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Optimal paths for UAV multi-express full delivery in 3D modeling

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Abstract. The use of drones in logistics is steadily becoming more common as drone technology advances. As a result, logistics path planning has become a viable research topic. The majority of previous research has concentrated on low-load vehicle-borne UAVs. DJI recently produced a high payload civilian delivery UAV with a maximum capacity of 30 to 40 kg, paving the path for high payload UAVs and providing the criteria for this research. The goal of this research is to increase the efficiency of UAV delivery while also reducing energy consumption, as well as to investigate the path planning problem for large load UAVs in batches. Prior to choosing the ACO method to determine the best route for a single batch, the genetic algorithm is used to achieve the entire load for express delivery in batches. After this, the whole path is determined and supported. The output of the program is the correlation between the number of iterations and the single optimal route, which is then added to produce the overall path. After showing this, we infer that the sum of single ideal paths is the best total path, which maximizes efficiency and saves energy. The significance of this research is to provide some directions for thinking and help for the research of UAV logistics, and we hope to further develop UAV logistics technology to some extent under the premise of energy saving and time saving.

Keywords: UAVs, Delivery, High Load, Optimal Paths, Logistics Technology.

1. Introduction

China's drone industry has advanced significantly in the recent decade, particularly in terms of civilian drone market share. Before January 20, 2016, for example, the number of drones registered for usage in the United States had surpassed 200000 [1]. One of the most important applications of civilian drones is courier delivery, which is part of the smart logistics sector. The Chinese smart logistics market increased from RMB 145.2 billion in 2013 to RMB 492 billion in 2019 in order to reduce cross infection [2]. Currently, thirteen drone test zones have been established in the country, including two pilot zones for drone logistics development and three pilot zones for urban drone logistics and distribution. Additionally, Jingdong, Baidu and other enterprises have obtained some regional flight licenses for unmanned aerial vehicle (UAV). They as well allocate a large amount of expenditure to invest in this field in order to strengthen the research and development of large-scale logistics drones and build air logistics network [3]. Furthermore, due to no-touch, drone delivery has risen, particularly after the 2020

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pandemic, and the industry is expanding exponentially [4]. Consequently, logistics would be an important area of drone application.

Previously, a shortage of capacity was regarded an impediment to the growth of UAV delivery [5]. Drone delivery skills have continued to expand and improve in recent years. DJI officially launched its first civilian delivery drone, the DJI FlyCart 30 (FC30), on August 16, 2023. The FC30 has a large load capacity as well as a long range. The equipment has a 4-axis, 8-propeller multi-rotor configuration and a dual-battery system, with a maximum load of 30 kilograms in dual-battery mode and 40 kilograms in single-battery mode, as well as a range of up to 28 kilometers, allowing it to perform more complex transport and delivery functions. With the arrival of high-loading drones, how to enhance the efficiency of transporting different weights of items in batches to accomplish the shortest overall journey in the least amount of time will become an interesting subject to investigate.

Currently, most of the research on multi-express delivery paths for UAVs is focused on vehicle-mounted UAVs (UAVs with low payloads), and there is a lack of research on stand-alone transportation of high payload UAVs [6]. And because of the vehicle-mounted function, how to maximize the efficiency by delivering in batches does not need to be taken into account due to the ample space of the vehicle. The optimal path issue for autonomous UAV transportation in batches (as fully as feasible each time) will be the main topic of this study.

In the article, the following contributions to optimizing the best paths for UAVs will be proposed. First, three-dimensional modeling was used in this experiment, and the data were distributed normally to simulate realistic scenarios better. Secondly, the algorithm considers the different weights of the courier and the resulting batch transportation, which is more in line with the practical scenario. In order to discover the best path under the batch premise, a hybrid method (Ant Colony method Nested Genetic Algorithm) is suggested in this research.

The structure of this article is as follows. Some fundamental information would be included in section 2. Section 3 would offer some details of optimal model, explaining cargo distribution and route optimization models respectively. In section 4, some evidence of the relationship between total path length and goods in batches would be pointed out. Conclusion would be discussed in section 5.

2. Problem description

The problem of this experiment is described as follows: a drone departs from a distribution center and independently delivers deliveries in batches to customers' homes and then returns to the distribution center. Two parts are included in the entire operation: allocating couriers in batches as full as feasible based on weight in the distribution center; and delivering the courier to the customer and then returning. Then repeat the above steps until the express delivery is complete. Our aim is to use full load as the criterion for batch delivery, together with the shortest single delivery path, to achieve the shortest total path, thus saving time and energy consumption, and maximizing the benefits of UAV delivery.

2.1. Problem assumption

Ignore the different charging times due to different loads; 2) Ignoring obstacles in drone delivery (disregarding the path recognition issue); 3) Ignore takeoff and landing paths.

2.2. Basic model and variable explanation

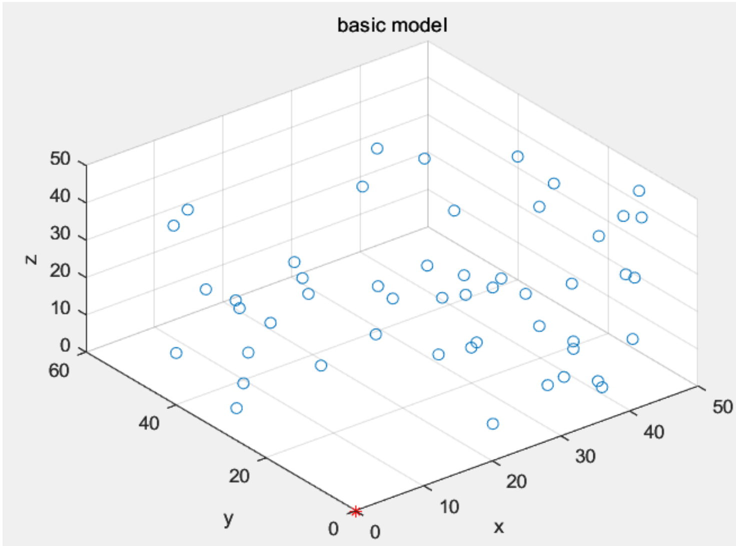

Figure 1. Basic model for the location of customers and distribution centers (photo credit: original)

Basic model is displayed in Figure 1. To be specific, modeling in 3D space, 50 coordinates are randomly selected as target customers (x,y,z). In addition to this, a point is selected as the starting point of the distribution center (0,0,0). Make the drone's maximum load thirty kilograms and randomly set 50 couriers with different loads (weight<30kg). In Figure 1, the blue hollow circle represents the -location of the target customer, while the red dot represents the distribution center (starting point).

3. Model optimization

The path optimization problem for the UAV delivery problem has become more common, and this research will optimize it based on the following aspects: cargo allocation using genetic algorithm, ant colony under three-dimensional.

3.1. Goods allocation model

Genetic Algorithm (GA) is one of the first population-based stochastic algorithm proposed in the history [7]. Here, Genetic Algorithm is chosen to be used in the goods allocation model. The goods allocation model is a matrix containing the "genetic information" of goods obtained based on genetic algorithms. It utilizes the powerful matrix operation and storage capabilities of MATLAB, and then saves the obtained answer matrix.

In this model, we first calculate the possible minimum batch, which is the total weight of the goods/maximum single load of the drone, and round it up. Once we have the smallest possible batch, we can start setting up "genetic information" about the goods. In genetic algorithms, we often use 0 and 1 to indicate whether the chromosome contains the target gene. In a single batch, all goods are randomly numbered and each goods is randomly assigned 0 and 1. When it is 1, it means it exists in this batch, and when it is 0, it means it does not exist. In MATLAB, we can save it in the form of a matrix. And retrieve coordinate information in the subsequent steps to find the shortest path.

However, in this issue, it is not the traditional 01 problem. The traditional 01 problem can only obtain the optimal single batch and cannot obtain the multi batch allocation model for the entire goods we need. Therefore, we refer to the idea of polyploid breeding in genetics and change the traditional 01 two random codes to multiple random codes (for example, we used 123 for 3 batches and so on). In this cargo allocation model, the number of randomly coded classes is equal to the number of minimum batches.

Due to the complexity of multi batch problems, in order to facilitate and quickly obtain the "genetic information" we need. We limit the required random codes during the random process, so that the total number of single type codes follows the rule of normal distribution, which is concentrated on the total quantity of goods/minimum batch. This can effectively reduce invalid solutions and reduce our computational steps. Whenever a set of grouping sequences is obtained, an inspection is conducted to calculate whether the total weight of each batch of goods is less than the weight of a single batch of goods. If the conditions are met, the set of data is recorded in the matrix, and if not, the set of data is not recorded. However, the minimum batch used at this time is not the actual minimum batch, it is only the possible minimum batch. We have artificially set an upper limit on the number of consecutive non compliant batches when no conditions are met. When this calculation upper limit is reached, we will add the total batch and continue to calculate until we find multiple solutions that match.

After obtaining multiple sets of matching data, you can proceed to the next step 3.2, where you can bring the obtained matrix data into the matrix to calculate their distance.

3.2. *Optimal path model*

The path planning problem in this research is solved based on Ant Colony Algorithm. Therefore, the following section will explain in detail the principle of the ACO algorithm and describe how it might be adopted to this 3D visualization.

First, we start by briefly outlining the fundamental ideas behind the ACO. When looking for food, ants produce a hormone called "pheromone" on the path they take; more pheromone is emitted as more ants go along the trail, which increases the amount of pheromone in the path and eventually leads to solution convergence, resulting in the best path [8].

To further describe the ACO algorithm, we might first design a two-dimensional scenario that is extremely comparable to this research. For example, how can ants visit all the cities in the smallest amount of time (each city has just one chance to be passed by)? Assume there are *m* ants, *n* cities, $d_{i,j}$ is the length from cities *i* to *j*, and the pheromone concentration at time t is $\tau_{i,j}(t)$ $P_{i,j}^{k}(t)$.

Assume that in the initial state, pheromone concentrations are the same in all parts of the city. The following equation can then be obtained:

$$\tau_{i,j}(0) = \tau_{init} \quad i,j = 1,2,\dots,n \tag{1}$$

After that, we assume that at time *t*, the likelihood of moving from location *i* to *j* for ant *k* is Moreover, ants can't go back to a city they've visited in one crawl. Thus, A_k represents the collection of cities that ant *k* has not visited. Then we introduce an heuristic value "$\eta_{i,j}(t)$ "for the route between cities *i* and *j* for each ant, and this value can commonly be represented by the reciprocal of the corresponding distance, such as:

$$\eta_{i,j}(t) = \frac{1}{d_{i,j}} \tag{2}$$

The definition formulas of likelihood is the following equations:

$$P_{i,j}^{k}(t) = \begin{Bmatrix} \dfrac{\left[\tau_{i,j}(t)\right]^{\alpha} \bullet \left[\eta_{i,j}(t)\right]^{\beta}}{\sum_{s\in A_k}\left[\tau_{i,s}(t)\right]^{\alpha} \bullet \left[\eta_{i,s}(t)\right]^{\beta}}, if\ \mathrm{j} \in A_K \\ 0, otherwise \end{Bmatrix} \tag{3}$$

α and ***β*** represent the corresponding weights of heuristic value and pheromone concentration. In this equation, the numerator represents the weights of the ant *k* at city *i* for selecting city *j* as the destination, while the denominator is the sum of the weights of all the paths to other cities from city *i* where ant *k* departs. Following the determination of each city's transfer probability, a roulette algorithm is used to select a city as a destination based on the probability, which will not be explained in detail here.

This research also needs to consider the upgraded process of pheromone. In the first iteration *g*, the following equation shows updating the pheromone:

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$$\tau_{i,j}(g+1) = (1-\rho) \bullet \tau_{i,j}(g) + \sum_{t=1}^{n} \Delta\tau_{i,j}\,(t) \tag{4}$$

where ρ represents evaporation rate of pheromones ($0<\rho<1$), and the addition of pheromones at time t from city i to city j can be represented by the equation:

$$\Delta\tau_{i,j}(t) = \sum_{k=1}^{m} \Delta\tau_{i,j}^{k}\,(t) \tag{5}$$

If the ant k does not traverse the way at the time t, the pheromone increase it causes is recorded as 0. Otherwise, the pheromone increase it causes is inversely proportional to the journey it has already taken. Thus, the pheromones left by ant k can be shown by the equation:

$$\Delta\tau_{i,j}^{k}(t) = \left\{\begin{matrix} \frac{Q}{L_k}, if\ ant\ k\ travels\ from\ i\ to\ j\ in\ time\ t \\ 0, otherwise \end{matrix}\right\} \tag{6}$$

The pheromone constant is Q, and the total length traversed by the ant k is L_k. That concludes the fundamental description of the ACO algorithm.

Then we'll talk about how to use this type of method into our study, namely 3-D modeling. In our investigation, some major principles do not show any alterations, where cities in the aforementioned text are replaced by customers.

For the 3-D model, except the need for creating a $3*n$ matrix and different formulas while calculating the distance, the main changes would be occurred in the heuristic function, which can be represented by the equation [9, 10]:

$$H(i,j,k) = D(i,j,k)^{\alpha} * S(i,j,k)^{\beta} * Q(i,j,k)^{\theta} \tag{7}$$

where $D(i,j,k)$ denotes the length connecting two cities and $S(i,j,k)$ is the safety factor, which is 1 when the choice point is reachable and 0 when it is not reachable, prompting the ants to choose the safe point;the ants may select a location nearer to the goal if $Q(i,j,k)$ is the distance from the next point to the target point; are three parameters. Except for a few nuances, the most of the processes in this research based on the ACO algorithm are comparable to the basic ACO methodological premise outlined in this paper.

3.3. Solution of the optimal total path

The total path would be obtained in 3.2 in terms of size, and finally output the minimum value, which is the shortest path calculated in this calculation. In the actual application process, since we use MATLAB for calculation and the data is stored in a matrix format, the goods information (azimuth coordinates) can be output together when outputting the shortest path.

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4. Results

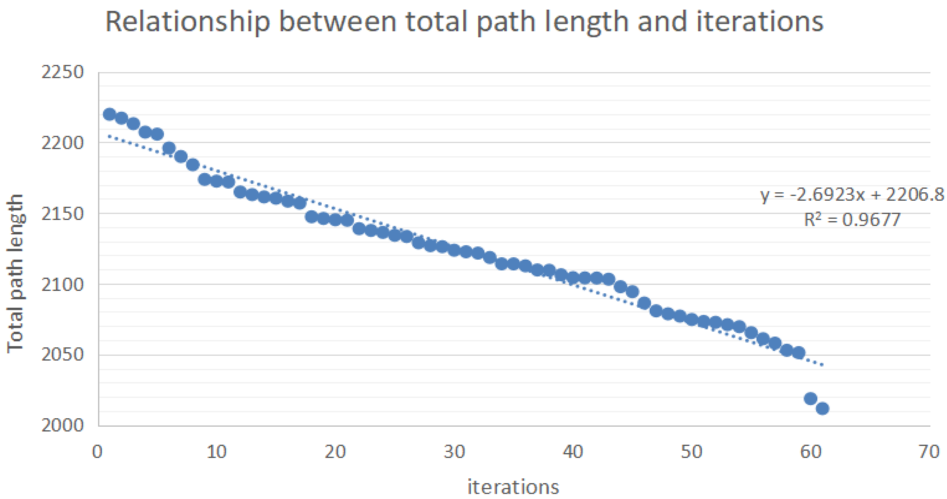

Figure 2. Relationship between total path length and iterations (photo credit: original).

According to the circumstances depicted in the image (see Figure 2), this research successfully processed data from the 3.1 cargo allocation stage and the 3.2 path planning algorithm thanks to MATLAB's tremendous matrix processing capabilities. We acquired the requisite shortest path information after around 60 data iterations. In the meantime, keep in mind that we also obtained distance planning data for the quickest way in another matrix. These new details are really useful and useful for future practical applications.

The collecting of these data will aid in the optimization of logistics and route planning, enhancing practical efficiency. This means we can better allocate items and plan routes, resulting in less time and resource waste. This might have a big influence on a variety of industries, including logistics and transportation.

In addition, when gathering distance planning data, we can evaluate it to optimize future route choices and resource allocation. In conclusion, MATLAB's matrix computing capacity provides us with a powerful tool for addressing complicated path planning issues, which is critical for increasing efficiency and maximizing resource consumption.

Drone delivery is projected to transform the logistics and delivery industries in the future. Although there are still some technical and regulatory issues, we believe that as technology advances and improves, drone delivery will become a more common and viable option, providing consumers with faster, more efficient, and environmentally friendly delivery services.

5. Conclusion

In this study, we investigated the optimal path problem for unmanned aerial vehicle (UAV) multi express delivery throughout the entire process, with a focus on the fact that the UAV delivery model in practical problems is a three-dimensional model. Through the analysis and processing of the data, we have reached the following conclusions: 1) Goods allocation: Through the genetic algorithm based goods allocation model, we can obtain the specific data of the goods batches we need and use it in subsequent path planning models. 2) Path planning: Using the ACO model, calculate the specific data of goods batches in the goods allocation model to find the shortest total path.

Currently, the domestic logistics industry's enthusiasm for drones derives from the bottleneck of traditional express shipping methods. Automobile saturation will worsen in the future, and traditional ground transit will become increasingly constricted. It is critical to construct an efficient and quick logistics system. Logistics companies will supplement their transportation capacity by obtaining capital financing, leasing, and purchasing mainline cargo planes; e-commerce companies will improve their

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warehousing capabilities to ensure that their warehouses are close enough to their target customers, reducing large-scale and high-timeliness trunk logistics. Although the approaches described above have reduced the logistics time of the main line, the bottleneck of branch logistics and last mile distribution cannot be effectively addressed with current technology. Therefore, all parties use airspace below 1000 meters as key resources, and branch fixed wing and tiny rotor drones have emerged as the key to growth.

Firstly, the safety of drones has always been a concern for people. Although technology has made significant progress, how to further reduce the probability of accident risk remains one of the challenges that industry experts need to solve.

Second, drone stability is more challenging than that of passenger airplanes or freight planes. Smaller drones, in particular, are more vulnerable to the effects of weather, including visible large-scale weather elements like wind, rain, snow, and fog, as well as unanticipated events like clear sky wind shear and abrupt airflow, which can have a substantial impact on drones.

Finally, policy considerations are a major element limiting drones. Regulation is just beginning, with significant uncertainty. Relevant departments must improve regulation and control the growth of the drone sector.

Authors Contribution

Each author made an equal contribution, and their names are presented alphabetically.

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