Service network design for emerging modes in air transport: autonomous airport inter-terminal bus shuttle and air metro

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Service network design for emerging modes in air transport: autonomous airport inter-terminal bus shuttle and air metro

Runqing Zhao

A thesis in fulfilment of the requirements for the degree of Master of Science (Research)

School of Aviation
Faculty of Science
The University of New South Wales

February 2022
Emerging modes of air transport such as autonomous airport shuttle and air taxi are potentially efficient alternatives to current transport practices such as bus and train. This thesis examines bus shuttle service within an airport and air metro as two examples of network design. Within an airport, the bus shuttle serves passengers between the terminals, train stations, parking lots, hotels, and shopping areas. Air metro is a type of pre-planned service in urban air mobility that accommodates passengers for intra- or inter-city trips. The problems are to optimise the service, and the outputs including the optimal fleet size, dispatch pattern and schedule. Based on the proposed time-space networks, the service network design problems are formulated as mixed integer linear programs. The heterogeneous multi-type bus fleet case and stochastic demand case are extended for the airport shuttle case, while a rolling horizon optimisation is adopted for the air metro case.

In the autonomous airport inter-terminal bus shuttle case, a Monte Carlo simulation-based approach is proposed to solve the case with demand stochasticity, which is then further embedded into an “effective” passenger demand framework. The “effective” demand is the summation of mean demand value and a safety margin. By comparing the proposed airport shuttle service to the current one, it is found that the proposed service can save approximately 27% of the total system cost. The results for stochastic problem suggest estimating the safety margin to be 0.3675 times of the standard deviation brings the best performance. For the second case, the service network design is extended with a pilot scheduling layer and simulation is undertaken to compare the autonomous (pilot-less) and piloted service design. The results suggest that an autonomous air metro service would be preferable if the price of an autonomous VTOL is less than 1.6 times the price of a human-driven one. The results for rolling horizon optimisation suggest to confirm the actual demand at least 45 minutes prior to departure. Based on data from the Sydney (Australia) region, the thesis provides information directly relevant for the service network design of emerging modes of air transport in the city.

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Abstract

Emerging modes of air transport such as autonomous airport shuttle and air taxi are potentially efficient alternatives to current transport practices such as bus and train. This thesis examines bus shuttle service within an airport and air metro as two examples of network design. Within an airport, the bus shuttle serves passengers between the terminals, train stations, parking lots, hotels, and shopping areas. Air metro is a type of pre-planned service in urban air mobility that accommodates passengers for intra- or inter-city trips. The problems are to optimise the service, and the outputs including the optimal fleet size, dispatch pattern and schedule. Based on the proposed time-space networks, the service network design problems are formulated as mixed integer linear programs. The heterogeneous multi-type bus fleet case and stochastic demand case are extended for the airport shuttle case, while a rolling horizon optimisation is adopted for the air metro case.

In the autonomous airport inter-terminal bus shuttle case, a Monte Carlo simulation-based approach is proposed to solve the case with demand stochasticity, which is then further embedded into an “effective” passenger demand framework. The “effective” demand is the summation of mean demand value and a safety margin. By comparing the proposed airport shuttle service to the current one, it is found that the proposed service can save approximately 27% of the total system cost. The results for stochastic problem suggest estimating the safety margin to be 0.3675 times of the standard deviation brings the best performance. For the second case, the service network design is extended with a pilot scheduling layer and simulation is undertaken to compare the autonomous (pilot-less) and piloted service design. The results suggest that an autonomous air metro service would be preferable if the price of an autonomous aircraft is less than 1.6 times the price of a human-driven one. The results for rolling horizon optimisation suggest to confirm the actual demand at least 45 minutes prior to departure. Based on data from the Sydney (Australia) region, the thesis provides information directly relevant for the service network design of emerging modes of air transport in the city.
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## Abbreviations

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<tr>
<td>AAITBS</td>
<td>Autonomous Airport Inter-Terminal Bus Shuttle</td>
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<tr>
<td>API</td>
<td>Application Programming Interface</td>
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<tr>
<td>AV</td>
<td>Autonomous Vehicle</td>
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<td>CBD</td>
<td>Central Business District</td>
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<td>ECP</td>
<td>Early Confirmation Period</td>
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<td>GA</td>
<td>Genetic Algorithm</td>
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<td>GIS</td>
<td>Geographic Information System</td>
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<td>GMAS</td>
<td>Greater Metropolitan Area of Sydney</td>
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<td>GPS</td>
<td>Global Position System</td>
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<td>ILP</td>
<td>Integer Linear Program</td>
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<td>ITT</td>
<td>Inter-Terminal Transport</td>
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<td>MILP</td>
<td>Mixed Integer Linear Program</td>
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<td>MSA</td>
<td>Metropolitan Statistical Areas</td>
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<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
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<td>OD</td>
<td>Origin-Destination</td>
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<td>SAE</td>
<td>Society of Automotive Engineers</td>
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<td>SKSA</td>
<td>Sydney Kingsford Smith Airport</td>
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<td>SNDP</td>
<td>Service Network Design Problem</td>
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<td>T1</td>
<td>Terminal 1</td>
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<td>Terminal 2</td>
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<td>T3</td>
<td>Terminal 3</td>
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<td>UAM</td>
<td>Urban Air Mobility</td>
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<td>UE</td>
<td>User Equilibrium</td>
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<td>Acronym</td>
<td>Description</td>
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<tr>
<td>UTM</td>
<td>Unmanned Traffic Management</td>
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<td>VOT</td>
<td>Value of Time</td>
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<td>VRP</td>
<td>Vehicle Routing Problem</td>
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<tr>
<td>VTOL</td>
<td>(Electrical-) Vertical Take-Off and Landing (Aircraft)</td>
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Chapter 1

Introduction

The background to the proposed service network design problem (SNDP) and the emerging modes of air transport are discussed in Chapter 1.1. Thereafter, two proposed services: the autonomous airport inter-terminal bus shuttle (AAITBS) and the air metro are discussed. In Chapter 1.2, the objectives of this thesis are outlined, including the purposes of the modelling and solution approaches, as well as the targets of the case study. Chapter 1.3 summarises the contribution of this thesis to the literature.

1.1 Background and motivation

Ground transport efficiency is an important issue with regard to sustainability and liveability of cities. During the urban development, traffic congestion has become an inevitable symptom, and caused loss of productivity and negative environmental impact (Lu et al. 2021). For example, it has been estimated that European road congestion costs 1% of GDP (Christidis et al. 2012); by 2030, the economic cost is expected to reach $186 billion in the United States (Chang et al. 2017); while the combined cost of congestion in Australia’s roads and public transportation is expected to total $39.6 billion by 2031 (Infrastructure Australia 2019). Policy and technology can play a crucial role in addressing these critical issues.

Air transport continues to expand and proves its long-term viability. Its network has connected cities and communities throughout the world, which greatly contributes to the economic growth
and to the promotion of international trade and tourism. For over a hundred years, air transport has improved accessibility and efficiency in the sphere of traffic and connected people between countries. Recently, the emerging modes of air transport, such as autonomous airport bus shuttle (e.g., Cao & Ceder 2019) and air taxi (e.g., Hasan 2018), have been studied with the view to improve the efficiency of the transport system. For example, the autonomous bus shuttle service may have a significant impact on aviation efficiency. Since the emergence of autonomous vehicles (AVs) in recent years, the cost to provide ground passenger bus services has been reduced (Lidestam et al. 2018). Furthermore, the concept of urban air mobility (UAM) has been proposed to alleviate urban traffic congestion, with a view to providing inter- or intra-city passenger service with electrical vertical take-off and landing aircraft (VTOL), also referred to as flying taxis.

Prior to committing investment, network modelling studies are often undertaken to analyse the main types of costs, and to determine the range of optimal dispatch patterns to establish a design for a potential service network. This provides useful information for decision making and analytically constructed scenario planning tools. Referred as network design problem, the modelling consists of finding the optimal layout of a road transport network, and can be classified into three levels: strategic, tactical, and operational (Magnanti & Wong 1984).

Strategic studies go to the root of the most aggregate and long-term decisions, such as the placement of airports (e.g., Yang et al. 2016) and the design of roads (e.g., Szeto et al. 2015). Strategic outputs dictate the availability of resources within the transport service network and have an impact on tactical and operational planning.

The studies at the tactical level aim to maximise the efficiency of the use of available resources in the service networks, given the location of strategic decisions. An objective is usually to reduce the operating costs or passenger travel time, or even to seek a balance between the service provider’s costs and the passengers’ journey times. The output of tactical decisions directly impacts the efficiency of a service network as well as the revenue and expenditure of a service provider. Examples of tactical studies include the problem of fleet and crew scheduling (e.g., Steinzen et al. 2010), where the stations/stops have been determined before, and the decisions involve frequency, timetable, and crew allocations. Moreover, the concept of user equilibrium (UE) is incorporated (e.g., Riemann et al. 2015), to describe how traffic flows in a network are assigned.
Operational decisions enhance the efficiency of transport networks at a micro-level and produce “shorter”-term effects, such as revenue management (e.g., Bilegan et al. 2015) or itinerary provision (e.g., Wang et al. 2015) in container liner shipping, as well as setting streetlights at intersections (e.g., Marcianò et al. 2015).

As will be seen, this thesis focuses mostly on the tactical level SNDP in two select areas of air transport services: i). inter-terminal transport (ITT), and ii). intra-, inter-city urban air mobility, as explained in turn below.

**Ground phase of air transport**

Air travel demand has grown significantly in the past decades along with the economic growth world-wide (Zhang & Graham 2020). In any trip involving air transport, it is inevitable that each phase of ground access is needed, from the origin of passengers (e.g., their homes or hotels) to the aircraft gate. Generally, the ground phase of accessing an aircraft can be divided into three mutually exclusive parts (Sigler et al. 2021). The first leg is from the passengers’ origin (any place within the city) to airports, which is also known as access-to-airport problem.

The second leg has received insufficient attention, which is the passenger ITT within an airport. Due to the fact that major airports tend to have multiple terminals and areas with different facilities and functions, many passengers are faced with making connections between points within or near the airport (e.g., terminals, parking lots, train and bus stations, shopping or entertainment areas). The long and uncertain connection times have posed a significant burden to passengers, especially when many passengers are carrying large luggage and having departure/arrival time constraints (e.g., to catch up with a flight). ITT trips may have a significant impact on aviation operating efficiency and result in potentially lengthy delays. Providing efficient ground passenger transport services in the airport and its surrounding areas is an important issue to be addressed. For instance, there have been bus service in Sydney Kingsford Smith Airport (SKSA) and its surrounding areas (with parking, train stations, hotels, entertainment areas). Compared to rail, the bus shuttle service is more flexible, since it does not rely on the availability of track network, and one may adopt different bus vehicle sizes to better accommodate demand variations (e.g., in the SKSA case, there are both conventional buses and articulated buses).
CHAPTER 1. INTRODUCTION

The third leg refers to the gate access process involved in accessing the aircraft gate after arrival at a terminal, including the time spent in a queue at the ticket counter, entrance to the check-in process and even boarding access (e.g., Hagspihl et al. 2021). Gate access is one of the most complex aspects of airports that is often out of the control of airport authorities and can prove difficult to solve by a unified optimisation framework (Sigler et al. 2021).

Among the three components, efficient ground passenger transport within an airport and the surrounding area is an important market (the second leg). Due to the substantial increase in air travel demand over the past decades, huge amount of traffic and passenger flows is attracted to airports (Jacquillat & Odoni 2018). Thus, ITT passenger demand is expected to increase rapidly in the future, and this trend will have an increased impact on the operation efficiency of airports based on passenger travel time. Moreover, in many cases, access-to-airport issues (the first leg) are modelled as on-demand vehicle routing problems (VRPs), where individual passengers who tend to have scattered origins and destinations are served by individual vehicles (e.g., Tang et al. 2015). The AAITBS is characterised by the fact that the origin-destination (OD) pairs can only be fixed terminals and other facilities within the airport (Sigler et al. 2021). Accordingly, AAITBS is more suitable for consideration as a scheduled service for major passengers and requires a potentially different approach from VRP models for the access-to-airport problem, considering fleet size, budgets, excessive waiting times, and stochasticity in passenger demand.  

Pre-planned passenger transport (e.g., buses in an urban transit systems) has a greater role to play in transport systems than on-demand individual passenger transport (e.g., taxis). Commonly, the pre-planned public transport serves major commuters. For example, in New York, 62% of commuters in low-income neighbourhoods use the bus, while 53% do so in high-income neighbourhoods. It is also estimated that a bus lane can accommodate 15,000 passengers per hour, the same as six lanes of car traffic (Litman 2006). Thus, the journey time of scheduled transport service could contribute more to the total system journey time than on-demand services. The optimisation of

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1This thesis refers to Tumeo (1994) regarding the different meanings between the synonyms “uncertainty”, “randomness” and “stochasticity”. It is “Stochasticity” that most appropriately discussed when studying travel demand in transport related research.

scheduled aggregate passenger transport might ultimately contribute more to alleviating traffic congestion and improving traffic efficiency than on-demand individual passenger transport. These also enhance the need for optimising the AAITBS.

Urban air mobility

NASA has provided an analysis of the market potential for UAM (Hasan 2018, Reiche et al. 2018). For example, Hasan (2018) presented three options for UAM: last-mile delivery, air metro, and air taxi, and evaluated their viability, potential barriers, and solutions. Reiche et al. (2018) estimated the potential demand for UAM to be 0.1% of all trips in the U.S.

In recent years, the potential of UAM has gained increasing attention from researchers due to the development of technology and other conditions; for example, autonomous mobility is suggested as a dependency for the UAM market. Nevertheless, a majority of previous UAM related studies have focused on air taxis, an on-demand passenger pick-up and delivery service (e.g., Rajendran et al. 2021). In addition to air taxi, other novel modes of air transport in the near future include last-mile delivery, airport shuttle, air ambulance, and air metro (Hasan 2018, Reiche et al. 2018). In particular, except the air taxi, the last-mile delivery is rapid parcel delivery service that are carried out by drones between stations, terminals, or vessels and can act as a complement to human-driven ground delivery services. The airport shuttle (defined in Reiche et al. (2018)) is a special form of air taxi that is intended to serve passengers who need to access the airport or have boarding assignments. Unlike air taxi, air metro is defined as a public transit alternative for aggregate passenger demand (e.g., commuters), with fixed routes and schedules pre-established prior to flight time. In addition, air metro has a lower density requirement for vertiports and is expected to enjoy a profitable first year earlier than an air taxi (Hasan 2018). However, compared to the on-demand air taxis, the pre-scheduled air metro service has captured little attention.

Due to UAM’s enormous market potential, many commercial companies are making efforts to assess UAM services. Uber Elevate plans to apply air taxis as an on-demand ride-sharing service and discussed the challenges for achieving a successful market in terms of vehicles, infrastructure, operations, consumer experience, and economics. VTOL was deemed to be an affordable means of transport for the masses in the long-term (Holden & Goel 2016). Porsche Consulting expected
CHAPTER 1. INTRODUCTION

that VTOL would begin offering commercial mobility services in 2025 and operate an elaborate passenger network of 23,000 aircraft by 2035 (Grandl et al. 2018). Airbus UTM measured the public perception of UAM through literature review, expert interviews, and a survey and the results suggested that the initial perception of UAM is quite positive (Yedavalli & Mooberry 2019). In Europe, commercial air taxis are expected to commence service as early as 2024, and a number of European companies are developing UAM vehicles for the delivery of packages and passengers.³ Uber has selected Melbourne as the first city outside of the United States to test UAM, while commercial service is expected to commence in 2023.⁴ Patterson et al. (2018) described a three-pronged approach to study passenger-carrying UAM missions that involves: defining mission requirements for multiple exemplar UAM missions; designing aircraft that conform to these requirements; and analysing the network simulations. As will be seen, this thesis focuses on the latter – network design.

The progressions from demand modelling to network design and then to physical system development are of great importance for a reliable, efficient, and safe integration of UAM (Balać et al. 2017). As the market for the emerging modes in air transport are still in their infancy, modelling approaches have not attracted sufficient research attention. Passenger demand is a major influence on determining the optimal location of vertiports because the selected locations need to accommodate the density of the passenger demand and accommodate future customers (Holden & Goel 2016). Demand forecast can serve as the first input for UAM modelling at the strategic level. In SNDP of air metro, Willey & Salmon (2021) have examined the vertiport location placement problem, which is a strategic level analysis considering the characteristics of pre-scheduled air metro. The research at the strategic level is important because they will determine whether UAM can be a successful alternative to existing ground transport Lim & Hwang (2019). However, in order to understand and simulate the economic feasibility of a new service network, it is necessary to consider the tactical decision, which aims to decide the routing and scheduling, while balancing the operating costs and service quality (Wang et al. 2019). That is, based on known vertiport locations,


⁴Melbourne will be the first city outside America to get Uber’s flying taxis (https://edition.cnn.com/2019/06/12/tech/uber-melbourne-flying-taxis/index.html/).
tactical level decisions making for air metro involve determining the optimal dispatch patterns. To the best of authors’ knowledge, despite the theoretical suitability, the SNDP modelling approach has not been applied to understand the feasibility and suitability of the air metro service.

**Two emerging modes: AAITBS and air metro**

This thesis focuses on the tactical SNDP relevant for two emerging modes in air transport: i). AAITBS and ii). air metro. The two modes are different from the existing public transit services as follows.

(a) They are pre-scheduled services with fixed stops (such as airport terminals or vertiports);

(b) They are designed for air transport passengers who are more sensitive to journey times and are more likely to generate greater values from using these services than passengers in urban transit systems or ferry systems (e.g., passengers of AAITBS have departure/arrival time constraints due to the flight schedule; UAM passengers have a higher business value of time (VOT));

(c) They are related to the technology of AVs, and the control is highly centralised and precise. There is no competition or conflicts between the homogeneous vehicles in the service network;

(d) The real-life application of the two modes is unlikely to be complicated by the need to share with other agents in the network (i.e., hybrid operation of autonomous and human-driven vehicles, pedestrians).

These characteristics of the two emerging modes require specific consideration when modelling the problems. In the AAITBS case, the focus is on a large volume, relatively simple network, whereas in the air metro case, the focus is on a small volume, but multi-layered problem (e.g., an additional pilot scheduling dimension). Subsequently, while similar in design, the computation is different in complexity and efficiency. The SNDP of these two types of passenger services will enable service providers to establish efficient service pattern optimised for varying levels of demand.
1.2 Aim and scope

This thesis aims to propose the service network for two emerging modes in air transport using Sydney (Australia) as a context. In doing so, we also examines the service network’s operational and economic feasibility by undertaking numerical studies. With few exceptions, the SNDP of the two emerging modes’ tactical and operational aspects has not been researched to date, despite their technological feasibility (see Chapter 2.5).

Specifically, the research has the following objectives:

(a) To propose a service network for autonomous inter-terminal bus shuttle (i.e., within the airport and its surrounding areas, including parking, train stations, hotels, entertainment areas, etc.) at a tactical level, which involves regular and ad-hoc services, heterogeneous arrival time window, heterogeneous multi-type bus fleet and stochastic demand, by incorporating these exogenous factors into capacitated (capacity-constrained) multi-commodity models with time-space networks, for recurrent air transport passenger flows that are often in large quantities;

(b) To mathematically formulate the optimisation models for AAITBS as a mixed integer linear program (MILP), in order to minimise the weighted sum of passenger travel time cost and ground transport operating cost;

(c) To propose a Monte Carlo simulation-based approach to solve the case with demand stochasticity, which is then further embedded into an “effective” passenger demand framework;

(d) To conduct a case study on the inter-terminal network at SKSA to illustrate the proposed models and solution procedure, including an assessment of the cost feasibility between homogeneous single-type fleet vs. heterogeneous multi-type fleet in the sensitivity analysis;\(^5\)

(e) To propose the passenger air metro service network at a tactical level, involving regular and ad-hoc services, heterogeneous arrival time window, and pilot scheduling, by incorporating these exogenous factors into capacitated multi-commodity models with time-space

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\(^5\)The SKSA consists of two domestic and one international terminals, and had 44.4 million passengers in 2019 (https://www.sydneyairport.com.au/investor/investors-centre/asx-newsroom/).
1.2. AIM AND SCOPE

networks, for potential UAM passengers with high a VOT;

(f) To formulate the optimisation models for air metro as an integer linear program (ILP), in order to minimise the weighted sum of passenger travel time cost and operating cost for service provider, where the operating cost also includes the pilot labour cost in piloted air metro scenario;

(g) To extend the air metro SNDP into dynamic modelling in rolling horizon in order to address the demand stochasticity. The concept of rolling horizon optimisation is particularly efficient when the passenger demand for the near future is available while that for far future is predicted according to the historical distribution in each rolling horizon (Gkiotsalitis 2021);

(h) To conduct a numerical study of an inter-city passenger network based on Greater Metropolitan Area of Sydney (GMAS) to illustrate the modelling approach, including an assessment of the cost feasibility between conventionally piloted (pilot on-board) fleet vs. pilot-less (autonomous) aircraft fleet in the sensitivity analysis.  

For AAITBS, the operation of the shuttles is not constrained by the availability of drivers. The operation of AVs in most urban settings is currently restricted to specific areas (Hatzenbühler et al. 2021). In airport case, there are barriers to prevent the entry of other vehicles and ensure the smooth operation of autonomous shuttle buses, which may provide an ideal environment for L4 automation. In addition, in the proposed AAITBS, the regular fleet operates with a fixed pre-planned schedule while ad-hoc service can be regarded as outsourcing services to a third party (e.g., on-demand mobility service provider), which often incurs a larger unit cost.

As introduced in Chapter 1.1, air metro is an aggregate form of air taxi, similar to bus or train in ground transport, while air taxi is an on-demand service, similar to ground taxi. To assess the impact of autonomous aviation on air metro service, the model is used to examine two scenarios (autonomous and human-driven aircraft). In the case of the AAITBS, the simulated period can

6The GMAS is approximately 20,185 square kilometres, including Sydney CBD, North Sydney, Newcastle, etc. (https://www.telco.nsw.gov.au/ccep/greater-metropolitan-area/).

be a part of the entire day’s operational period (e.g., simulating a 2-hour period while the entire
day’s operations may be 18 hours). The entire day’s schedule can be assembled from decomposed
periods, which reduces computational complexity. For air metro, the scheduling of pilots is a di-

mension in the model. Transport schedules are typically longer than a single shift (e.g., operational
18 of the 24 hours). Therefore, the simulation in this thesis represents an entire workday, and the
pilots are scheduled for the morning and afternoon shifts (so as to not exceed a typical pilot duty
hour of 10 hours). Hence, compared with the AAITBS, the air metro case has a larger computation
complexity.

Potentially, although not necessarily, they are two phases of a complete aviation trip (ground trip
phase and an air trip phase). However, the airports that require the AAITBS service usually have a
larger minimum scale than the scale required for an UAM vertiport. Hence, we separately model
the two cases.

1.3 Contribution

This thesis contributes to the literature in several ways.

First, as mentioned in Chapter 1.1, most existing studies focus on airport-access, while very few
studies pay attention to shuttle services within airports. Furthermore, few studies consider the
SNDP problems as VRPs. Airport traffic efficiency can be improved by paying attention to the
latter. This thesis proposes and formulates the ground transport service network design problem
for the airport while considering the unique features of airport passengers (e.g., for the sensitive-
ness of airport passengers towards journey time, we develop time-space networks for each time-
dependent passenger group (see Chapter 3.1.1)), and the problem is formulated as a capacitated
multi-commodity model.

Second, it may be not realistic to guarantee the availability of real-time passenger demand for air-
port operators in advance, especially for airports with high ITT demand, and precisely obtaining
the real-time information would involve a considerable amount of expense. However, estimating
demand can be accomplished by analysing historical flight information and distribution. In ad-
dition to existing approaches in estimating the stochasticity in traffic conditions (e.g., the service
1.3. CONTRIBUTION

reliability-based approach (An & Lo 2016, Lo et al. 2013) and the concept of “effective travel time” (Hall 1983), in view of the features of AAITBS, this thesis adds to the literature by proposing the concepts of “effective” demand to produce a demand estimate for AAITBS, and thus provide an interpretable modelling approach, where the “effective” demand is the summation of mean demand value and a safety margin.

Third, this thesis adopts a Monte Carlo simulation-based approach coupled with “effective” demand concept to solve the demand stochasticity. The computational results and performance of the proposed method is compared with those of Genetic Algorithm (GA) to demonstrate the computation efficiency. While GA is a common method to solve the stochasticity on demand (e.g., Dimitriou et al. 2008) or travel time (e.g., Liu et al. 2013) in the transport network modelling related literature, the proposed “effective” demand-based approach is demonstrated to be an alternative that outperforms GA on this instance.

Fourth, this thesis proposes a new pre-scheduled service, the air metro, which has not been extensively studied in the literature (as mentioned in Chapter 1.1, all available studies focus on on-demand air taxis or/and demand side considerations of UAM). The SNDP modelling approach for the air metro, despite its theoretical suitability, has not been applied to study the tactical and operational aspects of the network design.

Fifth, this thesis extends the SNDP for air metro to a rolling horizon optimisation. In most existing studies relating to rolling horizon optimisation, the focus is on bus operation, where once dispatched from the origin, a vehicle’s schedule is not changed (e.g., Gkiotsalitis 2021). In this thesis, considering the unique operational features of air metro (e.g., VTOLs are centralised controlled throughout the operation), a novel approach for rolling horizon is proposed, where a single aircraft’s journey can be continuously re-scheduled. In particular, for each individual aircraft at any time, the trips in the near-future (e.g., within 3 hours) are determined, while the trips in the far-future (e.g., longer than 3 hours) are continuously adjusted according to the available passenger demand.
Chapter 2

Literature Review

This chapter comprehensively reviews the existing related studies in the literature. Chapter 2.1 reviews the papers that are supportive for the feasibility of the proposed services. Chapter 2.2 reviews the studies regarding the modelling approaches for SNDP problems at strategic, tactical, and operational levels, respectively. Chapter 2.3 reviews the papers whose services are related or similar to the proposed AAITBS and air metro, respectively. Chapter 2.4 summarises the inspiration from the previous papers. Chapter 2.5 identifies the current knowledge gap of existing studies.

2.1 Feasibility of emerging modes in air transport

Feasibility of AAITBS

The airport shuttle service has existed for many years, but the idea of using AVs for mass passenger shuttle service within an airport is still relatively new, and has limited studies and application. However, the feasibility of the concept can be demonstrated by the rapid development of autonomous shuttle buses and the corresponding optimisation.

Iclodean et al. (2020) reviewed the development of AVs and their implementation in bus shuttle. The mechanical construction of autonomous shuttle bus resembles that of existing vehicles, including a steering wheel, accelerator, and braking pedals, but a complex network of sensors is added. In terms of their flexibility, AVs can be considered as large computers on wheels, whose
2.1. FEASIBILITY OF EMERGING MODES IN AIR TRANSPORT

capabilities are dependent on their software. The development of AV technology has matured to some extent, and it is anticipated that there will be designated legislation and establishment for their primary use. A shuttle bus with a maximum capacity of 15 persons is used for urban transport with the capability of establishing fixed routes based on traffic conditions. This study concluded that autonomous shuttle buses could be used successfully in niche areas of public transport, such as routes within airports, supporting the feasibility of an autonomous bus shuttle service at an airport.

Cao & Ceder (2019) integrated stop-skipping with vehicle scheduling to optimise the timetable of autonomous shuttle bus service based on real-time passenger demand, which improves the accessibility of transport hubs at airport terminals and main train stations. With the recent development of AVs, they pointed out that opportunities for autonomous shuttle bus services have arisen. The automation technology makes it easier and more attractive for passengers to access airport terminals, increasing the seamless movement of passengers. They proposed the service at the stage of “conditional automation”, with a human driver providing oversight and intervening only when necessary.

Studies above show that automation is one of the key factors in determining the feasibility of bus shuttle services, and the technology for AVs is sufficiently mature for the purpose of bus shuttle applications in a controlled environment such as the area within an airport. Once the legislation has been enacted, the bus shuttle system and market can become a reality.

**Feasibility of air metro**

Hasan (2018) defined air metro as that “... resembles current public transit options such as subways and buses, with pre-determined routes, regular schedules in advance of flight time, and set stops in high traffic areas throughout each city”. Air metro has a lower density for vertiports than the air taxis, which is about 100-300 vertiports per MSA in high traffic areas. The vertiports should be capable of handling about three to six VTOLs simultaneously. It is proposed that two types of vertical airports be implemented: “hubs” would be located in heavy traffic areas to accommodate the high passenger demand, while “spokes” would serve suburban areas. The mandatory infrastructures for a well-established air metro network include charging stations, service stations, as well as UTM. The potential regulation involves the air worthiness standards, UTM, weight and altitude
restrictions, etc. The certification costs of vehicles, the number of verticals, the maintenance costs, the cost of energy, the number of passengers per trip, the number of passenger rides per hour, as well as factory productivity are the variables that have a significant impact on the overall cost of a trip. Hasan (2018) also suggested that air metro would become profitable starting in 2028 (earlier than that for air taxi), when there would be 130 million passenger trips annually (assuming a market exists).

2.2 Service network design problem


2.2.1 SNDP at a strategic level

As mentioned in Chapter 1.1, studies at the strategic level offer insight into the most aggregate and long-term decisions. In SNDP, strategic studies usually involve the location placement of transport infrastructures and the determination of fleet size.

Zhao et al. (2014) developed a lane-based optimisation model for determining the optimal combination of reversible lanes and other traffic management measures in congested roadway sections in which reversible lanes facilitate the balance of traffic flow between two directions. It was formulated as a multi-objective mixed-integer non-linear programming problem. In determining the control objectives, four factors were considered: maximising the number of permitted movements in the intersections, minimising the number of lane adjustments in the segments, maximising the
reserve capacity of the arterial, and maximising the sum of the reserve capacities at all intersections. With the aid of a series of non-negative variables, the optimisation model can be transformed into a single-objective MILP formulation, which is then solved using the branch and bound technique to arrive at a global optimum solution.

He et al. (2020) proposed a model to identify the optimal location of wireless charging lanes by taking into account road capacity and traveller route choice. Wireless charging lanes are an infrastructure used for charging electric vehicles while driving on road networks. The model was formulated as a nonlinear programming problem, where the non-linearity comes from the mean route travel time function. A bisection-based method was proposed to partition the domain of the nonlinear function to minimise the maximum error and the model can be solved by linearisation. Their results suggested that the charging power should be used for consideration of the charging lanes deployment and a proper budget should be provided. Charged vehicles may have adverse effects on the equilibrium path flow and link flow patterns.

The studies for the optimisation of the charging facility location placement for electric vehicles are hot topic at strategic level. Riemann et al. (2015) optimised the location of charging facilities for electric vehicles, where the objective is to capture the maximum traffic flow on a network. The multinomial logit model-based stochastic equilibrium principle is employed to capture drivers’ routing preferences. A mixed integer nonlinear program is formulated, which is then transformed into an MILP by using a reformulation-linearisation technique along with a piece-wise linear approximation, from which the global optimum can be determined. An (2020) modelled the location of charging stations considering the bus fleet size, time-of-use electricity price and stochastic charging demands. A small fleet of diesel buses to is employed to handle the rare event of extremely high charging demands. The problem is formulated into a stochastic integer program and then solved by customised Lagrangian relaxation and branch-and-bound algorithm.

Hatzenbühler et al. (2021) studied the transit network design problem considering the characteristics of autonomous buses. With the addition of line-based and connectivity characteristics to the problem formulation, the study investigates near future and transition scenarios from traditional to autonomous transit operations. A multi-objective optimisation and multi-agent simulation framework is developed to analyse the difference between conventional public transport and autonomous
CHAPTER 2. LITERATURE REVIEW

buses. Three conflicting objectives, i.e., total user cost, total operator cost and infrastructure preparation cost are minimised in the objective function. The outputs contain the number of routes, number of stops, etc.

2.2.2 SNDP at a tactical level

Most of SNDP studies focus on the tactical level which is to make the efficient use of available infrastructures in the networks. In order to better understand the development of existing studies for service network at the tactical level, this chapter reviews the literature by different transport modes as follows.

Flight

The study by Yan & Young (1996) is the first to use time-space network graphs to formulate the passenger service network as a capacity-constrained, multi-commodity model. Based on the assumption that three different types of fleets are in operation, this study represented the basic multi-fleet model as a single-fleet time-space network. Several optimisation models are developed from the basic model to assist carriers with fleet routing and flight scheduling. For the solution approach, the Lagrangian relaxation accompanied by the network simplex method, a Lagrangian heuristic and a modified sub-gradient method are used to solve the problems, while a flow decomposition algorithm is suggested to trace every aircraft route.

By using time-space networks and multi-commodity models with real constraints, Yan & Tseng (2002) first developed a model of the airline cabin crew scheduling problem. Due to their size and complexity, airline crew scheduling problems are traditionally divided into crew pairing and crew rostering problems. Specifically, the first task is to identify a set of minimum-cost pairings such that each flight leg is covered by exactly one pairing; the second task is to assign the crews to the designed flight pairs and generate individual schedules. Crew pairing is intended to minimise operating costs for flight crews, subject to a daily duty time limit, robustness of the schedule, and coverage of all flights exactly once; while in crew rostering, factors such as fairness, fatigue, and comfort of the crew must be accounted for. This paper presented a pure network model that solves crew scheduling problems efficiently and effectively.
Yan et al. (2008) introduced the concept of passenger demand stochasticity for the first time into service network design for flight scheduling. In the study, a stochastic-demand flight scheduling model was developed using a two-stage stochastic programming approach, while a fleet-flow network, a passenger-flow network, and a passenger choice model were used to assist. Two heuristic algorithms were developed to solve the model using arc- and route-based strategies.

**Freight transport**

Meng & Wang (2011) designed a service network for liner shipping which incorporated hub-and-spoke and multi-port calling operations, as well as the re-positioning of empty containers. In this paper, the concept of a segment, that is, two ports served by the same shipping line, is introduced first, followed by an MILP model for solving the problem. The commercial solver CPLEX was used to model and solve real-case problems in their numerical experiment.

Scherr et al. (2018) investigated the problem of urban freight shipment by first introducing AVs into a time-space MILP model. It examined the same-day parcel delivery two-tier city logistics and the mixed fleet in the first tier of city logistics. Platooning was originally considered as a solution to bridge the gaps between AV zones in the network, which refers to a group of vehicles following each other closely. Based on the results, mixed autonomous fleets may provide cost savings when used in city logistics. Scherr et al. (2019) extended the previous work and studied two-tier city logistic. They considered a heterogeneous infrastructure where such AVs could operate only within their feasible zones and would have to be guided by human-driven vehicles in platoons to reach other zones. To formulate the ILP, a time-expanded network was developed. Using the model, the size and mix of fleets and the routes of vehicle and goods flows can be determined.

**Ferries**

The first application of ferry service network was made by Lai & Lo (2004). For both direct and multi-stop services, they optimised the fleet size, routing, and scheduling. To measure model performance, a combination of the service provider’s cost and revenue as well as the passengers’ waiting and ride time is considered as part of the total system cost. With the assistance of multiple OD network flows, a mathematical model was developed as a capacitated MILP model. On
their developed time-space network schematic, each node corresponds to a stop at a particular time point, whereas each arc corresponds to a ferry trip, whose journey time, origins and destinations are specified by the corresponding time-space nodes. Each arc’s cost includes operating expenses, including fuel, maintenance, and labour. The fixed cost of owning or hiring a ferry per day is imposed on arcs originating from the beginning of the planning horizon. This paper developed a time-space network of passenger flow for each passenger OD pair, whereas only one ferry flow time-space network is required. To solve this problem of practical size, this study developed a heuristic algorithm that exploits the polynomial-time performance of shortest path algorithms. According to the results, the heuristic produced solutions that were within 1.3% of the CPLEX optimal solutions.

Wang & Lo (2008) extended the work by Lai & Lo (2004) by investigating the ferry service network in greater depth. A faster service with a higher fare was considered in addition to the regular service as part of the study of the ferry network design problem. There is the option for passengers with different preferred arrival times to choose what works best for them. Stochastic UE is used to model the passenger traffic assignment for the various service types. Due to the objective function of this study being to minimise the operator’s cost, a weighting value was imposed on service performance from the perspective of passengers in the overall cost of the system. The problem was formulated as an MILP and an iterative heuristic solution algorithm was developed to solve the nonlinear, non-convex integer program. By relaxing the nonlinear logit modal-split constraints and separating the problem by ferry types, the original problem was decomposed into a set of mixed integer linear sub-problems, which were solved iteratively.

Lo et al. (2013) developed the two-stage stochastic program by introducing the concept of service reliability, which is an extension of the previous work conducted by Lai & Lo (2004) to study the ferry service network. Service reliability is defined as a schedule of regular services that is designed to meet stochastic demand to a certain level of reliability. Regular services have a fixed schedule, while ad-hoc services are those that are subcontracted or outsourced to a third party and have a higher unit cost. The schedules for regular and ad hoc services are derived sequentially. Based on their results, the reliability-based approach showed promising results in terms of solution quality and computational efficiency when compared to existing methods.
2.2.2 SNDP at a tactical level

An & Lo (2014) encapsulated stochastic demand, UE, hard capacity constraints, regular and ad-hoc services into the service reliability-based formulation for ferry service network design. Two ad-hoc provision schemes were studied, where one considers that the company utilises a passenger reservation system to gain demand information in advance and plan ad-hoc service deployment accordingly, while in the second, demand is not realised until the last moment. Based on the results, the value of advance reservations between two schemes can be as high as 30%.

Ng & Lo (2016) provided a new robust modelling approach for studying ferry network based on previous research. The passenger demand was assumed to be only the mean and an upper bound, in contrast to previous studies that assumed the availability of probability distributions describing passenger demand. In their first model, the mean and an upper bound are supplemented by a lower bound on the demand; whereas in the second model, that the variance of the demand is known, in addition to the mean and upper bound. The results of their numerical studies indicated that using “loose information” in the absence of more exact values can lead to costs that are substantially higher.

Urban bus & transit systems

Liu et al. (2013) proposed mixed nonlinear integer programming models for bus stop-skipping problem at the planning level, where stop-skipping strategy allows the buses to skip one or more stops when late or behind schedule, to reduce its travel time and provide the optimal operating plans for bus operator and passengers. As objective functions, they included waiting and in-vehicle ride times, as well as bus travel times. The model was solved using a GA incorporating Monte Carlo Simulation, where the Monte Carlo Simulation addressed the stochastic in-vehicle travel time. Moreover, deadheading, which occurs when a bus bypasses a stop between the dispatching terminal point and a designated stop, was regarded as a special case of the stop-skipping problem. The numerical results indicated that the optimal plans of stop-skipping and deadheading are inherently different.

Chen et al. (2015) further considered stochastic bus travel time, vehicle capacity, and the effects of in-vehicle congestion on dwell time to study the bus stop-skipping strategy at planning level. As well in this research, even if a bus skips a stop, then the next bus of the same line can still skip
stops. A hybrid artificial bee colony algorithm incorporating the Monte Carlo simulation method was developed to solve the problem. A sensitivity analysis is conducted on the effects of demand on the optimal stop-skipping strategy.

An & Lo (2015) and An & Lo (2016) are two papers for the transit network design problem under stochastic demand. An & Lo (2015) proposed a multi-modal network combining rapid transit and flexible transport modes, and optimise the combination of the two service types under UE for a given urban density. Rapid transit services operate on fixed routes and dedicated lanes, while dial-a-ride services use the existing road network, making them more economically feasible. Instead of the robust optimisation model in An & Lo (2015), it is a two-phase stochastic program that is developed to address the demand stochasticity in An & Lo (2016). The difference in costs between the two approaches (robust model and stochastic program) can be used to estimate the value of collecting information regarding the distribution of demand.

Wang et al. (2018) optimised the bus service with limited stops considering both operator’s and users’ perspective. The common line approach is used to determine the passenger assignment on the transit corridor. The problem is mathematically formulated as a mixed integer nonlinear program and then transferred into an MILP by various linearisation techniques. Then, the global optimum can be obtained by solving the approximated MILP.

**Dynamic programming**

The service network design problem can be extended into dynamic programming for re-scheduling studies. Dynamic bus holding (e.g., Xuan et al. 2011), stop-skipping (e.g., Gkiotsalitis 2021) and bus dispatching problem (e.g., Gkiotsalitis & Van Berkum 2020) are typical cases.

Xuan et al. (2011) proposed dynamic holding strategies that use bus arrival deviations from a virtual schedule at the control points, as opposed to traditional schedule-based strategies which require too much slack that slows the bus. The proposed method allows the bus not just to maintain regular head-ways but also to adhere to their schedule. According to the results, the proposed method is able to maintain quasi-regular head-ways with a higher commercial speed than other existing methods. This study contributed to the improvement of bus schedule reliability while maximising buses’ commercial speed.
2.2.2 SNDP at a tactical level

The concept of rolling horizon is particularly useful in dynamic stochastic environments, such as when forecasts of information (travel times, passenger demand) are not reliable (Sethi & Sorger 1991). The approaches for rolling horizon optimisation have been widely applied in public transport control. Gkiotsalitis & Van Berkum (2020) and Gkiotsalitis (2021) are recent studies applying these approaches.

Gkiotsalitis & Van Berkum (2020) adopted a rolling-horizon approach to study the bus dispatch time problem, considering the travel time stochasticity, where the rolling horizon method simultaneously adjusts the dispatching times of all trips that operate during a pre-determined time interval resulting in a coordinated effort to maintain the target head-ways. A nonlinear program and a novel reformulation that limits the recursive relations of the optimisation problem were proposed to reduce the computational complexity. The convex formulation can be solved for global optimality in determining the optimal dispatching times in near real-time.

Gkiotsalitis (2021) adopted the rolling-horizon approach on bus stop-skipping problem. This study introduces a rolling-horizon stop-skipping model that determines the stop-skipping strategies of several bus trips within a rolling horizon, as compared to previous dynamic stop-skipping approaches that determine the stop-skipping strategies for each individual trip. The problem is mathematically formulated as an integer nonlinear program and can be solved to global optimality for small-scale cases. The numerical results demonstrated a potential performance improvement of 13% when using our rolling horizon stop-skipping approach in the stochastic travel time.

Compared with tactical problems, the operational studies focus on micro-issues and the optimised scopes are typically short time periods, while rolling time periods constitute a full operational day. The purpose of using the rolling horizon is to address the inaccurate prediction of traffic variables, as well as to address demand stochasticity in cases where only the near future demand is available. This strategy is suitable for air metro service in this thesis, because it is fitting for air metro to require passengers to confirm their itinerary and pay the fee to the service provider (e.g., via mobile apps) a certain time in advance (e.g., passengers are required to confirm their trip 1.5 or 2 hours before departure), and the seats are then locked for them. With this method, the actual demand for the near two hours can be available to the service provider. The rolling horizon can be conducted based on an existing pre-planned schedule. This can make the service more reliable.
CHAPTER 2. LITERATURE REVIEW

and support the rolling horizon method for the air metro study.

2.2.3 SNDP at an operational level

The SNDP studies at an operational level provide decisions with the short-term effect. For example, Marcianò et al. (2015) examines the traffic signal optimisation problem considering the dynamics of the arrival flow profiles at junctions of a congested road network. The behavioural constraints are provided by a model of within-day dynamic assignment. There are two interrelated procedures, the optimisation procedure and the assignment procedure, where the former is to determine the optimal signal setting parameters and the latter is to determine the effect of signal settings configuration on user path choice behaviour. The simulation shows significant savings in total vehicle delay on the network and evacuation time, as a result of the small network size with few alternative routes. The behavioural constraints are provided by a model of within-day dynamic assignment. Wang et al. (2015) use the logit model to determine which itinerary to use or whether to use other shipping lines’ routes. Bilegan et al. (2015) proposed a revenue management policy to study the revenue maximisation problem of a rail freight transport company or an inter-modal marketing company selling freight transport services.

2.3 Studies related to the proposed services

2.3.1 Airport shuttle modelling approaches

Access an airport

As mentioned in the Introduction chapter, the ground phase of accessing an airport can be split into three mutually exclusive portions the first of which concerns accessing an airport from other places (e.g., city town). Following are the recent studies under this topic.

Tang et al. (2015) studied a typical access to airport problem and considered the door-to-door service of pick-up and delivery of passengers to the airport. The service aims to pick up customers at the specified position at any preferred time and deliver to the airport. A multi-trip mode of service is proposed to reduce travel distances, fleet size, and operating costs. An exact algorithm using a trip-chain-oriented set-partitioning model that can be solved by CPLEX is developed. In
the exact algorithm, an improved label-correcting method is proposed to construct the feasible trip-chains and to save computation time.

In Chen et al. (2017), bus routes were specified for airport access in a suburban area including several zones with the aim of minimising the total travel time for vehicles. By using an optimisation model, the pick-up locations from the candidate stops and the corresponding visiting sequence are determined. A special model and a generic model are developed. The suburban zones in the special model are sequentially distributed along the bus route from the original terminal to the airport station; in the generic model, all suburban zones are randomly distributed. For a special model, the dynamic programming approach is able to solve the problem.

In view of the fact that passengers’ origins are dispersed over a wide range, this problem is typically mathematically modelled as a vehicle routing problem of pick-up and delivery or a dial-a-ride problem. The pick-up sites for individuals are distributed throughout the city, whereas the delivery sites are located at airports. There is a major difference between this type of problem and the bus shuttle in this thesis (pick-up and delivery positions within airports are fixed), and this is the reason why this thesis does not mathematically formulate the bus shuttle within an airport as a dial-a-ride problem.

**Shuttle within an airport**

Reinhardt et al. (2013) studied the multi-modal dial-a-ride problem with synchronisation constraints for airport passengers with reduced mobility. The objective is to schedule as many of the passengers as possible, while ensuring smooth transport with short waiting times. A simulated annealing-based heuristic is developed to solve the dial-a-ride problem. The developed heuristic performs well under the time constraint of a short solution.

Sigler et al. (2021) sought to solve the “travel within the airport premises” shuttle route optimisation problem by optimising the airport shuttle routes under a given set of constraints. The objective is to find a trade-off between passenger waiting time and shuttle energy consumption. A route optimisation model is proposed to solve the dispatching problem, provide a set of shuttle routes, and determine the number of shuttles and shuttle type to serve each route, such that the minimisation of fleet energy consumption is achieved. Also, a discrete-event simulator is used to test the model’s...
performance under stochastic dwell times, travel times, and arrival rates. The problem is mathematically formulated as an MILP constrained by shuttle head-ways, maximum passenger ride times and passenger arrival rates, where the user can specify the number of routes, capacity, head-ways, and maximum in-vehicle travel time parameters.

Gate access

Tang et al. (2012) develop an aircraft boarding process considering passengers’ individual properties and explore the aircraft boarding behaviour. Three different aircraft boarding strategies are designed and assessed, including the random boarding strategy, the boarding strategy based on passenger’s seat serial number and individual properties.

Hagspihl et al. (2021) studied a dynamic configuration of passenger boarding bridges for airport gates, where the objective is to minimise investment, operating costs, and the penalty costs due to the unavailable gates. The decisions include whether and how many passenger boarding bridges of each type should be installed. The problem is formulated as a mix integer model under the assistance of time-space networks.

2.3.2 Urban air mobility service network modelling approaches

When a new technology emerges, people are often both intrigued and concerned at the same time. Gaining an understanding of the factors that affect adoption on passengers’ perception has been a subject of study. As well known in travel demand studies, there is a trade-off between the savings of travel time and the willingness to pay for air services (Al Haddad et al. 2020, Merkert & Beck 2017). For example, Al Haddad et al. (2020) identified and quantified the factors that affect the adoption and use of UAM. These included perceived safety, perceived benefits, as well as general willingness to accept new technology. In that study, the UAM was assumed to be fully autonomous (pilot-less). Although pilot-less aircraft has advantages, until considerable trust is built in the new technology, it is likely the aircraft will involve a pilot, at least in the foreseeable future, because potential passengers have considerable trust in the pilot on-board (Molesworth & Koo 2016). Thus, SNDP of air metro should have a pilot scheduling incorporated in the model.

Beyond demand, studies have examined vertiport location placement at the strategic level (Fadhil
2.3.2 Urban air mobility service network modelling approaches


Fadhil (2018) identified the suitable location for vertiports relying on GIS. Lim & Hwang (2019) adopted the k-means clustering approach to study the air taxi vertiport location placement problem. The results demonstrate that the proposed service can improve traffic efficiency. Rath & Chow (2019) modelled the vertiport location placement problem as an ILP, where the objective is to minimise the travel cost for each OD pair. According to the results of numerical studies conducted on New York City, the proposed method is superior to the existing clustering method. Willey & Salmon (2021) modelled the vertical placement problem as a single-allocation p-hub median location problem that incorporates aspects important to the operation of transportation networks. In that study, in order to make the vertiports suitable for use by air metro systems, the features unique to pre-planned service were taken into consideration.

Rajendran & Zack (2019) adopted a two-phase approach to study air taxi vertiport location placement problem, where phase 1 is to estimate the demand for air taxi services according to the number of ground taxi passengers who are likely to take air taxi service, and phase 2 proposes a k-means clustering approach to identify potential location for vertiport placement based on the estimated demand. Rajendran & Shulman (2020), a subsequent work of Rajendran & Zack (2019), focuses on air taxi operation network modelling. Based on the selected vertiport location in Rajendran & Zack (2019), this study proposed a framework and integrated it with the approach of systems simulation to determine the number of air taxis needed to meet passenger demand for UAM in New York City. According to the results, an initial fleet size of 70 air taxis is recommended to balance passenger wait time and operating costs.
Roy et al. (2020) modelled the on-demand air taxi service through a multi-commodity network flow approach at the tactical level. The results provided the optimal fleet size and identified the factors that have significant impact on operating cost and profitability. Additionally, Shihab et al. (2019) proposed three different types of UAM service, i.e., on-demand service, pre-planned service, hybrid service, and then tested the performance and computation cost. Kleinbekman et al. (2020) introduced the concept of rolling horizon optimisation to study the VTOL arrival scheduling problem at the operational level, in which the operation is limited by the vertiport capacity, traffic density and remaining battery energy. Rajendran (2021) developed a hybrid simulation goal programming algorithm that comprehensively incorporates the problems at different levels, including the fleet size, passenger time cost, and real-time dispatch patterns.

For UAM studies, contribution has also been made in terms of the airspace availability (Murça 2021), weather barrier (Reiche et al. 2021), and operational constraints (Vascik et al. 2018). The practice of UAM is also highly related to the design and development of VTOLs, where the cruise speed, maximum mission distance and capacity for passengers or cargo are mainly constrained. For example, a cruise speed of between 150 km/h and 200 km/h and payload of 545 kg or up to six passengers are suggested by Patterson et al. (2018); while Holden & Goel (2016) suggest the minimum cruise speed and the capacity to be 240 km/h and 500kg, respectively. In addition, batteries, autonomous flight, and detect-and-avoid technologies are among the technologies that still require further development (Hasan 2018).

2.4 Summary from literature

Optimisation models

This chapter has provided a description of the main modelling approaches to the service network design. Flight service and freight shipment studies are intended to reduce operating costs. The time spent waiting and riding become important aspects of urban public transport, and these studies generally assign a weighting percentage to each type of time cost. However, because each bus line is modelled separately, it is difficult to precisely study the entire bus network for a local region. Ferry service networks have specific coverage areas, and the service is either provided on a pre-planned schedule or a combination of regular and ad-hoc routes. Fleet sizes are constrained by the
storage space or budget available to service providers.

A ferry’s service characteristics are similar to those of the proposed bus shuttle service within an airport and air metro service described in this thesis. However, in the bus shuttle case of this thesis, it should be noted that passengers travelling to or within airports often have departure/arrival time constraints (e.g., due to the flight schedule), and in the air metro case, passengers are expected to have high VOT. The evidence indicates that the passengers of emerging modes in air transport are more sensitive to journey times and are more likely to generate greater value from using these services, which further distinguishes them from those in urban bus/transit systems or ferry systems.

For the time-space network graphs, typically a service time-space network for fleet flow is needed to assist in modelling the problem; while there can be multiple passenger time-space networks according to the actual needs of the problem. This thesis also employs a different method which distinguish the passenger group by OD pair and arrival time window to expand the time-space network for airport and air metro passenger groups.

**ILP & MILP**

In most existing studies, when formulating the service network design problem as a capacitated multi-commodity model for passenger transport, two types of flows (commodities) are transported in the networks: vehicle fleet flow and passenger flow. Each vehicle has its capacity, and the flow value can determine the passenger flow on the same path, the fleet flow is usually defined as integer variables and cannot be spilt. However, passenger flow is often set to be a continuous variable. This is because the computation time for solving an ILP is considerably long. Setting the passenger flow to be continuous variable does not have an obvious impact on system solution and can largely improve the computation efficiency. Therefore, the integer variables (fleet flows) and continuous variables make the model to be a MILP. Moreover, an MILP model is linear which has a simple computation complexity and can be solved by commercial optimisation solvers (e.g., CPLEX, Gurobi). MILP is, however, only suitable when passenger demand is high. In air metro context, the passenger flows have to be considered as integer variables, because of the small passenger amount for UAM trips. Thus, in the models for air metro case, ILP is adopted.
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Time-space network

The time-space network graphs are developed to assist the modelling of service network (Hagspihl et al. 2021, Lai & Lo 2004, Lo et al. 2013, Wang & Lo 2008, Yan et al. 2008, Yan & Young 1996). Commonly, the fleet flows do not have fixed depot and time window constraints. Thus, a fleet flow time-space service network is used to represent the movement of all vehicles in the system. The columns denote the stops/stations/piers in reality while the rows denote the discrete time step/slice. Therefore, this type of network is also regarded as time-discretised space-time network (Liu & Zhou 2016). The nodes denote the stops at a particular time step, and the arcs represent the vehicle movement. The passenger flow time-space networks have the same structure with fleet flow time-space service network. According to the different requirement of the problem, the passenger time-space network can be further developed. For example, Lo et al. (2013) developed a passenger time-space network for each OD pair. Some arcs that exist in fleet flow time-space service network but is infeasible of an OD pair can be eliminated from the network graph for this OD pair. For capacitated multi-commodity models, the fleet and passenger flows represent the two dimensions of commodities. For the case that there are more types of flows (e.g., there is a pilot scheduling dimension in air metro case, see Chapter 3.2.1), more dimension of network can be developed.

As mentioned in Chapter 1.2, in the environment of aviation, airport area, or AVs, there is almost no traffic congestion and no interaction from other vehicles. This is deemed as a clean environment and the disorder in the system is mainly from the delay of vehicles and passengers. Thus, the system is sensitive towards waiting time which can be represented by time steps. Therefore, the time-space networks are suitable for the characteristics of the air transport environments and help to formulate the particular time and place in the network without considering the interactions between vehicles. The accuracy of time can even be adjusted as needed (the length of a unit time step).

Endogenous & exogenous factors

The endogenous and exogenous factors are the essential part of optimisation models. Note that the endogenous factors are usually decision variables in the optimisation models while the exogenous factors are often used for sensitivity analysis. Table 2.1 lists the endogenous and exogenous factors of main studies that formulated the problems as the multi-commodity network flow models.
Table 2.1: Endogenous & exogenous factors in the literature

<table>
<thead>
<tr>
<th>Studies</th>
<th>Endogenous factors</th>
<th>Exogenous factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yan &amp; Young (1996)</td>
<td>Fleet flow</td>
<td>Travel cost, max fleet size, fleet flow upper bound</td>
</tr>
<tr>
<td>Lai &amp; Lo (2004)</td>
<td>Fleet flow, passenger flow</td>
<td>Travel cost, max fleet size, fleet flow upper bound, passenger flow upper bound,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>fleet owning cost, demand, capacity, fare</td>
</tr>
<tr>
<td>Yan et al. (2008)</td>
<td>Fleet flow, passenger flow</td>
<td>Travel cost, max fleet size, fleet flow upper bound, capacity, passenger waiting</td>
</tr>
<tr>
<td></td>
<td></td>
<td>cost</td>
</tr>
<tr>
<td>Wang &amp; Lo (2008)</td>
<td>Fleet flow, passenger flow</td>
<td>Travel cost, max fleet size, fleet owning cost, demand, capacity, fare, time-window,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>VOT, fleet flow upper bound</td>
</tr>
<tr>
<td>Lo et al. (2013)</td>
<td>Fleet flow, regular service passenger</td>
<td>Travel cost, max fleet size, fleet flow upper bound, fleet owning cost, demand,</td>
</tr>
<tr>
<td></td>
<td>passenger flow, regular service</td>
<td>capacity, passenger waiting cost</td>
</tr>
<tr>
<td></td>
<td>reliability, ad-hoc passenger flow</td>
<td></td>
</tr>
<tr>
<td>Riemann et al. (2015)</td>
<td>Fleet flow, travel time</td>
<td>Free flow travel time, demand, capacity</td>
</tr>
<tr>
<td>Liu &amp; Zhou (2016)</td>
<td>Fleet flow</td>
<td>Travel cost, capacity, financial budget</td>
</tr>
<tr>
<td>Scherr et al. (2019)</td>
<td>Manual vehicle service, AV service,</td>
<td>Travel cost, max fleet size, demand, capacity</td>
</tr>
<tr>
<td></td>
<td>flow of goods</td>
<td></td>
</tr>
</tbody>
</table>

Among the endogenous factors, the fleet flow and regular service passenger flow always exist. If a special requirement is required, additional services (e.g., regular vs. ad-hoc services, manual vs. autonomous vehicles) can provide more types of endogenous variables. The travel cost, the maximum fleet size, the fleet flow upper bound, demand, capacity, and fleet ownership costs are common exogenous factors. In addition, the passenger waiting cost should also be taken into ac-
CHAPTER 2. LITERATURE REVIEW

count when studying passenger service network since people are more sensitive to waiting times. From the literature, this thesis selects travel cost, maximum fleet size, fleet ownership costs, passenger demand, vehicle capacity, vertiport capacity, passenger VOT, and passenger time window as primary exogenous factors. Among these, travel cost, max fleet size, fleet owning cost, passenger demand, and vehicle capacity have been widely considered in previous studies. Passenger VOT is a significant factor to assess the monetary time cost when considering the passenger journey time and operating cost at the same time. The passenger time window is an important element when passengers are sensitive to journey times (e.g., to catch a flight) or if the passenger has a high VOT (i.e., business travellers using air metro).

Stochastic programming & robust optimisation

Stochasticity of traffic conditions is an intrinsic property of SNDP problems. In mathematical optimisation, stochastic programming and robust optimisation are two main approaches to address the stochasticity. The stochastic programming aims at minimising the average cost of a set of scenarios in which the possibility of stochastic factors (e.g., demand distribution) in each scenario occurring is assumed to be known (e.g., Lo et al. 2013). However, it is limited to the case in which the distributions of stochastic factors are available. The robust optimisation considers the uncertain values as uncertainty set, and provides the optimal solution in the worst case scenario within the set (e.g., Wang & Qi 2020). The robust optimisation can be regarded as a kind of implicit stochastic programming, where the resource decisions are implicitly restricted. A stochastic programming designs the service that can be adjusted to meet demand at the least expected cost. A drawback of robust optimisation is that the cost for robust optimisation might be higher than that for stochastic programming (Mulvey et al. 1995).

In SNDP, stochastic programming is a common approach. Studies have proposed stochastic models for SNDP when considering stochastic passenger demand (e.g., Lo et al. 2013) or stochastic travel time (e.g., Liu et al. 2013). Moreover, for the AAITBS case, the probability distribution can be surveyed beforehand. In this thesis, we examine a two-stage stochastic programming model for AAITBS in Chapter 3.1.4.
2.5 Knowledge gap of existing studies

The main modelling approaches for SNDP with different modes of transport have been introduced in Chapter 2.2. The modelling in this thesis addresses the following gaps.

AAITBS

For the airport shuttle, as stated in Chapter 1.1, the phase of passengers accessing an aircraft can be divided into three legs: airport access, inter-terminal transport, and gate access. The first leg has received the most attention in existing studies. The second and third legs have received less attention. With respect to the second and third legs, Cao & Ceder (2019) and Sigler et al. (2021) are the two papers most similar to our proposed AAITBS.

Cao & Ceder (2019) analysed how stop-skipping tactic can be used to enhance the bus shuttle service and how this relates to the availability of real-time demand which is precisely captured via smartphones. Cao & Ceder (2019) proposed an on-demand airport bus shuttle service, and with the input of real-time demand changes, the vehicle schedules can be optimised based on the pre-scheduled timetable. As stated in Chapter 1.3, there are important difficulties in acquiring real-time ITT passenger demand information, particularly when the demand is large. Also, since airport ITT is a quick service lasting only a few minutes, the cost for precisely tracking demand data via smartphones may incur a large proportion of the total system cost. Different from the on-demand setting by Cao & Ceder (2019), in this thesis, we propose a completely pre-scheduled AAITBS service. However, the impact of the deviation between the predicted and actual demand can be addressed by the stochastic demand model (proposed in Chapter 3.1.4). Potentially, but not necessarily, the proposed SNDP can be a prior stage of the on-demand scheduling method. The on-demand timetable re-scheduling could be a subsequent process after obtaining the optimal pre-planned schedules by the proposed SNDP. In addition, the proposed AAITBS adds to the literature by fully considering the passenger arrival time constraint, which is crucial for airport ITT passengers.

As stated in Chapter 1.1, VRP is a typical formulation for passenger pick-up and delivery problem. Sigler et al. (2021) is a paper that studies the bus shuttle within an airport by optimising routes and schedules, which is a similar problem to the AAITBS in this thesis, where the problem is modelled
CHAPTER 2. LITERATURE REVIEW

as a variant of VRP. It is worth mentioning that although in the formulation of VRP model, the passenger time window, the pick-up/drop-off locations, capacity of buses, and allowable headways can be incorporated, and total journey time is the optimised object, it is difficult to consider the passenger demand for the same OD pair at different times in the same optimisation, since VRP models tend to visit each position only once. This thesis proposes to use a capacitated multi-commodity model in order to incorporate passenger demand over the simulated period in a single optimisation. This is different from previous studies that have formulated the problems as VRPs.

Air metro

As mentioned in Section 1.1, the SNDP for UAM, i.e., air metro, is important because the pre-planned service may contribute more to transport efficiency than the on-demand air taxi service. Previous studies have designed the service network for on-demand air taxi (e.g., Roy et al. 2020). However, to the best of our knowledge, there has not been a service network design study for an air metro service.

Further, when studying the dispatch pattern of UAM service, pilot scheduling has not been considered as an endogenous factor in the models of existing studies. For fatigue and safety, pilots are constrained by duty hours (start and end duty time), which is likely less than the expected air metro operation period of an entire day. In an established UAM service network, there could be dozens or hundreds of vehicles and pilots. Hence, pilot scheduling can be a dimension in the system total cost. There has not been a study for UAM service network that considers pilot scheduling dimension.

Although autonomous aviation is a potential reality, and some studies have already implicitly assumed fully autonomous aircraft in UAM (e.g., Al Haddad et al. 2020), there has not been a study for the comparison of operating cost between piloted and pilot-less UAM service.

Moreover, as stated in Chapter 1.2, rolling horizon optimisation is particularly efficient when the information for only the near future is available. For UAM modelling, Kleinbekman et al. (2020) studied the VTOL arrival scheduling problem in a rolling horizon. However, the studies that optimise the VTOL dispatch patterns (between vertiports) have not considered rolling horizon optimisation as a means to address stochasticity in the demand.
Chapter 3

Modelling Approaches

In this chapter, the capacitated multi-commodity models and time-space networks from the literature are further developed and adopted to study the proposed SNDP. The AAITBS and air metro cases are mathematically formulated as MILP and ILP, respectively. For each case, graphs are drawn to represent the transport movements in the network that specify both the time and space dimensions, where each node represents a particular location at a specific time, whereas each arc represents the temporal and spatial connection between the two corresponding nodes.

3.1 Modelling approaches for AAITBS

The AAITBS involves determining fleet size and dispatch pattern during the planning horizon. We draw upon directed graphs for a fleet flow time-space service network and passenger flow time-space networks, that specify both the time and space dimensions in the network to model the fleet and passenger movements. In the time-space networks, each node represents a particular location (bus stop) at a specific time, whereas each arc represents the temporal and spatial connection between the two corresponding nodes. The bus shuttle fleet flows and passenger flows are specified by arcs in the fleet flow time-space service network and passenger flow time-space networks, respectively. In this study, we define passenger groups based on their origin stop, arrival time at the origin stop, their destination stop, and their tolerable latest arrival time (i.e., arrival time constraint) at the destination (e.g., due to flight schedules). To ease the presentation, we refer to each group
as a time-dependent OD pair. As will be introduced in Chapter 1.1, we will define a passenger time-space network for a specific passenger group (a time-dependent OD pair), where their arrival time constraint at the destination stop is explicitly incorporated. We consider that the airport is always able to provide ad-hoc services (e.g., outsourced to a third party) with a cost higher than regular service. The passengers must be served by either regular or ad-hoc service, and they are indifferent to either service type. We also consider that the shuttle buses do not have fixed depots during the service period.

### 3.1.1 Network description for AAITBS

Table 3.1 lists the main notations used for AAITBS case. Those not listed here will be specified in the texts. Note that super/sub-scripts might be added to some notations later on to indicate vehicle type and/or demand scenario (related to stochastic demand). In the following, we will further introduce the time-space networks for bus flows and passenger flows.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>set of time-dependent OD pairs (equivalent to the set of passenger groups)</td>
</tr>
<tr>
<td>$d \in R$</td>
<td>the $d$th OD pair in the set of time-dependent OD pairs</td>
</tr>
<tr>
<td>$N^q, A^q$</td>
<td>sets of nodes and arcs in the bus fleet flow time-space service network</td>
</tr>
<tr>
<td>$N^d, A^d$</td>
<td>sets of nodes and arcs in the $d$th passenger flow time-space network, i.e., the time-space network for passengers of the $d$th time-dependent OD pair (or passenger group)</td>
</tr>
<tr>
<td>$N^q_o, N^q_t$</td>
<td>sets of nodes at the beginning and ending of the planning duration, respectively, in the fleet flow time-space service network</td>
</tr>
<tr>
<td>$S^q, S^d$</td>
<td>sets of service arcs in the fleet flow time-space service network and the $d$th passenger flow time-space network, respectively</td>
</tr>
<tr>
<td>$W^q, W^d$</td>
<td>sets of waiting arcs in the fleet flow time-space service network and the $d$th passenger flow time-space network, respectively</td>
</tr>
<tr>
<td>$M^d$</td>
<td>the artificial node in the $d$th passenger flow time-space network</td>
</tr>
</tbody>
</table>
3.1.1 Network description for AAITBS

\((O^d, M^d)\) origin arc in the \(d\)th passenger flow time-space network

\((M^d, D^d)\) destination arc in the \(d\)th passenger flow time-space network

Definitional variables

- \(F_1\): fixed cost associated with providing a regular shuttle bus
- \(F_2\): fixed cost associated with providing a vehicle for ad-hoc service
- \(J\): maximum fleet size of regular service
- \(B^d\): travel demand in the \(d\)th passenger flow time-space network
- \(\xi\): the capacity of a single shuttle bus
- \(C_{ij}\): vehicle operating cost per trip between nodes \(i\) and \(j\)
- \(L_{ij}\): upper bound of fleet flow on service arc \((i, j)\) \(\in S^q\) in the fleet flow time-space service network
- \(\rho^a_{ij}\): waiting time cost per passenger on waiting arc \((i, j)\) \(\in W^d, \forall d\)
- \(\rho^b_{ij}\): riding time cost per passenger on service arc \((i, j)\) \(\in S^d, \forall d\)

Decision variables

- \(X_{ij}^d\): decision variable indicating the passenger flow on arc \((i, j)\) taking the regular service in the \(d\)th passenger flow time-space network
- \(Y_{ij}\): integer decision variable indicating the bus fleet flow for regular service on arc \((i, j)\) in the fleet flow time-space service network
- \(U^d\): decision variable indicating the passenger flow taking the ad-hoc service in the \(d\)th passenger flow time-space network
- \(\tau^d\): passenger cost of taking the ad-hoc service in the \(d\)th passenger flow time-space network
- \(V^d\): integer decision variable indicating the number of vehicles for ad-hoc service in the \(d\)th passenger flow time-space network

Fleet flow

The time-space service network with airport shuttle fleet flow is defined by a graph \(G^q(N^q, A^q)\). Only one bus fleet flow time–space service network is needed for a planning period. The arc set \(A^q\) consists of two subsets: service arc set \(S^q\) and wait arc set \(W^q\). Each service arc describes a
CHAPTER 3. MODELLING APPROACHES

vehicle trip with a certain travel time. Origins and destinations are specified by the corresponding nodes. The interval between two adjacent time rows is called a time step. The flow on each arc is represented by a non-negative integer variable. The cost on each arc encompasses operating costs. The flow on each waiting arc denotes the number of shuttle buses waiting at a stop without providing service. We assume that waiting arcs for buses have negligible operating cost. Figure 3.1 depicts an example of a time-space network with \( n \) stops. Typically, for the passenger service in the airport, the number of stops is often relatively small when compared to the number of time steps.

For each time-dependent OD pair (i.e., each passenger group), we define a specific passenger flow time-space network, where the group-specific departure time at the origin stop and the constraint on the arrival time at the destination stop are explicitly incorporated in this time-space network. We can obtain the time-space network with passenger flows defined by a collection of graphs

Passenger flow

For each time-dependent OD pair (i.e., each passenger group), we define a specific passenger flow time-space network, where the group-specific departure time at the origin stop and the constraint on the arrival time at the destination stop are explicitly incorporated in this time-space network. We can obtain the time–space network with passenger flows defined by a collection of graphs
3.1.2 Single-type fleet AAITBS under deterministic demand formulation

$G^d(N^d, A^d)$, where $d$ refers to a time-dependent OD pair. The passenger time-space networks for different time-dependent OD pairs can have different sizes.

$A^d$ consists of two subsets: service arc set $S^d$ and wait arc set $W^d$. Service arcs denote passenger trips between stops, whose riding time, origins, destinations are specified by the corresponding nodes. The flow on each arc is represented by a non-negative variable, subject to both the capacity of the shuttles and the upper bound of fleet flow on the arc. The flow on each wait arc describes the number of passengers waiting at the stop, subject to the bus dispatch pattern. Moreover, associated with each graph $G^d(N^d, A^d)$ are artificial node $M^d$ and artificial arcs: origin arc $(O^d, M^d)$ and destination arc $(M^d, D^d)$. The flow on the origin arc represents the number of passengers failed to be served by regular service and finally served by ad-hoc service, while the flow on the destination arc represents the number of passengers successfully served by the regular service.

Figure 3.2 illustrates an example of passenger time–space network with three stops. In a passenger flow time-space network, the demand $B^d$ for a time-dependent OD pair $d$ occurs only once. In the example, the demand arrives at stop $a$ (origin) at 21:30, and they should arrive at stop $c$ (destination) before 21:45. The passengers taking regular service will be transported by the destination arc to the artificial node $M^d$ once they arrive at the destination column $c$, while those failed to take the regular service will be allocated to the origin arc (i.e., the ad-hoc service). For each time-dependent OD pair, only a part of nodes and arcs are effective, subject to the arrival time constraint at the destination and trip feasibility. The shape of the fleet flow time-space service network graph can be regarded as an assembly of that of all passenger flow time-space networks.

3.1.2 Single-type fleet AAITBS under deterministic demand formulation

Basic formulations

We now examine the case where all regular services use the same type of buses and the travel demand is based on historical average (deterministic demand). The bus shuttle service in the airport is often not for profit, and therefore we consider it as free and there is no fare.

In order to minimise the total system cost, the AAITBS under single-type fleet and deterministic demand, i.e., problem (P0), can be formulated as follows.
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Figure 3.2: Passenger flow time-space network for AAITBS

(P0):

\[ \min_{x, y, u, v} Z = \sum_{i \in N_o^q} \sum_{j \in N^q \setminus N_o^q} Y_{ij} F_1 + \sum_{ij \in S^q} Y_{ij} C_{ij} + \sum_{d \in R} \sum_{ij \in W^d} X_{ij}^d \rho_{ij}^a + \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^d \rho_{ij}^b + \sum_{d \in R} U_d \tau_d + \sum_{d \in R} V_d F_2 \] (3.1)

subject to:

\[ \sum_{j \in N^q} Y_{ij} - \sum_{k \in N^q} Y_{ki} = 0 \quad \forall i \in N^q \setminus (N_o^q \cup N_t^q) \] (3.2)

\[ \sum_{i \in N_o^q} \sum_{j \in N^q \setminus N_o^q} Y_{ij} \leq J \] (3.3)

\[ \sum_{j \in N^d} X_{ij}^d - \sum_{k \in N^d} X_{ki}^d = \begin{cases} B_d - U_d & \text{if } i \text{ is the origin for group } d \\ 0 & \text{otherwise} \end{cases} \quad \forall d \in R \] (3.4)
3.1.2 Single-type fleet AAITBS under deterministic demand formulation

\[ \sum_{d \in R} X_{ij}^d \leq Y_{ij} \xi \quad \forall ij \in S^q \]  

\[ U^d \leq V^d \xi \quad \forall d \in R \]  

\[ 0 \leq Y_{ij} \leq L_{ij} \quad \forall ij \in S^q \]  

\[ 0 \leq U^d \leq B^d \quad \forall d \in R \]  

\[ Y_{ij} \in \text{integer} \quad \forall ij \in A^q \]  

\[ V^d \in \text{integer} \quad \forall d \in R \]  

where \( X = \{ X_{ij}^d \} \), \( Y = \{ Y_{ij} \} \), \( U = \{ U^d \} \), and \( V = \{ V^d \} \).

The objective function in Eq. (3.1) is to minimise the total system cost, including the service operating cost and passenger travel time cost, which consists of six terms: (i) fixed cost associated with providing a shuttle bus for regular service for the planning period; (ii) vehicle operating cost of regular service trips; (iii) passengers’ waiting time cost on regular service; (iv) passengers’ riding time cost on regular service; (v) fixed cost associated with providing ad-hoc services for the planning period; (vi) passengers’ travel cost on ad-hoc service. In the objective function, the summation of fleet flows, i.e., \( \sum_{i \in N^q} \sum_{j \in N^q \setminus N^o} Y_{ij} \), measures the number of shuttle buses in operation at the beginning of the planning horizon, which is equivalent to the deployed fleet size.

As for the constraints, Eq. (3.2) represents the conservation of fleet flows at each node \( i \) in the fleet flow time-space service network. Eq. (3.3) requires that the fleet size is no greater than the maximum allowable fleet size for regular service (e.g., due to operation or storage limitation). Eq. (3.4) states the passenger conservation at each node in the passenger flow time-space network. Eq. (3.5) combines the passenger flows from all passenger flow time-space networks in which the service arc \((i, j)\) is effective, and requires that the total passenger volume taking regular service is
no greater than the supplied capacity \( Y_{ij} \xi \) on each service arc \((i, j)\). Similarly, Eq. (3.6) requires that the total passenger volume taking ad-hoc service is no greater than the supplied capacity \( V^d \xi \) for each passenger flow time-space network. Eq. (3.7) sets the upper bound of fleet flow for each service arc \((i, j) \in S^q\) in the fleet flow time-space service network (e.g., due to road capacity constraints). Eq. (3.8) requires that the passenger volume taking ad-hoc service is no greater than the demand for each passenger flow time-space network. Eq. (3.9) and Eq. (3.10) define the regular and ad-hoc service fleet flow variables to be integers, respectively.

To summarise, the proposed model is to determine the fleet flow variables \( Y_{ij} \) and \( V^d \) and the passenger flow variables \( X_{ij}^d \) and \( U^d \) so as to minimise the total system cost in Eq. (3.1). All of these are to be sorted out after the solution to Eq. (3.1) - Eq. (3.10) is determined. The above formulations constitute an MILP, which can be solved through commercial optimisation solvers/packages (e.g., Gurobi). Note that the constraints on arrival time at the destination stops are incorporated in the passenger flow time-space networks defined in Chapter 3.1.1, and thus are not directly involved in the formulations here.

Alternative objective functions

In the objective function in Eq. (3.1), the first, second and fifth terms reflect the operating cost of the bus shuttle service provider, while the third, fourth and sixth terms are to represent the travel time cost of passengers in the network. For the bus shuttle service provider, the relatively importance of the operating cost and passenger travel time cost might vary, depending on their specific targets in practice. The operating cost and passenger cost can be written as follows.

\[
Z_1 = \sum_{i \in N^q} \sum_{j \in N^q \setminus N^a} Y_{ij} F_1 + \sum_{i \in S^q} Y_{ij} C_{ij} + \sum_{d \in R} V^d F_2 \tag{3.11}
\]

\[
Z_2 = \sum_{d \in R} \sum_{ij \in W^d} X_{ij}^d \rho^q_{ij} + \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^d \rho^b_{ij} + \sum_{d \in R} U^d \tau^d \tag{3.12}
\]

Then, a weighted objective can be written as follows.

\[
Z = \omega_1 Z_1 + (1 - \omega_1) Z_2 \tag{3.13}
\]

where \(\omega_1\) and \((1 - \omega_1)\) are the weights of total operating cost and passenger time cost, respectively. The constraints of the problem remain the same. A smaller \(\omega_1\) means that operating cost is less
valued and passenger experience is prioritised, and vice versa.

In addition, in the objective function in Eq. (3.1), the first four terms are related to regular service while the last two terms are related to the ad-hoc service. An operator may value regularity in the operation differently, depending on the specific conditions. We can write down regular service related cost and ad-hoc service related cost as follows.

\[
Z'_1 = \sum_{d \in R} U^d \tau^d + \sum_{d \in R} V^d F_2
\]

\[
Z'_2 = \sum_{i \in N} \sum_{j \in N \setminus N^q} Y_{ij} F_1 + \sum_{ij \in S^q} Y_{ij} C_{ij} + \sum_{d \in R} \sum_{ij \in W^d} X_{ij}^d \rho_{ij}^d + \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^d \rho_{ij}^b
\]

We then can consider the following weighted objective function.

\[
Z = \omega_2 Z'_1 + (1 - \omega_2) Z'_2
\]

where \( \omega_2 \) and \( 1 - \omega_2 \) are the weights of total ad-hoc and regular service costs, respectively.

Again, the constraints remain the same as the basic problem (P0). A larger \( \omega_2 \) means that costs related to ad-hoc service are more heavily penalised and regularity in operation is more preferred, and vice versa.

While we may replace the objective function in Eq. (3.1) by Eq. (3.13) or Eq. (3.16), the problem is still to determine the fleet flow variables \( Y_{ij} \) and \( V^d \) and the passenger flow variables \( X_{ij}^d \) and \( U^d \), in order to minimise a linear objective function. This means that the optimisation models for these two variants are still MILPs, where \( Y_{ij} \) and \( V^d \) are integer variables and \( X_{ij}^d \) and \( U^d \) are continuous variables. These problems can still be solved by commercial solvers for MILPs (for very large-scale problems, heuristics will be needed).

### 3.1.3 Heterogeneous multi-type fleet under deterministic demand formulation

In Chapter 3.1.2, we only consider the homogeneous single-type fleet. We now further consider that the different types of bus (the capacity of the bus is different) might be used to better accommodate the spatio-temporal variation in demand, i.e., heterogeneous multi-type fleet case. Let \( E \) be the set of vehicle types. \( e \in E \) is a vehicle type with a particular capacity \( \xi^e \). A superscript \( e \) is added to other notations to indicate the vehicle type where appropriate. We also let \( \xi^0 \) be the
capacity of vehicles used for ad-hoc service. Let $Y^e_{ij}$ be the fleet flow of a particular vehicle type $e$ on arc $(i, j)$. $X^{d,e}_{ij}$ denotes the passenger flow taking a particular vehicle type $e$ on service arc $(i, j) \in S^d$ for time-dependent OD pair $d$. $J^e$ represents the maximum fleet size of type $e$, while $J$ denote the maximum allowed fleet size of all types of shuttle buses in the network. We also let $X = \{X^{d,e}_{ij}\}$, $Y = \{Y^e_{ij}\}$, $U = \{U^d\}$, and $V = \{V^d\}$.

The optimisation problem for the multi-type fleet case, i.e., problem (P1), can be written as follows.

(P1): 

$$
\begin{align*}
\min_{X,Y,U,V} Z &= \sum_{e \in E} \sum_{i \in N^q} \sum_{j \in N^q \setminus N^q_o} \sum_{i \in N^q} \sum_{j \in N^q \setminus N^q_t} Y^e_{ij} F^e_1 + \sum_{e \in E} \sum_{ij \in S^q} Y^e_{ij} C^e_{ij} + \sum_{e \in E} \sum_{d \in R} \sum_{ij \in W^d} X^{d,e}_{ij} \rho^a_{ij} \\
&\quad + \sum_{e \in E} \sum_{d \in R} \sum_{ij \in W^d} X^{d,e}_{ij} \rho^b_{ij} + \sum_{d \in R} U^d r^d + \sum_{d \in R} V^d F_2 \\
\text{s.t.:} \quad &\sum_{j \in N^q} Y^e_{ij} - \sum_{k \in N^q} Y^e_{ki} = 0 \quad \forall i \in N^q \setminus (N^q_o \cup N^q_t) \quad \forall e \in E \quad (3.18) \\
&\sum_{e \in E} \sum_{i \in N^q} \sum_{j \in N^q \setminus N^q_t} Y^e_{ij} \leq J \quad (3.19) \\
&\sum_{i \in N^q_o} \sum_{j \in N^q \setminus N^q_t} Y^e_{ij} \leq J^e \quad \forall e \in E \quad (3.20) \\
&\sum_{e \in E} \sum_{j \in N^q} X^{d,e}_{ij} - \sum_{e \in E} \sum_{k \in N^q} X^{d,e}_{ki} = \begin{cases} 
B^d - U^d & \text{if } i \text{ is the origin for group } d \\
0 & \text{otherwise} 
\end{cases} \quad \forall d \in R \quad (3.21) \\
&\sum_{d \in R} X^{d,e}_{ij} \leq Y^e_{ij} \quad \forall ij \in S^q \quad \forall e \in E \quad (3.22) \\
&U^d \leq V^d \xi^0 \quad \forall d \in R \quad (3.23) \\
&0 \leq Y^e_{ij} \leq L_{ij} \quad \forall ij \in S^q \quad (3.24) \\
&0 \leq U^d \leq B^d \quad \forall d \in R \quad (3.25)
\end{align*}
$$
3.1.4 Stochastic demand formulation

\[ Y_{ij}^{e} \in \text{integer} \quad \forall ij \in A^q \quad \forall e \in E \]  \hspace{1cm} (3.26)

\[ V^{d} \in \text{integer} \quad \forall d \in R \]  \hspace{1cm} (3.27)

where most constraints have similar physical meanings as those in \((P0)\) in Chapter 3.1.2. Some constraints now become vehicle type specific. For instance, Eq. (3.19) requires that the fleet size of all vehicle types is no greater than a maximum allowed value, and Eq. (3.20) requires that the fleet size for each type \(e\) is smaller than a vehicle type specific maximum \(J^{e}\). It is expected that \(J^{e} \leq J\).

The multi-type fleet model is able to take advantage of heterogeneous vehicle sizes, where a mixed fleet may potentially further reduce the total system cost, e.g., for a low demand route, smaller buses might be used to save the operating cost. The multi-type fleet model is again an MILP and can be solved by commercial solvers for MILPs while more variables are involved given the same service network. Note that the multi-type fleet model might produce an optimal solution that only involves a single-type fleet, which means that under certain demand conditions (e.g., demand is quite evenly distributed over time and OD pairs), it might be preferred to adopt a single-type fleet.

3.1.4 Stochastic demand formulation

We now further examine the case with stochastic demand. We assume that the distribution of the demand is known, which can be estimated from historical demand data. In the following, we only present the model formulations for the single-type fleet case with stochastic demand. The case with heterogeneous multi-type fleet and stochastic demand can be readily formulated based on Chapter 3.1.3 and 3.1.4.

Let \(H\) denote the set of scenarios for the demand pattern, and \(h \in H\) is a member of scenario set \(H\) with a corresponding probability \(P_h\). Let \(X_{ij,h}^{d}\) be the passenger flow on arc \((i,j)\) taking regular service, \(U_{h}^{d}\) be the passenger flow taking ad-hoc service, \(V_{h}^{d}\) be the number of vehicles for ad-hoc service, and \(B_{h}^{d}\) be the demand in the \(d\)th passenger flow time-space network under scenario \(h\), respectively. We also let \(X = \{X_{ij,h}^{d}\}\), \(Y = \{Y_{ij}\}\), \(U = \{U_{h}^{d}\}\), and \(V = \{V_{h}^{d}\}\).
Similar to Lo et al. (2013), the optimisation problem for the case with single-type fleet and stochastic demand, i.e., problem (P2), can be written as a two-stage program as follows.

(P2):  
\[
\min_{X,Y,U,V} \quad Z = \sum_{i \in N_q} \sum_{j \in N_q \setminus N_o} Y_{ij} F_1 + \sum_{ij \in S} Y_{ij} C_{ij} + \varphi(Y) 
\]

subject to:

\[
\sum_{j \in N_q} Y_{ij} - \sum_{k \in N_q} Y_{ki} = 0 \quad \forall i \in N_q \setminus (N_o \cup N_t) 
\]

\[
\sum_{i \in N_o} \sum_{j \in N_q \setminus N_o} Y_{ij} \leq J 
\]

\[
0 \leq Y_{ij} \leq L_{ij} \quad \forall ij \in S_q 
\]

\[
Y_{ij} \in \text{integer} \quad \forall ij \in A_q 
\]

where \(\varphi(Y)\) is an average performance metric defined as follows:

\[
\varphi(Y) = \min_{X,U,V} \sum_{h \in H} P_h \cdot \varphi_h(Y) 
\]

where for each \(h \in H\):

\[
\varphi_h(Y) = \sum_{d \in R} \sum_{ij \in W_d} X_{ij,h}^{d,a} P_{ij}^{a} + \sum_{d \in R} \sum_{ij \in S_d} X_{ij,h}^{d,b} P_{ij}^{b} + \sum_{d \in R} U_{h}^{d} T_{d}^{d} + \sum_{d \in R} V_{h}^{d} F_2 
\]

and is subject to the following constraints:

\[
\sum_{j \in N^d} X_{ij,h}^{d} - \sum_{k \in N^d} X_{ki,h}^{d} = \begin{cases} B_{h}^{d} - U_{h}^{d} & \text{if } i \text{ is the origin for group } d \\ 0 & \text{otherwise} \end{cases} 
\]

\(\forall d \in R \quad \forall h \in H\)

\[
\sum_{d \in R} X_{ij,h}^{d} \leq Y_{ij,h} \xi \quad \forall ij \in S_q \quad \forall h \in H 
\]

\[
U_{h}^{d} \leq V_{h}^{d} \xi \quad \forall d \in R \quad \forall h \in H 
\]
3.1.4 Stochastic demand formulation

\[ 0 \leq U^d_h \leq B^d_h \quad \forall d \in R \quad \forall h \in H \quad (3.38) \]

\[ V^d_h \in \text{integer} \quad \forall d \in R \quad \forall h \in H \quad (3.39) \]

For the above problem, the first stage can be regarded as finding a fleet dispatch pattern for regular service given an average efficiency metric that is obtained from the second stage under multiple possible demand scenarios, and the second stage is to determine ad-hoc services and passenger flow patterns given the fleet dispatch pattern for regular service from the first stage. In particular, Eq. (3.28) is the objective function for Stage 1, where \( \varphi(Y) \) is the average performance metric based on all possible demand scenarios, as given in Eq. (3.33). \( \varphi(Y) \) is obtained by solving optimisation problems in Stage 2. The constraints remain similar to those in the deterministic model (P0) in Chapter 3.1.2.

Solution Approach

We now examine a Monte Carlo simulation-based approach to solve the above problem with stochastic demand. Firstly, we propose the concept of “effective” demand which is to provide a solution of \( Y = \{Y_{ij}\} \) in the first stage. For each passenger group \( d \), suppose demand \( B^d \) follows a distribution with a mean of \( m_d \) and a standard deviation of \( s_d \). We define an “effective” demand as \( B^d_{\Delta} = m_d + \Delta \cdot s_d \) for all \( d \), where \( \Delta \) is a coefficient for \( s_d \). For simplicity, we consider a single \( \Delta \) for all \( d \) (one can also consider different \( \Delta \) for each passenger group, i.e., \( \Delta_d \) for group \( d \)). If \( B^d_{\Delta} \) is regarded as an estimate of the demand, a larger \( \Delta \) means that we tend to have a larger demand estimation.

Each value of \( \Delta \) has a corresponding “effective” demand. By inputting the “effective” demand into the deterministic problem (P0), a corresponding dispatch solution (i.e., \( Y \)) can be obtained. In the second stage, the Monte Carlo simulation method is used to generate adequate demand scenarios (from set \( H \)) in order to provide an estimate of \( \varphi(Y) \) in the second stage. Based on the Monte Carlo simulation, a corresponding \( \varphi(Y) \) can be gained with each solution, which is a part in the objective function (3.28). Therefore, each value of \( \Delta \) has a corresponding objective value \( Z \), and the value of \( \Delta \) that has the minimum objective value is the (sub-)optimal solution to the stochastic
CHAPTER 3. MODELLING APPROACHES

problem. The proposed solution approach will try to identify a value of \( \Delta \) that can help us to find a (sub-)optimal solution to the problem \( (P2) \).

- Step 0: Given the lower and upper bounds of \( \Delta \) where \( \Delta \in [\Delta_l, \Delta_u] \);

- Step 1: Use golden-section search (or other interval reduction method) to update \([\Delta_l, \Delta_u]\) until \( \Delta_u - \Delta_l \) is sufficiently small,\(^1\), where for each value of \( \Delta \) to be assessed, calculate the corresponding \( Z \) as follows:
  - Step 1-0: For a specific value of \( \Delta \), calculate \( B^d_\Delta \) for each passenger group \( d \) based on \( \Delta \), then take \( B^d_\Delta \) as the demand for each group \( d \) and solve the deterministic model \( (P0) \);
  - Step 1-1: Take the solution \( Y = \{Y_{ij}\} \) from Step 1-0 as given, then utilise the Monte Carlo simulation-based approach to estimate \( \varphi(Y) \) as follows:
    * Step 1-1-0: Generate a demand pattern for all passenger groups based on the distributions of \( B^d \) for each passenger group \( d \), where each demand pattern can be regarded as a demand scenario \( h \);
    * Step 1-1-1: Take the demand pattern in scenario \( h \) from Step 1-1-0 and the solution \( Y = \{Y_{ij}\} \) from Step 1-1 as given, and then use the commercial solver (Gurobi) to solve the deterministic model \( (P0) \) and calculate \( \varphi_h(Y) \) under the demand scenario \( h \);
    * Step 1-1-2: Calculate the mean value \( \varphi(Y) \) based on \( \varphi_h(Y) \) for all scenarios \( h \) that have been generated so far;
    * Step 1-1-3: If the number of demand scenarios considered is less than the required threshold (it often means that the estimation of \( \varphi(Y) \) does not stabilise),\(^2\) go to Step

\(^1\)The golden-section search method can be used for finding the minimum of the objective function (minimisation problem) inside a specified interval of \( \Delta \) (Kiefer 1953). For a strictly uni-modal function, the golden-section search is able to find the minimum (minimisation problem).

\(^2\)We have conducted extensive numerical experiments in order to identify a proper threshold, where the value of \( \varphi(Y) \) tends to stabilise, i.e., the percentage error between two recent values of \( \varphi(Y) \) is no greater than 0.1%. In our case study, with 30 runs of simulations the estimation of \( \varphi(Y) \) stabilises. To ensure consistency and solution quality, we indeed use 100.
3.2 MODELLING APPROACHES FOR AIR METRO

1-1-0; otherwise, go to Step 1-2;

- Step 1-2: Update $Z$ in Eq. (3.28) with the $\varphi(Y)$ from Step 1-1-3;

• Step 2: Determine the value of $\Delta$ with the lowest value of $Z$.

The procedure has two layers of extension. The one in Step 1 is to discuss the different values of $\Delta$ with the corresponding values of $Z$, while another in Step 1-1 is to generate different demand scenarios and calculate the corresponding $\varphi(Y)$.

We further discuss the above solution procedure below. i). In Step 0, the initial $[\Delta_l, \Delta_u]$ can be divided into multiple smaller intervals, and for each smaller interval, we can adopt the above solution approach independently and then choose the solution of $\Delta$ among different intervals that yield the minimal system cost. Doing so reduces the risk of the interval reduction method (mentioned in Step 1) to stop at a local optimum when the objective function is not uni-modal. This is adopted in the case study. ii). The Monte Carlo simulation-based process in Step 1-1 can be embedded into other meta-heuristics such as GA, i.e., Monte Carlo simulation coupled with GA. We indeed compare the proposed approach (Monte Carlo simulation coupled with “effective” demand) with the Monte Carlo simulation coupled with GA approach in the case study. iii). An interpretation of the above procedure is that $B_{\Delta} = m_d + \Delta \cdot s_d$ provides a demand estimation that differs from the mean demand value, where $\Delta > 0$ is likely to occur at the (sub-)optimal solution. This means that in order to accommodate demand stochasticity, the service should be pre-scheduled based on a larger demand than mean estimation, where $\Delta \cdot s_d$ can be considered as a safety margin of the demand estimation (above the mean value).

3.2 Modelling approaches for air metro

3.2.1 Network description for air metro

For this case, we first mathematically formulate the SNDP as an ILP, under the assumptions that the passenger demand is deterministic and the vertiports are established and available. The SNDP for air metro involves determining the fleet size and dispatch pattern during the planning horizon. We draw upon directed graphs for a fleet flow time-space service network, passenger flow time-space networks, and pilot time-space duty networks that specify both the time and space dimensions in
the network to model the fleet, passenger and pilot movements. In the time-space networks, each node represents a particular location (vertiport) at a specific time, whereas each arc represents the temporal and spatial connection between the two corresponding nodes. The VTOL fleet flows, passenger flows, and pilot flows are specified by arcs in the fleet flow time-space service network, passenger flow time-space networks, and pilot time-space duty networks, respectively. We define passenger groups based on their origin vertiport, arrival time at the origin vertiport, their destination vertiport, and their tolerable latest arrival time (i.e., arrival time constraint) at the destination. To ease the presentation, we refer to each group as a time-dependent OD pair. We define a passenger time-space network for a specific passenger time-dependent OD pair, where their arrival time constraint at the destination vertiport is explicitly incorporated. We consider that the service providers are always able to provide ad-hoc services with a cost higher than regular service. The passengers must be served by either regular or ad-hoc service, and they are indifferent to either service type. We also assume that the VTOLs do not have fixed depots during the service period. Table 3.2 lists the main notations used in the air metro case. Those not listed here will be specified in the texts. Note that in Chapter 3.2.4, super/sub-scripts might be added to some notations (e.g., $U_{ij,h}$) to indicate the simulated horizon (related to rolling horizon optimisation).

Table 3.2: Nomenclature for air metro

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indices &amp; sets</td>
<td></td>
</tr>
<tr>
<td>$E$</td>
<td>set of time-dependent OD pairs (equivalent to set of passenger groups)</td>
</tr>
<tr>
<td>$e \in E$</td>
<td>the $e$th OD pair is a member of the set of time-dependent OD pairs</td>
</tr>
<tr>
<td>$T$</td>
<td>set of pilot duty hours within a working day</td>
</tr>
<tr>
<td>$t \in T$</td>
<td>the $t$th duty is a member of the set of duty period</td>
</tr>
<tr>
<td>$N^f, A^f$</td>
<td>sets of nodes and arcs in the VTOL fleet flow time-space service network</td>
</tr>
<tr>
<td>$N^e, A^e$</td>
<td>sets of nodes and arcs in the $e$th passenger flow time-space network, i.e., the time-space network for passengers of the $e$th time-dependent OD pair (or passenger group)</td>
</tr>
<tr>
<td>$N^t, A^t$</td>
<td>sets of nodes and arcs in the $t$th pilot flow time-space duty network</td>
</tr>
</tbody>
</table>
3.2.1 Network description for air metro

\( N_0^f, N_d^f \) sets of nodes at the beginning and ending of the planning duration, respectively, in the fleet flow time-space service network

\( N_o^t, N_d^t \) sets of nodes at the beginning and ending of the planning duration, respectively, in the \( t \)th pilot flow time-space duty network

\( S^f, S^t, S^e \) sets of service arcs in the fleet flow time-space service network, the \( t \)th pilot flow time-space duty network, and the \( e \)th passenger flow time-space network, respectively

\( M^e \) the artificial node in the \( e \)th passenger flow time-space network

\((O^e, M^e)\) the origin arc in the \( e \)th passenger flow time-space network

\((M^e, D^e)\) the destination arc in the \( e \)th passenger flow time-space network

Definitional variables

\( \xi^e \) travel demand in the \( e \)th passenger flow time-space network

\( C \) the capacity of a single VTOL for regular service

\( J \) maximum fleet size of regular service

\( L \) capacity of vertiports, i.e., the maximum number of VTOLs landing at the same vertiport at the same time-step

\( F_1 \) acquisition cost associated with long-term hiring a human-driven VTOL for regular air metro service for the planning period, including the opportunity cost of capital

\( F_2 \) acquisition cost associated with long-term hiring an autonomous VTOL for regular air metro service for the planning period, including the opportunity cost of capital

\( F_3 \) salary associated with long-term employing a pilot for regular air metro service for the planning period, including the opportunity cost of capital

\( F_4 \) outsourcing cost associated with providing a single ad-hoc service

\( R_{ij} \) operating cost per trip between nodes \( i \) and \( j \) for regular service provided by human-driven VTOLs

\( R'_{ij} \) operating cost per trip between nodes \( i \) and \( j \) for regular service provided by autonomous VTOLs
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\[ \rho_{ij}^e \] monetary time cost per passenger taking regular service on the arc \((i, j) \in A^e\) in the \(e\)th passenger flow time-space network

\[ \tau^e \] passenger cost of taking the ad-hoc service in the \(e\)th passenger flow time-space network

**Decision variables**

\[ U_{ij} \] integer variable indicating the bus fleet flow for regular service on arc \((i, j)\) in the fleet flow time-space service network

\[ V_{ij}^e \] integer variable indicating the passenger flow on arc \((i, j)\) taking the regular service in the \(e\)th passenger flow time-space network

\[ W_{ij}^t \] integer variable indicating the pilot flow on arc \((i, j)\) for driving a VTOL for regular service in the \(t\)th pilot flow time-space duty network

\[ X^e \] integer variable indicating the number of vehicles for ad-hoc service in the \(e\)th passenger flow time-space network

\[ Y^e \] integer variable indicating the passenger flow taking the ad-hoc service in the \(e\)th passenger flow time-space network

**Fleet flow**

The time-space service network for VTOL fleet flow is defined by a graph \(G^f(N^f, A^f)\). Only one fleet flow time-space service network is needed for a planning period. \(A^f\) consists of service arcs and waiting arcs. Each service arc \((i, j) \in S^f\) describes a vehicle trip and the travel time. Origins and destinations are specified by the corresponding nodes. The interval between two adjacent time rows is called a time step. The flow on each arc is represented by a non-negative integer variable. The cost on each arc encompasses operating costs. The flow on each waiting arc denotes the number of aircraft waiting at a vertiport without providing service. We assume that waiting arcs for aircraft have negligible operating cost. Figure 3.3 depicts an example of a fleet flow time-space service network with \(n\) vertiports. Typically, the number of vertiports is often relatively small when compared to the number of time steps.
3.2.1 Network description for air metro

Figure 3.3: Fleet flow time-space service network for air metro

**Passenger flow**

For each time-dependent OD pair (i.e., each passenger group), a specific passenger flow time-space network is defined, where the group-specific departure time at the origin vertiport and the constraint on the arrival time at the destination vertiport are explicitly incorporated in this time-space network. We can obtain the time-space network with passenger flow defined by a collection of graphs $G^e(N^e, A^e)$, where $e$ refers to a time-dependent OD pair. The passenger time-space networks for different time-dependent OD pairs can have different sizes.

$A^e$ consists of service arcs and waiting arcs. Each service arc $(i, j) \in S^e$ denotes a passenger trip between two vertiports, whose riding time, origins, destinations are specified by the corresponding nodes. The flow on each arc is represented by a non-negative variable, subject to both the capacity of the VTOLs. The flows on the waiting arcs describe the number of passengers waiting at a vertiport, subject to the air metro dispatch patterns. Moreover, associated with each graph
CHAPTER 3. MODELLING APPROACHES

$G^e(N^e,A^e)$ are an artificial node $M^e$ and artificial arcs: an origin arc $(O^e,M^e)$ and a destination arc $(M^e,D^e)$. The flow on an origin arc represents the number of passengers failed to be served by regular service therefore will be served by ad-hoc service, while the flow on a destination arc represents the number of passengers successfully served by the regular service in a passenger flow time-space network.

Figure 3.4 illustrates an example of a passenger time–space network with three vertiports. In a passenger flow time-space network, the exogenous demand for a time-dependent OD pair $e$ occurs only once. In the example, passengers have a maximum acceptable journey time of 75 minutes. The demand arrives at the vertiport $a$ (origin) at 21:30, and they should arrive at the vertiport $c$ (destination) before 22:45. The passengers taking regular service will be transported by the destination arc $(M^e,D^e)$ to the artificial node once they arrive at column $c$, while those failed to take the regular service will be allocated to the origin arc $(O^e,M^e)$ (i.e., the ad-hoc service). For each time-dependent OD pair, only a part of nodes and arcs are effective, subject to the arrival time constraint at the destination and trip feasibility.

![Figure 3.4: Passenger flow time-space service network for air metro](image)
3.2.1 Network description for air metro

Pilot flow

For pilot operation, a duty is a working duration within a working day of a pilot and consists of a sequence of consecutive flights, connections (transition time between flight legs) and deadheads. According to the duty period and depot of pilots, the pilot flows are segregated into different networks. For each pilot flow time-space duty network, only parts of nodes and arcs are effective, subject to the duty period, depot, and trip feasibility. The pilot flow time-space duty networks for different pilot groups can have different sizes. The time-space duty networks with air metro pilot flow are defined by a collection of graphs $G^t(N^t, A^t)$, where $t$ is a member of set $T$. The flow on each arc is represented by a non-negative integer variable, denoting the pilot flow movements. In each pilot flow time-space duty network, the pilots have the same depot and the same duty period. Figure 3.5 depicts an example of a pilot flow time-space duty network, with vertiport $b$ serving as the depot. In this example, all pilots depart from vertiport $b$ at the beginning of the planning horizon. The duty period starts from 07:00 and have a maximum flight duty period of 7 hours. The pilots must arrive at vertiport $b$ by the end of the duty period, i.e., 14:00.

Figure 3.5: Pilot flow time-space duty network for air metro
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Fleet flow, passenger flow and pilot flow are three different commodities in this case, and thus there are the three dimensions of time-space networks: a fleet flow time-space service network, passenger time-space networks, and pilot time-space duty networks.

3.2.2 Piloted air metro formulation

In this chapter, all regular services use single-type aircraft fleet, and the travel demand is based on historical average (deterministic demand). Since an aircraft is usually expensive, there is a high opportunity cost of capital, including the cost for hiring an aircraft and employing a pilot. One needs to long-term hire a fleet of VTOLs and employ pilots, which is necessary for providing regular air metro services. The opportunity cost of capital refers to the loss of capital when investing in one asset as opposed to another. Ad-hoc service can be outsourced to a third party (e.g., air taxi companies), and this type of service does not bring opportunity cost for the air metro provider. However, ad-hoc service has a higher cost per use.

In order to minimise the total system cost, the SNDP for piloted air metro, i.e., problem (P3), can be mathematically formulated as follows.

(P3): 

\[
\begin{align*}
\min_{U, V, W, X, Y} \quad Z &= \sum_{i \in N_f} \sum_{j \in N_f \backslash N_d} U_{ij} F_1 + \sum_{t \in T} \sum_{i \in N_f} \sum_{j \in N_f \backslash N_d} W_{ij}^t F_3 + \sum_{ij \in S_f} U_{ij} R_{ij} \\
&\quad + \sum_{e \in E} \sum_{ij \in A_e} V_{ij}^e \rho_{ij}^e + \sum_{e \in E} X^e F_4 + \sum_{e \in E} Y^e C \\
\text{subject to:} \\
&\quad \sum_{j \in N_e} V_{ij}^e - \sum_{k \in N_e} V_{ki}^e = \begin{cases} 
\xi^e - Y^e & \text{if } i \text{ is the origin for group } e \\
0 & \text{otherwise} 
\end{cases} \quad \forall e \in E \\
&\quad \sum_{e \in E} V_{ij}^e + \sum_{t \in T} W_{ij}^t \leq U_{ij} C \quad \forall ij \in S_f \\
&\quad Y^e \leq X^e C \quad \forall e \in E \\
&\quad \sum_{j \in N_f} U_{ij} - \sum_{k \in N_f} U_{ki} = 0 \quad \forall i \in N_f \backslash (N_d \cup N_d') 
\end{align*}
\]

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3.2.2 Piloted air metro formulation

\[ U_{ij} \leq \sum_{t \in T} W^{t}_{ij} \quad \forall ij \in S^f \]  
(3.45)

\[ \sum_{j \in N^f} W^{t}_{ij} - \sum_{k \in N^f} W^{t}_{ki} = 0 \quad \forall i \in N^f \setminus (N^f_o \cup N^f_d) \quad \forall t \in T \]  
(3.46)

\[ \sum_{j \in N^f \setminus N^f_o} U_{ij} \leq J \quad \forall i \in N^f_o \]  
(3.47)

\[ \sum_{k \in N^f} U_{ki} \leq L \quad \forall i \in N^f \setminus N^f_o \]  
(3.48)

\[ 0 \leq U_{ij} \quad \forall ij \in A^f \]  
(3.49)

\[ 0 \leq X_e \quad \forall e \in E \]  
(3.50)

\[ 0 \leq W^{t}_{ij} \quad \forall ij \in A^t \quad \forall t \in T \]  
(3.51)

\[ 0 \leq Y^e \leq \xi^e \quad \forall e \in E \]  
(3.52)

\[ U_{ij} \in \text{integer} \quad \forall ij \in A^f \]  
(3.53)

\[ V^e_{ij} \in \text{integer} \quad \forall ij \in A^e \quad \forall e \in E \]  
(3.54)

\[ W^{t}_{ij} \in \text{integer} \quad \forall ij \in A^t \quad \forall t \in T \]  
(3.55)

\[ X^e \in \text{integer} \quad \forall e \in E \]  
(3.56)

\[ Y^e \in \text{integer} \quad \forall e \in E \]  
(3.57)
where \( U = \{ U_{ij} \}, \ V = \{ V^e_{ij} \}, \ W = \{ W^t_{ij} \}, \ X = \{ X^e \}, \) and \( Y = \{ Y^e \} \).

The objective function (3.40) is to minimise the total system cost, including the service operating cost and passenger travel time cost, and consists of six terms: (i) Opportunity cost of capital for VTOL fleet acquisition for regular services for the planning period; (ii) salary cost of long-term pilot employment for flying VTOLs for regular services for the planning period; (iii) operating cost of trips for regular services (e.g., energy cost, battery reserve cost, maintenance cost); (iv) passengers’ monetary travel time cost on regular services, including waiting and riding time; (v) outsourcing cost associated with providing an ad-hoc service for the planning period; (vi) passengers’ travel cost on ad-hoc service (monetary travel time cost, or plus a penalty for the use of ad-hoc service).

As for the constraints, Eq. (3.41) states the passenger flow conservation at each node in the passenger flow time-space network. Eq. (3.42) requires that the total passenger volume taking regular service on each service arc is no greater than the supplied capacity \( U_{ij} C \) on each service arc \( (i,j) \). Similarly, Eq. (3.43) requires that the total passenger volume taking ad-hoc service is no greater than the supplied capacity of ad-hoc aircraft \( X^e C \) for each passenger flow time-space network. Eq. (3.44) represents the conservation of fleet flows for regular service at each node \( i \) in the fleet flow time-space service network. Eq. (3.45) requires at least one pilot for each VTOL for regular service on service arc in the fleet flow time-space service network. Eq. (3.46) requires the conservation of pilot flows at each node \( i \) in each pilot flow time-space duty network. Eq. (3.47) requires that the fleet size for regular service is no greater than the maximum allowable fleet size for regular service (e.g., due to operation or storage limitation). Eq. (3.48) sets the upper bound of in-flows for vertiports (e.g., due to the capacity of vertiports. Eq. (3.49) and (3.50) define the regular and ad-hoc service fleet flow variables to be non-negative, respectively. Eq. (3.51) sets the pilot flows to be non-negative. Eq. (3.52) requires that the passenger volume taking ad-hoc service is non-negative and no greater than the demand for each passenger flow time-space network. Eq. (3.53) - (3.57) define all the decision variables to be integer.

The proposed model is to determine the fleet and pilot flow variables \( U_{ij}, W^t_{ij} \) and the number of ad-hoc service \( X^e \), as well as the passenger flow variable \( V^e_{ij} \) and \( Y^e \) to determine the total system cost in Eq. (3.40). All of these are to be solved after the solutions to Eq. (3.40) - Eq. (3.57)
are determined. The formulation constitutes an ILP which can be solved by commercial solvers (e.g., Gurobi, CPLEX). In addition to the constraints on the arrival time at the destinations, the departure and arrival time at the depots are also incorporated in the pilot flow time-space duty networks defined in Chapter 3.2.1.

### 3.2.3 Pilot-less air metro formulation

In this chapter, we examine the modelling approach for the pilot-less air metro scenario, where the service is provided by autonomous VTOLs. Hence, the labour cost of pilots is not taken into consideration and the pilot scheduling is exempted. Then, an optimisation model for the pilot-less air metro, i.e., problem \((P4)\), can be formulated as following.

\[(P4)\]
\[
\begin{align*}
\min_{U, V, X, Y, Z} & \quad Z = \sum_{i \in N^f} \sum_{j \in N^f \setminus N^d} U_{ij} F_2 + \sum_{ij \in S^f} U_{ij} R_{ij}^p + \sum_{e \in E} \sum_{ij \in A^e} V_{ij}^e \rho_{ij}^e \\
& \quad + \sum_{e \in E} X_e F_4 + \sum_{e \in E} Y_e \tau^e
\end{align*}
\]

subject to:

\[
\sum_{j \in N^e} V_{ij}^e - \sum_{k \in N^e} V_{ki}^e = \begin{cases} 
\xi^e - Y^e & \text{if } i \text{ is the origin for group } e \\
0 & \text{otherwise}
\end{cases} \quad \forall e \in E
\] (3.59)

\[
\sum_{e \in E} V_{ij}^e \leq U_{ij} C \quad \forall ij \in S^f
\] (3.60)

\[
Y^e \leq X^e C \quad \forall e \in E
\] (3.61)

\[
\sum_{j \in N^f} U_{ij} - \sum_{k \in N^f} U_{ki} = 0 \quad \forall i \in N^f \setminus (N^d \cup N^f)
\] (3.62)

\[
\sum_{j \in N^f \setminus N^d} U_{ij} \leq J \quad \forall i \in N^d
\] (3.63)

\[
\sum_{k \in N} U_{ki} \leq L \quad \forall i \in N^f \setminus N^d
\] (3.64)
CHAPTER 3. MODELLING APPROACHES

\[ 0 \leq U_{ij} \quad \forall ij \in A^f \]  
\[ 0 \leq X^e \quad \forall e \in E \]  
\[ 0 \leq Y^e \leq \xi^e \quad \forall e \in E \]  
\[ U_{ij} \in \text{integer} \quad \forall ij \in A^f \]  
\[ V_{ij}^e \in \text{integer} \quad \forall ij \in A^e \quad \forall e \in E \]  
\[ X^e \in \text{integer} \quad \forall e \in E \]  
\[ Y^e \in \text{integer} \quad \forall e \in E \]

where \( U = \{U_{ij}\}, V = \{V_{ij}^e\}, X = \{X^e\}, \) and \( Y = \{Y^e\} \).

The objective function (3.58) is to minimise the total system cost, including the service operating cost and passenger travel time cost. It consists five terms: (i) fixed opportunity cost of capital for providing an autonomous VTOL for regular service for the planning period; (ii) aircraft operating cost of regular service trips (e.g., energy cost, battery reserve cost, maintenance cost); (iii) passengers’ monetary time cost on regular service, including waiting and riding time; (iv) fixed cost associated with providing an ad-hoc service for the planning period; (v) passengers’ travel cost on ad-hoc service (monetary travel time cost, or plus a penalty for the use of ad-hoc service). Note that the pilot flows and corresponding flow conservation are not considered in this problem. The constraints are the same as those in (P3).

3.2.4 Rolling horizon optimisation formulation

In this chapter, a dynamic optimisation in rolling horizon is examined. Since the piloted air metro model involved a large number of variables, especially integer variables, the computation time
3.2.4 Rolling horizon optimisation formulation

could be considerably large. In the following, we only present the model formulations for the piloted air metro in rolling horizon. The case of pilot-less air metro in rolling horizon can be readily formulated based on the presented piloted model. Moreover, (P3) model considered deterministic passenger travel demand only. The fact that the SNDP for the entire day’s operations is large and that passenger demand might not be recurrent and fully predictable means a rolling horizon model from a dynamic perspective can be more effective and practical. In the rolling horizon approach, the duration of the day’s operations is split into discrete time slice, similar to the time step concept. However, a single rolling horizon (e.g., 2-hour period) can contain several time steps (e.g., 10-minute step). The dispatch patterns in certain time steps are allocated to a rolling horizon. At the start of each rolling horizon, dispatch patterns in time steps belonging to this rolling horizon are determined simultaneously by solving an ILP with a combinatorial passenger demand pattern. In practice, the rolling horizon optimisation is akin to asking passengers to confirm their trips via smartphone applications a certain hours before departure (e.g., if a customer hope to take air metro that departs at 8 a.m., he/she needs to confirm the trip 2 hours in advance, at 6 a.m.), and then the seat would be locked for the passenger.\(^3\) Therefore, the actual demand in the near future is known (e.g., 2-hour period); while beyond this time interval, the demand is assumed as the predicted value. We define this time period (e.g., 2 hours) as early confirmation period (ECP).

Let \( h \) denote the number of rolling horizons, and \( H = \{h\} \) is the set of all rolling horizons. Figure 3.6 is a schematic diagram that explains the process of SNDP in rolling horizon. In this example, rolling horizon \( h = 0 \) is the start of the daily operations. Before the start of rolling horizon 0, the demand in time step 0 (or a larger period) is known. An ILP in the same shape with that in Chapter 3.2.2 with a combinatorial demand pattern is solved, and the corresponding solution (dispatch pattern for the whole day) is temporarily adopted. Thus, the dispatch pattern for time step 0 is adopted. Then, it comes to the rolling horizon \( i = 1 \), an ILP with an updated combinatorial demand pattern is solved, and the new solution is updated to be temporarily adopted. The new dispatch pattern for time step 1 is adopted, while the dispatch pattern for time step 0 is already fixed in rolling horizon 0. For rolling horizon \( i = 2 \), trips in time step 0 have been completed, dispatch pattern for time step 1 is already determined in rolling horizon 1, while dispatch pattern

\(^3\)The idea of using smartphone applications to obtain or capture actual passenger demand has been widely applied in previous studies (e.g., Aguiléra et al. 2014, Cao & Ceder 2019).
for time step 2 is adopted according to the new updated demand and solution. The time slice is continuously rolling every time when the rolling horizon updates. The entire day’s dispatch pattern consists of the actually adopted patterns across all rolling horizons.

**Figure 3.6: Dispatch patterns for time steps in rolling horizon**

**Fleet flow**

Figure 3.7 further shows an example of fleet flow service time-space network under rolling horizon \( h = 0 \), with a 30-minute period of ECP (in reality, this value could be longer. However, it is set at 30 minutes here for illustration purposes). At 07:00, the actual passenger demand for passenger OD pairs whose departure time is within ECP (e.g., before 07:30) is available. However, a rolling horizon simulates a longer period, e.g., 2-hour period, instead of the 30-minute window. This is because if only the 30-minute window is simulated, there can be a decision divergence between the simulated horizon and subsequent time steps. A safety margin is introduced to achieve a smooth transition between multiple time steps. In \( h = 0 \), the optimised rolling horizon is the ECP (30 minutes) plus a safety margin (45 minutes), and the total length of the rolling horizon is 75 minutes. While a short rolling horizon reduces the computational complexity, a long safety margin can ensure the reliability of solutions. The passenger demand for OD pairs whose depa-
3.2.4 Rolling horizon optimisation formulation

ture time is between [07:00, 08:15) is considered in this horizon. In this rolling horizon, the actual passenger demand whose departure is between [07:00, 07:30) is available; while the actual passenger demands whose departure outside the 30-minute window, i.e., [07:30, 08:15), is not available. Therefore, the demand for the [07:30, 08:15) is based on predicted values.

For the outputs, the decision variables (e.g., $U_{ij}$, $V_{ij}^e$, etc.) for fleet flows that depart at 07:00 (blue arcs in Figure 3.7) is determined and will not be changed in the subsequent rolling horizons (e.g., $h = 1$, $h = 2$, etc.). However, although fleet flows for marginal arcs (black arcs in Figure 3.7) that depart at [07:15, 08:15) is optimised, they can be further changed in the next rolling horizons to suit the actual demand.

![Figure 3.7: Fleet flow time-space service network for air metro at rolling horizon $h = 0$](image)

Here the time-space networks for the circumstance that $h0$ is introduced. Figure 3.8 shows an example of fleet flow time-space service network for $h = 1$. The optimised rolling horizon becomes [07:15, 08:30), where the ECP is [07:15, 07:45) and safety margin is [07:45, 08:30). The passenger demand for OD pairs who can be transported between (07:15, 08:30] is considered. The fleet flows that depart at 07:00 is already determined in the last rolling horizon, i.e., $h = 0$, and would not be optimised in $h = 1$. However, the flows on the completed arcs (yellow in Figure 3.8) are still involved in flows conservation in $h = 1$.

For the outputs, the fleet flows are determined and fixed for those whose origin is 07:15 in $h = 1$.
(blue in Figure 3.8). While those flows whose origin is during [07:30, 08:30) is considered, it can still be re-scheduled in the next rolling horizon (black in Figure 3.8).

Figure 3.8: Fleet flow time-space service network for air metro at rolling horizon $h = 1$

**Passenger flow**

The time window of an OD pair should be shorter than a rolling horizon, to ensure passengers have sufficient time to be transported to their destination by regular services. Figure 3.9 shows an example of passenger flow time-space network at rolling horizon $h = 0$ when the optimised rolling horizon is [07:00, 08:15). The departure time for this time-dependent OD pair is 07:00 while the preferred arrival time is 08:30. In this case, the exogenous demand occurs within the optimised rolling horizon. The passengers can be either transported to destination by regular service or by ad-hoc service if they wait at the origin column until 07:45. It is noted that in the rolling horizon model, the origin arc for ad-hoc service appears at the end of the network instead at the start.

For the outputs, the passenger flows whose departure time is 07:00 is determined in this rolling horizon (blue in Figure 3.9) and cannot be changed in the next rolling horizons; while those whose departure time is between [07:15, 08:15) is determined but can still be adjusted in the following
rolling horizons (black in Figure 3.9).

Figure 3.9: Passenger flow time-space network for air metro at rolling horizon $h = 0$

Figure 3.10 shows the subsequent rolling horizon, i.e., $h = 1$, for that in Figure 3.9. Exogenous passenger demand is no longer generated. The optimised rolling horizon is [07:15, 08:30). The flows on completed arcs (yellow in Figure 3.10) who were already determined in the last rolling horizon, i.e., $h = 0$, are used to achieve the passenger flow conservation in $h = 1$. The passengers can be either transported to the destination by regular service or by ad-hoc service if they wait at the origin column until 08:00.

As for the outputs of $h = 1$, the passenger flows whose origin is 07:15 (blue in Figure 3.10) is determined and cannot be changed in the next rolling horizons; while those whose origin is between [07:30, 08:30) is determined but can still be adjusted in the following rolling horizons (black in Figure 3.10).
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Figure 3.10: Passenger flow time-space network for air metro at rolling horizon $h = 1$

Pilot flow

We now examine the pilot flow time-space duty networks at different phases in the rolling horizon. Figure 3.11 is the starting stage, i.e., $h = 0$, for pilots whose depot is vertiport $b$. The optimised rolling horizon is [07:00, 08:15). The movement of pilots between [07:00,08:15) is optimised in this rolling horizon. Pilots start their duty from vertiport $b$ in this rolling horizon. For the outputs, decisions for those trips from 07:00 (blue in Figure 3.11) cannot be changed in the next rolling horizons; while those whose departure time is between [07:15, 08:15) is determined but can still be adjusted in the following rolling horizons (black in Figure 3.11).

Figure 3.12 shows a return stage of pilots who need to return to depot $b$ by the end of their duty, e.g., 14:00. The optimised rolling horizon is [13:00,14:00). The trips with departure before 13:00 (yellow in Figure 3.12) were already determined in the past rolling horizons, but are involved in
pilot flow conservation in this rolling horizon. The decisions for those arcs starting at 13:00 (blue in Figure 3.12) are determined and cannot be adjusted in the next rolling horizons; while optimised flows for marginal arcs that start after 13:00 (black in Figure 3.12) can still be changed.

Figure 3.11: Pilot flow time-space duty network for air metro in rolling horizon at starting stage

Figure 3.12: Pilot flow time-space duty network in for air metro rolling horizon at return stage
Optimisation model for an individual rolling horizon

In order to minimise the total system cost, the objective of SNDP for piloted air metro is to optimise the variables $U = \{U_{ij}\}$, $V = \{V_{ij}^e\}$, $W = \{W_{ij}^e\}$, $X = \{X^e\}$, and $Y = \{Y^e\}$. The decision variables are split into each rolling horizon, i.e., $U_h$, $V_h$, $W_h$, $X_h$, $Y_h$ are the subsets of $U$, $V$, $W$, $X$, $Y$, for the rolling horizon $h$, respectively, and are determined in each rolling horizon $h$.

We now examine how to assign the decision variables into different rolling horizons. The problem for each rolling horizon $h \in H$ involves the determination of $U_h$, $V_h$, $W_h$, $X_h$, $Y_h$. A superscript $h$ is added to other notations to indicate the particular rolling horizon. $A_h$ is a subset of $A$, where the members in $A_h$ are able to be optimised within the rolling horizon $h$. For the OD pairs, to guarantee the feasibility of model, we consider that $E_h$ is a subset of $E$, where the arrival time windows of elements in $E_h$ are within the rolling horizon $h$, and there is at least one trip leg for OD pair $e \in E_h$ can be determined within the rolling horizon $h$. For example, suppose a 15-minute time step, a rolling horizon $h$ simulates the period $[13:00, 14:00)$, then an OD pair $e \in E_h$ can be included by set $E_h$ if the arrival time window of $e$ is between $[13:15, 14:00)$. Note that the temporal length of a rolling horizon is usually longer than the temporal length of passenger OD pairs. $E_h$ is followed by $X_h$ and $Y_h$. $V_h$ is a subset of $V$, where the members $V^e_{ij,h} \in V_h$ are able to be optimised within the rolling horizon $h$, and $e \in E_h$. For pilot flow, $W_h$ is a subset of $W$, where the elements in $W_h$ are able to be optimised within the rolling horizon $h$. The composition of $X_h$ and $Y_h$ can be determined in a similar way. Moreover, a superscript $\hat{h}$ is added to other notations to indicate the antecedent time steps before $h$. For example, $V^e_{ij,\hat{h}}$ denotes the passenger flows on arc $(i, j)$, which has been determined before, and cannot be changed in the rolling horizon $h$.

Then, the problem for each rolling horizon $h \in H$ i.e., problem (P5), can be formulated as follows.

\[
\min_{U_h,V_h,W_h,X_h,Y_h} \quad Z = \sum_{ij \in S_h^f} U_{ij,h} R_{ij} + \sum_{e \in E_h} \sum_{ij \in A_h^f} V^e_{ij,h} R_{ij} + \sum_{e \in E_h} X^e_{i} F_4 + \sum_{e \in E_h} Y^e_{e} \tau^e + \sigma(U_h) + \omega(W_h) 
\]

where

\[
\sigma(U_h) = \begin{cases} 
\sum_{i \in N_h^f} \sum_{j \in N_h^f \setminus N_h^o} U_{ij,h} F_1 & \text{if } N_h^o \subseteq N_h^f \\
0 & \text{otherwise}
\end{cases}
\]
3.2.4 Rolling horizon optimisation formulation

\[
\omega(W_h) = \begin{cases} 
\sum_{t \in T} \sum_{i \in N_h^f \setminus N_h^d} \sum_{j \in N_h^f} W_{ij,h}^t F_{ij} & \text{if } N_h^f \in N_h^l \\
0 & \text{otherwise}
\end{cases} \quad (3.74)
\]

subject to

\[
\sum_{j \in N_h^f} V_{ij,h}^e - \sum_{k \in N_h^e} V_{ki,h}^e = \begin{cases} 
\sum_{t \in N_h^l} V_{li,h}^e + \xi_{e}^i & \text{if } i \text{ is the origin for group } e \\
\sum_{t \in N_h^l} V_{li,h}^e & \text{otherwise}
\end{cases} \quad (3.75)
\]

\[
\forall e \in E_h
\]

\[
\sum_{e \in E_h} V_{ij,h}^e + \sum_{t \in T} W_{ij,h}^t \leq U_{ij,h} C \quad \forall ij \in S_h^f
\]

\[
Y_{h}^e \leq X_{h}^e C \quad \forall e \in E_h
\]

\[
\sum_{j \in N_h^f} U_{ij,h} - \sum_{k \in N_h^f} U_{ki,h} = \sum_{l \in N_h^l} U_{li,h} \quad \forall i \in N_h^f \setminus (N_h^f \cup N_h^d)
\]

\[
U_{ij,h} \leq \sum_{t \in T} W_{ij,h}^t \quad \forall ij \in S_h^f
\]

\[
\sum_{j \in N_h^f} W_{ij,h}^t - \sum_{k \in N_h^f} W_{ki,h}^t = \sum_{l \in N_h^l} W_{li,h}^t \quad \forall i \in N_h^f \setminus (N_h^f \cup N_h^d) \quad \forall t \in T
\]

\[
\sum_{k \in N_h^l} U_{ki,h} + \sum_{l \in N_h^l} U_{li,h} \leq L \quad \forall i \in N_h^f \setminus N_h^f
\]

\[
0 \leq U_{ij,h} \quad \forall ij \in A_h^f
\]

\[
0 \leq X_{h}^e \quad \forall e \in E_h
\]

\[
0 \leq W_{ij,h}^t \quad \forall ij \in A_h^l \quad \forall t \in T
\]
CHAPTER 3. MODELLING APPROACHES

\[ 0 \leq Y^e_h \leq \xi^e \quad \forall e \in E_h \]  
(3.85)

\[ U_{ij,h} \in \text{integer} \quad \forall i,j \in A^f_h \]  
(3.86)

\[ V^e_{ij,h} \in \text{integer} \quad \forall i,j \in A^e_h \quad \forall e \in E_h \]  
(3.87)

\[ W^t_{ij,h} \in \text{integer} \quad \forall i,j \in A^t_h \quad \forall t \in T \]  
(3.88)

\[ X^e_h \in \text{integer} \quad \forall e \in E_h \]  
(3.89)

\[ Y^e_h \in \text{integer} \quad \forall e \in E_h \]  
(3.90)

while \( N^f_i \in N^f_h \)

\[ \sum_{j \in N^f_i \setminus N^f_i} U_{ij,h} \leq J \quad \forall i \in N^f_o \]  
(3.91)

where \( U = \{U_{ij,h}\}, V = \{V^e_{ij,h}\}, W = \{W^t_{ij,h}\}, X = \{X^e_h\}, \) and \( Y = \{Y^e_h\}. \)

The objective function (3.72) is to minimise the total system cost under each rolling horizon. Eq. (3.73) and (3.74) indicate that the opportunity costs of capital to employ aircraft or pilots are calculated at the beginning of a service/duty period. Eq. (3.91) provides the maximum fleet size constraint, which applies at the beginning of the aircraft fleet time-space network, i.e., \( h = 0. \)

Other constraints remain the same as those in (P3).

Rolling and iteration approach

(P5) can solve the individual problem for each rolling horizon. The general solution \( U, V, W, X, Y \) are the rolling iteration of \( U_h, V_h, W_h, X_h, Y_h \) enabled by the following steps.

• Step 0: Set the temporal length of ECP and safety margin for the problem. Initialise the cumulative for general decision variables sets \( U, V, W, X, Y. \)
3.2.4 Rolling horizon optimisation formulation

- Step 1: Start with the rolling horizon \( h = 0 \), determine the composition of \( E_h \) and decision variable set \( U_0, V_0, W_0, X_0, Y_0 \), and run the model in (P5) for the problem for \( h = 0 \). Then, update \( U, V, W, X, Y \) by the determined decision variable sets;

- Step 2: iteration of \( U, V, W, X, Y \) with the fixed temporal length of rolling horizons:
  - Step 2-0: Go to the next rolling horizon, i.e., \( h = h + 1 \). Update the available demand in rolling horizon \( h \);
  - Step 2-1: determine the composition of \( U_h, V_h, W_h, X_h, Y_h \) that are considered at the rolling horizon \( h \). Run the model in (P5) and obtain the sets for decision variables \( U_h, V_h, W_h, X_h, Y_h \). Update the value of cumulative decision variables \( U, V, W, X, Y \) by \( U_h, V_h, W_h, X_h, Y_h \);
  - Step 2-2: If the current safety margin has contained the latest time step of an entire day’s operation, go to Step 3. Otherwise, go to Step 2-0;

- Step 3: iteration of \( U, V, W, X, Y \) with the decreasing temporal length of rolling horizons:
  - Step 3-0: Go to the next rolling horizon, i.e., \( h = h + 1 \). Update the available demand at the rolling horizon \( h \);
  - Step 3-1: Set length of safety margin to one unit less than the current one;
  - Step 3-2: Determine the composition of \( U_h, V_h, W_h, X_h, Y_h \) and \( E_h \). Run the model in (P5) and obtain the sets for decision variables. Update the value of \( U, V, W, X, Y \) by \( U_h, V_h, W_h, X_h, Y_h \);
  - Step 3-3: If the current ECP has contained the latest time step of an entire day’s operation, end the iteration. Otherwise, go to Step 3-0;

The collected decision sets \( U, V, W, X, Y \) are the final solution in a rolling horizon approach. Note that at Step 3, although the entire day’s operation period has been covered at the rolling horizon \( h \), because of the exist of safety margin, i.e., a time period after the ECP, the demand for the marginal time steps has been be available. Hence, the iteration need to be continued until all the actual demand is available, i.e., the ECP has contained the latest time steps.
Chapter 4

Numerical Studies

This chapter presents the numerical studies of the proposed modelling approaches and the results. The AAITBS and air metro cases are independently illustrated in the inter-terminal network on SKSA and inter-city network on GMAS, respectively. For each case, sensitivity analysis is conducted to determine the significant exogenous factor that can potentially affect the system. We use the commercial solver Gurobi to solve all MILPs, where to ensure the computational consistency and efficiency, we adopt a gap tolerance of 1% (the objective value gap between the MILP/ILP and the relaxed linear programming model). In the sensitivity analysis, the exogenous factors other than the analysed factor remain the benchmark value. Note that the unit of monetary cost in this thesis is Australian dollar.

4.1 Numerical studies for AAITBS

4.1.1 Basic settings for AAITBS

This chapter applies the proposed models and approach on the inter-terminal passenger service network at SKSA, where there are three terminals. Terminal 1 (T1) is an international terminal while Terminal 2 (T2) and Terminal 3 (T3) are two domestic terminals. The stops in the case study are set to be the three terminals. Figure 4.1 shows the physical inter-terminal network structure at SKSA. The parameters of the network are summarised in Table 4.1, where the distances are based on data from Google Maps. Moreover, we consider a two-hour period for the AAITBS with a time...
4.1.1 Basic settings for AAITBS

step length of 3 minutes. Hence, there are 40 time slices (rows) and 3 stops (columns) in the fleet flow time-space service network.

![Inter-terminal network at SKSA](image)

Figure 4.1: Inter-terminal network at SKSA

<table>
<thead>
<tr>
<th>OD pair</th>
<th>distance (km)</th>
<th>travel time (min)</th>
<th>passenger demand per 3 minutes</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1 ↔ T2</td>
<td>4</td>
<td>15</td>
<td>16</td>
</tr>
<tr>
<td>T1 ↔ T3</td>
<td>3.7</td>
<td>12</td>
<td>37</td>
</tr>
<tr>
<td>T2 → T3</td>
<td>0.4</td>
<td>3</td>
<td>28</td>
</tr>
<tr>
<td>T3 → T2</td>
<td>1.2</td>
<td>6</td>
<td>28</td>
</tr>
</tbody>
</table>

Table 4.1: Network parameters for AAITBS

The VOT is $12.8 per person hour and the vehicle operating cost is $2.6/km (for a bus with a capacity of 40 persons per vehicle in the benchmark case). For OD pairs, we assume 60% of passengers have a tight time window, while 40% have a loose one. Particularly, for OD pairs T1 ↔ T2, 10 persons and 6 persons per time step should arrive within 21 minutes and 42 minutes, respectively (after their arrival at the origin stop); for OD pairs T1 ↔ T3, 22 persons and 15 persons per time step should arrive within 21 minutes and 42 minutes, respectively; for OD pairs T2 ↔ T3, 17 persons and 11 persons per time step should arrive within 9 minutes and 18 minutes,

CHAPTER 4. NUMERICAL STUDIES

respectively.² Note that this is the demand setting in the benchmark case, while we will conduct sensitivity analysis on the demand level, and also we will further examine the stochastic demand case (the values in the benchmark case become the mean demand values).

When we consider a single-type bus fleet, the vehicle capacity is assumed as 40 persons per vehicle. When we consider a multi-type fleet, we consider three capacity types, i.e., 10, 25, 40 persons per vehicle. The fixed cost associated with providing a shuttle bus per planning period is $82 per vehicle (related to purchasing and maintenance).³ The fixed costs of other two bus types are $41 (10 persons) and $66 (25 persons), respectively. As introduced before, the operating cost of a bus with a capacity of 20 persons is set as $2.6/km. The operating costs of other two types of buses are set as $1.3/km and $2.08/km. For the ad-hoc service, the cost is $128 per vehicle hour.⁴ The maximum fleet size of regular service in the benchmark case was set to be 30 vehicles. The upper bound of fleet flow on all service arcs is set as 10 vehicles per time step.

4.1.2 Numerical study for single-type fleet AAITBS

We first examine the single-type fleet case with deterministic demand. We vary the passenger demand from 0.4 to 3.1 times of that in the benchmark case with an increment of 0.3. Figure 4.2 shows the total system cost gap between the existing service⁵ and the proposed bus shuttle service against the demand level, where the cost under the current service is calculated by assuming that

²The demand is generated according to the following. We first obtain the hourly flight volume in 2019 for each terminal in SKSA. We then estimate the number of passengers arriving at terminals based on the flight volume and capacities of domestic and international flights. We further assume that a certain percentage of these passengers will make a connection trip.


⁴The value of ad-hoc service operating cost is comparable to the car rental cost (https://gogocharters.com/blog/charter-bus-prices/).

⁵For the inter-terminal network at SKSA, currently passengers can only walk for the connection trips between two domestic terminals T2 and T3 (in both directions and it takes 5 minutes), and can take bus line 400 or 420 for connection trips between terminal T1 and terminal T2 or T3 (e.g., 20 minutes headway).
value of walking time is identical to value of bus travel time. The total cost can be reduced by approximately 27% (on average) after introducing the proposed bus shuttle service.

Figure 4.3 shows how five different efficiency metrics vary against the demand level, and Figure 4.4 shows the corresponding changes in the optimal regular fleet size and the percentage of passengers taking ad-hoc service. In this thesis, we consider the total system cost to be more intuitively reflect the difference between the two services (e.g., Lai & Lo 2004), rather than “average cost per passenger” or other index to reflect “economies of scale”. The total system cost is the sum of operating cost and monetary passenger travel time cost; at the same time, it is also the sum of regular cost and ad-hoc cost. The operating cost is defined by Eq. (3.11), the monetary passenger travel time can be calculated by Eq. (3.12). The regular cost is the total cost (including operating cost and monetary passenger travel time) for regular service, which can be defined by Eq. (3.15); while the ad-hoc cost is the total cost for ad-hoc cost, defined by Eq. (3.14). It is evident that in general, all the efficiency metrics increase with respect to the demand level or at least does not decrease. It is also noted that “2.2” corresponds to a critical demand level where the optimal service design solution starts to change substantially.

Figure 4.2: Total system cost of current service and proposed single-type AAITBS service against the demand level
Figure 4.3: Different efficiency metrics against the demand level under a single-type fleet for AAITBS

Figure 4.4: Optimal fleet size and ad-hoc usage percentage against the demand level under a single-type fleet for AAITBS

We now further examine how the maximum allowed fleet size that is allowed may affect the system (e.g., due to parking/storage limitation). We vary the maximum allowed fleet size from 6 to 30. Figure 4.5 displays how five different efficiency metrics vary and Figure 4.6 displays how the optimal regular fleet size and the percentage of passengers taking ad-hoc service vary. It can be
seen that when the maximum allowed fleet size is smaller than 16, the optimal solution is to set the fleet size as the maximum, and still the deployed regular service cannot meet the total passenger demand. The maximum fleet size has a direct impact on the availability of the regular service and so as to affect the total system cost.

Figure 4.5: Different efficiency metrics under different fleet size limitation (a single-type fleet, AAITBS)

Figure 4.6: Optimal fleet size and ad-hoc usage percentage under different fleet size limitation (a single-type fleet, AAITBS)

We also vary the unit cost for providing a shuttle bus, and Figure 4.7 displays how five different
efficiency metrics vary and Figure 4.8 displays the variation of the optimal regular fleet size and the percentage of passengers taking ad-hoc service. It can be seen that the total system cost and operating cost both increase with the unit cost for providing a shuttle bus of the same vehicle size. When the regular bus is relatively expensive (higher than 4.5 times of the value in benchmark), ad-hoc services will be used.

Figure 4.7: Different efficiency metrics under different shuttle bus cost (a single-type fleet, AAITBS)

Figure 4.8: Optimal fleet size and ad-hoc usage percentage under different shuttle bus cost (a single-type fleet, AAITBS)
4.1.2 Numerical study for single-type fleet AAITBS

We then vary the capacity of the bus (other settings remain the same), and examine how different efficiency metrics, the optimal fleet size and ad-hoc usage vary. The results are displayed in Figure 4.9 and Figure 4.10. It can be seen that when the capacity of a regular service bus is smaller than 20 (with the same purchase cost), the regular service becomes insufficient for the passenger demand, and the system has to use ad-hoc service and the total system cost becomes higher.

![Figure 4.9: Different efficiency metrics under different shuttle bus capacities (a single-type fleet, AAITBS)](image1)

![Figure 4.10: Optimal fleet size and ad-hoc usage percentage under different shuttle bus capacities (a single-type fleet, AAITBS)](image2)
CHAPTER 4. NUMERICAL STUDIES

We next consider the weighted objectives discussed in Chapter 3.1.2. Figure 4.11 shows $Z_1$ and $Z_2$ values when we have different $\omega_1$ (related Eq. (3.13)) and $Z_1'$ and $Z_2'$ values when we have different $\omega_2$ (related to Eq. (3.16)). As can be seen, the points in Figure 4.11(A) (or Figure 4.11(B)) that correspond to different values of $\omega_1$ (or $\omega_2$) show a trade-off between two objectives and form a Pareto frontier considering bi-objective optimisation.

Figure 4.11: Alternative objective functions for the single-type fleet for AAITBS

We also tested the model performance for different operation scales (2 hours to 18 hours). The corresponding computation times for MILPs with deterministic demand and single-type fleet are summarised in Table 4.2.

Table 4.2: Computation times of MILPs for different operation scales

<table>
<thead>
<tr>
<th>Scale (hour)</th>
<th>Comp. time (second)</th>
<th>Scale (hour)</th>
<th>Comp. time (second)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>7</td>
<td>12</td>
<td>488</td>
</tr>
<tr>
<td>4</td>
<td>29</td>
<td>14</td>
<td>798</td>
</tr>
<tr>
<td>6</td>
<td>50</td>
<td>16</td>
<td>962</td>
</tr>
<tr>
<td>8</td>
<td>85</td>
<td>18</td>
<td>1,476</td>
</tr>
<tr>
<td>10</td>
<td>270</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
4.1.3 Numerical study for heterogeneous multi-type fleet AAITBS

We now turn to the multi-type fleet case. As introduced in Chapter 4.1.1, we have three different vehicle sizes (small, medium, large) which involve different unit purchase costs and operating costs. We mainly focus on two issues: how the system will react and perform when demand level, the maximum allowed fleet size or the unit cost for providing a shuttle bus increases.

To facilitate the analysis, we further define two ratios, i.e., volume sharing rate $\gamma^e$ and the loading rate $\eta^e$ for type $e$ bus, where the two ratios are calculated as follows.

$$\gamma^e = \frac{\left( \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e} \right)}{\left( \sum_{e \in E} \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e} \right)}$$

$$\eta^e = \frac{\left( \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e} \right)}{\left( \sum_{ij \in S^q} Y_{ij}^{e} \right)}$$

where $\sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e}$ is the total passenger-time served by the fleet of type $e$ bus, while $\sum_{e \in E} \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e}$ denotes the total passenger-time served by all regular services.

When the demand level increases (similar to that in Chapter 4.1.2 for the single-type fleet case), Figure 4.12 shows the total system cost gap between the current service and the proposed bus shuttle service. The proposed mixed fleet further reduces the total system cost when compared to the proposed single-type fleet in Chapter 4.1.2 (also evidently outperforms current service). In particular, under the benchmark demand setting, the multi-type bus fleet scheme further saves 2% of total system cost. Moreover, the mixed fleet is relatively useful in the lowest demand condition (0.4 times of benchmark demand value), where it further saves 6.5% of the total system cost when compared against the proposed single-type fleet.

Figure 4.13 shows how five efficiency metrics vary, and Figure 4.14 shows how different types of buses are used to serve passengers (the two ratios $\gamma^e$ and $\eta^e$ are examined), when the passenger demand level varies. The results in Figure 4.13 for the multi-type fleet case are consistent with those in Figure 4.3 for the single-type fleet case. Figure 4.14 further shows that when demand is
larger, the system tends to use more large shuttles, and vice versa, which indicates the benefit of the mixed fleet to better accommodate different demand levels.

Figure 4.12: Total system cost of current service and proposed multi-type AAITBS service against the demand level

Figure 4.13: Different efficiency metrics against the demand level under a multi-type mixed fleet for AAITBS
4.1.3 Numerical study for heterogeneous multi-type fleet AAITBS

When the maximum allowed fleet size increases (similar to that in Chapter 4.1.2 for the single-type fleet case), Figure 4.15 shows how five efficiency metrics vary and Figure 4.16 shows how different types of buses are used to serve passengers. The results in Figure 4.15 for the multi-type fleet case are consistent with those in Figure 4.5 for the single-type fleet case. Figure 4.16 further indicates that when the overall fleet size is more tightly bounded, the system tends to use more large shuttles to increase its capacity. Differently, when the overall fleet size is less tightly bounded, the system is able to incorporate a mixed fleet to better accommodate the variations in the demand level. This again illustrates the potential benefit from the flexibility of a mixed fleet.

Figure 4.14: Usage pattern of the mixed fleet for AAITBS against the demand level

When the maximum allowed fleet size increases (similar to that in Chapter 4.1.2 for the single-type fleet case), Figure 4.15 shows how five efficiency metrics vary and Figure 4.16 shows how different types of buses are used to serve passengers. The results in Figure 4.15 for the multi-type fleet case are consistent with those in Figure 4.5 for the single-type fleet case. Figure 4.16 further indicates that when the overall fleet size is more tightly bounded, the system tends to use more large shuttles to increase its capacity. Differently, when the overall fleet size is less tightly bounded, the system is able to incorporate a mixed fleet to better accommodate the variations in the demand level. This again illustrates the potential benefit from the flexibility of a mixed fleet.
CHAPTER 4. NUMERICAL STUDIES

Figure 4.15: Different efficiency metrics against the maximum allowed fleet size under a multi-type mixed fleet for AAITBS

Figure 4.16: Usage pattern of the mixed fleet for AAITBS against the maximum allowed fleet size
When the unit cost for providing a shuttle bus increases (similar to that in Chapter 4.1.2 for the single-type fleet case), Figure 4.17 shows how five efficiency metrics vary and Figure 4.18 shows how different types of buses are used to serve passengers. The results in Figure 4.17 for the multi-type fleet case are consistent with those in Figure 4.7 for the single-type fleet case. However, the ad-hoc service in mixed fleet scenario is not activated throughout the variation in bus unit cost.

In terms of computation time, as discussed before, it costs 7 seconds to solve the MILP for a single-type bus type scenario with deterministic demand (as shown in Table 4.2), while that for multi-type bus type scenario is much larger (314 seconds). These indicate that the mixed fleet case requires much more computation time than the single-type fleet case. In addition, we found that the computation time for the mixed fleet case also increases with the operation duration considered (details are omitted), which is expected and consistent with that for the single-type fleet case. To solve very large-scale problem with a mixed fleet, efficient heuristics should be further developed.

Figure 4.17: Different efficiency metrics under different shuttle bus cost (a multi-type mixed fleet, AAITBS)
4.1.4 Numerical study for AAITBS under stochastic demand

We now examine the stochastic demand case. All other settings are similar to those in Chapter 4.1.1 for the single-type fleet case with deterministic demand except the demand stochasticity. Firstly, we define the loading rate $\eta$ as follows.

\[
\eta = \left( \frac{\sum_{d \in R} \sum_{ij \in S^d} X_{ij}^d}{\sum_{ij \in S^q} Y_{ij} \xi} \right)
\]  

(4.3)

where $\sum_{d \in R} \sum_{ij \in S^d} X_{ij}^d$ is the total passenger-time served by regular services and $\sum_{ij \in S^q} Y_{ij} \xi$ is the total capacity provided through the regular fleet.

For the demand distribution, we assume that the demand distributions for each group are independent and follow the Poisson distribution.\(^6\) The demand values in Chapter 4.1.2 for the deterministic

\(^6\)Larson & Odoni (1981) recommended that in urban service systems, the Poisson distribution can be used as a reasonable model for the customer arrival process. Therefore, in this thesis, the number of passenger arrivals over a time step is assumed to follow the Poisson distribution.
demand case are taken as the mean values, while in stochastic demand case, the standard deviation is equal to the square root of the mean for group $d$, i.e., $s_d = \sqrt{m_d}$, where $s_d$ and $m_d$ are the standard deviation and mean of demand for group $d$, respectively.

As for the update and iteration of $\Delta$, the initial interval for $\Delta$ is $[-1.96, 1.96]$ (this associates with the 95-percent confidence interval for the demand if a standard normal distribution is assumed). One can readily verify that $\Delta$ outside this interval will yield worse solutions. We evenly divide this interval into 8 smaller intervals. The solution approach discussed in Chapter 3.1.4 for each small interval, i.e., the golden-section search, is implemented for each small interval to explore the minimised total system cost. Once the (sub-)optimal solutions for the small intervals are obtained, we choose the $\Delta$ that yields the smallest objective value among the (sub-)optimal objective values.

Figure 4.19 compares solutions of the 8 small intervals of $\Delta$. The optimal $\Delta$ is obtained from the fifth interval, i.e., $[0.0, 0.49]$, where $\Delta$ converges to 0.3675. As can be seen in Figure 4.19 (A), (C) and (D), a too large $\Delta$ yields a too large a regular service fleet. This means that the bus shuttle supplement could be redundant ($\eta$ is considerably low), which is too costly for the system. As can be seen in Figure 4.19 (A), (B), and (D), a too small $\Delta$ yields an insufficient regular service fleet and the over-usage of ad-hoc service, which is also costly. It is also worth mentioning that when $\Delta$ is close to 0.3675, the objective value varies only very slightly with respect to $\Delta$. Moreover, the standard deviation is one of the lowest at the fifth interval, as shown in Figure 4.19 (A), which means the solution has a better stability over the probability scenarios. Therefore, a value of $\Delta$ that is close to 0.3675 indeed produces comparable total system cost.

As mentioned in Chapter 3.1.4, we can replace the “effective” demand-based approach by GA for providing candidate solutions in Step 1 of the solution procedure in Chapter 3.1.4, while still using the Monte Carlo simulation in Step 1-1 to estimate $\bar{\mathcal{F}}(\mathbf{Y})$ in the objective function (MILPs are still solved by the commercial solver), i.e., Monte Carlo simulation coupled with GA. We set the crossover rate and mutation rate for the GA to be 0.25 and 0.01, respectively, and test different chromosome population and generation size. The corresponding objective values and computation times based on GA are shown in Table 4.3. Our tests show that the Monte Carlo simulation coupled with GA is unable to yield a better solution than Monte Carlo simulation coupled with the “effective demand” concept proposed in this thesis while GA takes much longer.
Moreover, for the Monte Carlo simulation-based solution approach, based on extensive experiments, we found that a sample size of 30 is often sufficient, where we have tested that the estimate of $\overline{\sigma}(Y)$ stabilises for the current case study (the percentage difference in the estimated $\overline{\sigma}(Y)$ with further runs of simulations will be less than 0.1%). To ensure consistency and solution quality, we set the sample size to be 100 ($> 30$).

![Graph showing solutions under stochastic demand](image)

**Figure 4.19:** Solutions under stochastic demand (with a single-type fleet, AAITBS)

**Table 4.3:** Monte Carlo simulation coupled with GA against Monte Carlo simulation coupled with “effective” demand
4.2 Numerical studies for air metro

4.2.1 Basic settings for air metro

In this chapter, a network based on GMAS is used to illustrate the modelling approach. Since there has not been any actual vertiport location in GMAS, and the vertiport location placement is not the main concern in this study, we manually select 6 sites as the potential position for vertiports, based on the combined consideration of terrain, commuting customer demand and coverage of high-income area. Table 4.4 shows the sites that are selected as the potential vertiports and the corresponding sets of approx. latitude and longitude. Figure 4.20 shows the positions of the vertiports on the map.

Table 4.4: Latitude and longitude of selected vertiports

<table>
<thead>
<tr>
<th>Vertiport</th>
<th>Site</th>
<th>Latitude</th>
<th>Longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>1#</td>
<td>Sydney central</td>
<td>-33.87084</td>
<td>151.20733</td>
</tr>
<tr>
<td>2#</td>
<td>Wollongong</td>
<td>-34.42483</td>
<td>150.89311</td>
</tr>
<tr>
<td>3#</td>
<td>Newcastle</td>
<td>-32.92827</td>
<td>151.78168</td>
</tr>
<tr>
<td>4#</td>
<td>Gosford</td>
<td>-33.42667</td>
<td>151.34167</td>
</tr>
<tr>
<td>5#</td>
<td>Woolwich</td>
<td>-33.84029</td>
<td>151.17063</td>
</tr>
<tr>
<td>6#</td>
<td>Cronulla</td>
<td>-34.05166</td>
<td>151.15451</td>
</tr>
</tbody>
</table>

The position data are obtained from Google Map API.
In the numerical setting, we adopt the VTOL model of *Joby Aviation*. The reference technical parameters are shown in Table 4.5. The acquisition cost for regular service fleet is the combination of the purchase price and the opportunity cost of capital. For the calculation of opportunity cost of capital, we adopt the suggested method by (Reiche et al. 2018). Then, the cost associated with long-term hiring a human-driven VTOL (including the opportunity cost) for the planning period, i.e., one day, is the acquisition cost for one VTOL divided by the lifespan (10 years × 365 days), set to be $585/day. The operating cost is set to be $2/km, suggested by Reiche et al. (2018). The salary cost associated with long-term employing a pilot for the planning period, i.e., one day, is set

8Joby Aviation (https://www.jobyaviation.com/).

4.2.1 Basic settings for air metro

to be $234.2/day.\textsuperscript{10} Note that the capacity is 4 passengers, which does not include the pilot.

<table>
<thead>
<tr>
<th>Cruise speed</th>
<th>Range</th>
<th>Capacity</th>
<th>Life span</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>200 MPH</td>
<td>150+ mile</td>
<td>4</td>
<td>10+ years</td>
<td>$1.76m</td>
</tr>
</tbody>
</table>

A 15-minute time step is adopted in this study. Based on the adopted cruise speed, as well as the latitude and longitude of vertiports, the trip time for air metro can be estimated, which is the sum of: i). cruise time; ii). trip time for ground phase (i.e., from a passenger’s home to origin vertiport, and from destination vertiport to the passenger’s workplace; iii). boarding and de-boarding time, take-off and landing time. The cruise time is the Euclidean distance between the origin and destination vertiports divided by cruise speed. The trip time for ground phase is the Manhattan distance (also known as taxicab distance) between home and origin vertiport, and between destination vertiport and workplace, divided by ground traffic speed (set to be 70 km/h). We set the boarding and de-boarding time, take-off and landing time are together 20 minutes. Then, the trip time for each OD pair in a unit of time step can be calculated, as shown in Table 4.6. Note that the longest trip in the network (between 2# and 3#) is feasible according to the range of VTOLs.

<table>
<thead>
<tr>
<th>Trip time step</th>
<th>1#</th>
<th>2#</th>
<th>3#</th>
<th>4#</th>
<th>5#</th>
<th>6#</th>
</tr>
</thead>
<tbody>
<tr>
<td>1#</td>
<td>/</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2#</td>
<td>2</td>
<td>/</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3#</td>
<td>3</td>
<td>4</td>
<td>/</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>4#</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>/</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>5#</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>/</td>
<td>2</td>
</tr>
<tr>
<td>6#</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>/</td>
</tr>
</tbody>
</table>

We adopt the assumed demand to simulate the operation network. The demand has two types: the commuting group and the non-commuting group. The commuting groups have a larger demand.

\textsuperscript{10}Pilot salary in Australia (https://au.indeed.com/career/pilot/salaries/).
and a tighter time window, and enter the network only during the morning and evening peak. The non-commuting groups exist throughout the operation hours, with a lower demand and looser time window. The commuting passenger demand for OD pairs is assumed based on the commuting demand for ground transport in GMAS.\textsuperscript{11} For current ground transport service, the travel time is the sum of ride time and waiting/parking time (set to be 10 minutes). The ride time is assumed to be the Manhattan distance between the origin and destination divided by ground traffic speed. For each OD pair, we adopt the assumption made by Holden & Goel (2016) that a passenger would be eligible for UAM if the estimated duration of the UAM trip is at least 40% faster than that of the ground trip. We also assume 1% of total commuters would take air metro service, and the commuting demand for an OD pair evenly enter the network over 2 time steps. Then, the commuting passenger demand per time step for morning peak can be calculated through the adopted data and assumptions, as shown in Table 4.7. The commuting demand for afternoon peak is considered to be the transpose matrix of that for morning peak. Moreover, the passenger demands for non-commuting groups have a 50% possibility of determination between “no passenger” and “1 passenger” for per time step. The passenger VOT is set to be $57.48/hour. For the preferred arrival time window, we consider the temporal lengths of time windows for commuting groups to be one step more than the trip time steps; while those for non-commuting groups are two steps more than the trip time steps. For example, for passengers from 1# to 2#, the trip cost 2 time steps, and thus the time windows for commuting passengers from 1# to 2# are 3 time steps and the time windows for non-commuting passengers from 1# to 2# are 4 time steps.

The ad-hoc service outsourcing cost is set to be $2,682 per vehicle hour.\textsuperscript{12} For passenger taking ad-hoc service, their monetary travel time costs are considered as the longest acceptable value, i.e., a full time window, for an OD pair. The operating period for a duty day is set to be [07:00, 23:00]. The pilots are divided into morning and afternoon shifts, where the duty period for morning shift is [07:00, 15:00] and that for afternoon shift is [15:00, 23:00]. Further, in the benchmark setting, we set the maximum allowed fleet size to be 50 aircraft. The capacity of vertiports, i.e., maximum


\textsuperscript{12} The ad-hoc service operating cost refers to “Air taxi cost” (https://skywayairtaxi.com/air-taxi-cost-pricing/).
4.2.2 Numerical study for piloted air metro

The number of VTOLs landing at the same vertiport at the same time-step, is set to be 25 aircraft.

Table 4.7: Commuting air metro passenger demand matrix during morning peak for OD pairs

<table>
<thead>
<tr>
<th>Demand (per time step)</th>
<th>1#</th>
<th>2#</th>
<th>3#</th>
<th>4#</th>
<th>5#</th>
<th>6#</th>
</tr>
</thead>
<tbody>
<tr>
<td>1#</td>
<td>/</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2#</td>
<td>22</td>
<td>/</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>3#</td>
<td>2</td>
<td>0</td>
<td>/</td>
<td>1</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>4#</td>
<td>21</td>
<td>0</td>
<td>1</td>
<td>/</td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>5#</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>/</td>
<td>0</td>
</tr>
<tr>
<td>6#</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>/</td>
</tr>
</tbody>
</table>

4.2.2 Numerical study for piloted air metro

Firstly, the piloted air metro scenario is examined. We vary the capacity of vertiports from 2 to 26 VTOLs (25 in the benchmark). Figure 4.21 (a) shows the changes in fleet and pilot employment, and Figure 4.21 (b) shows the changes in efficiency metrics against the different vertiport capacity. The performance can be viewed in three parts: First, when the capacity of vertiports is smaller than 8 VTOLs, the supply of regular air metro service is insufficient (fleet size is less than 44), the ad-hoc service accommodates a large number of passengers, and the total system cost is large. When the capacity is between 8 and 20, the fleet size is 44 VTOLs, and the capacity of vertiports is close to sufficient. However, the ad-hoc service still accommodates a small number of passengers (ad-hoc cost is approx. $2,000) and the total system cost has a marginal decrease of approx. $6,000, when the capacity varies from 8 to 20. When the vertiport capacity is larger than 22 VTOLs, the fleet size becomes 46 aircraft, the ad-hoc cost becomes 0, and the total system cost stabilises at the lowest level. The operating cost is a larger component in the total system cost (approx. 74%) than the monetary passenger travel time cost (approx. 36%). In this experiment, the number of employed pilots is always at least the twice the fleet size (because of the morning and afternoon shift). The results suggest the capacity of vertiport to be no less than 8 VTOLs to reach a trade-off between the performance of service network and the construction cost.

Moreover, as mentioned in Chapter 2.1, the vertiports can be classified into “hubs” in heavy traffic area (i.e., vertiports 1#, 2#, 4#) and “spokes” in suburban area (i.e., vertiports 3#, 5#, 6#). The
CHAPTER 4. NUMERICAL STUDIES

suggested capacity in this experiment, i.e., 8 VTOLs, is particularly for the largest “hub” in the network. While this study considers homogeneous vertiport capacity, the heterogeneous case can be readily adopted, where the capacity of “spokes” can be obtained by fixing the capacity of “hubs” to be the suggested value (8 VTOLs).

Next we study the impact of different maximum allowed fleet size on the service network performance. We vary the maximum fleet size from 20 to 60 VTOLs (50 in the benchmark), with an increment of 5. Figure 4.22 (a) shows the changes in fleet and pilot employment, and Figure 4.22 (b) shows those in different efficiency metrics against the different maximum fleet size. When the maximum allowed fleet size is smaller than 50, the regular service is insufficient to accommodate the passenger demand. The actual fleet size is equal to the maximum value, and the ad-hoc service shares a large number of passenger trips. When the maximum fleet size is more than 50, the regular service provides sufficient capacity for the entire air metro service and the ad-hoc cost becomes 0. The fleet size is 46 VTOLs when the fleet size in not restricted. In most situation, the number of employed pilots is twice the fleet size, although in extreme cases (e.g., when maximum fleet size

Figure 4.21: Performance under different vertiport capacity for piloted air metro
is 20), the required pilot number is 41 to satisfy the scheduling.

This chapter examines the impact of different commuting passenger demand on the service performance. In the benchmark, the commuting demand is assumed to be 1% of total commuters. In this experiment, we change the demand to be 0.2 to 2 times of benchmark value (i.e., 0.2% to 2% of total commuting passengers), with an increment of 0.2; while the non-commuting passenger demand remains the same (50% for “1 passenger” and 50% for “no passenger”). Figure 4.23 (a) shows the changes in fleet and pilot employment and Figure 4.23 (b) shows the changes in different efficiency metrics against the different commuting demand. As can be seen from the Figure 4.23, when the commuting demand is less than 1.2 times of the benchmark value, the regular service is sufficient. When the commuting demand exceeds 1.2 times, ad-hoc service becomes necessary, and this contributes to a marked increase in total system cost.

Figure 4.22: Performance under different maximum allowed fleet size for piloted air metro

<table>
<thead>
<tr>
<th>Fleet size</th>
<th>Operating cost</th>
<th>Regular cost</th>
<th>Pilot number</th>
<th>Passenger travel time</th>
<th>Ad-hoc cost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
We now study the influence of aircraft capacity. The results are shown in Figure 4.24. Note that the capacity does not include the pilot who fly the VTOL. When VTOL capacity is less than 4 passengers, the regular service cannot accommodate all demand. There is considerable increase in total system cost when VTOL capacity decrease from 4 to 1. When VTOL capacity increase from 4 to 6, there is a slight decrease in total system cost and operating cost, and also a decline in fleet size and number of employed pilots. In this experiment, the monetary passenger travel time cost does not have an obvious trend and fluctuates around $50,000.

Figure 4.25 shows the monetary passenger travel time cost gap between current ground transport and proposed air metro service, where the cost under the current service is calculated by assuming that the ground travel time for each OD pair is the Manhattan distance divided by the ground traffic speed (70 km/h). As can be seen from Figure 4.25, the monetary passenger travel time can be reduced by 50.8% (on average) if air metro service is introduced.
4.2.2 Numerical study for piloted air metro

Figure 4.24: Performance under different VTOL capacity for piloted air metro

![Graph](image)

Figure 4.24: Performance under different VTOL capacity for piloted air metro

Figure 4.25: Monetary travel time of ground transport and proposed air metro against demand

![Graph](image)

Figure 4.25: Monetary travel time of ground transport and proposed air metro against demand
4.2.3 Numerical study for pilot-less air metro

In pilot-less air metro scenario, there is no pilot labour cost. However, the fixed cost associated with providing an autonomous VTOL can be more expensive than a human-driven one. Also, extra cost for the service provider may occur in autonomous control equipment (e.g., an autonomous functionality server cost as suggested by Hasan (2018)). The acquisition cost associated with providing an autonomous VTOL is set to be $648/day.

Figure 4.26 (a) shows the changes in fleet employment and Figure 4.26 (b) shows those in different efficiency metrics against the different vertiport capacity for pilot-less air metro. Similar to Figure 4.21, the performance in Figure 4.26 can be viewed in three parts. When the vertiport capacity is less than 10, the ad-hoc service is used. When the vertiport capacity is between 10 and 18, the ad-hoc cost becomes 0. However, there is still a marginal decline in total system cost and operating cost (both are approx. $4,000) when vertiport capacity increases from 10 to 18. When the vertiport capacity is more than 18, the total system cost and operating cost maintain the lowest level. The results suggest the vertiport capacity (“hub” in particular) to be 10 at least.

![Figure 4.26: Performance under different vertiport capacity for pilot-less air metro](image_url)
4.2.3 Numerical study for pilot-less air metro

Figure 4.27 (a) shows the changes in fleet employment and Figure 4.27 (b) shows those in different efficiency metrics against the different maximum fleet size for pilot-less air metro. The results show a similar trend with the piloted air metro performance. When the maximum allowed fleet size is smaller than 50, the regular service is insufficient to accommodate the passenger demand; when the maximum fleet size is more than 50, the regular service become sufficient for air metro service, and there is no ad-hoc cost.

![Figure 4.27: Performance under different maximum allowed fleet size for pilot-less air metro](image)

Figure 4.28 (a) shows the changes in fleet employment and Figure 4.28 (b) shows the changes in different efficiency metrics against the different commuting demand. When the commuting demand increases from “0.2” to “1.0”, the total system cost shows a slight increase, and the fleet size increases from 23 to 46. “1.0” is a critical point. When the commuting passenger demand is more than the benchmark value, the ad-hoc service is used, which leads to an obvious increase in total system cost.

![Figure 4.28: Performance under different maximum allowed fleet size for pilot-less air metro](image)
Figure 4.28: Performance under different commuting passenger demand for pilot-less air metro

Figure 4.29 (a) shows the changes in fleet employment and (b) shows the changes in different efficiency metrics against the capacity of aircraft. As can be seen, if the VTOL can only accommodate 1 passenger, the total system cost is up to approx. $600,000, and the fleet size is the maximum value (50 VTOLs). When the VTOL capacity varies from 1 to 3, the fleet size remains at 50 VTOLs. The total system cost and operating cost show a marked decrease. When the capacity varies from 4 to 6, the ad-hoc cost is 0, and there is a slight decrease in total system cost and operating cost.

We vary the unit purchase cost of autonomous VTOLs from 1 to 2 times the benchmark value, with an increment of 0.2. Figure 4.30 shows that when the unit purchase cost of an autonomous VTOL is 1.6 times the benchmark value, the system total cost of two scenarios are similar. However, the passenger monetary travel time costs for pilot-less scenario fluctuate around that of the piloted air metro scenario. The critical points for operating cost and total system cost are the same (1.6). The results suggest that the pilot-less air metro can be a better choice if the purchase price is less than 1.6 times the benchmark value.
4.2.3 Numerical study for pilot-less air metro

Figure 4.29: Performance under different VTOL capacity for pilot-less air metro

Figure 4.30: Efficiency metrics with the increase of autonomous VTOL purchase cost
4.2.4 Numerical study for air metro in rolling horizon

This chapter takes the piloted air metro scenario to illustrate the rolling horizon optimisation approach. We set the ECP and safety margin to be 60 minutes (4 time steps), respectively, as the benchmark. Then, we change the temporal length of ECP and safety margin to determine their impact on the solutions. Figure 4.31 (a) shows the impact of varied ECP (the safety margin is fixed at 60 minutes), while Figure 4.31 (b) studies the different length of safety margin (the ECP is fixed at 60 minutes). If all the actual demand is known, the system total cost is $170,000, which is a lower bound for the rolling horizon approach. Moreover, to compare the cost gap between the rolling horizon optimisation and the static method, we solve the problem (P3) with predicted demand, and illustrate the generated solution on the actual demand. The performance of the predicted demand scenario is the upper bound in Figure 4.31, accompanied by a total system cost of approx. $302,000 (approx. 44% higher than the demand available scenario). As can be seen from both axes, if the length of a single rolling horizon is 90 minutes (30 for ECP, 60 for safety margin; or 60 for ECP, 30 for safety margin), the performance is unsatisfactory. The total system cost (approx. $360,000) is even higher than that for predicted demand scenario. This can be due to the inconsistency between multiple rolling horizons, resulting from the inadequate length of a single rolling horizon. In both axes, when the values of horizontal coordinate increase from 45 to 90, the total system cost shows a considerable decline. When the values increase from 90 to 120, there is not any obvious decrease in total system cost. The results suggest to confirm the actual demand at least 45 minutes prior to departure, and the length of a single rolling horizon should be longer than 150 minutes. In addition, the increased ECP has a more obvious impact on total system cost than the increase in the safety margin.

The computation time is an important element in the numerical results. Comparing the AAITBS and air metro cases together, Table 4.8 illustrates the computation time for each MILP/ILP (under benchmark settings). The single-type fleet case for AAITBS cost the least computation time, while that for autonomous air metro case study have higher time cost. A reason can be that the air metro case has a longer simulation period (16 hours) than AAITBS (2 hours). The multi-type fleet AAITBS and human driven air metro have markedly longer computation time, since they have a more variable dimension in bus type and pilot scheduling, respectively. The rolling horizon cost
4.2.4 Numerical study for air metro in rolling horizon

the most computation time since problem consists of multiple ILPs.

Figure 4.31: Performance of rolling horizon optimisation for air metro

Table 4.8: Computation time of single MILP/ILPs for different SNDP models

<table>
<thead>
<tr>
<th>Problem</th>
<th>Model</th>
<th>Comp. time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Airport shuttle – single-fleet</td>
<td>MILP</td>
<td>7</td>
</tr>
<tr>
<td>Airport shuttle – multi-fleet</td>
<td>MILP</td>
<td>314</td>
</tr>
<tr>
<td>Air metro – piloted</td>
<td>ILP</td>
<td>257</td>
</tr>
<tr>
<td>Air metro – pilot-less</td>
<td>ILP</td>
<td>31</td>
</tr>
<tr>
<td>Air metro – rolling horizon</td>
<td>ILPs</td>
<td>367</td>
</tr>
</tbody>
</table>
Chapter 5

Conclusions

This chapter concludes with the main findings from the proposed SNDP, the merits of the modelling approaches, solution methods and numerical results. Also, the contribution of this thesis is reiterated. Lastly, a recommendation is made for a future research direction.

Overview of the results

This thesis selects AAITBS and air metro as two cases of the emerging modal technologies in air transport, from ground and skyscape levels, respectively, to design the service network as well as examine their economic feasibility by undertaking numerical studies using Sydney area as a context. The two share similarities, including the objective (minimising the total system cost), service types (they are pre-planned services with regular routes and schedules), served passengers (aviation passengers who are sensitive towards waiting time and the fairness of waiting time), expected outputs (optimal dispatch patterns and fleet size), and operation environment (no traffic congestion in the system). Together, these similarities create a context in which the research can focus on the tactical issues pertinent to air transport.

The AAITBS case designs the passenger shuttle service network considering both regular and ad-hoc services, heterogeneous multi-type fleet, stochastic demand, and air passengers’ arrival time constraints at their destinations. In Chapter 3.1.2, the problem is mathematically formulated as capacity-constrained multi-commodity model under the assistance of discrete time-space network
graphs, where there is one fleet time-space service network and several time-space network for
different passenger groups (with different time-dependent OD pairs). The optimisation model is
an MILP, subject to flow conservation in the networks and capacity constraints, while the objective
function is to minimise the operating cost for service provider as well as the monetary passenger
tavel time cost. The model can be solved through commercial solvers. In Chapter 3.1.3 and 3.1.4,
the problem is then further extended into heterogeneous multi-type fleet and stochastic demand
cases, where the multi-type fleet cases can also be solved by commercial solvers while the stochastic
demand problem is formulated as a two-stage stochastic program. The first stage is to generate
the solutions while the sub-stage is to assess the solutions under the stochastic demand. This thesis
proposes a Monte Carlo simulation-based approach coupled with the “effective demand” concept
to solve the stochastic demand problem. An “effective” demand is defined as the sum of the mean
value and a certain level of standard deviation, i.e., \( B^d_\Delta = m_d + \Delta \cdot s_d \), where \( \Delta \) is a coefficient
for \( s_d \). In the first stage, the “effective demand” is adopted to generate the solutions. The Monte
Carlo simulation is used to address the demand stochasticity under a given solution, to assess the
performance of the solution.

The results for the AAITBS case on the inter-terminal network at the SKSA have shown that the
proposed methods and solution approach can design an effective alternative airport ground passen-
ger shuttle service, which saves approx. 27% of total system cost (shown in Figure 4.2 and 4.12).
The sensitivity analysis reveals that the service is more sensitive to the passenger demand, the
maximum allowed fleet size and vehicle capacity, while the variation in total system cost with
respect to the unit purchase cost was not significant (Figure 4.2 - 4.10). This trend occurs in both
single-type and multi-type scenarios (Figure 4.13 - 4.18). In Chapter 3.1.4, the proposed “effec-
tive” demand-based approach is illustrated to solve the stochastic demand case. The results in
the numerical study suggests predicting the passenger demand slightly larger than the mean value
performs the best, e.g., given the mean and standard deviation of demand \( (m_d \text{ and } s_d) \) estimate
the safety margin to be 0.3675 times the standard deviation (Figure 4.19). Moreover, the widely
used GA is unable to yield a better solution than utilising the “effective” demand-based method
proposed. In addition, GA took much longer computation time.

The air metro case further expands the time-space network and multi-commodity model by adding
CHAPTER 5. CONCLUSIONS

pilot scheduling as a new dimension in Chapter 3.2.1, to study the SNDP for the pre-scheduled air metro service. To accommodate fatigue and safety, pilot’s working hours are divided into a morning and afternoon shift, and the simulation period is the entire duration of the day’s operations. For pilot time-space duty networks, the time windows represent the pilots’ duty time. As part of the optimisation process, the models are formulated as ILPs, subject to flow conservation in the network and capacity constraints, while the objective function is to minimise the operating costs for the service provider (including the pilot employment cost) as well as the monetary passenger travel costs. The aim of this study was to analyse and compare the cost metrics of piloted and pilot-less air metro scenarios, where piloted air metro has a labour cost for pilots, while autonomous aircraft may have a higher vehicle manufacturing cost in pilot-less scenario. The model for piloted and pilot-less air metro scenarios are developed in Chapter 3.2.2 and 3.2.3, respectively. Given that air metro is geared towards business users with high VOT, it is important to understand the feasible lead time between booking and departure in order to understand the optimal balance between operations and passenger benefits. It is feasible to ask passengers to confirm their reservations via a mobile app several hours prior to departure time, which would allow the operator to determine the actual demand for the trip. In order to solve this problem, this thesis utilises the concept of rolling horizons, which is to continuously update the demand and solve the problem within a given period.

The rolling horizon optimisation model for piloted air metro is studied in Chapter 3.2.4.

Based on the results presented in Chapter 4.2.2 and 4.2.3, the proposed methods for modelling air metro service in GMAS have shown their effectiveness for recommending the optimal dispatch patterns, hired fleet size, and pilot scheduling under piloted and pilot-less scenarios. In the sensitivity analysis for two scenarios, it is evident that the capacity of vertiports is the most significant exogenous factor affecting the system, with the total system cost having a sharp increase when the maximum fleet size is less than 8 VTOLs (Figure 4.21 and 4.26). Comparing the two scenarios reveals that the autonomous air metro service could be the better choice if the unit purchase price for an autonomous VTOL is less than 1.6 times that of the human-driven aircraft (Figure 4.30). Chapter 4.2.4 illustrates the concept of rolling horizon. The results suggest to confirm the actual demand at least 45 minutes prior to departure, and the length of a single rolling horizon should be longer than 150 minutes (Figure 4.31).
Comparing the two cases together, the monetary passenger travel time cost is a major part of the system total cost for AAITBS, while the operating cost is the major part of the air metro service. This is due to the large difference in the purchase price between autonomous shuttle bus and VTOL. The sensitivity analysis reveals that the total system costs in both cases decrease significantly with an increase in the passenger demand and vehicle capacity. However, the AAITBS is more sensitive to the maximum allowed fleet size, where the regular fleet would become insufficient to accommodate the passenger demand once the allowed fleet size falls below 15 buses. The air metro is considerably sensitive to capacity of a vertiport. For most situations, the number of pilots is assigned to be approx. double the fleet size (there is a morning and afternoon shift). The single-type fleet AAITBS case study costs the least computation time, while the computation time for autonomous air metro case study is a bit higher. The multi-type fleet AAITBS and human driven air metro have markedly longer computation time, because they have a more variable dimension in bus type and pilot scheduling, respectively (Table 4.8).

**Contribution to the literature**

Technology for autonomous shuttle buses has advanced rapidly (Iclodean et al. 2020). Yet, the design AAITBS has received little attention in the literature. Additionally, Hasan (2018) identified air taxi, air metro, and last-mile delivery as emerging UAM modes that may prove to be profitable in the not too distant future. The on-demand air taxi service has recently been studied in terms of passenger demand (e.g., Al Haddad et al. 2020), vertiport location placement (e.g., Willey & Salmon 2021), and network operation (e.g., Rajendran 2021). A pre-scheduled air metro service has been mentioned by Hasan (2018) at a conceptual level, however, to author’s best knowledge to-date it has not received analytical research. As these modes do not currently exist in service in Sydney, to understand their feasibility it is informative to simulate the details of the potential service network design. This thesis analyses the endogenous and exogenous factors of the two services and proposes (and implements) the modelling approaches under the assistance of time-space network graphs.

Based on existing infrastructure and historical travel demand for passengers, the proposed model for airport shuttle service considers the multi-type bus fleet, passenger demand stochasticity, and arrival time constraints of passengers in order to determine the optimal operating cost - travel time
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balance. Airport shuttle model extensions assist service providers to select the most appropriate service type in practice (e.g., a multi-type fleet model is able to take advantage of heterogeneous vehicle sizes to reduce the total system cost, where the smaller buses might be used on a route with low demand.). The Monte Carlo simulation-based approach coupled with "effective demand" concept is demonstrated to be able to generate satisfactory solutions within reasonable computation time for stochastic demand problems. This provides the analytical framework for the service manager to adjust the pre-scheduled service to be more resilient to stochastic demand.

At the time of writing, and to best of author’s knowledge, the air metro case was the first study specifically focusing on the service network design of pre-planned, scheduled UAM services. Using the proposed modelling approach in this thesis, the service providers can design a network of services for intra- or inter-city urban air passenger transport. Based on a set of assumptions regarding passenger demand, purchase and operating costs, a comparison between human-driven and autonomous air metro schemes shows that there is a significant cost difference between the two schemes. In light of the prices of different VTOL types at any given time, such a comparison is helpful in order to minimise the costs and determine the most appropriate service type, especially when mixed aircraft configuration (degree of automation) is being considered. Having this type of information will be useful for UAM design and technology as the market grows and the technology gains public acceptance. Furthermore, the proposed rolling horizon model is valuable for re-scheduling the dispatch pattern at the operational level. Through this re-scheduling, the total system cost can be markedly reduced.

Future directions

The studies presented in this thesis can be built upon in several ways in the future.

First and foremost, most parameters are assumed in numerical studies because actual values are not yet available, e.g., the purchase price for autonomous shuttles and VTOLs. The quantitative results may differ from those in this thesis when the actual value becomes available. However, the modelling approach has been demonstrated to be effective and the qualitative results of exogenous factors are informative.

Second, the proposed approaches in this thesis for both cases might be less applicable for very
large-scale problems, especially when demand stochasticity has to be considered. A future study might further propose efficient meta-heuristics in order to solve large-scale problems.

Third, the thesis only considers the autonomous bus shuttle service in the AAITBS case. The future mobility might include the hybrid services of autonomous, human-driven, or other transport modes. A future study may consider the passenger mode choice and study the autonomous shuttle service in a multi-modal transit system.

Fourth, this study only considers the stochasticity in the passenger travel demand side, but not in the supply side (e.g., stochastic travel time). A future study may wish to incorporate both demand and supply stochasticity in order to produce a more robust service network design for the air transport passengers.

Fifth, in the AAITBS case, the thesis have proposed a two-stage stochastic programming to address the stochasticity in passenger demand. In addition to stochastic programming, robust optimisation is an alternative approach to address the stochasticity, which may provide solutions with different quality and robustness. A future study may adopt the concept of robust optimisation to model the problems with stochasticity in traffic conditions.

Sixth, the two cases could potentially be the two phases of a complete aviation trip (passengers take the air metro after taking AAITBS in a comprehensive transport station). This thesis separately models the two cases. A future study might optimise the AAITBS and air metro service sequentially or optimise them jointly.
References


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