National Cheng Kung University

Department of Transportation and Communication Management Science

Master Thesis

# A Tabu Search Solution Algorithm for Autonomous Truck-Drone Delivery

禁忌搜尋法於自駕卡車搭配無人機模式之最佳配送

Student: Guan-Jie Huang

Advisor: Dr. Ta-Yin Hu

July, 2020

doi:10.6844/NCKU202002083

# 國立成功大學

## 碩士論文

禁忌搜尋法於自駕卡車搭配無人機模式之最佳配送

A Tabu Search Solution Algorithm for Autonomous Truck-Drone Delivery

研究生：黃冠捷

本論文業經審查及口試合格特此證明

論文考試委員：魏健宏

朱致遠

董啟崇

陳麗雯

指導教授：胡大瀛

系(所)主管：陳勁甫

中 華 民 國 109 年 7 月 14 日



doi:10.6844/NCKU202002083

# Abstract

Between August 6, 2009, and August 10, 2009, the deadly typhoon Morakot has hit Taiwan which brought the rainfall and the worst flooding across the country. Due to the devasting flooding incident, 681 people were dead and 18 went missing. Furthermore, the flooding washed away buildings, roads, bridges, and destroyed the only way back and forth of several mountain areas. Once the villages and towns lose the important traffic, air-delivery becomes the only choice to obtain supplies. However, the shortness of the air-delivery made the villages face tough trials. In such an emergency, the most concerned in this research is delivering numerous supplies quickly, properly, and accurately to meet everyone who is in urgent need.

In recent years, most logistics service providers are desired to seek innovative delivery options to fight with time pressure and labor shortages. In that case, autonomous vehicles seem to be the most appropriate solution to solve the problem. In Singapore, Jurong Island has applied autonomous trucks because of the shortage of labor. In America, autonomous trucks are the only solution in increasing efficiency to fight against the increasing volume of freights. According to National Development Council in Taiwan, the total population from 2020 to 2065 will decrease from 23 million to 17 million. The shortage of labor will bother Taiwan. The autonomous truck can redeem the shortage of labor and increase the efficiency in transportation and safety by automotive control. All the strengths can be achieved by autonomous vehicles, that is why this research focuses on ITS technologies such as an autonomous truck.

The objective of this research aims to develop a model for delivering relief resources in an emergency using Intelligent Transportation System (ITS) such as autonomous vehicles



doi:10.6844/NCKU202002083

and unmanned aerial vehicles (UAVs). This research focuses on the routing problem in emergency logistics. Logistics has been mostly utilized in the commercial field. However, logistics is also an important tool to transport relief resources when a disaster occurs.

Once the emergency occurs, autonomous vehicles can prevent the labor shortage. In limited time, UAVs are useful to do humanitarian logistics and the most important for those injuries is to deliver relief resources fast and moderately. By optimizing the route and distributing the resource moderately, relief transporting by autonomous vehicles can efficiently transport to injuries from the disaster. Despite the autonomous trucks are mostly utilize in delivering cargos, the development of the intelligent transportation system is the trends sweeping across the whole world. Thus, this research is desired to adopt autonomous trucks cooperating with two UAVs to transport supplies when an emergency occurs. To enhance the efficiency in delivering supplies, this research aims to develop a model for traveling salesman problem with two drones based on tabu search algorithm. Finally, the results are expected to present optimal routes for an autonomous truck and UAVs and be compared with a standard commercial solver, GUROBI. This research is contributed to providing some ideals for delivering relief resources in an emergency adopting the autonomous truck cooperating with two UAVs.

**Keywords:** Tabu Search, Autonomous Vehicle, Unmanned Aerial Vehicle, Traveling Salesman Problem, Flying Sidekick Traveling Salesman Problem



doi:10.6844/NCKU202002083

# 摘要

近年來，研究廣泛應用於物流領域且物流服務業者極力尋求創新的交付方式以應對時間壓力和勞動力短缺，卻於緊急情況下的物資配送尚未有完善研究。2009 年 8 月 6 日至 8 月 10 日，莫拉克颱風襲擊台灣並帶來嚴重水災。莫拉克颱風引起的水災造成 681 人死亡及 18 人失蹤。更嚴重的是，洪水破壞了建築物、道路、橋樑，甚至是數個山區的唯一聯外道路。一旦山區失去聯外交通道路，空投就成為獲取食糧、物資的唯一選擇。然而，空投的資源短缺使這些村莊面臨艱困考驗。此次事件亦突顯出緊急情況下，如何應用空投並以快速且準確地援助大量備品，以滿足所有急需的民眾。

儘管有多數研究討論物流領域的車輛路徑問題，但多數都是以民眾購買日常用品之物流方面為主，然而物流同時也是發生災難時運送物資的重要工具；故本研究希望能利用創新的智慧型運輸系統，對於自駕卡車以及無人機緊急物資的運輸進行探討。本研究認為一旦發生緊急情況，透過自駕車隨時待命並且無須人員駕駛的優點，在有限的時間內將助於進行人道物流，若發生道路損毀之災害時，搭配雙無人機進行物資的投遞亦是一大幫助。然而，對於傷患而言，最重要的是快速而適度地運送醫療物資。通過優化路線和適度分配資源，自駕車與無人機進行醫療救災運輸可以有效地救助受難患者，為了提高運送醫療物資的效率，自駕車以及無人機的串聯運用應能成為該問題的最佳解決方案。

本研究開發一模型為運用雙無人機搭配自駕卡車之模式進行緊急物資運輸，將物流領域中創新的思維應用於緊急物資配送中的車輛路徑問題，考量運送時間最佳化目標下，基於禁忌搜尋演算法求解最佳路徑並與商業求解器 GUROBI 進行比較；結果有望為自駕車及無人機提供最佳路線。期望提供利害關係人在緊急情況下採用自駕卡車及無人機運送醫療物資有更進一步之參考及建議。

**關鍵詞**：禁忌搜尋演算法、自駕車、無人機、搭配無人機之旅行銷售員問題



doi:10.6844/NCKU202002083

# Contents





doi:10.6844/NCKU202002083

doi:10.6844/NCKU202002083

# List of Table





doi:10.6844/NCKU202002083

# List of Figure





doi:10.6844/NCKU202002083

doi:10.6844/NCKU202002083

# CHAPTER 1 INTRODUCTION

## 1.1 Research Motivation and Background

Between August 6, 2009, and August 10, 2009, the deadly typhoon Morakot has brought a large amount of rainfall to hit Taiwan. The flooding incident caused by Morakot was Taiwan’s worst flooding. Due to the devasting flooding incident, 681 people were dead and 18 went missing. The flooding made the rivers wash away the building, roads, and bridges, cut up power lines. Moreover, landslides caused by the rainfall destroyed the only way back and forth for several mountain areas. Because the roads had been destroyed, mountain areas lose the important traffic and had to rely on air-delivery to obtain resources such as food, water, and supplies. However, the shortness of the air-delivery made the mountain areas face tough trials. In such an emergency, the most concerned are delivering supplies and resources quickly to meet everyone who is in urgent need of the proper vehicles.

In actual life, the disaster always comes in very timely, seriously and unpredictable. Once the disaster occurs, no matter the earthquake, flood, hurricane, or fire explosion it is, human and financial losses are inflicted significantly. In consideration of the disaster effects, the emergency transportation network can play a vital role, especially in delivering resource relief after a disaster. Unlike the developed countries after suffering the disaster in which the goal is to return the city to the pre-disaster condition quickly, the developing countries are attempting to rescue more people in the response phase (Khademi et al., 2015). Once a serious disaster strikes in Taiwan, the consequences always come with destructive and irreducible. For instance, the devastating the 921 earthquake in Nantou in 1990 almost destroyed the whole cities in the middle of Taiwan and almost 14,000 were injured or even dead. In 2014, a series of gas explosions happened in the southern Taiwanese city of



doi:10.6844/NCKU202002083

Kaohsiung which destructed the city roads and caused 321 injured and 32 killed. Another case in 2016, the Meinong earthquake, which is the most serious earthquake after the 921 earthquake, crush several buildings in Tainan, the worst situation is that Meinong earthquake caused the most sufferer of the collapse of a single building in Taiwan's history. In terms of the disaster which is an unpredictable and serious outcome, the problem of delivering relief resources should be noticed in an emergency that may destroy the roads.

In recent years, logistics service providers (LSPs) are regularly adopting innovative technologies such as autonomous vehicles and drones to improve the parcel delivery process (Joerss et al., 2016). The expectation for fast delivery is the reason why more than half of LSPs are nowadays offering same-day and next-day delivery options to their customers (Saleh, 2017). Furthermore, while facing emergency disasters, autonomous vehicles can shortage numerous relief resource equipment without the driver's seat. The emerging technologies V2I or V2V can also make inventory transparent cooperate with fleet and even help unmanned aerial vehicles (UAVs), as called drones, to plan ideal route feasibly and efficiently. On the other hand, UAVs have been also proposed to assist in releasing natural disasters emergency (Estrada and Ndoma, 2019). Undoubtful, fast and unlimited by terrain, which is the characteristic of UAVs to deliver goods reasonable such as relief supplies in emergency transportation.

This research aims to develop a model for emergency relief and resource transportation by autonomous truck cooperating with two UAVs and further construct a heuristics algorithm which is tabu search to minimize delivery time. The proposed model is tested on a realistic Kaoshiung network in Taiwan. This research is expected to provide recommendations for the relevant organization (Humanitarian relief, government, sufferer) in an emergency.



doi:10.6844/NCKU202002083

## 1.2 Research Objectives

The purpose of this research is to enhance the efficiency and response quickly on the route assignment to demand points that need relief and resources adopting the autonomous truck with drones in an emergency. Thus, scheduling, distribution and cooperating with drones should be completed within the least amount of time when planning distribution routes according to the practical demand for the resource at different locations. To find the optimal distribution route necessarily according to the needs of the demand points and delivery time, this research is desired to execute a model concerning a traveling salesman problem (TSP). The results are expected to provide practical and specific recommendations and comments for relevant authorities such as hospitals, government, and autonomous vehicle operators. The objectives are summarized as follows:

1. The problem of optimal delivery with the autonomous truck and two drones is introduced and formulated.
2. An efficient heuristic algorithm which is Tabu Search is proposed to solve the problem.
3. This research demonstrates the improvement of the delivery time within the UAVs by computational experiments.
4. This research indicates the proposed heuristic algorithm can obtain a better feasible solution than a commercial solver, GUROBI comparing solution time.

## 1.3 Research Flow Chart

Figure 1-1 is the research flow chart and the following briefly describe research tasks respectively.

1. Research Background and Motivation

Explain the important issue of the emergency such as an earthquake or explosion in



doi:10.6844/NCKU202002083

Taiwan. Moreover, define the purpose of the research and outline the research objectives.

2. Literature Review

   Review the vehicle routing problem (VRP), the features of autonomous vehicles and UAVs and the traveling salesman problem (TSP) related to UAVs.

3. Problem Statement

   Based on the background of this research, describe the issue in detail and define the problem in this research.

4. Model Formulation and Solution Algorithms

   This research proposes a model for emergency relief distribution adopting the autonomous vehicle cooperating with two UAVs. Present the algorithm for route optimization with the objective of the minimum travel times. Further, present the detailed definition, formulation, and solution algorithms.

5. Numerical Experiments and Analysis

   The performance between the proposed heuristics algorithm and the commercial solver, GUROBI are discussed by solution time.

6. Empirical Study

   This research executes the model of delivery problem adopting the autonomous truck with two drones in the empirical network which is Kaoshiung City giving various numbers of demand points

7. Results and Discussion

   This research presents the results of route optimization solution time via the proposed heuristics algorithm and the commercial solver.

8. Conclusion and Suggestion

   Due to the rareness of Taiwan research related to emergency transportation, especially adopting the autonomous vehicle as well as UAVs, this research is desired to contribute



doi:10.6844/NCKU202002083

to providing recommendations and reference for relevant authorities based on the results of numerical experiments.

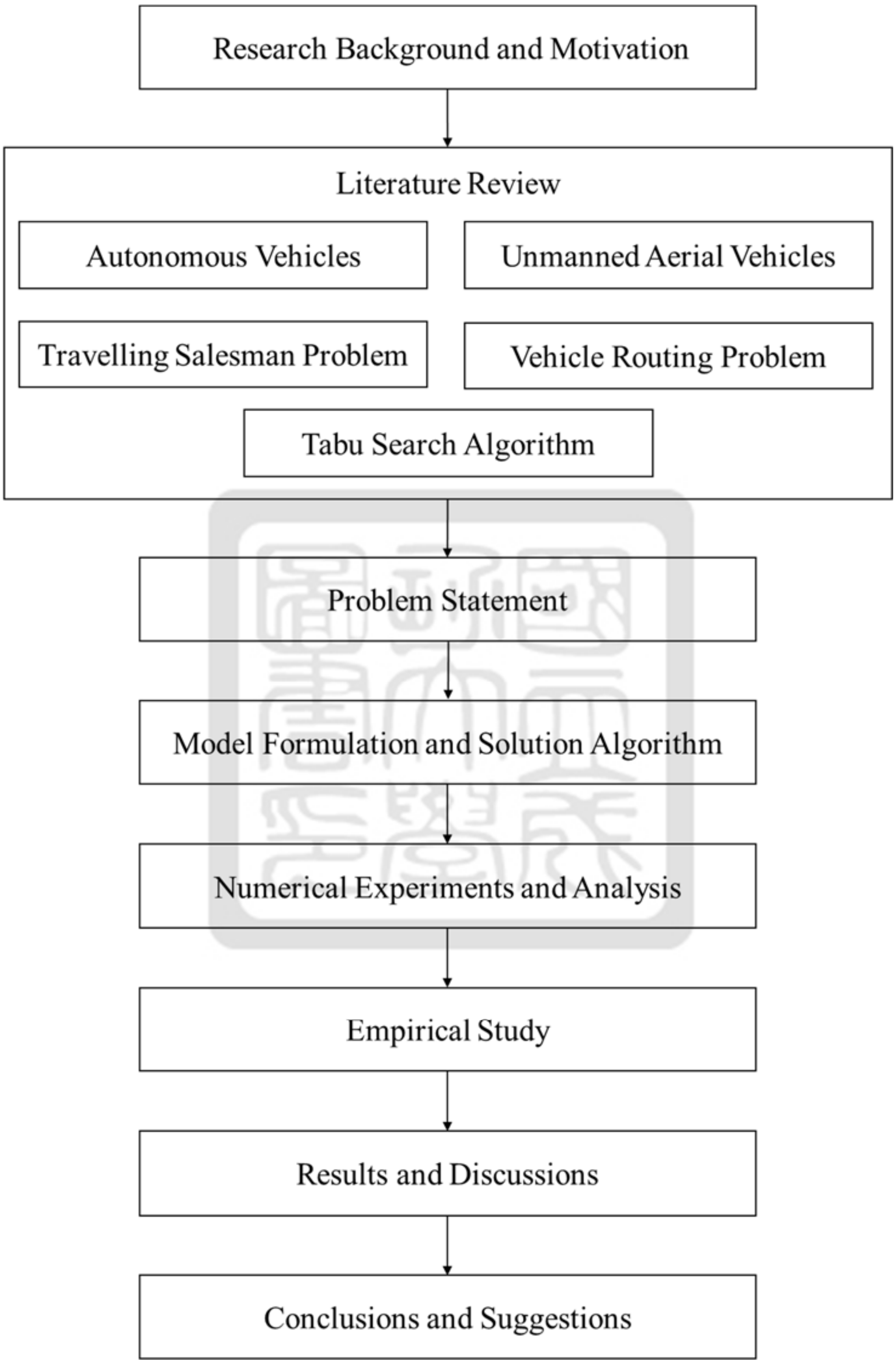



Figure 1-1 Research flow chart



doi:10.6844/NCKU202002083

# CHAPTER 2 LITERATURE REVIEW

In this research, the purpose is to solve the problem concerning emergency transportation by adopting autonomous vehicles cooperating with unmanned aerial vehicles. Therefore, this research focuses on describing the problem as a traveling salesman problem (TSP). Each of the sections is detailed summarizing as followed: Section 2.1 reviews the features with autonomous vehicles. Section 2.2 reviews the features and developments of the unmanned aerial vehicles (UAV). Section 2.3 reviews the traveling salesman problem (TSP) and the extended problem related to UAVs. Section 2.4 further reviews the basic introduction and the extended problem of vehicle routing problem (VRP). Section 2.5 reviews the tabu search Optimization approach. Section 2.6 states a summary in Chapter 2 by providing the key points in each of the sections.

## 2.1 Autonomous Vehicles

In recent years, autonomous vehicles (AVs) are a recent phenomenon that a range of studies focuses on. Most researchers are focusing on examining the technical aspects, feasibility, and the impacts on safety and congestion of AVs. As an emergency technology in Intelligent Transportation System (ITS), AVs can be applied in logistics or as a hub for UAVs. In the following context, a brief introduction of AVs is shown.

Autonomous vehicles are also called automated vehicles, self-driving vehicles, and driverless vehicles. The driving automation levels of AVs can be divided into six degrees from full manual to full automation. The Society of Automotive Engineers International (SAE International, 2014) defines six different levels are shown in Table 2-1.



doi:10.6844/NCKU202002083

Table 2-1 SAE International's levels of driving automation for on-load vehicles

| SAE level | Statement | Brief description |
|---|---|---|
| Human driver monitors the driving environment | | |
| 0 | No Automation | Zero autonomy; the driver performs all driving tasks. |
| 1 | Driver Assistance | Vehicle is controlled by the driver, but some driving assist features may be included in the vehicle design |
| 2 | Partial Automation | Vehicle has combined automated functions, like acceleration and steering, but the driver must always remain engaged with the driving task and monitor the environment. |
| Automated driving system monitors the driving environment | | |
| 3 | Conditional Automation | Driver is a necessity but is not required to monitor the environment. The driver must always be ready to take control of the vehicle with notice. |
| 4 | High Automation | The vehicle can perform all driving functions under certain conditions. The driver may have the option to control the vehicle. |
| 5 | Full Automation | The vehicle can perform all driving functions under all conditions. The driver may have the option to control the vehicle. |

(Reference: SAE International, 2014)



doi:10.6844/NCKU202002083

In recent years, autonomous vehicles have been a prominent role across the Information and Communication Technology (ICT) industry and the automotive industry. With the increasing maturity and breakthrough of self-driving technologies, many corporations in different fields have invested in developing AVs and implemented lots of AVs tests. Such as the United Kingdom, the United States, Japan, and Singapore, they are all developing the AVs and starting the project to test the AVs.

## 2.2 Unmanned Aerial Vehicle (UAV)

The researches related to UAV today involving lots of papers on different topics such as battery endurance improvement, GPS enhancements, navigation, and obstacle avoidance. Most researchers are focusing on examining the technical aspects, feasibility, and the safety of UAVs. As an emergency technology in Intelligent Transportation System (ITS), UAVs can be applied in either last-mile delivery with fast and flexible or deliver lightweight reliefs such as food, water, and medicine after a disaster. Thus, this section states a brief introduction and the development of UAVs by focusing on resource distribution in an emergency.

### 2.2.1 Current States of Unmanned Aerial vehicles

Unmanned aerial vehicle is also called drone, unmanned aircraft system (UAS) or uncrewed aerial vehicle (UAV). Due to the characteristics that drones can be easily operated, controlled without a human pilot, and the cost is relatively lower compared with human labor, they must be implemented as an alternative delivery way in the future. The topics in different countries for drones involve legal issues, environment, political issues, and economics are various. However, the most concern and the challenge is whether the broader society would accept it or not. In the previous literature, privacy seems to be the most trouble concern for the public. Also, safety concerns closely follow privacy. Unsurprised, the phenomenon also



doi:10.6844/NCKU202002083

happens on another emerging technology, autonomous vehicles (Rosenfeld, 2019).

Despite the privacy and safety bother the public, it is estimated that drones would be widely used in each territory such as logistics, agriculture, observation of infrastructure, film or cinema used and emergency supplies (Watkins et al., 2019). In this research, the goal is to implement the characteristics of drones that they can fly over rough or difficult terrain in which the road access is limited to discuss with the use of emergency supplies transportation.

### 2.2.2 Developments of Unmanned Aerial vehicles

In recent years, many companies have been tested the UAVs for various use and been used for the rapid delivery of lightweight freight such as goods that need to be transported for a limited distance. Therefore, this research reviewed the developments of drones by different two companies and are described as followed:

(1) Amazon

In 2013, Amazon CEO Jeff Bezos announced that Amazon would develop a fleet of UAVs for small parcel delivery within 30 minutes for its customers. The plan by Bezos was called Amazon Prime Air. In 2017, Amazon completed its first public demonstration of a Prime Air drone delivery in the U.S. It is worthy to mention that the flight was completed fully autonomously with Amazon's software without human intervention or guidance.

(2) UPS

In 2017, UPS tested the use of drones for residential delivery on a blueberry. The test was set to launch a multi-rotor drone from the top of a delivery truck. The drone delivered a package directly to a home, then returned to the van which had moved down the road to a new location. While the drone dock on the top of the delivery truck, it can recharge through a physical connection between its arms and the truck's electric battery.



doi:10.6844/NCKU202002083

And the UAV is capable of a 30 minutes flight time at a top speed of 45 miles. However, the UPS has investigated that the drones will only fly for about 22 minutes to deliver goods to customers.

According to UPS Vice President of Engineering, John Dodero, the company's goal is to have drones work off any type of vehicle, whether gas-powered or electric, to make last-mile deliveries.

## 2.3 Traveling Salesman Problem

As was mentioned at the beginning of this chapter, this research focusses on emergency transportation adopting the autonomous truck cooperating with UAVs. Due to the speediness of UAVs, once the UAVs delivers more, the demand points will be satisfied more quickly. In other words, in such a limited time, the goal of this research is to achieve high efficiency.

In this chapter, the traveling salesman problem related to the UAVs would be discussed to help construct the problem. Chapter 2.3.1 briefly defines and introduces the traveling salesman problem. Chapter 2.3.2 discusses the extended problem of traveling salesman problem related to UAVs.

### 2.3.1 Traveling Salesman Problem (TSP)

In recent years, there is a vast number of works of literature on the traveling salesman problem TSP and VRP. TSP is a fundamental, special case on VRP. The first to propose the TSP was Dantzig and Ramser (1959).

The basic assumptions in TSP are as followed:

1. The salesman departs the depot and finally backs to the depot,
2. At the journey, the salesman must visit all the customers; and
3. The customers must be visited at most once.



doi:10.6844/NCKU202002083

As in Figure 2-1, a simple illustration shows the difference between the VRP and TSP. The difference between the TSP and VRP is that the capacity of the vehicle (salesman) can not be constrained in TSP. Furthermore, the criteria of VRP is under the capacity constraints of the vehicles and seek to satisfy all the customers on different paths. Lastly, the objective of TSP is to optimize the travel cost or minimize path length.

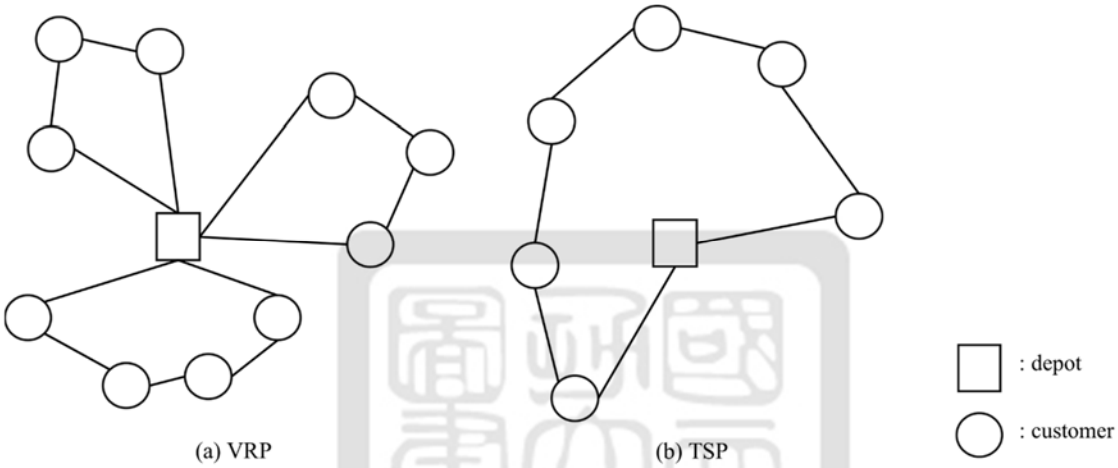



Figure 2-1 Illustration of the VRP and TSP

In Section 2.3.2, this research would discuss with the variant of TSP, which is FSTSP. The idea of FSTSP would be implemented to help construct our problem.

### 2.3.2 The Flying Sidekick Traveling Salesman Problem (FSTSP)

There are numerous literatures on the traveling salesman problem (TSP) and vehicle routing problem (VRP). Meanwhile, an increasing number of studies investigate the efficiency of delivery systems that deploy UAVs.

Murray and Chu (2015) were the first to propose a variant of the traditional TSP, the “Flying Sidekick Traveling Salesman Problem” (FSTSP). In their paper, they constructed the problem in mixed-integer linear programming. In FSTSP that they proposed, each customer must be served exactly once by a delivery truck or by a UAV which operates in



doi:10.6844/NCKU202002083

coordination with the truck. Once launched, the UAV must visit a customer and return, within its flight endurance limit, to the truck or the depot. The objective is to minimize the total service time while all customers are visited, and both the truck and the UAV return to the depot. The ideological framework in FSTSP is that a drone should cooperate with a truck to visit the customer. The truck and the drone depart from a single depot together or independently, fulfill the customers' demand and return to the same depot. However, some customers are visited by the drone, others are visited by the truck, but when traveling in tandem, the drone is transported by the truck.

Take an insight into FSTSP, the general notation is as followed:

Let $C = \{1,2,\cdots,c\}$ be the set of all customers and $C' \epsilon\, C$ denotes the subset of customers that may be serviced by the UAV. The depot is set as node $0$ at the departure of the truck and UAV and is set as node c + 1 at their return. Therefore, the sets to operate with are $N = \{0,2,\cdots,c+1\}$ donate the set of all nodes. To further facilitate the network structure of the problem, let $N_0 = \{0,1,\cdots,c\}$ be the set of all nodes the two vehicles may depart from, and let $N_+ = \{1,2,\cdots,c+1\}$ be the set of all nodes visited by a vehicle along a tour.

Let parameter $\tau_{ij}$ be the time required for the truck to travel from node $i$ to node $j$, parameter $\tau'_{ij}$ be the analogous travel times for the UAV. Given the logical restrictions that $\tau_{0,C+1} \equiv 0$.

The following parameters, measured in units of time, are considered:

$s_L$ - the time required to prepare the UAV for launch;

$s_R$ - the time required for the UAV recovery, after the truck and UAV reaches rendezvous.

The traveling speeds are constant for both trucks and drones.



doi:10.6844/NCKU202002083

In the algorithm in FSTSP that Murray and Chu (2015) proposed, they computed the saving of serving the node $j$ by the drone for each $j \in C'$, The method computes the greatest saving by testing all the possible sorties of the current truck subroute, and also by testing all possible insertions of other truck nodes in other positions in the current truck subroute. Starting from the depot, the drone is set to fly to $j$ if the greatest saving is positive, and the method is iterated for the remaining truck route.

Meanwhile, other researches continuously propose either the various algorithms or the different criteria to build an environment that is matching the real-life aspects according to the FSTSP.

Agatz et al. (2018) generate combinations of truck and drone routes between each possible launch and pickup nodes. They refer to each combination as an operation and propose an operation-based formulation. Two heuristics based on local search and dynamic programming were proposed by Agatz et al. (2018). Different from the assumptions made by Murray and Chu (2015), the truck can meet with the drone at the starting node of the flight.

Ha et al. (2018) were the first to define the delivery cost of the TSP-D. They provide two different heuristics that are inspired by the route first-cluster second heuristic, which is based on local search and GRASP. The results in their research were probably obtained for large instances with 50 and 100 customer nodes.

Wang et al. (2017) is the first research to consider a more general case with multi-trucks and multi-UAVs. They investigate this version of the problem in which one or more UAVs can travel with every truck from a theoretical aspect that provides worst-case analysis and bounds for several considerations. In their research, the objective function is to minimize the delivery completion time, that is, the time when the last truck or UAV returns to the depot.

Yurek and Ozmutlu (2018) presented an iterative algorithm based on a decomposition



doi:10.6844/NCKU202002083

approach to minimize the delivery completion time of Traveling Salesman Problem with Drone (TSP-D).

de Freitas and Penna (2018) provided a randomized variable neighborhood descent heuristic to solve FSTSP, in which the initial solution is created from the optimal TSP solution obtained by the Concorde solver. In the second phase, an implementation of the Randomized Variable Neighborhood Descent (RVND) heuristic is used as a local search to obtain the problem solution.

## 2.4 Vehicle Routing Problem

In this research, as a result of the focus is to develop a TSP model that adopting AVs and UAVs, the VRP related to vehicles should be noticed and identified. By reviewing the VRP researches in recent literature, this research can confirm the problem more clearly.

### 2.4.1 The Introduction of Vehicle Routing Problem

The vehicle routing problem (VRP) is the most well-studied optimization problem in operations research. This problem was first proposed by Dantzig and Ramser (1959). They defined the truck dispatching problem as a linear programming formulation. In their paper, they define VRP by given a network $G = (V, E)$, with a node set V consisting the depot and the customer node. Under the limited capacity of the truck, the goal is to satisfy all the demand stations with minimum possible covered mileage. Since then, such variants have been considered, incorporating capacities, service time windows, maximum route lengths, distinguishing pickups and deliveries, fleet inhomogeneities, and so forth. However, in the consideration of real-life aspects associated with largescale problems, the VRP has extended to different kinds of problems concerning different settings.



doi:10.6844/NCKU202002083

### 2.4.2 The extended problem of VRP

As discussed above, the vehicle routing problem is extended into different types considering different constraints. As Table 2-2, different factors lead to related variants in terms of VRP.

Table 2-2 The factor of the Vehicle Routing and Scheduling Problem

| Factor | Classification |
|---|---|
| Time windows | Yes; No |
| Number of depots | Single; Multiple |
| The size of vehicle fleet | One; Many |
| The categories of vehicle fleet | Single; Multiple |
| Type of demand points | Deterministic; Stochastic |
| Position of the demand points | On node; On arc; Both on node and arc |
| Type of network | Undirect; Direct |
| Capacity of vehicles | Same; Different |
| The range of routing distance | Same constraints; Different constraints |
| Cost | Variable; Fixed |
| Operation type | Pick-up; Delivery; Pick-up and Delivery; Backhauls; Dial-a-ride |
| Objective | Minimize the distance; Minimize the cost; Minimize the number of vehicles |

To understand the variants of VRP, some papers in the literature were reviewed concerning each variant and the contributions were compared analytically. For instance, the literatures were widely studied such as VRP with Pick-up and Delivery (VRPPD),



doi:10.6844/NCKU202002083

Capacitated VRP (CVRP), Multi Depot VRP (MDVRP), Periodic VRP (PVRP), Flexible VRP (FVRP), VRP with Backhauls (VRPB), Rich VRP (RVRP), Green VRP (VRP) and so forth.

Gribkovskaia et al. (2008) proposed a mixed-integer linear programming (MILP) formulation to minimize the total cost associated with the covered routes with totally delivered orders, and partially satisfied pickups. They defined the problem as a VRPPD and consider whether it is more beneficial to satisfy the identical customer twice rather than creating a full route circle.

Recently, Belgin et al. (2018) published research related to VRPPD with two-echelon (2E-VRPPD). They were desired to make pickup and delivery operations accomplish simultaneously, with the same vehicle delivering all the orders from the depot to the destinations, and from destinations back to the depot. Moreover, a Node-based mathematical model and a hybrid heuristic algorithm were used to solve the 2E-VRPPD.

To solve the Capacitated Vehicle Routing Problem (CVRP), Lahyani et al. (2015) noticed that the capacity of the vehicle is one of the important decisions that impact the optimal VRP network choices. The objective is to provide a solution with minimum costs with a closed route circle, one-time customer service by one vehicle and the route total demand must not exceed the assigned vehicle capacity.

Li et al. (2016) focus on combination-vehicle attributes as a Combination Truck Routing problem (CTRP). Types of vehicle and travel distance were considered, and a heuristic algorithm was applied to solve a real logistical case.

However, Montoya-Torres et al. (2015) published a literature review about the MDVRP considering different VRP variants. In their paper, different approaches were proposed to solve the problem with the final clients, who are not clustered around every single depot. Consequently, research was extended to the MDVRP and deemed to be realistic and served



doi:10.6844/NCKU202002083

real applications as effectively as possible.

Lahyani et al. (2018) introduced a combination of Multi-Depot Fleet Size and Mix VRP (MDFSMVRP). They compared different formulations related to Branch-and-Cut and Branch-and-Bound algorithms to solve the suggested formulations with different indexes. An improvement in the lower and upper bounds on the tested instances has been considerably achieved. This problem extends the multi depot vehicle routing problem and the fleet size and mix vehicle routing problem and combines complex assignment and routing decisions under the objective of minimizing fixed vehicle costs and variable routing costs.

Refer to the Periodic Vehicle Routing Problem (PVRP), Campbell and Wilson (2014) proposed a VRP with multiple service periods. The objective in their paper is to satisfy the orders from customers during multiple periods with the same fixed quantity.

Archetti et al. (2017) present the PVRP with a flexible characteristic, Flexible PVRP (FPVRP). In their paper, the objective function is to minimize the total routing costs, while allowing some flexibility to customer satisfaction frequencies and quantity during the planning horizon, rather than fixed frequencies and quantity. On the other hand, the FPVRP considers the inventory costs accompanied by the objective function, which is modeled in the Inventory Routing Problem (IRP). The results reveal that the costs were minimized better than when using PVRP or IRP.

Another variant, VRP with Backhauls (VRPB) emerged depends on the route types planned to be covered by the available fleet of trucks where both delivery and pickup are available on the same routes.

Koç and Laporte (2018) analyzed different VRPB literature and compared the exact and heuristic algorithms. They made a classification for VRPB in different variants tabulating in their research with the defined mathematical model and solution.



doi:10.6844/NCKU202002083

On the other hand, Bortfeldt et al. (2015) had extended VRPB into clusters with a three-dimensional loading problem (3L-VRPCB). In their paper, the line-haul customers should be served before the backhaul ones. They also proposed two hybrid algorithms to deal with the packing and routing procedures.

García-Nájera et al. (2015) proposed a multi-objective model that minimizes the number of vehicles, traveling costs, and the un-serviced backhauls. In their paper, a similarity-based selection evolutionary algorithm approach is proposed for finding improved multi-objective solutions for VRPB.

In recent years, to be a Rich VRP (RVRP), three VRP variants such as Open VRP (OVRP), the Dynamic VRP (DVRP), and the Time-Dependent VRP (TDVRP) are more important to be noticed and considered in a combined VRP model (Braekers et al., 2016).

Marinakis and Marinaki (2014) suggest a newly developed Bumble Bees Mating Optimization (BBMO) algorithm to solve the OVRP. In their paper, the algorithm was compared with several metaheuristics, evolutionary and nature-inspired algorithms. They believed that the results were satisfactory and better solutions were revealed.

Another important variant, the DVRP, presents that the real-life aspects are mostly dynamic in nature and requirements. Wide researches were conducted and accompanied by a different mix of other variants.

Pillac et al. (2013) published a review paper that comprehensively studied various DVRP works from different perspectives. It is specifically that the evolution and quality of the information being transferred across the planning horizon are two dimensions importantly to understand when studying the DVRP. Regarding the evolution, the information can be changed after the planners defined a routing plan, while the quality of the information emerges from the uncertain demand of available data. By the improvement of recent technology, it provides an easier follow-up system for the routing planning process,



doi:10.6844/NCKU202002083

as the complexity of the DVRP increases and the need for richer VRP models emerges.

Furthermore, another important variant of VRP, Time-dependent VRP (TDVRP) is also vital. It is worth mentioning that the routing plan of the previous VRP variants was static with vehicle speed and journey time. On the opposite, the optimal solution of planned routes from cost and distance overviews should be aggressively impacted by traffic congestion. Thus, the research of VRP must be more realistic while considering the current traffic conditions. In recent years, real-time information in traffic conditions on a certain route may help to identify the expected time to cross a certain route. Therefore, Time-Dependent VRP would greatly improve the optimal solution of the routing plan with minimum cost and time. Furthermore, the optimal solution is expected to be enhanced not only in minimizing time durations for planned routes but also in $CO_2$ emissions of the traveled routes (Maden et al., 2010).

Maden et al. (2010) proposed a heuristic algorithm that minimizes the total travel time of TDVRP. They considered the problem with the expected traffic congestion, which is usually higher during rush hours. A sample in the United Kingdom was conducted and the results show 7% of $CO_2$ emissions were reduced compared to the traditional VRP model with an emission saving objective.

Huang et al. (2017) considered the path selection decision with a TDVRP problem. In their paper, the conventional assumption of the given customer nodes and arcs were improved by providing a path selection choice in the road network. They proposed a model that provided a solution with an optimal route and path selection decision depending on both departure times and congestion levels related to the suggested network. The contribution of their paper is to solve Time-Dependent VRP with Path Selection (TDVRP-PS) using The Route-Path Approximation (RPA) method, which provides a near-optimal solution, taking into consideration stochastic traffic conditions.



doi:10.6844/NCKU202002083

In the summary of classical VRP, it is vital to continuously develop effective VRP models. The variants VRP model can be applied in many different territories such as logistics and transportation. Later in below, the Rich VRP (RVRP) and Green VRP (G-VRP) are more discussed below.

As the technology grew up and the damage that people did to the earth, different researches are now focusing on green policy applications and seeking sustainable VRP models to deal with the trend worldwide.

Erdoğan and Miller-Hooks (2012) added a battery capacity constraint along with the option of recharging at a station with constant time. They assumed a full-charge policy and proposed two heuristics to solve the problem by minimizing the total travel distance. In the settings of their paper, the charging stations are scarce in the network and the vehicle can visit the same station multiple times. Numerical experiments showed that these techniques perform well compared to exact solution methods and that they can be used to solve large problem instances.

Lin et al. (2014) comprehensively review the literature on GVRP. The proposed models and categorized into GVRP and Pollution Routing Problems (PRPs). The idea of their work considered how traditional VRP can interact with the GVRP in the coming inspired research topics. The contributions of the paper are they created a starting point for researchers and logistics practitioners to construct sustainable VRP work that considers the important variants, combining the most important real-life aspects with continual green needs.

Burer and Letchford (2012) proposed a three-objective mathematical model to solve the problem: first is to minimize the traveling costs and consumed energy; the second is to minimize the fuel consumption rate by minimizing the incurred environmental penalty and the last is to maximize customer satisfaction levels in terms of maximum possible average velocity. The results revealed that by considering the relationship between route type and



doi:10.6844/NCKU202002083

certain fuel consumption rates associated with $CO_2$ emissions, an improvement exists for reducing environmental pollution and planning eco-friendly routes. They also suggested that the model is NP-Hard programmed and will be time-consuming for solving larger instances. Thus, using heuristics, meta-heuristics, or an exact method, such as spatial branch-and-bound and branch-and-reduce would be more realistic to solve the model.

After reviewing the previous Green-VRP, the Rich VRP would be reviewed as followed. Lahyani et al. (2015) present a taxonomy of PVRP as Table 2-3. The most important that they mentioned was the gap between the suggested RVRP models in the literature and the complexity of the real-life aspects. They questioned that most researches focus on providing a mathematical model with solutions rather than adjusting the real-life characteristics. In their paper, they provided the requirements as optimization criteria, constraints, and preferences that should be available to produce an RVRP model.

Table 2-3 A taxonomy of PVRP

| Scenario characteristics | |
|---|---|
| 1. Input data | Static |
| | Dynamic |
| | Deterministic |
| | Stochastic |
| 2. Decision management component | Routing |
| | Inventory and routing |
| | Location and routing |
| | Routing and driver scheduling |
| | Production and distribution planning |



doi:10.6844/NCKU202002083

| | | |
|---|---|---|
| 3. Number of depots | | Single |
| | | Multiple |
| 4. Operation type | | Pickup or delivery |
| | | Pickup and delivery |
| | | Backhauls |
| | | Dial-a-ride |
| 5. Load splitting constraints | | Splitting allowed |
| | | Splitting not allowed |
| 6. Planning period | | Single period |
| | | Multiple periods |
| 7. Multiple uses of vehicles | | Single-trip |
| | | Multiple-trip |
| Problem physical characteristics | | |
| 1. Vehicles | (1) Type | Homogeneous |
| | | Heterogeneous |
| | (2) Number | Fixed |
| | | Unlimited |
| | (3) Structure | Compartmentalized |
| | | Not compartmentalized |
| | (4) Loading policy | Chronological order |
| | | No policy |
| | (5) Capacity constraints | |
| | (6) Driver regulations | |
| 2. Time constraints | | Restriction on customer |



doi:10.6844/NCKU202002083

| | |
|---|---|
| | Restriction on road access |
| | Restriction on depot |
| | Service time |
| | Waiting time |
| 3. Time window structure | Single time windows |
| | Multiple time windows |
| 4. Incompatibility constraints | |
| 5. Specific constraints | |
| 6. Objective function | Single objective |
| | Multiple objectives |

(Reference: (Lahyani et al., 2015))

One more work on the RVRP was presented by Goel and Gruhn (2008). The variants that were studied as combined are time windows restrictions, a heterogamous fleet of trucks with variable travel times, travel costs and capacity, multi-dimensional capacity constraints, multiple pickups and delivery location service, different starting and ending points, and route restrictions. Despite the literature related to RVRP are taking consideration of the various characteristics to deal with real-life conditions, each of the researches is focusing on the problem that they faced.

Considering the variants of different characteristics of previous literature, this research categorized VRP into seven types of classical VRP and described the objectives in detail. It is shown as followed:

1. Capacitated Vehicle Routing Problem, CVRP

   The objective of CVRP is to minimize total distribution cost and there is one single depot that the vehicle starting to serve each customer. Each customer can only be serviced once. Besides, the vehicles must return to the depot under the capacity or travel



doi:10.6844/NCKU202002083

distance.

2. Period Vehicle Routing Problem, PVRP

The objective of PVRP is to minimize the cost and meet customers' needs simultaneously in each period. Each customer can only be serviced once and the constrains of vehicles are the same.

3. Stochastic Vehicle Routing Problem, SVRP

The demand for customer points is a random variable of probability. The route of vehicles must be given. The objective of the SVRP is to minimize the cost.

4. Multi-Depot Vehicle Routing Problem, MDVRP

The objective of MDVRP is to minimize the cost. The vehicle starts from the depot and returns to the same depot after serving each customer. In the network of MDVRP, multiple depots are depending on the setting of the research. Besides, each customer can only be serviced once.

5. Vehicle Routing Problem with Backhauls, VRPB

The vehicles from the depot start to deliver for customers, and on the route of backing to the depot, the vehicles receive the goods from the customer under the constraints of capacity and routing distance. The objective of VRPB is to minimize the cost considering the least of trips

6. Pick-up and Delivery Vehicle Routing Problem, PDVRP

The difference between VRPB and PDVRP is that pickup and delivery are synchronized. Therefore, it is necessary to consider the capacity of the vehicles. The objective of PDVRP is to minimize the cost considering the least of trips

7. Vehicle Routing Problem with Time Window, VRPTW

The vehicles must satisfy the customers at a certain time. In the setting of a hard time window, the vehicles do not exceed the customer's demand time. In the setting of a soft



doi:10.6844/NCKU202002083

time window, if the vehicle arrives early, it will wait for the customer. On the contrary, if it arrives late, it needs to be punished. The objective of VRPTW is to minimize the cost under the harsh conditions in the time request of the customer.

## 2.5 Tabu Search Method

In 1986, Glover (1986) first proposed tabu search (TS) which is employing local search methods used for mathematical optimization. The word "tabu" in English socially equals to "forbidden to be used, mentioned, or approached". As a meta-heuristic, TS is inspired by the principles of artificial intelligence (AI) and has been applied intensively for various types of optimization problems with good results. The basic idea of the TS is to identify specific moves as forbidden to prevent cycling. In a general form, the composition of TS contains five components. They are neighborhood solution, move, tabu list, aspiration criterion, and stopping criterion. Moreover, tabu search is based on introducing flexible memory structures in conjunction with strategic restrictions and aspiration levels as a means for exploiting search spaces. Also, it can find reasonable and optimal solutions within a quick time. In Figure 2-2, an optimization framework in the tabu search algorithm is illustrated as followed.



doi:10.6844/NCKU202002083

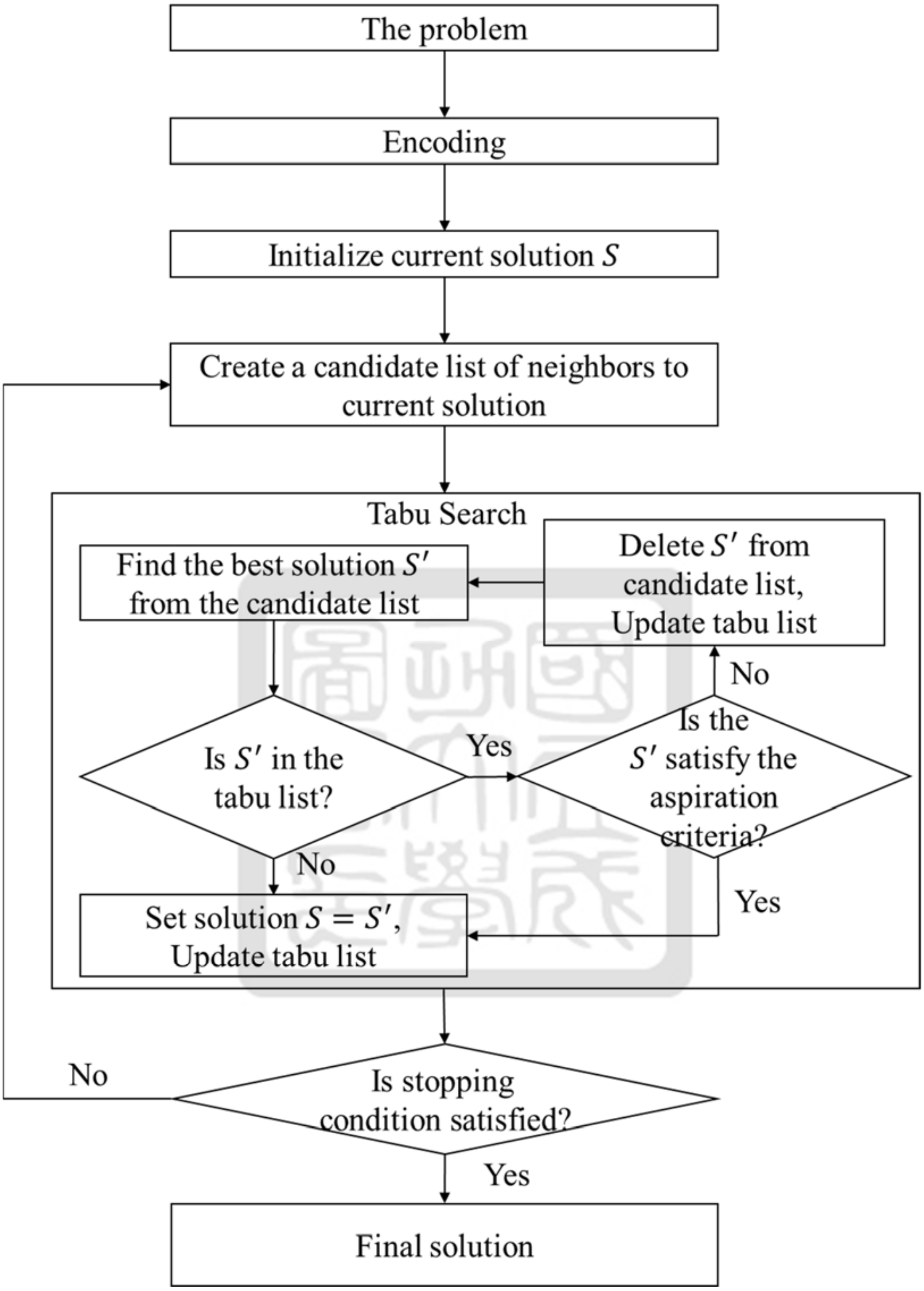



Figure 2-2 Tabu search framework



doi:10.6844/NCKU202002083

Encoding:

Encoding represents that the problem is transferred to program language such as binary digit $\{0,1\}$. Then various presenting method has been raised to evaluate the problem. Thus, the encoding code corresponds to moves, and the moves are also the unit of the candidate list. Lastly, the final solution is selected by TS.

1. Initialize current solution $S$

   Each move is a path from the node to node. The initial solution must set up by the moves. First, a solution must be captured which is not optimal. Then optimal the solution by TS and make the solution better and better.

2. Create a candidate list

   After obtaining the current solution, create a candidate list for the current solution. The constructive methods that seeking possible solutions are different such as random search and neighborhood search. Once the adjacent solutions have been obtained, the moves may be swapped.

3. Tabu search

   After swapping the moves, find the solution $S'$ from the candidate list. Then select a move and judge whether the move is tabu or not. If it is tabu, the move would be further determined if it is satisfied aspiration criteria. The aspiration criteria means once the move results in a solution much better than any visited before, tabu restriction may be violated. In this condition, the aspiration can be happened such as better than the currently known best solution and significant improvement. At the same time, the move enters aspiration criteria then becomes an admissible solution. Once the move is tabu and not satisfied the aspiration criteria. The move should be deleted from the candidate list then update the tabu list and finally back to the previous step that restarts to find the other best solution $S'$ from the candidate list. On the opposite, once the move is not



doi:10.6844/NCKU202002083

tabu, the move is the admissible solution.

4. Stopping condition

   General stopping condition contains several situations and means that reach the optimal solution.

   (1) The maximum number of solutions to be explored is fixed.

   (2) The number of iterations since the last improvement is larger than a specified number.

   (3) The total number of iterations of the TS algorithm is fixed.

## 2.6 Summary

As this research mentioned in the previous sections, the flying sidekick traveling salesman problem was first proposed in 2015 (Murray and Chu, 2015). After that, the problem related to drones is increasing more and more. The variants of TSP and VRP with UAVs mostly discuss how to construct the problems and approaches well. All evaluated manner mainly considered the most important objective which is travel times. Thus, according to the model that Murray and Chu (2015) proposed and constructed. Many pieces of research focus on the real aspects to match their problem and many variants of VRP related to UAVs such as VRP-D and TSPD.

Since the TSP is an NP-hard problem in combinatorial optimization which means the computing time is too long to generate effective solutions. This research constructs a heuristics algorithm based on tabu search. With the ability of tabu search, this research is desired to solve the problem concerning the UAVs working with the truck in tandem.

In the next chapter, this research describes our problem as a problem statement and research assumptions. Then transform it to the model formulation. Finally, the solution algorithm will be proposed in detail.



doi:10.6844/NCKU202002083

# CHAPTER 3 RESEARCH METHODOLOGY

As described in Chapter 1, the purpose of this research is to propose a model for the optimal delivery of relief transportation by adopting autonomous vehicles cooperating with drones. Chapter 3 is organized as follows. In Section 3.1, the conceptual framework is presented. In Section 3.2, the problem and the research assumptions of this research are described in detail. In Section 3.3, the research framework is presented. In Section 3.4, the model formulations of the problem are proposed, and Section 3.5 discusses the tabu search solution algorithm.

## 3.1 Conceptual Framework

In recent years, most of the researches consider adopting Intelligent Transportation System (ITS). However, as an innovative option for traditional vehicles, autonomous vehicles and drones should be discussed. In a real environment as an emergency occurs, applying autonomous vehicles to arrive on-site is urgent. However, while the road may have been destroyed, the UAVs should cooperate with autonomous vehicles to complete the mission. Additionally, while there is a disaster such as an earthquake or explosion, it is important to apply UAVs more because the delivery speed of UAVs is quicker than using only autonomous vehicles. Thus, the problem for the coordination of the autonomous truck and drones to achieve optimal routes in limited time is the most concern. As discussed above, this research considers one objective which is the time when both vehicles return to the depot after satisfying whole the demand points. As discussed above, this research extends the idea of applying Intelligent Transportation System in logistics to transportation in an emergency. Based on the tabu search algorithm, this research obtains the minimal time of delivery tasks on the network. The main conceptual framework is formulated in Figure 3-1.



doi:10.6844/NCKU202002083

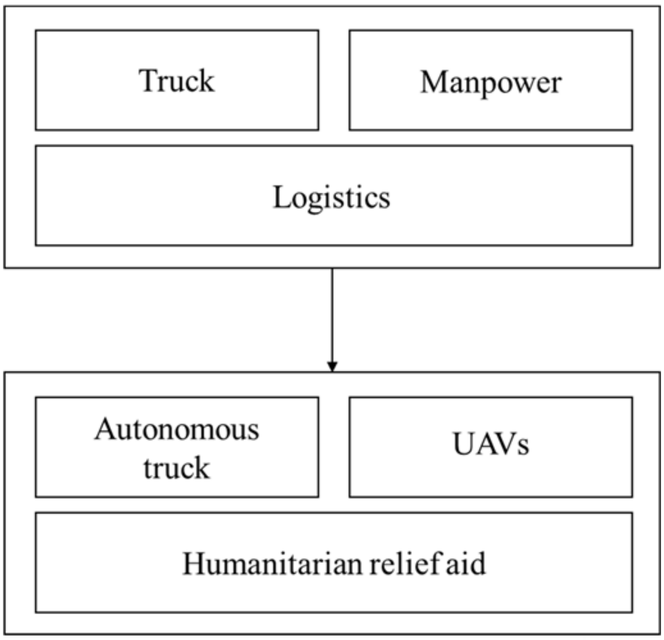


Figure 3-1 Conceptual framework

## 3.2 Problem Statement and Research Assumptions

In the problem of this research, the problem is defined on a directed network $G = (N, A)$, where $N$ is the set of nodes representing the depot and the demand points set and $A$ is the set of directed arcs. The speed of the autonomous truck and UAVs are different. Each link $(i, j)$ is associated with travel times of autonomous truck $\tau_{ij}$ and each link $(v, i, j, k)$ is associated with travel times of drones $\tau'_{vij}$. In this network, the depot serves as starting and ending nodes, are defined as node $0$ and node $(n + 1)$ respectably. Next, denote the set of demand points by $D = \{1,2,3, \cdots, n\}$ and also denote $D_0 = D \cup \{0\}$ as the set of demand points with the starting depot that vehicle may depart and $D_+ = D \cup \{(n + 1)\}$ as the set of demand points with the ending depot that the vehicle may visit.

Following the formulation proposed by Murray and Chu (2015), this research defines $F = \{(v, i, j, k)\}$ as three nodes in UAVs' travel arcs. Note that $F = \{(v, i, j, k)\}$, if node $i$ is not the ending depot ($i \epsilon D_0$), the delivery node $j$ must be in the demand points set that



doi:10.6844/NCKU202002083

can be served by UAVs and is not same as the launch node ($j \epsilon D$, $i \neq j$) and the rendezvous node $k$ can be either demand points or the ending depot and cannot equal to $i$ or $j$ ($k \epsilon D_+$, $k \neq i$, $k \neq j$).

This research defines the decision variables. Set $x_{ij}$ equals to 1 if an autonomous truck travels an arc $(i, j) \epsilon A$ from node $i$ to node $j$ and 0 otherwise, on this situation, the autonomous truck travels from node $i \epsilon D_0$ to node $j \epsilon D_+$ where $i \neq j$. Set $y_{vijk}$ equals to 1 if the drone travels an arc $(v, i, j, k) \epsilon F$ from node $i$ to node $j$ and merges at node $k$ and 0 otherwise, on this situation, the UAVs launch from node $i \epsilon D_0$ to node $j \epsilon D$ and merges with the autonomous truck or the ending depot at node $k \epsilon D_+$ where $(v, i, j, k) \epsilon F$.

At the particular demand point, the truck may launch, retrieve, and re-launched multiple UAVs, it is crucial to coordinate all the process to avoid air collisions. Thus, we denote $t_i$ as the autonomous truck arrival time at node $i \epsilon N$, $st_i$ as the service time at node $i \epsilon D_+$, $ct_i$ as the completion time at node $i \epsilon N$. Moreover, denote the $t'_{vi}$ as the UAV $v \in V$ arrival time at node $i \epsilon N$ and $ct'_{vi}$ as the UAV $v \in V$ completion time at node $i \epsilon N$. The decision variables $t_i$ and $t'_{vi}$ are representing the arrival times of the autonomous truck and UAVs at node i respectively. All the decision variables related to times are used to sequence the launch, retrieve, and truck service. Next, four binary decision variables are presented as $O^R_{v_1,v_2,k}$, $O^L_{v_1,v_2,k}$, $O'_{v_1,v_2,i}$, $O''_{v_1,v_2,i}$, these are established to coordinate the ordering and sequencing for the drones to launch and retrieve at each node. Set $O^R_{v_1,v_2,k}$ equals to 1 if one UAV $v_1 \in V$ and another one $v_2 \in V$ are both retrieved at node $k \in D_+$ and $v_1$ is retrieved before $v_2$. Conversely, set $O^L_{v_1,v_2,k}$ equals to 1 if one UAV $v_1 \in V$ and another one $v_2 \in V$ are both launched from node $i \in D_0$ and $v_1$ is launched before $v_2$. Besides, set $O'_{v_1,v_2,i}$ equals to 1 if one UAV $v_1 \in V$ launches from node $i \in D$ before another one $v_2 \in V$ retrieves at node $i \in D$ and conversely set $O''_{v_1,v_2,i}$ equals to 1 if one UAV $v_1 \in V$ retrieves at node $i \in D$ before another one $v_2 \in V$ launches from node $i \in$



doi:10.6844/NCKU202002083

$D$.

After denoting all the decision variables, this research set the auxiliary decision variable $u_i$ to be used in the TSP subtour elimination constrains (Desrochers and Laporte, 1991).

After describing the operations process, the research assumptions are listed as followed:

A. To reduce the complexity of the problem, this research assumes that the autonomous truck is capable to have enough capacity to load resources and UAVs through the entire delivery process. Due to one of the characteristics in autonomous vehicles is no front seat, the autonomous truck stores more resource. Thus, this assumption can ensure the autonomous truck operates from exceeding its capacity.

B. The model constructed by this research does not consider the build-up time for the UAV to load reliefs. Because this research doubted that build-up time can be so short to be negligible while comparing to the travel time of the autonomous truck and UAVs. On the other hand, the problem concerning the preparation time of the UAVs for launching and rendezvousing with the vehicle can be overcome. The actual operation case in February 2017 has shown that a drone above the UPS delivery trucks can deliver the package and return to the truck autonomously (Hughes, 2017). Also, this research assumes that the preparation time is too minimal to be measured.

C. This research considers the battery level of the UAVs and reflected it into the fixed time-based flight endurance. The flight endurance $e_{vijk}$ is addressed in Constraint (3-33) standing for the flight endurance. An Amazon's conference in Las Vegas in June 2019 has unveiled the latest drone design and Amazon's UAVs can fly up to 15 miles and deliver packages under five pounds to customers in less than 30 minutes (Wilke, 2019). However, the battery level is reflected in flight endurance and this assumption ensures all the UAVs can complete the tasks before running out of battery.

D. This research assumes UAVs to be homogeneous that can only carry relief for a demand



doi:10.6844/NCKU202002083

point once. In case the UAV finishes delivering to demand point, it must move to the next node which has not been visited immediately. UAVs must be launched from and rendezvous by the autonomous truck at particular demand points or depot. Further, once the UAVs are retrieved by the autonomous truck, the battery of UAVs is fully charged immediately until the next launched.

E. This assumption assumes that the UAVs can only launch and rendezvous at the node instead of an arc. In practice, to make UAVs fall-off on a moving truck is difficult. Due to the travel speed, the autonomous truck and the UAVs must coordinate and match. While a drone is going to merge with a moving truck, it requires to reduce its speed. On the opposite, the truck is asked to increase its speed, too. Such the situation violates the constant speed assumption of the UAVs and the autonomous truck. On the other hand, the trucks and drones must wait for each other whenever one arrives at the demand point nodes before the others. To prevent such a situation, this research assumes that UAVs can only rendezvous with the autonomous truck at a node instead of an arc.

F. In this research, all the demand points are served either by the autonomous truck or the UAVs at most once. The autonomous truck and UAVs can work independently while UAV is launched so that the route of the autonomous truck and UAVs are nonoverlapping. Besides, this research set number of two drones are within the autonomous truck to deliver the relief over the network.

G. This research sets the nodes that UAVs launch, travel, and rendezvous as three nodes $F = \{v, i, j, k\}$. The three nodes must be consistent within the ordering of the autonomous truck's traveling sequence.



doi:10.6844/NCKU202002083

## 3.3 Research Framework

The research framework of optimal delivery with the autonomous truck-drone is presented in Figure 3-2. The framework contains five main parts: objective setting, construct the model, verify the model, apply the model to a realistic network, and assess the effectiveness of the model. The details of each part are described as followed:

1. Objective setting: As previously reviewed in Section 2.3.2, much researches were desired to solve the problem and the objective is minimizing the travel times after serving all the customer nodes. Similarly, the objective of this research is to optimize the travel times in delivery using the autonomous truck and UAVs in an emergency.
2. Construct the model: In this research, the model is constructed by mathematical formulation. To match the real-life aspects, the battery consumption of the UAVs is considered and discuss how the drones cooperate with the autonomous truck.
3. Verify the model: After constructing the model, this research tests whether the model is reasonable with an exact solution by using the mathematical optimization solver, GUROBI to solve a small-scale network. Then this research verifies if the model appropriate to use. If no, restart the research flow of clarifying the problem and revising the model.
4. Apply the model to a realistic network: After verifying the model, this research proposed a tabu search algorithm to solve the problem in a realistic network. Section 2.5 shows the basic concept and flow chart of the tabu search.
5. Assess the effectiveness of the model: Finally, the solution from the proposed tabu search algorithm offered the effectiveness of the model. In this research, the effectiveness of the proposed heuristics will be compared with the commercial solver, GUROBI, by solving the problem in a large-scale network.



doi:10.6844/NCKU202002083

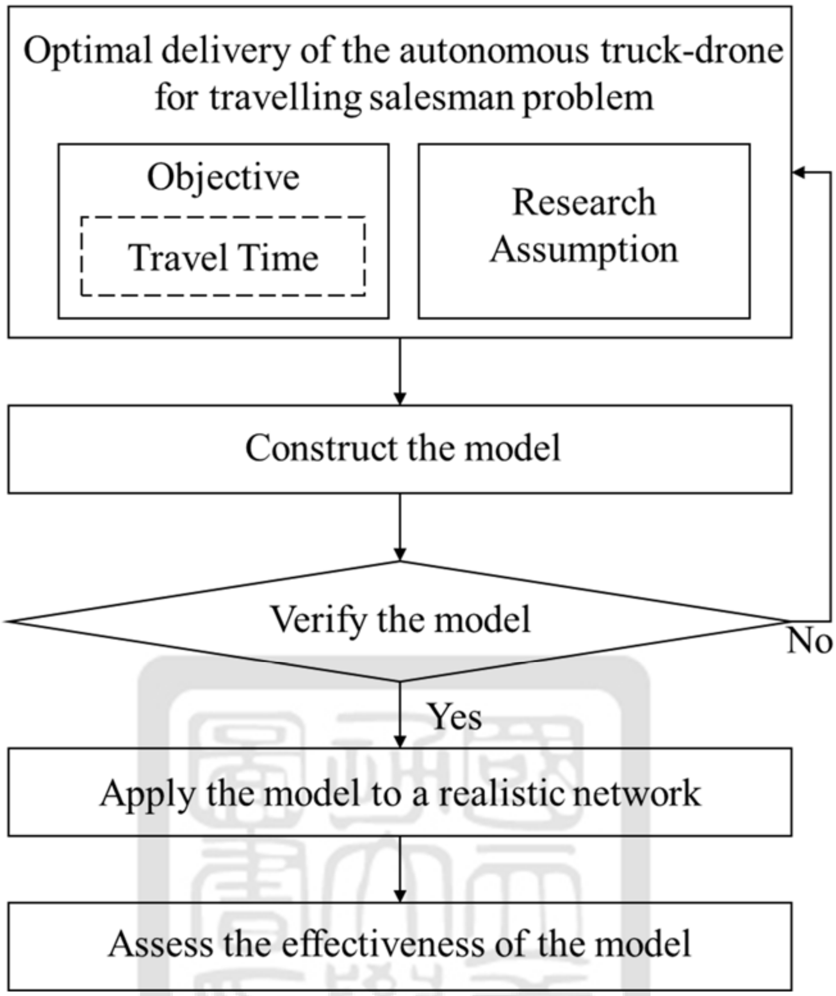



Figure 3-2 Research framework



doi:10.6844/NCKU202002083

## 3.4 Mathematical Formulation

As shown in Figure 3-3, a simple example illustrates the problem in this research. The tour of the autonomous truck and the UAVs are presented separately as the solid line and dotted line. This research assumes that the autonomous truck can carry two drones. The autonomous truck by carrying UAVs must start at the depot which is node $0$. The demand points $\{1,2,3,4,5,6,7,8,9\}$ are satisfied exactly once either by the autonomous truck or the UAVs. The route of the autonomous truck is $\{0 \rightarrow 1 \rightarrow 2 \rightarrow 4 \rightarrow 7 \rightarrow 9 \rightarrow 0\}$, while the routes of two UAVs are $\{(2,3,4), (4,5,9), (4,6,7), (7,8,9)\}$. After completing the tasks, the autonomous truck must return to the depot which is node $0$. Lastly, the objective is to minimize travel times after serving all demand points.

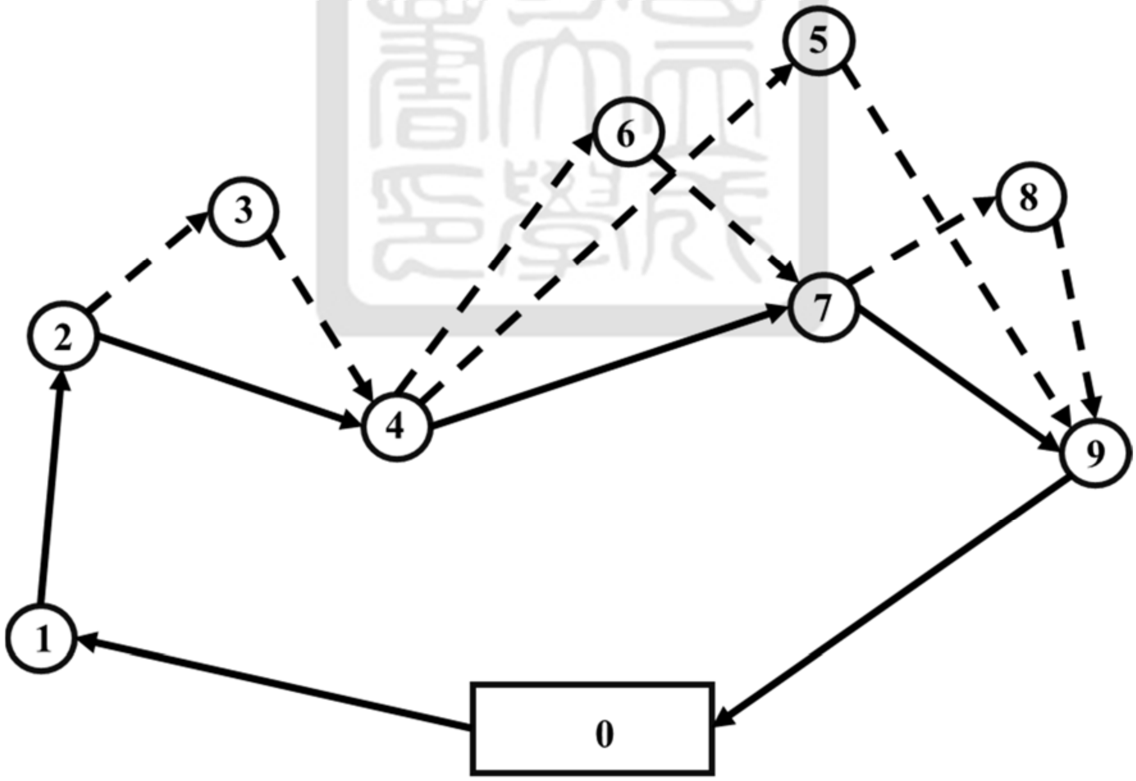



Figure 3-3 Illustration of the coordinated route with autonomous truck and UAVs



doi:10.6844/NCKU202002083

At a particular demand point, the autonomous truck can launch, retrieve, and even re-launch UAVs. Thus, it is critical to coordinate the sequencing of launching, retrieving for UAVs and the serving process of the autonomous truck. Besides, this research considers no driver within the autonomous truck. As long as there is no driver to engage in the launch or retrieve process of UAVs, all the process included the serving process of the truck and the launching and retrieving process of UAVs are being performed simultaneously. For example, at demand points node 7 in Figure 3-3, assume that one UAV $v_1 \in V$ and another one $v_2 \in V$ are both retrieved, and one UAV is re-launched later at node 7. The possible scenarios maybe $v_1$ retrieve before $v_2$ then $v_1$ is re-launched, or $v_1$ retrieve before $v_2$ then $v_2$ is re-launched, or $v_1$ retrieve after $v_2$ then $v_1$ is re-launched, or $v_1$ retrieve after $v_2$ then $v_2$ is re-launched. However, the autonomous truck serves the demand point node 7 without driver independent of the UAV launches and retrieves.

After demonstrating the simple example based on Figure 3-3, the following shows the description and definition of the problem related to this research. A model based on TSP problem with UAV cooperating with the autonomous truck is developed. The objective of this problem is to minimize the travel times to deliver all reliefs and return to the depot. The definitions of the set, parameters, decision variables as well as objective and constraints are listed as Table 3-1.



doi:10.6844/NCKU202002083

Table 3-1 Notation of the model formulation

| Notation | | Definition |
|---|---|---|
| Set | | |
| $G = (N, A)$ | | A set of nodes N and a set of arcs A build up the network |
| $N$ | | $N = \{0,1,2,3,\cdots,n+1\}$<br>A set of n nodes, consisting of demand points, the origin depot (0) where the autonomous truck starts to travel and the destination depot (n+1) where the autonomous truck ends traveling. |
| $A$ | | A set of arcs contains links connecting nodes of $N$ |
| $D$ | | $D = \{1,2,3,\cdots,n\}$<br>A set of demand points nodes |
| $D_0$ | | $D_0 = \{0,1,2,3,\cdots,n\}$<br>A set of nodes that vehicle may depart consisting of starting depot and demand points |
| $D_+$ | | $D_+ = \{1,2,3,\cdots,n+1\}$<br>A set of nodes that vehicle may visit consisting of ending depot and demand points |
| $V$ | | $V = \{v_1, v_2\}$<br>A set of UAVs contains two UAVs. |
| $F$ | | $F = \{(v,i,j,k)\}$,<br>All possible three nodes of the UAV path by UAV $v \in V$ |
| | $i$ | $i \epsilon D_0$, the launch node $i$ must not be the ending depot |
| | $j$ | $j \epsilon D$, $i \neq j$, the delivery node $j$ must be in the demand points set and must not be the same as the launch node |
| | $k$ | $k \epsilon D_+$, $k \neq i$, $k \neq j$ , the rendezvous node $k$ can be either demand points or the ending depot and cannot equal to $i$ or $j$ |



doi:10.6844/NCKU202002083

| Decision variables | |
|---|---|
| $x_{i,j}$ | If an autonomous truck travels an arc $(i,j)$ from node $i$ to node $j$, $x_{ij}$ = 1;<br>Otherwise, $x_{ij}$ = 0 |
| $y_{v,i,j,k}$ | If one UAV $v \in V$ travels an arc $(i,j)$ and $(j,k)$ from node $i$ to node $j$ and from node $j$ to node $k$, $y_{vijk}$ = 1;<br>Otherwise, $y_{vijk}$ = 0 |
| $t_i$ | The autonomous truck's arrival time at node $i$, where $t_0 = 0$ |
| $st_i$ | The autonomous truck's service time completion at node $i$, where $st_0 = 0$ |
| $ct_i$ | The autonomous truck's completion time at node $i$ |
| $t'_{vi}$ | UAV's $v \in V$ arrival time at node $i$ |
| $ct'_{vi}$ | UAV's $v \in V$ completion time at node $i$ |
| $O^R_{v_1,v_2,k}$ | If one UAV $v_1 \in V$ and another one $v_2 \in V$ are **both retrieved** at node $k \in D_+$ and $v_1$ is retrieved **before** $v_2$, $O^R_{v_1,v_2,k} = 1$.<br>Otherwise, $O^R_{v_1,v_2,k} = 0$ |
| $O^L_{v_1,v_2,k}$ | If one UAV $v_1 \in V$ and another one $v_2 \in V$ are **both launched** from node $i \in D_0$ and $v_1$ is launched **before** $v_2$, $O^L_{v_1,v_2,k} = 1$.<br>Otherwise, $O^L_{v_1,v_2,k} = 0$ |
| $O'_{v_1,v_2,i}$ | If one UAV $v_1 \in V$ launches from node $i \in D$ before another one $v_2 \in V$ retrieves at node $i \in D$, $O'_{v_1,v_2,i} = 1$<br>Otherwise, $O'_{v_1,v_2,i} = 0$ |
| $O''_{v_1,v_2,i}$ | If one UAV $v_1 \in V$ retrieves at node $i \in D$ before another one $v_2 \in V$ launches from node $i \in D$, $O''_{v_1,v_2,i} = 1$<br>Otherwise, $O''_{v_1,v_2,i} = 0$ |
| $p_{i,j}$ | If the autonomous vehicle visits demand point $i$ before demand point $j$, $p_{ij}$ = 1;<br>Otherwise, $p_{ij}$ = 0 |
| $u_i$ | Position of node $i \epsilon D_+$ at the route of the autonomous truck, it is employed for the autonomous truck subtour elimination and $1 \le u_i \le (n+2)$. |
| Parameters | |
| $\tau_{i,j}$ | $(i,j) \in A$, Travel times of the autonomous truck associated with $A$ |
| $\tau'_{v,i,j}$ | $(i,j) \in A$, Travel times of the UAV associated with $A$ |
| $S_k$ | The autonomous truck service time at node $k \epsilon D_+$, where $S_{n+1} = 0$ |
| $S'_{vk}$ | The UAV $v \in V$ service time at node $k \epsilon D_+$, where $S'_{v,(n+1)} = 0$ |
| $e_{v,i,j,k}$ | The endurance, measured in time units for UAV $v \in V$ to travel from $i \epsilon D_0$ to $j \epsilon D$ to $k \epsilon D_+$ |



doi:10.6844/NCKU202002083

| Objective function | | |
|---|---|---|
| $Min\ \ t_{(n+1)}$ | | (3-1) |
| *Subject to* | | |
| **Routing Constrains** | | |
| $\sum_{\substack{i\epsilon D_0 \\ i\neq j}} x_{i,j} + \sum_{v\in V}\sum_{\substack{i\epsilon D_0 \\ i\neq j}} \sum_{\substack{k\epsilon D_+ \\ (v,i,j,k)\epsilon F}} y_{v,i,j,k} = 1$ | $\forall j \in D$ | (3-2) |
| $\sum_{j\epsilon D_+} x_{0,j} = 1$ | | (3-3) |
| $\sum_{i\epsilon D_0} x_{i,n+1} = 1$ | | (3-4) |
| $u_i - u_j + 1 \leq (n+2)(1 - x_{i,j})$ | $\forall i \in D$<br>$\forall j \in D_+$<br>$i \neq j$ | (3-5) |
| $\sum_{\substack{i\epsilon D_0 \\ i\neq j}} x_{i,j} = \sum_{\substack{k\epsilon D_+ \\ k\neq j}} x_{j,k}$ | $\forall j \in D$ | (3-6) |
| $\sum_{\substack{j\epsilon D \\ i\neq j}} \sum_{\substack{k\epsilon D_+ \\ (v,i,j,k)\epsilon F}} y_{v,i,j,k} \leq 1$ | $\forall i \in D_0$<br>$\forall v \in V$ | (3-7) |
| $\sum_{\substack{i\epsilon D_0 \\ i\neq k}} \sum_{\substack{j\epsilon D \\ (v,i,j,k)\epsilon F}} y_{v,i,j,k} \leq 1$ | $\forall k \in D_+$<br>$\forall v \in V$ | (3-8) |
| $2y_{v,i,j,k} \leq \sum_{\substack{h\epsilon D_0 \\ h\neq i}} x_{h,i} + \sum_{\substack{l\epsilon D \\ l\neq k}} x_{l,k}$ | $\forall v \in V$<br>$\forall i,j \in D$<br>$i \neq j$<br>$\forall k \in D_+$<br>$(v,i,j,k) \in F$ | (3-9) |
| $y_{v,0,j,k} \leq \sum_{\substack{h\epsilon D_0 \\ h\neq k}} x_{h,k}$ | $\forall v \in V$<br>$\forall j \in D$<br>$\forall k \in D_+$<br>$(v,i,j,k) \in F$ | (3-10) |
| $u_k - u_i \geq 1 - (n+2)(1 - \sum_{\substack{j\epsilon D \\ (v,i,j,k)\epsilon F}} y_{v,i,j,k})$ | $\forall i \in D$<br>$\forall k \in D_+$<br>$k \neq i$ | (3-11) |



doi:10.6844/NCKU202002083

| | | |
|---|---|---|
| | $\forall v \in V$ | |
| $u_i - u_j \geq 1 - (n+2)p_{i,j}$ | $\forall i, j \in D$<br>$i \neq j$ | (3-12) |
| $u_i - u_j \leq -1 + (n+2)(1 - p_{i,j})$ | $\forall i, j \in D$<br>$i \neq j$ | (3-13) |
| $p_{i,j} + p_{j,i} = 1$ | $\forall i, j \in D$<br>$i \neq j$ | (3-14) |

The objective function is described in Equation (3-1). The objective is to minimize the arrival time of the autonomous truck and UAVs returning to the depot which is node $(n+1)$ after serving all the demand points. The objective function (3-1) is equivalent to $min\{max\{t_{n+1}, t'_{v,n+1}\}\}$ due to both the autonomous truck and UAVs must wait for each other based on timing and sequencing constraints. Therefore, the arrival time of the autonomous truck and UAVs at the depot are adjusted to be the same.

In the mathematical model of this research, all constraints are divided into four parts. First is FSTSP base model by Constraint (3-2) to Constraint (3-14). The second part is the timing constraints of truck (Constraints (3-15) to (3-19)). The third part is timing constraints of UAVs (Constraints (3-20) to (3-33)) and the final part are sequencing constraints in various scenarios (Constraints (3-34) to (3-49))

Constraints (3-2) to (3-14) are associated with the routing problem based on FSTSP model of the autonomous truck and drones. Separately, Constraint (3-2) guarantees that each demand point must be visited once either by the autonomous truck or UAVs. Constraint (3-3) and Constraint (3-4) guarantee the autonomous truck must depart from and return to the depot. Constraint (3-5) and Constraint (3-11) are subtour elimination equations that guarantee no subtour is within the route of the autonomous truck and UAV according to Desrochers and Laporte (1991). Constraint (3-6) guarantees that whenever the autonomous truck visits at a node $j$, it must depart from the node $j$ as well. Constraint (3-7) represents that at most one UAV can depart at nodes when the autonomous truck visits at the identical



doi:10.6844/NCKU202002083

nodes. Similarly, Constraint (3-8) represents that at most one UAV can merge at nodes when the autonomous truck visits at the identical nodes. Constraint (3-9) guarantees if the UAV $v \in V$ is launched from node $i$, travels node $j$ then is rendezvoused at node $k$, the autonomous truck must visit node $i$ and node $j$. Similarly, Constraint (3-10) guarantees that if the UAV $v \in V$ is launched from the depot, travels to node $j$ then is rendezvoused at node $k$, the autonomous truck must depart from the depot and eventually arrive at node $k$. Constraint (3-12) and Constraint (3-13) are subtour elimination equations that guarantee no subtour that the autonomous truck visits. Constraint (3-14) guarantees the correct ordering of node $i$ and node $j$. Besides, $u_i$ and $p_{i,j}$ are two auxiliary decision variables to describe the ordering demand points nodes by the autonomous truck only. Constraint (3-12) to Constraint (3-14) can also determine the accurate values of $u_i$ and $p_{i,j}$.

| **Timing Constraints of truck** | | |
|---|---|---|
| $t_j \geq ct_i + \tau_{i,j} - M(1 - x_{i,j})$ | $\forall i \in D_0$<br>$\forall j \in D_+$<br>$\forall i \neq j$ | (3-15) |
| $st_k \geq t_k + S_k(\sum_{\substack{j \epsilon D_0 \\ j \neq k}} x_{j,k})$ | $\forall k \in D_+$ | (3-16) |
| $ct_k \geq st_k$ | $\forall k \in D_+$ | (3-17) |
| $ct_k \geq t'_{vk} - M(1 - \sum_{\substack{i \epsilon D_0 \\ i \neq k}} \sum_{\substack{j \epsilon D \\ (v,i,j,k) \epsilon F}} y_{v,i,j,k})$ | $\forall k \in D_+$<br>$\forall v \in V$ | (3-18) |
| $ct_k \geq ct'_{vk} - M(1 - \sum_{\substack{l \epsilon D \\ i \neq k}} \sum_{\substack{m \epsilon D_+ \\ (v,k,l,m) \epsilon F}} y_{v,k,l,m})$ | $\forall k \in D_0$<br>$\forall v \in V$ | (3-19) |

Constraints (3-15) to (3-19) are associated with travel times of the autonomous truck. Constraint (3-15) incorporates the travel times of the autonomous truck. Constraint (3-16) establishes the completion service time at a demand points $k$ by computing the arrival time and serving time. It describes that the completion service time at node $k$ must not be before



doi:10.6844/NCKU202002083

the arrival time and the service time. Constraints (3-17) to (3-19) establish the departure time of the autonomous truck from a demand point node. Constraint (3-17) prevents the autonomous truck from departing node $k$ before it has finished serving the demand points. Constraint (3-18) and Constraint (3-19) present if the UAV $v \in V$ is retrieved or launched at node $k$, the autonomous truck must wait until the UAV $v \in V$ has completed arriving or launching at node $k$.

| Timing Constraints of UAVs | | |
|---|---|---|
| $ct'_{vl} \geq t'_{vk} - M\Big(3 - \sum_{\substack{j \in D \\ (v,i,j,k) \in F \\ j \neq l}} y_{v,i,j,k} - \sum_{\substack{m \in D \\ m \neq i \\ m \neq k \\ m \neq l}} \sum_{\substack{n \in D_+ \\ (v,l,m,n) \in F \\ n \neq i \\ n \neq k}} y_{v,l,m,n} - p_{i,l}\Big)$ | $\forall i \in D_0$<br>$\forall k \in D_+$<br>$k \neq i$<br>$\forall l \in D$<br>$l \neq i$<br>$l \neq k$<br>$\forall v \in V$ | (3-20) |
| $ct'_{vi} \geq t'_{vi} - M\Big(1 - \sum_{\substack{j \in D \\ i \neq j}} \sum_{\substack{k \in D_+ \\ (v,i,j,k) \in F}} y_{v,i,j,k}\Big)$ | $\forall v \in V$<br>$\forall i \in D_0$ | (3-21) |
| $ct'_{vi} \geq t_i - M\Big(1 - \sum_{\substack{j \in D \\ i \neq j}} \sum_{\substack{k \in D_+ \\ (v,i,j,k) \in F}} y_{v,i,j,k}\Big)$ | $\forall v \in V$<br>$\forall i \in D_0$ | (3-22) |
| $ct'_{vi} \geq ct'_{v_2 i} - M(1 - O^L_{v_2,v,k})$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall i \in D_0$ | (3-23) |
| $ct'_{v_2 i} \geq t'_{vi} - M(1 - O''_{v,v_2,i})$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall i \in D$ | (3-24) |
| $t'_{vj} \geq ct'_{vi} + \tau'_{v,i,j} - M\Big(1 - \sum_{\substack{k \in D_+ \\ (v,i,j,k) \in F}} y_{v,i,j,k}\Big)$ | $\forall v \in V$<br>$\forall j \in D$<br>$\forall i \in D_0$<br>$i \neq j$ | (3-25) |



doi:10.6844/NCKU202002083

| | | |
|---|---|---|
| $t'_{vj} \leq ct'_{vi} + \tau'_{v,i,j} + M(1 - \sum_{\substack{k \epsilon D_+ \\ (v,i,j,k) \in F}} y_{v,i,j,k})$ | $\forall v \in V$<br>$\forall j \in D$<br>$\forall i \in D_0$<br>$i \neq j$ | (3-26) |
| $ct'_{vj} \geq t'_{vj} + S'_{vj}(\sum_{\substack{i \epsilon D_0 \\ i \neq j}} \sum_{\substack{k \epsilon D_+ \\ (v,i,j,k) \epsilon F}} y_{v,i,j,k})$ | $\forall v \in V$<br>$\forall j \in D$ | (3-27) |
| $ct'_{vj} \leq t'_{vj} + S'_{vj} + M(1 - \sum_{\substack{i \epsilon D_0 \\ i \neq j}} \sum_{\substack{k \epsilon D_+ \\ (v,i,j,k) \epsilon F}} y_{v,i,j,k})$ | $\forall v \in V$<br>$\forall j \in D$ | (3-28) |
| $t'_{vk} \geq t_k - M(1 - \sum_{\substack{i \epsilon D_0 \\ i \neq j}} \sum_{\substack{j \epsilon D \\ (v,i,j,k) \epsilon F}} y_{v,i,j,k})$ | $\forall v \in V$<br>$\forall k \in D_+$ | (3-29) |
| $t'_{vk} \geq t'_{v_2 k} - M(1 - O^R_{v_2,v,k})$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall k \in D_+$ | (3-30) |
| $t'_{vk} \geq ct'_{v_2 k} - M(1 - O'_{v_2,v,k})$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall k \in D$ | (3-31) |
| $t'_{vk} \geq ct'_{vj} + \tau'_{v,j,k} - M(1 - \sum_{\substack{i \epsilon D_0 \\ (v,i,j,k) \epsilon F}} y_{v,i,j,k})$ | $\forall v \in V$<br>$\forall k \in D_+$<br>$\forall j \in D$<br>$j \neq k$ | (3-32) |
| $t'_{vk} - ct'_{vj} \leq e_{v,i,j,k} + M(1 - y_{v,i,j,k})$ | $\forall v \in V$<br>$\forall i \in D_0$<br>$\forall j \in D$<br>$j \neq i$<br>$\forall k \in D_+$<br>$(v,i,j,k) \in F$ | (3-33) |

Constraints (3-20) to (3-33) are associated with travel times and the endurance limitations of the UAVs. Constraint (3-20) presents that if there are two routes of UAVs that are $(i, j, k)$ and $(l, m, n)$ and node $i$ is visited before node $l$ by the autonomous truck, node $l$ must be visited after node $k$. Constraints (3-21) to (3-24) state the launching of



doi:10.6844/NCKU202002083

UAVs. Constraint (3-21) presents the UAV $v \in V$ must be launched at node i before arriving node i. Similarly, Constraint (3-22) presents the UAV $v \in V$ must be launched at node i before the autonomous truck has arrived at node i. On the other hand, Constraint (3-23) presents if one UAV $v_2 \in V$ is launched before another one UAV $v \in V$, $v \in V$must not be launched from node $i$ until $v_2 \in V$ has been launched. While Constraint (3-24) presents if one UAV $v \in V$ is launched before another one UAV $v_2 \in V$, $v_2 \in V$ must not be launched from node $i$ until $v \in V$ has been launched. Constraints (3-25) and (3-26) address the arrival timing for UAV serving a demand point node $j$. And Constraints (3-27) and (3-29) address the departure timing for UAV serving a demand point node $j$. Constraints (3-25) to (3-28) ensure one UAV travels to the demand point node directly and must depart the demand point node immediately after completing the service. However, the retrieving of the UAVs must occur at the location by the autonomous truck. Constraints (3-29) to (3-33) state the retrieving of UAVs. Constraint (3-29) presents the UAV $v \in V$ must be retrieved at node $k$ before the autonomous truck has arrived at node $k$. On the other hand, Constraint (3-30) presents if one UAV $v_2 \in V$ is retrieved before another one UAV $v \in V$, $v \in V$ must not be retrieved at node $k$ until $v_2 \in V$ has retrieved. While Constraint (3-31) presents if one UAV $v \in V$ is retrieved before another one UAV $v_2 \in V$, $v_2 \in V$ must not be retrieved at node $k$ until $v \in V$ has retrieved. Constraint (3-32) states one UAV $v \in V$ must not be retrieved at node $k$ before launching from node $i$ and traveling from node $j$ to node $k$. The last Constraint (3-33) addresses to the endurance limitations of UAVs. While a UAV $v \in V$ travels from node $j$ to node $k$, the flying time between the arrival time at node $k$ and the departure time from node $i$ must not exceed the endurance ($e_{v,i,j,k}$).



doi:10.6844/NCKU202002083

| | | |
|---|---|---|
| **Sequencing Constraints when UAVs are both retrieved** | | |
| $O^{R}_{v,v_2,k} \le \sum_{\substack{i\epsilon D_0 \\ i\neq k}} \sum_{\substack{j\epsilon D \\ (v,i,j,k)\epsilon F}} y_{v,i,j,k}$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall k \in D_+$ | (3-34) |
| $O^{R}_{v,v_2,k} \le \sum_{\substack{i\epsilon D_0 \\ i\neq k}} \sum_{\substack{j\epsilon D \\ (v_2,i,j,k)\epsilon F}} y_{v_2,i,j,k}$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall k \in D_+$ | (3-35) |
| $O^{R}_{v,v_2,k} + O^{R}_{v_2,v,k} \le 1$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall k \in D_+$ | (3-36) |
| $O^{R}_{v,v_2,k} + O^{R}_{v_2,v,k} + 1 \ge \sum_{\substack{i\epsilon D_0 \\ i\neq k}} \sum_{\substack{j\epsilon D \\ (v,i,j,k)\epsilon F}} y_{v,i,j,k} + \sum_{\substack{i\epsilon D_0 \\ i\neq k}} \sum_{\substack{j\epsilon D \\ (v_2,i,j,k)\epsilon F}} y_{v_2,i,j,k}$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall k \in D_+$ | (3-37) |
| **Sequencing Constraints when UAVs are both launched** | | |
| $O^{L}_{v,v_2,i} \le \sum_{\substack{j\epsilon D \\ j\neq i}} \sum_{\substack{k\epsilon D_+ \\ (v,i,j,k)\epsilon F}} y_{v,i,j,k}$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall i \in D_0$ | (3-38) |
| $O^{L}_{v,v_2,i} \le \sum_{\substack{j\epsilon D_0 \\ j\neq i}} \sum_{\substack{k\epsilon D_+ \\ (v_2,i,j,k)\epsilon F}} y_{v_2,i,j,k}$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall i \in D_0$ | (3-39) |
| $O^{L}_{v,v_2,i} + O^{L}_{v_2,v,i} \le 1$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall i \in D_0$ | (3-40) |
| $O^{L}_{v,v_2,i} + O^{L}_{v_2,v,i} + 1 \ge \sum_{\substack{j\epsilon D \\ j\neq i}} \sum_{\substack{k\epsilon D_+ \\ (v,i,j,k)\epsilon F}} y_{v,i,j,k} + \sum_{\substack{j\epsilon D \\ j\neq i}} \sum_{\substack{k\epsilon D_+ \\ (v_2,i,j,k)\epsilon F}} y_{v_2,i,j,k}$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v \neq v_2$<br>$\forall i \in D_0$ | (3-41) |
| **Sequencing Constraints if one UAV is launched and another one is retrieved** | | |



doi:10.6844/NCKU202002083

| | | |
|---|---|---|
| $O'_{v_2,v,k} \leq \sum_{\substack{l \epsilon D \\ l \neq k}} \sum_{\substack{m \epsilon D_+ \\ (v_2,k,l,m) \epsilon F}} y_{v_2,k,l,m}$ | $\forall v_2 \in V$<br>$\forall v \in V$<br>$v \neq v_2$<br>$\forall k \in D$ | (3-42) |
| $O''_{v_2,v,k} \leq \sum_{\substack{l \epsilon D \\ l \neq k}} \sum_{\substack{m \epsilon D_+ \\ (v,k,l,m) \epsilon F}} y_{v,k,l,m}$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v_2 \neq v$<br>$\forall k \in D$ | (3-43) |
| $O'_{v_2,v,k} \leq \sum_{\substack{i \epsilon D_0 \\ i \neq k}} \sum_{\substack{j \epsilon D \\ (v,i,j,k) \epsilon F}} y_{v,i,j,k}$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v_2 \neq v$<br>$\forall k \in D$ | (3-44) |
| $O''_{v_2,v,k} \leq \sum_{\substack{i \epsilon D_0 \\ i \neq k}} \sum_{\substack{j \epsilon D \\ (v_2,i,j,k) \epsilon F}} y_{v_2,i,j,k}$ | $\forall v_2 \in V$<br>$\forall v \in V$<br>$v \neq v_2$<br>$\forall k \in D$ | (3-45) |
| $O'_{v_2,v,k} + O''_{v,v_2,k} + 1 \geq \sum_{\substack{i \epsilon D_0 \\ i \neq k}} \sum_{\substack{j \epsilon D \\ (v,i,j,k) \epsilon F}} y_{v,i,j,k} + \sum_{\substack{l \epsilon D \\ l \neq k}} \sum_{\substack{m \epsilon D_+ \\ (v_2,k,l,m) \epsilon F}} y_{v_2,k,l,m}$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v_2 \neq v$<br>$\forall k \in D$ | (3-46) |
| $O'_{v_2,v,k} + O''_{v,v_2,k} \leq 1$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v_2 \neq v$<br>$\forall k \in D$ | (3-47) |
| $O'_{v_2,v,k} + O'_{v,v_2,k} \leq 1$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v_2 \neq v$<br>$\forall k \in D$ | (3-48) |
| $O''_{v_2,v,k} + O''_{v,v_2,k} \leq 1$ | $\forall v \in V$<br>$\forall v_2 \in V$<br>$v_2 \neq v$<br>$\forall k \in D$ | (3-49) |

In Constraints (3-34) to (3-49), the decision variables ($O^R_{v,v_2,k}, O^L_{v,v_2,i}, O'_{v_2,v,k}, O''_{v,v_2,k}$) are used to sequence the process at each demand point node. Constraints (3-34) to (3-37) are associated with the scenario concerning the sequence when both UAVs are retrieved.



doi:10.6844/NCKU202002083

Constraints (3-34) and (3-35) present if both the UAVs are not retrieved at node $k$, $O^R_{v,v_2,k}$ is not equal to one. Constraint (3-36) states either one UAV $v \in V$ is retrieved before another UAV $v_2 \in V$, one UAV $v_2 \in V$ is retrieved before another UAV $v \in V$ or at least one of these UAVs is not retrieved at node $k$. Constraint (3-37) addresses if both UAVs are retrieved at node $k$, then either the UAV $v \in V$ is retrieved before another UAV $v_2 \in V$ or the UAV $v_2 \in V$ is retrieved before another UAV $v \in V$. Constraints (3-38) to (3-41) are associated with the scenario concerning the sequence when both UAVs are launched. Constraint (3-38) and Constraint (3-39) present if both the UAVs are not launched at node $i$, $O^L_{v,v_2,i}$ is not equal to one. Constraint (3-40) states either one UAV $v \in V$ is launched before another UAV $v_2 \in V$, one UAV $v_2 \in V$ is launched before another UAV $v \in V$ or at least one of these UAVs is not launched at node $i$. Constraint (3-41) addresses if both UAVs are launched at node $i$, then either the UAV $v \in V$ is launched before another UAV $v_2 \in V$ or the UAV $v_2 \in V$ is launched before another UAV $v \in V$. Constraints (3-42) to (3-49) are associated with the scenario concerning the sequence when one UAV is launched, and another is retrieved. Constraints (3-42) and (3-43) state that $O'_{v_2,v,i}$ and $O''_{v_2,v,i}$ is equal to zero if the UAV $v_2 \in V$ or the UAV $v \in V$ is not launched from node $k$. Constraints (3-44) and (3-45) state that $O'_{v_2,v,i}$ and $O''_{v_2,v,i}$ is equal to zero if the UAV $v_2 \in V$ or the UAV $v \in V$ is not retrieved at node $k$. Constraint (3-46) addresses if the UAV $v \in V$ is retrieved at node $k$ and the UAV $v_2 \in V$ is launched from node $v_2 \in V$, then either the UAV $v_2 \in V$ is launched before the UAV $v \in V$ is retrieved or the UAV $v \in V$ is retrieved before the UAV $v_2 \in V$ is launched. Constraint (3-47) states when UAV $v \in V$ is retrieved before UAV $v_2 \in V$ is launched, it is not possible for UAV $v_2 \in V$ to be launched before UAV $v \in V$ is retrieved. Constraint (3-48) states when UAV $v \in V$ is launched before UAV $v_2 \in V$ is retrieved, it is not possible for UAV $v_2 \in V$ to be launched before UAV $v \in V$ is retrieved. Constraint (3-49) states when UAV $v \in V$ is



doi:10.6844/NCKU202002083

retrieved before UAV $v_2 \in V$ is launched, it is not possible for UAV $v_2 \in V$ to be retrieved before UAV $v \in V$ is launched.

## 3.5 Solution Algorithm

This section presents the overall model of delivery optimization with the autonomous truck and the UAVs. Thus, this research adopts a tabu search algorithm with one objective including minimum travel times. The problem which is proposed is classified to be a traveling salesman problem. Further, TSP problem has been proved an NP-Hard problem and only a small-sized problem can be solved by a commercial solver such as GUROBI within a reasonable run time. To overcome the issue, this research introduces a tabu search algorithm for solving the problem. This section provides the basic procedure of tabu search. The solution process is presented in Figure 3-4.

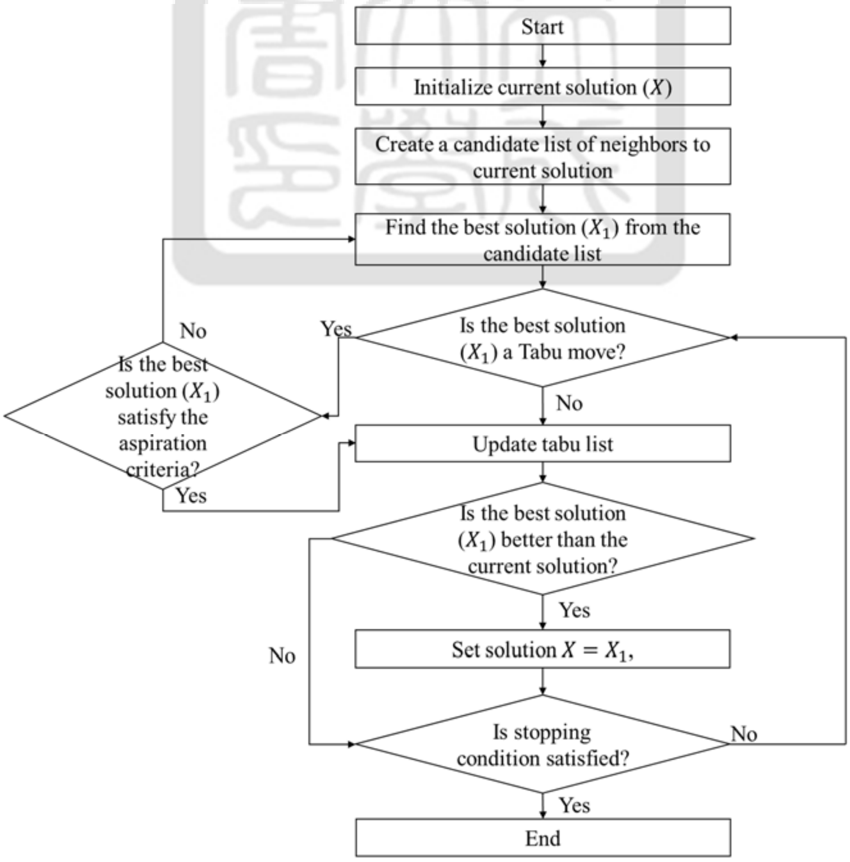



Figure 3-4 Solution process of tabu search



doi:10.6844/NCKU202002083

Step 1 Start

This research set up an experimental network, model parameters and the setting related to tabu search algorithm such as tabu list, tabu tenure, and the aspiration criteria.

Step 2 Initialize current solution ($X$)

In this phase, a simple heuristic generates an initial solution quickly. By optimizing the travel times of the autonomous truck and UAVs, the initial feasibly solution is constructed.

Step 3 Create a candidate list of neighbors to the current solution

After generating the initial solution, this research further creates a candidate list for the current solution. The constructive methods are used for seeking possible solutions that are neighborhood search.

Step 4 Find the best solution ($X_1$) from the candidate list

In this phase, the most important is to search by moving iteratively from one solution to another until a satisfactory solution is obtained. By the previous steps, the neighbor solutions can be obtained and compare whether it is the best.

**Process of Tabu Search**

Step 5 Is the best solution ($X_1$) in the tabu list?

Tabu list is to record a limited number of attributes of solutions. The moves, selections and assignments can be tabu to be discouraged. To avoid local solution, the tabu list is adopted to record moves by tabu tenure that determines the number of the moves are in the tabu list.

Step 6 Is the best solution ($X_1$) satisfy the aspiration criteria?

The aspiration criteria is to accept an improving solution even if generated by a tabu move. Due to the aspiration criteria in tabu search, tabu search finds a more efficient solution. In the process, while the best solution is tabu, this research continues to judge



doi:10.6844/NCKU202002083

whether the best solution is in aspiration criteria or not. If it is not in the aspiration criteria, the current best solution is instituted by another best solution.

Step 7 Update tabu list

After the solution moves to another current solution, the tabu list must be updated including the tabu tenure. Tabu tenure set in the previous step controls the number of iterations a tabu move which is considered to remain tabu list.

Step 8 Is the best solution ($X_1$) better than the current solution ($X$)?

Based on finishing the previous step, this research keeps considering if the best solution ($X_1$) better than the current solution ($X$). If yes, set $X_1$ equals to the best solution. On the opposite, if no, check whether the stopping condition is satisfied or not.

Step 9 Is the stopping condition satisfied?

In the final step of the process of the tabu search algorithm, the process ends while the algorithm reaches the stopping condition. This research set the model to stop when the maximum number of solutions to be explored is fixed and the number of iterations since the last improvement is larger than a specified number. It can prevent the iterations from unlimited.

As discussed above, the tabu search uses a local or neighborhood search procedure, to iteratively move from one potential solution $X$ to an improved neighborhood solution $X'$ until the stopping condition has been satisfied.



doi:10.6844/NCKU202002083

# CHAPTER 4 NUMERICAL ANALYSIS

Based on the solution approach mentioned in Chapter 3, Chapter 4 discusses the details of the mathematical model and the heuristic approach. Sections 4.1 and 4.2 present the structure of the mathematical model which is Mixed Integer Linear Programming and the heuristic algorithm which is a tabu search algorithm. In Section 4.3, two small-scale test networks are developed for mathematical models and heuristic algorithm, and Section 4.4 presents the results of two test instances in various solution approaches.

## 4.1 The Structure of Mathematical Model

In this research, the mathematical model constructed and described in Chapter 3 is solved by the mathematical programming software, GUROBI Optimizer. Figure 4-1 illustrates the detailed procedure of experiments, and GUROBI Optimizer is modeling with python interface.

In GUROBI Optimizer, this research starts with input data and constructs three components including objective function, decision variables, and constraints. Through the mathematical programming software, GUROBI, the output solution provides optimal routes, objective function value, and total runtime for running the program.

In terms of mathematical programming software, GUROBI is coded in Python and tested on a Windows 10 machine (Intel(R) Core (TM) i5-8250U/ 1.80GHz processor with 8GB RAM).



doi:10.6844/NCKU202002083

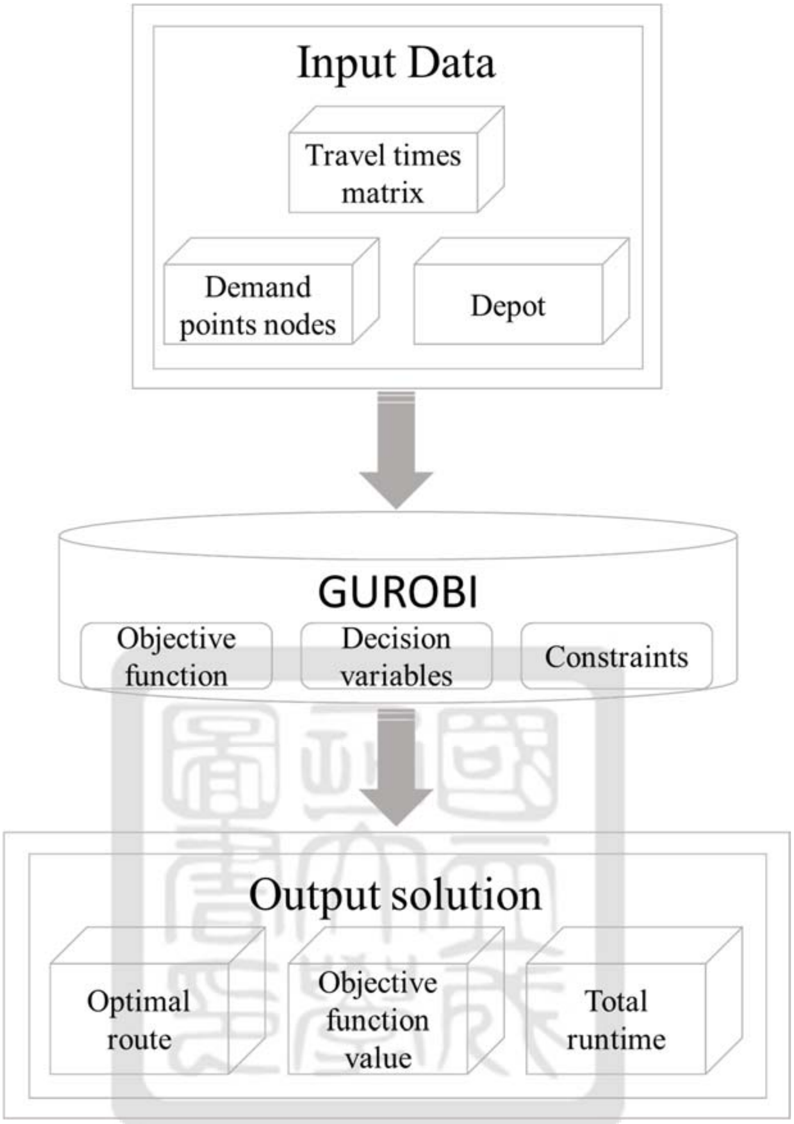



Figure 4-1 The overall solution procedure by GUROBI

## 4.2 The Structure of Heuristic Approach

### 4.2.1 Tabu Search Solution Algorithm

TSP problem is an NP-Hard problem and only a small-sized problem can be solved by a commercial solver, GUROBI within a reasonable time. However, based on the proposed tabu search (TS) approach by Glover (1986), TS is a metaheuristic that guides a local search out of local optima. Tabu search is effective on a wide variety of classical optimization



doi:10.6844/NCKU202002083

problems, such as traveling salesman problems, and also be applied to practical problems. In that case, this research applies the tabu search solution algorithm to solve practical problems. Tabu search is a local search method that begins with an initial solution and explores the solution space by iteratively examining the neighbor solutions.

Basic components of the tabu search heuristic include initial solution, neighborhood solution, move, tabu list, aspiration criterion, and stopping criterion. In this research, the components which are designed to solve the optimal delivery with the autonomous truck and UAVs is described as followed:

**Initial solution:**

In terms of the tabu search algorithm, the initial solution must be constructed first. In a general TSP problem, the initial solution is usually generated by simple heuristics such as insertion heuristic, greedy heuristic, or saving-based heuristic. However, as a variant of TSP problem, the optimal delivery with the autonomous truck and two drones is more complex considering various constraints in the autonomous truck and drones. This research generates an initial solution by randomly assigning the demand point nodes to the autonomous truck and the UAVs under the constraints of the fixed time-based flight endurance and testify if the initial solution is in a reasonable situation. For example, given a network with depot (node 0) and four demand points (nodes 1, 2, 3, 4). Assumed that initial solution is {0,2,1,3,4,0} and objective function value is 20. The demand points served by UAV 1 and UAV 2 are node 2 and node 4. The heuristics algorithm must test whether the routes of UAV 1 and UAV 2 are under the constraints of the fixed time-based flight endurance or not. If the routes of UAVs are over flight endurance, this initial solution is infeasible. Moreover, the initial solution will be generated until it is feasible.

**Neighborhood solution and move:**

The solutions in the neighborhood of a given solution are the solutions that can be



doi:10.6844/NCKU202002083

obtained by applying move operations to the current solution. The move operation involves relocating a demand point node from its current node to another node that minimizes the fitness, which is calculated by travel times of the autonomous truck and drones. Continuing the example from the previous paragraph, assumed the neighborhood solution is {0,3,1,2,4,0} and objective function value is 16. The initial solution makes a move to this neighborhood solution and the objective function value is decreased from 20 to 16. The process of moving between solution and solution is defined as a move. Additionally, whenever the demand point changes, the demand points must be reassigned to UAVs and re-calculate the total cost which is total travel times.

In each iteration of the search process, all possible move operations for all demand point nodes are evaluated and the best one is subsequently performed. The best move operation is the one that leads to the minimized objective function value. To prevent cycling, if a demand point has been moved from the delivery route in given iterations which means the current solution is optimal, then moving the same demand point into the tabu list and declared the move is tabu, for the following iterations. Whenever the move is in the tabu list, it must be fixed in a length of $n$ iterations which is tabu tenure. However, there are no related literature applying tabu search in a Flying Sidekick Traveling Salesman Problem territory. Thus, the length of tabu tenure is set 7 according to Glover (1990).

**Aspiration criterion:**

While a tabu move is in the tabu list, it can be allowed only when the resulting solution is feasible and has an objective function value that is better than that of the current best feasible solution found by the search. In this research, a common-sense-based approach is applied to relax the tabu restriction if a solution happens to produce a better result than the currently best solution. The tabu move can only satisfy the aspiration criterion in three situations synchronous, that is



doi:10.6844/NCKU202002083

1. The move is in the tabu list
2. The move is the best in the tabu list
3. The objective function value corresponds to the move is better than the current solution

**Termination condition:**

The termination condition is a user-controlled parameter by setting iterations. The greater the number of iterations is, the runtime of the program coding by Python in this research is longer. Therefore, the number of iterations must be suitable while processing the tabu search algorithm.



doi:10.6844/NCKU202002083

### 4.2.2 Heuristic Flowchart

To solve the problem of optimal delivery with the autonomous truck and the UAVs, the proposed algorithm, tabu search is coded in Python and tested on a Windows 10 machine (Intel(R) Core (TM) i5-8250U/ 1.80GHz processor with 8GB RAM).

Figure 4-1 shows the heuristic flowchart and the explanations of each step are described as follow:

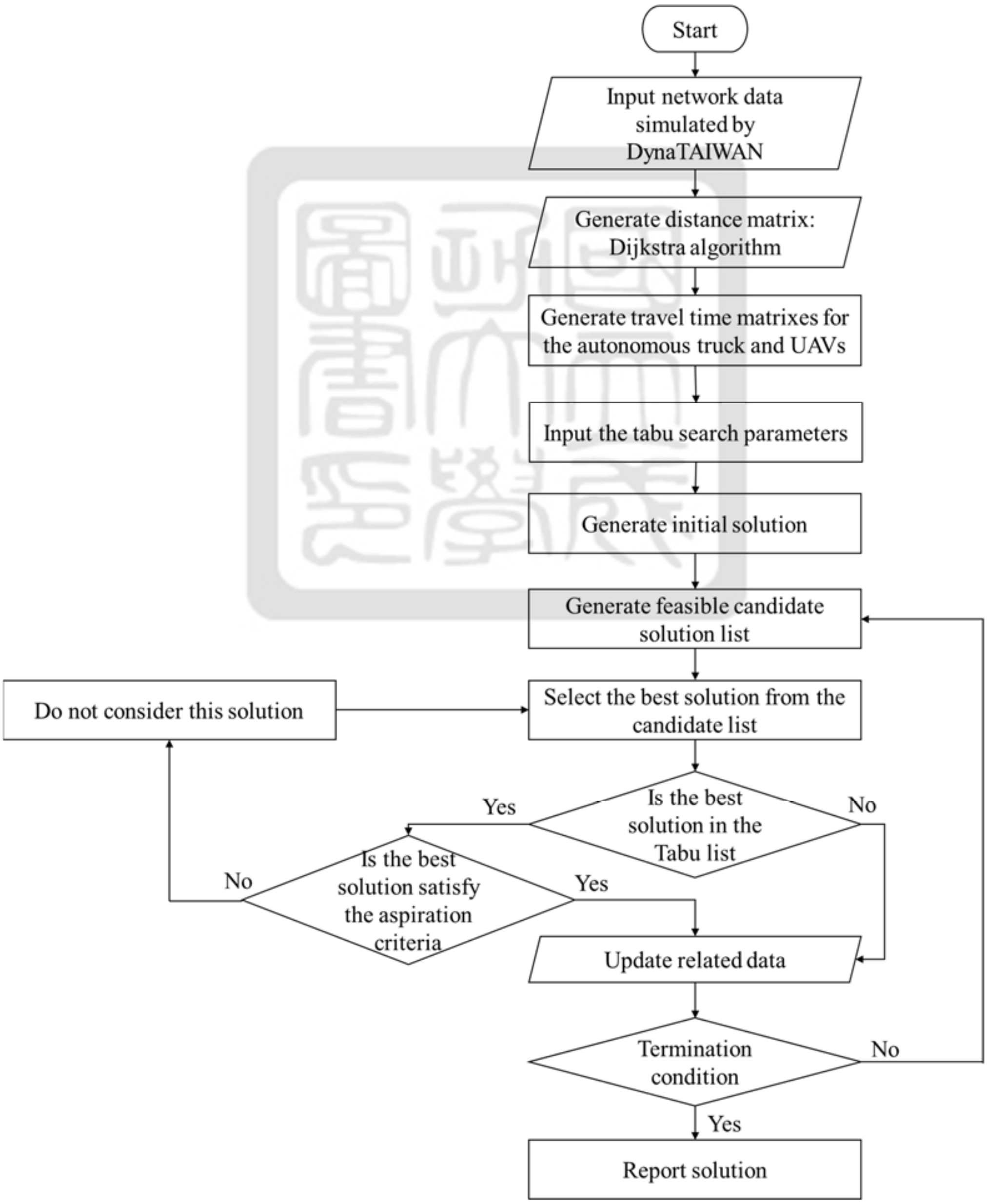



Figure 4-2 Heuristic flowchart



doi:10.6844/NCKU202002083

Step 1: To generate the travel times matrixes of the autonomous truck and UAVs, the first step is to obtain network data simulated by DynaTAIWAN.

Step 2: After obtaining network data simulated by DynaTAIWAN, the program generates a distance matrix of the empirical network by Dijkstra algorithm to generate the shortest path between demand points and demand points.

Step 3: After getting the distance matrix between demand points and demand points, the program generates the travel times matrixes of the autonomous truck and UAVs.

Step 4: After acquiring the most important data which are the travel time matrixes of the autonomous truck and UAVs. This research continues to input the program parameters concerning the tabu search algorithm that is the number of nodes, service times of the demand points for autonomous truck and UAVs, fixed time-based flight endurance of UAVs, tabu tenure, aspiration criteria, termination condition.

Step 5: After input the program parameters, it starts to generate one initial solution randomly. In this step, the travel route is determined first. Secondly, the demand points in the travel route are assigned to the autonomous truck or UAVs. Simultaneously, the program checks if the travel route by UAV exceed the fixed time-based flight endurance ($e_{vijk}$) or not. If exceeds, repeats this step until generating the feasible solution. Otherwise, the initial solution is generated successfully.

Step 6: The candidate solutions of the candidate list are continuously generated by swap two nodes using the 2-Opt algorithm.

Step 7: The program selects the best solution of the candidate list and tests whether the solution is in the tabu list, if no, the program records the solution as the current solution and updates the tabu list. On the opposite, if the solution is in the tabu list, the program continuously checks whether the best solution meets the aspiration criteria or not.

Step 8: While the solution is in the tabu list, the program test whether the solution meets



doi:10.6844/NCKU202002083

the aspiration criteria or not. As mentioned in the previous section, a common-sense-based approach is applied to relax the tabu restriction if a solution happens to produce a better result than the currently best solution. The tabu move can only satisfy the aspiration criterion in three situations synchronous, which is that the solution is the best in the tabu list, and the objective function value corresponds to the solution is better than the current solution. Lastly, if the solution meets the aspiration criteria, then the program moves to Step 9 and records such a solution as a new current solution. Otherwise, the program restarts Step 7 to find the other solution which is best from the candidate list.

Step 9: Update related data in the tabu list such as current solution, tabu tenure, objective function value, and tabu list.

Step 10: As long as meeting the termination condition, the program reports the solution related to the optimal route of the autonomous truck and UAVs, objective function value, and runtime of the heuristic program. However, if the termination condition is not satisfied, the program must restart with Step 6.

## 4.3 Test Network Development

To develop an actual network for optimal delivery problems concerning minimal travel times, test instances are constructed in two different networks. In this research, the commercial solver, GUROBI and tabu search algorithm are used to solve the small-scale networks and also be tested if the model in Section 3.4 properly reflects the optimal delivery route. Moreover, two test networks are described as followed.

### 4.3.1 Test Network I

As shown in Figure 4-2, the test network I is an undirected graph and comprises ten nodes includes one depot and nine demand points and 45 arcs. The distance matrix in the



doi:10.6844/NCKU202002083

test network I is presented in Table 4-1. Additionally, this research sets the speed of the autonomous truck as 14 m/s (equals to 50 kph). The travel times matrix for the autonomous truck is shown in Table 4-2.

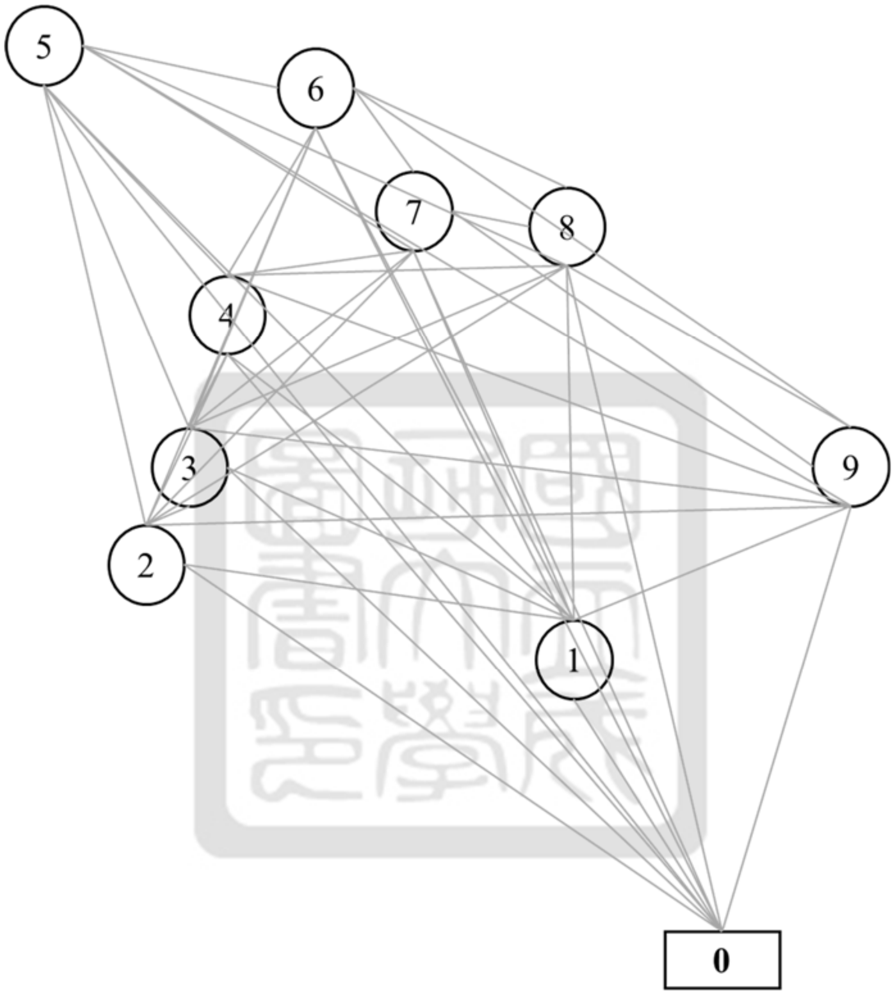



Figure 4-3 Test Network I with ten nodes



doi:10.6844/NCKU202002083

Table 4-1 Distance matrix in Test Network I (meters)

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | 2000 | 6000 | 5000 | 5000 | 7000 | 7000 | 5000 | 5000 | 3000 |
| 1 | 2000 | | 3000 | 2000 | 3000 | 5000 | 5000 | 4000 | 3000 | 2000 |
| 2 | 6000 | 3000 | | 535 | 1000 | 3000 | 3000 | 3000 | 4000 | 5000 |
| 3 | 5000 | 2000 | 535 | | 1000 | 3000 | 3000 | 2000 | 3000 | 4000 |
| 4 | 5000 | 3000 | 1000 | 1000 | | 2000 | 2000 | 2000 | 2000 | 4000 |
| 5 | 7000 | 5000 | 3000 | 3000 | 2000 | | 2000 | 3000 | 4000 | 6000 |
| 6 | 7000 | 5000 | 3000 | 3000 | 2000 | 2000 | | 1000 | 2000 | 4000 |
| 7 | 5000 | 4000 | 3000 | 2000 | 2000 | 3000 | 1000 | | 787 | 3000 |
| 8 | 5000 | 3000 | 4000 | 3000 | 2000 | 4000 | 2000 | 787 | | 3000 |
| 9 | 3000 | 2000 | 5000 | 4000 | 4000 | 6000 | 4000 | 3000 | 3000 | |

Table 4-2 Travel time matrix of the autonomous truck in Test Network I (seconds)

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | 142.86 | 428.57 | 357.14 | 357.14 | 500.00 | 500.00 | 357.14 | 357.14 | 214.29 |
| 1 | 142.86 | | 214.29 | 142.86 | 214.29 | 357.14 | 357.14 | 285.71 | 214.29 | 142.86 |
| 2 | 428.57 | 214.29 | | 38.21 | 71.43 | 214.29 | 214.29 | 214.29 | 285.71 | 357.14 |
| 3 | 357.14 | 142.86 | 38.21 | | 71.43 | 214.29 | 214.29 | 142.86 | 214.29 | 285.71 |
| 4 | 357.14 | 214.29 | 71.43 | 71.43 | | 142.86 | 142.86 | 142.86 | 142.86 | 285.71 |
| 5 | 500.00 | 357.14 | 214.29 | 214.29 | 142.86 | | 142.86 | 214.29 | 285.71 | 428.57 |
| 6 | 500.00 | 357.14 | 214.29 | 214.29 | 142.86 | 142.86 | | 71.43 | 142.86 | 285.71 |
| 7 | 357.14 | 285.71 | 214.29 | 142.86 | 142.86 | 214.29 | 71.43 | | 56.21 | 214.29 |
| 8 | 357.14 | 214.29 | 285.71 | 214.29 | 142.86 | 285.71 | 142.86 | 56.21 | | 214.29 |
| 9 | 214.29 | 142.86 | 357.14 | 285.71 | 285.71 | 428.57 | 285.71 | 214.29 | 214.29 | |



doi:10.6844/NCKU202002083

### 4.3.2 Test Network II

As shown in Figure 4-3, the test network II is an undirected graph and comprises ten nodes includes one depot and nine demand points and 45 arcs. The distance matrix in test network II is presented in Table 4-1. Additionally, this research sets the speed of the autonomous truck as 14 m/s (equals to 50 kph). The travel times matrix for the autonomous truck is shown in Table 4-2.

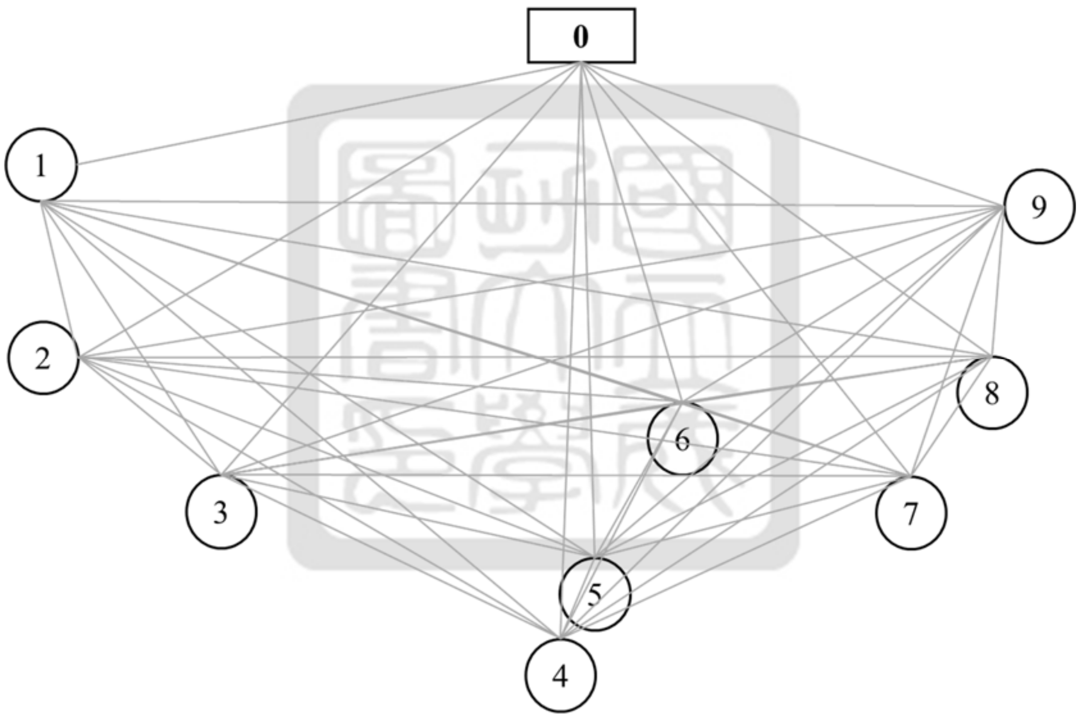



Figure 4-4 Test Network II with ten nodes



doi:10.6844/NCKU202002083

Table 4-3 Distance matrix in Test Network II (meters)

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | 1800 | 2050 | 1950 | 2100 | 1800 | 1350 | 1900 | 1800 | 1600 |
| 1 | 1800 | | 650 | 1250 | 2400 | 2270 | 2280 | 3050 | 3180 | 3250 |
| 2 | 2050 | 650 | | 760 | 2000 | 1950 | 2100 | 2850 | 3100 | 3300 |
| 3 | 1950 | 1250 | 760 | | 1280 | 1220 | 1550 | 2250 | 2550 | 2850 |
| 4 | 2100 | 2400 | 2000 | 1280 | | 255 | 840 | 1230 | 1650 | 2180 |
| 5 | 1800 | 2270 | 1950 | 1220 | 255 | | 590 | 1100 | 1460 | 1950 |
| 6 | 1350 | 2280 | 2100 | 1550 | 840 | 590 | | 760 | 1000 | 1400 |
| 7 | 1900 | 3050 | 2850 | 2250 | 1230 | 1100 | 760 | | 470 | 1100 |
| 8 | 1800 | 3180 | 3100 | 2550 | 1650 | 1460 | 1000 | 470 | | 660 |
| 9 | 1600 | 3250 | 3300 | 2850 | 2180 | 1950 | 1400 | 1100 | 660 | |

Table 4-4 Travel time matrix of the autonomous truck in Test Network II (seconds)

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | 128.57 | 146.43 | 139.29 | 150.00 | 128.57 | 96.43 | 135.71 | 128.57 | 114.29 |
| 1 | 128.57 | | 46.43 | 89.29 | 171.43 | 162.14 | 162.86 | 217.86 | 227.14 | 232.14 |
| 2 | 146.43 | 46.43 | | 54.29 | 142.86 | 139.29 | 150.00 | 203.57 | 221.43 | 235.71 |
| 3 | 139.29 | 89.29 | 54.29 | | 91.43 | 87.14 | 110.71 | 160.71 | 182.14 | 203.57 |
| 4 | 150.00 | 171.43 | 142.86 | 91.43 | | 18.21 | 60.00 | 87.86 | 117.86 | 155.71 |
| 5 | 128.57 | 162.14 | 139.29 | 87.14 | 18.21 | | 42.14 | 78.57 | 104.29 | 139.29 |
| 6 | 96.43 | 162.86 | 150.00 | 110.71 | 60.00 | 42.14 | | 54.29 | 71.43 | 100.00 |
| 7 | 135.71 | 217.86 | 203.57 | 160.71 | 87.86 | 78.57 | 54.29 | | 33.57 | 78.57 |
| 8 | 128.57 | 227.14 | 221.43 | 182.14 | 117.86 | 104.29 | 71.43 | 33.57 | | 47.14 |
| 9 | 114.29 | 232.14 | 235.71 | 203.57 | 155.71 | 139.29 | 100.00 | 78.57 | 47.14 | |



doi:10.6844/NCKU202002083

## 4.4 Results of Test Networks

To test whether the mathematical model mentioned in Chapter 3 can solve the problem of optimal delivery with the autonomous truck and two UAVs or not. The mathematic model is tested on various test networks with ten nodes by MILP solver, GUROBI. Furthermore, the tabu search algorithm approach is tested on the test networks to solve the optimal delivery with the autonomous truck and two UAVs. The results of two test networks solving by GUROBI and tabu search are presented in the following context. In this research, the program coded in Python is tested on a Windows 10 machine (Intel(R) Core (TM) i5-8250U/ 1.80GHz processor with 8GB RAM).

### 4.4.1 Results of Test Network I Solving by GUROBI

In the test of the mathematical model, some important input is determined before running the GUROBI. The travel times and speed of the autonomous truck is presented in Section 4.3.1. Secondly, the service times of the autonomous truck and the UAVs are assumed to be 30 and 60 seconds. Finally, as a constraint concerning the battery capacity to drones, this research applies fixed time-based endurance where two drones cooperating with the autonomous truck are considered to have the same maximum flight endurance. The flight endurance is constant for all three demand point nodes without considering speed and distance. In this experiment, the missions for the drones in this research are to deliver medical relief after disasters as soon as possible. Thus, this research set the UAV can reach 20 m/s and flight 200 seconds by carrying 70lbs (equals to 30 kg) medical reliefs. By calculating the distance matrix in Table 4-1 and the speed of the UAV. The flight constraint between nodes and nodes is presented in Table 4-5. For instance, while the UAV is desired to launch from node 4, satisfy node 5 then retrieving at node 7, the program calculates the



doi:10.6844/NCKU202002083

travel times between node 4 to node 5 and node 5 to node 7. Due to the travel times between node 4 to node 5 and node 5 to node 7 are 100 seconds and 150 seconds, the UAV under the flight endurance is not able to deliver reliefs to node 5 in this case.

Table 4-5 The travel times matrix with the UAV in Test Network I (seconds)

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | 100 | 300 | 250 | 250 | 350 | 350 | 250 | 250 | 150 |
| 1 | 100 | | 150 | 100 | 150 | 250 | 250 | 200 | 150 | 100 |
| 2 | 300 | 150 | | 26.75 | 50 | 150 | 150 | 150 | 200 | 250 |
| 3 | 250 | 100 | 26.75 | | 50 | 150 | 150 | 100 | 150 | 200 |
| 4 | 250 | 150 | 50 | 50 | | 100 | 100 | 100 | 100 | 200 |
| 5 | 350 | 250 | 150 | 150 | 100 | | 100 | 150 | 200 | 300 |
| 6 | 350 | 250 | 150 | 150 | 100 | 100 | | 50 | 100 | 200 |
| 7 | 250 | 200 | 150 | 100 | 100 | 150 | 50 | | 39.35 | 150 |
| 8 | 250 | 150 | 200 | 150 | 100 | 200 | 100 | 39.35 | | 150 |
| 9 | 150 | 100 | 250 | 200 | 200 | 300 | 200 | 150 | 150 | |

As mentioned in Chapter 3, this research sets the optimal delivery problem with two UAVs as a MILP mathematical model solving by a commercial solver, GUROBI. The results are presented in Table 4-6 and visualized in Figure 4-5. In this case, GUROBI spends almost 80 seconds to generate the optimal solution and the optimal delivery time in test network I is 1463.84 seconds. In Figure 4-4, the results provide that the autonomous truck starts at the starting depot, node 0 and satisfies node 9, node 7; continuously, the UAV 1 is launched from the autonomous truck at node 7, travels and delivers supplies to node 8, and retrieved by the autonomous truck at node 6. After finishing the first delivery task, the autonomous truck keeps traveling to node 5, node 4 and the UAV 1 is launched from the autonomous truck at node 4, travels and delivers supplies to node 2, and retrieved by the autonomous truck at



doi:10.6844/NCKU202002083

node 3. Finally, the autonomous truck by carrying two drones travel from node 3 to node 1 and back to the ending depot (node 0).





doi:10.6844/NCKU202002083

Table 4-6 The results of Test Network I solving by GUROBI

| Total Runtime (seconds) | Objective Function Value | Number of UAV | Number of Customers |
|---|---|---|---|
| 79.36 | 1463.84 | 2 | 9 |
| Delivery nodes | | | |
| UAV 2 | | | |
| UAV 1 | 8 2 | | |
| The autonomous truck | Start → 9 → 7 → 6 → 5 → 4 → 3 → 1 | | |

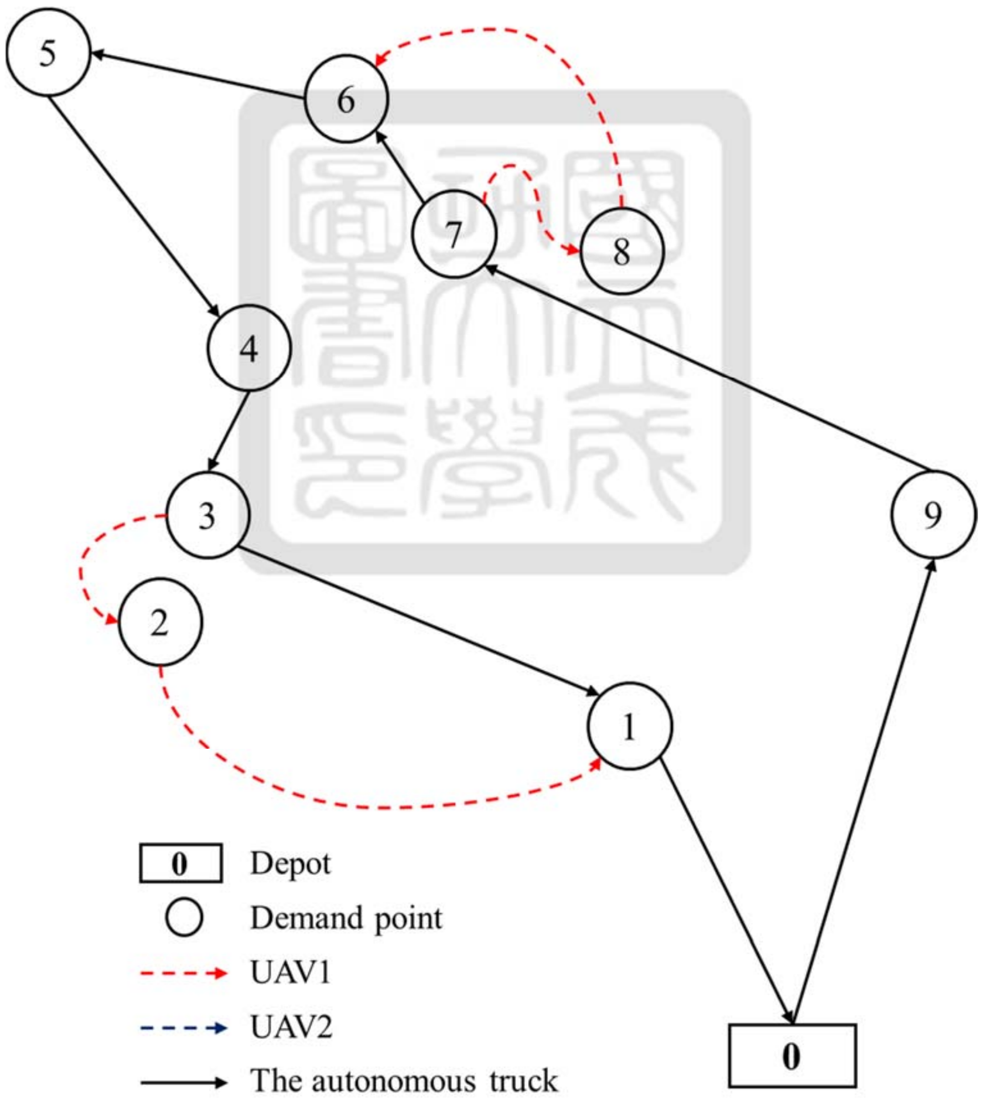



Figure 4-5 The visual results of Test Network I solving by GUROBI



doi:10.6844/NCKU202002083

### 4.4.2 Results of Test Network I Solving by Tabu Search Algorithm

Tabu search algorithm approach is tested on the test network I to solve the optimal delivery with the autonomous truck with two UAVs. The travel times matrix of the autonomous truck and the UAVs are presented in Table 4-2 and Table 4-5. Additionally, the service times of the autonomous truck and the UAVs are 30 and 60 seconds. Finally, the UAVs can reach 20 m/s and flight 200 seconds by carrying 70lbs (equals to 30 kg) medical reliefs under fixed time-based flight endurance constraint. Based on the components in the tabu search algorithm mentioned in Section 4.2, the tabu tenure, aspiration criterion, and the termination condition are set to generate a feasible solution. The termination condition is set as 200 iterations.

The results in test problem solving by tabu search are presented in Table 4-7 and visualized in Figure 4-6. In this case, the tabu search algorithm spends almost 26 seconds to generate the optimal feasible solution and the optimal delivery time in test network I is 1568.20 seconds. In Figure 4-5, the results present that the autonomous truck starts at the starting depot, node 0, and satisfies node 9, node 7; continuously, the UAV 1 is launched from the autonomous truck at node 7, travels and delivery supplies to node 8, and retrieved by the autonomous truck at node 6. After finishing the first delivery task, the autonomous truck keeps traveling to node 5, node 4 and the UAV 1 is launched from the autonomous truck at node 4, travels and delivers supplies to node 2, and retrieved by the autonomous truck at node 3. Finally, the autonomous truck by carrying two drones travel from node 3 to node 1 and back to the ending depot (node 0).



doi:10.6844/NCKU202002083

Table 4-7 The results of Test Network I solving by tabu search algorithm

| Total Runtime (seconds) | Objective Function Value | Number of UAV | Number of Customers |
|---|---|---|---|
| 26.15 | 1568.20 | 2 | 9 |
| Delivery nodes | | | |
| UAV 2 | | | |
| UAV 1 | 8  2 | | |
| The autonomous truck | Start → 9 → 7 → 6 → 5 → 4 → 3 → 1 | | |

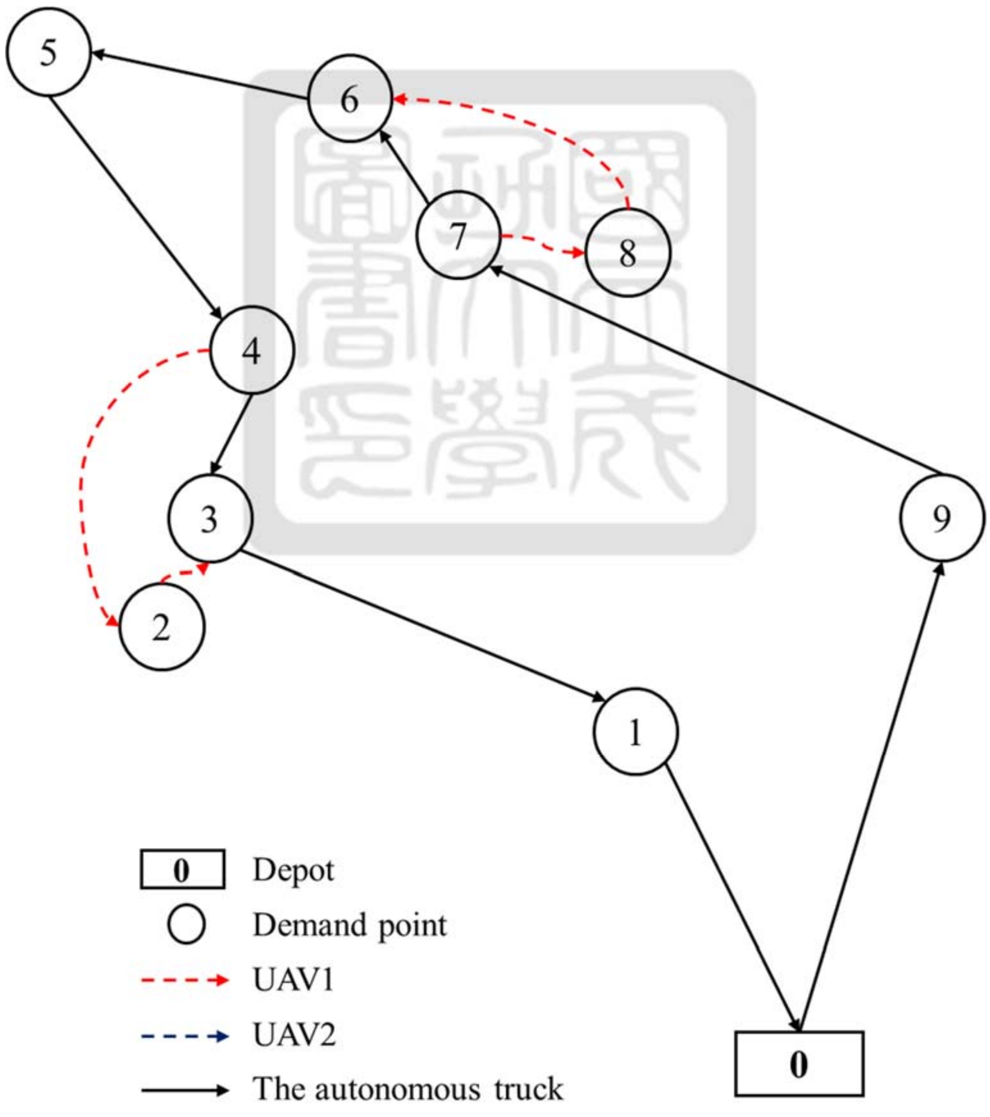



Figure 4-6 The visual results of Test Network I solving by the tabu search algorithm



doi:10.6844/NCKU202002083

### 4.4.3 Results of Test Network II Solving by GUROBI

In test network II, the travel times and speed of the autonomous truck are presented in Section 4.3.2 and the service times of the autonomous truck and the UAVs are assumed to be 30 and 60 seconds. Based on the endurance constraint of UAVs, this research set the UAV can reach 20 m/s and flight 200 seconds by carrying 70lbs (equals to 30 kg) medical reliefs. Furthermore, two drones cooperating with the autonomous truck are considered to be homogeneous to have the same maximum flight endurance. By calculating the distance matrix in Table 4-3 and the speed of the UAV. The flight constraint between nodes and nodes is presented in Table 4-8.

Table 4-8 The travel times matrix with the UAV in Test Network II (seconds)

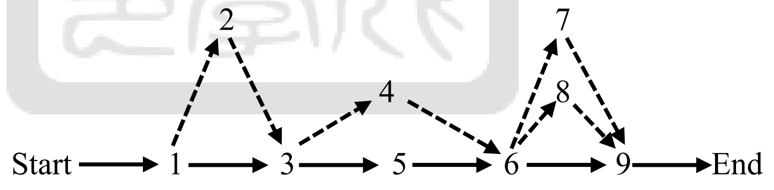
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | 90 | 102.5 | 97.5 | 105 | 90 | 67.5 | 95 | 90 | 80 |
| 1 | 90 | | 32.5 | 62.5 | 120 | 113.5 | 114 | 152.5 | 159 | 162.5 |
| 2 | 102.5 | 32.5 | | 38 | 100 | 97.5 | 105 | 142.5 | 155 | 165 |
| 3 | 97.5 | 62.5 | 38 | | 64 | 61 | 77.5 | 112.5 | 127.5 | 142.5 |
| 4 | 105 | 120 | 100 | 64 | | 12.75 | 42 | 61.5 | 82.5 | 109 |
| 5 | 90 | 113.5 | 97.5 | 61 | 12.75 | | 29.5 | 55 | 73 | 97.5 |
| 6 | 67.5 | 114 | 105 | 77.5 | 42 | 29.5 | | 38 | 50 | 70 |
| 7 | 95 | 152.5 | 142.5 | 112.5 | 61.5 | 55 | 38 | | 23.5 | 55 |
| 8 | 90 | 159 | 155 | 127.5 | 82.5 | 73 | 50 | 23.5 | | 33 |
| 9 | 80 | 162.5 | 165 | 142.5 | 109 | 97.5 | 70 | 55 | 33 | |



doi:10.6844/NCKU202002083

In test network II, the results are presented in Table 4-9 and visualized in Figure 4-6. The results describe that GUROBI spends 232 seconds to generate the optimal solution and the optimal delivery time in test network II is 747.09 seconds. In Figure 4-6, the autonomous truck starts at the starting depot, node 0, serves node 3 and the UAV 2 is launched from node 1, serves 2 and retrieved with the autonomous truck at node 3. After satisfying node 3, the autonomous truck continuously serves node 5, node 6 and the UAV 1 is simultaneously launched, serves node 4 then retrieved at node 6. At node 6, two UAVs are both launched, UAV 1 and 2 serve node 8 and node 7 then retrieved at node 9. Completing satisfying node 9, the autonomous truck by carrying two UAVs heads to the ending depot (node 0).

Table 4-9 The results of Test Network II solving by GUROBI

<table>
<tr><td>Total Runtime (seconds)</td><td>Objective Function Value</td><td>Number of UAV</td><td>Number of Customers</td></tr>
<tr><td>232.90</td><td>747.09</td><td>2</td><td>9</td></tr>
<tr><td colspan="4">Delivery nodes</td></tr>
<tr><td>UAV 2<br>UAV 1<br>The autonomous truck</td><td colspan="3">
</td></tr>
</table>



doi:10.6844/NCKU202002083

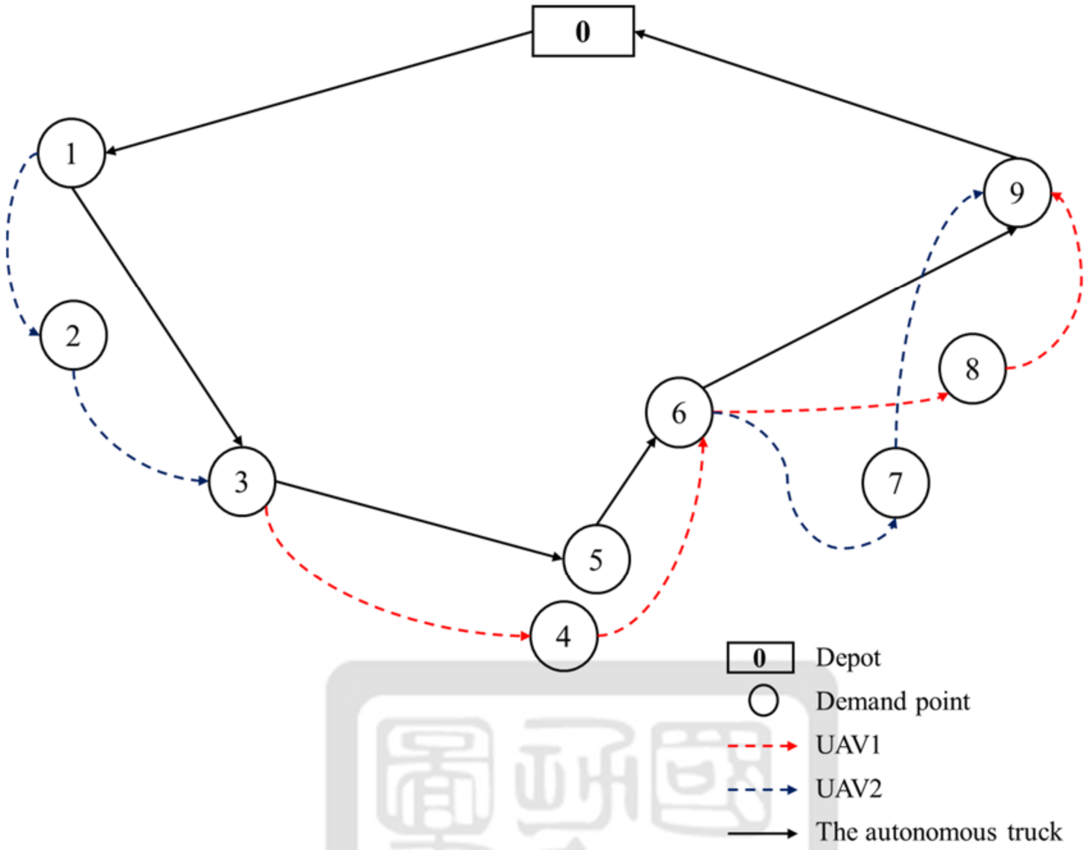



Figure 4-7 The visual results of Test Network II solving by GUROBI

### 4.4.4 Results of Test Network II Solving by Tabu Search Algorithm

In test network II, the service times of the autonomous truck and the UAVS are 30 and 60 seconds. Moreover, the UAVs can reach 20 m/s and flight 200 seconds by carrying 70lbs (equals to 30 kg) medical reliefs under fixed time-based flight endurance constraint. The travel times matrix of the autonomous truck and the UAVs are presented in Table 4-2 and Table 4-6. Based on the components in the tabu search algorithm mentioned in Section 4.2, the tabu tenure, aspiration criterion, and the termination condition are set to generate a feasible solution. The termination condition is set as 200 iterations.

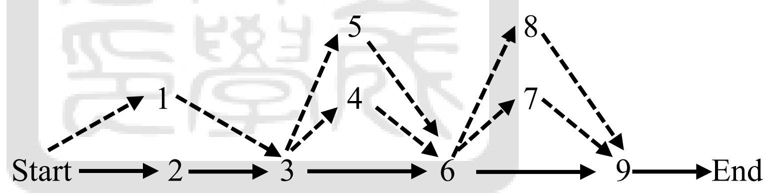
The results in test network II solving by tabu search are presented in Table 4-10 and visualized in Figure 4-7. In this instance, the tabu search algorithm spends almost 3.23 seconds to generate the optimal feasible solution and the optimal delivery time in test



doi:10.6844/NCKU202002083

network II is 765.71 seconds. In Figure 4-7, the results present that the autonomous truck starts at the starting depot, node 0 and satisfies node 2, node 3. At the starting depot, the UAV 1 is launched, serves node1 and retrieved with the autonomous truck at node 3. At node 3, two UAVs are both launched, UAV 1 and 2 serve node 4 and node 5 then retrieved at node 6. Completing satisfying node 6 by the autonomous truck, two UAVs are continuously launched at node 6, UAV 1 and 2 serve node 7 and node 8 then retrieved at node 9. Finishing completing serving node 9, the autonomous truck by carrying two UAVs travels back to the ending depot (node 0).

Table 4-10 The results of Test Network II solving by tabu search algorithm

| Total Runtime (seconds) | Objective Function Value | Number of UAV | Number of Customers |
|---|---|---|---|
| 3.23 | 765.71 | 2 | 9 |
| Delivery nodes | | | |
| UAV 2<br>UAV 1<br>The autonomous truck |  | | |





doi:10.6844/NCKU202002083

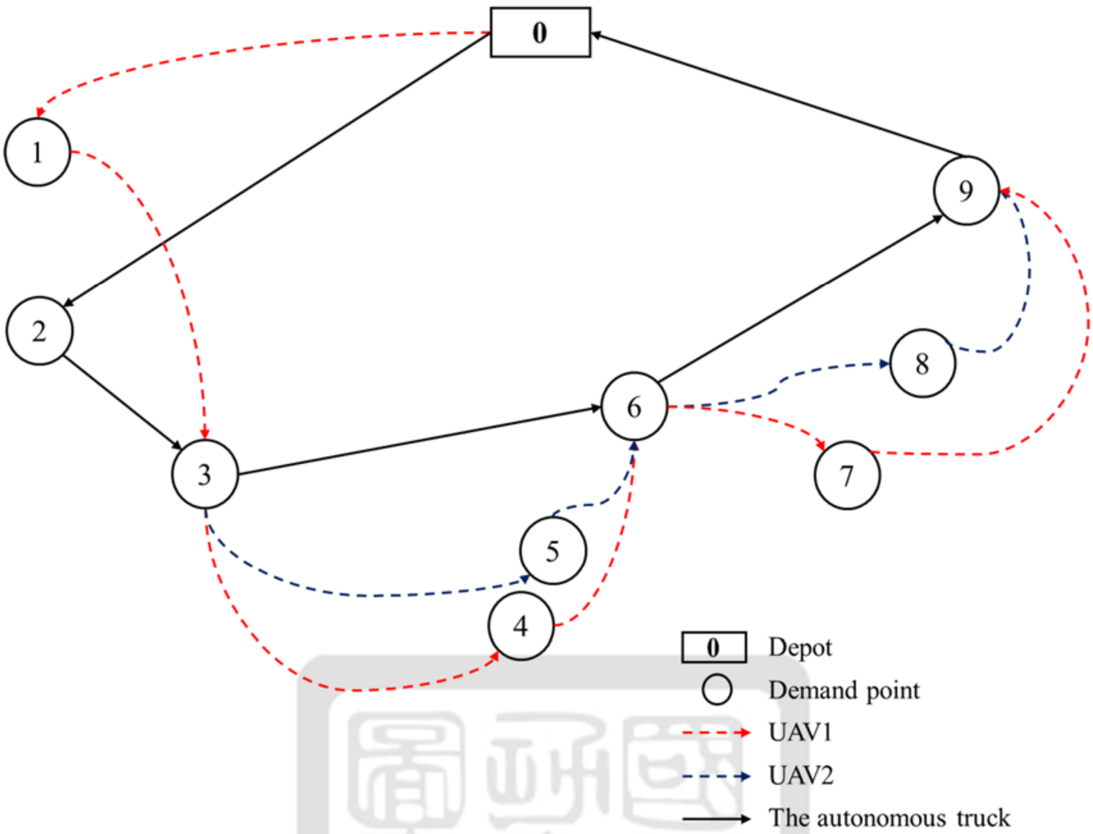



Figure 4-8 The visual results of Test Network II solving by the tabu search algorithm

## 4.5 Summary

In the test of the mathematical model, the service times of the autonomous truck and the UAVs are assumed to be 30 and 60 seconds. The fixed time-based flight endurance is 200 seconds and can reach 20 m/s. The termination condition of the tabu search is set as 200 iterations.

In Table 4-11, the results of the test network I and test network II by GUROBI and tabu search is presented. In terms of objective function value, the gap with GUROBI in test network I and test network II are within 8% and 3%. On the other hand, the runtime comparing with GUROBI are improved a lot by tabu search. In conclusion, the tabu search solution algorithm can generate the best feasible solutions in less runtime comparing with GUROBI.



doi:10.6844/NCKU202002083

Table 4-11 Results of test network I and test network II

| Solution Algorithm | Runtime (Seconds) | Obj. (Seconds) | Routes of the autonomous truck | Routes of UAV 1 | Routes of UAV 2 |
|---|---|---|---|---|---|
| Test Network I | | | | | |
| GUROBI | 79.36 | 1463.84 | (0,9,7,6,5,4,3,1,0) | (7,8,6)(3,2,1) | |
| Tabu search | 26.15 | 1568.20 | (0,9,7,6,5,4,3,1,0) | (7,8,6)(4,2,3) | |
| Test Network II | | | | | |
| GUROBI | 232.90 | 747.09 | (0,1,3,5,6,9,0) | (3,4,6)(6,8,9) | (1,2,3) (6,7,9) |
| Tabu search | 3.23 | 765.71 | (0,2,3,6,9,0) | (0,1,3)(3,4,6) (6,7,9) | (3,5,6) (6,8,9) |



doi:10.6844/NCKU202002083

# CHAPTER 5 EMPIRICAL STUDY

After constructing the small-scale test network instances, this research designs the empirical experimental network, Kaoshiung City, in Chapter 5. Section 5.1 discusses the experimental design, including experimental network, design, setup, and process. Section 5.2 introduces an empirical network with three various numbers of demand points. Section 5.3 presents the results of the empirical network in different amounts of demand points. Section 5.4 summarizes Chapter 5 by providing the results of the analysis.

## 5.1 Experimental Design and Setup

To develop an actual network for optimal delivery problems concerning minimal travel times, this section describes the empirical experimental network in Kaoshiung City. The basic data of the experimental network and the settings related to the model such as the fixed time-based flight endurance of UAVs are described in this section. Finally, the results of the optimal delivery with the autonomous truck and two UAVs solving by tabu search algorithm is presented as followed in Section 5.3.

### 5.1.1 Experimental Design

In this research, three random various test instances are used for testing purposes. Different test instances established on the empirical network, Kaoshiung City, include 20, 30 and 40 nodes.

The demand point nodes in the empirical study are randomly generated, and the detailed setting is further discussed in Section 5.2.

On the other hand, the most important element in this research is the travel times related to the autonomous truck and two UAVs. However, it is difficult to set the distances and the



doi:10.6844/NCKU202002083

speed between nodes properly. In this case, the San-min District of Kaoshiung City shown in Figure 5-1 with real geometric data is adopted. The characteristics of arcs between nodes and nodes are determined by DynaTAIWAN simulation software. DynaTAIWAN (Dynamic Traffic Assignment and Information in Wide Area Network) is structured based on the notion of the simulation-assignment method (Jayakrishnan et al, 1994; Mahmassani et al., 1994). DynaTAIWAN simulation software considers theoretical foundations and implements the system based on the software development process, including mesoscopic mixed traffic flow mode, driving decision behavior, traffic control strategy, simulation method, and dynamic traffic assignment. The major characteristics of DynaTAIWAN are to reflect the impact on a traffic network for motorcycles in Taiwan. As shown in Figure 5-2, the conceptual framework of DynaTAIWAN based on mixed traffic flow and driving behavior in Taiwan can develop multiple simulation scenarios such as simulation of event impact, simulation analysis of electronic toll collection, activities impact analysis, dynamic route guide, multiple vehicle types analysis, vehicle routing problem (VRP), and bus, light rail transit (LRT), mass rapid transit (MRT) exclusive lane. In conclusion, the range of the empirical network, San-min District of Kaoshiung City in this research is 19.79$km^2$, consisting of 132 nodes and 363 arcs. Additionally, the empirical network with three different amounts of nodes is used for testing purposes.



doi:10.6844/NCKU202002083

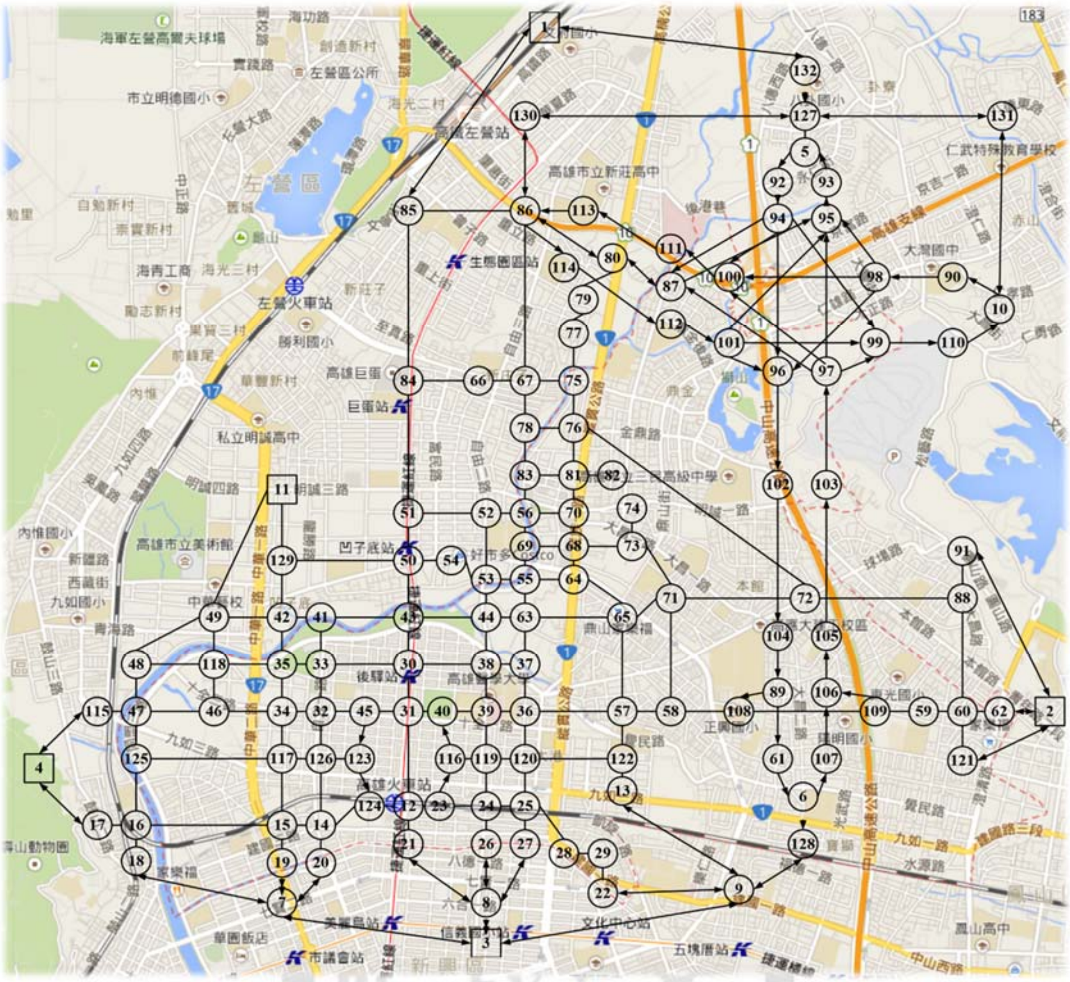


Figure 5-1 The San-min District network of Kaoshiung City

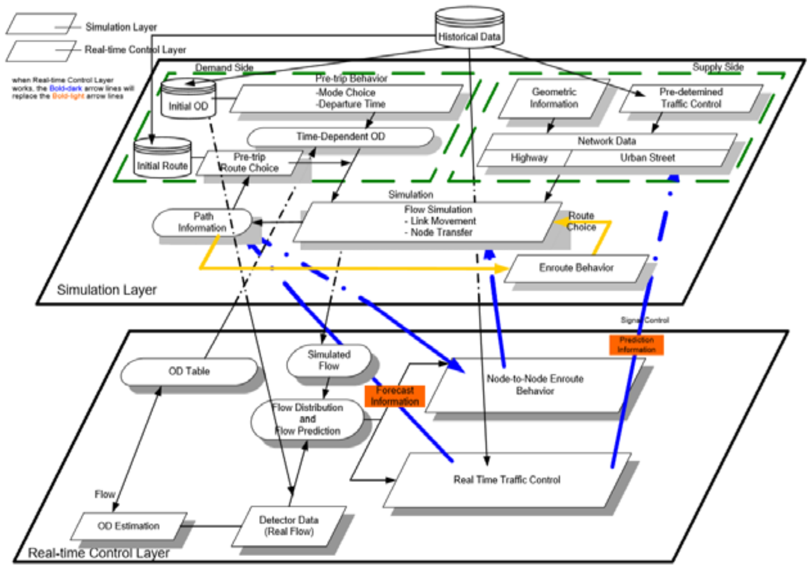



Figure 5-2 The conceptual framework of DynaTAIWAN

(Source: Hu et al., 2005)



doi:10.6844/NCKU202002083

### 5.1.2 Experimental Setup

In terms of the length between nodes and nodes, this research applies the Dijkstra algorithm to reach the shortest path and continuously builds the distance matrix. Dijkstra algorithm is described as follow:

Step 1: Assign to every node a tentative distance value. Set the distance value of the initial node to zero and the distance value of all other nodes to infinity.

Step 2: Generate a set of visited nodes with just the initial node and unvisited set with all nodes without the initial node.

Step 3: For the initial node or current node, consider all its unvisited neighbors and calculate the distance (distance to the current node and distance from the current node to the neighbor). If the calculated distance is less than their current tentative distance, replace it with this new distance.

Step 4: While the process has done considering neighbors of the current node, put the current node into the visited set and remove it from the unvisited set.

Step 5: If the destination node has been put into the visited set, the algorithm has finished. If not, go to step 6.

Step 6: Set the unvisited node marked with the smallest tentative distance as the next current node and go back to step 3.

After the procedure to calculate the shortest path, the distance matrix is generated by the Dijkstra algorithm.

In terms of empirical network, the starting depot and the ending depot are set as the same. And the demand point nodes are randomly generated from 132 nodes without repetition.

In terms of input data, Table 5-1 provides the design of an empirical network with three



doi:10.6844/NCKU202002083

types of amounts of demand point nodes instance. The speed of the autonomous truck is 14 m/s (equals to 50 kph). Under fixed time-based flight endurance constraint, the UAVs reaches 20 m/s (equals to 72 kph). Secondly, the service times of the autonomous truck and the UAVs are 30 and 60 seconds. Based on the test problem in the empirical network, the fixed time-based flight endurance is set in different scenarios that are 400, 800 seconds. Moreover, the termination condition is set in 200 iterations. And all the experiments are conducted on a Windows 10 machine (Intel(R) Core (TM) i5-8250U/ 1.80GHz processor with 8GB RAM).

Table 5-1 The parameters setting

| Notation | Value |
|---|---|
| Speed of the autonomous truck | 14 m/s |
| Speed of the UAVs | 20 m/s |
| Service time of the autonomous truck | 30 |
| Service time of the UAVs | 60 |

## 5.2 Empirical Experiments

As the input data and settings are described in experimental design and setup in Section 5.1. This section further discusses the experimental network with 20, 30, and 40 nodes.

### 5.2.1 Empirical Instance with 20 Nodes

The 20 nodes are randomly selected for testing purposes. As presented in Figure 5-3, one depot and 19 demand point nodes are included in the empirical network.

The round symbols in black are represented as the demand point nodes and the square symbol in black is represented as the starting depot and ending depot.



doi:10.6844/NCKU202002083

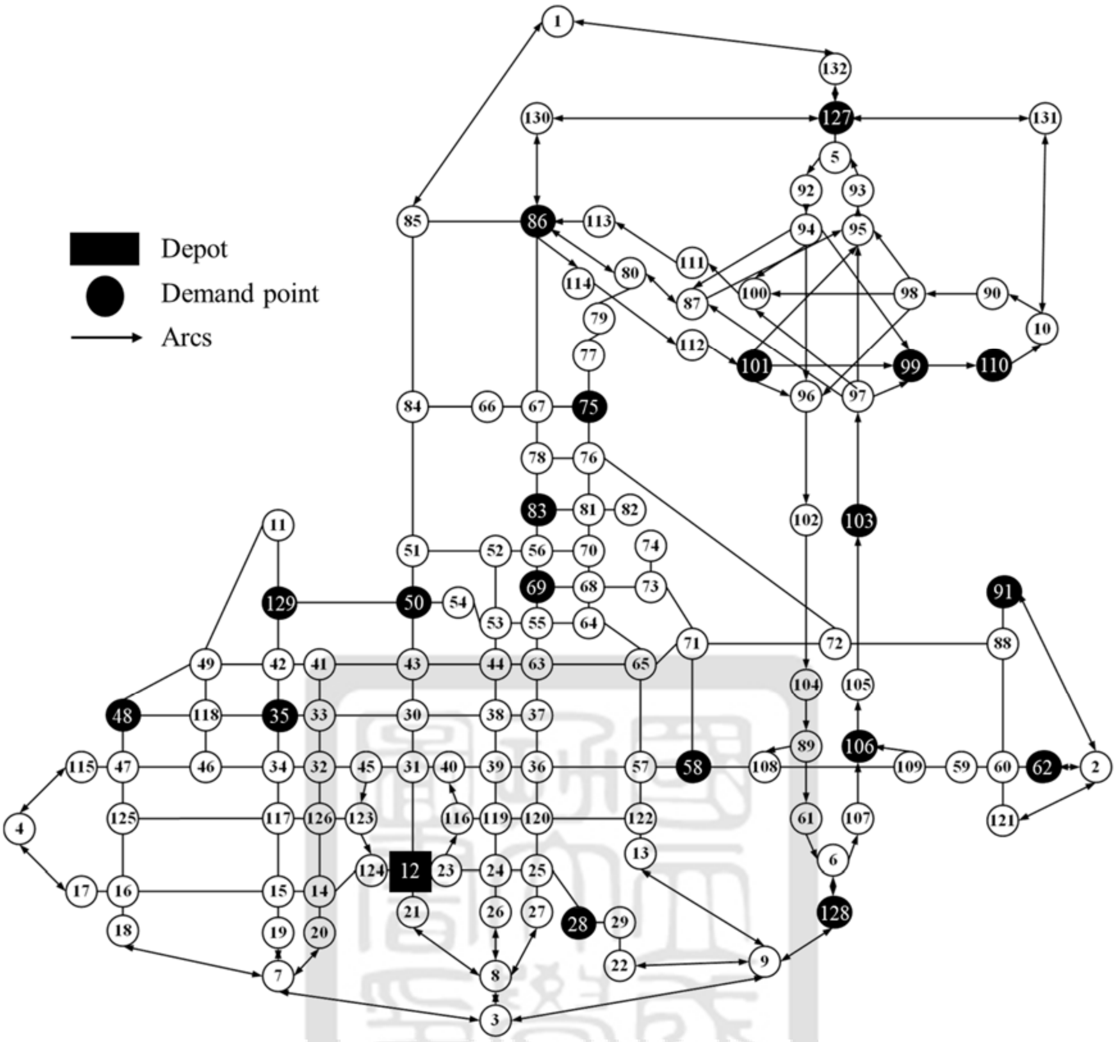



Figure 5-3 Experimental instances with twenty nodes in the empirical network



doi:10.6844/NCKU202002083

### 5.2.2 Empirical Instance with 30 Nodes

The 30 nodes are randomly selected for testing purposes. As presented in Figure 5-4, one depot and 29 demand point nodes are included in the empirical network.

The round symbols in black are represented as the demand point nodes and the square symbol in black is represented as the starting depot and ending depot.

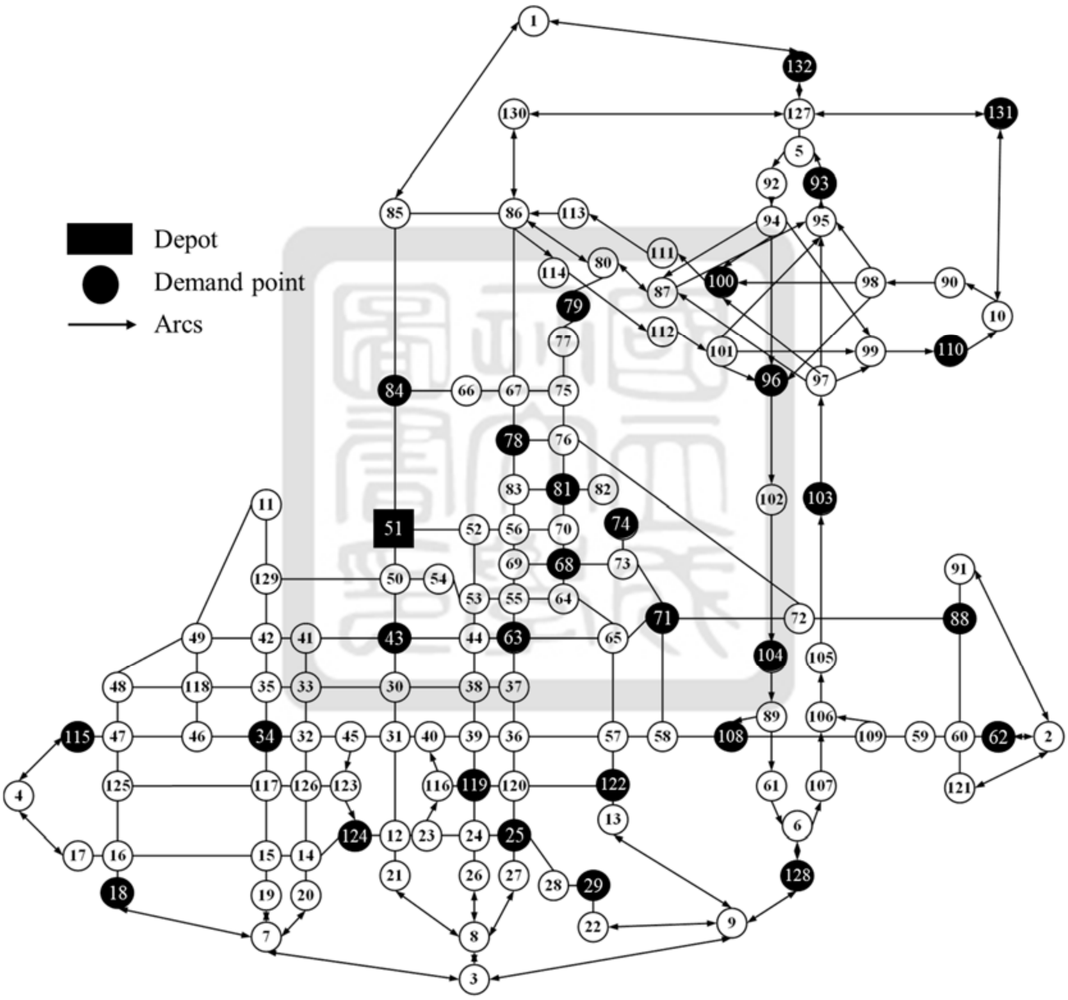



Figure 5-4 Experimental instances with twenty-nine nodes in the empirical network



doi:10.6844/NCKU202002083

### 5.2.3 Empirical Instance with 40 Nodes

The 40 nodes are randomly selected for testing purposes. As presented in Figure 5-5, one depot and 39 demand point nodes are included in the empirical network.

The round symbols in black are represented as the demand point nodes and the square symbol in black is represented as the starting depot and ending depot.

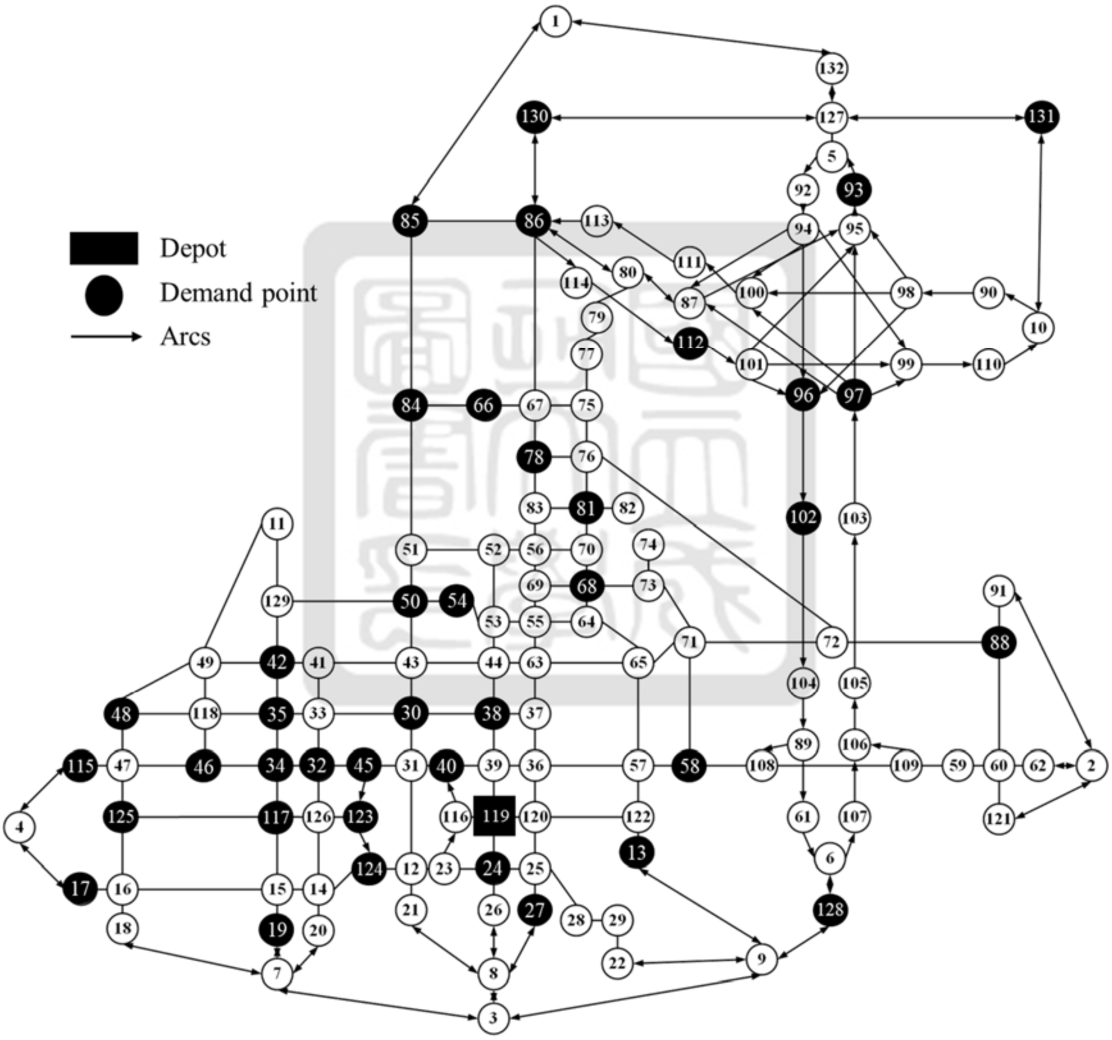



Figure 5-5 Experimental instances with thirty-nine nodes in the empirical network



doi:10.6844/NCKU202002083

## 5.3 Results of Experimental Network

This research executes the tabu search algorithm with parameters based on the experimental setup in Section 5.1. Given 20, 30, 40 nodes and the empirical network with travel times, the results of the optimal route in delivering supplies by the autonomous truck with two drones are presented. The optimal routes related to the different number of nodes and fixed time-based flight endurance and objective function value which is the total travel times are listed in Table 5-2.

Table 5-2 Optimal delivery routes of empirical network

| Number of nodes | Flight endurance ($e_{vijk}$) | Termination condition (iterations) | Objective function value [hr:min:sec] | Total runtime [seconds] | The optimal route |
|---|---|---|---|---|---|
| 20 | 400 | 200 | 00:48:71 | 9 | **The autonomous truck**<br>[12,110,103,129,69,106,62,127,91,86,99,50,12]<br>**UAV1**<br>[(12,128,110),(110,28,129),(69,75,106),(106,58,62)(91,83,86)]<br>**UAV 2**<br>[(12,48,129),(110,101,62),(62,35,50)] |
| | 800 | 200 | 00:39:19 | 42 | **The autonomous truck**<br>[12,58,62,91,127,110,86,69,48,129,12]<br>**UAV 1**<br>[(12,28,58),(62,103,91),(110,101,86),(86,75,69),(69,50,48)] |



doi:10.6844/NCKU202002083

| | | | | | |
|---|---|---|---|---|---|
| | | | | | **UAV 2**<br>[(12,106,58),(91,128,127),(110,99,86),(86,83,69),(69,35,48)] |
| 30 | 400 | 200 | 01:26:24 | 537 | **The autonomous truck**<br>[51,96,68,110,103,88,124,122,79,119,115,63,25,128,18,29,51]<br>**UAV 1**<br>[(51,78,96),(96,71,68),(68,62,88),(88,131,124),(124,104,122),(122,81,79),(79,93,119),(25,84,29)]<br>**UAV 2**<br>[(68,74,88),(124,100,122),(122,132,79),(79,34,119),(115,43,63),(25,108,29)] |
| | 800 | 200 | 01:19:91 | 106 | **The autonomous truck**<br>[51,96,25,29,84,124,88,71,68,78,63,119,128,108,115,51]<br>**UAV 1**<br>[(51,79,96),(96,100,124),(124,103,88),(88,81,71),(63,43,119),( 119,18,128),(128,110,108),(108,132,115)]<br>**UAV 2**<br>[(51,131,96),(124,122,88),(88,74,71),(63,93,119),(119,34,128),(128,104,108),(108,62,115)] |



doi:10.6844/NCKU202002083

| | | | | | |
|---|---|---|---|---|---|
| 40 | 400 | 200 | 01:45:65 | 1131 | **The autonomous truck**<br>[119,35,40,88,130,128,117,17,38,84,66,85,<br>19,112,32,48,115,97,102,96,78,68,24,119]<br>**UAV 1**<br>[(119,42,35),(40,30,88),(88,86,130),(128,34,117),<br>(38,50,84),(66,27,19),(19,58,112),(112,46,32),<br>(97,131,78),(78,125,68)]<br>**UAV 2**<br>[(88,13,130),(117,93,85),(85,123,19),(19,54,32),<br>(115,124,78),(78,81,68),(68,45,24)] |
| | 800 | 200 | 01:30:93 | 594 | **The autonomous truck**<br>[119,35,66,81,45,58,86,97,130,17,<br>54,13,38,30,42,50,34,84,124,123,119]<br>**UAV 1**<br>[(119,48,35),(81,27,45),(58,46,86),(86,102,97),<br>(130,131,17),(54,112,13),(13,32,38),<br>(38,19,30),(50,24,34),(34,68,84),(84,93,124)]<br>**UAV 2**<br>[(81,115,45),(58,85,86),(86,117,97),<br>(130,128,17),(17,40,54),(54,88,13),<br>(13,125,38),(34,78,84,),(84,96,124)] |



doi:10.6844/NCKU202002083

In terms of the fixed time-based flight endurance, as expected, different flight endurance setting produces different objective function values for the empirical study. The UAVs can satisfy the demand points which is far away in larger flight endurance.

As shown in Table 5-3, while the flight endurance is larger, the UAVs serve the demand points farther. However, the degree of difference is not quite large. Refer to the empirical network, Kaoshiung city, the distance between some demand points is short which means the UAVs in 400 seconds endurance can serve most of the demand points, in this case, the benefits that adopting high-level UAVs which is in 800 seconds endurance is less.

Table 5-3 The number of nodes satisfied by various vehicles

| Number of nodes | Flight endurance ($e_{vijk}$) | Satisfied by the autonomous truck | Satisfied by the UAVs | Satisfied by the UAV 1 | Satisfied by the UAV 2 |
|---|---|---|---|---|---|
| 20 | 400 | 11 | 8 | 5 | 3 |
| | 800 | 9 | 10 | 5 | 5 |
| 30 | 400 | 15 | 14 | 8 | 6 |
| | 800 | 14 | 15 | 8 | 7 |
| 40 | 400 | 22 | 17 | 10 | 7 |
| | 800 | 19 | 20 | 11 | 9 |



doi:10.6844/NCKU202002083

In terms of the different number of demand points, the convergence in various flight endurance is presented in Figure 5-6, Figure 5-7, and Figure 5-8. The results of convergence show while setting the termination condition as 200 iterations, the tabu search algorithm continued searching for better solutions and finally find the solution which is minimized travel times.

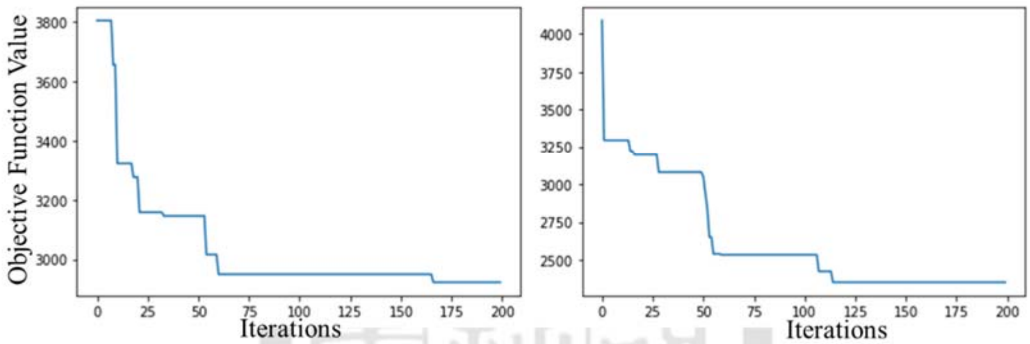



Figure 5-6 Convergence of 20 nodes with 400 and 800 endurance in 200 iterations

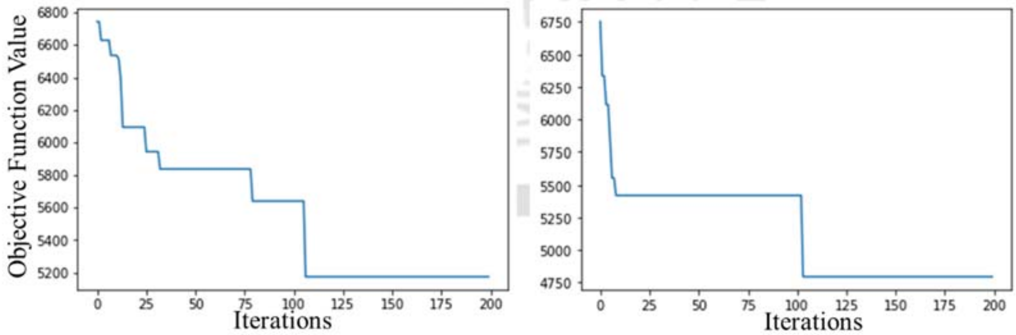
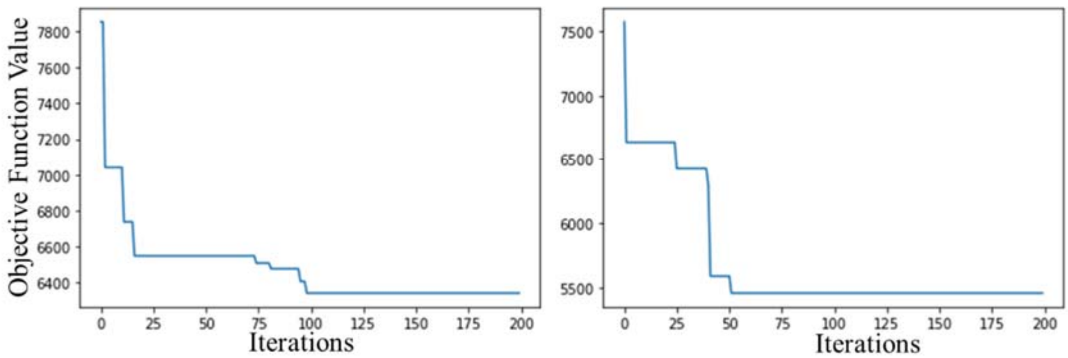



Figure 5-7 Convergence of 30 nodes with 400 and 800 endurance in 200 iterations






doi:10.6844/NCKU202002083

Figure 5-8 Convergence of 40 nodes with 400 and 800 endurance in 200 iterations

As shown in Table 5-4, the results of empirical experiments are compared with TSP solutions. Table 5-4 summarizes the total travel times and percentage improvement over TSP solutions in empirical networks with 20, 30, 40 nodes and various flight endurance. In terms of flight endurance, the improvement rate over TSP in higher flight endurance is better than the lower one in 20, 30, 40 nodes network. However, in 30 and 40 nodes network, the improvement rate is presented as a non-increasing behavior. This research summarizes and suggests two possible explanations. First, the heuristic algorithm is probably not providing near-optimal solutions for larger empirical networks. Nevertheless, there is no existing method to assess the optimal gap for the Multiple Flying Sidekick Traveling Salesman Problem (mFSTSP). Secondly, in terms of the coordination with the autonomous truck and two UAVs. While the UAV is going to merge with the autonomous truck, different vehicles must wait for each other. Additionally, in 40 nodes network, the density of demand points increases and the distance between nodes and nodes become shorter. In this case, it is less beneficial to deploy UAVs. In conclusion, two factors diminish the rates of improvement as the demand points are increasing. However, the results indicate that higher flight endurance leads to a reduction of total travel times comparing with the lower flight endurance.



doi:10.6844/NCKU202002083

Table 5-4 Comparison of travel times between FSTSP and TSP problems

| Number of nodes | Flight endurance ($e_{vijk}$) | FSTSP problem (The autonomous truck and two UAVs) [hr:min:sec] | TSP problem (Only truck) [hr:min:sec] | Improvement rate over TSP problem [%] |
|---|---|---|---|---|
| 20 | 400 | 00:48:71 | 01:00:14 | 18.3 |
| | 800 | 00:39:19 | 01:00:14 | 34.7 |
| 30 | 400 | 01:26:24 | 01:29:03 | 3.0 |
| | 800 | 01:19:91 | 01:29:03 | 9.6 |
| 40 | 400 | 01:45:65 | 01:27:19 | -21.5 |
| | 800 | 01:30:93 | 01:27:19 | -4.8 |

## 5.4 Summary

In empirical experiments, this research discusses the empirical network, Kaoshiung City. Additionally, in terms of NP-Hard problems in Flying Sidekick Traveling Salesman Problem, the optimal delivery problems with the autonomous truck and two UAVs in various flight endurance are solved by the tabu search algorithm.

Based on the results, this research presents the related data in optimal delivery routes of the empirical network including the total runtime of the program, optimal routes divided by the autonomous truck and two drones, the convergence of the solutions, and the minimized travel times which is an objective function value. This research further discusses that flight endurance impacts objection function value. Besides, due to the inability of GUROBI to generate optimal solutions for large-scale problems within reasonable runtime, there is no benchmark comparing to the total runtime of the program of the tabu search algorithm.



doi:10.6844/NCKU202002083

# CHAPTER 6 CONCLUSIONS AND SUGGESTIONS

This research develops a tabu search algorithm to solve the delivery problem with the autonomous truck and UAVs in an emergency within the least amount of time. The conclusions and suggestions are summarized in Section 6.1 and Section 6.2.

## 6.1 Conclusions

This research develops a model applying the autonomous truck and the UAVs to deliver medical reliefs in an emergency. Based on the conception of the mathematical model and the results of the empirical study, the conclusions of this research are summarized as follows:

1. This research executes a model for a variant of traveling salesman problem. The problem of optimal delivery with the autonomous truck and drones is introduced and formulated by the mathematical model and the definitions of the problem statement.
2. This research develops a tabu search algorithm to enhance the efficiency and response quickly on the route assignment to demand points that need reliefs and resources adopting the autonomous truck with drones in an emergency. By discussing the basic components of the tabu search, the heuristic algorithm is proposed to solve the problem efficiently.
3. This research constructs the practical network which is Kaoshiung City and adopts a tabu search algorithm to find the solutions in different flight endurance related to drones.
4. The results within reasonable runtime and the optimal delivery routes are generated by the tabu search algorithm.



doi:10.6844/NCKU202002083

## 6.2 Suggestions

The suggestions for future study on optimal delivery of the autonomous truck and the drones in an emergency are summarized as follows:

1. In this research, the mathematic model is provided and allows one autonomous truck and two drones to serve demand points. However, the problem can be extended to allow more autonomous trucks carrying three to six drones to compare the efficiency of delivery tasks in the different number of vehicles.
2. In this research, the problem is defined as Flying Sidekick Traveling Salesman Problem which means the UAVs cannot travel to demand points from and back to the depot directly. In the future, the problem might be a mixed problem that the drones can satisfy the demand points nearby the depot and simultaneously sending vehicles by carrying drones to serve the demand points far away.
3. This research assumes that the performance of the drones are analogs and the demand point can be satisfied without considering the capacity limitations of drones. It is worthy to mention if the drones should be heterogeneous in a fleet to be realistic in a real situation.
4. This research applies an empirical network, San-min District in Kaoshiung City. The area of the empirical network is $19.79 km^2$, consisting of 132 nodes and 363 arcs. However, the ability of UAVs such as velocity and battery constraints are becoming better and better. It is necessarily applying a larger network to highlight the importance of the UAVs in FSTSP.



doi:10.6844/NCKU202002083

# REFERENCE


Agatz, N., Bouman, P., & Schmidt, M. (2018). Optimization approaches for the traveling salesman problem with drone. *Transportation Science, 52*(4), 965-981.

Archetti, C., Fernández, E., & Huerta-Muñoz, D. L. (2017). The flexible periodic vehicle routing problem. *Computers & Operations Research, 85*, 58-70.

Belgin, O., Karaoglan, I., & Altiparmak, F. (2018). Two-echelon vehicle routing problem with simultaneous pickup and delivery: Mathematical model and heuristic approach. *Computers & Industrial Engineering, 115*, 1-16.

Bortfeldt, A., Hahn, T., Männel, D., & Mönch, L. (2015). Hybrid algorithms for the vehicle routing problem with clustered backhauls and 3D loading constraints. *European Journal of Operational Research, 243*(1), 82-96.

Braekers, K., Ramaekers, K., & Van Nieuwenhuyse, I. (2016). The vehicle routing problem: State of the art classification and review. *Computers & Industrial Engineering, 99*, 300-313.

Burer, S., & Letchford, A. N. (2012). Non-convex mixed-integer nonlinear programming: A survey. *Surveys in Operations Research and Management Science, 17*(2), 97-106.

Campbell, A. M., & Wilson, J. H. (2014). Forty years of periodic vehicle routing. *Networks, 63*(1), 2-15.

Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science, 6*(1), 80-91.

de Freitas, J. C., & Penna, P. H. V. (2018). A Randomized Variable Neighborhood Descent Heuristic to Solve the Flying Sidekick Traveling Salesman Problem. *Electronic Notes in Discrete Mathematics, 66*, 95-102.

Desrochers, M., & Laporte, G. (1991). Improvements and extensions to the Miller-Tucker-Zemlin subtour elimination constraints. *Operations Research Letters, 10*(1), 27-36.

Erdoğan, S., & Miller-Hooks, E. (2012). A green vehicle routing problem. *Transportation Research Part E: Logistics and Transportation Review, 48*(1), 100-114.

Estrada, M. A. R., & Ndoma, A. (2019). The uses of unmanned aerial vehicles–UAV's-(or drones) in social logistic: Natural disasters response and humanitarian relief aid. *Procedia Computer Science, 149*, 375-383.

García-Nájera, A., Bullinaria, J. A., & Gutiérrez-Andrade, M. A. (2015). An evolutionary approach for multi-objective vehicle routing problems with backhauls. *Computers & Industrial Engineering, 81*, 90-108.

Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Computers & Operations Research, 13*(5), 533-549.




doi:10.6844/NCKU202002083

Glover, F. (1990). Tabu search: A tutorial. *Interfaces, 20*(4), 74-94.

Goel, A., & Gruhn, V. (2008). A general vehicle routing problem. *European Journal of Operational Research, 191*(3), 650-660.

Gribkovskaia, I., Laporte, G., & Shyshou, A. (2008). The single vehicle routing problem with deliveries and selective pickups. *Computers & Operations Research, 35*(9), 2908-2924.

Ha, Q. M., Deville, Y., Pham, Q. D., & Ha, M. H. (2018). On the min-cost traveling salesman problem with drone. *Transportation Research Part C: Emerging Technologies, 86*, 597-621.

Huang, Y., Zhao, L., Van Woensel, T., & Gross, J.-P. (2017). Time-dependent vehicle routing problem with path flexibility. *Transportation Research Part B: Methodological, 95*, 169-195.

Joerss, M., Schröder, J., Neuhaus, F., Klink, C., & Mann, F. (2016). Parcel delivery: The future of last mile. *McKinsey & Company*.

Khademi, N., Balaei, B., Shahri, M., Mirzaei, M., Sarrafi, B., Zahabiun, M., & Mohaymany, A. S. (2015). Transportation network vulnerability analysis for the case of a catastrophic earthquake. *International journal of disaster risk reduction, 12*, 234-254.

Koç, Ç., & Laporte, G. (2018). Vehicle routing with backhauls: Review and research perspectives. *Computers & Operations Research, 91*, 79-91.

Lahyani, R., Coelho, L. C., & Renaud, J. (2018). Alternative formulations and improved bounds for the multi-depot fleet size and mix vehicle routing problem. *OR Spectrum, 40*(1), 125-157.

Lahyani, R., Khemakhem, M., & Semet, F. (2015). Rich vehicle routing problems: From a taxonomy to a definition. *European Journal of Operational Research, 241*(1), 1-14.

Li, H., Lv, T., & Lu, Y. (2016). The combination truck routing problem: a survey. *Procedia engineering, 137*, 639-648.

Lin, C., Choy, K. L., Ho, G. T., Chung, S. H., & Lam, H. (2014). Survey of green vehicle routing problem: past and future trends. *Expert systems with applications, 41*(4), 1118-1138.

Maden, W., Eglese, R., & Black, D. (2010). Vehicle routing and scheduling with time-varying data: A case study. *Journal of the Operational Research Society, 61*(3), 515-522.

Marinakis, Y., & Marinaki, M. (2014). A bumble bees mating optimization algorithm for the open vehicle routing problem. *Swarm and Evolutionary Computation, 15*, 80-94.

Montoya-Torres, J. R., Franco, J. L., Isaza, S. N., Jiménez, H. F., & Herazo-Padilla, N. (2015). A literature review on the vehicle routing problem with multiple depots. *Computers & Industrial Engineering, 79*, 115-129.



doi:10.6844/NCKU202002083

Murray, C. C., & Chu, A. G. (2015). The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery. *Transportation Research Part C: Emerging Technologies, 54*, 86-109.

Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research, 225*(1), 1-11.

Rosenfeld, A. (2019). Are drivers ready for traffic enforcement drones? *Accident Analysis & Prevention, 122*, 199-206.

Wang, X., Poikonen, S., & Golden, B. (2017). The vehicle routing problem with drones: several worst-case results. *Optimization Letters, 11*(4), 679-697.

Watkins, S., Burry, J., Mohamed, A., Marino, M., Prudden, S., Fisher, A., . . . Clothier, R. (2019). Ten questions concerning the use of drones in urban environments. *Building and Environment*, 106458.

Yurek, E. E., & Ozmutlu, H. C. (2018). A decomposition-based iterative optimization algorithm for traveling salesman problem with drone. *Transportation Research Part C: Emerging Technologies, 91*, 249-262.



doi:10.6844/NCKU202002083