

UAV Logistics Route Planning Based on Improved Adaptive Genetic Algorithm

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ABSTRACT

In intelligent logistics, parcel delivery is a big challenge for logistics companies. Using drones for parcel delivery is a very efficient method. Due to limited drone power and carrying capacity, it's very hard to find best paths for fewer drones to cover all delivery points. In this paper, we use an improved adaptive genetic algorithm to design reasonable paths to solve this problem. So we can use the smallest number of drones and take the optimal route of short total distance and minimum total power consumption to cover all delivery points. However, for mutation probability influences the accuracy of the algorithm, the proper value of mutation probability of obtaining optimal route will be given according to experiments. The simulation results show that the planned drone routes are obviously better than the random routes. Furthermore, the number of drones required is also greatly reduced and optimal mutation probability can improve the accuracy of algorithm.

Keywords - logistics; drone; optimal route; genetic algorithm (GA); mutation probability

I. INTRODUCTION

Nowadays, intelligent logistics play a pivotal role in Smart City (SC). In intelligent logistics, the problem of logistics planning between cities has been solved in the modern logistics industry [1]. But in the field of logistics distribution, logistics efficiency still needs to be improved. With rapid development of UAV technology, as delivery vehicles in logistics [2], drones have the characteristics of strong controllability, high efficiency and low cost [3]. So, it's very efficient to use drones to delivery packages.

From Figure1, we can learn about the specific flow about the delivery. First, UVA approaches the delivery point and slow down. Second, it hovers and descends to place the package. Finally, it rises to continue to delivery. The whole efficient process is fully automated. Most of the domestic and foreign route planning for drones is in the military, such as the formation of multiple drone formations [4], multi-aircraft coordinated attacks [5]. However, there is a lack of research on the path planning of civil drones. And due to the limited

power of drones, it's very hard to design reasonable paths for fewer drones to cover all delivery points.

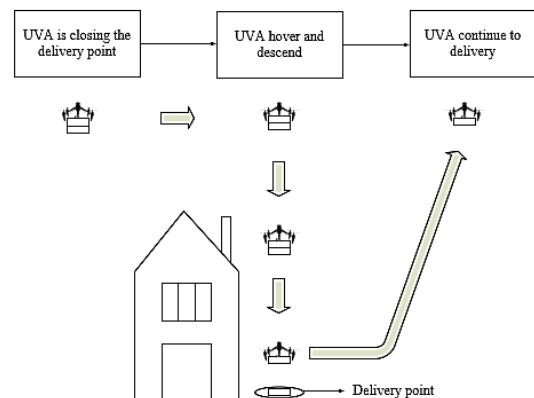


Figure1 UVA delivery package specific flow chart

Therefore, based on an improved adaptive genetic algorithm, with an appropriately raised mutation probability [6], an optimal path design method for drone is proposed. We use the existing programming software to achieve the realization of the theoretical algorithm, data, so that the algorithm and path planning through the software is more clear and easier to put into practical applications. Taking into account the timeliness and power consumption of drones, the path planning is based on three factors: the number of drones, the power consumption, and the total distance required for delivery of all drones. When performing a mission, drones need to cover all delivery points in a region. But considering the number of drones in logistics companies is limited, so the minimum number of drones should be used. Therefore, the number of drones should be considered firstly in this algorithm, and then consider power consumption and total distance. The three factors above are connected together by three weights, which are working in the fitness function of the adaptive genetic algorithm. Finally, the optimal path will be obtained by iterating.

Figure 2 shows that all delivery points for a region will be divided into many tasks. And it will be completed by multiple UVA (the least UVA should be used). This type of delivery achieves the efficiency of the task.

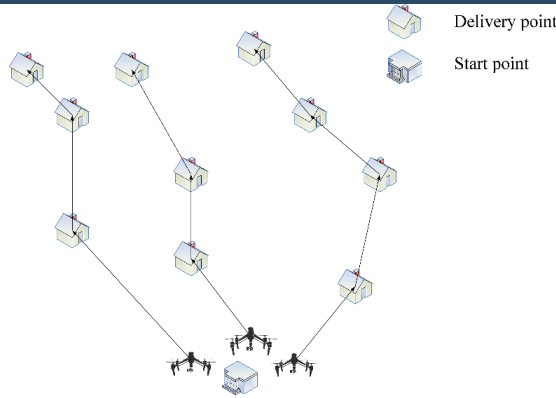


Figure 2. The flow chart of multiple UAV covering all delivery points

To sum up, there are two main contributions in this paper. Firstly, a path design method of drones based on an improved adaptive genetic algorithm is proposed, which can greatly reduce the number of drones used, the total drones flight distance and the total power consumption of drones. It makes drones more efficient and feasible to deliver packages. Secondly, by appropriately adjusting mutation probability, the algorithm accuracy is improved accordingly, which makes it easier to get the optimal solution.

The rest of the paper is organized as follows: In Section III, we will introduce related data collection and algorithm improvement. Section IV will present the system model. Finally, we will give simulation results in the Section V.

II. RELATED WORK

In this section, we will give the results of data of collection in part 1. And algorithm improvement will be given in part 2.

2.1 Collection of data

In this part, we focus on data collection on relevant application scenarios, such as the scope of delivery, the number and weight of parcels delivered under normal circumstances and the approximate flight time of the drone under heavy load conditions. According to the data, the delivery range is generally not more than 1.5km, the drone's maximum flying speed does not exceed 8m/s, and the weight of each parcel is an average of 200g[7]. The purpose of the above work is to understand the specific information of the application scenarios, and the parameters can be reasonably set when we do the simulation experiments.

2.2 Genetic algorithm

The genetic algorithm is a computational model that simulates Darwin's natural selection theory and the natural biological evolution process. It uses simple coding techniques to represent a variety of complex structures, which guides

learning and determines the direction of search through simple genetic manipulation of a set of coded representations and natural selection of the survival of the fittest. It has features of fast searching ability, iterative using probabilistic mechanism, has the characteristics of randomness, strong expansion ability, and easy combination with other algorithms [8]. It has been widely used in computer research filed which are used for combinatorial optimization, machine learning, signal processing, adaptive control and artificial life and other fields [9]. Thus, it is a key technology in modern intelligent computing.

2.3 Algorithm improvement

In this part, we will improve the traditional genetic algorithm. Because the crossover probability and mutation probability of the traditional genetic algorithm cannot be adjusted during the iterative process, the global search ability and local search ability of the algorithm cannot achieve a good balance. For this problem, an adaptive genetic algorithm is proposed [10]. By adjusting the crossover probability and mutation probability, a certain relationship between the fitness of individuals and the average fitness of the population was established, which greatly improved the convergence accuracy of the genetic algorithm and accelerates the convergence rate. The formula is as follows:

$$pc = \begin{cases} pcmax - \frac{(pcmax - pcmin) \times (\alpha - \beta)}{\delta - \beta}, & \alpha > \beta \\ pcmax, & \alpha \leq \beta \end{cases} \quad (1)$$

Where pc is the crossover probability, $pcmax$ is the largest crossover probability, $pcmin$ is the smallest crossover probability, δ is the maximum fitness in the population, α is the one with the highest fitness among the two individuals to cross and β is the average fitness of the population.

$$pm = \begin{cases} pmmax - \frac{(pmmax - pmmin) \times (\delta - \mu)}{\delta - \beta}, & \mu > \beta \\ pmmax, & \mu \leq \beta \end{cases} \quad (2)$$

Where pm the probability of mutation is, $pmmax$ is the largest mutation probability, $pmmin$ is the smallest mutation probability, and μ presents the fitness of the current individual.

III. SYSTEM MODEL FOR UAV SYSTEM

This section is divided into four parts. The first part will list the considerations for planning the drone path. In the second path, the hypotheses based on the actual situation of the application scenario will be given. In the third part, we will perform mathematical modeling based on parts 1 and 2. In the last part, pseudo code of the genetic algorithm based on parts 3 will be given.

According to the application scenario and the purpose of this project, the number of drones has the greatest impact on the model, followed by the total length of the drone path and the total power consumption of the drone. Therefore, the factors affecting drones can be divided into three, which is shown as follows:

1. The drone's number.
2. The total distance required for the drone to complete the mission.
3. Power consumption of drones, which can be continuously divided into three parts. They are power consumption of the drone during flight, the power consumption of the drone when hovering and the consumption of electricity by the wind (this can be ignored when the wind is small).

Since some small errors in the application scene do not have an excessive impact on the overall (for example, the different quality of the package, the wind speed is not constant, and the acceleration and deceleration of drones), the following assumptions are made:

1. The route of drones is straight and is flying at a constant speed (regarded as stationary when hovering).
2. The weight of the package can be considered the same.
3. After the drone has landed all packages, it must have enough power to return to the starting point.
4. The wind speed is considered unchangeable.

3.1 The calculation of the optimized objective function

Suppose the speed of drone is v , required number of drones is Num , the total length of the drone path is $Length$ and the total power consumption of the drone is W .

When the influence of wind is not considered:

This step is to normalize the data, so that all data is changed to (0,1) this interval, the purpose is to reduce the impact of data caused by different data types, in order to facilitate the subsequent weight settings. The normalized formula is calculated as:

$$Nor(x) = \left[1 - \frac{x - \min(x)}{\max(x) - \min(x) + 0.01}\right]^2 \quad (3)$$

Where $\max(x)$ indicates to the maximum value of x , and $\min(x)$ indicates the minimal value of x .

Mass of drone:

$$m(j) = m1 + m2 \times (\gamma - j) \quad (4)$$

Where $m1$ is the weight of the drone, $m2$ is the quality of the unit package, and j starts at 0 and increases by 1 each time the

drone completes a delivery. γ is the number of package which the drone will delivery.

$$W(j) = k1 \times [k2 \times m(j) \times tf(j) + m(j) \times th] \quad (5)$$

Where $W(j)$ is power consumption per segment. $k1$ is a constant, $k2$ represents the ratio of the power of a drone at uniform speed to the power at hovering, $tf(j)$ is the flight time for each segment. th represents the hover time when the drone delivers the package.

(3), (4) and (5) can be used to determine the individual's fitness:

$$fitness = a1 \times Nor(Num) + a2 \times Nor(Length) + a3 \times Nor\left[\sum_{j=0}^{\gamma} W(j)\right] \quad (6)$$

$a1, a2, a3$ are the weights of $Num, Length$ and W , respectively. Due to the priority given to the number of drones, so $a1 \gg a2 + a3$.

When the influence of wind is considered:

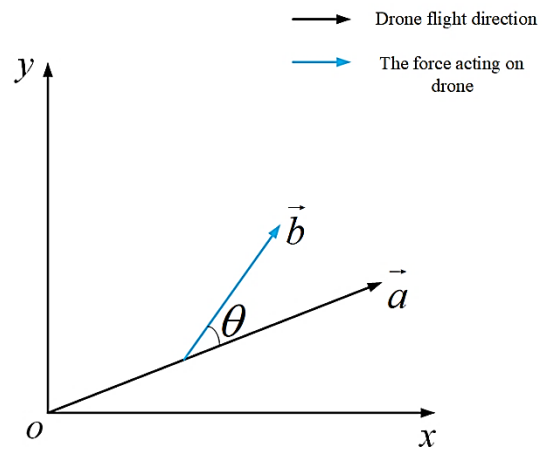


Figure 3 Vector exploded view of wind acting on drone

The figure presents the relationship between flight direction and the wind direction.

From the above figure, the angle between \vec{a} and \vec{b} is:

$$\theta(j) = \arccos\left(\frac{\vec{a} \times \vec{b}}{|\vec{a}| \times |\vec{b}|}\right) \quad (7)$$

Where \vec{a} is the drone flight direction, \vec{b} presents wind direction.

$$\begin{cases} FH(j) = F \times \cos[\theta(j)] \\ FV(j) = F \times \sin[\theta(j)] \end{cases} \quad (8)$$

Where $F = |\vec{b}|$ is the wind force acting on the drone, $FH(j)$ is the resolution of the wind in the direction of flight, and

$FV(j)$ presents the resolution of the wind in the vertical direction of flight.

Wind consumption is:

$$WD = \sum_{j=0}^Y [FV(j) \times tf(j) + FH(j) \times tf(j)] + F \times \text{totalth} \quad (9)$$

Where totalth presents total hover time period.

Drone total power consumption is:

$$WT = WD + W \quad (10)$$

The optimization function:

$$\text{fitness}' = a1 \times \text{Nor}(\text{Num}) + a2 \times \text{Nor}(\text{Length}) + a3 \times \text{Nor}(WT) \quad (11)$$

As above, the same $a1 \gg a2 + a3$.

3.2 Application of Genetic Algorithm in Model

Assuming that the starting point is a "1" point, each number represents a point, and there are $N - 1$ delivery points, then each track can be represented as $(1, p_1, p_2, \dots, p_{N-1})$.

Genetic Algorithm

1. Input the parameters. (Include $N, M, m1, m2, k1, k2, a1, a2, a3, v, th, \text{totalth}$ and the coordinates of all points)
2. Calculate the distance between x and y and store it in array $D(x, y)$. And calculate the time of each segment $th(j)$ by formula $t = \frac{d}{v}$.
3. Generate a $M \times N$ -dimensional matrix named *Pop* whose first number of each individual is "1".
4. for $j = 1: M$
 - Set the counter $\epsilon = 1$ to record how many points the drone has passed.
 - Selecting judgments and calculating models based on consideration of wind conditions.
 - while 1
 - If (The drone has enough power to complete the next delivery and return enough power to the starting point) && ($\epsilon \neq N + 1$)
 - change the track of the No. Num Drone to $(1, p_\epsilon \dots)$;
 - $\epsilon = \epsilon + 1$;
 - else
 - change the track of the No. Num drone to $(1, p_1 \dots, p_{\epsilon-1}, 1)$;
 - if all delivery points are covered
 - break;
 - else
 - $\text{Num} = \text{Num} + 1$;

end

Through the above steps, Num Length and W of all individuals in the population can be obtained.

5. Calculate population fitness and average fitness. Use roulette and elite retention strategies for selection operations.

6. Calculate the crossover and mutation probability according to formula (1) and formula(2). Then do traditional crossovers and mutations to create a new population. Remove the least adaptive individuals in the population.

7. When there is no change in fitness function value after 250 iterations, output the result. Otherwise, return to 4.

IV. RESULTS

In this section, we will introduce the simulation environment, important parameter settings and final results. In order to verify the validity of the algorithm, we will compare the results of the no-planned and planned routes and display them in the form of tables and pictures.

4.1 simulation environment and the important parameter settings

We simulate in MATLAB, and the parameters are set as follows:

Table 1 the setting of important parameters ($pmmax$ will be determined after optimizing it)

Parameters	Value
N	13
M	50
$pcmax$	0.9
$pcmin$	0.6
$pmmax$	0.2~0.8
$pmmin$	0.1

4.2 final results

(a) Does not consider the influence of the wind

Change the $pmmax$ and do 50 experiments for each group (perform a set of experiments every 0.05). Get the average data of the total drone distance, the total drone power consumption, and the total number of drones when testing $pmmax$ from 0.2 to 0.8. The results are shown in the following figures:

As we can see from given figures that the shortest path and the least power consumption appears while the mutation probability ($pmmax$) is approximately 0.41. When it is greater than or less than 0.41, they show an upward trend.

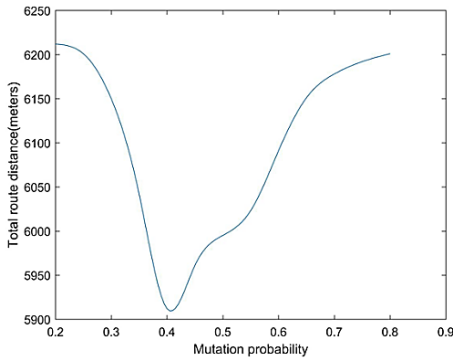


Figure 4 Relationship between total route distance and mutation probability (Does not consider the influence of the wind)

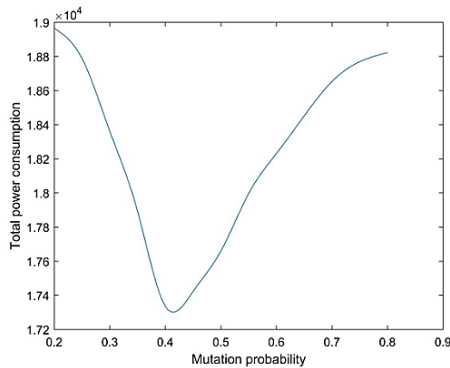


Figure 5 Relationship between total power consumption and mutation probability (Does not consider the influence of the wind)

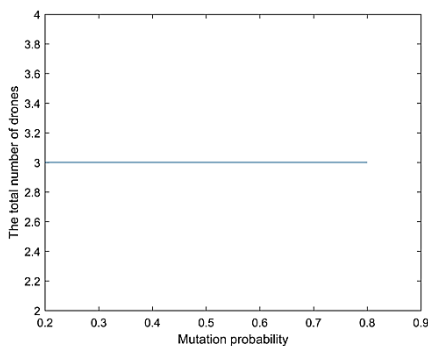


Figure 6 Relationship between the total number of drones and mutation probability (Does not consider the influence of the wind)

Through the simulation results, we can see that for the total distance of drones and the total power consumption of drones, the best outcome is when the $pmmax$ is approximately 0.41. And it can be seen from the simulation results that for the number of drones, the change in the mutation probability has no effect on it. According to Table 1, set $pmmax$ to 0.41 and other parameters remain unchanged. Through the simulation

of MATLAB, the following two figures are obtained, representing the no-planned drone path and the planned drone path.

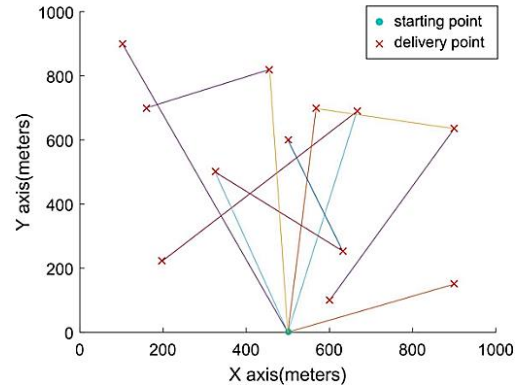


Figure 7 Path before planning (Does not consider the influence of the wind)

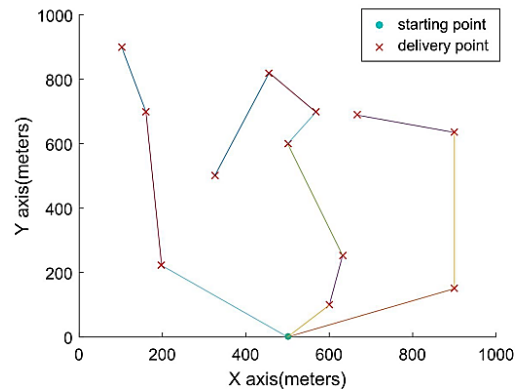


Figure 8 Path after planning (Does not consider the influence of the wind)

Table 2 Average data (50 times) (Does not consider the influence of the wind)

Condition	Num	Length	W
Before planning	5.35	9975	29862
After planning	3	5912	17336

As we can see from Fig.7, the path before planning is very disorder. Many drones are needed to take a long way to complete the delivery. It's very inefficient and so, it's needed to be optimized. And Fig.8 shows that the route after planning is obviously better than that before planning. The number of drones and the total distance is obviously reduced. On the basis of the above, 50 data records are made for the pre-planned path and the planned path, and the average value is calculated. The results are shown in the following table. From the above table and figure, we can see that after a reasonable

path planning can greatly reduce the number of drones used and the total power consumption, and can reduce the total distance, greatly improves the efficiency of drone delivery packages. It verifies the effectiveness of the algorithm when not considering the wind.

(b) Consider the influence of the wind

Considering the wind factor, the wind is set as a vector (-0.1,0.1)(The starting point of the vector is the origin of the coordinates). As the above steps, experiments were conducted with the consideration of the wind. The results are as follows:

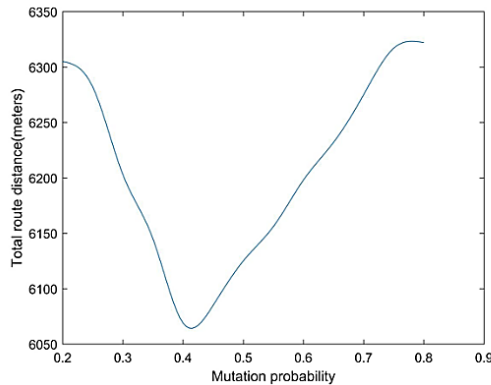


Figure 9 Relationship between total route distance and mutation probability (consider the influence of the wind)

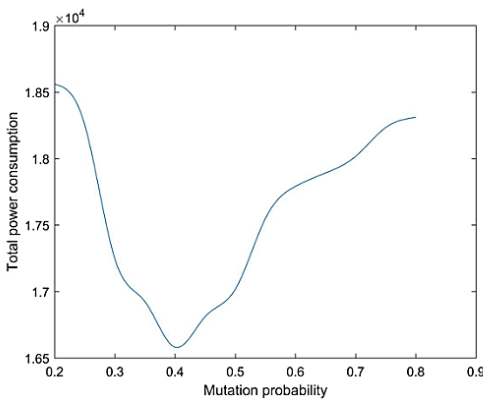


Figure 10 Relationship between total power consumption and mutation probability (consider the influence of the wind)

From figures 10, the shortest path and least power consumption appears while the mutation probability is approximately 0.41. When it is greater than or less than 0.41, they show an upward trend. The figure 11 shows that with increasing mutation probability, the number of drones remains unchanged. Through the simulation results, when the wind factor is considered, we can see that for the total distance of drones and the total power consumption of drones, the best outcome is when the *pmmax* is also approximately 0.41. And it can be seen from the simulation results that for the number

of drones, the change in the mutation probability has no effect on it. According to Table 1, set *pmmax* to 0.41 and other parameters remain unchanged. Under the consideration of wind, the following two figures are obtained, representing the no-planned drone path and the planned drone path by the simulation of MATLAB.

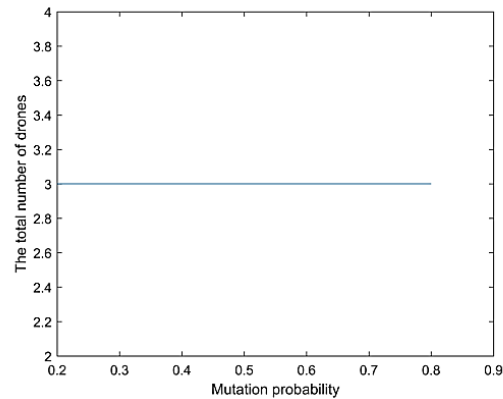


Figure 11 Relationship between the number of drones and mutation probability (consider the influence of the wind)

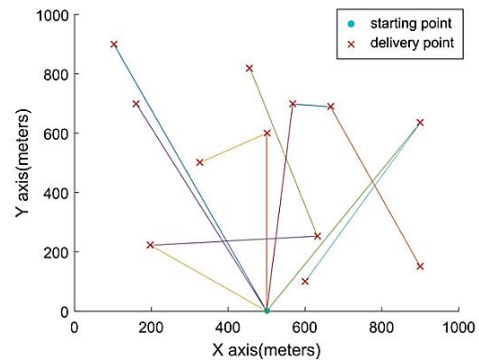


Figure 12 Path before planning (Consider the influence of the wind)

Figure 12 shows that the path before planning is inefficient, it needs too many drones and takes too long way to finish it when consider the influence of the wind. It's also should be optimized when consider the influence of the wind. We can get from Figure 13 that the route after planning is obviously better than that before planning. The number of drones and the total distance is obviously reduced. Record 50 data as above. The results are shown in the table 3. According to Table 3, under the consideration of wind, we can see that routes can be greatly optimized by the algorithm. It verify the effectiveness of the algorithm when considering the wind. From the simulation results, in contrast to the absence of consideration for wind factors, we can see that the value of the optimal solution of the number of drones is basically

unchanged. But the average total distance increases and the average total power consumption decreases.

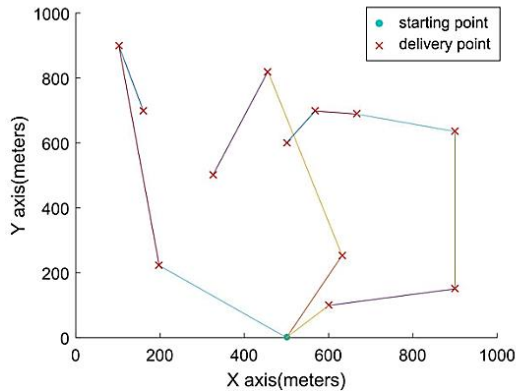


Figure 13 Path after planning (Consider the influence of the wind)

Condition	Num	Length	WT
Before planning	5.36	10025	28554
After planning	3	6069	16581

Table 3 Average data (50 times) (Consider the influence of the wind)

V. CONCLUSION

In this paper, a UAV path planning based on an improved adaptive genetic algorithm is proposed and two problems are solved. Firstly, through experiments, it is found that appropriately adjusting the mutation probability (pmmax) can get better results. Secondly, according the simulation results in MATLAB, it turns out that this improved adaptive genetic algorithm cooperates with adjusting the mutation probability to solve this kind of path planning problem is efficient. The number of drones, total distance and total power consumption have been greatly reduced, making it practical and feasible to use drones to deliver packages.

Acknowledgments

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