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Optimization of Drone-Assisted Delivery System

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Abstract

Recently, a new parcel delivery method has been emerged, which involves Unmanned Aerial Vehicles, also known as drones, assisting traditional trucks in last-mile delivery across logistic networks. This method generally combines a truck and one drone or more to handle the delivery processes to customers. And this paper tends to calculate the optimal route of this drone-assisted delivery system, the objective is to minimize the operational time and energy cost. I developed a heuristic solution approach which implements an effective Genetic Algorithm to solve and simulate this delivery system of practical size, this program can automatically generate the on-screen best route results and show the total operational time and energy cost.

Key words: Traveling Salesman Problem with Drone, Heuristic, Genetic Algorithm, Delivery System

1. Introduction

During the past few years, the commercial use of drones has been more frequent, and the technology for drones and the relative delivery network has also increased rapidly. Therefore, the necessity of studying the effectiveness and result of this drone-assisted delivery system is existential. This new distribution model is the use of a regular delivery truck that collaborates with drones to support parcel delivery. The drones have the advantages such as flexibility and speed which the trucks do not have. In addition, the long-range transportation ability and high capacity of trucks are not available in drones. Thence, there are complementary advantages when using drones to assist parcel delivery.

Some companies are experimenting and examining the new technology of drones to support the mails and parcels delivery. Amazon Prime Air has planned to use multirotor Miniature UAV to automatically carry packages from Amazon order fulfillment center to customers' locations within 30 minutes of ordering. And China's biggest internet retailer—Alibaba, said it had begun testing drone-based deliveries to hundreds of customers.

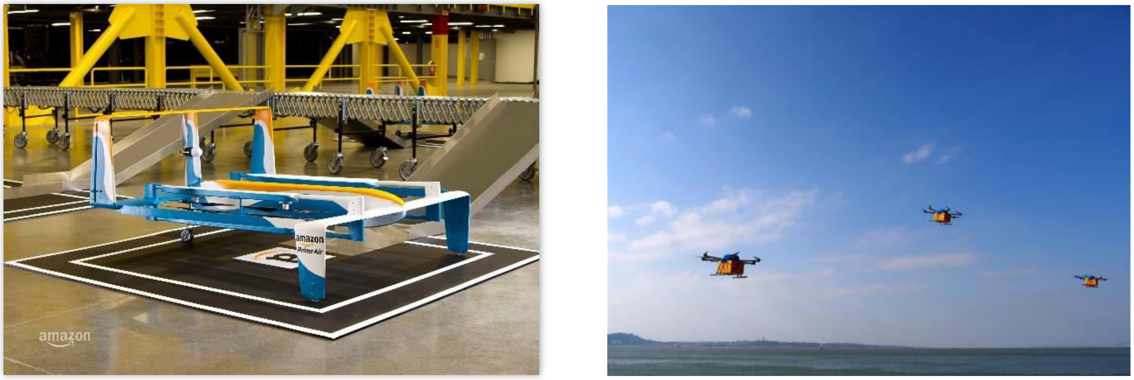


Figure 1. Amazon’s Prime Air UAV and Alibaba’s drone

I have researched and investigated some related literature, in every logistics activity, operational costs and time play important roles in the overall business cost. Hence, minimizing these costs by optimizing min-time and min-energy drone-assisted delivery system (DADS) is a vital objective of every company involved in transport and logistics activities.

2. Related Literature

I am aware of several related literature on the Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP), while these publications are not very suitable for this new truck-drone tandem delivery system. We call this new distribution method the Traveling Salesman Problem with Drone (TSP-D). Perhaps there are different names and for this kind of problem. But in general, this problem aims to find an optimal route for both trucks and drones, that minimize the total joint time to complete the delivery tasks of all packages.

Solution approaches	Literature
Integer linear programming	*Agatz et al. (2016); Murray & Chu (2015)*
Approximation algorithms	*Agatz et al. (2016)*
Dynamic programming	*Bouman et al. (2017)*
Simple heuristics	*Murray & Chu (2015); Ha & Deville et al. (2015)*
Simulated annealing	*Ponza (2016)*
Genetic algorithms	*Ferrandez & Harbison et al. (2016)*

Table 1. Solution approaches proposed for different literature

Table 1 summarizes the present solution procedures and approaches that have been studied for several slightly variants of the TSP-D.

Murray & Chu (2015) called the problem “Flying Sidekick Traveling Salesman Problem”, which developed a mixed integer linear programming (MILP) formulation and a simple heuristic solution to solve this TSP-D problem. They first find the best route for the truck as a typical TSP. Then, they run a relocation procedure which will check each node’s possibility for drone service. *Ponza (2016)* extended *Murray & Chu (2015)*’s work by proposing a Simulated Annealing approach to solve the problem.

Agatz et al. (2016) presented a MILP formulation and developed several Route first-cluster second approximation heuristic algorithms to solve the TSP-D. *Bouman et al. (2017)* extended *Agatz et al. (2016)*'s study and raised an exact solution which formed on dynamic programming. Their work can resolve the problem of practical size.

Ferrandez & Harbison et al. (2016) used K-means clustering and Genetic algorithm to investigate the effectiveness and compare the difference between the truck-drone tandem delivery system and stand-alone truck delivery network.

3. Problem Description

The DADS can be modeled as a set of N customers and one Distribution Center (D.C.), each customer should only be served by either a traditional delivery truck or an unpiloted drone. The determining factors are the available flight range of drones and the parcels' size, because the drone can carry this package only if its size is small enough to fit in the cargo box, and the drones are battery-driven, which means they have a restriction on their flight range.

The driver-operated truck will carry the drone and packages, then depart from the D.C.. After delivering all packages to the customers, the truck and the drone can return to the D.C. independently or in tandem. During the delivery process, the truck and the drone can also travel independently or in tandem. While working independently the drone is launched from the truck and served a nearby customer with one package, when the drone is in service, the truck should continue its delivery. Then the drone must return to the truck and recharge or change the battery and pick up a package for next delivery task. The launch points and the reunion points must be one of the customer locations. While working in tandem the drone will be carried by truck, which can conserve the energy cost of the drone.

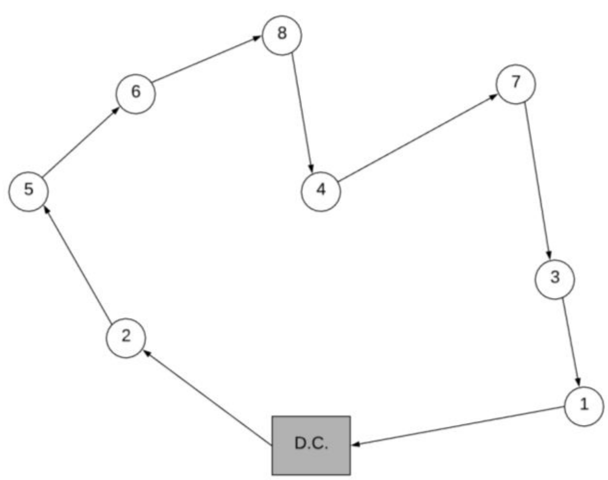


Figure 2.1. The optimal route for TSP

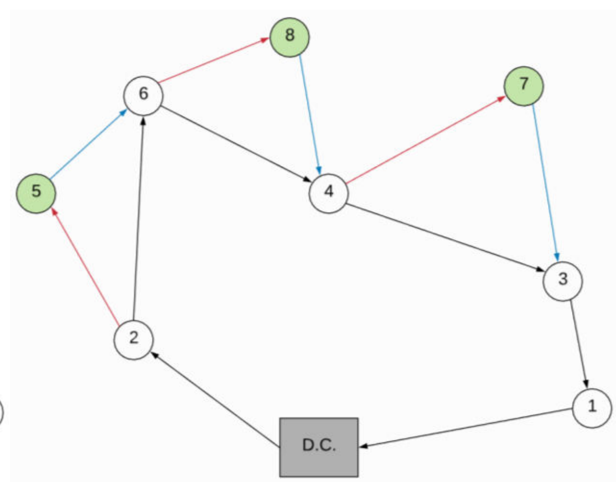


Figure 2.2. The optimal route for TSP-D

Fig.2.1 is an example of the traditional TSP with standalone truck delivery, and the Fig.2.2 is an example of drone-assisted delivery. The white point means this customer is served by truck, the green point means it is served by drone. The black line is the truck transportation route, the red line represents the drone departure route while the blue line represents the drone arrival route. Apparently, during these sections, $D.C. -> \ 2, 3 -> \ 1 \ and \ 1 -> \ D.C.$, the truck and the drone transport in tandem.

3.1. Notation

The DADS is defined on a graph which is a square area($s \times s$), the D.C. (denoted by 0) is located at the mid-bottom $(s/2,0)$ of this square. The set of customers $Num = \{N_1, \dots, N_n\}$ represents all places that need to be delivered.

• $Loc = \{C_0, C_1, \dots, C_n\}$ represents the customer locations matrix, each row $(n = customer\ amount)$ of the matrix respectively means one customer's abscissa (x-coordinate) and ordinate (y-coordinate). Denoted by $C_i \subseteq Loc = (x_i, y_i),\ C_0 = (\mathrm{s}/2,0)$.

• $Pop = \{P_1, \dots, P_p\}$ represents the population matrix, each row $(p = population\ amount,$ $and\ p\ is\ a\ multiple\ of\ 5)$ of the matrix means a possible route of the truck and the drone. $P_i \subseteq Pop = \{0 + Permuted\ Num + 0\ \}\ (e.g.\ \ n = 10,\ \ P_i = \{0, 3, 6, 2, 1, 4, 8, 9, 7, 10, 5, 0\})$. Since the truck and the drone always leave the D.C. with packages, and both the truck and the drone need to return to D.C. after delivery processes, I add "0" i.e. D.C to the beginning and the end of P_i.

• $Dist = \begin{bmatrix} d_{0,0} & \cdots & d_{0,n} \\ \vdots & \ddots & \vdots \\ d_{n,0} & \cdots & d_{n,n} \end{bmatrix}$ represents the distant matrix, $d_{i,j}$ means the distant between the N_i and $N_j \in Num$. And $Dist$ is a $((n+1) \times (n+1))$ matrix, $d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$.

• $Route_t = \begin{bmatrix} Rt_{0,0} & \cdots & Rt_{0,n+1} \\ \vdots & \ddots & \vdots \\ Rt_{p,0} & \cdots & Rt_{p,n+1} \end{bmatrix}$ represents the truck-route matrix, each row means a complete route of truck, and this matrix has p rows. Originally, $Rt_{i,j} = \ P_{i,j} = N_r \in Num,\ \ N_r$ is a random number from Num, because $P_{i,j} \in Pop$, which is generated stochastically.

• Similarly, $Route_d = \begin{bmatrix} Rd_{0,0} & \cdots & Rd_{0,n+1} \\ \vdots & \ddots & \vdots \\ Rd_{p,0} & \cdots & Rd_{p,n+1} \end{bmatrix}$ represents the drone-route matrix. Furthermore, I will assign each node of the row as either the truck-served or the drone-served due to its feasibility for drone-assisted. Reassign the corresponding points in both $Route_t$ and $Route_d$. Because the $Route_t$ and $Route_d$ are corresponding row by row, the same rows of them will indicate one complete delivery process for the truck and the drone.

• $Time = \{t_1, \dots, t_m\}\ (m = iteration\ number)$ represents the operational time history set, each element of this set indicates the corresponding time of each iteration.

• $Engy = \{e_1, \dots, e_m\}$ represents the energy cost history set, each element of this set indicates the corresponding energy cost of each iteration.

• $Sol_t = \{St_0,\ St_1, \dots,\ St_{n+1}\}$ represents the optimal solution of the truck-route, $\ St_i = Rt_{b,i} \in$ $Route_t, b$ means the $index$ of the best row among the whole $Route_t$ matrix. And the determining factor is either the t_b or e_b, while analyzing the min-time delivery system, I choose the $index$ of minimal t_b; while analyzing the min-energy delivery system, I choose the index of minimal e_b.

- Similarly, $Sol_d = \{Sd_0,\ Sd_1, \ldots,\ Sd_{n+1}\}$ represents the optimal solution of the drone-route.

3.2. Assumptions and Constraints

There are some assumptions and constraints to ensure this D-A delivery system can be developed successfully:

1. Only one truck and one drone will participate in all delivery processes.
2. The truck and the drone can only visit customers locations and D.C..
3. Each customer must be served by either the truck or the drone, which means all nodes could only be touched once (except D.C. which will be touched twice).
4. After departing from the truck, the drone can only serve one customer, then it needs to return to the truck. The recharge or change battery time will not be concerned.
5. The truck can visit one or two customers while the drone is in the delivery task.
6. All launching places and reunion places must be at the customers' locations, not any intermediate locations.
7. After returning to the truck, the drone can be launched at the same location, which means a node can be a reunion point and the next service launching point.
8. The truck and the drone can return to the D.C. independently or in-tandem.
9. The truck and the drone can leave the D.C. independently or in-tandem.
10. When we calculate the total operational time of the delivery processes, we will only sum the time spent on the road (i.e. neglect the time spent at customers and the deployment time of drone). At each reunion points, we will choose the longer time between the truck and the drone for the summation, in this case, the waiting time has already been considered.
11. We will only calculate the energy cost on road for both the truck and the drone. If either the truck or the drone arrives early at a reunion point, it will wait till the other one shows up.

3.3. Objective

The objective of this DADS optimization is to find a min-time route and a min-energy route for the delivery processes.

Thence, there are two cost functions:

1. $t_i \in Time = \left(for\ each\ section\ \langle P_{i,j}, P_{i,j+1}\rangle : P_i\right) \sum_0^{n+1}(d_{u,v}/Sp)$, u means the first point $P_{i,j}$ and v means the second point $P_{i,j+1}$ of this section. Sp means the speed (i.e. kilometer per hour) of the truck or the drone, choosing whoever's speed depends on the delivery option of this section.
2. $e_i \in Engy = \left(for\ each\ section\ \langle P_{i,j}, P_{i,j+1}\rangle : P_i\right) \sum_0^{n+1}(d_{u,v} \times Co)$. Co means the unit energy cost (i.e. fuel/battery consumption per kilometer) of the truck or the drone. Similarly, choosing whoever's unit energy cost depends on the delivery option of this section.

4. Heuristic Solution

4.1. Effective Genetic Algorithm

In reference to Ferrandez & Harbison et al. (2016)'s publications, an efficient Genetic Algorithm (GA) has been modified and implemented into the DADS program, which can relatively reduce the solving time of the program for a large practical problem. The basic ideas of this efficient GA are:

1. Divide the $Route$ into $(P/5)$ parts (denoted by $Five = \begin{bmatrix} R_{i,0} & \cdots & R_{i,n+1} \\ \vdots & \ddots & \vdots \\ R_{i+5,0} & \cdots & R_{i+5,n+1} \end{bmatrix}$), the GA will be proceed in groups of five populations.
2. Find the optimum from every 5 populations, set it as temporary best route (denoted by $local = min(Route)$).
3. Utilize effective GA to mutate the $local$, and generate a new $Five$ with different five delivery routes.
4. Exchange the original part of the $Route$ with the new $Five$.
5. Iterate step 1 to step 4, until all parts in the $Route$ have been changed.

Pseudocode that implements the effective GA is proposed in Algorithm 1.

Algorithm 1: effective Genetic Algorithm

Data: $Five$, three randomly selected locaiton N_a, N_b and N_c, $only\ if$ $N_a < N_b < N_c$;
Result: new Pop;

- **while** $i < p$ **do**
  - **for**($\forall row \subseteq Five$)
    - ith row: keep it unchanged;
    - $(i+1)th$ row: $flip(row)$, reverse a short segment $\langle N_a, N_b \rangle$'s order of this row;
    - $(i+2)th$ row: $flip(row)$, reverse a short segment $\langle N_b, N_c \rangle$'s order of this row;
    - $(i+3)th$ row: $swap(row)$, swap the position of N_a and N_b;
    - $(i+4)th$ row: $slide(row)$, slide a short segment $\langle N_a, N_b \rangle$ one space left, and replace the position of N_b with N_a. Then switch N_1 with N_n.
    - $i = i + 5$;
  - **Return**: new $Five$;
  - new $Pop\{P_i, \dots, P_{i+4}\}$ = new $Five$;
- **Return**: new Pop;

For instance, if the first row in $Five$ is $\{0, 3, 6, 2, 1, 4, 8, 9, 7, 10, 5, 0\}$, and $N_a = 2,\ N_b = 6\ and\ N_c = 9$. Then after being mutated by GA, $Five$ would be like this:

$$Five = \begin{bmatrix} 0,3,6,2,1,4,8,9,7,10,5,0 \\ 0,3,8,4,1,2,6,9,7,10,5,0 \\ 0,3,6,2,1,4,10,7,9,8,5,0 \\ 0,3,8,2,1,4,6,9,7,10,5,0 \\ 0,5,2,1,4,8,3,9,7,10,6,0 \end{bmatrix}$$

Clearly, the effective GA can validly complete the functions of traditional Genetic Algorithm with using relatively short time.

4.2. Procedure

The procedure and specific algorithms of this DADS have been proposed here, where the pseudocodes of main functions are provided in Algorithm 2 and Algorithm 3, and the framework for the heuristic approach of the DADS is presented in Flowchart 1.

Algorithm 2: Initialize Algorithm

Data: Num, n, p, s;
Result: $Loc, Dist \text{ and } Pop$;

```
for(∀ C_i ⊆ Loc, i ∈ n)
    C_i = (x_i, y_i) = (s × random(0,1), s × random(0,1));
Return: Loc;
for(∀d_{i,j} ⊆ Dist)
    d_{i,j} = sqrt((x_i − x_j)^2 + (y_i − y_j)^2);
Return: Dist;
for(∀P_i ⊆ Pop)
    P_i = permutate(Num);
Return: Pop;
```

Algorithm 2's role is to complete the initialization phase, and prepare for further analyzation. Note that the Permutate formulation can generate a permutation from 1 to n, which can represent a random delivery route, Pop will contain p random delivery routes. Next, use Algorithm 3 to analyze each node $\in P_i$, check its feasibility for drone-assisted.

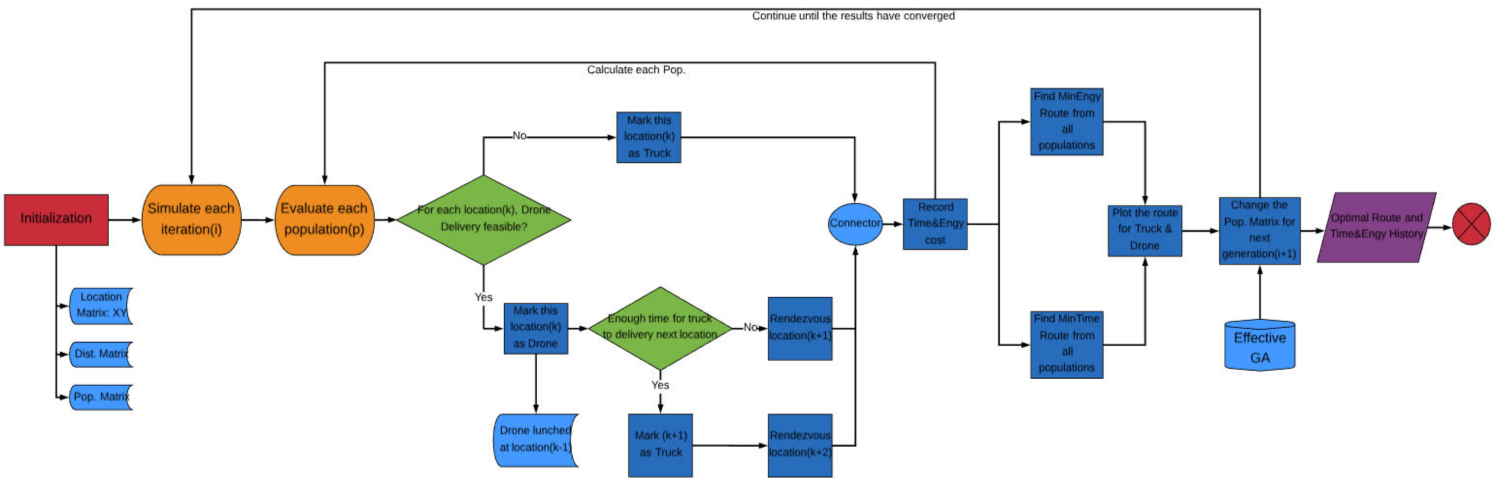
Algorithm 3: Feasible Algorithm

Data: $Dist, Pop, Range$ (Drone flight range), $Delta$ (Waiting time for truck), $k = 0$;
Result: $Route, Time \text{ and } Engy$;

```
    Route = Pop;
for(∀ i ∈ p)
    for(∀ R_k ∈ Route, k ∈ n)
        if (d_{k,k+1} + d_{k+1,k+2}) < Range
            R_k = drone launch point;
            R_{k+1} = drone-assisted node;
            if (d_{k+2,k+3}/Sp) < Delta
                R_{k+2} = truck-served node;
                R_{k+3} = drone reunion point;
            else R_{k+2} = drone reunion point;
        else R_{k+1} = truck-served node;
        t_i ∈ Time = t + d/Sp;
        e_i ∈ Engy = e + d × Co;
    Return: Route;
Return: Time and Engy;
```

Algorithm 3 can return the $Route_t$ & $Route_d$, and according to $Time \text{ and } Engy$, the min-time and min-energy route (Sol_t & Sol_d) will be selected from the $Route_t$ & $Route_d$. Then plot these $Sols$ which are the best route for this iteration.

Flowchart 1:



The flowchart 1 above shows the main steps of the DADS program:

a) Used $Java^{TM}$ to develop an Application, which can randomly generate n locations, and according to the distant matrix, select the optimal route (Sol_t & Sol_d) for the Truck and the Drone.
b) The fitness values of this system are Operational Time and Energy Cost.
c) First, used Initialize Algorithm to produce original matrices: $Loc, Dist\ and\ Pop$.
d) Second, used Feasible Algorithm to determine the feasibility of deploying a drone for each location.
e) Third, selected and plotted the optimal route from each iteration due to required criteria.
f) Last, used effective GA to optimize the delivery route and generate new Pop for next iteration. The iteration stop criteria is that the values of $Time\ and\ Engy$ have converged.

5. Results

To study and analyze the realistic problem, some parameters of the DADS have been pre-defined:

Factor	Notation	Value
Size (operational space)	S	25 km
No. Customers	Num	(20:5:40)
Population	Pop	500
Truck Speed	Sp_t	40 km/h
Drone Speed	Sp_d	50 km/h
Truck Unit Energy	Co_t	0.325 MJ/h
Drone Unit Energy	Co_d	0.00324 MJ/h
Drone Flight Range	$Range$	10 km

Table 2. Initialization parameters

In Table 2, the operational space of the delivery system is 25 km × 25 km; the number of customers is investigated starting at 20 locations, then incremented by 5 locations to a maximum number of 40 (denoted by 20:5:40); the number of population for this heuristic approach is 500; the speed of truck is held constant at 40 km/h, and the speed of drone is 50 km/h; the unit energy cost of truck is 325 kJ/h, and the unit energy cost of drone is 3.24 kJ/h (data sources: *Ferrandez & Harbison et al. (2016)*); the available flight range (i.e. total flying distance for a full-charged drone) for drone is 10 km.

Experiments are conducted on various numbers of customers to gain the optimal solutions. Here are some sample results for different numbers of customers:

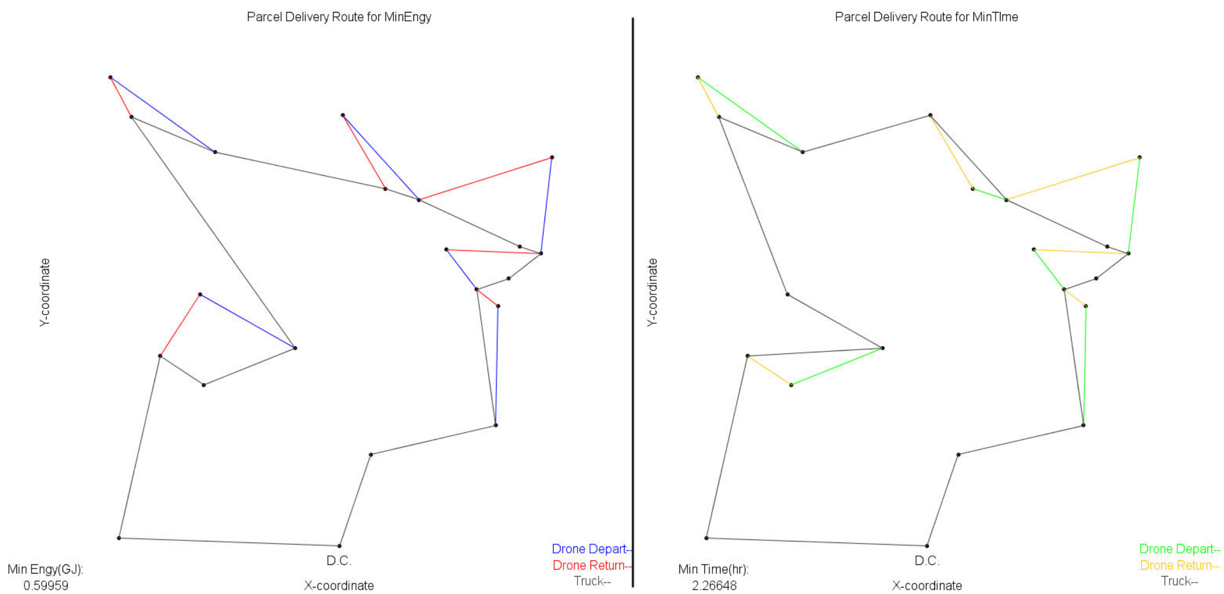


Figure 3.1. Optimal delivery route for 20 customers

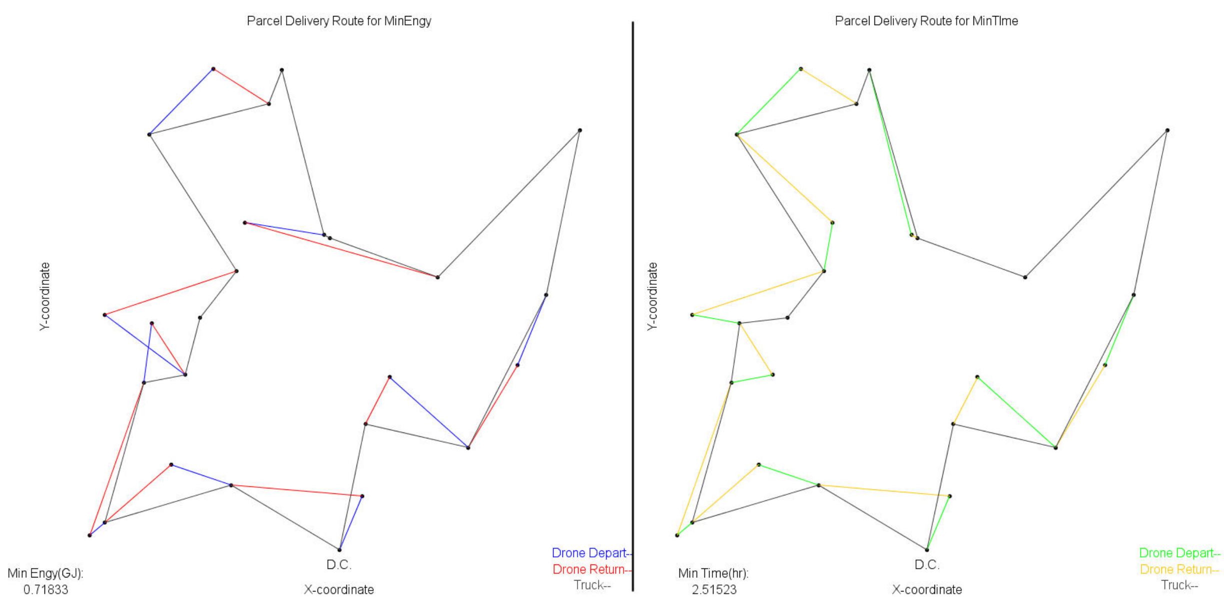


Figure 3.2. Optimal delivery route for 25 customers

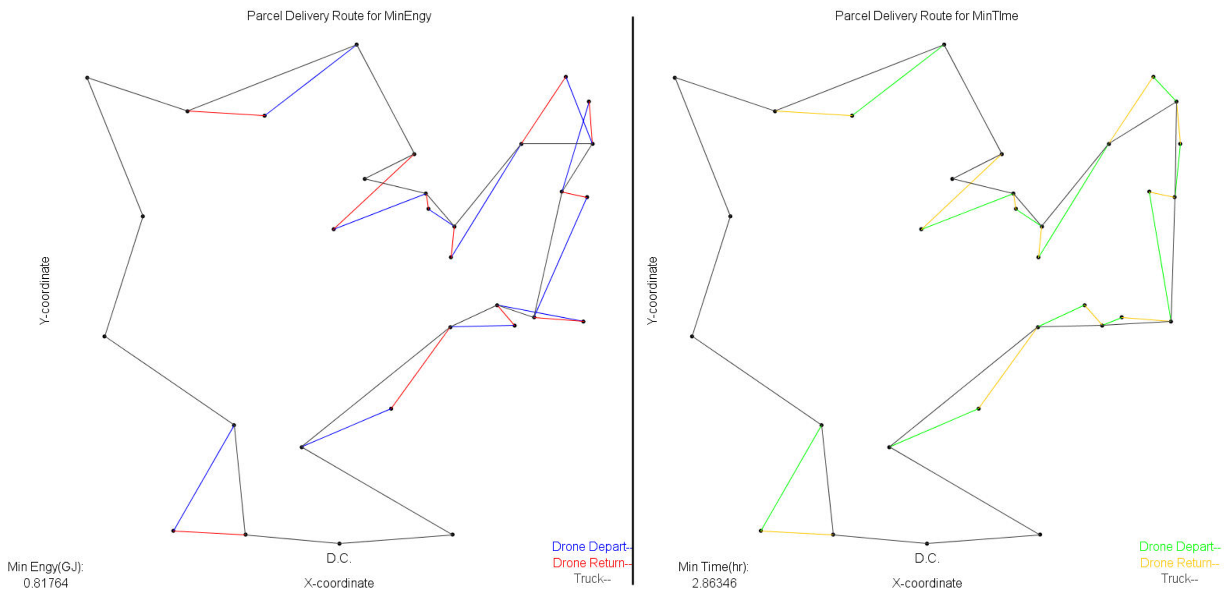


Figure 3.3. Optimal delivery route for 30 customers

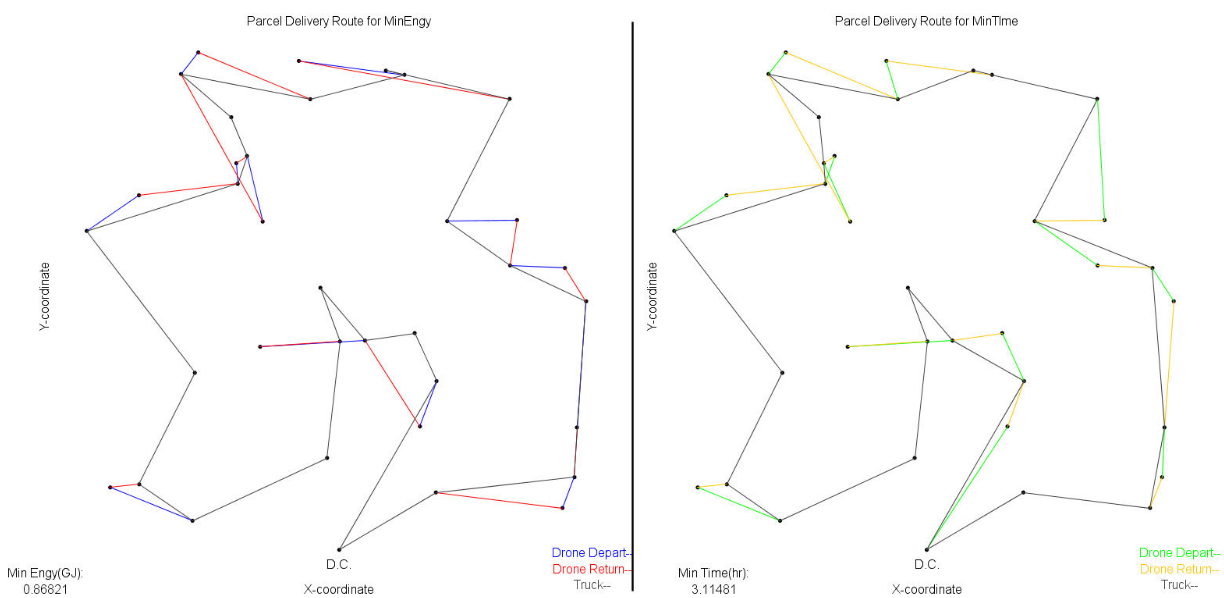


Figure 3.4. Optimal delivery route for 35 customers

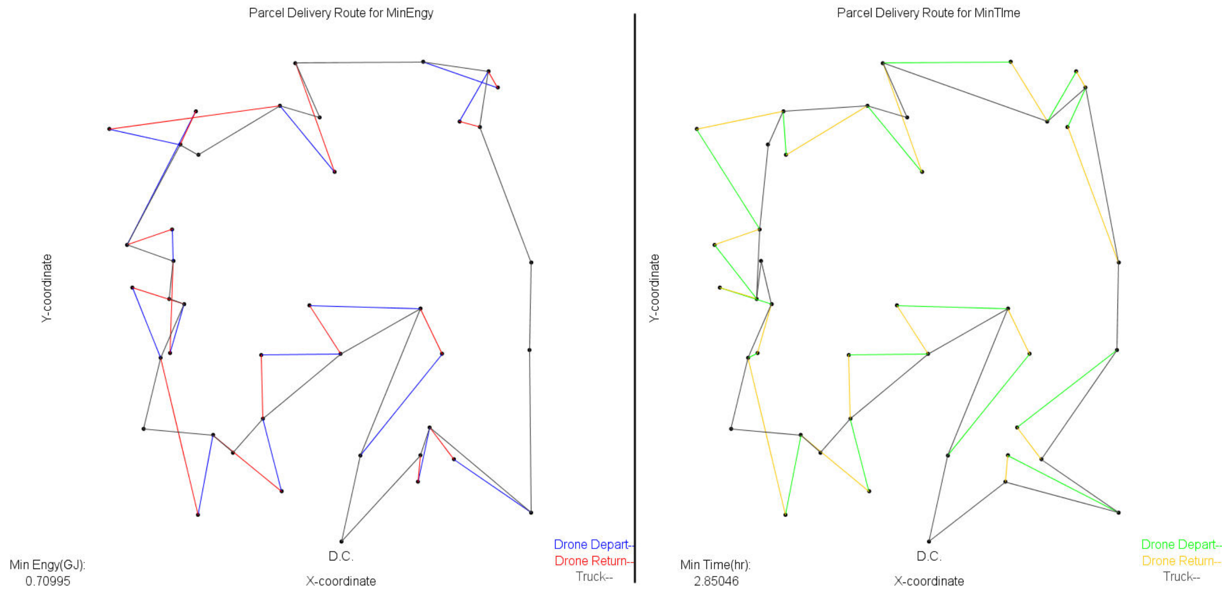


Figure 3.5. Optimal delivery route for 40 customers

As shown in Figure 3, the optimal route for the truck and the drone is drawn with different colored lines. In the $MinEngy$ case, the black line represents the route of the truck, the blue line represents the departure route of the drone, while the red line represents the arrival route of the drone; In the $MinTime$ case, the route of the truck is still represented by black line, the departure route of the drone is indicated by green line and the arrival route of the drone is indicated by yellow line.

The performance criteria of experiments include the total delivery time, total energy cost and runtime of each experiment. The table and figure below show the performance results for each experiment.

No. Customers	Runtime (s)	$MinTime$ (h)	$MinEngy$ (GJ)
20	97	2.2664825	0.599591157
25	110	2.5152285	0.71833282
30	154	2.8634615	0.81764237
35	220	3.114807	0.868213164
40	257	2.8504555	0.70995195

Table 3. Discrete customers number

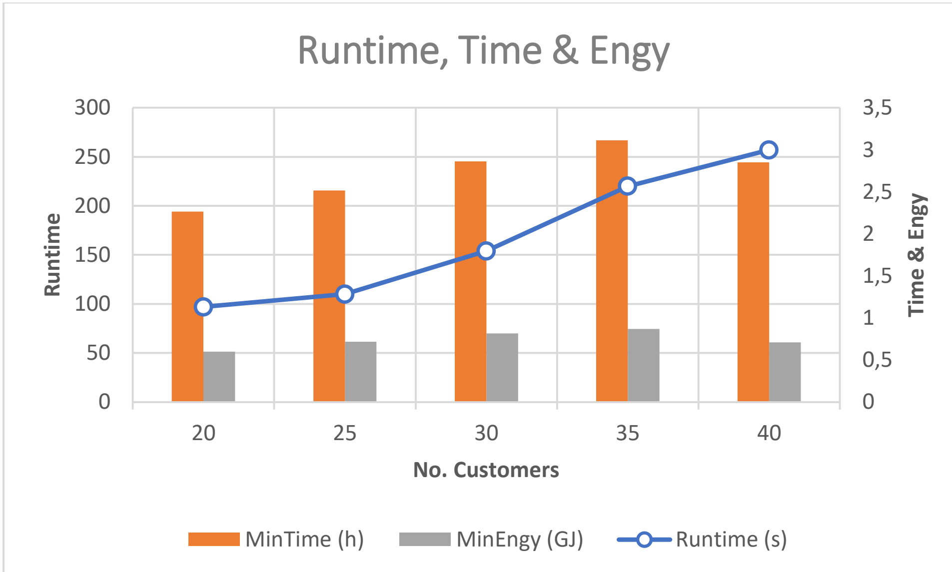


Figure 4. Influence of different customers' numbers

From the Fig.4. above, we can indicate that the running time of this program is positively correlated with customers size. And due to the fact that the locations of customers are generated randomly, the $MinTime$ and $MinEngy$ may vary unpredictably.

Particularly, the last experiment (i.e. n=40) shows that its total time and total energy cost of the delivery system is less than the smaller amount of customers' (i.e. n=30 or 35). Because the customer's locations are unpredictable, maybe when n is larger, these customers are located closely and compactly than the case when n is smaller; and the program also neglects the waiting time of the delivery processes, both above can lead to a reduction of total time or total energy cost. In our case, we can see when n=40, customers are located densely, while when n=35, they are located more dispersedly. In result of that, no matter how optimal the delivery route is, the total time of n=35 is always larger than n=40.

6. Conclusion and Future Research

In this optimization of DADS project, I analyzed the scenario of a drone-assisted delivery system. Some past researches proved drone-assisted delivery is faster than truck standalone delivery, because the advantages of drones can offset the disadvantages of trucks. Hence, I developed a program to calculate the operational time and energy cost, and select the best solution of delivery route on the basis of $MinTime$ and $MinEngy$.

Additionally, this program can optimize the delivery route based on the heuristic method-Genetic Algorithm, which can ensure the results are infinitely close to the global optimum. Owing to the deployment of effective GA, the program can solve the large-sized practical problem within a related short time, yet only has minimal influence on the quality of overall solutions.

Future research may aim to:

1. Simulate the logistics system using two or more drones;
2. Update the program to include the consideration of waiting time, and propose a reasonable model to evaluate the waiting penalties;
3. Improve this program to get a better performance when analyzing the larger practical size of scenario, and in the meanwhile reduce the runtime of the program by optimizing its structure.
4. Implement Google Map API to my program, to solve the realistic problem;

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References

[1] Murray, C., & Chu, A. (2015). The flying sidekick traveling salesman problem: optimization of drone-assisted parcel delivery. *Transportation Research Part C,* 54, 86-109.
https://www.sciencedirect.com/science/article/pii/S0968090X15000844?via%3Dihub
[2] Ferrandez & Harbison et al. (2016). Optimization of a Truck-drone in Tandem Delivery Network Using K-means and Genetic Algorithm. *Journal of Industrial Engineering and Management.*
http://www.jiem.org/index.php/jiem/article/view/1929

[3] Ha & Deville et al. (2018). On the min-cost Traveling Salesman Problem with Drone. *Transportation Research Part C 86 (2018) 597–621.*
https://www.sciencedirect.com/science/article/pii/S0968090X17303327?via%3Dihub

[4] Ha & Deville et al. (2015). Heuristic methods for the Traveling Salesman Problem with Drone.
Technical Report _ September 2015 _ ICTEAM/INGI/EPL.

https://pdfs.semanticscholar.org/59b4/8e77e710917d85facb5d2cebf2e2ebd5dfae.pdf

[5] Niels Agatz, Paul Bouman, and Marie Schmidt. Optimization approaches for the traveling salesman problem with drone. *Transportation Science, Forthcoming, 2017.*

https://repub.eur.nl/pub/101691/ERS-2017-011-LIS.pdf

[6] Bouman & Agatz et al. (2017). *Dynamic Programming Approaches for the Traveling Salesman Problem with Drone*. Available at SSRN:

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3035323

[7] Amazon Prime Air. https://www.amazon.com/Amazon-Prime-Air/b?ie=UTF8&node=8037720011

[8] Xinhua Net. http://www.xinhuanet.com/english/2017-11/08/c_136735278.htm

[9] Wikipedia-Heuristic Algorithem. https://en.wikipedia.org/wiki/Heuristic_(computer_science)

[10] Andrea Ponza (2016). Optimization of drone-assisted parcel delivery. *UNIVERSITA DEGLI STUDI DI PADOVA.* http://tesi.cab.unipd.it/51947/

[11] Lucidchart. https://www.lucidchart.com/