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Ground Vehicle and Drone Collaborative Delivery Planning using Genetic Algorithm

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Abstract

Global e-commerce and delivery companies are actively pursuing last-mile delivery service using drones, and various delivery schedule planning studies have been conducted. In this study, separate individual route networks were constructed to reflect drone route constraints such as prohibited airspace and truck route constraints such as rivers, which previous studies did not incorporate. The A* algorithm was used to calculate the shortest path distance matrix between the starting point and destinations. In addition, we proposed an optimal delivery schedule plan using genetic algorithms and applied it to compare the efficiency with that of vehicle-only delivery.

Key Words: Unmanned Aerial Vehicle, Drone Delivery, Routing Planning, Traveling Salesman Problem, A* Path Planning, Genetic Algorithm

1. Introduction

In recent years, numerous companies have put extensive efforts into developing a more efficient delivery method following the rapid development of the e-commerce industry [1]. Global e-commerce and delivery companies including Amazon, Alibaba, Google, and DHL are actively promoting the use of drone delivery services, and they have already demonstrated promising results with successful trial deliveries. At the 2019 Amazon re:MARS event held in June 2019 in Las Vegas, Amazon unveiled its in-house built drones that can carry packages under 5 lbs (approximately 2.3 kg) and proposed a plan to deliver packages to customers in less than 30 min in the coming months. Furthermore, the United Parcel Service, an American logistics giant, received approval from the Federal Aviation Administration for the first time in the industry in October 2019 to deliver packages weighing less than 55 lbs (approximately 25 kg) using drones. As such, drone deliveries are quickly becoming a reality. Drones are predicted to fly in urban areas in the coming years, with the development of obstacle recognition and avoidance and automatic take-off and landing technologies [2,3]. The primary reason why many companies are actively developing drone-based delivery systems is because drones are not affected by traffic congestion, thereby providing shorter delivery times and lower logistics cost per km compared to those of truck-based deliveries [4].

Studies on delivery system route planning that link vehicles and drones have been conducted both domestically and internationally to reduce delivery times while minimizing the logistics costs. Most studies have been conducted to transform or develop systems based on the traveling salesman problem (TSP).

The TSP considering drones was first presented by Murray and Chu (2015). They proposed a flying sidekick TSP (FSTSP) algorithm that employs drones and trucks to collaboratively deliver packages to customers and a parallel drone scheduling TSP algorithm that employs drones and trucks to deliver packages separately. In their study, mixed-integer linear programming was applied to minimize the delivery time in the objective function,

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and a heuristic technique was used for the actual problem-solving because the computational complexity was nondeterministic polynomial-time (NP)-hard [5].

Agatz et al. (2015) proposed the traveling salesman problem with a drone algorithm. While this solution is similar to that of the FSTSP algorithm, it achieved higher delivery efficiency by adding revisiting conditions for the previously visited delivery nodes, enabling drone delivery even when the truck is on its way back to the warehouse [1]. Ha et al. (2015) proposed the cluster first-route second heuristic method, which enables more efficient delivery schedule planning by first selecting the route combination of the truck and drone deliveries and then finds the optimal truck routes [6]. In addition to the objective of minimizing delivery times, studies have been conducted on delivery schedule planning that consider factors affecting delivery cost. Mathew et al. (2015) and Dorling (2017) attempted to reduce fuel consumption [7,8], and Ha et al. (2018) studied the waiting time for the location synchronization of trucks and drones to minimize the overall logistics cost [4].

To derive the travel times of drones and trucks, the existing studies simply divided the distance between the starting and destination points by the average moving speed of the trucks and drones. While certain studies attempted to use the Euclidean distance method for the drone distances and the Manhattan distance method for the truck distances [4,5,9,10], there were limitations to reflecting the characteristics of the actual road network and route. Furthermore, the studies failed to reflect the areas that are unavailable for drone delivery, such as prohibited airspace, or situations requiring drone detours.

To overcome the limitations of existing studies, this study constructed separate delivery route networks for trucks and drones, searched for the optimal delivery plan that reflects truck movement constraints, such as rivers and mountains, and drone movement constraints, such as prohibited airspace, and then compared the efficiencies of the drone and vehicle-based delivery methods.

2. Method and Experiment

2.1 Problem definition

This study assumed a random delivery situation by presuming the drone and truck environments and movement constraints. The study searched for a delivery plan solution through delivery route optimization. Fig. 1 illustrates the situation of the assumed problem. The problem situation requires delivering packages to 10 fixed delivery destinations in a virtual 100×100 size grid site with a river and prohibited airspace to induce drone no-fly zone and road network disconnection constraints. Truck movement occurs on the uniform grid of the road network.

For delivery using a truck and a drone, both vehicles are designed to begin at the same position and collaborate to deliver the packages. It is assumed that the drone only delivers one package at a time in consideration of its limited payload and loading and unloading apparatus. Thus, each time the drone completes a delivery, it must return to the truck to charge its battery or to load a new package for delivery.

The delivery depot where delivery starts and ends is located at the center of the site. The small dots in Fig. 1 indicate delivery destinations, with Destination 9 located inside the prohibited airspace where drone delivery is unavailable. While the prohibited airspace is typically configured based on the radius around a certain facility or area, in this study, it was configured using a rectangle considering the grid structure road network for calculation convenience. When searching for a delivery route, the drone can fly over the river region during package delivery, while the truck can only complete deliveries through the established road network, requiring it to use the bridge constructed in the middle of the river. Moreover, although factors such as the moving speed of both vehicles and the drone remaining flight time should be applied using actual values to conduct a more realistic experiment, this study used dimensionless time and distance units for simplified calculation and performance comparison as the scope of the study was limited to the relative comparison of delivery planning optimization. The conditions assumed in this study are as follows.

1) The drone can travel both along the grid and diagonally.

2) The drone vertical takeoff and landing times are not considered.

3) For the drone, only the distance traveled is considered and not flight time.

4) One truck and one drone are operated.

5) Both the truck and drone travel at a constant speed.

6) Drone return only occurs at the delivery destination node.

7) The truck does not travel solely to reunite with the drone.

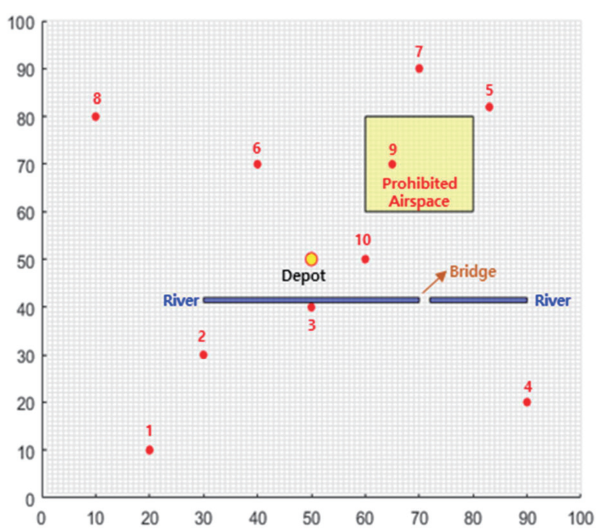

Fig. 1 Delivery map with constraints.

2.2 Shortest path search

The shortest distances between the delivery depot and delivery destinations are required to derive the optimal delivery route plan. The shortest path was searched for using the A* algorithm, and the shortest route for each delivery vehicle was calculated by reflecting the specific network and movement characteristics of the drone and truck. The A* algorithm assists in finding the shortest path from the start point to the destination point, and its objective function $f(n)$ can be expressed as follows.

$$f(n) = g(n) + h(n) \tag{1}$$

where $g(n)$ denotes the cost of the shortest path from the starting point to the current point, and $h(n)$ denotes the estimated cost of the shortest path from the current point to the destination point. Figs. 2 and 3 display examples of the shortest paths derived using the A* algorithm. In the 100×100 size grid network, the straight-line distance between each node is 1, and the diagonal distance between each node is $\sqrt{2}$. While the truck can only move in a straight direction along the grid network, the drone can also move diagonally. Thus, in Fig. 2, the shortest distance of the truck delivery from the start point to the destination point is 4, but that of the drone delivery is significantly reduced to $2\sqrt{2}$.

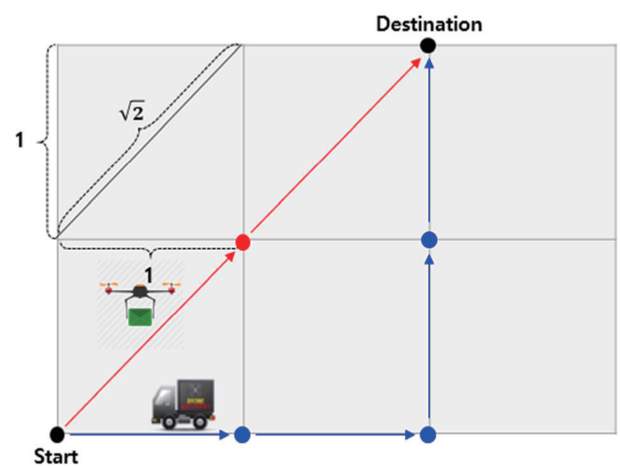

Fig. 2 A* shortest path without constraints.

Fig. 3 displays a situation where constraints are induced on the drone and truck movements. As the drone makes its delivery by bypassing the prohibited airspace, the shortest distance becomes $2+\sqrt{2}$, which is an increase from the shortest distance in Fig. 2 ($2\sqrt{2}$). For the truck, although the prohibited airspace can be neglected, the shortest distance is increased to 6 due to the introduction of a river.

In this study, the A* algorithm was employed to analyze the shortest paths while reflecting the constraints for each delivery vehicle type. Fig. 4 displays the shortest delivery route search result of the truck, which involves bypassing the river to reach all 10 delivery destinations. Fig. 5 displays the shortest delivery route search result of the drone. For the drone, the shortest delivery routes for Destinations 5 and 7 were derived by bypassing the prohibited airspace. Additionally, unlike the truck delivery, the drone did not fly to Destination 9 for the delivery, and the routes were searched for without any interference by the river.

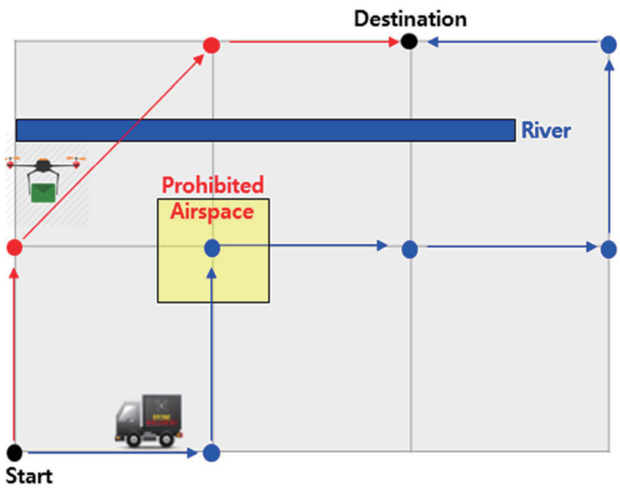

Fig. 3 A* shortest path with constraints.

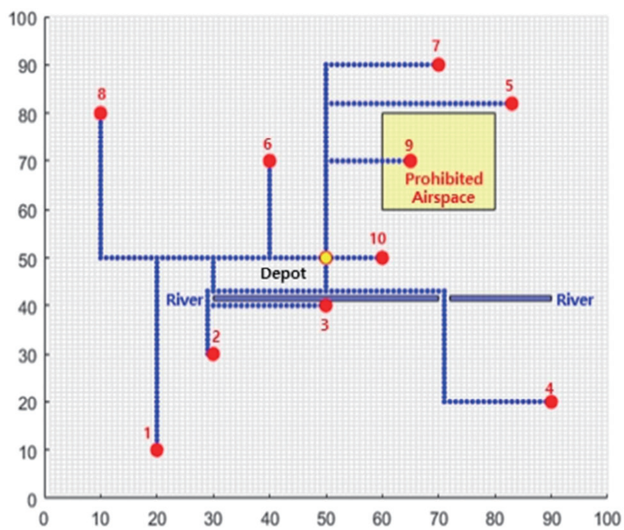

Fig. 4 Truck delivery route planning.

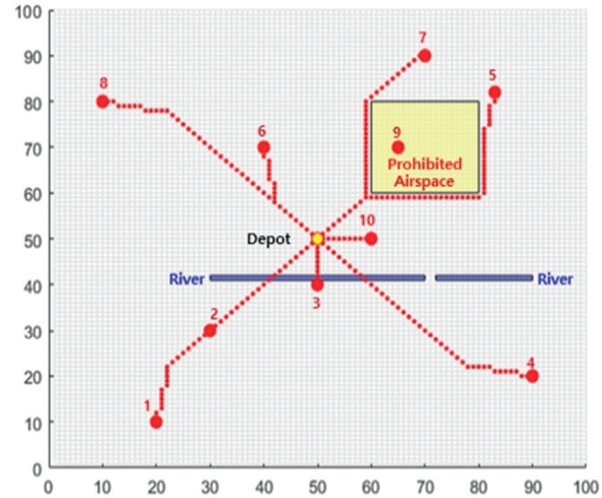

Fig. 5 Drone delivery route planning.

2.3 Distance Matrix

The distances for all cases where the drone and truck can travel were calculated using the iterative shortest path search process. As a heuristic technique, the A* algorithm derives an approximate solution instead of an optimal solution as it does not search for all possible paths. Therefore, the minimum distance of the distance matrix uses the minimum value derived after 10 iterations for each start point and destination point to minimize the error between the approximate and optimal solutions. This calculation is expressed as Eq. (2).

$$d(i,j) = \min\{f_{1,i}(j) + f_{2,i}(j) + \cdots + f_{10,i}(j)\} \tag{2}$$

where $d(i,j)$ denotes the minimum distance from the start point i to the destination point j, and $f_{k,i}(j)$ indicates the k-th distance value from point i to point j searched for by the A* algorithm. In addition, $d(i,j)$ and $d(j,i)$ are the same assuming that the mobile network is symmetrical.

The distance matrices of the truck and drone are displayed in Tables 1 and 2, respectively. D denotes the delivery depot, which is the delivery starting point, and numbers 1 to 10 represent the 10 delivery destinations.

For Destination 3, the delivery distance traveled by the truck is $d_{truck}(D,3) = 52$, as the river must be bypassed. In contrast, the drone can fly straight to the destination; hence, the distance traveled by the drone is approximately five times smaller, with $d_{drone}(D,3) = 10$. Additionally, both the truck and the drone exhibit the same delivery distance of 10 for Destination 10.

In Table 2, $d_{drone}(i,9)$, which indicates the distance from each starting point to Destination 9, and $d_{drone}(9,j)$, which indicates the distance from Destination 9 to each node, are null. This is because Destination 9 is located within prohibited airspace; hence, the drone cannot make the delivery.

Table 1 Truck distance matrix

	D	1	2	3	4	5	6	7	8	9	10
D	-	70	42	52	70	65	30	60	70	35	10
1	70	-	30	60	80	135	80	130	80	105	80
2	42	30	-	30	70	105	52	102	70	77	52
3	52	60	30	-	60	75	62	72	80	57	42
4	70	80	70	60	-	71	100	90	140	75	60
5	65	135	105	75	71	-	55	21	75	30	55
6	30	80	52	62	100	55	-	50	40	25	40
7	60	130	102	72	90	21	50	-	70	25	50
8	70	80	70	80	140	75	40	70	-	65	80
9	35	105	77	57	75	30	25	25	65	-	25
10	10	80	52	42	60	55	40	50	80	25	-

Table 2 Drone Distance Matrix

	D	1	2	3	4	5	6	7	8	9	10
D	-	52	28	10	52	58	24	49	52	-	10
1	52	-	24	42	74	105	68	101	74	-	57
2	28	24	-	24	64	86	44	77	58	-	38
3	10	42	24	-	48	62	34	59	57	-	14
4	52	74	64	48	-	65	71	79	105	-	42
5	58	105	86	62	65	-	49	16	74	-	48
6	24	68	44	34	71	49	-	38	34	-	28
7	49	101	77	59	79	16	38	-	64	-	48
8	52	74	58	57	105	74	34	64	-	-	65
9	-	-	-	-	-	-	-	-	-	-	-
10	10	57	38	14	42	48	28	48	62	-	-

2.4 Optimal route selection using genetic algorithm

In this study, optimal routes were derived using an objective function that minimizes the truck and the drone return times to the delivery depot after completing all deliveries (Eq. 3).

$$\min(t_{n+1}) \tag{3}$$

where t_i is the cumulative delivery time to arrive at point i, and n indicates the number of delivery destinations. Accordingly, $n+1$ represents the delivery depot, the return point after completing all deliveries, and t_{n+1} represents the return time to the depot.

The problem of deriving the optimal route for an environment containing a combination of drones and trucks is a TSP with an NP-hard computational complexity. Hence, a genetic algorithm, which is a widely used search heuristic technique, was employed in this study to solve the problem.

The genetic algorithm is a computational model based on natural world evolutionary phenomena; it is an adaptive search technique inspired by the survival of the fittest concept of evolutionary theory and the genetics of natural selection [11]. The technique searches for an optimal solution by first selecting the most optimal gene in a given environment and then increases the probability of finding a superior solution by passing down the dominant genetic trait to the next generation. Genetic algorithms are widely used in permutation optimization problems as they do not require standardized computation processes such as crossover, mutation, and substitution. Instead, they can be uniquely designed by researchers to suit the individual research characteristics. Reducing the variability of the solution via the genetic operator is an important task in the TSP-based delivery route search problem in this study. This can be reflected in the genetic operation process by excluding any unnecessary operation iterations and by deriving an efficient and accurate solution. Fig. 6 illustrates the flow chart of the optimal route calculation using a genetic algorithm.

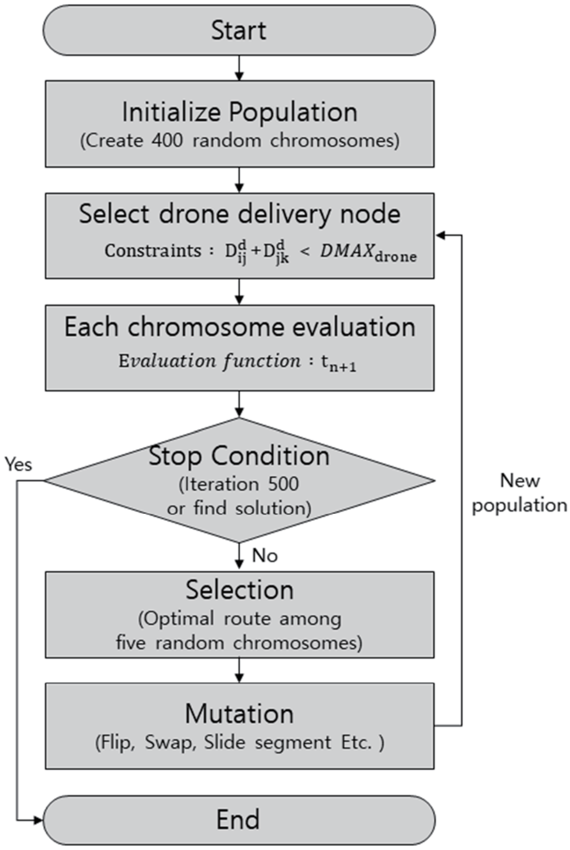

Fig. 6 Genetic algorithm flow chart

In this study, 400 random chromosomes are generated for initial solution calculation, and the chromosomes are expressed as the sequence of visited nodes for delivery. Subsequently, the nodes that can be delivered to by the drone are considered to determine the nodes to be delivered by the truck and drone. The delivery route that begins from node i, passes through node j, and finally reaches the destination node k can be expressed as two cases as illustrated in Fig. 7. When the drone and the truck perform collaborative deliveries, the drone departing from node i delivers the package to node j and travels to the destination node k, while the truck travels to from node i to node k to reunite with the drone. The drone has a limited flight time, which causes limitations in its travel distance capability. Thus, when the drone is unable to fulfill the delivery, package delivery for nodes i, j, and k is performed by the truck as displayed on the right side of Fig. 7.

The availability of drone delivery can be determined using Eq. (4). D_{ij}^{d} and D_{jk}^{d} indicate the distances that the drone must travel from node i to node j and from node j to node k, respectively, and $DMAX_{drone}$ denotes the maximum flight distance of the drone.

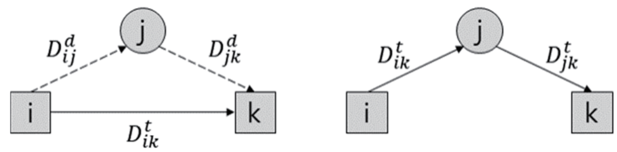

Fig. 7 Delivery routes between nodes.

$$D_{ij}^{d} + D_{jk}^{d} < DMAX_{drone} \tag{4}$$

When the delivery is only conducted by truck, the arrival time t_k at node k can be obtained through $D_{ij}^{t} + D_{jk}^{t}$. For the collaborative delivery with the truck and drone, the arrival time can be derived using Eq. (5).

$$t_k = \max[D_{ik}^{t}, \frac{D_{ij}^{d}+D_{jk}^{d}}{v_d/v_t}] \tag{5}$$

The longer delivery time between that of the truck and drone is selected as the final delivery time, and it was assumed that the truck or drone, whichever arrives first, waits for the other vehicle at the node. Furthermore, v_d/v_t denotes a variable that controls the relative speed of the drone compared to that of the truck. It was assumed that the drone travels faster than the truck as it does not face delay factors such as traffic lights and congestion.

The route with the minimum travel time is stored as a solution. The algorithm is terminated once it fulfills one of the algorithm stop conditions: the same solution is repeatedly obtained more than 10 times or the solution is obtained after 500 iterations. If the stop condition is not fulfilled, a superior chromosome is selected to generate offspring chromosomes through mutation operations.

In this study, 400 chromosomes are randomly classified into 80 chromosome groups composed of 5 chromosomes each, and chromosomes exhibiting the minimum travel distance in each population are selected. Subsequently, four new offspring chromosomes are generated through four mutations as illustrated in Fig. 8. The probability of passing down suitable chromosomes to offspring increases by replacing the existing five chromosomes with four newly generated chromosomes and five chromosomes with the minimum travel distance. This mutation process is performed for all 80 groups to derive a new population composed of 400 offspring chromosomes, and based on the iterations of this process, an optimal delivery route is derived. The mutation operation in the genetic algorithm reduces the number of unnecessary computations and quickly finds the optimal solution by passing down the superior chromosomes to the offspring chromosomes while avoiding the local solution trap. In the TSP, the route sequence is a critical factor in the solution search; thus, the mutation operation used a method that does not significantly harm the sequence of the superior chromosomes.

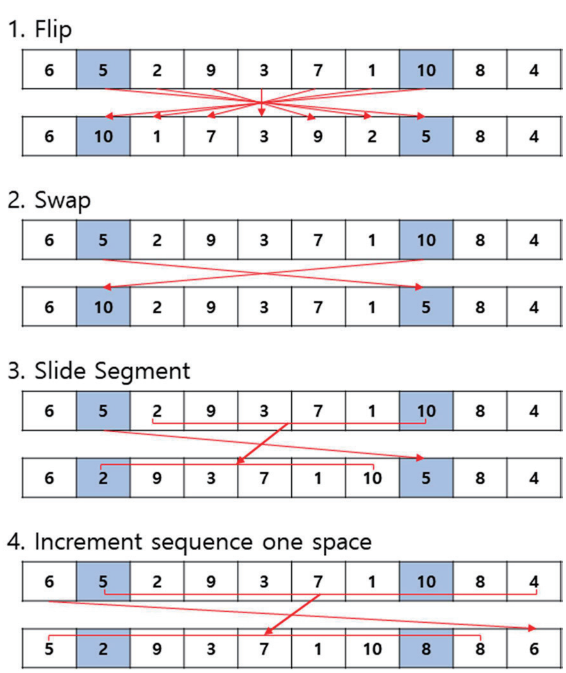

Fig. 8 Genetic algorithm mutations.

2.5 Optimal delivery route simulation results

Fig. 9 displays the optimal routes derived using the genetic algorithm. The first graph depicts the delivery route using only the truck, while the other graphs depict the collaborative delivery routes using both the truck and drone. The speed ratio (v_d/v_t) of drone to truck is 1.5, and the maximum flight distances of the drone in each graph are set as 50, 70, and 100, respectively. The solid lines represent the truck delivery routes, and the dotted lines represent the drone delivery routes. When the delivery was simulated using only the truck, 422 time units were consumed, which was the longest delivery time. As the drone maximum flight distance increases in the collaborative delivery, the number of drone delivery nodes increases, and the time taken to complete the delivery decreases. In all cases, the delivery to Destination 9 is made by the truck as it is located within the prohibited airspace. The delivery time involving both the drone and truck is shorter than that of truck-only delivery, indicating a higher efficiency for collaborative delivery.

Fig. 10 displays the total delivery times according to the drone maximum flight distance and the relative speed of the drone/truck. Overall, the total delivery time decreases as the maximum flight distance increases. It can be inferred that the increase in the maximum flight distance increases the total number of destinations where the drone can make deliveries, and delivery time is therefore reduced as the effect of adding a separate delivery method is generated regardless of the truck delivery speed.

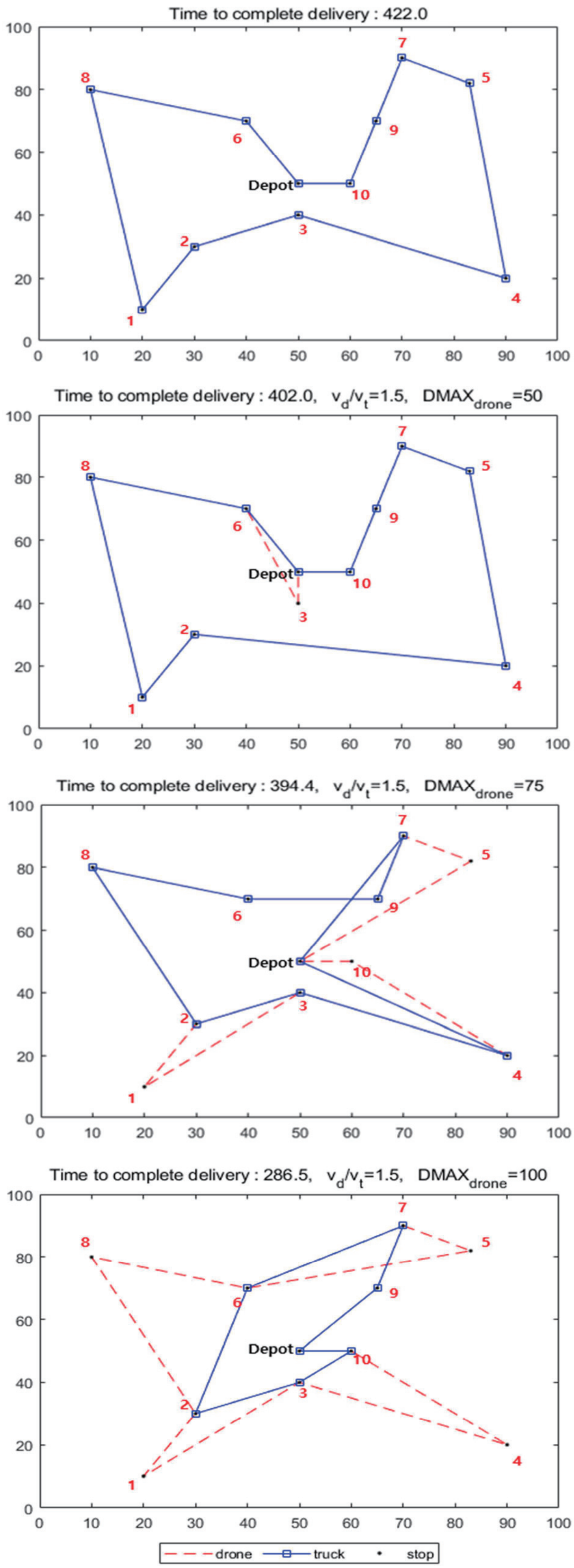

Fig. 9 Delivery trajectories.

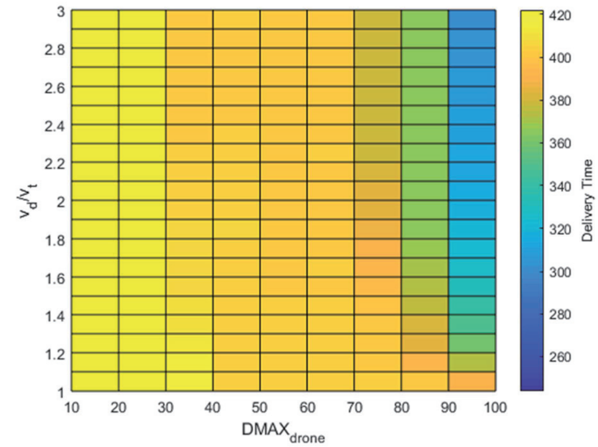

Fig. 10 Total delivery times under various conditions.

Changes in the relative speed did not result in any significant difference in the total delivery time for the same maximum flight distance. This result is because the truck or drone, whichever finishes their deliveries first, waits for the other vehicle at the point where they reunite. In the existing studies, both drones and trucks were assumed to share the same route network; thus, the difference in waiting time at the point where both vehicles reunite was small because it was considered to be the simple difference in unit speed for each vehicle. In contrast, the waiting time was more significant in this study because various constraints on the movement of each vehicle type were added.

3. Conclusions

This study searched for the optimal delivery route plan in a delivery system composed of a drone and a truck and then compared its efficiency with that of delivery using only a truck. The limitations of existing studies were remedied by applying the constraints of drone prohibited airspace and road network disconnection. The routes were generated using the A* algorithm, and the distance matrices were derived using the distance information between the delivery depot and each delivery destination. Additionally, a genetic algorithm was used to find the optimal route for truck and drone cooperative delivery.

The simulation results demonstrated that the collaborative delivery method using both the truck and drone improves the delivery efficiency by reducing delivery times compared to those of the delivery method using only the truck. However, there is the drawback of incurring waiting time at the point where the drone and the truck reunite. Thus, it is necessary to reduce this time in actual situations. We intend to consider the cost and energy consumption incurred during the operation of drones and trucks in addition to the delivery time in a future study.

References

[1] N. Agatz, P. Bouman, and M. Schmidt, “Optimization approaches for the traveling salesman problem with drone,” ERIM Report Series Reference No. ERS-2015-011-LIS, 2015.

[2] J. Nicas and G. Bensinger, “Delivery drones hit bumps on path to doorstep,” The Wall Street Journal, 2015.

[3] T. Chang, “Regulatory environment and structural change of UAV industry,” Journal of Aerospace System Engineering, vol. 9, no. 3, pp.17-22, 2015

[4] Q. M. Ha, Y. Deville, Q. D. Pham, and M. H. Hà, “On the min-cost Traveling Salesman Problem with Drone,” Transp. Res. Part C Emerg. Technol., vol. 86, pp. 597–621, 2018.

[5] C. C. Murray and A. G. Chu, “The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery,” Transp. Res. Part C Emerg. Technol., vol. 54, pp. 86–109, 2015.

[6] Q. M. Ha, Y. Deville, Q. D. Pham, and M. H. Hà, “Heuristic methods for the Traveling Salesman Problem with Drone,” Transp. Res. Part C Emerg. Technol., 2015.

[7] N. Mathew, S. L. Smith, and S. L. Waslander, “Planning Paths for Package Delivery in Heterogeneous Multirobot Teams,” IEEE Trans. Autom. Sci. Eng., vol. 12, no. 4, pp. 1298–1308, 2015.

[8] K. Dorling, J. Heinrichs, G. G. Messier, and S. Magierowski, “Vehicle Routing Problems for Drone Delivery,” IEEE Trans. Syst. Man, Cybern. Syst., vol. 47, no. 1, pp. 70–85, 2017.

[9] K. Wang, B. Yuan, M. Zhao, and Y. Lu, “Cooperative route planning for the drone and truck in delivery services: A bi-objective optimisation approach,” J. Oper. Res. Soc., pp. 1–18, 2019.

[10] E. Es Yurek and H. C. Ozmutlu, “A decomposition-based iterative optimization algorithm for traveling salesman problem with drone,” Transp. Res. Part C Emerg. Technol., vol. 91, pp. 249–262, 2018.

[11] C. Kong, . M. Kang, and G. Park, “Study on Fault Diagnostics Considering Sensor Noise and Bias of Mixed Flow Type 2-Spool Turbofan Engine using Non-Linear Gas Path Analysis Method and Genetic Algorithms,” Journal of Aerospace System Engineering, vol. 7, no. 1, pp. 8-18, 2013