Design of Suburban Bus Route for Airport Access

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ABSTRACT

Suburban bus routes usually serve a city's peripheral areas with sparse density of travel demand. The distribution of many suburban trips is many-to-one, with all the passengers bound for a common destination like an airport. This paper aims to propose a methodology for the optimal design of a suburban bus route for airport access, with the objective of minimizing the total access time. Its decisions are the selection of pickup locations from the candidate stops and the corresponding visiting sequence. We first consider a special model which is polynomially solvable, and then develop a dynamic programming approach to address this special case. Later, we formulate a generic model and prove it to be NP-hard. Apart from the dynamic programming approach, an artificial bee colony (ABC) approach is developed for good-quality solutions of the practical-size problem. Finally, case studies based on a square-block example and two suburban bus routes in Melbourne are carried out to validate the applicability of the proposed models and solution methods.

Keywords: bus operations; airport access; suburban bus route; dynamic programming approach

1. Introduction

As one of the most important components in the transportation system, public transport is considered a pivotal backbone of sustainable urban development. Enhancing public transport service and raising its attractiveness is an effective way to alleviate the problems attributed to the automobile, such as road congestion, energy consumption and air pollution (Ceder, 2007; Currie and Wallis, 2008; Yan et al., 2012; Liu et al., 2013; de Oña, R. and de Oña, J., 2015; Orth et al., 2015; Chen et al., 2016; Ermagun and Levinson, 2016; Fan et al., 2016; among many others). For a bus service, systematic planning is needed before entering into the regular operation, which is comprised of five key components: network design, frequency setting, timetabling, vehicle scheduling, and driver scheduling/rostering (Guihaire and Hao, 2008; Kepaptsoglou and Karlaftis, 2009; Ibarra-Rojas et al., 2015).

Bus network design is an elementary planning procedure with the aim of determining the routes, types of vehicles and stop spacing to meet the demand of travel (Guihaire and Hao, 2008). Currently, there are numerous optimizations models that have been dedicated to the optimal design of bus networks (Lam et al., 1999; Currie and Loader, 2010; Roca-Riu et al., 2012; Szeto and Jiang, 2012, 2014; Yan et al., 2013; Fu and Lam, 2014; Amiripour, 2015; Pternea et al., 2015). Most of these previous studies focused on the bus routes located in urban central areas where the majority of bus trips are clustered in these areas. In comparison, the suburban bus routes which are located in the city's outskirts have received relatively less attention.

One distinctive feature of suburban bus routes is that they serve peripheral areas with sparse density of travel demand (Bell and Cloke, 1991). Therefore, it is not cost-effective to construct a dense bus network in the suburban areas. Instead, suburban bus routes mainly provide a feeder service which connects suburban areas and some demand concentrated places (e.g. airports, transit hubs/stations). Among these places, airports are usually located far away from residential areas due to the aircraft noise. This gives rise to inconvenience for residents living in the suburban residential areas who plan to access the airports. Taking a taxi is quite expensive thus not chosen by many travelers. At the same time, if most suburban residents choose to drive, it will have a detrimental effect on the traffic congestion and also cause a parking problem at the airports. Since these suburban trips present a many-to-one traveling character, the suburban bus route exclusive for airport access and airport shuttle van provide two alternative modes for airline passengers. This study focuses on the former one whose role is to offer an express bus service delivering passengers from multiple origins to a certain airport.

Such suburban bus feeder service is commonly implemented in practice. For instance, Fig. 1 presents three typical suburban bus routes access to the airport in Melbourne, Australia. Route 1 mainly serves the Melbourne's eastern suburb, route 2 mainly serves the southeastern suburban area, and route 3 mainly serves the southern suburb of Melbourne. These suburban bus routes have some analogous properties: (i) there is little congestion on suburban roads; (ii) only one bus route is available for airport access in each suburban area, and hence passengers have no other bus route choice; and (iii) the suburban area has a number of candidate pickup locations to collect passengers.

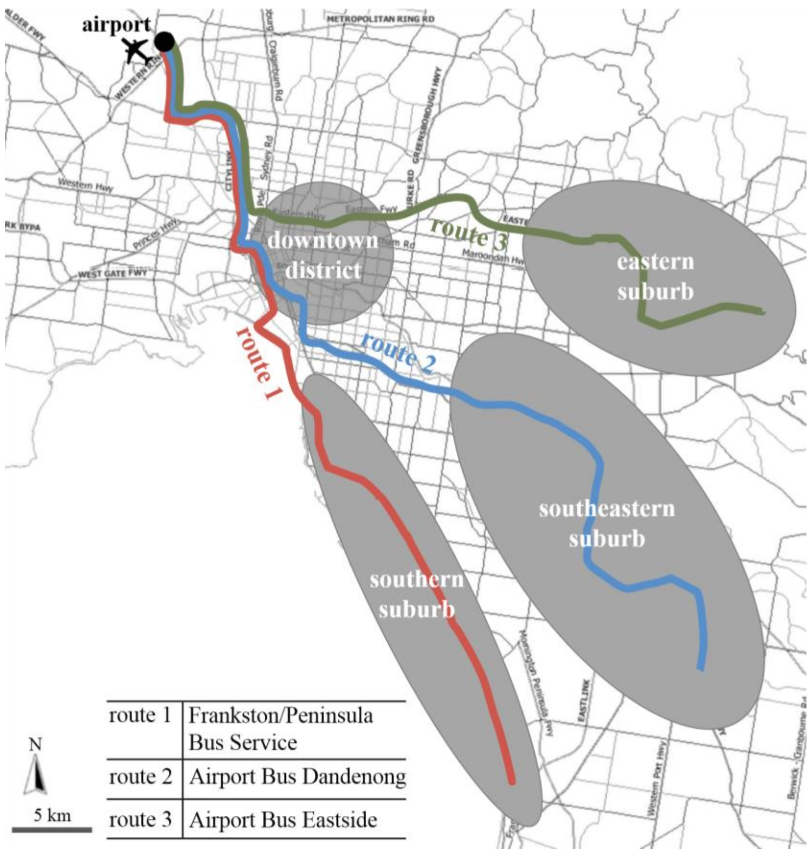


Fig. 1. Three typical suburban bus routes access to the Melbourne Airport.

In view of these properties, the design of a suburban bus route for airport access is relatively independent, which differs from the general bus network design in dense urban areas. Regarding the general bus network design, passengers' route choice behaviors have to be considered, due to the frequent transfers and complicated route plans. The general bus network design problem is usually an NP-hard problem, and most of extant studies use heuristic and metaheuristic methods to obtain potentially good solutions (Ibarra-Rojas et al., 2015). In contrast, the many-to-one travel pattern as well as three abovementioned properties make the suburban bus route design problem easier, and hence we expect that exact solution approaches may be proposed to design a practical suburban bus route.

1.1. Literature Review

Airports are among the largest activity centers in a city. For decades, transportation planners have endeavored to handle the airport access problem. For airline passengers, public transport is an effective way to provide airport access service that has attracted considerable interest from researchers, especially in recent years.

Mandle et al. (2000) reviewed the use of public transport modes (e.g. rail, bus and van service) at U.S. airports. They found that many U.S. cities provide rail transit service between the airport and downtown district (or major activity centers). Nevertheless, most suburban areas do not have direct rail transit service. In this case, bus and shared-ride van services were recommended as a proxy to serve these suburban areas. Coogan (2008) reported a similar result that most major airports in Europe and Asia are served by heavy-rail connections to the city's downtown district, whereas airport access in suburban areas is a bottleneck that greatly affects travel reliability of suburban airline passengers. Orth and Weidmann (2014) conducted a case study of Zurich Airport, which is a pivotal hub in Zurich, Switzerland. They indicated that many offices and shopping centers are located at the airport and these places generate high nonaviation activities (travel to airport to work or shop rather than take a flight). Such nonaviation travel demand is a main reason why Zurich Airport has a high public transport mode share. However, most trips in suburban areas are aviation-related travel, and hence the Zurich case is not suited to suburban airline passengers.

Apart from the qualitative analysis, a large number of authors have worked on the modeling of mode choice decisions for airport access. Many studies have developed models to identify the dominant factors that influence the airport ground access mode choices, including multinomial logit model (Harvey, 1986; Tam et al., 2008; Tsamboulas et al., 2012), nested logit model (Hess and Polak, 2006; Wen et al., 2012; Hess et al., 2013), mixed logit model (Jou et al., 2011), and logistic regression models (Chang, 2013; Choo et al., 2013). All these studies indicated that access time and access cost are most significant explanatory variables in an access mode decision. Therefore, public transport is attractive to more airline passengers only in cases when public transport modes can provide direct and reliable access service with less access time and access cost.

Previous studies have reported many useful findings on how to raise mode shares of public transport users. These findings are mainly applicable to urban central areas where bus, rail and other access mode choices are available. As multiple access modes are closely related, the design of bus routes in central areas has to consider many external factors, which poses a very complex problem. It is quite different in suburban areas that bus is the primary public transport mode for airport access, and the design of a suburban bus route is relatively independent. In addition, the distribution of suburban trips for airport access is many-to-one, with all airline passengers bound for the airport. Currently, a number of studies have been conducted on many-to-one travel pattern (Kuah and Perl, 1988; Lam and Huang, 1995; Spasovic et al., 1994; Chien and Yang, 2000; Daganzo, 2005; Sivakumaran et al., 2012). These studies can be further divided into two categories: (i) a continuous form, parameters and variables are approximated as continuous functions, such that stops are expressed per unit length; and (ii) a discrete form, parameters and variables take discrete values, e.g. the locations available for stops are expressed by site-specific details.

The many-to-one bus travel access to the airport is a discrete location-routing problem. Before proceeding to the designated airport, a bus vehicle first serves a certain suburban area which is comprised of several zones. Each zone has a number of candidate stops, which can be chosen by expert judgment or based on vehicle GPS trace data to identify places with high travel demand (Chen et al., 2014). These candidate stops may be selected as the real pickup locations. For a specific suburban bus route, the design task is to find the optimal bus routing with the least travel time that delivers passengers from selected pickup locations to the airport. The suburban bus feeder service provides benefits for suburban airline passengers, with real implementations in Melbourne (see Fig. 1). However, none of previous studies have investigated the optimization of bus routing pertinent to suburban routes for airport access, which is addressed in this paper.

1.2. Objectives and Contributions

The main objective and contribution of this study is to propose a methodology for the optimal bus routing of a suburban bus route exclusively for airline passengers. Considering the practical circumstances, the bus routing is not necessary to cover all the candidate stops. Meanwhile, at least one candidate stop per zone should be selected as a pickup location in ways that walking access distance is reachable for passengers in each zone.

The suburban bus routing problem (SBRP) is a practical research topic which is of particular significance for the airport access. The SBRP modeling framework is proposed for the optimal bus routing through minimizing the total travel time. Its decisions are the selection of pickup locations from the candidate stops and the corresponding visiting sequence. A special model of SBRP is first considered that all the zones are sequentially distributed along the bus route from the original terminal to the airport station. We demonstrate that the special model is polynomially solvable, and then develop a dynamic programming approach to address this special case. Afterwards, a generic model of SBRP is discussed that all the zones of a suburban area are randomly distributed. We prove that the generic model belongs to the NP-hard class. A dynamic programming approach and a metaheuristic approach are proposed to solve the generic model.

The remainder of this paper is organized as follows. Section 2 below describes the problem and develops an optimization model. In Section 3, the proposed model is further categorized into a special model and a generic model. Then, the computational complexity of two models and associated solution methods are discussed. Numerical examples are presented in Section 4. Finally, conclusions are provided in the last section.

2. Problem Statement and Model Development

In this section, we present an integer programming formulation for the suburban bus routing problem (SBRP). The variables used in the model and their notation are summarized in Table 1. Consider a suburban bus route that originates from a bus terminal (e.g. one depot), denoted by node 0 and terminates at the airport station, denoted by node N+1. The bus starts from node 0, then travels through the suburban area which contains N candidate stop pairs, and finally ends at node N+1. It should be noted that there are usually two bus stops at a location, one bus stop on each side of a road segment. Then, we use $1, 1', 2, 2', \ldots, N, N'$ to denote the sequence of these candidate stop pairs, where nodes h and h' correspond to a stop pair at the identical geographical location but on both sides of a street, $h = 1, 2, ..., N$. Here, h is denoted as the opposite bus stop of h', and vice versa. We define set $H = \{1, 2, ..., N\}$, set $H' = \{1', 2', ..., N'\}$, and set $\bar{H} = H \cup H' \cup \{0, N+1\}$.

Table 1 List of Notation

Indices	
i, j	the index of stops/nodes, $i, j \in \bar{H} = H \cup H' \cup \{0, N+1\}$
h, h'	the index of a stop pair, $h \in H$ and $h' \in H'$ correspond to a stop pair at the same geographical location but on the opposite sides of a street
c	the index of zones, $c \in C$
Sets	
C	a set of zones within the suburban area
$\bar{H}$	a set of stops, including two terminals and all the intermediate candidate stops
H, H'	a set of candidate stops, $H = \{1, 2, ..., N\}$ and $H' = \{1', 2', ..., N'\}$
$\underline{H}$	an arbitrary subset of $\bar{H}$
G_c	a set of candidate stops located in zone c
Parameters	
d_{ij}	distance between nodes i and j
N	the number of candidate stops in set H and set H'
v	average bus cruising speed
τ	average dwell time at each stop
Variables	
δ_i	a binary variable which equals 1 if candidate stop $i \in \bar{H}$ is visited by the suburban bus route, and 0 otherwise
x_{ij}	a binary variable which equals 1 if the bus visits stop $j \in \bar{H}$ immediately after stop $i \in \bar{H}$, and 0 otherwise

The travel demand of a bus vehicle is given and the suburban area includes a total of $|C|$ zones that needs to be visited. Note that zones can be determined based upon the administrative division and some other division criterions. Each zone c ($\forall c \in C$) subsumes a set of candidate stops, denoted by G_c. Candidate stops of all these zones constitute the set $H \cup H'$. To ensure that any resident is reachable from his/her house to the nearest bus stop, at least one of the candidate stops in each zone must be served by the bus route.

We let d_{ij} denote the distance between stops i and j ($i, j \in \bar{H}$). Distances are assumed to be nonnegative and satisfy the triangle inequality ($d_{ij} \le d_{ik} + d_{kj}, \forall i, j, k \in \bar{H}$). The bus is assumed to have an average cruising speed v and a common dwell time τ at each stop. Parameters d_{ij}, v, and τ are already known. We define δ_i as the decision variable which equals 1 if node $i \in \bar{H}$ is visited by the bus, and 0 otherwise, and define x_{ij} as the decision variable which equals 1 if and only if the bus visits node $j \in \bar{H}$ immediately after node $i \in \bar{H}$, and 0 otherwise.

The suburban bus routing problem is formulated as follows:

$$\min \quad z = \frac{1}{v}\sum_{i\in\bar{H}}\sum_{j\in\bar{H}} d_{ij}x_{ij} + \tau \sum_{i\in\bar{H}\setminus\{0,N+1\}} \delta_i \tag{1}$$

subject to:

$$\sum_{j\in\bar{H}\setminus\{0\}} x_{0j} = 1 \tag{2}$$

$$\sum_{i\in\bar{H}\setminus\{N+1\}} x_{i,N+1} = 1 \tag{3}$$

$$\sum_{j\in\bar{H}} x_{ij} - \sum_{j\in\bar{H}} x_{ji} = 0 \quad \forall i \in H \cup H' \tag{4}$$

$$\sum_{i\in G_c} \delta_i \ge 1 \quad \forall c \in C \tag{5}$$

$$\delta_0 = \delta_{N+1} = 1 \tag{6}$$

$$\delta_h + \delta_{h'} \le 1 \quad \forall h \in H \tag{7}$$

$$\sum_{j\in\bar{H}\setminus\{0\}} x_{ij} = \delta_i, \quad \forall i \in \bar{H} \setminus \{N+1\} \tag{8}$$

$$\sum_{i\in\underline{H}}\sum_{j\in\underline{H}} (x_{ij} + x_{ji}) \le |\underline{H}| - 1 \quad \forall \underline{H} \subseteq \bar{H} \tag{9}$$

$$x_{ii} = 0 \quad \forall i \in \bar{H} \tag{10}$$

$$x_{hh'} = 0, x_{h'h} = 0 \quad \forall h \in H \tag{11}$$

$$x_{ij} \in \{0,1\} \quad \forall i, j \in \bar{H} \tag{12}$$

$$\delta_i \in \{0,1\} \quad \forall i \in \bar{H} \tag{13}$$

The objective function is to minimize the total vehicular travel time within a suburb area for a suburban bus. It contains two terms: the first term is the total cruise time and the second term is the total dwell time. Constraint (2) and (3) ensure that only one bus stop connects with the terminal node 0 and node $N+1$, respectively. Constraint (4) ensures that with the exception of two terminal nodes, any visiting node on a service route has one preceding node and one following node. If one candidate stop $i \in \bar{H}$ is not selected as the visiting node, constraint (4) is also satisfied since all the decision variables with respect to node i (i.e. x_{ij} and x_{ji}) equal zero. Constraint (5) is the zone coverage constraint, and ensures that at least one of the candidate stops in each zone is served by the bus. Constraint (6) underscores that two bus terminal stops (node 0 and N+1) must be visited. Constraint (7) and (8) ensure that exactly one of node h and its corresponding opposite node h' is visited if one of them is selected as a visiting stop. Constraint (9) is the sub-tour elimination constraints, which should be satisfied by any subset $\underline{H}$ of $\bar{H}$. Constraint (10) and (11) underscore that the bus does not visit a bus stop twice including its opposite stop. Constraint (12) and (13) define x_{ij} and δ_i as binary variables.

Remark 1. Once the optimal bus routing is designed, bus frequencies need to be determined for temporal variations in travel demand to the airport during the practical uses. We can partition one day into many time periods. As the travel demand in the suburban area is far less than that in the city's central district, suburban buses can be dispatched at relatively low frequencies that vary with multiple time periods. At the same time, bus frequencies should satisfy the minimal service level which ensures that the provided bus capacity is greater than or equal to the total passenger demand in any given time period.

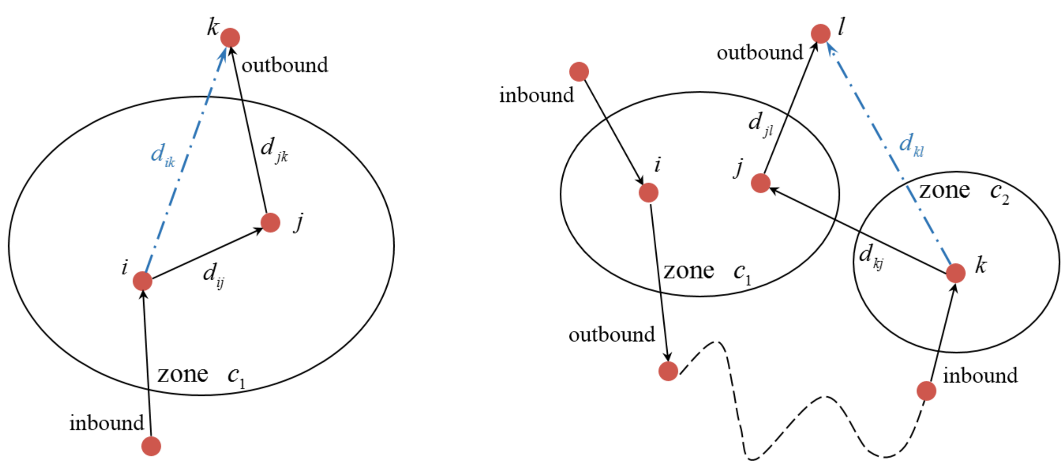
Remark 2. When the served suburban area is sufficiently large, the wandering time for the first passenger needs to be considered. We define an upper bound limit of wandering time. Then, the wandering time for the first passenger is required to be not larger than the upper bound limit value. Such feature can be seen either as a constraint or as a new term of the objective function in Eq. (1) which represents an additional time penalty when the maximum wandering time exceeds the upper bound limit value. It can be easily incorporated into the proposed model and algorithm.

In this formulation, the zone coverage constraint (5) requires that at least one candidate stop of each zone is selected by the bus route. In reality, to achieve the minimization of Eq. (1), we find that the bus should visit each zone exactly once and only one stop per zone during the bus tour. Then, we give the proof of this property in Proposition 1.

Proposition 1. The zone coverage constraint (5) can be replaced by

$$\sum_{i \in G_c} \delta_i = 1 \quad \forall c \in C \tag{14}$$

Proof. This proposition is proven to consider two cases in Fig. 2 by contradiction. Consider the Case I, suppose that the optimal solution of SBRP contains one zone in which the bus visits two consecutive stops as shown in Fig. 2A. In this case, the bus travels from node i to node j, and then leaves zone c_1 to arrive at node k. Then, the travel distance equals $d_{ij} + d_{jk}$. Note that the arcs in Fig.2 are fictitious which correspond to the traveling path in the real streets and roads. We now consider the scenario that bus only visits one stop of zone c_1 (i.e. node i) and directly goes to node k. The travel distance equals d_{ik}. As distances are assumed to satisfy the triangle inequality, we get $d_{ij} + d_{jk} \geq d_{ik}$. Adding the dwell time at node j, the bus travel time of the optimal solution is larger than the scenario that bus goes directly from node i to node k. This is a contradiction, and hence bus visits only one stop of an arbitrary zone each time in the optimal solution.



(a) Case I (b) Case II

Fig. 2. Zone coverage constraint in two cases.

Consider the Case II, suppose that the optimal solution of SBRP subsumes one zone that is visited twice. As shown in Fig. 2b, node j is the second stop that bus visits in zone c_1. In this case, the bus travels from node k in zone c_2 to node j in zone c_1, and later arrives at node l. The total travel distance of this route segment is $d_{kj}+d_{jl}$. Here, consider the other scenario that bus travels directly from node k to node l, the travel distance equals d_{kl}. Since the triangle inequality holds (i.e. $d_{kj}+d_{jl}\geq d_{kl}$) and the optimal solution includes an extra dwell time at node j, its total travel time is no longer optimal, and we have a contradiction.

Thus, in the optimal solution, the bus visits only one stop of each zone during the bus tour, and Eq. (14) is acquired. □

Proposition 2. The objective function (1) is equivalent to:

$$\min \quad z=\sum_{i\in\bar{H}}\sum_{j\in\bar{H}} d_{ij}x_{ij} \tag{15}$$

Proof. According to Proposition 1, each zone only has one stop to be visited by the bus vehicle. Since the number of zones within the suburban area is known, the second term in the objective function (1) equals a constant value, namely $|C|\tau$. The bus cruising speed v is also a known parameter, and thus the objective function (1) is equivalent to $\min \sum_{i\in\bar{H}}\sum_{j\in\bar{H}} d_{ij}x_{ij}$ in Eq. (15). □

3. Quantitative Analysis and Solution Method

3.1 A special model of SBRP

We first discuss a special model that the bus starts from node 0 and proceeds to visit $|C|$ zones within a suburban area. Fortunately, all the zones are sequentially distributed along the bus route from the original terminal to the airport station, and they are ordered by their distance from node 0 (see Fig. 3). In this simple case, it is easy to verify that to obtain the optimal solution, the bus should take turns to visit zone 1, zone 2,… and finally zone $|C|$ within the suburban area.

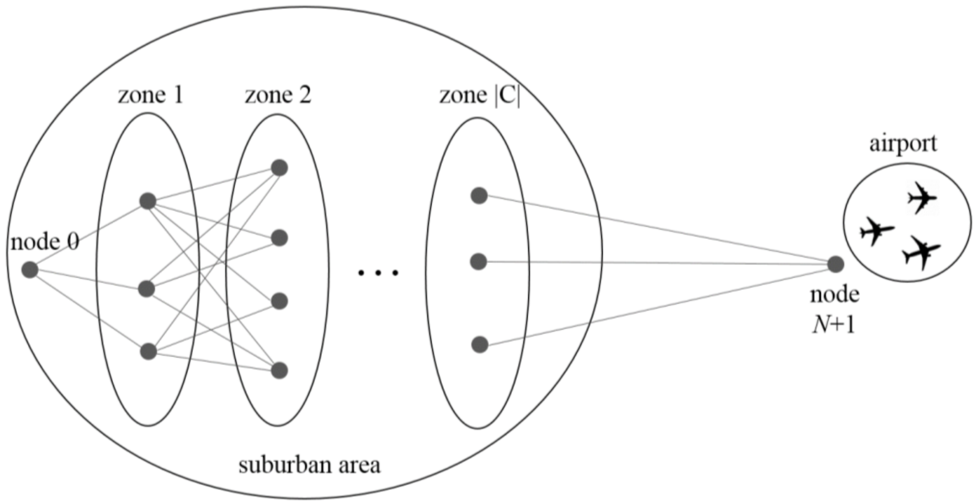


Fig. 3. Schematic diagram of the special model.

According to Proposition 2, the special model is equivalent to the shortest path problem. Hence, it can be polynomially solved by several methods (e.g. simplex method, dynamic programming approach). Here, a dynamic programming approach is proposed to address this special model of SBRP.

3.1.1 Dynamic programming approach

Consider the problem as a multistage decision problem. Computations are carried out for each stage separately. The crucial element of the dynamic programming approach is the definition of recursive equation at stage *c*:

$$f_c(i,S) := \text{The shortest sub-tour from node } i \text{ located in zone } c \text{ (i.e. } i \in G_c) \text{ to node } N+1, \text{ and set } S \text{ denotes the candidate stops that are potentially visited along this sub-tour, } S \subseteq H \cup H' \quad (16)$$

It is noteworthy that in above function, set S is a collection of intermediate candidate stops that may be visited at the succeeding stages (i.e. stage $c+1, c+2, ..., |C|$). For an arbitrary stop pair, $h \in H$ and $h' \in H'$ belong to the identical zone, and hence this candidate stop pair should satisfy either (i) $h \in S$ and $h' \in S$, or (ii) $h \notin S$ and $h' \notin S$.

The special model of SBRP has a salient feature: the sequence of stages is the same as the visiting sequence of zones. It means that the state at stage *c* corresponds to the candidate stops in set G_c.

In this study, we use backward recursion in which the computations proceed from stage $|C|$ to stage 1. Clearly, we have:

$$f_{|C|}(i,S) = d_{i,N+1} \quad i \in G_{|C|} \quad \text{if} \quad S = \varnothing \tag{17}$$

Then, these distances in stage $|C|$ are used as input data to compute the immediately preceding stage. Without the loss of generality, we discuss the recursive equation of an arbitrary stage c:

$$f_c(i,S) = \min_{j \in G_{c+1}} \{d_{ij} + f_{c+1}(j, S/G_{c+1})\} \quad i \in G_c, c < |C| \quad \text{if} \quad S \neq \varnothing \tag{18}$$

The dynamic programming approach is executed in an iterative form. In each iteration, several candidate stops of one zone in S will be eliminated. When $S = \varnothing$, we can use Eq. (17) to compute the final stage. Therefore, at any stage, the corresponding function $f_c(i,S)$ can be computed.

The recursive equation of node 0, denoted by stage 0 can also be obtained:

$$f_0(0, H \cup H') = \min_{i \in G_1} \{d_{0i} + f_1(i, S/G_1)\} \quad i \in G_1 \tag{19}$$

Then, we can readily get the optimal bus tour from node 0 to node N+1, which just is the optimal solution of Eq. (1). It should be mentioned that the proposed approach in this section can be utilized to solve the special model of SBRP in polynomial time with regard to the size of the suburban bus route design.

3.2 A generic model of SBRP

We now turn our attention to a generic model that zones are no longer sequentially distributed along the bus route from the original terminal 0 to the airport station N+1. Instead, they are randomly distributed within the suburban area. In other words, the generic model of SBRP has no information about the visiting sequence of all the zones located in the suburban area. We first examine the tractability of this generic model and later give the algorithm design.

3.2.1 Computational complexity

Computational complexity theory presents that if an optimization problem belongs to the NP-hard class, an efficient algorithm for the exact solution of this problem does not exist (e.g. Garey and Johnson, 1979; Papadimitriou, 2003). In this section, we prove that the generic model of SBRP is NP-hard by proving that its decision version is NP-complete. The decision version of

SBRP (called dSBRP) is that are there any values for variables x_{ij} and δ_i of SBRP $\forall i, j \in \bar{H}$ that satisfy constraints (2)-(13) and such that the total vehicular travel time in Eq. (1) is less than a given constant T ?

We propose a polynomial reduction from the Travelling Salesman Problem (TSP), whose NP-completeness is assured by Papadimitriou (1977), to dSBRP. The decision version of TSP is described as: given a set of cities $\{1, 2, ..., N\}$ and the distance d_{ij} from city i to j, is there a tour that starts and ends at city 0, and visits the remaining city exactly once such that the total travel distance is of the tour is shorter than T ?

Next, we show the proposition of the complexity for dSBRP.

Proposition 3. dSBRP is NP-complete.

Proof. The description of two steps for the complexity proof are the following.

1. $\text{dSBRP} \in \text{NP}$

Assume there exists an algorithm that generates a solution for dSBRP. Determining if the solution is feasible for dSBRP needs several steps. First, check if constraints (2)-(13) are satisfied for each decision variable of the solution (i.e. x_{ij} and δ_i). Then, verify if the sum of the travel time resulted from the solution is less than or equal to T (one constraint). Considering all the constraints, we need a polynomial number of steps to verify the feasibility of a dSBRP solution, i.e., $\text{dSBRP} \in \text{NP}$.

2. $\text{TSP} \prec_p \text{dSBRP}$

Consider an arbitrary instance of TSP. We build a particular instance of dSBRP, called dSBRP*, as follows. Suppose that node 0 and node N+1 coincide. Hence, $d_{0i} = d_{N+1,i}$, $d_{i0} = d_{i,N+1}$ for all $i \in H \bigcup H'$. Then suppose that node h and h' coincide for all the candidate stop pairs $h \in H$, that is $d_{ih} = d_{ih'}, d_{hi} = d_{h'i}$ for all $i \in \bar{H}$ and all $h \in H$. Suppose further that each zone only has one candidate stop. Therefore, the number of zones equals the number of intermediate stops, namely $|C| = |N|$, and based on Constraint (5), each candidate stop is visited exactly once, i.e. $\delta_i = 1, \forall i \in \bar{H}$. Set the average bus cruising speed $v = 1$. The dwell time at each stop is set to be $\tau = 0$, and then the second term of objective (1) vanishes. As per dSBRP* definition, the solution of dSBRP* is equivalent to TSP. Thus, it is easily to verify that TSP can be solved by solving a decision version of SBRP. □

3.2.2 Dynamic programming approach

The generic model of SBRP can also be solved by the dynamic programming approach. Computations are implemented in a fashion analogous to the proposed method in Section 3.1.1. The main difference between these two models of SBRP is that in the special model, the sequence of stages is identical to the visiting sequence of zones, while in the generic model, there are still a total of $|C|$ stages but the visiting sequence of zones is not predetermined.

For the generic model, the state at stage *c* corresponds to the candidate stops in set $H \cup H'$. It is because there is no information about the visiting zone sequence, and the bus can dwell at almost any candidate stop in set $H \cup H'$ at stage *c*.

Thus, we redefine the recursive equation of the generic model. The backward recursion is utilized to compute from stage $|C|$ to stage 1. The recursive equation of stage $|C|$ is as:

$$f_{|C|}(i,S) = d_{i,N+1} \quad i \in H \cup H' \quad \text{if} \quad S = \varnothing \tag{20}$$

With a little abuse of the notation, all the zones are also labeled from 1 to $|C|$ but have no relations with the sequence of stages. Given that node $j \in G_c$, we first let $\varphi(j)$ be the zone number *c* in which node j is located, i.e. $\varphi(j) = c$.

Then, we discuss the recursive equation of an arbitrary stage *c*, $f_c(i,S)$.

$$f_c(i,S) = \min{}_{j \in S}\{d_{ij} + f_{c+1}(j, S/G_{\varphi(j)})\} \quad i \in H \cup H' \quad c < |C| \quad \text{if} \quad S \neq \varnothing \tag{21}$$

Eq. (21) means that the bus travels from node i to node $j \in S$ with the travel distance d_{ij}. When the bus is at node j , according to Proposition 1, none of candidate stops in $G_{\varphi(j)}$ need to be visited. $f_c(i,S)$ is acquired when the best node $j \in S$ is selected.

Later, the recursive equation of node 0 at stage 0 is calculated as follows.

$$f_0(0, H \cup H') = \min{}_{i \in H \cup H'}\{d_{0i} + f_1(i, S/G_{\varphi(i)})\} \tag{22}$$

Finally, we procure the optimal bus tour from node 0 to node N+1, which is the optimal solution of the objective function (1). Since the generic model of SBRP is proved to be NP-hard, the above dynamic programming approach cannot be applied to solve the practical-size problem. We can use some heuristic and metaheuristic methods (e.g. genetic algorithm, artificial bee colony algorithm) to search good-quality solutions, which can be seen as an approximation of the optimal suburban bus route design.

3.2.3 Metaheuristic approach

An artificial bee colony (ABC) approach is proposed in this section to solve the practical-size problem in regard to the generic model of SBRP. The ABC algorithm is a population-based metaheuristic approach which is inspired by the foraging behaviors of honey bees searching nectar sources around the hive (Karaboga, 2005). More recently, the ABC algorithm has been applied to solve several transit optimization problems (Szeto et al., 2011; Szeto and Jiang, 2012, 2014; Chen et al., 2015; Jiang and Szeto, 2015).

3.2.3.1 ABC algorithm

In the ABC algorithm, a food source represents a feasible solution and nectar amount of a food source reflects the solution quality. The bee colony is classified into three categories: employed bees, onlookers and scouts. Employed bees are mainly responsible for exploiting available food sources and getting their nectar amount. Then, they share such information with onlookers, and each onlooker tends to select a food source found by employed bees according to the probability proportional to the quality of that food source. In this study, the traditional roulette wheel selection method is used to calculate the probability (Szeto and Jiang, 2014). Onlookers continue to exploit the solution space in the hope of finding better quality solutions. When the quality of one food source cannot improve for a predetermined number of iterations, this source will be abandoned, and the employed bee will become a scout and start to look for a new source in the vicinity of the hive. Any interested readers could refer to Chen et al. (2015) for a detailed description of the ABC algorithm.

We describe the basic structure of the proposed algorithm below.

Step 1: Initialize the parameters: set the colony size N_c, the number of employed bees N_e, and the number of onlookers N_o; set the counter of iterations, I and its initial value as one; set the maximum number of iterations, I_{max}; let l_m be the count of previous successive iterations that food source m does not improve; let *limit* be the maximal trial count of iterations; let the fitness of food source m be the reciprocal of $z(m)$ in Eq. (1).

Step 2: Randomly generate a set of solutions as initial food sources. Assign each employed bee to an arbitrary food source m, and set the limit counter l_m to be zero.

Step 3: Perform the employed bee phase. Conduct a neighborhood search for food source m on $m \rightarrow \tilde{m}$. If $z(\tilde{m}) < z(m)$, then replace m with $\tilde{m}$ and $l_m = 0$, else $l_m = l_m + 1$.

Step 4: Perform the onlooker phase. Execute the fitness-based roulette wheel selection method to select a food source m for an onlooker from all the food sources obtained by employed bees. Continue to conduct a neighborhood search for food source m on $m \rightarrow \tilde{m}$. If $z(\tilde{m}) < z(m)$, then replace m with $\tilde{m}$ and $l_m = 0$, else $l_m = l_m + 1$.

Step 5: Perform the scout phase. Compare the fitness of all the renewed food sources originated from N_e employed bees, and find the best food source with the highest fitness. If the limit counter l_m of food source m reaches the maximal trial number *limit*, and meanwhile it is not the best food source, replace it with a new solution generated randomly, and set its limit counter to zero.

Step 6: Termination test. Increase the number of iterations by 1: i.e., $I = I + 1$. Check the stopping criterion: If $I < I_{\max}$, return to Step 3; otherwise, terminate and output the best solution.

For the proposed ABC algorithm, solution generation and neighborhood search procedures should be specifically designed in order to search all of the possible suburban bus route structures.

3.2.3.2 Solution generation procedure

In the ABC algorithm, new solutions are generated in the initialization and scout phases, both of which use the identical steps to produce a random solution.

For a new solution, a set of decision variables x_{ij} and δ_i need be initialized. According to Proposition 1, each zone only has one stop to be visited by the bus. The suburban area has a total of $|C|$ zones, and hence only $|C|$ intermediate candidate stops will be visited along the bus tour. It means that the number of binary variables x_{ij} and δ_i whose values equal 1 is $|C|$ and $|C|+1$, respectively. All the remaining decision variables are equal to 0.

To create a random solution, the following steps are carried out. First, generate a random permutation of the integers from 1 to $|C|$ inclusive. As abovementioned, all the zones already have a set of serial numbers (i.e. $1,2,...,|C|$). The generated permutation is seen as the visiting sequence of $|C|$ zones. Then, for an arbitrary zone c, randomly select one of the candidate stops in set G_c as the visiting node. Finally, variables δ_i corresponding to the visiting nodes and variables x_{ij} corresponding to the bus tour equal 1. Set the rest of decision variables, if any, to zero.

3.2.3.3 Neighborhood search procedure

Each employed bee or onlooker conducts a neighborhood search around a food source. For each food source, since the visiting sequence of zones is given, the dynamic programming approach of the special model in Section 3.1.1 can be incorporated in the neighborhood search procedure. It is available to find the optimal bus tour under the current zone visiting sequence in polynomial time. Furthermore, a greedy search procedure is also considered. Specifically, for a food source, swap the visiting sequence of two zones each time to form a new permutation, and then execute the dynamic programming approach in Section 3.1.1. As the number of zones is $|C|$, the dynamic programming approach are conducted $\frac{1}{2}|C|(|C|-1)$ times.

Then, evaluate the fitness of all neighbor solutions and find the best neighbor solution. Replace the solution with the best neighbor solution, if the fitness of this neighbor solution is better. Otherwise, hold the current solution. The pseudo-code of the neighborhood search procedure are as follows:

For each ABC solution m

Set $c_1 = 1$

While $c_1 \leq$ the number of zones $|C|-1$

Set $c_2 = c_1 + 1$

While $c_2 \leq |C|$

Swap the visiting sequence of zone c_1 and c_2

Conduct the dynamic programming approach of the special model

Record the temporarily optimal neighbor solution $\tilde{m}$

Restore the original solution m

$c_2 = c_2 + 1$

endwhile

$c_1 = c_1 + 1$

endwhile

Search the best neighbor solution $\hat{m}$, $z(\hat{m}) = \min\{z(\tilde{m})\}$

If the objective value $z(\hat{m}) < z(m)$,

then replace m with $\hat{m}$

else

retain m

endif

Next ABC solution

4. Numerical Examples

In this section, the proposed models are verified based on a square-block example and two real-case examples in Melbourne, Australia. The solution methods are coded in *Matlab* R2013b and implemented on a personal computer with Inter Core i7-4700 CPU @ 2.40 GHz, 2.40 GHz and 8.00 G RAM. Both models can be efficiently solved.

4.1 A square-block example

A square-block example, set out in Fig. 4, is first used to demonstrate calculation of the special model of SBRP. In this example, two bus terminal stops 0 and N+1 are located at the bottom-left and upper-right corner of the square-block suburban area, respectively. Furthermore, three zones are sequentially distributed along the suburban bus route. Each zone has two candidate stop pairs and each stop pair has two stops on both sides of a road segment.

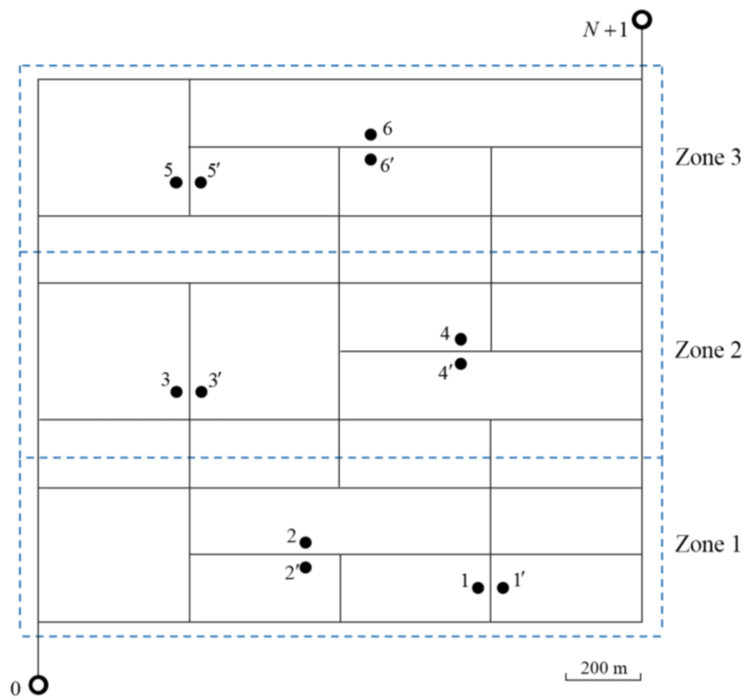


Fig. 4. A square-block example of special model.

To be coherent with the real-case examples in the next section, it is required that drivers should drive on the left side in Fig. 4. We further assume that (i) vehicles are only allowed to make left-turn, right-turn and U-turn at intersections, rather than in the middle of route segments; (ii) an average cruising speed is considered to adequately account for the effects of turning at intersections and other such factors which are not explicitly modeled, because there is little congestion in suburban area. Then, the values of v and τ in the objective function (1) are taken as 20 km/h and 2 min, respectively. Table 2 presents the pairwise distances of all the candidate stops.

Table 2 Pairwise Distances of Candidate Stops (unit: km)

i \ j	0	1	1′	2	2′	3	3′	4	4′	5	5′	6	6′	7
0	0	1.5	1.7	1.1	1.3	1.3	1.9	2.1	2.3	1.9	2.5	2.5	3.1	3.6
1	1.7	0	0.2	1.2	0.6	1.4	2.0	1.4	1.6	2.0	2.2	1.8	2.4	2.1
1′	1.5	0.2	0	1.4	0.8	1.6	2.2	1.6	1.8	2.2	2.4	2.0	2.6	2.3
2	1.3	0.8	0.6	0	0.2	1.0	1.6	1.8	2.0	2.4	2.6	2.2	2.8	2.5
2′	1.1	1.4	1.2	0.6	0	0.8	1.4	1.6	1.8	2.2	2.4	2.0	2.6	3.1
3	1.9	2.2	2.0	1.4	1.6	0	0.6	1.2	1.6	1.4	1.6	1.2	1.8	2.3
3′	1.3	1.6	1.4	0.8	1.0	0.2	0	1.0	1.2	1.6	1.8	1.4	2.0	2.5
4	2.3	1.8	1.6	1.8	2.0	1.2	1.6	0	0.2	1.4	1.6	1.2	1.0	1.5
4′	2.1	1.6	1.4	1.6	1.8	1.0	1.2	0.6	0	1.2	1.4	1.0	1.6	2.1
5	2.5	2.4	2.2	2.4	2.6	1.8	1.6	1.4	1.6	0	0.2	0.6	1.2	1.7
5′	1.9	2.2	2.0	2.2	2.4	1.6	1.4	1.2	1.4	0.2	0	0.8	1.4	1.9
6	3.1	2.6	2.4	2.6	2.8	2.0	1.8	1.6	1.0	1.4	1.2	0	0.6	1.1
6′	2.5	2.0	1.8	2.0	2.2	1.4	1.2	1.0	1.2	0.8	0.6	0.2	0	1.3
7	3.6	2.3	2.1	3.1	2.5	2.5	2.3	2.1	1.5	1.9	1.7	1.3	1.1	0

Note: d_{ij} is the distance from the row node *i* to the column node *j*

The dynamic programming approach in Section 3.1.1 is applied to solve this square-block example. Table 3 presents the computation results: the set G_c of three zones, pairwise distances of candidate stops that are really used during the calculation, and optimal solutions of backward recursion. After calculation, we get the optimal suburban bus routing: $0 \rightarrow 2' \rightarrow 3 \rightarrow 6 \rightarrow 7$ as described in Fig. 5. It is noteworthy that this example has alternative optima apart from the already obtained optimal solution (see Fig. 5). In practice, alternative optima are beneficial because we can select from several bus routing plans without experiencing deterioration in the objective value.

Table 3 Results of the Square-block Example

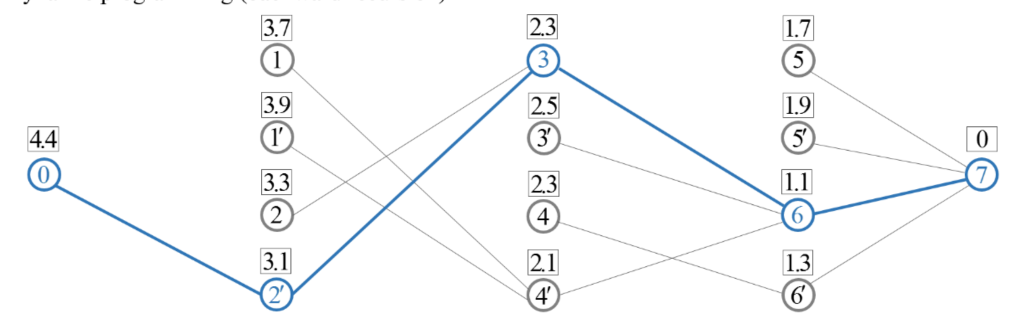
SBRP

Node 0	Zone 1	Zone 2	Zone 3	Node 7
Set G_c	$G_1 = \{1, 1', 2, 2'\}$	$G_2 = \{3, 3', 4, 4'\}$	$G_3 = \{5, 5', 6, 6'\}$	

Pairwise distances d_{ij} (unit: km)

i	j	d_{ij}	i	j	d_{ij}	i	j	d_{ij}	i	j	d_{ij}	i	j	d_{ij}	i	j	d_{ij}
0	1	1.5	1	3	1.4	1′	3	1.6	3	5	1.4	3′	5	1.6	5	7	1.7
	1′	1.7		3′	2.0		3′	2.2		5′	1.6		5′	1.8	5′		1.9
	2	1.1		4	1.4		4	1.6		6	1.2		6	1.4	6		1.1
	2′	1.3		4′	1.6		4′	1.8		6′	1.8		6′	2.0	6′		1.3
			2	3	1.0	2′	3	0.8	4	5	1.4	4′	5	1.2			
				3′	1.6		3′	1.4		5′	1.6		5′	1.4			
				4	1.8		4	1.6		6	1.2		6	1.0			
				4′	2.0		4′	1.8		6′	1.0		6′	1.6			

Dynamic programming (backward recursion)



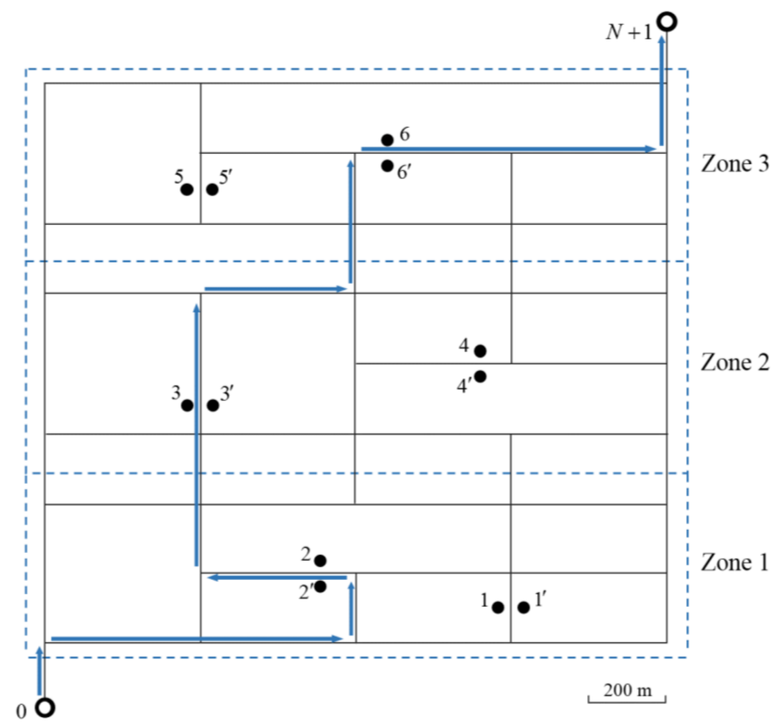


Fig. 5. Optimal bus route design via the dynamic programming approach.

4.2 Real-case examples

4.2.1 Example I

The suburban bus route 1 in Fig. 1 is taken as the first real-case example. It mainly provides airport access service for the southern suburb of Melbourne. The suburban area in this real case contains 15 zones. In each zone, the candidate stops are selected at the locations with aggregate demand nearby, such as residential neighborhoods, hotels, universities, and some public places like local shopping centers. A total of 36 places are chosen to be the candidate stop pairs which are located at both sides of associated road segments.

No.	Zone name	Pickup location
1	—	Rosebud 967 Pt. Nepean Road
2	Dromana	Harvey World Travel
3	Mornington	Main St & Queen St
4	Mount Eliza	84 Mount Eliza Way
5	Frankston	Pragmatic Training
6	Chelsea	Nepean Hwy & The Beach Way
7	Mentone/ Parkdale	Parkdale Motor Inn
8	Southland	Southland Shopping Centre
9	Moorabbin	Moorabbin Ten Pin Bowling
10	Brighton I	392-394 Bay Street
11	Brighton II	New St & Bay St
12	Brighton III	Elsternwick Park
13	Elsternwick I	128 Glenhuntly Rd
14	Elsternwick II	Blessington St & Barkly St
15	St Kilda I	Novotel
16	St Kilda II	Charsfield St Apartments
17	—	Melbourne Airport

Fig. 6. Optimal bus routing of route 1 serving the southern suburban area.

In addition, route 1 has a special property that the bus route is parallel to the coastline of Port Phillip Bay and all the suburban zones are sequentially distributed along the bus route. Therefore, route 1 can be seen as a special case of SBRP. We then use the dynamic programming approach in Section 3.1.1 to compute the optimal bus routing of the suburban bus route 1. Fig. 6 presents the results of the final selected pickup locations, their attached zones and the corresponding visiting sequence.

4.2.2 Example II

The second real-case study is conducted on the suburban bus route 2, Airport Bus Dandenong. It mainly serves the southeastern suburb of Melbourne. The suburban area in this case contains 25 zones and a total of 73 candidate stops. Fig. 7 shows all the candidate stops of these suburban zones. Candidate stops in various zones are distinguished in different colors.

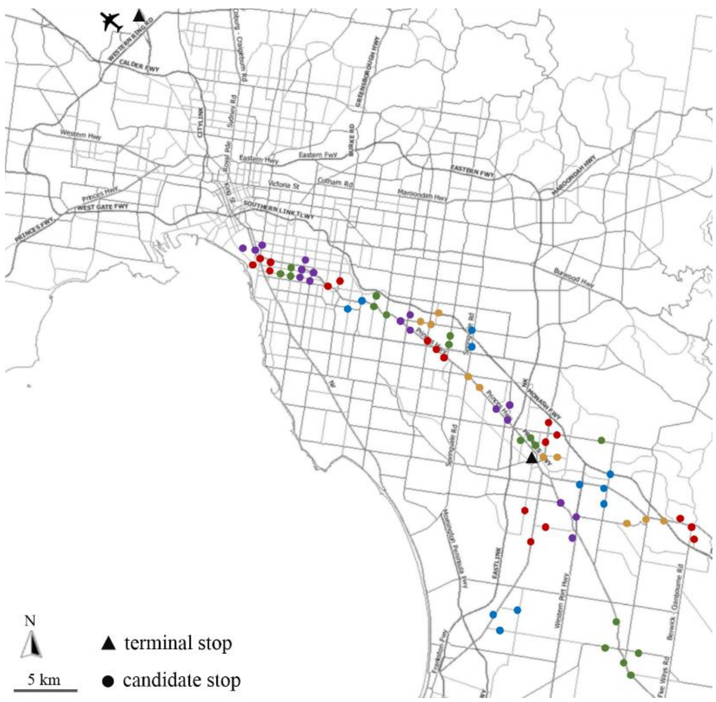
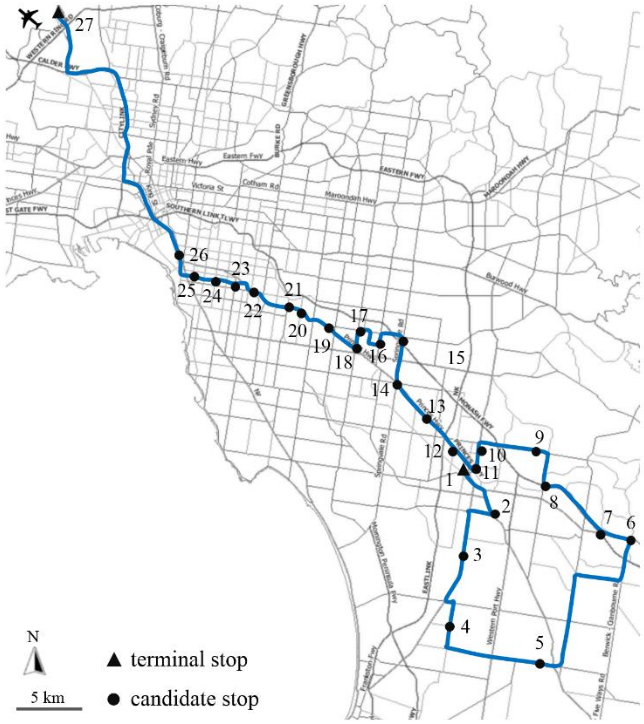


Fig. 7. Zones and associated candidate stops along the suburban bus route 2.

Different from route 1, the suburban zones of route 2 are randomly distributed which correspond with the generic model of SBRP in Section 3.2. In this case, we use the proposed ABC algorithm to seek the optimal bus routing of the suburban bus route 2. Fig. 8 intuitively illustrates the results of the final selected stops, their attached zones and the corresponding visiting sequence in the suburban bus route 2.



No.	Zone name	Pickup location
1	—	Dandenong Railway Station
2	Hallen I	Hallam Valley Road
3	Dandenong South	Grays Online
4	Carrum Downs	McCormicks Rd & Wedge Rd
5	Cranbourne	Comfort Inn Mahogany Park
6	Berwick	The Berwick Inn
7	Narre Warren	Quest Apartments
8	Hallen II	Hallam Hotel
9	Endeavour Hills	Endeavour Hills Shopping Centre
10	Dandenong I	Dandenong TAFE Chisholm
11	Dandenong II	Punt Hill Dandenong
12	Dandenong III	Dandenong Motel
13	Noble Park	Noble Park KFC
14	Springvale	Bikes Direct
15	Village Green	Village Green Hotel
16	MONASH University	Farrer Hall
17	Notting Hill	BP Service Station
18	Clayton	Princes Hwy & Clayton Rd
19	Oakleigh	Lamplighter Motor Inn
20	Chadstone	Chadstone Executive Motel
21	Carnegie	Carnegie Motor Inn
22	Caulfield	Church of Christ
23	St Kilda East I	Hawthorn Rd & Inkerman Rd
24	St Kilda East II	Orrong Rd & Inkerman St
25	St Kilda I	Chapel St & Inkerman St
26	St Kilda II	Princes St & Barkly St
27	—	Melbourne Airport

Fig. 8. Optimal bus routing of route 2 serving the southeastern suburban area.

5. Conclusions

This paper focused on the bus routing problem of a suburban bus route for airport access. The bus route serves a certain suburban area including several zones. Each zone has a number of candidate stops. The bus routing does not necessarily cover all the candidate stops while at least one candidate stop per zone must be visited in ways that walking access distance is reachable for airline passengers in each zone. The suburban bus routing problem (SBRP) in this circumstance was formulated as an optimization model, with the objective of minimizing the total travel time.

The proposed model of SBRP was further categorized into a special model and a generic model. The special model was first considered in which suburban zones are sequentially distributed along the bus route from the original terminal to the airport station. It can be solved in polynomial time. A dynamic programming approach was developed to address this special model. Later, the generic model, in which all the suburban zones are randomly distributed, was discussed. We proved that the generic model is NP-hard. A dynamic programming approach and a metaheuristic method were developed. Case studies based on a square-block example and two suburban bus routes access to the Melbourne Airport were conducted to demonstrate the applicability of the proposed models and solution methods. Our findings could serve as guidelines for designing the bus routing of suburban bus routes for airport access.

Admittedly, our proposed models come with some limitations, and the following improvements are suggested: (i) It could be considered to extend the model to apply into a broader service area for airport access rather than the suburban area only; (ii) Research is needed to propose a more generalized model which is capable to consider congestion effect and multiple bus routes; (ii) Different population-based algorithms could be systematically compared to solve the proposed problem in this study. The authors recommend that future studies could focus on these issues.

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