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공학석사 학위논문

Capacitated Vehicle Routing Problem with Truck-Drone team using Truck as a Mobile Depot

트럭을 이동형 드론 기지로 사용하는 한정용량 트럭-드론 경로 배정 문제

2022년 2월

서울대학교 대학원
공과대학 건설환경공학부

신 호 철

Capacitated Vehicle Routing Problem with Truck-Drone team using Truck as a Mobile Depot

지도 교수 김 동 규

이 논문을 공학석사 학위논문으로 제출함

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공과대학 건설환경공학부

신 호 철

신호철의 공학석사 학위논문을 인준함

2022년 2월

위 원 장 _____ 고 승 영 _____ (인)

부위원장 _____ 이 청 원 _____ (인)

위 원 _____ 김 동 규 _____ (인)

Abstract

Drones initially received attention for military purposes as a collective term for unmanned aerial vehicles (UAVs), but recently, efforts to use them in logistics have been actively underway. If drones are put into places where low-weight and high-value items are currently difficult to deliver by existing delivery means, it will have the effect of greatly reducing costs. However, the disadvantages of drones in delivery are also clear. In order to improve the delivery capacity of drones, the size of drones must increase when drones are equipped with large-capacity batteries.

This thesis introduced two methods and presented algorithms for each method among VRP-D. First of all, CVP-D is a method in which carriers such as trucks and ships with large capacity and slow speed carry robots and drones with small capacity. Next, in the CVRP-D, the vehicle and the drone move different paths simultaneously, and the drone can visit multiple nodes during one sortie.

The two problems are problems in which restrictions are added to the vehicle route problem (VRP), known as the NP-hard problem. The algorithm presented in this study derived drone-truck routes for two problems within a reasonable time. In addition, sensitivity analysis was conducted to observe changes in the appropriate network structure for the introduction of drone delivery and the main parameters of the drone. In addition, the validity of the proposed algorithm was verified through comparison with the data used as a benchmark in previous studies. These research results will contribute to the creation of delivery routes quickly, considering the specification of a drone.

Keyword : Drone, CVRP, Two-echelon VRP, Heuristic Algorithm
Student Number : 2020-28796

Table of Contents

Chapter 1. Introduction 1
1.1 Research Background 1
1.2 Research Purpose 3
1.3 Contribution of Research 4
Chapter 2. Literature review 5
2.1 Vehicle Routing Problems with Drone 5
2.2 Carrier Vehicle Problem with Drone(CVP-D) 10
2.3 Capacitated VRP with Drone(CVRP-D) 12
Chapter 3. Mathematical Formulation 14
3.1 Terminology 14
3.2 CVP-D Formulation.....15
3.3 CVRP-D Formulation 19
Chapter 4. Proposed Algorithms 23
4.1 Heuristic Algorithm 23
4.1.1 Knapsack Problem 23
4.1.2 Parallel Machine Scheduling (PMS).....25
4.1.3 Set Covering Location Problem (SCLP).....27
4.1.4 Guided Local Search (GLS) Algorithm.....28
4.1.5 Genetic Algorithm (GA) 29
4.2 Proposed Heuristic Algorithm : GA-CVPD 30
4.3 Proposed Heuristic Algorithm : GA-CVRPD.....33
Chapter 5. Numerical Analysis 36
5.1 Data Description.....36
5.2 Numerical experiment 37
5.3 Sensitivity analysis.....39
5.3.1 Analysis on GA-CVPD.....39
5.3.2 Analysis on GA-CVRPD 42
5.3.3 Result on different Instances.....45
Chapter 6. Conclusion 48
Bibliography 50
Abstract in Korean 53

List of Abbreviations

CVP−D	Carrier Vehicle Problem with Drones
CVRP	Capacitated Vehicle Routing Problem
CVRP−D	Capacitated Vehicle Routing Problem with Drones
GA	Genetic Algorithm
GA−CVPD	Proposed heuristic algorithm for CVP−D
GA−CVRPD	Proposed heuristic algorithm for CVRP−D
MIP	Mixed Integer Program
PMS	Parallel Machine Scheduling
RP−D	Routing Problem with Drones
SCLP	Set Covering Location Problem
TSP	Traveling Salesman Problem
VRP	Vehicle Routing Problem
VRP−D	Vehicle Routing Problem with Drones
2E−CVRP	Two−echelon Capacitated Vehicle Routing Problem

Chapter 1. Introduction

1.1. Research Background

Drones initially received attention for military purposes as a collective term for unmanned aerial vehicles (UAVs), but recently, efforts to use them in logistics have been actively underway. If drones are put into places where low-weight and high-value items are currently difficult to deliver by existing delivery means, it will have the effect of greatly reducing costs. However, the disadvantages of drones in delivery are also clear. In order to improve the delivery capacity of drones, the size of drones must increase when drones are equipped with large-capacity batteries.

This thesis introduced two methods and presented algorithms for each drone, also known as Unmanned Aerial Vehicles (UAV), which were first utilized for military purposes and have demonstrated their military utility in surveillance, reconnaissance, and strikes. However, it has been employed for various areas in the civilian market in recent years. Drones are widely utilized in the civilian sectors, including filming, agriculture, maintenance, and security, and they have proved their usefulness and significant impact in the sectors. As a result, the use of drones is increasing year over year.

Drones have been used for logistics purposes in the past few years. Amazon, DHL, and Google, among others, are already undergoing research and development to adapt them to logistics. (McKinsey, 2017) Drone delivery technology is being tested and commercialized in Korea for regions difficult to reach by vehicles, such as islands, mountainous areas, and anchored ships. In reality, drone delivery has a considerable advantage over existing logistics transport systems based on ground vehicles, according to the Korea

Post's results of comparing vehicle delivery and delivery time. Due to their aerial mobility features, drones are less influenced by traffic and terrain than automobiles.

Furthermore, extensively used commercially, rotary wing-type drones can take off and land vertically and do not require a runway, making them ideal for delivery to inaccessible places such as islands and mountainous areas. In reality, the majority of sites that have commercialized drone delivery have these qualities. Ships anchored at sea, alpine areas, and island areas are among the sites where drones have been adopted for domestic and overseas delivery. Drones would be quite beneficial as supplementary materials to existing logistics systems.

Given these circumstances, drones are likely to play an important role in delivering low-weight, high-value commodities to locations where vehicle access is restricted. Drones, in particular, might save much money if they can take over some of the distribution tasks currently done by helicopters, planes, or humans. In addition, compared to the operational cost and initiation cost of manned aircraft, the cost of acquisition and operational cost of drones is relatively low. As a result, people and time can be saved if drone delivery is enabled in areas where conventional transport is problematic.

On the other hand, drones have as many disadvantages as their advantages in logistics. Most drones have relied on limited battery packs capacity and motor powers. Drone delivery capacity is highly dependent on battery capacity at a current technology level. Drones must be equipped with large-capacity batteries to improve their transport capacity. The problem is that when equipped with large-capacity batteries, the size of drones will inevitably increase significantly in proportion to this. This can lead to many problems

when operating drones, such as safety issues. Moreover, based on technical and institutional limitations, we can control the drones in limited range. Drones must be institutionally managed and kept visible in urban areas. Furthermore, even in areas where beyond visual-range drone flight is possible, expensive communication equipment is required to be installed in a drone to control drones. It will increase the cost of drone acquisition and add the drone's empty weight. Drones that use batteries, in particular, have a substantial difference in mileage based on weight, making it difficult to remove the distance limitation by increasing the battery size effectively. So, drone delivery is hard to replace existing delivery systems substantially.

For these reasons, various techniques for drone operation have been proposed to overcome the shortcomings of drones mentioned earlier. One of the ways is to elevate a drone's mechanical performance, such as raising the drone's power and battery efficiency, has been proposed. Second, combining drones and other operations to overcome their different flaws and increase their efficiency. Earlier researches have provided diverse types of drone operations. Some researchers have suggested a way for determining the best location for drone deliveries and a strategy for using drones in tandem with other means of transportation. This thesis examines how to employ drones in cooperation with other vehicles.

1.2. Research Purpose

This thesis proposed two operational approaches in a combined environment with an existing truck delivery system utilizing drones with limited performance. We devise an algorithm implementing combinatorial optimization techniques to generate an optimal delivery

route when drones and trucks operate together as a team and trucks serve as mobile drone bases.

1.3. Contribution of Research

This thesis has created an algorithm that can identify appropriate solutions to problems involving immensely complicated computations in a reasonable amount of time. According to earlier researches, the computational time of Mixed Integer Programming (MIP) has risen exponentially for a condition with more exceeding 20 nodes. Therefore, it is necessary to use Heuristic algorithms to find feasible solutions in a larger network within a reasonable time. As a result, a heuristic algorithm is proposed in this thesis. Furthermore, even when there are more than 100 nodes, the proposed algorithm allows solutions to be obtained in a reasonable amount of time.

Based on proposed algorithm, it has been verified that introducing a drone-truck operation system for transport is efficient in this thesis. As a result, when drones are used in cooperation with trucks, the cumulative distance traveled by trucks is reduced in most instances, compared to the traditional truck-only strategy.

In addition, studies so far have rarely compared the effects of differences in drone-truck operation strategies. Therefore, this thesis conducted a sensitivity analysis to compare the two distinct operating strategies' responses to changes in parameters such as drone capacity and distance limitations. As a result, the effectiveness of the delivery method was confirmed based on the critical variables of a drone. In conclusion, criteria for which approaches are desirable in a given environment were presented when designing a delivery system deploying drones by comparing the advantages and disadvantages of the two strategies.

Chapter 2. Literature review

2.1. Vehicle Routing Problem with Drone

Drone TSP and VRP studies have constantly been progressing. There is already a common name in academia for various modification problems of TSP or VRP. However, the terminology of the variants concerns involving drones has yet to be characterized in academic circles. Therefore, the classification approaches and terminologies used in Macrina et al. (2020), an article that analyzed and summarized several VRP research among existing studies, were used the same in this study. According to this paper, depending on the limitations, drone routing problems can be classified as TSP-D, CVRP-D, or CVP-D. It is structured in Figure 2.1. The same nomenclature was referenced in this thesis. The following is a description of each approach.

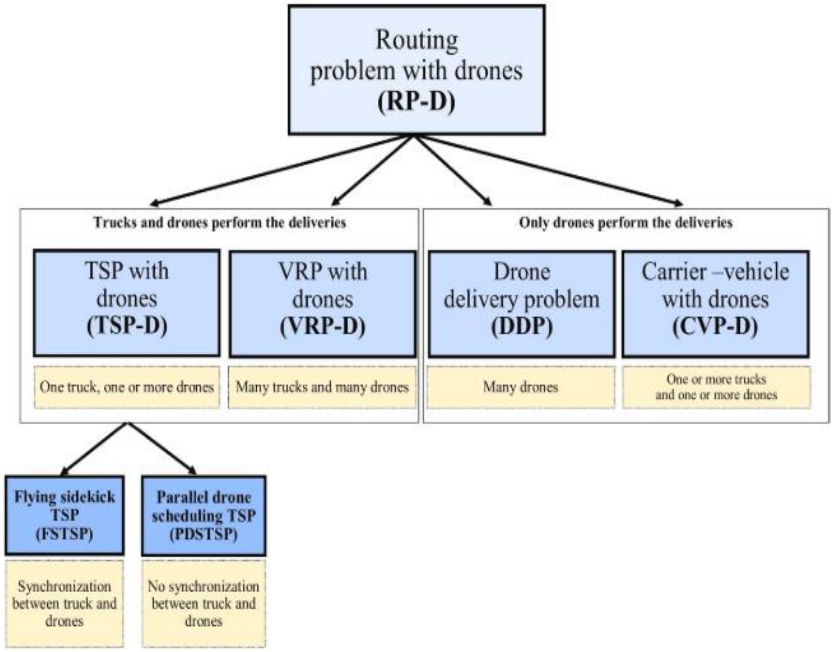

Figure 2.1 Classification of routing problem with drone

Source : Macrina et al. (2020)

The Traveling Salesman Problem with Drone (TSP-D) is a problem where several drones and one vehicle travel simultaneously. Because TSP-D is a TSP variant, just a few drones are installed on a single vehicle. It also ignores the capacity of cars and drones and the demand for nodes, and this problem typically restricts drone flight only to short distances (Murray and Chu, 2015; Ha et al., 2018). Vehicle Routing Problem with Drone (VRP-D) is a catch-all term for all VRPs using drones.

One variant of VRP-D, Capacitated VRP with Drone (CVRP-D), is a problem that considers the demand for nodes and the capacity of drones. Thus, the individual vehicle route is now comparable to that of TSP-D, with the addition of drone capacity constraints (Kitjacharoenchai et al., 2020; Sacramento et al., 2019; Schermer et al., 2019a).

The Carrier-Vehicle Problem with Drone (CVP-D) has the same capacity constraints as the CVRP-D, but the truck can travel simultaneously as the drone. This problem is similar to Two-echelon CVRP(2E-CVRP), solving a problem with capacitated vehicles in a network with two echelons (Crainic et al., 2010). In 2E-CVRP, large carriers are in charge of shipping from depot to warehouses, and small vehicles ship from warehouses to consumer nodes. There are two differences between CVP-D and 2E-CVRP. The intermediate warehouse is not set in advance, and the other is that drones that act as vehicles cannot visit multiple times. Thus, trucks serve an important function as a mobile base for drones in CVP-D.

As a consequence, trucks are referred to as carriers in the CVP-D. Furthermore, previous research has typically restricted the transport function of automobiles. On the other hand, vehicles were deemed to have a transport function in this thesis.

TSP, a problem in which a single mode of transportation visits all sites on the network only once and returns to the starting point, was the basis for early studies on the routing problem of drones and trucks. Since Murray and Chu (2015) published TSP-D as FSTSP, a form of drone addition to TSP, follow-up studies have been conducted on drone routing issues. This study is a pioneering study that considers the operation of drones and trucks simultaneously.

One vehicle is used in processes that follow the FSTSP concept, one drone installed on the vehicle departs and returns to the vehicle (Gonzalez-R et al., 2020). The flight route is generated independently of the vehicle. In other words, trucks and drones travel different routes, and each node is only visited once by drones or vehicles, except for the rendezvous point (RP) for the drone and vehicle. In RP, drones replace batteries, and during one sortie, drones can only travel a restricted distance. Thus, TSP is a representative NP-hard issue, and TSP-D is an NP-hard problem due to drone flight constraints.

Murray and Raj (2020) further developed FSTSP in subsequent studies, leading to mFSTSP. mFSTSP distinguishes itself from FSTSP in that it uses many drones rather than just one. Furthermore, safety time was applied when drones took off and landed without landing simultaneously to prevent accidents when several drones operate around the same time. This research suggested an exact approach and a three-step heuristic approach. Some MIP formulas are utilized in some circumstances for each step of the heuristic algorithm.

In the FSTSP approach, Liu et al. (2020) assigned a route in a condition where only one drone is operated for each vehicle. Metaheuristic algorithms, such as Simulated Annealing (SA), Tabu-

search (TS), etc., were integrated to address this problem. In addition, this study considered changes in battery consumption as a proportion of delivery weight, which has been overlooked in previous studies. In addition, the purpose formula calculated how much cost may be saved compared to the current truck operation, based on the total of the drone and truck's operating costs.

VRP is a general problem for TSP that deals with routing in scenarios when many vehicles are operated. In contrast, TSP is a problem dealing with routes for a single vehicle. Variations of VRP include:

- A problem where the vehicle's capacity is limited (CVRP).
- A problem where the visit time for each node is set (VRPTW).
- A problem where the demand for pickup and delivery is set differently (VRPPD).

Like the relationship between TSP and VRP, the drone VRP problem (VRP-D) is a generalized problem of TSP-D. This problem contains a combination of vehicles and how to control many drones installed on them. Variants exist in VRP-D, just as they do in VRP. The results of the literature review are recorded in Table 2.1.

Table 2.1 Summary of Researches on drone routing problem

Reference	Drone	Truck	Problem type	Objective	MILP	Heuristic	Capacity	Multi -visit
Murray and Chu (2015)	1	1	TSP-D	Min. TT*	yes	yes	no	no
Murray and Raj (2020)	1	m	TSP-D	Min. CT*	yes	yes	no	yes
Yao et al. (2020)	1	m	TSP-D	Min. TC*	no	yes	yes	yes
Wang and Sheu (2019)	m	m	CVRP-D	Min. TC	yes	no	yes	yes
Deshen et al. (2019)	1	m	VRP-D	Min. CT	no	yes	yes	yes
Kaipeng et al. (2019)	m	1	CVP-D	Min. TT	no	yes	no	yes
Salama and Srinivas (2020)	m	1	CVRP-D	Min. CT	yes	yes	no	no
Chen et al. (2020)	m	m	CVP-D	Min. TT	yes	yes	yes	no
Kitjacharoenchai et al. (2020)	m	m	CVRP-D	Min. TT	yes	yes	yes	yes
Schermer et al. (2020)	m	m	CVRP-D	Min. TT	yes	yes	no	no
Gonzalez-R et al. (2020)	1	1	CVP-D	Min. CT	yes	yes	no	yes
This Study	**m**	**m**	**CVRP-D, CVP-D**	**Min. TT**	**yes**	**yes**	**yes**	**yes/no**

TT* : Total travel time of trucks, CT* : Completion time of last truck, TC* : Costs of vehicles

2.2. Carrier Vehicle Problem with Drone (CVP-D)

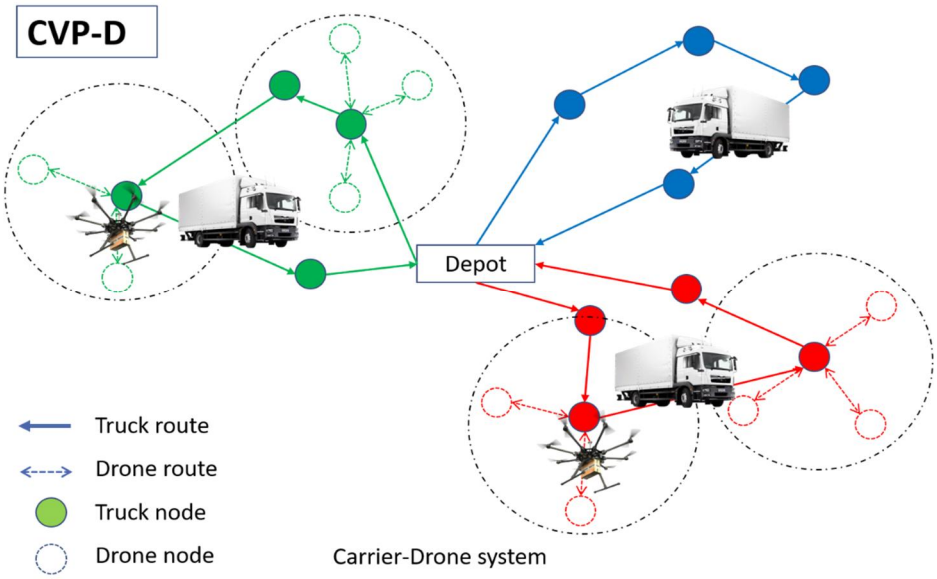

Figure 2.2 Concept map of CVP−D

The CVP−D is a problem that focuses on how large and slow carriers transport small−capacity mobility such as robots, drones, etc. Figure 2.2 shows the operational process of CVP−D.

A parallel drone TSP (PDTSP) is the problem that is comparable to CVP−D. The truck travels in the TSP, while the drone travels in its route, departing from the depot and returning to it. There is no synchronization between drones and vehicles. This research determines which nodes will be chosen as drone or vehicle nodes. According to a related study, Kim and Moon (2019) suggested a drone station exclusively acting as a drone depot.

In CVP−D, truck can be considered a mode that performs the function of the drone station. Peng et al. (2019) integrated the Facility Location Problem (FLP) with the Bin packing problem (BPP) to solve CVP−D. A drone travels each demand node, and when the drone departs the vehicle, it returns to the vehicle. In this research,

the vehicle comes to a standstill at an anchor point (AP), an imaginary node in the network. Rather than a demand node and controls the flight of drones at that position.

Chen et al. (2021) solved VRPTWDR; a VRP with Time Window (VRPTW) was solved with a robot instead of a drone. Robots are slower than drones, but they have more storage and can manage larger numbers. Trucks function as both delivery vehicles and launching stations for drones. A single vehicle can carry multiple robots, but each robot can only make one trip at a time. The heuristic algorithm used in this work consisted of two steps: grouping nodes and then solving VRPTDR after clustering was complete. CVP−D was handled with the same notion as this research in our thesis.

2.3. Capacitated Vehicle Routing Problem with Drone (CVRP-D)

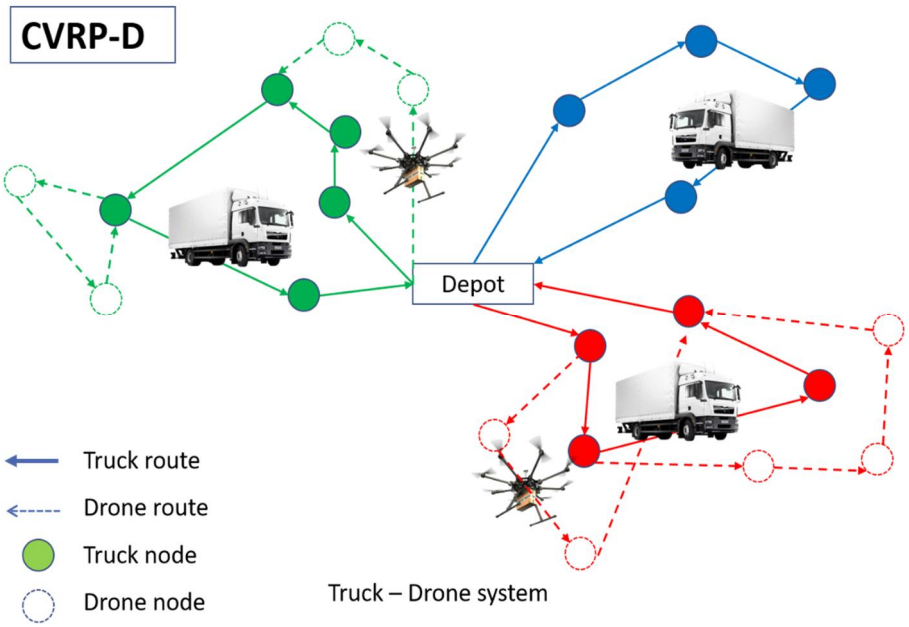

Figure 2.3 Concept map of CVRP−D

CVRP−D and CVP−D differ because CVRP−D allows both the vehicle and the drone to travel simultaneously, whereas CVP−D allows just the drones to travel while the trucks remain stationary. Figure 2.3 illustrates the CVRP−D operational mechanism.

Compared to previous research in which one drone is flown in one truck, Wang and Sheu (2019) and Schermer, Moeini, and Wendt (2019b) proposed CVRP−D under conditions where multiple trucks operate multiple drones. According to those studies, drones differentiate launching and landing trucks among distinct trucks. This permission is significant since it allows for a more generalized CVRP−D to be introduced.

Because CVRP−D is an NP−Hard problem, heuristic algorithms should generate solutions if the network size grows beyond a reasonable scale. D. Wang et al. (2019) proposed a network

clustering algorithm for optimization. DBSCAN was used in the clustering step to classify nodes far from the cluster as isolated nodes and visit them by vehicle. Clustering and routing algorithms are being used again within the clusters in this research. This clustering technique was applied in previous research; however, the truck stop location can be selected as any point in the cluster in this study.

Salama and Srinivas (2020) also studied that carriers can stop at any point. In this study, trucks can stop anywhere other than network nodes, and drones can take off and land there, and two objective formulae were considered. The two objective formula intends to minimize transport costs and delivery time. However, the two equations are incompatible. As a result, the study aims to discover a Pareto optimum solution between two trade-off objectives. Furthermore, this study found that if any node other than the existing node can visit the truck's visit location, the problem's computational time rises exponentially. Consequently, from the perspective of algorithm design, pre-designating the truck's stop location plays an important role in decreasing computational time in a large-scale network.

According to Kitjacharoenchai, Min and Lee (2020), drones can visit multiple destinations on a single flight (sortie), but they can only fly once along the truck's route. The efficiency of CVRP-D was demonstrated in this study through a CVRP comparison using datasets commonly used in CVRP.

Chapter 3. Mathematical Formulation

3.1. Terminology

Carrier	In CVP−D, a term for vehicle that carries drones and items and delivers them.
Truck	In CVRP−D, a term for vehicle that carries drones and items and delivers them.
Drone	A small Unmanned Aerial Vehicle installed on a truck and carrier that delivers shipments.
Node	The location on the network where drones, trucks, and carriers should visit.
Demand	Digits in Node, that must be met by trucks and drones.
Capacity	Delivery ability for truck and Carrier. The sum of the demand for nodes visited by drones mounted on trucks and the demand for nodes visited by trucks cannot exceed.
Payload	Capacity of drone
GA−CVRPD	Heuristic algorithm for CVRP−D based on GA
GA−CVPD	Heuristic algorithm for CVP−D based on GA
Routing Problem (RP)	Term for all problems related routing, including not only TSP and VRP but also drone variants such as CVRP−D and CVP−D.

3.2. CVP−D Formulation

The formulas and notations presented in this thesis is mainly referenced from Chen et al. (2020).

<u>Sets</u>

$C = \{1,2,3 \dots n\}$: A set of all demand nodes existing in the network.

$K = \{1,2 \dots k\}$: A set of trucks

$DR = \{1,2 \dots kd\}$: A set of drones installed on each truck.

$V = C \cup \{0\}$: A set of all nodes including Depot.

$A = \{(i,j)\} | i,j \in V, i \neq j \}$: A set of all the arcs in the network.

$G = (V, A)$: Network consisting of node V and arc A.

<u>Parameters</u>

t_{ij}^{t} : Travel time of truck along arc A

t_{ij}^{d} : Travel time of drone along arc A

d_{ij} : Distance along arc A

p_{ij}^{k} : Payload of truck *k* along arc A

q_i : Demand of node *i*

M : Big number

<u>Variables</u>

x_{ij}^{k} : 1 if a truck *k* is traveled along arc A, otherwise 0

$y_{ij}^{kd,k}$: 1 if a drone *kd* installed on a truck k traveled along along arc A, otherwise 0

w_i^{k} : Waiting time of truck k at node *i*

tt_i^{k} : Arrival time of truck k at node *i*

$dt_i^{kd,k}$: Arrival time of drone *kd* installed on turck *k* at node

The proposed mathematical formulation of CVP−D is presented as follows.

$$\text{minimize} = \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} x_{ij}^{k} t_{ij}^{t} + \sum_{i \in C} w_i \tag{1}$$

Objective equation (1) means to minimize the sum of the moving time and the waiting time of the carriers.

subject to

$$\sum_{i \in V} \sum_{k \in K} x_{ij}^{k} \leq 1 \ ; \forall \ j \in C \tag{2}$$

Constraint (2) means that the carriers may visit the node at most once.

$$\sum_{i \in V} \sum_{k \in K} x_{ij}^{k} + \sum_{i \in C} \sum_{kd \in DR} \sum_{k \in K} y_{ij}^{kd,k} \geq 1; \forall j \in C \tag{3}$$

By constraint (3) node j in demand must be visited by a vehicle or drone. According to other constraints, the number of visits to the vehicle's steering wheel is one, and the number of visits to the drone may be one or more.

$$\sum_{i \in V} \sum_{k \in K} x_{ij}^{k} \times \sum_{i \in C} \sum_{kd \in DR} \sum_{k \in K} y_{ij}^{kd,k} = 0 \ ; \forall \ j \in C \tag{4}$$

Constraint (4) prevents drones from visiting nodes visited by vehicles, and conversely, nodes visited by drones cannot be visited by vehicles. And it is impossible not to visit both by constraint (3).

$$\sum_{i \in C} \sum_{kd \in DR} \sum_{k \in K} y_{ij}^{k,kd} \leq f_{j}^{kd} \ ; \forall \ j \in C \tag{5}$$

Constraint (5) indicates that the maximum number of starts of a drone is limited.

$$\sum_{j\in C}\sum_{kd\ in DR} y_{ij}^{kd,k} \le DR\sum_{j\in V} x_{ji}^{k} \quad ;\forall\ i \in C \tag{6}$$

In the constraint 6, the drone can depart only when the vehicle stops, and the maximum number of departures of the drone must be less than DR times.

$$\sum_{k\in K}\sum_{i\in C} x_{0i}^{k} = K \tag{7}$$

$$\sum_{k\in K}\sum_{i\in C} x_{i0}^{k} = K \tag{8}$$

By constraints (7) and (8), carriers must depart from depot and return to depot.

$$\sum_{i\in V} x_{ij}^{k} = \sum_{i\in V} x_{ji}^{k} \quad ;\forall j \in C \tag{9}$$

Constraint (9) means that when a vehicle visits node j, it must come from node j, and vice versa.

$$\sum_{i\in V}\sum_{k\in K} p_{ij}^{k} - \sum_{i\in V}\sum_{k\in K} p_{ji}^{k} = q_j * \sum_{i\in V}\sum_{k\in K} x_{ij}^{k} + \sum_{i\in C}\sum_{k\in K}\sum_{kd\in DR} q_i\, y_{ji}^{kd,k} \quad ;\forall\ j \in C \tag{10}$$

$$p_{ij}^{k} \le \left(Q - q_i - \sum_{\theta\in C}\sum_{kd\in DR} q_\theta\, y_{i\theta}^{kd,k}\right) x_{ij}^{k} \quad ;\forall i \in C, \forall j \in C, \forall k \in K \tag{11}$$

Constraints (10) and (11) are constraints that maintain the payload of the carrier.

$$\mathrm{dt_j} \geq \mathrm{dt_i} + \mathrm{t_{ij}^d} - \mathrm{M}\left(1 - \mathrm{y_{ij}^{kd,k}}\right) + \mathrm{tt_i} \sum_{\theta \in C} \sum_{k \in K} \mathrm{x_{\theta i}^k} \;\; ; \;\; \forall i \in C, \forall j \in C \tag{12}$$

Constraint (12) refers to the arrival time of node j of the drone.

$$\mathrm{tt_j} \geq tt_i + \mathrm{t_{ij}^k} - \mathrm{M}\left(1 - \mathrm{x_{ij}^k}\right) \;\; ; \;\; \forall i \in C, \forall j \in C \tag{13}$$

Constraint (13) represents the arrival time of node j of the carrier.

$$\mathrm{dt_j} - \mathrm{tt_j} \leq \mathrm{w_j} \;\; ; \;\; \forall i \in C, \forall j \in C \tag{14}$$

Constraint (14) represents the waiting time of the vehicle, and the carrier must wait for the last drone to return.

$$tt_i - \mathrm{tt_j} + \mathrm{w_i} + \mathrm{t_{ij}^k} \leq \mathrm{M}\left(1 - \sum_{k \in K} \mathrm{x_{ij}^k}\right) \;\; ; \;\; \forall i \in C, \forall j \in C \tag{15}$$

$$tt_j - \mathrm{tt}_i - \mathrm{w_i} - \mathrm{t_{ij}^k} \leq \mathrm{M}\left(1 - \sum_{k \in K} \mathrm{x_{ij}^k}\right) \;\; ; \;\; \forall i \in C, \forall j \in \tag{16}$$

Constraints 15 and 16 are constraints that eliminate the subtour of the carrier.

$$\sum_{i \in C} \sum_{j \in C} \mathrm{d_{ij}}\, y_{ij}^{kd,k} \leq \mathrm{B} \tag{17}$$

Constraint (17) restricts drones from visiting nodes exceeding the maximum travel distance.

$$\mathrm{x_{ij}^k} \;, y_{\mathrm{ij}}^{\mathrm{k,kd}} \in \{0,1\} \;\; ; \;\; \forall i \in C, \forall j \in C, \forall \; k \in K, \forall \; kd \in KD \tag{18}$$

$$\mathrm{p_{ij}^k} \;, \mathrm{w_i^k}, \mathrm{tt_i^k}, \mathrm{dt_i^{kd,k}} \;\; \geq 0 \;\; ; \;\; ; \;\; \forall i \in C, \forall j \in C, \forall \; k \in K, \forall \; kd \in KD \tag{19}$$

Constraints (18) and (19) limit the range of each variable.

3.3. CVRP-D Formulation

The formulation and notations used in this thesis is mainly referenced from Kitjacharoenchai et al. (2020).

<u>Sets</u>

$C = \{1,2,3 \dots n\}$: A set of all demand nodes existing in the network.

$K = \{1,2 \dots k\}$: A set of trucks

$DR = \{1,2 \dots kd\}$: A set of drones installed on each truck.

$V = C \cup \{0\}$: A set of all nodes including depot.

$A = \{(i,j)\} | i,j \in V, i \neq j \}$: A set of all the arcs in the network.

$G = (V, A)$: Network consisting of node V and arc A.

<u>Parameters</u>

t_{ij}^{t} : Travel time of truck along arc A

t_{ij}^{d} : Travel time of drone along arc A

d_{ij} : Distance along arc A

p_{ij}^{k} : Payload of truck k along arc A

q_i : Demand of node *i*

M : Big number

<u>Variables</u>

x_{ij}^{k} : 1 if a truck *k* travels between nodes *i* and *j* is 1, otherwise 0

$y_{ij}^{kd,k}$: 1 if a drone *kd* installed on a truck k traveled along arc A, otherwise 0

w_i^k : Waiting time of truck k at node *i*

tt_i^k : Arrival time of truck k at node *i*

$dt_i^{kd,k}$: Arrival time of drone *kd* installed on turck *k* at node

la_i : 1 if a node *i* is launch node, otherwise 0

The proposed mathematical formulation of CVP−D is presented as follows.

$$\text{minimize} \;=\; \sum_{i\in V}\sum_{j\in V}\sum_{k\in K} x_{ij}^{k} t_{ij}^{t} + \sum_{i\in C} w_i \qquad (1)$$

Objective equation (1) minimizes the sum of the travel time and waiting time of the entire trucks.

subject to

$$\sum_{i\in V}\sum_{k\in K} x_{ij}^{k} + \sum_{i\in C}\sum_{kd\in DR}\sum_{k\in K} y_{ij}^{k} = 1 \;\; ; \forall j \in C \qquad (2)$$

By constraint (2), demand node j must be visited only once by drone or truck.

$$\sum_{k\in K}\sum_{i\in C} x_{0i}^{k} \;=\; K \qquad (3)$$

$$\sum_{k\in K}\sum_{i\in C} x_{i0}^{k} \;=\; K \qquad (4)$$

Constraints (3) and (4) make all trucks depart from depot and necessarily return to depot.

$$\sum_{i\in V} x_{ij}^{k} \;=\; \sum_{i\in V} x_{ji}^{k} \;\; ; \forall j \in C \qquad (5)$$

By constraint (5) when the vehicle enters an arbitrary node j on the route of the vehicle, a route from j must be created. Conversely, if it has not visited any node j, no route from j should be generated.

$$y_{ij}^{kd,k} \le \left(2 - \sum_{i\in V} x_{ij}^{k} - \sum_{i\in V} x_{ji}^{k}\right) \;\; ; \forall j \in C \qquad (6)$$

Constraint (6) means that when nodes I and j have all visited by the vehicle, the drone means arc(i,j).

$$\sum_{i \in C} y_{ji}^{kd,k} = \sum_{i \in C} y_{ij}^{kd,k} \quad ; \forall j \in C \tag{7}$$

Constraint (7) preserves the flow of the drone. If node i is a node serviced by a drone, it must be leaked from drone that enters node i.

$$\sum_{i \in C} x_{ij}^{k} \geq la_i \quad ; \forall j \in C \tag{8}$$

$$la_i \leq \sum_{i \in C} y_{ij}^{kd,k} \quad ; \forall j \in C \tag{9}$$

$$1 + M\left(\sum_{j \in C} y_{ij}^{kd,k} - 1\right) + M\left(\sum_{j \in C} x_{ij}^{k} - 1\right) \leq la_i \tag{10}$$

$$; \ \forall i \in C \ , \forall kd \in DR, \forall k \in K$$

If the truck visits the demand node i by constraints (8), (9), and (10), the drone launches from node i, the variable la_i must be 1. That is, if node i is a launching node, la_i is 1, otherwise 0.

$$la_i \left(\sum_{i \in C} x_{ij}^{k}\right)\left(\sum_{i \in C} y_{ji}^{kd,k}\right) = 0 \ ; \forall j \in C \ , \forall kd \in DR, \forall k \in K \tag{11}$$

According to constraint (11), if node i is a launching node the drone does not deliver node i.

$$\sum_{i \in C} \sum_{j \in C} d_{ij} y_{ij}^{kd,k} \leq B \ ; \forall j \in C \ , \forall kd \in DR, \forall k \in K \tag{12}$$

Constraint (12) restricts drones from visiting nodes exceeding the maximum travel distance.

$$\sum_{i \in C} q_i\left(y_{ij}^{kd,k}\right) \leq QD \ ; \forall j \in C \ , \forall kd \in DR, \forall k \in K \tag{13}$$

Constraint (13) means that the sum of demands of nodes visited by a drone should be smaller than the capacity of the drone.

$$\sum_{i \in C} q_i x_{ij}^k + \sum_{i \in C} \sum_{kd \in DR} q_i y_{ij}^{kd,k} \leq Q \ ; \forall j \in C \ , \forall k \in K \tag{14}$$

By constraint (14), the sum of the demand delivered by the truck and the demand delivered by the drone should be less than the capacity of the truck.

$$tt_j^k \geq tt_i^k + t_{ij}^t - M\left(1 - x_{ij}^k\right) ; \forall i, j \in C, \ \forall k \in K \tag{15}$$

$$dt_j^{kd,k} \geq dt_i^{kd,k} + t_{ij}^d \quad - M\left(1 - y_{ij}^{kd,k}\right) \tag{16}$$

$$; \forall i, j \in C, \ \forall k \in K, \forall \ kd \in \ KD$$

$$dt_i \geq la_i tt_i \ ; \forall i \in C \ ; \forall \ i \in \ C \tag{17}$$

$$dt_i \geq tt_j^k \quad ; \ \forall i, j \in \ C \ (i \ \neq \ j), \forall \ k \in \ K \tag{18}$$

Arrival times of the vehicle and the drone at each node i and j are coordinated by constraints (15), (16), (17), and (18).

$$u_i^k - u_j^k + Qx_{ij}^k \leq Q - q_i \ ; \ ; \ \forall i, j \in \ C \ , \forall \ k \in \ K \tag{19}$$

$$q_i \leq u_{k_i} \leq Q \quad ; \forall \ i \in \ C \tag{20}$$

Constraints 19 and 20 prevent the generation of sub−tours in the truck path. This constraint is a variant of MTZ subtour estimation. (Desrochers and Laporte 1991)

$$x_{ij}^k, y_{ij}^{kd,k}, la_i, \in \{0,1\} \ ; \forall i \in C, \forall j \in C, \forall \ k \in K, \forall \ kd \in KD \tag{21}$$

$$tt_i^k, dt_i^{kd,K}, u_i \geq 0 \ ; \ \forall i \in C, \forall k \in K, \forall \ kd \in KD \tag{22}$$

Constraints (21) and (22) limit the range of variables.

Chapter 4. Proposed Algorithms

4.1. Heuristic Algorithm

Using mixed-integer planning programming only can find solutions in small networks in a reasonable computation time. This thesis developed a heuristic algorithm to overcome these limitations. The thesis objectives find solutions with each heuristic algorithm, CVRP-D, and CVP-D. Each algorithm comprises various sub-problems, which are detailed in the following sections.

4.1.1. Knapsack Problem

Objective of Knapsack problem is maximizing the sum of values when putting items having weight and value in a limited capacity backpack. The mathematical formula for this problem is as follows.

<u>Variables & Parameters</u>

v_i : Distance from launching node to landing node i

x_i : If node i is drone node then 1, otherwise 0

w_i : Demand of node i

W : Drone's capacity

$$\text{maximize} = \sum_{i=1}^{n} v_i x_i \tag{1}$$

subject to

$$\sum_{i=1}^{n} w_i x_i \leq W \tag{2}$$

$$x_i \in \{0,1\} \tag{3}$$

Knapsack problem is a classic combinatorial optimization problem with several variants that are constantly being researched. Furthermore, it is well known that the Knapsack problem manages to find exact solutions handling large-scale problems. However, at a subproblem scale of CVRP-D or CVP-D, an optimization solver can efficiently discover optimal solutions.

Both the CVRP-D and CVP-D algorithms utilize the Knapsack problem. Knapsack problem determines which nodes the drone will visit among nodes not visited by a truck within the range the drone can cover when a carrier is holding.

The backpack's capacity is set from CVP-D to the carrier's current payload as one of the variables. On the other hand, the drone's capacity is considered the capacity of the backpack in the Knapsack problem in CVRP-D. Therefore, the weight is a node demand for both CVRP-D and CVP-D, and the value is the distance from the vehicle stop location to the node the drone visited. Because the waiting time happens when the vehicle stops, the more points the drone delivers when the vehicle comes to a standstill, the better. As a result, nodes distant from the truck or carrier route are generated, allowing for fast drone processing.

Intuitively, it creates a new route to visit the isolated node where the vehicle stops, penalizing its total travel time. Therefore, it is more cost-effective to use drones to visit isolated nodes to take isolated nodes. Based on the solution of the knapsack problem, a distant node from the carrier's stop is selected and relatively lightweight.

4.1.2. Parallel Machine Scheduling (PMS)

When separate machines with totally identical task processing capabilities are operated simultaneously, and in parallel, PMS is a problem of finding a solution to process multiple tasks in the quickest duration. Figure 4.1 depicts how PMS is used in the thesis graphically.

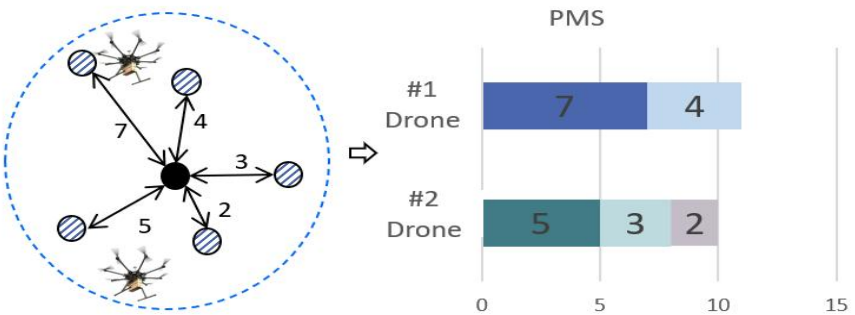

Figure 4.1 Concept diagram of PMS

The objective of this problem is to minimize the work of the machine that takes the longest. The formula for this problem is as follows.

<u>Variable & Parameter</u>

x_{ki} : If drone k deliveries to node j then 1, otherwise 0

p_i : Round trip time from launching node to node i

<u>Mathematical Formulation</u>

$$\text{minmize} = C \tag{1}$$

subject to

$$\sum_{i=1}^{n} x_{kj} p_j \leq C \quad ; \forall \ i \in Node \tag{2}$$

$$\sum_{i=1}^{n} x_{ki} = 1 \ \forall \quad ; k \in \text{Drone} \tag{3}$$

$$x_{kj} \in \{0,1\} \quad ; \forall k \in Drone, \forall j \in Node \tag{4}$$

PMS solved the CVP-D sub-problem. The PMS facilitated delivery locations to multiple drones for drone nodes selected through the knapsack program. Multiple drones are considered parallel machines in this instance, and the processing time is calculated by the round trip travel distance to each delivery destination. If a node's payload exceeds that of a drone, it is assumed to conduct delivery n times in order. To that objective, if a node's demand exceeds the capacity of the drone, the node needs to repeat the demand by the number of rounds divided by the drone's capacity.

4.1.3. Set Covering Location Problem (SCLP)

Set Covering Location Problem (SCLP) is one of the typical location problem. If the maximum distance from the facility is given, this problem can be solved by calculating the facility's location that can take charge of all nodes while having the minimum facility. This problem's formulation is as follows:

<u>Variable & Parameter</u>

x_i : If node j is truck stop node then 1, otherwise 0

f_i : Cost of truck stop (All nodes have the same value)

a_{ij} : If drone can fly from node i to node j then 1, otherwise 0

<u>Mathematical Formulation</u>

$$\text{minimize} = \sum_{i=1}^{n} f_i x_i \tag{1}$$

subject to

$$\sum_{i=1}^{n} a_{ij} x_i \geq 1, \qquad \forall j \in C \tag{2}$$

$$x_i \in \{0,1\}, \qquad \forall i \tag{3}$$

SCLP is applied to select nodes for drones in GA-CVPD. The solution of SCLP varies from arbitrary radius, which is one of input values. When solving SCLP as sub-component of GA-CVPD in this thesis, the radius continuously is updated for each iteration within a range that do not exceed the drone's maximum flying radius. The reason to follow those procedures is to establish the different delivery destinations of trucks and drones for each iteration. Several nodes become candidate nodes for carrier stop nodes as a result of the SCLP. A carrier stop candidate node is where a carrier stops and operates drones.

4.1.4. Guided Local Search (GLS) Algorithm

One of the proposed algorithms in this thesis, the first calculation step for the heuristic approach uses the CVRP solution. The initial CVRP solution is obtained by Or-tools, an open-source optimization solver (Google, 2021). OR-tools selects the best solutions from initial CVRP solutions using algorithms like Sweep, Saving, and Nearest. Then, to improve the initial solution, metaheuristic algorithms such as Tabu-Search (TS) and Simulated Annealing are used to identify the best local and global solutions. In this thesis, GLS algorithm is used as a local search algorithm. Compared to other algorithms available in Or-tools, it is known that GLS finds solutions close to a global optimum solution of CVRP more effectively than others. The following is a brief description of GLS.

GLS is a metaheuristic search algorithm. This algorithm imposes penalties to prevent the solutions from failing into local optimum solutions. This strategy is modified when falling into a locally optimal solution by adding a specified value to the objective equation, escaping from the local optimum, and discovering different options. The technique of modifying the objective equations impacts GLS's productivity. GLS alters the purpose equation, causing local optimal solutions to pursue alternative solutions by paying higher costs than those in the vicinity. Repeat this process until algorithm found the best solution or till the termination condition is reached (Voudouris et al., 2010).

4.1.5. Genetic Algorithm (GA)

The Genetic Algorithm (GA) is a metaheuristic algorithm that mimics natural phenomena such as gene selection, crossover, and mutation in which genes acquire diversity. GA was used to discover solutions to a variety of combinatorial optimization problems. This algorithm uses chromosomes to represent a group of solutions. GA develops different chromosomes for each iteration and evolves chromosomes through crossover and mutation mechanisms to improve the objective formula.

GA was used as the main component algorithm of proposed algorithms in this thesis. GA was used to find the optimal combination of the radius of each truck, a variable of SCLP, which is the component of GA-CVPD. Figure 4.2 depicts the chromosome expression at this period.

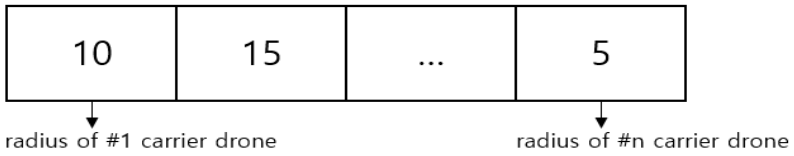

Figure 4.2 Chromosome in GA-CVPD

Launch and Land nodes of the drone route was determined by generating the route of each drone. The chromosome which represents launch and land nodes launching and landing nodes of the drone is visualized in Fig 4.3.

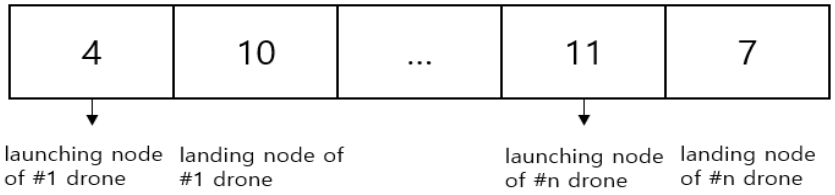

Figure 4.3 Chromosome in GA-CVRPD

4.2. Proposed Heuristic Algorithm : GA-CVPD

In this study, a heuristic algorithm (GA-CVPD) was designed to examine the optimal CVP-D solutions. Heuristic algorithms use the following steps to discover solutions.

Step 1: SCLP selects a possible stop location for the truck. At this moment, the key variable in SCLP, radius, is decided within the drone's maximum maneuverable distance. Because the radius value is assigned, the truck stop location, which SCLP determines, is also set. The diameter of the radius varies from iteration to iteration to guarantee the construction of distinct CVP-D routes. Then, the candidate location for the stop position will change for each iteration.

Step 2: The node farthest from the depot is selected as the initial carrier stop location among the carrier stop candidate locations. The next stop node is determined from the initial node among the candidate nodes using the near-search algorithm. The reason is that the drone's speed is faster than that of the carrier, and by removing nodes isolated from the depot, the carrier's traveling length can be decreased.

Step 3: Using Knapsack Problem, select the drone node the drone should visit at each stop location. In this case, the drone node is selected based on the payload of the present carrier. The demands of some nodes may exceed the drone's capacity, and we can call them excess demand nodes. Some excess demand nodes are divided by the drone's capacity when excess demand nodes are used. Drones are therefore expected to visit excess demand nodes multiple times.

Step 4: PMS decides the delivery order for the selected drone nodes. In this case, the processing time is determined by the distance between the truck stop location and each drone node. As a result, the order in which the deliveries are executed in the quickest length of

time is established. The vehicle's waiting time at the stop location is considered the delivery time of the drone with the longest delivery time.

Step 5: The carrier goes to the next stop candidate node if the demand of the next stop candidate node is less than the payload of the carrier. The carrier returns to the depot if the remaining payload is less than the smallest demand among the stop candidate nodes. Steps 3 and 4 are repeated at the next stop node.

Step 6: After the carrier's initial route is generated, the carrier stop locations are classified as TSPs, and the order of visits to the stop locations is reorganized. Finally, the route time is calculated by adding the carrier's travel and waiting times.

Step 7: To remember the best radius combination, save the radius required in step 1 as GA. Steps 1 to 6 are repeated for each carrier until the termination condition is reached. The route for each carrier is completed, and the algorithm is ended when the termination condition is reached.

Figure 4.3 is a pseudo algorithm of GA−CVPD that illustrates the entire procedure written in pythonic coding style.

Algorithm : GA-CVPD

Input : Trucks, Drones, All Nodes, Demand, Capacity, Radius

Output: S^{CVP-D}

1. **For** Carrier ∈ **Trucks**
2. **For** Drone ∈ **Drones**
3. Initialize problem , Aps=[], Truck Route=[], Total Travel time=0:
4. Set random radiuses using GA
5. Update Aps solving SCLP
6. Select Anchor node in Aps
7. Truck Route = Truck Route ∪ Anchor node
8. Update DroneN = Select DroneN using Knapsack problem
9. Total Travel time = Total Travel time + waiting time
10. Select Next Anchor node
11. **If** remain_truck capacity < Demand of Next Anchor point:
12. Return to depot
13. **Else: Back to line(5)**
14. **End For**
15. Calculate the truck route travel time
16. Total Travel time = Total Travel time + truck route travel time
17. **End For**
18. **Return** $\mathbf{S^{CVP-D}}$

Figure 4.3 Pseudo algorithm of GA-CVPD

4.3. Proposed Heuristic Algorithm : GA-CVRPD

Step 1: Initial solution of CVRP is obtained using Or-tools. The initial solution is utilized as the initial route for each truck.

Step 2: Select the drone's launching and landing nodes arbitrarily from the truck's initial route. However, a genetic algorithm improves the drone's launching and landing locations while the algorithm is repeated. Depots are also nodes that can be selected as launching and landing locations. Time synchronization between the vehicle and the drone is not necessary if the landing node is a depot.

Step 3: Create a delivery route for the drone from the launching node. The following is the procedure for generating the drone's route:

1. Selects the node that the drone will visit, solving the Knapsack problem.
2. Weight is the node's demand, and value is the distance from the launching node to each drone node, and these are the determinants of the Knapsack problem. The route from the initial node to the selected nodes is then constructed.
3. Add the previously selected landing node to the last drone node.

If the total drone route length exceeds the drone's maximum flight distance, the total route time is penalized, preventing the route from being selected as the outcome.

Step 4: A new route is generated by eliminating nodes from the initial truck route included in the drone route. The next drone's route is repeatedly obtained in steps 2 and 3 using the newly constructed truck route. Until the tour is complete, this process is repeated for all drones installed on the vehicle. If flying a drone is a worse alternative than driving a truck, the original vehicle's route is selected as the final route.

Step 5: Repeat steps 2 to 4 until the termination condition is reached. The algorithm is executed again to generate the subsequent drone−truck route if the termination condition is reached. Terminate the algorithm once all trucks and drones have routes generated. Figure 4.4 represents the pseudo algorithm of GA−CVRPD.

Algorithm : GA−CVRPD

Input: Trucks, Drones, All Nodes, Demand, Capacity, Battery

Output: S^{CVRP-D}

```
Generate S^CVRP using OR−tools(Truck, Demands, Nodes, Capacity)
For Route ∈ S^CVRP
    For Drone ∈ Drones
        Select Launch/Land nodes in {All nodes in Route} using GA
        Initialize 1st node = Launch node, DroneN = []:
        Update DroneN = Find available DroneN using SCLP
        Update Drone route = Nearest Neighbor Search(DroneN)
        Last Drone route = Land nodes
            If total drone distance > Battery:
            Back to Select Launch state
            Drone delivery route = Drone route −{Launch, Land node}
            Update Route = Route\Drone route
        End For
    End For
    DT route = Route ∪ Drone routes
    Update DT Travel time = Calculate Travel time(S^CVRP−D)
    IF DT Travel time < Travel Time :
        Travel Time = DT Travel time
        Route = DT route
Return S^CVRP−D
```

Figure 4.4 Pseudo algorithm of GA−CVRPD

Chapter 5. Numerical Analysis

5.1. Data Description

CVRP-lib test network instances organized by Uchoa et al. (2017) were used to demonstrate the performance of the proposed algorithm in this thesis. Those instances are well-known CVRP benchmark problems in VRP and its variant research, and the size of some instances is too large to be solved by MIP solvers within reasonable computation time. Therefore, we used the same instances in the benchmark to compare with the prior CVRP-D research (Kitjacharoenchai, Min, and Lee, 2020). Figure 5.1 shows the Visualization of example instances. When the sum of truck travel times is the objective function, there is an optimal solution to verify how good the drone-truck delivery is compared to truck-only delivery. All algorithms used in this thesis were coded by Python 3.8.4, and some MIPs were solved by Gurobi 9.1 (2021), a well-known commercial MIP solver. The running environment is windows 10, AMD Ryzen 5 2600 3.40Ghz, 16GB RAM.

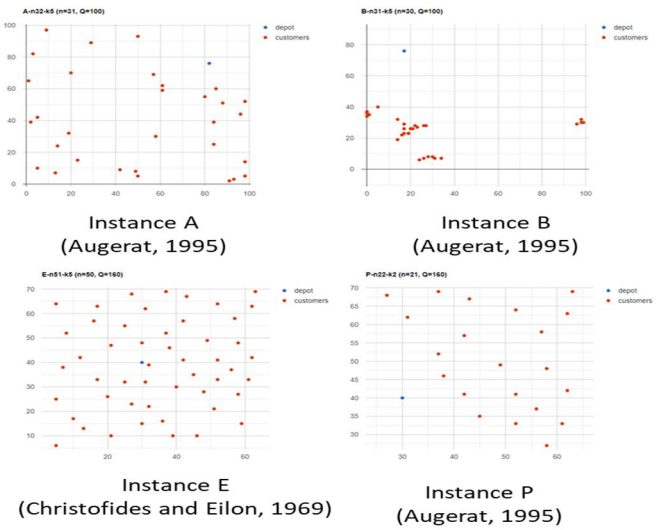

Figure 5.1 CVRP-lib instance samples

5.2 Numerical Experiment

The effectiveness of the CVRP-D algorithm and CVP-D algorithm presented in this study was verified in the same environment as the previous study.

The object value in CVRP-D was improved above the existing CVRP's optimal object value. Table 5. 1 shows the results of previous research and the proposed thesis. The proposed algorithms are heuristic algorithms, and the results vary from trier to trier. Therefore, it was executed ten times for each instance, and the average and best values were recorded. In most instances, the object value was improved due to the algorithm described in this thesis compared to the value presented in the previous research. However, in some cases, the performance of the proposed algorithm in thesis results to be inferior to previous research.

In Figure 5.2, we can intuitively see the comparison of the algorithm's performance presented in the previous study and the algorithm presented in the paper. Overall, in the same environment, the CVP-D method did not have many benefits in reducing truck travel time compared to the existing CVRP. However, the CVRP-D method showed a greater reduction in truck travel time than CVRP in most cases.

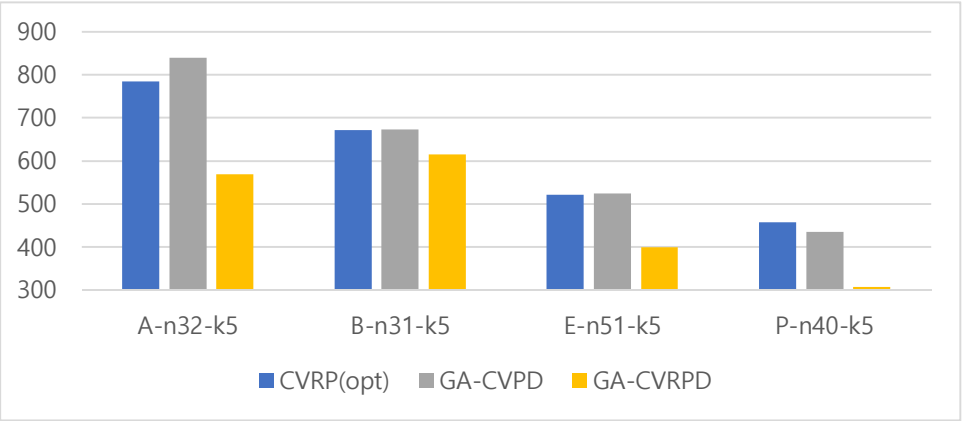

Figure 5.2 Comparison of proposed algorithms with CVRP

Table 5.1 Comparison between proposed algorithm and earlier research

Instance	n	k	Q	KD	QD	CVRP(opt)	K* (GAP)	CVP-D				CVRP-D			
								Average	Best	GAP (From K)	GAP (From CVRP)	Average	Best	GAP (From K)	GAP (From CVRP)
A-n32-k5	31	5	100	2	35	784	677(-13.6%)	840	840	24.08%	7.14%	568.3	568.3	-16.06%	-27.51%
A-n33-k5	32	5	100	2	35	661	546(-17.4%)	701	701	28.39%	6.05%	505.3	505.3	-7.45%	-23.56%
A-n33-k6	32	6	100	2	35	742	614(-17.2%)	739.926	731.3	19.10%	-1.44%	595.667	595.667	-2.99%	-19.72%
A-n34-k5	33	5	100	2	35	778	644(-17.2%)	740	740	14.91%	-4.88%	557.11	556.66	-13.56%	-28.45%
A-n36-k5	35	5	100	2	35	799	652(-18.4%)	842.579	838.3	28.57%	4.92%	664	664	1.84%	-16.90%
A-n37-k5	36	5	100	2	35	669	532(-20.4%)	673.48	662	24.44%	-1.05%	491.998	490.33	-7.83%	-26.71%
A-n37-k6	36	6	100	2	35	949	834(-12.1%)	958.34	940.7	12.79%	-0.87%	828.833	826	-0.96%	-12.96%
A-n38-k5	37	5	100	2	35	730	589(-19.3%)	777	762.7	29.49%	4.48%	558.2	556.3	-5.55%	-23.79%
A-n39-k5	38	5	100	2	35	822	689(16.2%)	782.6	782.6	13.58%	-4.79%	683	683	-0.87%	-16.91%
B-n31-k5	30	5	100	2	35	672	655(-2.5%)	673	673	2.75%	0.15%	615	615	-6.11%	-8.48%
B-n34-k5	33	5	100	2	35	788	740(-6.1%)	798.3	798.3	7.88%	1.31%	721	721	-2.57%	-8.50%
B-n35-k5	34	6	100	2	35	955	890(-6.8%)	945	945	6.18%	-1.05%	963	963	8.20%	0.84%
B-n38-k6	37	6	100	2	35	805	712(-11.5%)	812.106	809.33	13.67%	0.54%	743.666	743	4.35%	-7.70%
B-n39-k5	38	5	100	2	35	549	499(-9.1%)	554	554	11.02%	0.91%	484.3	484.3	-2.95%	-11.79%
B-n41-k6	40	6	100	2	35	829	810(-2.3%)	842.393	837.3	3.37%	1.00%	736	736	-9.14%	-11.22%
E-n51-k5	50	5	160	2	50	521	426(-18.2%)	524	524	23.00%	0.58%	399	399	-6.34%	-23.42%
E-n76-k7	75	7	220	2	55	682	631(-7.5%)	712.6	712.6	12.93%	4.49%	462	462	-26.78%	-32.26%
P-n22-k2	21	2	160	2	40	216	154(-28.7%)	195.6	195.6	27.01%	-9.44%	150	150	-2.60%	-30.56%
P-n40-k5	44	5	150	2	40	458	367(-19.8%)	435	435	18.53%	-5.02%	308	308	-16.08%	-32.75%
P-n45-k5	44	5	150	2	40	510	400(-21.6%)	500.6	500.6	25.15%	-1.84%	340	340	-15.00%	-33.33%
P-n50-k7	49	7	150	2	40	554	470(-15.2%)	536.992	510	8.51%	-7.94%	392.986	392	-16.60%	-29.24%
P-n55-k7	54	7	170	2	45	568	501(-11.8%)	583.325	562.3	12.24%	-1.00%	401	401	-19.96%	-29.40%
			Average.				-14.2%			16.71%	-0.35%			-7.50%	-20.65%

Note K* : Kitjacharoenchai et al. 2020

n : No. of nodes , k : No. of trucks, Q : Capacity of truck, KD : No. of drones, QD : Capacity of drone CVRP : Optimal value of original CVRP (truck only)

5.3. Sensitivity Analysis

Sensitivity analysis was performed while changing major parameters using the E-51n-k5 instance. This network has 51 nodes, and the depot's location is located in the center of the network. In addition, nodes are distributed randomly.

Sensitivity analysis was tested by changing the velocity, battery, capacity, and the number of drones. The analysis confirmed the sensitivity by fixing the initial parameter and changing only one parameter.

5.3.1. Analysis on GA-CVPD

<u>Sensitivity to Drone Velocity</u>

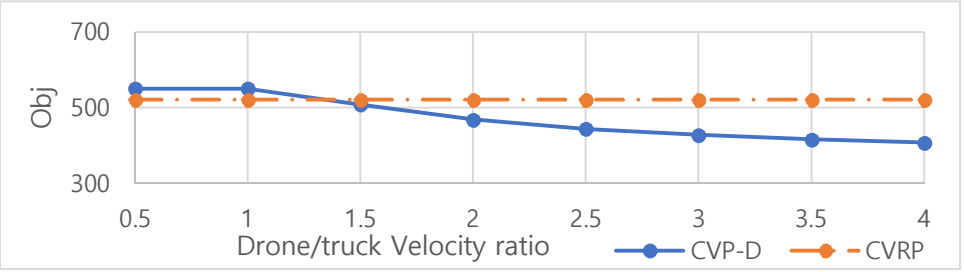

Figure 5.3.1

Figure 5.3.1 depicts the change in the purpose equation as a function of the drone's relative velocity to the vehicle. The objective equation improves as the drone speed increases, similar to the CVRP-D experimental results. CVP-D, contrary to CVRP-D, does not converge and, as the velocity increases, constantly decreases the value of the objective equation.

Sensitivity to Drone Battery

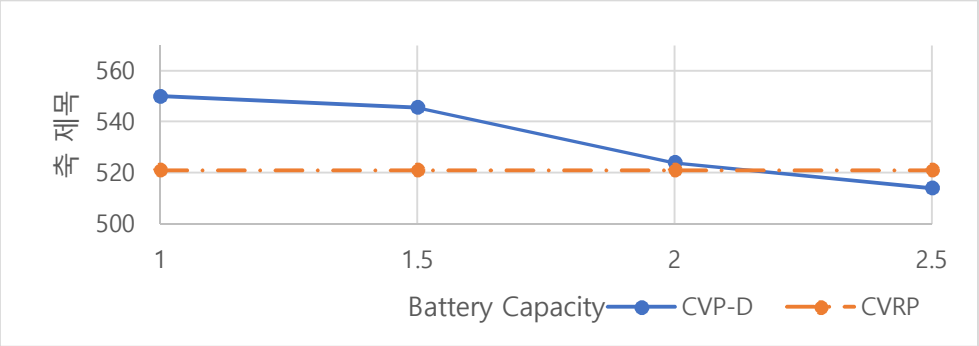

Figure 5.3.2

Figure 5.3.2 demonstrates the experimental observations based on the drone's battery capacity. Drones can only tour one node at a time with CVP−D. As a result, increasing the travel distance of drones does not contribute much to improving the objective.

Sensitivity to Drone Capacity

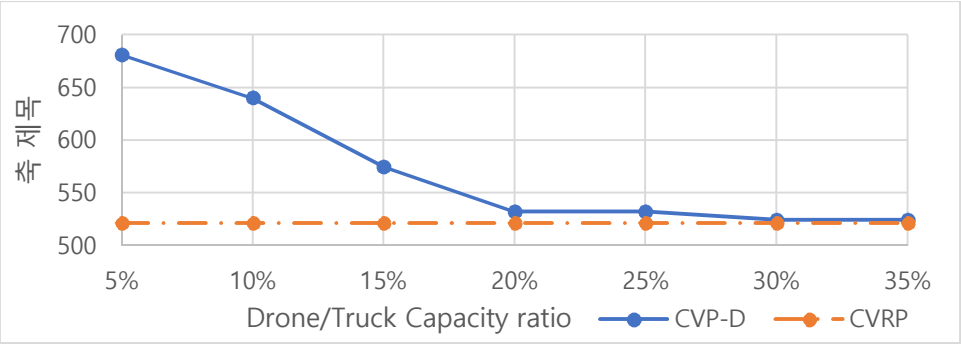

Figure 5.3.3

Figure 5.3.3 shows the results of a sensitivity analysis based on the drone's capacity change. The x−axis indicates the capacity of individual drones compared to the truck's capacity. If the drone's capacity exceeds a certain threshold, it improves the objective equation.

Sensitivity to Drone number

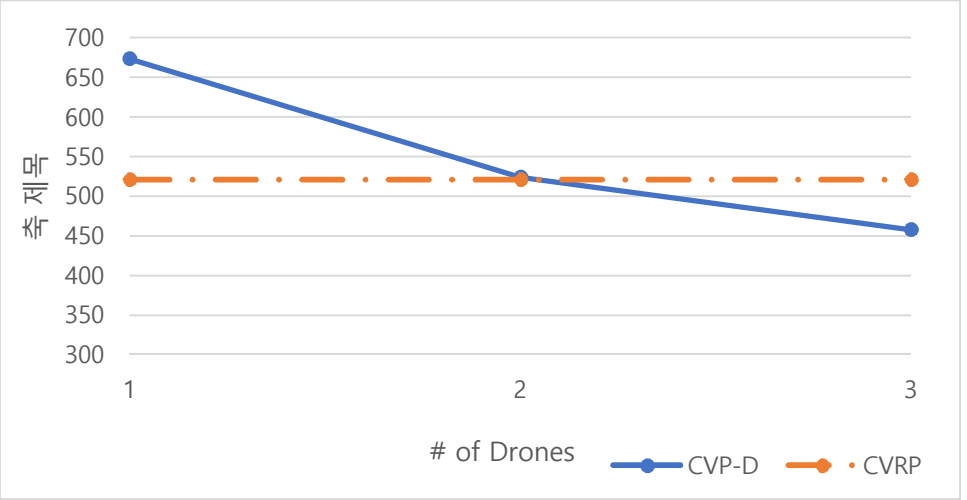

Figure 5.3.4

Figure 5.3.4 is the result of sensitivity analysis according to the change in the number of drones. As the number of drones increases, the objective equation improves, but it can be seen that the marginal gain decreases the same as other sensitivity analysis results.

5.3.2. Analysis on GA-CVRPD

Sensitivity to Drone Velocity

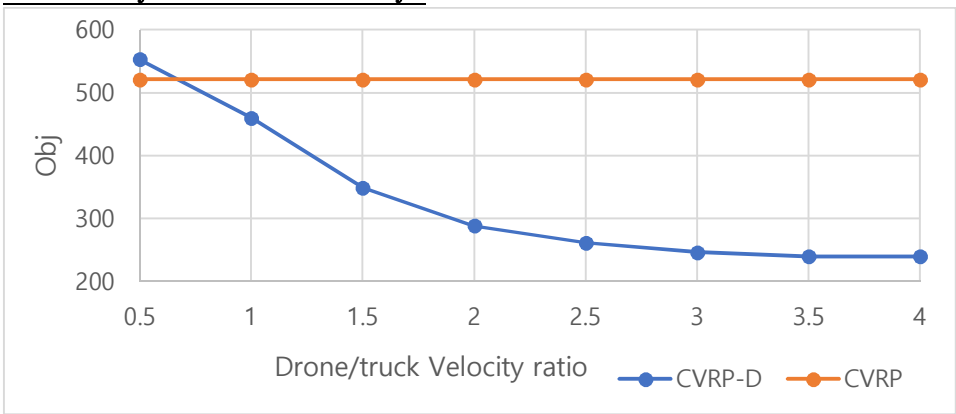

Figure 5.4.1

The change in the objective equation as a function of the drone's relative speed to the vehicle is shown in Figure 5.4.1. The velocity of the drone divided by the vehicle's speed is the x-axis value. As a result of the experiment, the value of the objective equation differed substantially as the velocity varied. There are also two facts to be discovered. To begin with, if the drone's velocity is slower than the vehicle's, it is pointless to use the drone. We've seen the marginal benefits of increasing drone velocity.

Sensitivity to Drone Battery

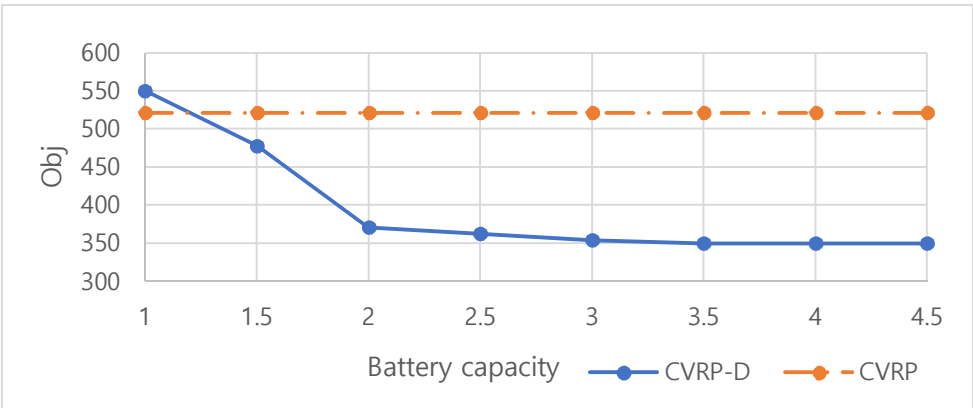

Figure 5.4.2

Figure 5.4.2 demonstrates the experimental results based on the drone's battery capacity. The drone's battery capacity is a major bottleneck in its travel distance. When the average distance between each node is set to 1, the x-axis is a measure that reflects the drone's moveable distance. As a result, increasing drone battery capacity does not significantly improve the purpose equation above a certain threshold.

<u>Sensitivity to Drone capacity</u>

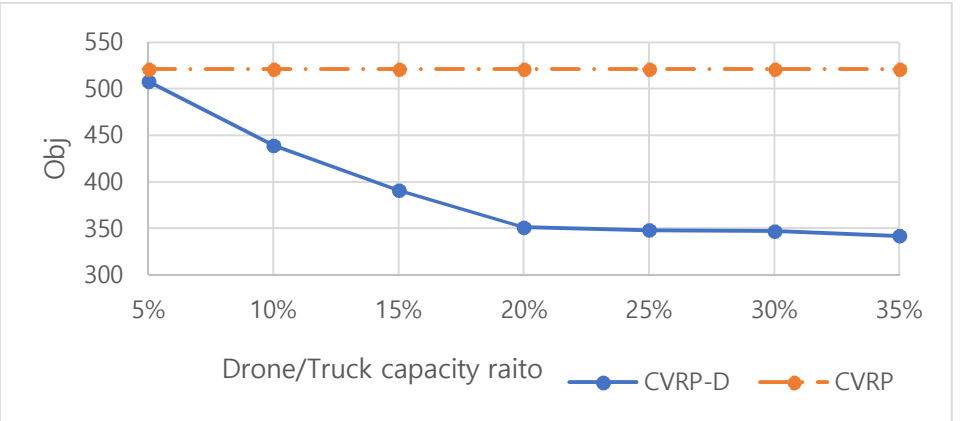

Figure 5.4.3

Figure 5.4.3 is the result of sensitivity analysis according to the capacity change of the drone. The x-axis represents the capacity of individual drone relative ratio to the capacity of the truck. It can be seen that if the capacity of the drone exceeds a certain level, it does not contribute meaningfully to the improvement of the objective equation.

Sensitivity to no. of drone

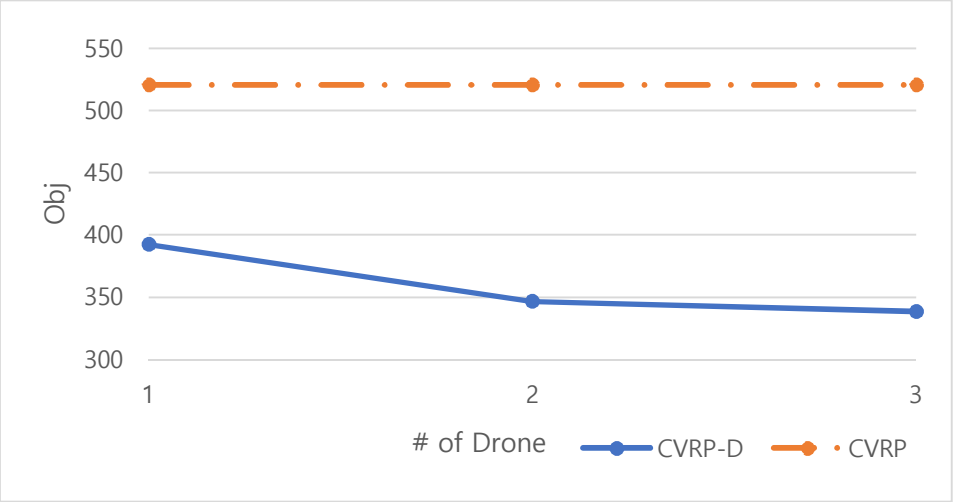

Figure 5.4.4

Figure 5.4.4 presents the results of a sensitivity analysis depending on the number of drones. The number of drones installed on each truck is indicated on the x-axis. It can be seen that the change in the number of drones produces a drop in the objective equation, which is identical to the previous experimental results.

5.3.3. Result on different Instances

We classified into five types according to the location of Depot and the distribution of nodes, and the change in algorithm result values was observed for each type. Each type of instance was used in the CVRP-lib. For example, in the original problem, the numbers and capacity of vehicles were set to 4, and the capacity of the vehicle was changed to a value obtained by dividing the total demand of nodes by 4.

The visualization of each type is represented in Figure 5.5. In addition, the number of drones mounted on the vehicle was changed and compared with the result of CVRP. Finally, sensitivity was analyzed as the average improvement by the algorithm presented for each type.

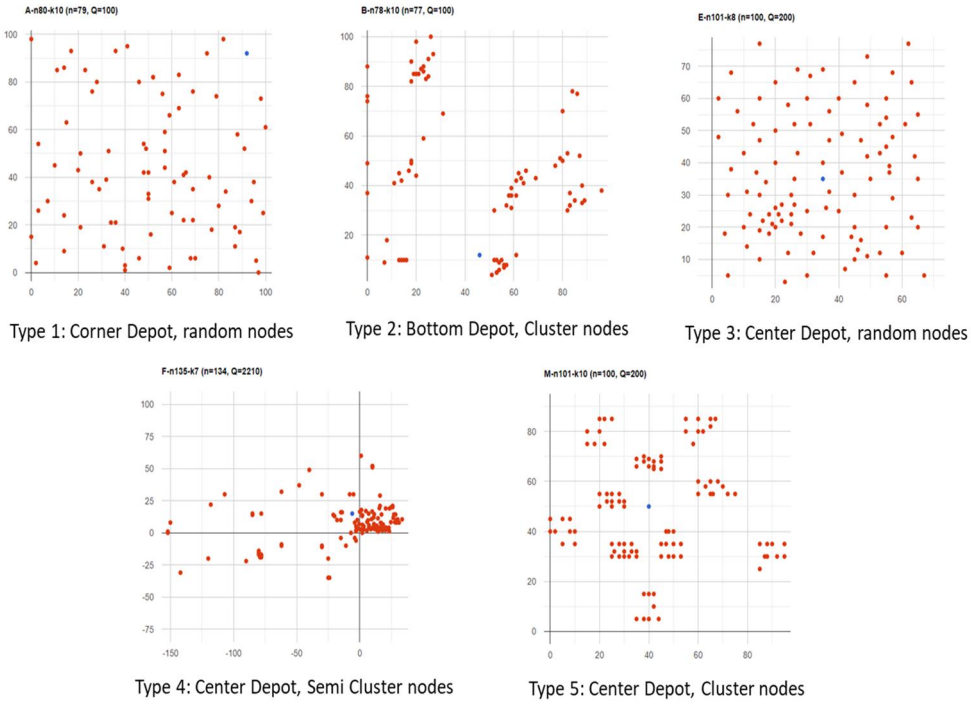

Figure 5.5 Different instances based on location of depot and nodes

In the numerical experiment conducted earlier, the parameters were the same as those used in previous studies compared with previous studies. However, in this sensitivity analysis, the capacity and speed of the drone were adjusted. In reality, the smallest vehicle used in last-mile delivery also has a 1-ton load weight. However, if the capacity ratio of drones and vehicles is 0.3, drones have at least 300kg of payload, limiting the operation of drones of this size on the vehicle. In addition, the average traffic speed of vehicles is 17km based on downtown Seoul. In contrast, the velocity of a logistics drone is more than 50 km/h. Therefore, the parameters were modified to reflect these considerations. As a result, the capacity ratio of drones and trucks decreased from 35% to 10%, whereas the speed ratio of drones and trucks increased from 1.5 to 3. Table 5.2 displays a summary of findings.

Table 5.2 Comparison the results based on different type of instances and the number of drones

Instance	Drones (KD)	CVRP Obj	BEST Obj	AVG Obj	Gap(%) from cvrp	BEST Obj	AVG Obj	Gap(%) from cvrp
A-n80-k4 Type1	1	1117	1123	1128	0.5%	1004	1005.2	-10.1%
	2	1117	1022	1056.6	-8.5%	865	865	-22.6%
	3	1117	1023	1042.6	-8.4%	784	788.6	-29.8%
			Mean		-5.5%			-20.8%
B-n78-k4 Type2	1	846	787	804.6	-7.0%	779	779.2	-7.9%
	2	846	763	781.4	-9.8%	720	720	-14.9%
	3	846	671	692.4	-20.7%	645	649.6	-23.8%
			Mean		-12.5%			-15.5%
E-n101-k4 Type3	1	750	740	771.8	-1.3%	622	623.8	-17.1%
	2	750	600	637.98	-20.0%	493	496.4	-34.3%
	3	750	503	575.6	-32.9%	427	432	-43.1%
			Mean		-18.1%			-31.5%
F-n135-k4 Type4	1	1029	1137	1317.6	10.5%	905	918.2	-12.1%
	2	1029	1159	1270.4	12.6%	856	856	-16.8%
	3	1029	1095	1260	6.4%	825	826.4	-19.8%
			Mean		9.8%			-16.2%
M-n101-k4 Type5	1	675	649	673.6	-3.9%	600	603.4	-11.1%
	2	675	552	628.6	-18.2%	542	542.8	-19.7%
	3	675	515	565.8	-23.7%	453	459.4	-32.9%
			Mean		-15.3%			-21.2%

The GAP of GA-CVPD and CVRP ranges from 9.8% to -18.1% depending on types and GAP differences up to 28%. However, considering that the smaller the GAP, the better because the objective is the total traffic time, it was advantageous not to operate a drone in some instances. The GAP of GA-CVRPD is -15.5% to -32.9%, and there is a difference of about 18%.

Both algorithms achieved relatively better results in Type 3 but not in Type 4. Type 4 has a depot in the center, but the node distribution is mixed with the cluster and random.

GA-CVPD showed relatively good results in Type 2 and Type 5, with a small difference from GA-CVRPD. However, these two types have something in common: the node distribution is a cluster. Therefore, it can be concluded that the CVP-D method is more advantageous in a network with clustered nodes. In contrast, the CVRP-D method is more advantageous in a network with randomly distributed nodes.

Both algorithms performed relatively poorly in Type 4, especially GA-CVPD was rather poor compared to CVRP. As in Type 4, when nodes are mixed with clusters and random, the efficiency of drone-truck operation methods is relatively low.

Chapter 6. Conclusion

This thesis has some limitations, and especially the real-world condition was not adequately reflected. The following are some of the study's limitations.

First, just the truck's trip time was considered in this thesis, and the running costs of trucks and drones were not. The common objective equation in routing problem research is to decrease operational costs. In general, the hourly running cost of a drone is low when compared to the cost of operating a truck. However, the economic assessment of drone introduction should continue from average operating costs when considering whole life cycle costs.

Second, research on the optimum number of drones and vehicles to operate is required as part of a broader discussion of running costs. It is clear that as the number of trucks and drones increases, the operating time of individual trucks will decrease. However, operating costs increase proportionally. In other words, there is a cost-benefit trade-off between reduced running time and lower operational costs. Aside from the two costs, there are many economical analysis criteria, such as the effects on safety and the benefits of lower traffic volume.

Third, many limitations of drones were ignored in this thesis. However, it is necessary to reflect the various limitations of drones at the current technology level. For example, a drone has a different maximum driving distance due to a change in the battery consumption rate according to the payload. In addition, drone batteries take a considerable amount of time to charge, and even though replaceable, cost and space constraints are created. Although these limitations were not considered in this paper, in future studies, it is necessary to design and experiment with sophisticated algorithms that can be

used commercially by considering these considerations.

Despite these limitations, this research developed an algorithm for solving the drone-truck route problem, which is hard to solve in a reasonable amount of time. When drone delivery becomes a reality, the results of this study are expected to help with real-time route generation and designing parameters for drone delivery.

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Abstract

드론은 무인항공기(UAV)의 통칭으로 초기에는 군사적 목적으로 주목을 받았으나 최근 물류에서 사용하려는 노력이 적극적으로 진행되고 있다. 드론은 기존 배송수단에 의해 배송이 어려운 곳에 투입이 된다면 배송의 비용절감과 속도향상에서의 효과가 있을 것이다. 하지만 배송에 있어서 드론의 단점도 명확하다. 드론의 배송능력을 향상시키기 위해서는 드론이 대용량 배터리를 탑재하여야 하는데 이는 필연적으로 드론 크기를 증가시킨다. 이러한 단점을 극복하기 위해서 드론과 트럭을 결합하여 운영하는 방식이 연구되어왔다.

이러한 방식 중 본 연구에서는 두 가지 방식을 소개하고, 각각의 방식에 대한 알고리즘을 제시하였다. 먼저, CVP-D는 용량이 크고 속도가 느린 트럭이나 배 등의 캐리어가 용량이 작은 로봇, 드론 등을 싣고 다니면서 배송을 하는 방식이다. 다음으로, CVRP-D는 차량과 드론이 동시에 각기 다른 경로를 이동하며, 드론은 1회 비행(sortie)시 다수의 노드를 방문하는 것이 가능하다.

두 문제는 차량경로문제(VRP)에 제약이 더해진 문제이다. VRP는 대표적인 NP-hard 문제로 해를 구하기 위해서 휴리스틱 알고리즘이 요구된다. 본 연구에서 제시하는 알고리즘은 합리적인 시간 내 두 문제의 드론-트럭 경로를 도출하였다. 또한 민감도 분석을 실시하여 드론 배송 도입을 위한 적절한 네트워크 구조 및 드론의 주요 파라미터 변화에 따른 민감도를 관찰하였다. 이는 차후 드론의 성능에 관한 의사결정 시 고려해야 할 요소들에 대한 기준이 될 수 있을 것으로 기대된다.

또한 선행연구에서 사용한 벤치마크 데이터와의 비교를 통해 본 연구에 제안된 알고리즘의 타당성을 검증하였다. 본 연구는 드론 도입이 배송시간을 감소시키며, 운영방법에 따라서 배송시간의 차이가 발생함을 보였다.

주요어 : 드론, 차량순회 문제, 휴리스틱 알고리즘
학번 : 2020-28796