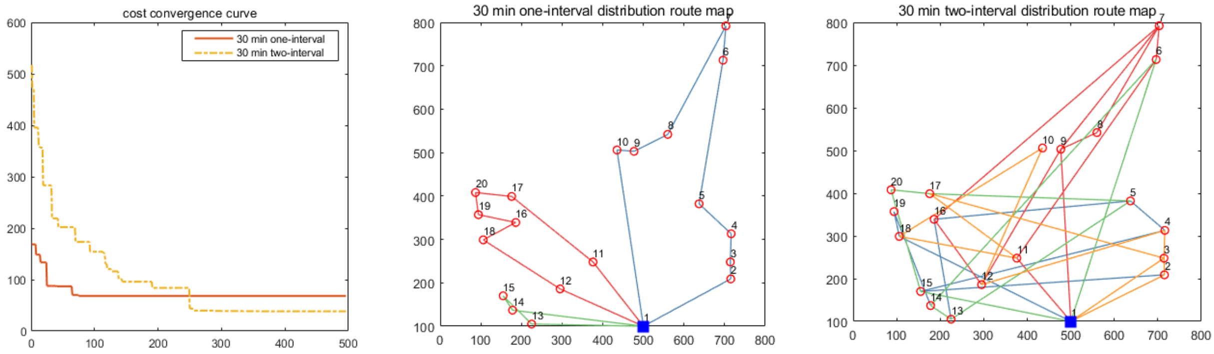

Figure 6: 30 min cost convergence curve and distribution route map.

Table V: 30 min one-interval distribution schemes.

Total operating cost (RMB¥)	68.4
Unit parcel operating cost (RMB¥/piece)	0.814
Total capacity utilization rate of vehicles	62.2 %
Route 1	1->2->3->4->5->6->7->8->9->10->1 (Completion time of distribution:33.7 min)
Order allocation	0101, 0201-0204, 0301-0303, 0401-0405, 0501-0509, 0601-0604, 0701-0704, 0801, 0901-0903
Route 2	1->11->17->20->19->16->18->12->1 (Completion time of distribution:27.1 min)
Order allocation	1001-1003, 1601-1606, 1901-1905, 1801-1805, 1501-1504, 1701-1703, 1101-1106
Route 3	1->13->15->14->1 (Completion time of distribution:15.4 min)
Order allocation	1201-1207, 1401-1407, 1301-1304

Table VI: 30 min two-interval distribution schemes.

Total operating cost (RMB¥)	38.5
Unit parcel operating cost (RMB¥/piece)	0.229
Total capacity utilization rate of vehicles	93.3 %
Route 1	1->2->15->4->5->16->13->14->19->18->1 (Completion time of distribution: 56.5 min)
Order allocation	0101-0108, 1501-1502, 0301-0306, 0401-0402, 3001-3007, 2701-2703, 2801-2807, 3301-3306, 3201-3202
Route 2	1->9->12->16->7->8->9->7->6->11->1 (Completion time of distribution:54.5 min)
Order allocation	0701-0702, 0901-0903, 1001-1008, 0601-0609, 2201-2204, 2301-2303, 2101-2104, 2001-2006, 2501-2504
Route 3	1->6->14->13->5->17->20->15->1 (Completion time of distribution:56.8 min)
Order allocation	0501-0509, 1401-1402, 1301-1305, 1901-1904, 3101-3108, 3401-3408, 2901-2904
Route 4	1->3->17->11->18->10->12->4->3->2->1 (Completion time of distribution: 52.1 min)
Order allocation	0201-0204, 1101-1104, 0801-0805, 1201-1209, 2401-2404, 2601-2604, 1801-1806, 1701-1702, 1601-1604

(3) Result analysis

The comparison results suggested that vehicles were appointed per hour and departed at each integral point of time at the Cainiao stations in East China Jiaotong University. The upper limit of loads of two vehicles within 1 h was 90 (piece), and optimization was implemented using the improved GA. After the optimization, each of the two vehicles inputted into the delivery service could operate twice, but the number of parcels distributed doubled that before the optimization. When the appointment time span was shortened to 30 min to improve customer satisfaction, the vehicle utilization rate was low under the one-interval loading mode accompanied by a large waste of transport capacity of vehicles. Under the two-interval loading mode, the vehicle utilization rate could reach as high as 93.3 %, and the unit distribution cost of parcels was slightly elevated compared with that under 1 h mode after optimization. However, customers' appointment time accuracy was enhanced evidently. Hence, if the appointment time span was set as 30 min for Cainiao stations in East China Jiaotong University, the customers' appointment time accuracy could be improved while ensuring the high vehicle utilization rate and low unit distribution cost of parcels, thus being a relatively suitable scheme.

5. CONCLUSION

The comprehensive promotion and commercial application of unmanned vehicles is an inevitable trend. With the campus distribution of Cainiao unmanned vehicles as an example, two appointment modes, namely, appointment time span of 1 h and 30 min, were proposed. Moreover, vehicle running and appointment order picking in different appointment times were planned by using the improved GA to solve current problems. Through the verification of the calculation example, the following conclusions were drawn:

(1) The quantity of unmanned vehicle inputs should be considered comprehensively according to the total number of parcels distributed at stations and customer satisfaction.

(2) The algorithm-based optimization can help change the current intensive operating status of unmanned vehicles, considerably increase the number of parcels distributed, improve the vehicle utilization rate, and reduce the unit distribution cost of parcels.

(3) Customer satisfaction can be improved with the progress of customers' appointment time window accuracy. However, the unit distribution cost of parcels will increase slightly. Given these instances, enterprises should make operation decisions by balancing customer satisfaction and economic benefits.

This study provides the optimal solutions to the upper limit of the number of customers' appointment orders, the number of unmanned vehicle inputs and their route planning, and the appointment order picking within a single period of time after the comprehensive promotion and application of unmanned vehicles. Thus, the construction of an intelligent unmanned vehicle scheduling and order allocation system according to the results of the calculation example will be the research direction in the future.

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