Passenger shuttle service network design in an airport

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Abstract

This study examines the service network design problem (SNDP) for passenger shuttle buses in the airport and nearby places (e.g., train stations, parking, hotels, shopping areas). A time-space service network for bus flows and time-space networks for passenger flows are developed. Based on proposed time-space networks, the studied SNDP is formulated as a mixed integer linear program (MILP) for a single-type bus fleet and deterministic passenger demand, where the objective is to minimise the weighted sum of passenger cost and service operating cost. We then extend the developed SNDP model to the heterogeneous multi-type bus fleet case and the stochastic demand case. To solve the stochastic demand case, a Monte Carlo simulation-based approach is adopted, which is further coupled with the "effective demand" concept (mean demand value plus a margin). The proposed SNDP models and solution approach are applied on the inter-terminal transport network at Sydney Kingsford Smith Airport for illustration.

Keywords: Airport, Passenger ground transport, Shuttle service, Time-space network, Monte Carlo simulation

1. Introduction

Air travel demand has grown significantly in the past decades along with the economic growth worldwide (Zhang and Graham, 2020). This yields huge amount of traffic and passenger flows to the airport (Tam et al., 2008; Jacquillat and Odoni, 2018). Since airports often involve multiple terminals and areas with different facilities and functionalities, many passengers have to make connection trips between places within or close to the airport (e.g., terminals, parking, train or bus stations, hotels close to the airport, shopping or entertainment areas). Moreover, sometimes passengers are carrying large luggage and have departure/arrival time constraints (e.g., to catch a flight). Providing efficient ground passenger transport services in the airport and its surrounding areas is an important issue to be addressed. For instance, there are bus services for the airport and surrounding areas (with parking, train stations, hotels, entertainment areas) in Sydney Kingsford Smith Airport and London Heathrow Airport. This study develops service network design models in order to optimise the bus shuttle service for passengers within the airport and its surrounding areas, which provide support for relevant operators/authorities to design the passenger bus shuttle service. We consider that the airport shuttles are autonomous, where the operation of the shuttles is not constrained by the availability of drivers.[1] It is noteworthy that the bus shuttle service is more flexible when compared to rail service 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 Sydney case, there are both conventional buses and articulated buses).

The proposed ground transport Service Network Design Problem (SNDP) for airports has received insufficient attention (Reinhardt et al., 2013; Sigler et al., 2021), while access to airport and aircraft boarding process have attracted much more efforts (e.g., Tang et al., 2012, 2015; Chen et al., 2017). In particular, Reinhardt et al. (2013) examined a model for the dial-a-ride transport problem particularly for passengers with reduced mobility at airports, where the synchronisation of vehicles requires that the disabled passengers are not left alone at any stage of their journey through the airport. Sigler et al. (2021) proposed a model to optimise the shuttle route between the rental car centre, parking facilities, the terminals within the airport, constrained by shuttle headway, maximum passenger ride times, etc.

[1] Autonomous vehicles have received substantial attentions in recent years (Chen et al., 2016; Liu, 2018; Wu et al., 2020; Zhang et al., 2020; Chen and Li, 2021) and have great potential to be utilised for fixed-line shuttle services.

For access to airports side, Tang et al. (2015) considered a door-to-door service of pick-up and delivery of passengers to the airport that is more conveniently than airport shuttles. Chen et al. (2017) designed the suburban bus service network for airport access, where the objective is to minimise the total access time. Many previous studies often focused on airport passengers with reduced mobility and considered the on-demand mobility assistance services, where the demand was in small and/or discrete quantities. This paper considers recurrent airport passenger flows that are often in large quantities, and models both shuttle bus flows and passenger flows at the tactical planning level.

It is worth mentioning that SNDP has been extensively studied for flight scheduling (e.g., Yan et al., 2008), freight transport (e.g., Crainic, 2000; Meng and Wang, 2011; Scherr et al., 2018, 2019), ferry networks (e.g., Wang and Lo, 2008; Lo et al., 2013; An and Lo, 2014; Ng and Lo, 2016), urban bus/transit systems with conventional vehicles or electric vehicles or buses (e.g., Liu et al., 2013; Chen et al., 2015; Szeto et al., 2015; Jiang and Szeto, 2015; An, 2020; Liu and Wang, 2017), and urban roads with reversible lanes or wireless charging lanes (Zhao et al., 2014; He et al., 2020). The SNDP is often formulated as a capacity constrained, multi-commodity or multi-mode problem, where service provisions are represented as integer decision variables and commodity flows as continuous variables (e.g., Wang, 2013; Wang et al., 2015). For example, Yan et al. (2008) considered the stochastic passenger demand cases when modelling the airline scheduling. Lo et al. (2013) formulated the two-stage stochastic program for SNDP through introducing the service reliability to optimally design the ferry service, in which the schedule of regular and ad-hoc services are derived sequentially. An and Lo (2014) encapsulated stochastic demand, user equilibrium, hard capacity constraints, regular and ad-hoc services into the service reliability-based formulation for ferry service network design. He et al. (2020) proposed a model to optimise the location of the wireless charging lanes while considering its negative impacts on road capacity. It should be noted that passengers travelling to or within airport often have departure/arrival time constraints (e.g., due to the flight schedule), who often differ from passengers in urban bus/transit systems or ferry networks.

In particular, this study designs the passenger service network within the airport and its surrounding areas (with parking, train stations, hotels, entertainment areas, etc.), which involves regular and ad-hoc services, heterogeneous multi-type bus fleet and stochastic demand, in order to minimise the weighted sum of passenger travel time cost and ground transport operating cost. The regular service 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. We formulate the SNDP as a mixed integer linear program (MILP) for the deterministic demand case, and conduct a case study on the inter-terminal network at Sydney Kingsford Smith Airport (SKSA) to illustrate the proposed models and solution procedure, where SKSA consists of two domestic and one international terminals, and had 44.4 million passengers in 2019.[2] In addition, to solve the case with stochastic demand, a Monte Carlo simulation-based approach is proposed, which is further embedded into an "effective" passenger demand framework. The "effective" demand is the summation of mean demand value and a safety margin. The proposed solution approach for the stochastic demand case is a variant of the reliability-based approach in previous studies (e.g., Lo et al., 2013). Note that the Monte Carlo simulation has been widely used to reproduce and accommodate the stochasticity in transport networks (Liu et al., 2013; Chen et al., 2015).

This study contributes to the literature from several aspects. Firstly, this study proposes and formulates the ground transport service network design problem for the airport and nearby places considering unique features of airport passengers, which can help improve airport ground transport efficiency and thus might further facilitate other airport operations. In particular, this study incorporates heterogeneous multi-type bus fleet, passenger demand stochasticity, and passengers' arrival time constraints into SNDP for airport ground transport. Secondly, this study illustrates how a Monte Carlo simulation-based approach can be utilised to solve the SNDP with stochastic demand, where the concepts of "effective" demand and safety margin are adopted to produce a demand estimate and thus provide an interpretable solution approach. Thirdly, the developed methods and approach are tested and illustrated on a real-world inter-terminal passenger service network at the Sydney Kingsford Smith Airport.

The remainder of this paper is structured as follows. Section 2 introduces the basic setting for the SNDP of airport bus shuttles, and depicts the time-space networks for the bus shuttles and passenger flows. Section 3 formulates the optimisation model for the basic SNDP with single-type fleet and deterministic demand. Section 4 extends the basic SNDP from two aspects, respectively, i.e., heterogeneous multi-type fleet and stochastic demand. Section 5 presents the case study on the inter-terminal network at SKSA of Sydney. Finally, Section 6 concludes.

[2] The passenger volume is obtained from "2019 Sydney Airport Full Year Results Release" that is released on 20 February 2020 (`https://www.sydneyairport.com.au/investor/investors-centre/asx-newsroom`).

2. Basic considerations and network representation

2.1. Basic considerations

The SNDP for airport passenger ground transport 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 Section 2.2, 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.

2.2. Network description

Table 1 lists the main notations used in this paper. 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 1: Notational glossary

Symbol	Definition
R	set of time-dependent OD pairs (equivalent to the set of passenger groups)
$d \in R$	the dth OD pair in the set of time-dependent OD pairs
N^q, A^q	sets of nodes and arcs in the bus fleet flow time-space service network

N^d, A^d	sets of nodes and arcs in the dth passenger flow time-space network, i.e., the time-space network for passengers of the dth time-dependent OD pair (or passenger group)
N_o^q, N_t^q	sets of nodes at the beginning and ending of the planning duration, respectively, in the fleet flow time-space service network
S^q, S^d	sets of service arcs in the fleet flow time-space service network and the dth passenger flow time-space network, respectively
W^q, W^d	sets of waiting arcs in the fleet flow time-space service network and the dth passenger flow time-space network, respectively
M^d	the artificial node in the dth passenger flow time-space network
(O^d, M^d)	origin arc in the dth passenger flow time-space network
(M^d, D^d)	destination arc in the dth passenger flow time-space network
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 dth passenger flow time-space network
ξ	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
ρ_{ij}^a	waiting time cost per passenger on waiting arc $(i,j) \in W^d, \forall d$
ρ_{ij}^b	riding time cost per passenger on service arc $(i,j) \in S^d, \forall d$
X_{ij}^d	decision variable indicating the passenger flow on arc (i,j) taking the regular service in the dth 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 dth passenger flow time-space network
τ^d	passenger cost of taking the ad-hoc service in the dth passenger flow time-space network
V^d	integer decision variable indicating the number of vehicles for ad-hoc service in the dth 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 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 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.

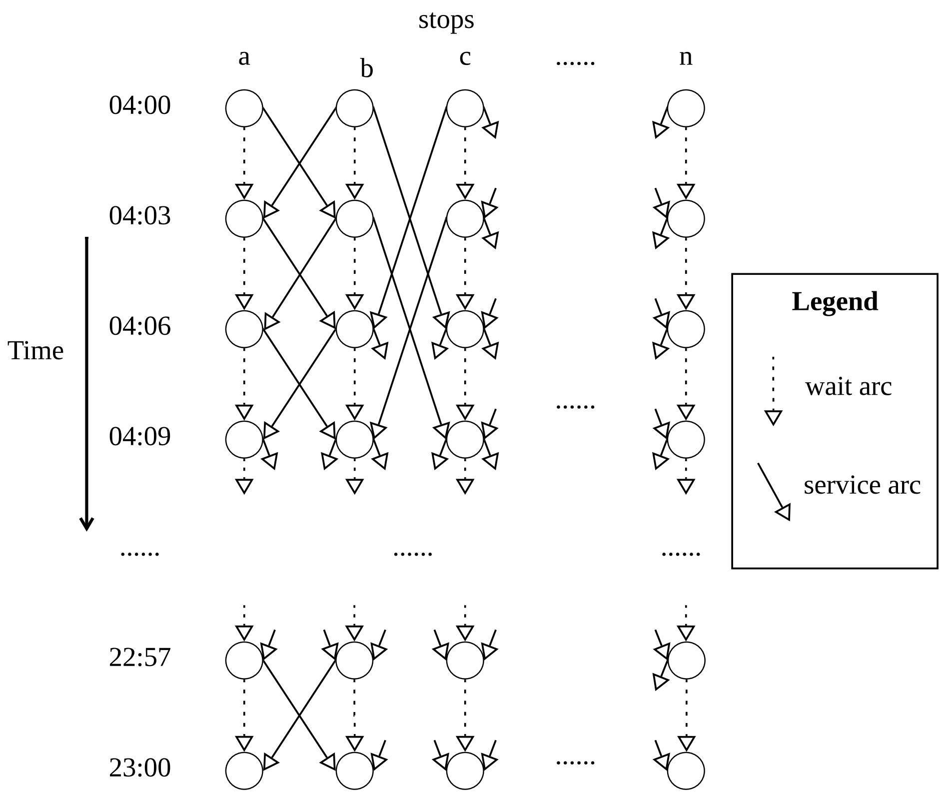

Figure 1: Bus fleet flow time-space service network

(**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

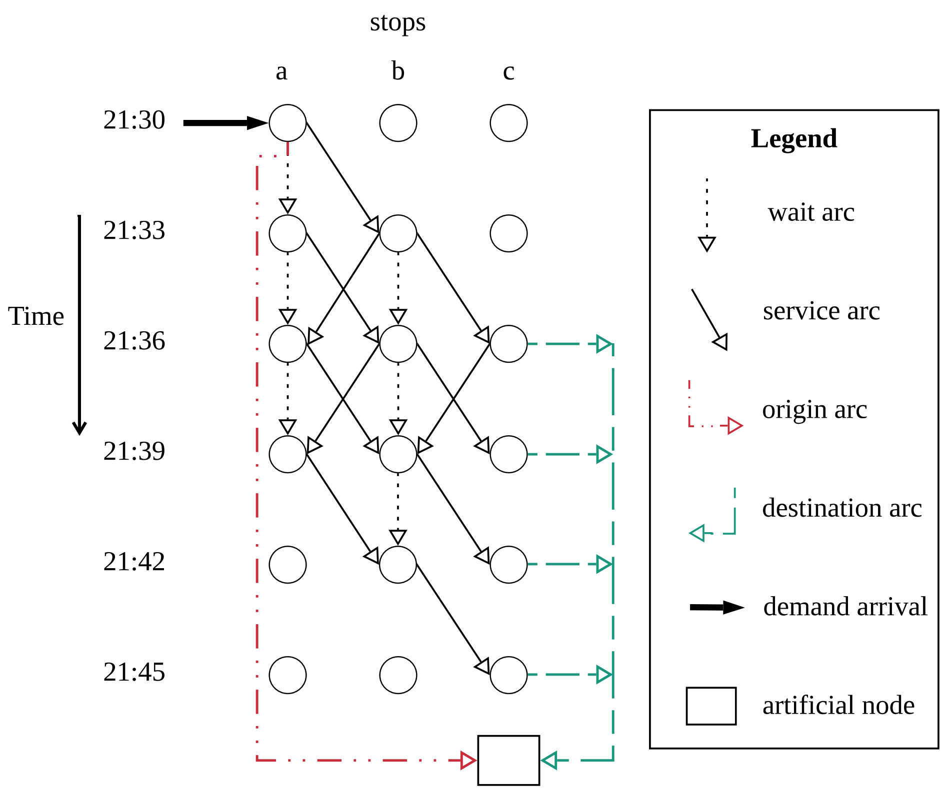

Figure 2: Passenger flow time-space network

$G^d(N^d, A^d)$, 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 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. Single-type fleet under deterministic demand

3.1. 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 SNDP under single-type bus fleet and deterministic demand, i.e., problem **(P0)**, can be formulated as follows.

(P0):

$$\min_{\mathbf{X},\,\mathbf{Y},\,\mathbf{U},\,\mathbf{V}} Z = \sum_{i\in N_o^q}\sum_{j\in N^q\setminus N_o^q} Y_{ij}F_1 + \sum_{ij\in S^q} Y_{ij}C_{ij} + \sum_{d\in R}\sum_{ij\in W^d} X_{ij}^d\rho_{ij}^a + \sum_{d\in R}\sum_{ij\in S^d} X_{ij}^d\rho_{ij}^b + \sum_{d\in R} U^d\tau^d + \sum_{d\in R} V^d F_2 \tag{1}$$

subject to:

$$\sum_{j\in N^q} Y_{ij} - \sum_{k\in N^q} Y_{ki} = 0 \quad \forall i \in N^q\setminus(N_o^q \cup N_t^q) \tag{2}$$

$$\sum_{i\in N_o^q}\sum_{j\in N^q\setminus N_o^q} Y_{ij} \le J \tag{3}$$

$$\sum_{j\in N^d} X_{ij}^d - \sum_{k\in N^d} X_{ki}^d = \begin{cases} B^d - U^d & \text{if } i \text{ is the origin for group } d \\ 0 & \text{otherwise} \end{cases} \quad \forall d \in R \tag{4}$$

$$\sum_{d\in R} X_{ij}^d \le Y_{ij}\xi \quad \forall ij \in S^q \tag{5}$$

$$U^d \le V^d\xi \quad \forall d \in R \tag{6}$$

$$0 \le Y_{ij} \le L_{ij} \quad \forall ij \in S^q \tag{7}$$

$$0 \le U^d \le B^d \quad \forall d \in R \tag{8}$$

$$Y_{ij} \in \text{integer} \quad \forall ij \in A^q \tag{9}$$

$$V^d \in \text{integer} \quad \forall d \in R \tag{10}$$

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

The objective function in Eq. (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., $\sum_{i\in N_o^q}\sum_{i\in N^q\setminus N_o^q} Y_{ij}$, 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. (2) represents the conservation of fleet flows at each node i in the fleet flow time-space service network. Eq. (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. (4) states the passenger conservation at each node in the passenger flow time-space network. Eq. (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. (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. (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. (8) requires that the passenger volume taking ad-hoc service is no greater than the demand for each passenger flow time-space network. Eq. (9) and Eq. (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. (1). All of these are to be sorted out after the solution to Eq. (1) - Eq. (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 Section 2.2, and thus are not directly involved in the formulations here.

3.2. Alternative objective functions

In the objective function in Eq. (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.

$$Z_1 = \sum_{i \in N_o^q} \sum_{j \in N^q \setminus N_o^q} Y_{ij} F_1 + \sum_{ij \in S^q} Y_{ij} C_{ij} + \sum_{d \in R} V^d F_2 \tag{11}$$

$$Z_2 = \sum_{d \in R} \sum_{ij \in W^d} X_{ij}^d \rho_{ij}^a + \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^d \rho_{ij}^b + \sum_{d \in R} U^d \tau^d \tag{12}$$

Then, a weighted objective can be written as follows.

$$Z = \omega_1 Z_1 + (1 - \omega_1) Z_2 \tag{13}$$

where ω_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 ω_1 means that operating cost is less valued and passenger experience is prioritised, and vice versa.

In addition, in the objective function in Eq. (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.

$$Z_1' = \sum_{d \in R} U^d \tau^d + \sum_{d \in R} V^d F_2 \tag{14}$$

$$\begin{aligned} Z_2' = \sum_{i \in N_o^q} \sum_{j \in N^q \setminus N_o^q} Y_{ij} F_1 + \sum_{ij \in S^q} Y_{ij} C_{ij} + \sum_{d \in R} \sum_{ij \in W^d} X_{ij}^d \rho_{ij}^a \\ + \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^d \rho_{ij}^b \end{aligned} \tag{15}$$

We then can consider the following weighted objective function.

$$Z = \omega_2 Z_1' + (1 - \omega_2) Z_2' \tag{16}$$

where ω_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 ω_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. (1) by Eq. (13) or Eq. (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).

4. Two extensions: multi-type fleet and stochastic demand

4.1. Heterogeneous multi-type fleet under deterministic demand

In Section 3, 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 ξ^e. A superscript e is added to other notations to indicate the vehicle type where appropriate. We also let ξ^0 be the capacity of vehicles used for ad-hoc service. Let Y_{ij}^e be the fleet flow of a particular vehicle type e on arc (i,j). $X_{ij}^{d,e}$ 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 $\mathbf{X} = \{X_{ij}^{d,e}\}$, $\mathbf{Y} = \{Y_{ij}^e\}$, $\mathbf{U} = \{U^d\}$, and $\mathbf{V} = \{V^d\}$.

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

(P1):

$$\min_{\mathbf{X},\mathbf{Y},\mathbf{U},\mathbf{V}} Z = \sum_{e \in E} \sum_{i \in N_o^q} \sum_{j \in N^q \setminus N_o^q} Y_{ij}^e F_1^e + \sum_{e \in E} \sum_{ij \in S^q} Y_{ij}^e C_{ij}^e + \sum_{e \in E} \sum_{d \in R} \sum_{ij \in W^d} X_{ij}^{d,e} \rho_{ij}^a + \sum_{e \in E} \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e} \rho_{ij}^b + \sum_{d \in R} U^d \tau^d + \sum_{d \in R} V^d F_2 \tag{17}$$

subject to:

$$\sum_{j \in N^q} Y_{ij}^e - \sum_{k \in N^q} Y_{ki}^e = 0 \quad \forall i \in N^q \setminus (N_o^q \cup N_t^q) \quad \forall e \in E \tag{18}$$

$$\sum_{e \in E} \sum_{i \in N_o^q} \sum_{j \in N^q \setminus N_o^q} Y_{ij}^e \leq J \tag{19}$$

$$\sum_{i \in N_o^q} \sum_{j \in N^q \setminus N_o^q} Y_{ij}^e \leq J^e \quad \forall e \in E \tag{20}$$

$$\sum_{e \in E} \sum_{j \in N^d} X_{ij}^{d,e} - \sum_{e \in E} \sum_{k \in N^d} X_{ki}^{d,e} = \begin{cases} B^d - U^d & \text{if } i \text{ is the origin for group } d \\ 0 & \text{otherwise} \end{cases} \quad \forall d \in R \tag{21}$$

$$\sum_{d \in R} X_{ij}^{d,e} \leq Y_{ij}^{e} \xi^{e} \quad \forall ij \in S^{q} \quad \forall e \in E \tag{22}$$

$$U^{d} \leq V^{d} \xi^{0} \quad \forall d \in R \tag{23}$$

$$0 \leq \sum_{e \in E} Y_{ij}^{e} \leq L_{ij} \quad \forall ij \in S^{q} \tag{24}$$

$$0 \leq U^{d} \leq B^{d} \quad \forall d \in R \tag{25}$$

$$Y_{ij}^{e} \in \text{integer} \quad \forall ij \in A^{q} \quad \forall e \in E \tag{26}$$

$$V^{d} \in \text{integer} \quad \forall d \in R \tag{27}$$

where most constraints have similar physical meanings as those in **(P0)** in Section 3.1. Some constraints now become vehicle type specific. For instance, Eq. (19) requires that the fleet size of all vehicle types is no greater than a maximum allowed value, and Eq. (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.

4.2. Stochastic Demand

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 Section 4.1 and Section 4.2.

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 dth passenger flow time-space network under scenario h, respectively. We also let $\mathbf{X} = \{X_{ij,h}^d\}$, $\mathbf{Y} = \{Y_{ij}\}$, $\mathbf{U} = \{U_h^d\}$, and $\mathbf{V} = \{V_h^d\}$.

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):

$$\min_{\mathbf{X},\,\mathbf{Y},\,\mathbf{U},\,\mathbf{V}} Z = \sum_{i \in N_o^q} \sum_{j \in N^q \setminus N_o^q} Y_{ij} F_1 + \sum_{ij \in S^q} Y_{ij} C_{ij} + \overline{\varphi}(\mathbf{Y}) \tag{28}$$

subject to:

$$\sum_{j \in N^q} Y_{ij} - \sum_{k \in N^q} Y_{ki} = 0 \quad \forall i \in N^q \setminus (N_o^q \cup N_t^q) \tag{29}$$

$$\sum_{i \in N_o^q} \sum_{j \in N^q \setminus N_o^q} Y_{ij} \leq J \tag{30}$$

$$0 \leq Y_{ij} \leq L_{ij} \quad \forall ij \in S^q \tag{31}$$

$$Y_{ij} \in \text{integer} \quad \forall ij \in A^q \tag{32}$$

where $\overline{\varphi}(\mathbf{Y})$ is an average performance metric defined as follows:

$$\overline{\varphi}(\mathbf{Y}) = \min_{\mathbf{X},\mathbf{U},\mathbf{V}} \sum_{h \in H} P_h \cdot \varphi_h(\mathbf{Y}) \tag{33}$$

where for each $h \in H$:

$$\varphi_h(\mathbf{Y}) = \sum_{d \in R} \sum_{ij \in W^d} X^d_{ij,h} \rho^a_{ij} + \sum_{d \in R} \sum_{ij \in S^d} X^d_{ij,h} \rho^b_{ij} + \sum_{d \in R} U^d_h \tau^d + \sum_{d \in R} V^d_h F_2 \tag{34}$$

and is subject to the following constraints:

$$\sum_{j \in N^d} X^d_{ij,h} - \sum_{k \in N^d} X^d_{ki,h} = \begin{cases} B^d_h - U^d_h & \text{if } i \text{ is the origin for group } d \\ 0 & \text{otherwise} \end{cases} \quad \forall d \in R \quad \forall h \in H \tag{35}$$

$$\sum_{d \in R} X^d_{ij,h} \leq Y_{ij,h} \xi \quad \forall ij \in S^q \quad \forall h \in H \tag{36}$$

$$U^d_h \leq V^d_h \xi \quad \forall d \in R \quad \forall h \in H \tag{37}$$

$$0 \leq U^d_h \leq B^d_h \quad \forall d \in R \quad \forall h \in H \tag{38}$$

$$V^d_h \in \text{integer} \quad \forall d \in R \quad \forall h \in H \tag{39}$$

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. (28) is the objective function for Stage 1, where $\overline{\varphi}(\mathbf{Y})$ is the average performance metric based on all possible demand scenarios, as given in Eq. (33). $\overline{\varphi}(\mathbf{Y})$ is obtained by solving optimisation problems in Stage 2. The constraints remain similar to those in the deterministic model **(P0)** in Section 3.1.

We now further discuss a Monte Carlo simulation-based approach to solve the above problem with stochastic demand. In particular, the Monte Carlo simulation method is used to generate adequate demand scenarios (from set H) in order to provide an estimate of $\overline{\varphi}(\mathbf{Y})$ in the second stage. Additionally, we will propose the concept of “effective” demand below, which helps us to provide a solution of

$\mathbf{Y} = \{Y_{ij}\}$ 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 Δ is a coefficient for s_d. For simplicity, we consider a single Δ for all d (one can also consider different Δ for each passenger group, i.e., Δ_d for group d). If B^d_Δ is regarded as an estimate of the demand, a larger Δ means that we tend to have a larger demand estimation. The proposed solution approach will try to identify a value of Δ that can help us to find a (sub-)optimal solution to the problem **(P2)**.

- Step 0: Given the lower and upper bounds of Δ 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,[3] where for each value of Δ to be assessed, calculate the corresponding Z by Steps 2, 3 and 4;
- Step 2: For a specific value of Δ, calculate B^d_Δ for each passenger group d based on Δ, then take B^d_Δ as the demand for each group d and solve the deterministic model **(P0)**;
- Step 3: Take the solution $\mathbf{Y} = \{Y_{ij}\}$ from Step 2 as given, then utilise the Monte Carlo simulation-based approach to estimate $\overline{\varphi}(\mathbf{Y})$ as follows:
  - Step 3-0: 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 3-1: Take the demand pattern in scenario h from Step 3-0 and the solution $\mathbf{Y} = \{Y_{ij}\}$ from Step 2 as given, and then use the commercial solver (Gurobi) to solve the deterministic model **(P0)** and calculate $\varphi_h(\mathbf{Y})$ under the demand scenario h;
  - Step 3-2: Calculate the mean value $\overline{\varphi}(\mathbf{Y})$ based on $\varphi_h(\mathbf{Y})$ for all scenarios h that have been generated so far;

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

– Step 3-3: If the number of demand scenarios considered is less than the required threshold (it often means that the estimation of $\overline{\varphi}(\mathbf{Y})$ does not stabilise),[4] go to Step 3-0; otherwise, go to Step 4;

- Step 4: Update Z in Eq. (28) with the $\overline{\varphi}(\mathbf{Y})$ from Step 3.

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 Δ 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 3 can be embedded into other meta-heuristics such as Genetic Algorithm (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 $B_{\Delta}^{d} = m_d + \Delta \cdot s_d$ 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).

5. Case study

5.1. Basic settings

This section applies the proposed models and approach on the inter-terminal passenger service network at Sydney Kingsford Smith Airport (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 3 shows the physical inter-terminal

[4] We have conducted extensive numerical experiments in order to identify a proper threshold, where the value of $\overline{\varphi}(\mathbf{Y})$ tends to stabilise, i.e., the percentage error between two recent values of $\overline{\varphi}(\mathbf{Y})$ is no greater than 0.1%. In our case study, with 30 runs of simulations the estimation of $\overline{\varphi}(\mathbf{Y})$ stabilises. To ensure consistency and solution quality, we indeed use 100.

network structure at SKSA. The parameters of the network are summarised in Table 2, where the distances are based on data from Google Maps. Moreover, we consider a two-hour period for the bus shuttle SNDP with a time step length of 3 minutes. Hence, there are 40 time slices (rows) and 3 stops (columns) in the fleet flow time-space service network. 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 and the relaxed linear programming model). Later on, we will also test longer operation periods (longer than 2 hours) in order to illustrate the computation times against problem size.

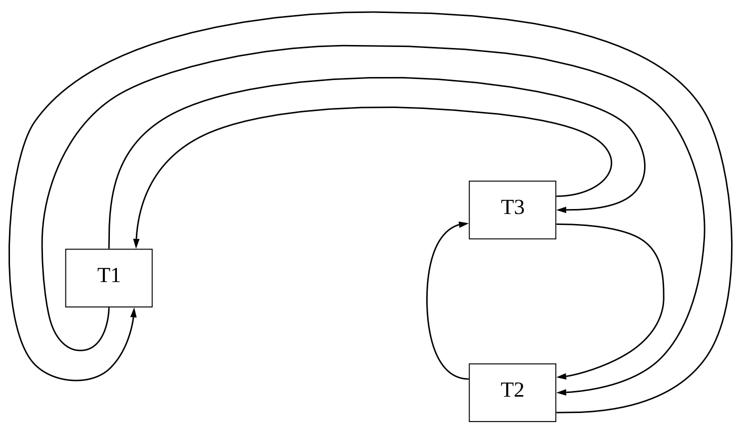

Figure 3: Inter-terminal network at Sydney Kingsford Smith Airport

Table 2: Network parameters

OD pair	distance (km)	travel time (min)	passenger demand per 3 minutes
T1 $\leftrightarrow$ T2	4	15	16
T1 $\leftrightarrow$ T3	3.7	12	37
T2 $\rightarrow$ T3	0.4	3	28
T3 $\rightarrow$ T2	1.2	6	28

The unit of monetary cost in this paper is Australian dollar. The Value of Time (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).[5] For OD pairs, we assume 60% of passengers have a tight time window, while 40% have a loose one. Particularly, for OD pairs T1 $\leftrightarrow$ 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 $\leftrightarrow$ T3, 22 persons and 15 persons per time step should arrive within 21 minutes and 42 minutes, respectively; for OD pairs T2 $\leftrightarrow$ T3, 17 persons and 11 persons per time step should arrive within 9 minutes and 18 minutes, respectively.[6] 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 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).[7] 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.[8] 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.

In the following, we will first examine the single-type fleet case, and then the multi-type fleet case, and finally the stochastic demand case. For the stochastic de-

[5]These settings are comparable to those suggested by "Transport for NSW Economic Parameter Values" (`https://www.transport.nsw.gov.au/news-and-events/reports-and-publications/tfnsw-economic-parameter-values/`).

[6]The 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.

[7]This is a daily value converted from the price and life span of reported small autonomous vehicles (`https://www.prnewswire.co.uk/news-releases/autonomous-shuttles-idtechex-report-reveals-the-future-of-last-mile-mobility-819532388.html/`) (`https://techcrunch.com/2019/08/26/ford-says-its-autonomous-cars-will-last-just-four-years/`).

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

mand case, the proposed Monte Carlo simulation coupled with "effective" demand solution approach will be compared against the Monte Carlo simulation coupled with GA approach (note that both requires Monte Carlo simulation to estimate an average efficiency metric given the demand variations).

5.2. Single-type fleet

We first examine the single-type fleet case with deterministic demand. As introduced in Section 5.1, the demand is obtained by converting flight volume at terminals into the passenger demand per unit time. We now vary the passenger demand from 0.4 to 3.1 times of that in the benchmark case. Figure 4 shows the total system cost gap between the existing service[9] and the proposed bus shuttle service against the demand level, where the cost under the current service is calculated by assuming that 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 5 shows how five different efficiency metrics vary against the demand level, and Figure 6 shows the corresponding changes in the optimal regular fleet size and the percentage of passengers taking ad-hoc service. 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.

We now further examine how the maximum fleet size that is allowed may affect the system (e.g., due to parking/storage limitation). We vary the upper bound of the fleet size from 6 to 30, Figure 7 displays how five different efficiency metrics vary and Figure 8 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.

[9] For 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).

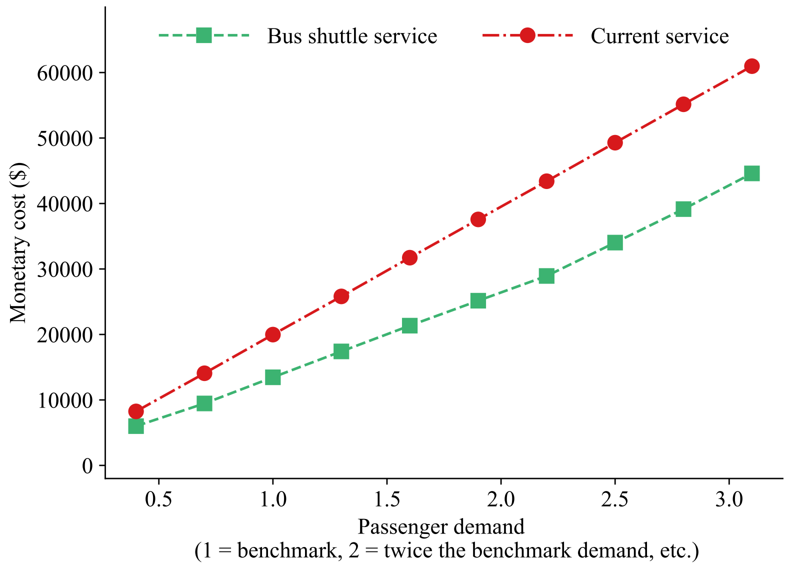

Figure 4: Total system cost of current service and proposed single-type bus shuttle service against the demand level

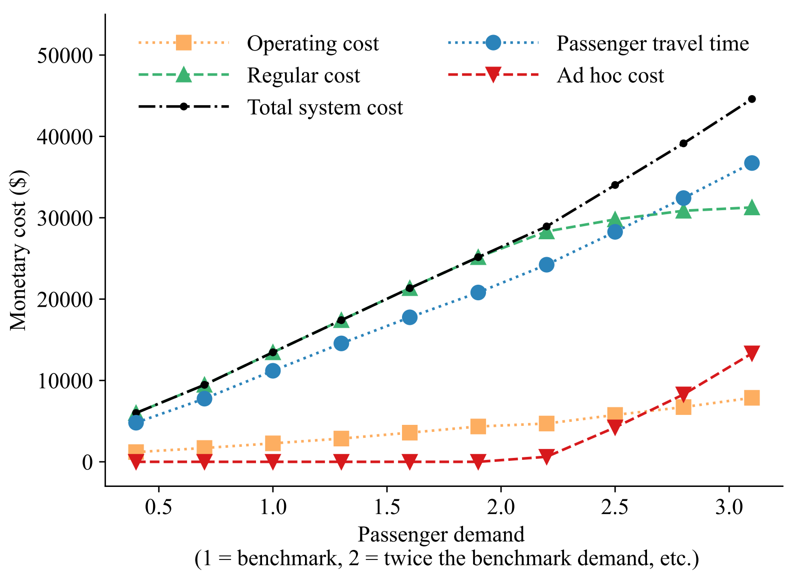

Figure 5: Different efficiency metrics against the demand level under a single-type fleet

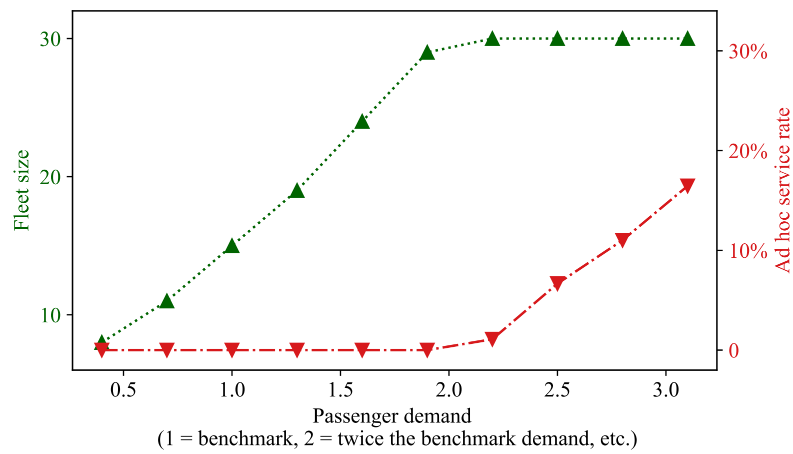

Figure 6: Optimal fleet size and ad-hoc usage percentage against the demand level under a single-type fleet

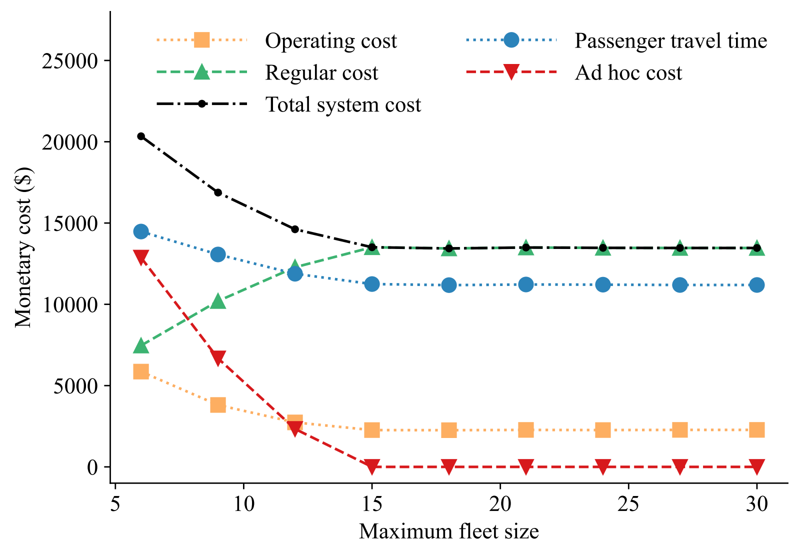

Figure 7: Different efficiency metrics under different fleet size limitation (a single-type fleet)

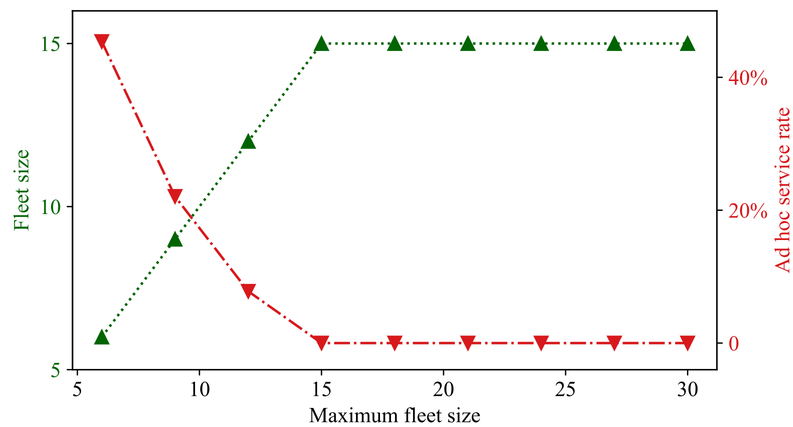

Figure 8: Optimal fleet size and ad-hoc usage percentage under different fleet size limitation (a single-type fleet)

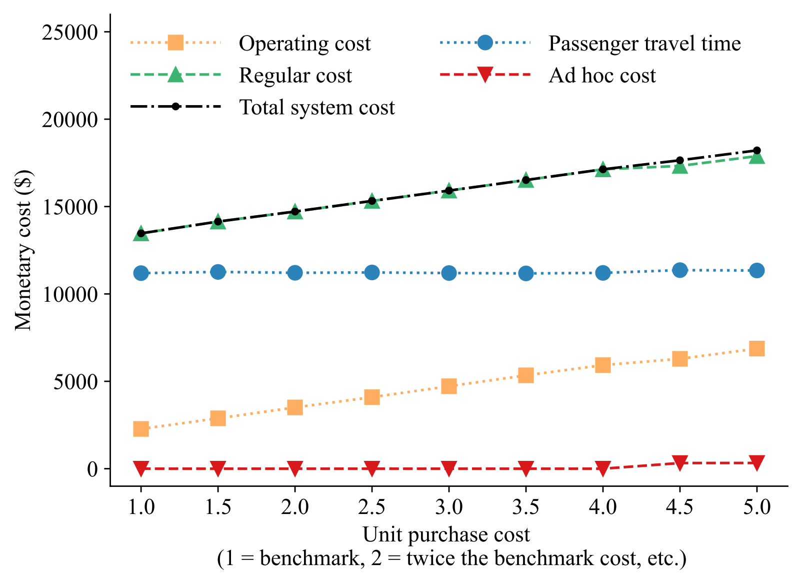

Figure 9: Different efficiency metrics under different shuttle bus cost (a single-type fleet)

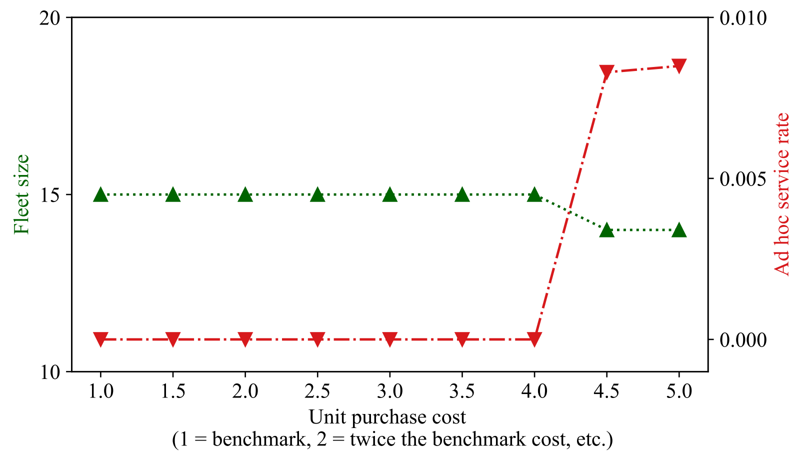

Figure 10: Optimal fleet size and ad-hoc usage percentage under different shuttle bus cost (a single-type fleet)

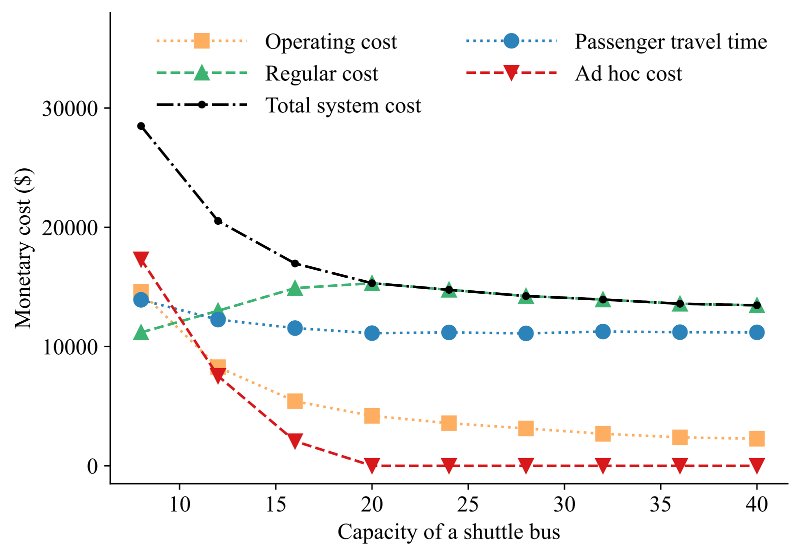

Figure 11: Different efficiency metrics under different shuttle bus capacities (a single-type fleet)

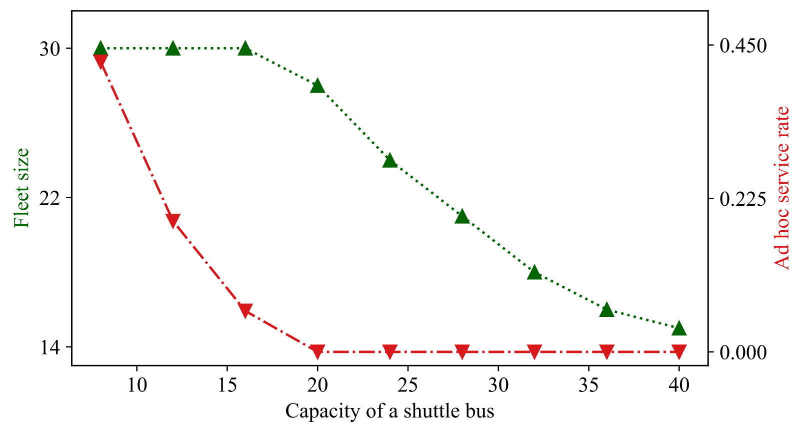

Figure 12: Optimal fleet size and ad-hoc usage percentage under different shuttle bus capacities (a single-type fleet)

We also vary the unit cost for providing a shuttle bus, and Figure 9 displays how five different efficiency metrics vary and Figure 10 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.

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 11 and Figure 12. 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.

We next consider the weighted objectives discussed in Section 3.2. Figure 13 shows Z_1 and Z_2 values when we have different ω_1 (related Eq. (13)) and Z_1' and Z_2' values when we have different ω_2 (related to Eq. (16)). As can be seen, the points in Figure 13(A) (or Figure 13(B)) that correspond to different values of ω_1 (or ω_2) show a trade-off between two objectives and form a Pareto frontier considering bi-objective optimisation.

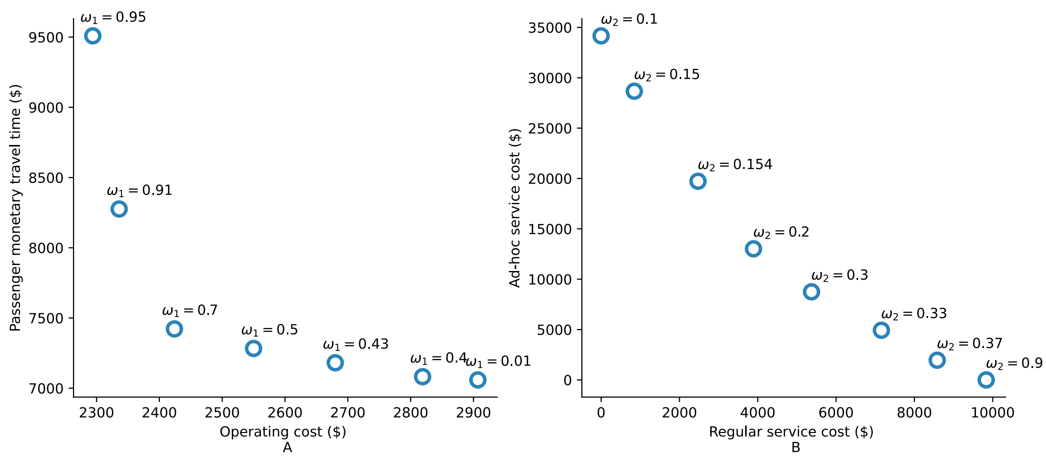

Figure 13: Alternative objective functions for the SNDP

We also tested different lengths of operation period (2 hours to 18 hours). The corresponding computation times for MILPs with deterministic demand and single-type fleet are summarised in Table 3 (as mentioned before, the tolerance gap in Gurobi is set as 1% for solving the MILPs).

Table 3: Computation times for MILPs with deterministic demand and a single-type fleet

Scale (hour)	Comp. time (second)	Scale (hour)	Comp. time (second)
2	7	12	488
4	29	14	798
6	50	16	962
8	85	18	1,476
10	270		

5.3. Heterogeneous multi-type fleet

We now turn to the multi-type fleet case. As introduced in Section 5.1, 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 γ^e and the loading rate η^e for type e bus, where the two ratios are calculated as follows.

$$\gamma^e = \left(\sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e} \right) \Bigg/ \left(\sum_{e \in E} \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e} \right) \tag{40}$$

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, $\sum_{e \in E} \sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e}$ denotes the total passenger-time served by all regular services.

$$\eta^e = \left(\sum_{d \in R} \sum_{ij \in S^d} X_{ij}^{d,e} \right) \Bigg/ \left(\sum_{ij \in S^q} Y_{ij}^e \xi^e \right) \tag{41}$$

where $\sum_{ij \in S^q} Y_{ij}^e \xi^e$ is the total capacity of the type e bus fleet. Note that when a specific bus type e is not used at all, the above two ratios are not defined as the denominators will be zero.

When the demand level increases (similar to that in Section 5.2 for the single-type fleet case), Figure 14 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 Section 5.2 (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 15 shows how five efficiency metrics vary, and Figure 16 shows how different types of buses are used to serve passengers (the two ratios γ^e and η^e are examined), when the passenger demand level varies. The results in Figure 15 for the multi-type fleet case are consistent with those in Figure 5 for the single-type fleet case. Figure 16 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.

When the maximum allowed fleet size increases (similar to that in Section 5.2 for the single-type fleet case), Figure 17 shows how five efficiency metrics vary and Figure 18 shows how different types of buses are used to serve passengers.

The results in Figure 17 for the multi-type fleet case are consistent with those in Figure 7 for the single-type fleet case. Figure 18 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.

When the unit cost for providing a shuttle bus increases (similar to that in Section 5.2 for the single-type fleet case), Figure 19 shows how five efficiency metrics vary and Figure 20 shows how different types of buses are used to serve passengers. The results in Figure 19 for the multi-type fleet case are consistent with those in Figure 9 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.

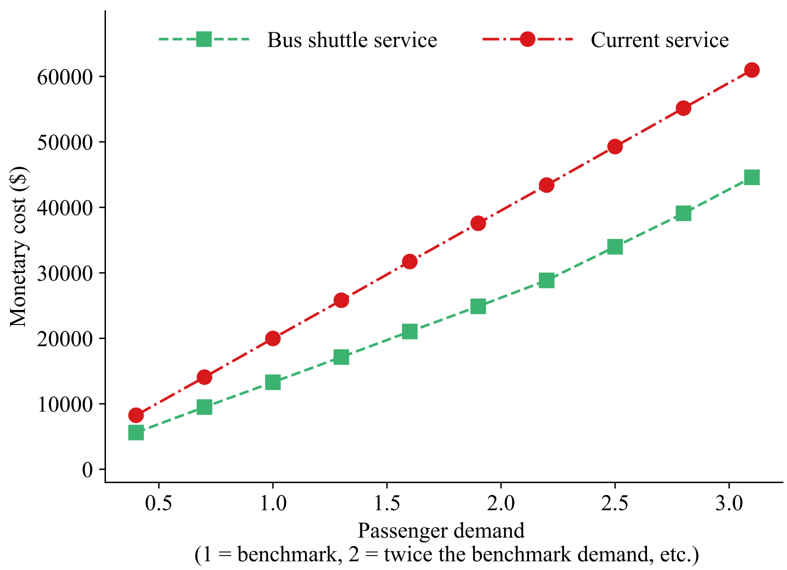

Figure 14: Total system cost of current service and proposed multi-type bus shuttle service against the demand level

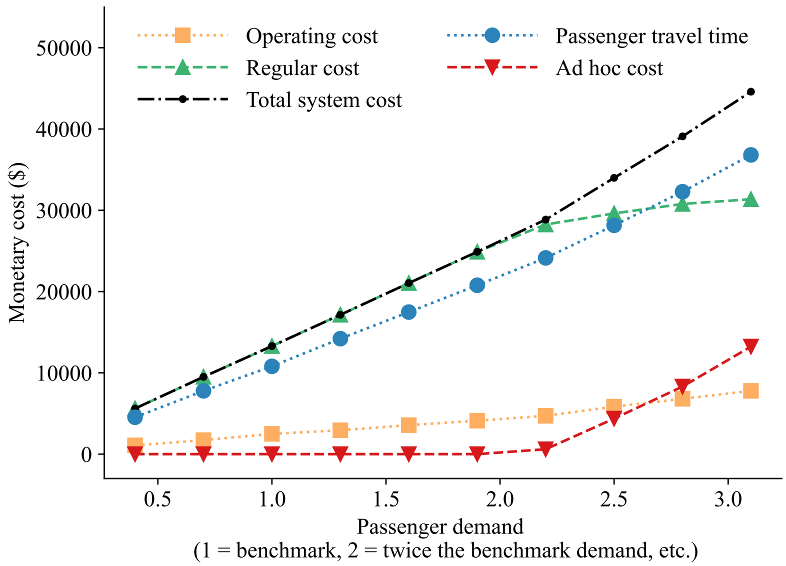

Figure 15: Different efficiency metrics against the demand level under a multi-type mixed fleet

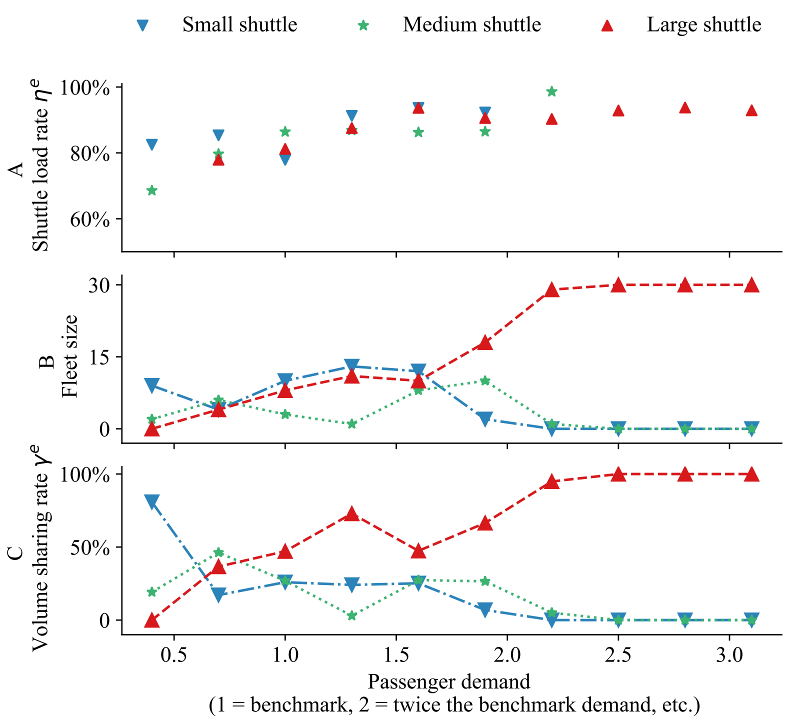

Figure 16: Usage pattern of the mixed fleet against the demand level

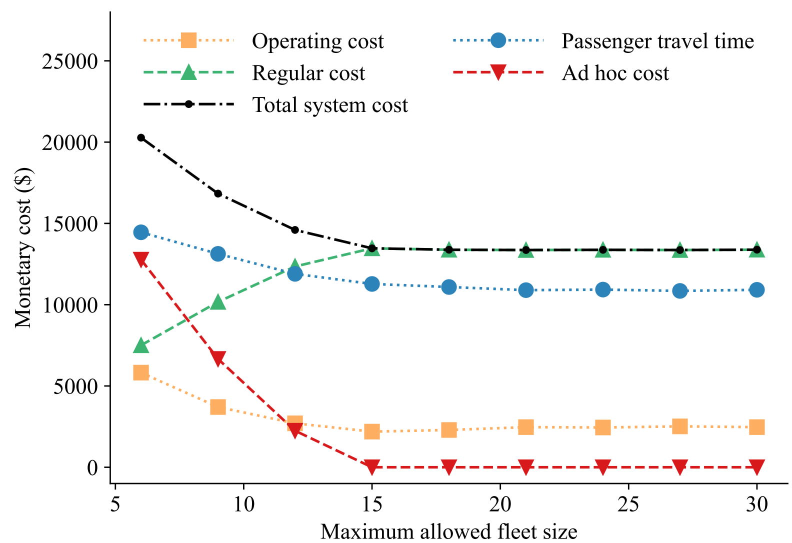

Figure 17: Different efficiency metrics against the maximum allowed fleet size under a multi-type mixed fleet

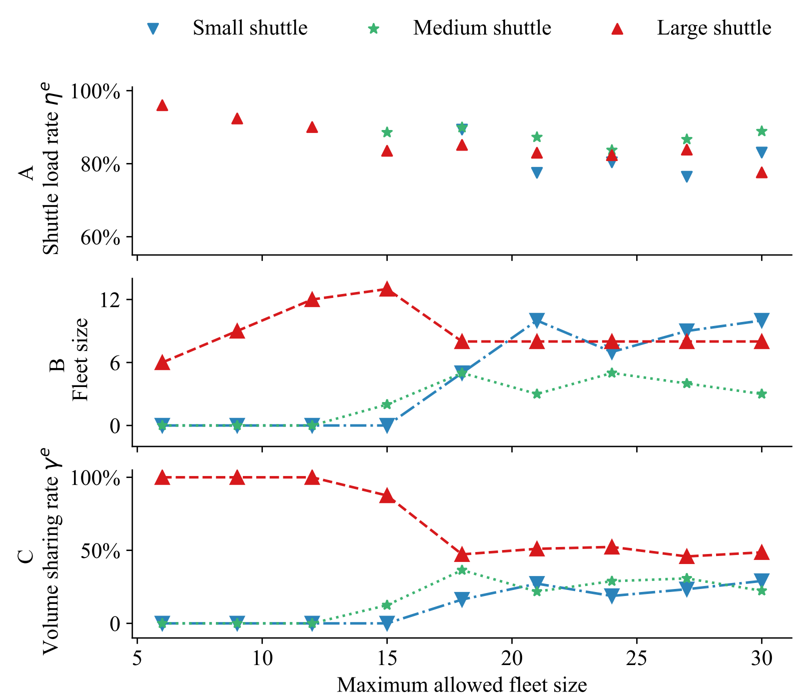

Figure 18: Usage pattern of the mixed fleet against the maximum allowed fleet size

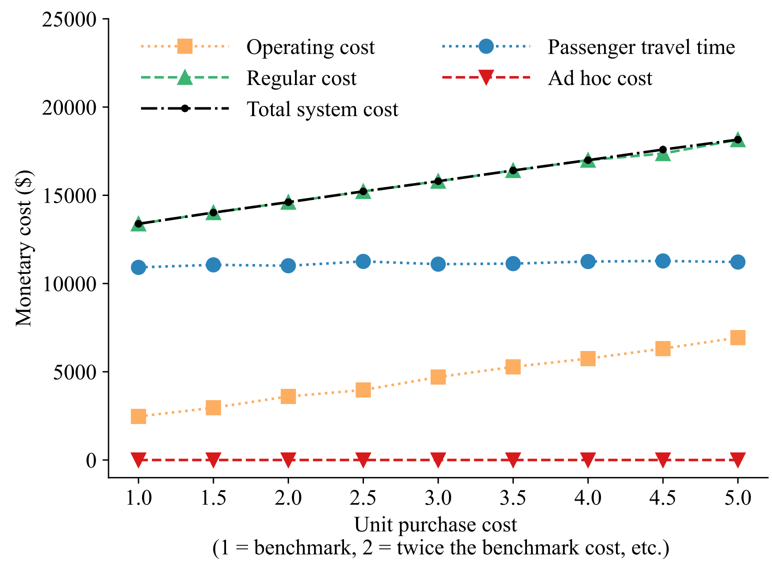

Figure 19: Different efficiency metrics under different shuttle bus cost (a multi-type mixed fleet)

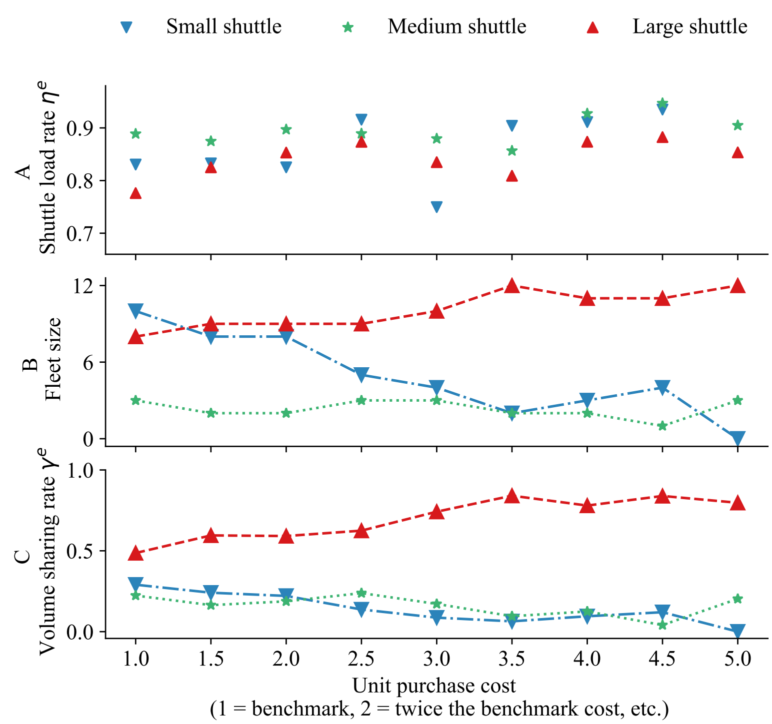

Figure 20: Usage pattern of the mixed fleet under different shuttle bus cost

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 3), 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.

5.4. Stochastic demand

We now further examine the stochastic demand case. All other settings are similar to those in Section 5.1 for the single-type fleet case with deterministic demand except the demand stochasticity. We assume that the demand distributions for each group are independent and follow the Poisson distribution. The demand values in Section 5.1 for the deterministic 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.

The initial interval for Δ 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 Δ outside this interval will yield worse solutions. Furthermore, we evenly divide this interval into 8 smaller intervals, and implement the solution approach discussed in Section 4.2 for each small interval. After the implementation of the proposed solution approach for each small interval, we choose the Δ that yields the smallest objective value.

Moreover, for the Monte Carlo Simulation-based solution approach discussed in Section 4.2, based on extensive experiments, we found that a sample size of 30 is often sufficient, where we have tested that the estimate of $\overline{\varphi}(\mathbf{Y})$ stabilises for the current case study (the percentage difference in the estimated $\overline{\varphi}(\mathbf{Y})$ 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).

We examined the total system cost, ad-hoc service rate and average loading rate η. In particular, η is defined as follows.

$$\eta = \left(\sum_{d\in R}\sum_{ij\in S^d} X_{ij}^d\right) \Bigg/ \left(\sum_{ij\in S^q} Y_{ij}\xi\right) \tag{42}$$

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. Note that we consider a single-type bus fleet and thus the superscript e is not involved.

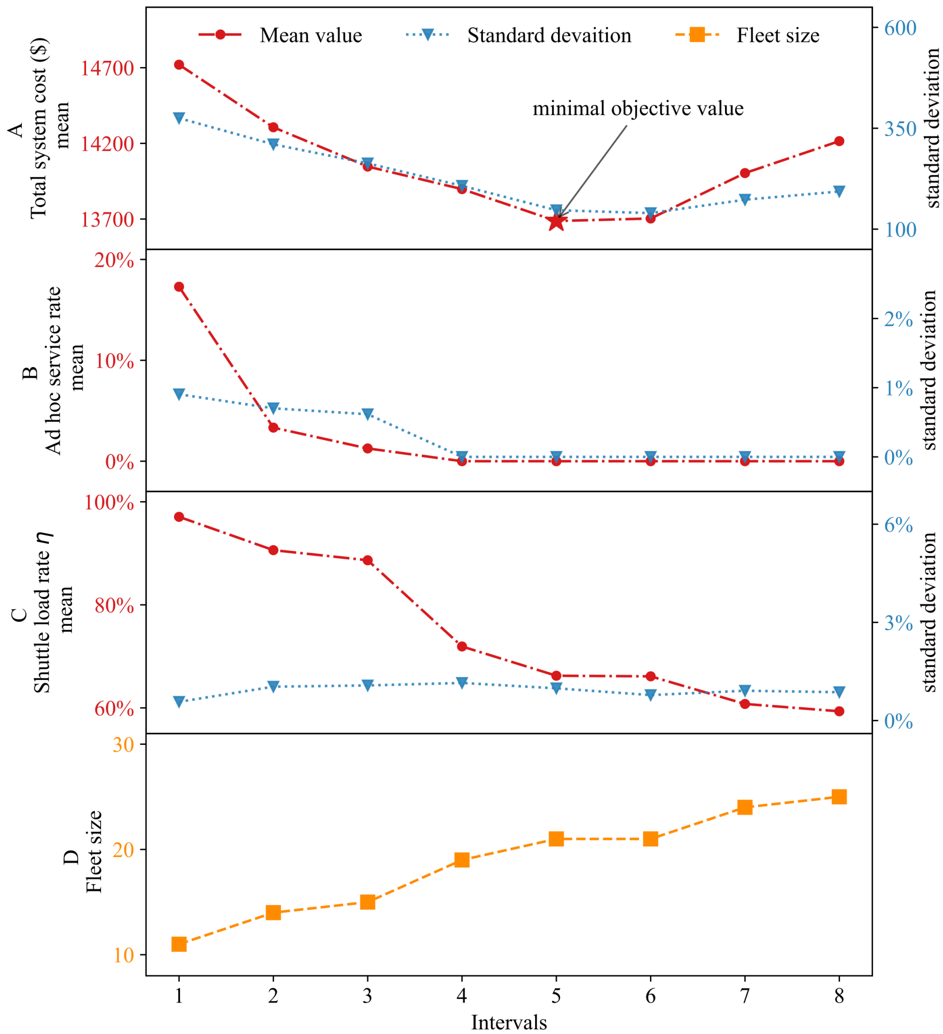

Figure 21: Solution under stochastic demand (with a single-type fleet)

Figure 21 compares solutions in the stochastic demand case for the 8 small intervals of Δ (total system cost is minimised). The optimal Δ is obtained from the fifth interval, i.e., $[0.0, 0.49]$, where Δ converges to 0.3675. As can be seen in Figure 21, a too large Δ yields an over-large regular service fleet, which is too costly for the system; a too small Δ yields an over-small regular service fleet and the over-usage of ad-hoc service, which is also costly. It is also worth mentioning that when Δ is close to 0.3675, the objective value varies only very slightly with respect to Δ. Moreover, there is demand stochasticity involved in the estimation of $\overline{\varphi}(\mathbf{Y})$ in the objective function in Eq. (33). Therefore, a value of Δ that is close to 0.3675 indeed produces comparable total system cost.

As mentioned in Section 4.2, we can replace the "effective" demand approach by GA, while we still use the Monte Carlo simulation in Step 3 of the solution procedure in Section 4.2 to estimate $\overline{\varphi}(\mathbf{Y})$ 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. 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 paper while GA takes much longer.

Table 4: Monte Carlo simulation coupled with GA against Monte Carlo simulation coupled with "effective demand"

Method	Population	Generation	Obj. value	Comp. time (min)
GA-0	10	10	21,758	182
GA-1	10	60	20,424	1,086
GA-2	100	20	19,912	3,818
Effective demand	-	-	13,703	144

6. Conclusion

This paper designs the passenger shuttle service network within an airport and its surrounding areas that may involve different facilities. This paper, when studying the shuttle service network design problem, incorporates both regular and ad-hoc services, heterogeneous multi-type fleet, stochastic demand, and air passengers' arrival time constraints at their destinations. The proposed models and methods are illustrated on the inter-terminal passenger service network at Sydney Kingsford Smith Airport.

When passenger demand pattern is recurrent and involves a low level of stochasticity, the proposed deterministic model might be sufficient to provide an efficient shuttle service network design, where the deterministic demand case can be formulated as a MILP and can be solved through commercial solvers. Moreover, if heterogeneous multi-type fleet is allowed in the shuttle service network, the proposed multi-type fleet model can better accommodate spatio-temporal heterogeneity of the passenger demand. When passenger demand involves a significant level of stochasticity, the stochastic model will be more useful where demand stochasticity is accommodated. In particular, the stochastic demand case can be formulated as a two-stage stochastic program, which is solved through the proposed Monte Carlo simulation-based approach coupled with the "effective demand" concept.

The numerical results for the inter-terminal passenger transport network at the Sydney Kingsford Smith Airport show that the proposed methods and solution approach can design a much more efficient airport passenger shuttle service than the current service, which saves more than 20% of total system cost (even with a single-type fleet). The sensitivity analysis also reveals how the service design varies against the passenger demand, the maximum allowed fleet size and the capacity, and the unit purchase cost for bus. The proposed Monte Carlo simulation-based approach coupled with the "effective demand" is used to solve the stochastic demand case. The results in the case study suggests that using a demand safety margin of 0.3675 times the standard deviation performs the best in the case study. The Monte Carlo simulation-based approach coupled with GA is unable to yield a better solution than utilising the "effective demand" method.

This study can be extended in several directions. Firstly, while this study proposes the airport ground transport service network design problem and solves the problem effectively for real-world networks, the proposed approach might be less applicable and requires considerable computation time for very large-scale problems (as shown in Table 3), especially when stochastic demand has to be considered. A future study might further propose efficient meta-heuristics in order to solve large-scale problems. Secondly, this study only considers the stochasticity in the demand side, but not in the supply side (such as trip time stochasticity). A future study might incorporate both demand and supply stochasticity in order to produce a more robust shuttle service network design for the airport passengers. Thirdly, this study only considers shuttle service network design for the airport passengers. A future study might consider shuttle service network design for not only passengers, but also freights, or even mixed flows of passengers and freights.

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