Modelling impacts of adverse weather conditions on activity-travel pattern scheduling in multi-modal transit networks

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In general, adverse weather has significant influence on individuals' activity/travel choice behaviour and such influence is obviously greater in cities which suffer frequent rainy periods. Thus, the impacts of weather conditions should be taken into account in long-term transit service planning. In this paper, an activity-based network equilibrium model for scheduling daily activity-travel patterns (DATPs) in multi-modal transit networks under adverse weather conditions (with different rainfall intensities) is developed. The interdependency of individuals' activity/travel choices and weather conditions are comprehensively investigated. In the proposed model, the DATP choice problem under adverse weather conditions is transformed into an equivalent static transit assignment problem by constructing a novel super-network platform. A rule-based algorithm is proposed to automatically generate the super-network taking into account the rain effects implicitly. The effects of adverse weather on different transit modes and different activities are explicitly modelled. An efficient solution algorithm without prior enumeration of DATPs is proposed for solving the DATP scheduling problem in multi-modal transit networks. Numerical examples are presented to illustrate application of the proposed model and the solution algorithm.

Keywords: daily activity-travel pattern; multi-modal transit network; adverse weather; network equilibrium problem

1. Introduction

Over the past decades, in addition to conventional trip-based transport models, activity-based approach is receiving increased attention in studying travel choice behaviour (Hirsh, Prashkea, and Ben-Akiva 1986; Kitamura 1988; Axhausen and Gärling 1992; Recker 1995; Yamamoto et al. 2000; Zhang, Timmermans, and Borgers 2002; Miller and Roorda 2003; Timmermans 2005; Horni et al. 2009; Ruiz and Roorda 2011; Chow and Recker 2012; Zhang and Timmermans 2012). This approach fully considers the underlying motivation of trips made, the linkages between the chosen activities and the trips which are necessitated, the temporal and spatial constraints, and the dependencies of activity scheduling.

Several network equilibrium models, which provide valuable insights into understanding individuals' activity-travel scheduling behaviour, have been proposed for long-term transport planning (Lam and Yin 2001; Lam and Huang 2002; Lam and Huang 2003; Huang and Lam 2005; Zhang et al. 2005; Li et al. 2010; Ramadurai and Ukkusuri 2010, 2011; Ouyang et al. 2011; Fu and Lam 2014). These models aim at and succeed in more comprehensively studying individuals' activity and travel choices. Recently, Ramadurai and Ukkusuri (2010) developed a single unified dynamic framework to jointly model activity choices and route choices. Ouyang et al. (2011) proposed an activity-based traffic assignment model for solving the daily activity-travel pattern (DATP) scheduling problem in congested road networks. Fu and Lam (2014) modelled the DATP scheduling problem in multi-modal transit networks under uncertainty.

None of these models, however, has incorporated the weather/climate effects on activity-travel pattern scheduling explicitly. A number of empirical studies have investigated the recurrent effects of adverse weather on individuals' activity choice and travel behaviour. Some studies have reported travellers' mode and departure time changes as affected by weather conditions (Khattak and De Palma 1997; Guo, Wilson, and Rahbee 2007), and some have indicated activity behaviour changes (Smith 1993; Khattak and De Palma 1997; Cools et al. 2010). Rainfalls have the most frequent and significant adverse weather effects on individuals' activity and travel choices in tropical and subtropical areas such as Hong Kong and Singapore. Based on data from the World Weather Information Services (http://www.worldweather.org/), Hong Kong has the highest average annual rainfall (2383 mm) of all the major Pacific Rim Cities, with Singapore achieving the second highest (2150 mm). The average annual number of rainy days in Hong Kong is as high as 104. Rainfall significantly affects individuals' activity and travel choices such as activity duration and travel mode choice. The long-term transit planning for areas with high average annual rainfall is considerably different from the planning for areas with less rainfall. Thus, clearly, particularly in areas such as Hong Kong and Singapore, rain effects should be considered when modelling individuals' activity and travel choices.

In order to incorporate rain effects in travel behaviour modelling, Lam, Shao and Sumalee (2008) proposed a network equilibrium model for road networks with specific consideration of rain effects on road capacity and link travel time, and Sumalee, Uchida, and Lam (2011) extended this work to model multi-modal transport networks under adverse weather conditions. The above two models are both trip-based transport models, so the trip making motivation, and the interdependency between activities and trips are not considered. Cools et al. (2010) found that individuals' travel behaviours under adverse weather conditions are highly dependent on trip purpose (i.e. activities). It is, thus, of serious interest to comprehensively model and investigate individuals' activity and travel choice behaviour under adverse weather conditions.

In many Asian cities such as Hong Kong and Singapore, most daily travel is made using various public transit modes (over 90% and over 55%, respectively). Hence, as a pioneering endeavour, a network equilibrium model for scheduling DATPs under adverse weather conditions (with different rainfall intensities) in multi-modal transit networks is proposed and described in this paper. In the proposed model, the DATP choice problem is transformed into an equivalent static transit assignment problem by constructing a novel super-network platform. The time and space coordination, activity location, activity sequence and duration, and the relationship between activity and route/mode choices, can be simultaneously investigated by solving the user equilibrium (UE) problem on the novel super-network platform. The study presented in this paper extends existing theories by developing a comprehensive framework which incorporates flexible activity sequence and duration, route and mode choices, together with effects of adverse weather conditions.

The structure of this paper is as follows. Assumptions and notations are firstly given, and a novel super-network platform is then elaborated. A DATP choice network equilibrium model is subsequently formulated as a variational inequality (VI) over the super-network platform, followed by the solution algorithm. Numerical examples illustrating the proposed model and algorithm are provided. Finally, conclusions are drawn, together with suggestions for further research.

2. Assumptions and network representation

2.1. *Assumptions*

In order to facilitate essential ideas without loss of generality, the following assumptions are made in this paper.

A1: The DATP is considered in a fixed study horizon, divided into K equally spaced time intervals (Lam and Yin 2001; Huang and Lam 2005; Zhang et al. 2005; Ouyang et al. 2011; Fu and Lam 2014).

A2: Only one behaviourally homogeneous group is considered (Lam and Yin 2001; Huang and Lam 2005; Ouyang et al. 2011). Activity interdependency of household members is not considered.

A3: The proposed model falls within the static model category for long-term planning at the strategic level. Therefore, it is assumed that individuals have perfect knowledge of traffic conditions throughout the whole network (Ouyang et al. 2011), and individuals can acquire weather forecast information for each time interval over the whole day (Lam, Shao, and Sumalee 2008; Sumalee, Uchida, and Lam 2011).

A4: The utility maximization principle is used to formulate the individuals' DATP choices (Lam and Huang 2002; Zhang et al. 2005; Li et al. 2010).

A5: The subway is weather-proof. Bus frequency and capacity are assumed to vary with weather condition (Sumalee, Uchida, and Lam 2011). No vehicle capacity constraint exists. In-vehicle crowding discomfort is modelled (Sumalee, Uchida, and Lam 2011; Fu and Lam 2014).

A6: The weather conditions for all zones in the study area are identical (Lam, Shao, and

Sumalee 2008; Sumalee, Uchida, and Lam 2011).

A7: In this study, the in-vehicle travel time for the bus mode is given exogenously by a scaled function dependent on rainfall intensity. The in-vehicle travel times by modes in the road network under different rainfall intensities, however, can be modelled explicitly by the activity-based traffic assignment model proposed by Ouyang et al. (2011).

A8: In this study, activity utility only depends on the start time of the activity and its duration. The activity utility is determined by a bell-shaped marginal utility function proposed by Joh, Arentze, and Timmermans (2002) and Ettema and Timmermans (2003). Many related studies adopted this type of function for modelling the marginal utility of activity (Ashiru, Polak, and Noland 2004; Zhang et al. 2005; Li et al. 2010). This function does not consider the needs of individuals. In future studies, the need-based utility functions (Arentze and Timmermans 2009) can also be incorporated in the model proposed in this paper.

Four types of activities are investigated in this study; namely, home, work, dinner, and shopping activities. The activity sequence and durations are not fixed (Ouyang et al. 2011; Fu and Lam 2014). Home and work are considered as compulsory activities, while dinner and shopping are non-compulsory activities (Fu and Lam 2014).

2.2. *A novel super-network platform*

Liao, Arentze, and Timmermans (2010, 2013) proposed a multi-state super-network and made all link costs time-dependent for modelling the activity-travel scheduling problem. Their proposed multi-state super-network, however, have difficulty in tackling the non-linear fare structures of public transit systems such as the one in Hong Kong. Activity duration is also required to be pre-determined in their model. Therefore, in this study, a novel super-network platform is proposed to incorporate non-linear fare structures (Lo, Yip, and Wan 2003) and flexible activity sequence/duration while the crowding and rain effects in the congested transit network have been considered explicitly in the proposed model. In addition, the relationship between activity choices and travel choices under different weather conditions can also be simultaneously addressed.

Consider a multi-modal transit network $M=\left(U,V\right)$, where $U=\left\{i\right\}$ and $V=\left\{v\right\}$ are, respectively, the set of physical nodes and the set of physical links. The multi-modal transit network M can be divided into w sub-networks $M_b=(U_b,V_b),\ b\in B,\ U_b\subseteq U,\ V_b\subseteq V,\ w=\left|B\right|$, where $b\in B$ is a specified transit mode, and U_b and V_b, respectively, are the set of nodes and the set of links associated with the sub-network M_b. The sub-networks are combined and represented by a strongly connected graph $G=\left(N,A\right)$ through a state-augmentation approach (Bertsekas 1995), where N is a set of nodes and A is a set of links. The resultant network G is termed the state-augmented multi-modal (SAM) network (Lo, Yip, and Wan 2003).

Based on the formation of the SAM network, presented in this paper, an activity-time-space SAM (ATS-SAM) super-network expansion approach is proposed to represent individuals' daily activity choices and travel choices over a multi-modal transit network under adverse weather conditions. In this approach, the SAM network is further developed by incorporating time-space coordinates and activity links. This augmentation produces the ATS-SAM super-network. The study horizon is divided into K equally spaced time intervals. Let $k = 1, 2, ..., K, K+1$ be the start time of a node or link. The framework of the ATS-SAM super-network is given below.

Nodes: Each node in the ATS-SAM super-network is described as $((i, s, n, l), k)$ (Lo, Yip, and Wan 2003), where i is the physical location of the node, and s is the transfer state used to model probable transfers. n is the number of transfers that have been made by an individual which is used to specify a constraint on the maximum number of transfers, and l is the alight or aboard indicator. k is the start time of the node. The value of l is equal to 1 (0) indicating that the individual is at the beginning (end) of an in-vehicle link. Specifically, each transfer state $s \in S$ associates with the use of a particular transit mode $\eta(s) \in B$ and a set of probable transfers $\xi(s) \subseteq S$. If individuals are at state s, the indication is that these individuals are using mode $\eta(s)$ and can only transfer to a state in $\xi(s)$.

Links: Links in the ATS-SAM super-network are classified into three categories, i.e. $A = A_{\mathrm{t}} \cup A_{\mathrm{d}} \cup A_{\mathrm{a}}$, where A_{t} is the set of transfer links between the modes, and A_{d} is the set of direct in-vehicle links made up of physical links. A_{a} is the set of activity links. Each transfer link $a_{\mathrm{t}} \in A_{\mathrm{t}}$ is constructed according to the probable transfer states. Each in-vehicle link $a_{sn}^{ij} \in A_{\mathrm{d}}$ represents a direct in-vehicle movement from location i to location j with transfer state s as its nth mode in the trip. At the end of each in-vehicle link, an activity can be conducted. A direct in-vehicle link may consist of more than one consecutive physical link, so non-linear fares can be directly represented on a node to node basis. It should be noted that in-vehicle links are constructed based on the weather conditions during each time interval, because different weather conditions result in different in-vehicle travel times. A_{a} is constructed between the augmented nodes at the same location to indicate that a particular activity is conducted for one interval. Each $a_{\mathrm{a}} \in A_{\mathrm{a}}$ is characterised by activity location, activity type, and activity start time. The activity utility by the time of day is adopted in this paper (Lam and Yin 2001; Fu and Lam 2014), therefore the activity time window is not required. The process of route searching in the ATS-SAM super-network can lead to realistic and more generalized results regarding the times to perform activities during the study period.

Figure 1 is an example of the ATS-SAM super-network consisting of two transit modes, i.e. subway, bus. Three activities (i.e. home, work, and dinner) are considered in this example. In this small example, the study horizon is divided into three equally spaced time intervals. Two weather categories (i.e. rain and no-rain) are considered. Travel time for each link under no-rain condition is one interval. Travel time for bus link under rain condition is two intervals. Weather forecast indicates the rain starts from the second time interval. The probable transfer states in Figure 1 follow that used by Lo, Yip, and Wan (2003). It can be seen from Figure 1 that different links are constructed according to the forecast of weather conditions by time of day. Individuals' activity and travel choices under different weather conditions can be explicitly depicted by the ATS-SAM super-network.

2.3. *ATS-SAM super-network expansion algorithm*

In this study, a rule-based algorithm is proposed to generate an ATS-SAM super-network with implicit consideration of rain effects. With this rule-based algorithm, the conventional multi-modal transit network can easily be automatically transformed into the ATS-SAM super-network. Each route from origin to destination in the novel super-network platform represents a feasible DATP. The detailed steps of the proposed ATS-SAM super-network expansion algorithm are presented as follows. Figure 1 is an example of the network expansion result.

Input: a multi-modal transit network M, transfer states $s \in S$, probable transfers $\xi(s) \subseteq S$ for each $s \in S$, maximum number of transfers κ, and number of time intervals K.

Output: the ATS-SAM super-network.

Step 1. Node augmentation.

For each node $i \in U$, expand the node into $(2+10\kappa)(K+1)$ nodes: $\left((i,0,0,l),k\right)$, $l=0,1,\quad k=1,2,...,K,K+1$; and $\left((i,s,n,l),k\right)$, $s=1,2,3,4,5,\quad n=1,2,...,\kappa$, $l=0,1,\quad k=1,2,...,K,K+1$. Denote the new node set as N.

Step 2. Construction of activity links.

Scan all nodes in set N. Construct activity links $a_{\mathrm{a}} \in A_{\mathrm{a}}$ between $\left((i,s,n,0),k\right)$ and $\left((i,s,n,0),k+1\right)$.

Step 3. Construction of transfer links.

Scan all nodes in set N. Construct transfer links $a_{\mathrm{t}} \in A_{\mathrm{t}}$ between $\left((i,s,n,0),k\right)$ and $\left((i,\xi(s),n+1,1),k\right)$.

Step 4. Construction of in-vehicle links.

Find all in-vehicle links in network M. On the basis of the weather condition for each time interval, obtain in-vehicle link travel times $t_{a_{\mathrm{d}}}$ for different times of day.

For each $i \in U$, find all $i' \in U$ which are connected to i by in-vehicle links. Record the mode b and the travel time $t_{a_{\mathrm{d}}}$ of each in-vehicle link.

For each i', construct ATS-SAM in-vehicle links between $\left((i,s,n,1),k\right)$ and $\left((i',s,n,0),k+t_{a_{\mathrm{d}}}\right)$, $\eta(s)=b$.

3. The model

3.1. *Effects of weather forecast information*

Five weather categories (denoted as wc) with different average rainfall intensity levels for each time period (denoted as π_{wc}) are adopted (Lam, Shao, and Sumalee 2008). With a 10-min interval in the study period, wc_1 indicates no rain or light rain with average rainfall intensity $\pi_{wc1}=5mm/h=0.3mm/interval$; wc_2 indicates normal rain with $\pi_{wc2}=20mm/h$ $=3.3mm/interval$; wc_3 indicates amber rainstorm with $\pi_{wc3}=30mm/h=5mm/interval$; wc_4 indicates red rainstorm with $\pi_{wc4}=50mm/h=8.3mm/interval$; wc_5 indicates black rainstorm with $\pi_{wc5}=70mm/h=11.7mm/interval$. It is assumed that weather forecast provides the chance of each weather category for each time interval in the study period. Each possible weather category is forecast with the probability of its occurrence $\breve{p}_{wc}(k)$. $\breve{p}_{wc}(k)$ is the prior probability of the weather category wc for time k to time $k+1$. For example, with a 10-min interval in the study period, $\breve{p}_{wc_4}(9:00)=40\%$ means that, on the basis of weather forecast, there is a 40% chance of a red rainstorm in the period 9:00-9:10.

However, the weather forecast may not be accurate. Thus, based on past experiences, individuals may perceive a posterior probability for each weather category. To ensure a more precise investigation of weather effects, the approach proposed by Lam, Shao, and Sumalee (2008) is adopted in this study. Bayes' Theorem is used to combine prior weather forecast accuracy beliefs and the current weather forecast information. Let $\widehat{p}_{wc/\breve{p}}$ be the conditional probability of $\breve{p}(k)$ (a vector of $\breve{p}_{wc}(k)$) given weather category wc occurs. The posterior probability of occurrence of wc given the weather forecast $\breve{p}(k)$ for time k to $k+1$ (denoted as $p'_{wc}(k)$) can then, be obtained on the basis of Bayes' Theorem (refer to Equation (32) in Lam, Shao, and Sumalee 2008).

3.2. *Link utility/dis-utility in ATS-SAM super-network under adverse weather conditions*

Many empirical studies reveal that adverse weather conditions have significant impacts on individuals' travel and activity decisions (Khattak and De Palma 1997; Cools et al. 2010). Under adverse weather conditions, individuals have less desire to take part in out-door activities or non-compulsory activities such as eating at restaurants and shopping in malls (Cools et al. 2010). Activity utility may broadly- consist of the following attributes: (a) an activity time window; (b) a degree of need for the activity; (c) a degree of satisfaction from the process; and (d) money gain or loss. Thus, it can be said that the utilities of some activities are in fact influenced by weather conditions due to the variation of need and satisfaction. The higher the rain fall intensity the lower the activity utility.

The previously proposed activity utility functions were mainly concerned with activity participation time and activity type. These functions may not be applicable directly in the case of adverse weather with various rainfall intensities. To capture the rain effects on individuals' activity choices, a modified activity utility function is proposed. The utility of performing activity link a_{a} from start time k for one interval under weather category wc is expressed by

$$u_{a_{\mathrm{a}}}(wc)=s_{u_{a_{\mathrm{a}}}}(wc)\cdot\int_{k}^{k+1}\bar{u}_{a_{\mathrm{a}}}(\omega)d\omega, \tag{1}$$

where $\bar{u}_{a_{\mathrm{a}}}(k)$ denotes the marginal utility of performing activity link a_{a}; k is the start time of activity link a_{a}; $s_{u_{a_{\mathrm{a}}}}(wc)$ is the scale function of activity utility under weather category wc. $s_{u_{a_{\mathrm{a}}}}(wc)\leq 1$ is a decreasing function with respect to wc, implying that activity utility decreases with the rainfall intensity. In this study, two activity types (i.e. compulsory/obligatory and non-compulsory/discretionary in nature) are considered. For compulsory activities such as home and work, $s_{u_{a_{\mathrm{a}}}}(wc)$ equals 1 for all wc, and for non-compulsory activities, $s_{u_{a_{\mathrm{a}}}}(wc)$ is less than 1. It can be seen that the higher the rainfall intensity the lower the utility of non-compulsory activity, and that the utility of compulsory activity is not influenced by weather conditions. Thus, under adverse weather conditions individuals may reduce or cancel their non-compulsory activities. This property is in accordance with the contentions expressed in the empirical study by Cools et al. (2010).

The resultant activity utility for time k to $k+1$ from different possible weather categories (denoted as $u_{a_{\mathrm{a}}}$) can be expressed as

$$u_{a_{\mathrm{a}}} = \sum_{wc_1}^{wc_5} p'_{wc}(k) \cdot u_{a_{\mathrm{a}}}(wc), \tag{2}$$

where $p'_{wc}(k)$ denotes the posterior probability of weather category wc from time k to $k+1$. $u_{a_{\mathrm{a}}}$ is the mixture activity utility considering all weather categories.

In this study, the following marginal utility function proposed by Ettema and Timmermans (2003) is adopted.

$$\bar{u}_{a_{\mathrm{a}}}(k) = \frac{\gamma_{a_{\mathrm{a}}} \cdot \beta_{a_{\mathrm{a}}} \cdot u_{a_{\mathrm{a}}}^{\max}}{\exp[\beta_{a_{\mathrm{a}}}(k-\alpha_{a_{\mathrm{a}}})]\left\{1+\exp[-\beta_{a_{\mathrm{a}}}(k-\alpha_{a_{\mathrm{a}}})]\right\}^{\gamma_{a_{\mathrm{a}}}+1}}, \tag{3}$$

where k is the time of day; $u_{a_{\mathrm{a}}}^{\max}$ is the maximum accumulated utility of activity a_{a}, and $\alpha_{a_{\mathrm{a}}}$, $\beta_{a_{\mathrm{a}}}$, $\gamma_{a_{\mathrm{a}}}$ are activity-specific parameters to be estimated. These parameters can be estimated on the basis of survey data (Ettema and Timmermans 2003; Ashiru, Polak, and Noland 2004). In this study, the DATP utility is assumed monotone with respect to DATP flow (Ouyang et al. 2011; Fu and Lam 2014). Activity utility in this study is a function of activity time and activity duration regardless of the DATP flow at activity location. In future study, the reality of positive bandwagon effects (e.g. a restaurant where more people present may attract more people going there) can be considered by incorporating DATP flow into the activity utility function.

To capture the rain effects, the in-vehicle link travel time under weather category wc (denoted as $t_{a_{\mathrm{d}}}(wc)$) can be expressed as

$$t_{a_{\mathrm{d}}}(wc) = t_{a_{\mathrm{d}}}^{0} \cdot s_{t_{a_{\mathrm{d}}}}(wc), \tag{4}$$

where $t_{a_{\mathrm{d}}}^{0}$ is the travel time of direct in-vehicle link a_{d} under no-rain weather condition, and $s_{t_{a_{\mathrm{d}}}}(wc) \geq 1$ is the scale function of in-vehicle link travel time under weather category wc (Lam, Shao, and Sumalee 2008). $s_{t_{a_{\mathrm{d}}}}(wc)$ represents the effects of adverse weather conditions on in-vehicle travel times. For the subway mode, $s_{t_{a_{\mathrm{d}}}}(wc)$ equals 1.

The resultant travel time of in-vehicle link a_{d} with start time k from different possible weather categories (denoted as $t_{a_{\mathrm{d}}}$) can be expressed as (Lam, Shao, and Sumalee 2008; Sumalee, Uchida, and Lam 2011)

$$t_{a_{\mathrm{d}}} = \sum_{wc_1}^{wc_5} p'_{wc}(k) \cdot t_{a_{\mathrm{d}}}(wc). \tag{5}$$

The in-vehicle link dis-utility is modelled with consideration of rainfall intensity. For congested in-vehicle links, the dis-utility of in-vehicle link a_{d} for mode b under weather category wc (denoted as $disu_{a_{\mathrm{d}}}(wc)$) is expressed to represent in-vehicle crowding discomfort (Sumalee, Uchida, and Lam 2011):

$$disu_{a_\mathrm{d}}(wc) = -\mathrm{vot}\cdot t_{a_\mathrm{d}}\cdot\left(1+\beta_b\left(\frac{f_{a_\mathrm{d}}}{h_b(wc)\cdot g_b(wc)}\right)^{\theta_b}\right)-\rho_{a_\mathrm{d}}, \tag{6}$$

where $h_b(wc)$ is the vehicle capacity of mode b under weather category wc. As regards the bus mode, $h_b(wc)$ decreases with wc because umbrellas occupy a degree of space. $g_b(wc)$ denotes the frequency of mode b under weather category wc. As regards the bus mode, $g_b(wc)$ decreases with wc due to the increased road travel time (Sumalee, Uchida, and Lam 2011). f_{a_d} denotes the passenger flow on the in-vehicle link; ρ_{a_d} is the fare of using the in-vehicle link; vot is the value of time; β_b and θ_b are model parameters relevant to mode b; wc is the weather category at the start time of the in-vehicle link.

The resultant dis-utility of in-vehicle link a_d with start time k from different possible weather categories (denoted as $disu_{a_\mathrm{d}}$) can be expressed as

$$disu_{a_\mathrm{d}} = \sum_{wc_1}^{wc_5} p'_{wc}(k)\cdot disu_{a_\mathrm{d}}(wc). \tag{7}$$

As regards transfer links by mode, the transfer link dis-utility under weather category wc can be expressed as

$$disu_{a_\mathrm{t}}(wc) = -\mathrm{vot}\cdot\frac{1}{2g_b(wc)} - pen_b, \tag{8}$$

where $g_b(wc)$ is the frequency of the mode to which individuals transfer on the transfer link concerned under weather category wc, and pen_b is the mode-specified transfer penalty. The resultant dis-utility of transfer link with start time k from different possible weather categories (denoted as $disu_{a_\mathrm{t}}$) can be expressed as

$$disu_{a_\mathrm{t}} = \sum_{wc_1}^{wc_5} p'_{wc}(k)\cdot disu_{a_\mathrm{t}}(wc). \tag{9}$$

Let P be the set of routes in the ATS-SAM super-network (i.e. DATP set). The daily utility gain, i.e. the utility of DATP $p \in P$ (denoted as u_p), can be obtained by summing dis-utilities of in-vehicle links, dis-utilities of transfer links, and utilities of activity links:

$$u_p = \sum_{a_\mathrm{d}\in A_\mathrm{d}} disu_{a_\mathrm{d}}\cdot\delta(p,a_\mathrm{d}) + \sum_{a_\mathrm{t}\in A_\mathrm{t}} disu_{a_\mathrm{t}}\cdot\delta(p,a_\mathrm{t}) + \sum_{a_\mathrm{a}\in A_\mathrm{a}} u_{a_\mathrm{a}}\cdot\delta(p,a_\mathrm{a}), \tag{10}$$

where $\delta(p,a)$ is the incidence relationship between DATP and link; $\delta(p,a)$ equals 1 indicating that this link is used in the DATP, 0 otherwise.

3.3. *Model formulation and solution algorithm*

With the use of the proposed ATS-SAM super-network, individuals' activity choices (i.e. activity locations, sequence and durations) and travel choices (i.e. route, mode, transfers, and departure time) under different weather conditions are explicitly represented by different links in the proposed super-network platform. Activities with different start times are constructed as different activity links. The time-dependent relationships between activity and travel choices can be modelled by the ATS-SAM super-network topology. Each route from origin to destination in the ATS-SAM super-network represents a feasible DATP. Therefore, the proposed time-dependent DATP scheduling problem is equivalent to a static multi-modal transit assignment model on the ATS-SAM super-network.

The proposed model falls into the category of static UE model in nature for long-term transit planning at the strategic level. As we postulate, individuals would select DATPs to maximize the daily utility and settle into a long-term equilibrium. Thus, although the activity utility may be specific to each individual in reality, it is postulated in this study that all individuals would have a UE activity-travel choice pattern: for each day, the utilities of all used DATPs are the largest and equal, and all unused DATPs have smaller utilities. Denote π as the optimal route (i.e. the optimal DATP) with the largest utility in the ATS-SAM super-network. u_π denotes the utility of route π. The UE condition can be formally expressed as

$$f_p(u_\pi - u_p) = 0, \tag{11}$$

$$q = \sum_{p\in P} f_p, \tag{12}$$

$$u_\pi - u_p \geq 0, \tag{13}$$

$$f_p \geq 0, \tag{14}$$

where f_p denotes the passenger flow on DATP p and q denotes the total population in the study network.

The above UE condition can be formulated as a VI: Find $f_p^* \in \Omega$ such that

$$\sum_{p\in P} u_p^*(f_p^* - f_p) \geq 0, \qquad \forall f_p \in \Omega \tag{15}$$

where Ω denotes the set of feasible DATP flow solutions; f_p^* and u_p^* denote the equilibrium DATP flow and equilibrium DATP utility, respectively. In this study, the DATP utility is continuous and strictly monotone with respect to the DATP flow, and the feasible set Ω is compact and convex. Facchinei and Pang (2003) indicate that it can be proved that the solution of this VI problem exists and the uniqueness of the solution can be guaranteed. In this paper, the VI problem is solved by the widely used method of successive average (MSA).

The solution algorithm for solving the DATP scheduling problem is outlined as follows.

Step 0. Calculate in-vehicle link travel time on the basis of the weather condition for each time interval. Transform the traditional multi-modal transit network to the ATS-SAM super-network by using the rule-based super-network expansion algorithm.

Step 1. Initialization. Let $n = 0$. Call the shortest path faster algorithm (SPFA) (Duan 1994) to find the optimal route in the ATS-SAM super-network (i.e. DATP) with the largest utility. Perform an all-or-nothing assignment. Obtain the route and link flows $\mathbf{f}^n$ in the ATS-SAM super-network.

Step 2. Update in-vehicle link dis-utilities.

Step 3. Call the SPFA algorithm to find the optimal route with the largest utility. Perform an all-or-nothing assignment and yield auxiliary link flows in the ATS-SAM super-network.

Step 4. Obtain updated link flows $\mathbf{f}^{n+1}$ using a MSA process.

Step 5. For an acceptable convergence level τ, if $\max_a \left| \mathbf{f}^{n+1} - \mathbf{f}^{n} \right| \le \tau$, then stop. Otherwise let $n = n+1$ and go back to Step 2.

4. Numerical example

The purposes of the numerical example are to illustrate: (a) application of the proposed model and solution algorithm; (b) how the adverse weather affects individuals' activity choices; (c) individuals' mode choice behaviour under various weather conditions; (d) the effects of adverse weather on individuals' departure time choices; (e) the impacts of adverse weather on the overall performance of the multi-modal transit networks such as the daily average travel time per individual.

In this numerical example, the total study period was from 06:00 to 24:00 (18 h per day) and was equally divided into 108 intervals (i.e. 10 min per interval). The weather forecast information for each time interval in the study period was given.

Figure 2 depicts a multi-modal transit network based on a study area in Singapore with various bus and subway lines. Two subway (i.e. MRT in Singapore) lines and three bus lines serve this study network. Four activities (i.e. home, work, shopping and dinner) are considered. The three circles shown in Figure 2 represent three study zones located in Singapore: (1) home area (H), (2) work area (W), and (3) shopping/dinner area (S&D). The home area, Clementi, is a major residential area. The work area, Tanjong Pagar, is one zone of the Central Business District. The shopping/dinner area, Harbour Front, is a recreational area with a large shopping mall. In this example, after deleting the nodes which are not two-way connected (except for origin and destination), the numbers of nodes and links in the super-network are 9811 and 25,441 respectively.

The data relating to transit lines were obtained from the website of the Land Transport Authority of Singapore. Table 1 shows the given parameters in the marginal utility function for the numerical examples. The scale function for the utility of non-compulsory activities is set as $s_{u_{a_a}}(wc) = \exp(-0.6 \cdot \pi_{wc})$. The scale function for bus travel time is set as $s_{t_{a_d}}(wc) = \exp(0.12 \cdot \pi_{wc})$ (Lam, Shao, and Sumalee 2008; Sumalee, Uchida, and Lam 2011). The vot is S\$ 60.00/h. Note that US\$ 1.00 is approximately equal to S\$1.30. $\beta_b = 0.1$, $\theta_b = 2$, $pen_b = -0.5$, $\tau = 0.1$.

The traffic assignment model proposed in this paper falls within the category of static UE model for strategic policy planning. Several weather forecast scenarios are obtained based on samples of multiple days' weather forecasts. The proposed model will be solved for each scenario to determine average effects of weather on the study area for long-term planning purpose. The five weather category scenarios used by Sumalee, Uchida, and Lam (2011), shown in Figure 3, were adopted in this study. According to this figure, it is found that from scenario S1 to S5, the weather conditions become increasingly adverse. This being the case, S1 represents good weather, and S5 represents severe weather in the following discussion. Note that in the numerical example, the five scenarios are applied at the morning peak (assumed 7 a.m. to 9 a.m.) and evening peak (assumed 5 p.m. to 8 p.m.) periods in the travel and activity choice investigation, as the weather conditions during the other time periods (i.e. work and home time) have little impact on individuals' travel and activity choices. For the other time periods, a good weather (i.e. S1) is applied. Under scenario S1, bus frequency and capacity are 9 veh/h and 110 passenger/veh. Under scenarios S2-S5, bus frequency and capacity are assumed to reduce to 6 veh/h and 100 passenger/veh, respectively (Sumalee, Uchida, and Lam 2011). Subway frequency and capacity for all scenarios are 12 veh/h and 400 passenger/veh.

Figure 4 shows two optimal DATPs under two weather scenarios (applying S1 and S5 in peak periods). The two DATPs are route searching results under free-flow condition. It can be seen that using the proposed super-network, activity choice, activity start/end time, activity duration, and activity location can be traced. Travel time of each trip, route choice and mode choice can also be found. Figure 4(a) illustrates the DATP under scenario S1 (i.e. good weather) and Figure 4(b) depicts the DATP under scenario S5 (i.e. severe weather). A comparison of these two DATPs indicates that under adverse weather conditions, individuals tend to carry out their compulsory activities and use the subway. It can be seen from Figure 4 that as the rainfall intensity increases, the duration of compulsory activities (i.e. home and work) is extended by about 3 h (from 14.5 to 17.3). In contrast, non-compulsory activities (i.e. shopping and dinner) are cancelled. Individuals leave work later (changing from 18:00 to 18:40), and return home earlier (changing from 21:10 to 19:00) under severe weather conditions so as to obtain maximum daily utility.

Individuals' overall activity choice behaviour can be effectively investigated under scenarios for different weather conditions by using the proposed model. Table 2 shows average duration variation of different activities under different weather scenarios (applying S1-S5 in peak periods). It is clear from Table 2 that the average duration of compulsory activities (i.e. home and work) increases with rainfall intensity, while the duration of non-compulsory activities (i.e. dinner and shopping) decreases. As the rainfall intensity increases, the average home activity and work activity durations show respective increases from 4.82 h/individual to 6.20 h/individual and from 10.03 h/individual to 10.65 h/individual. In contrast, the dinner duration and shopping duration, show respective decreases from 0.95 h/individual to 0.10 h/individual and from 1.23 h/individual to 0.24 h/individual. It is due to that adverse weather significantly affects the utility of non-compulsory activities, while compulsory-activities have to be performed regardless of weather condition. It can also be seen from the study network that as most people tend to cancel non-compulsory activities under severe weather conditions, the daily average travel time decreases from 0.97 h/individual under S1 to 0.81 h/individual under S5.

Under adverse weather conditions, individuals who choose the bus mode for travel may change their departure time in the morning to accommodate the increased road travel time. Table 3 shows the average departure time and average travel time per trip for bus riders. It is seen that under severe weather conditions, earlier morning departure times are chosen by bus riders, and the average bus trip travel time increases. For instance, under scenario S1 (i.e. good weather), bus riders depart to work at 8:37 a.m., and the average per-trip travel time over the whole day is 26.3 min. However, under scenario S5 (i.e. severe weather), they should depart quite early, i.e. 6:30 a.m. in the morning, and that the average per-trip travel time increases to 33.0 min. This is due to the influence of adverse weather conditions on bus frequency, bus capacity, and road travel time.

Individuals' travel mode choice behaviour can also be examined by the proposed model. Figure 5 depicts the variation of modal split with different population levels under different weather scenarios (applying S1-S5 in peak periods). The test fully considers the increased road travel time, reduced bus frequency and capacity under severe weather. It can be found from Figure 5 that a drastic demand shift from bus to subway exists under severe weather conditions. For instance, with a population of 5000, the modal share for subways is 18% under weather scenario S1 (i.e. good weather). However, under S5 (i.e. severe weather), the modal share for subways increases to 42% as the subway mode is weather-proof. From Figure 5, population level effects on individuals' mode choice can also be found. It is seen that, with a large population, individuals tend to use subways rather than buses under any weather scenario. For example, under scenario S1, most individuals choose buses for their travel (i.e. 82%) when the population is only 5000. However, when the population is 50,000, the bus modal share decreases to 50%. In the study network, this figure can be explained by the fact that, the subway has a larger capacity than that of bus. When the population is large, individuals tend to choose the subway to avoid bus in-vehicle crowding.

5. Conclusions

An activity-based network equilibrium model for scheduling DATPs in multi-modal transit networks under adverse weather conditions with different rainfall intensities has been proposed and described in this paper. The proposed model is designed for long-term planning of multi-modal transit network in cities with frequent rainy periods (e.g. Singapore and Hong Kong). In the proposed model, weather forecast information was incorporated for solving the individuals' DATP scheduling problem. This model explicitly considers the effects of adverse weather on the performances of different transit modes, and the effects on the utilities of the various activities (i.e. compulsory or non-compulsory). The proposed model extends existing studies by developing a comprehensive framework which incorporates flexible activity sequences and durations, route and mode choices, and also adverse weather effects.

A novel super-network platform, the ATS-SAM super-network, has been generated automatically by the rule-based algorithm proposed in this study. Not only can this network explicitly model the transfers and non-linear fare structures in multi-modal transit networks but also simultaneously addresses the activity choices and travel choices in time-space coordinates under conditions of different rainfall intensities. The ATS-SAM super-network was constructed based on link travel times for different times of day according to the provided weather forecast information. Individuals schedule their DATPs based on the trade-off between the utility gained from activity participation and the dis-utility of the travel required. Further, it has been shown that the DATP scheduling problem can be transformed into a static transit assignment problem with the use of the generated ATS-SAM super-network.

An efficient solution algorithm without prior DATP enumeration has been developed for solving the equivalent static transit assignment problem on the ATS-SAM super-network. The proposed model and solution algorithm were tested with a real multi-modal transit network in Singapore. The numerical results showed that the proposed model can be used to investigate individuals' DATPs and overall average effects on multi-modal transit networks under adverse weather conditions. The numerical results have highlighted the key role of weather-proof systems (i.e. subways) as the main transit mode under severe weather condition. In addition, individuals' attitudes towards compulsory and non-compulsory activities vary and their DATP choices change according to weather conditions. It has been shown that the carrying out of compulsory activities and the use of subways will be underestimated if weather effects are not explicitly considered for long-term transit planning.

On the basis of the proposed model, the following further work should be considered:

- Calibration and validation of the proposed model with empirical data. Rainfall intensity data, mobile phone data and activity-travel diaries data will be collected.
- Inclusion of destination choice (Chow 2014), as individuals may face mutually exclusive location choice such as alternative dinner location. This problem may be tackled by implicitly define proper links in the super-network expansion algorithm.
- The extension of the proposed model to multi-modal transport networks including road networks. Consideration of road congestion and travel time variation in advanced models to investigate the DATP scheduling problems in multi-modal transport networks.
- The extension of the UE problem to stochastic user equilibrium;
- In addition to the rain effects, the extension of the proposed model to consider other adverse weather conditions such as typhoons and heavy snow.
- Relaxation of the assumption of identical weather condition for all study zones. Consideration of different weather conditions in different zones in future work.

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List of Tables and Figures

Table 1. Given parameters in the marginal utility function (Equation (3)).

	Work (6:00-12:00)	Work (12:00-24:00)	Home (6:00-12:00)	Home (12:00-24:00)	Shopping	Dinner
$u_{a_a}^{\max}$ (S$)	1440	1440	1000	1000	1080	1440
α_{a_a}	600	900	360	1440	1180	1080
β_{a_a}	0.021	0.021	0.0048	0.0048	0.018	0.05
γ_{a_a}	0.8	0.8	1.8	1.8	1	1

Table 2. Average durations of activities and travel under different weather scenarios.

		Scenario				
		S1 (good weather)	**S2**	**S3**	**S4**	**S5** (severe weather)
Activity	**Home**	**4.82 h (26.8%)**	5.54 h (30.8%)	5.93 h (32.9%)	6.09 h (33.8%)	**6.20 h (34.4%)**
	Work	**10.03 h (55.7%)**	10.54 h (58.5%)	10.65 h (59.2%)	10.65 h (59.2%)	**10.65 h (59.2%)**
	Dinner	**0.95 h (5.3%)**	0.40 h (2.2%)	0.19 h (1.1%)	0.12 h (0.7%)	**0.10 h (0.6%)**
	Shopping	**1.23 h (6.8%)**	0.64 h (3.6%)	0.40 h (2.2%)	0.32 h (1.8%)	**0.24 h (1.3%)**
Travel		**0.97 h (5.4%)**	0.88 h (4.9%)	0.83 h (4.6%)	0.82 h (4.5%)	**0.81 h (4.5%)**
Total time		18 h (100%)	18 h (100%)	18 h (100%)	18 h (100%)	18 h (100%)

Table 3. Average departure time and travel time per trip for bus riders.

Scenario	Average departure time in the morning	Average travel time per trip (minutes)
S1	**8:37 a.m.**	**26.3**
S2	7:18 a.m.	26.8
S3	6:43 a.m.	29.8
S4	6:30 a.m.	32.2
S5	**6:30 a.m.**	**33.0**

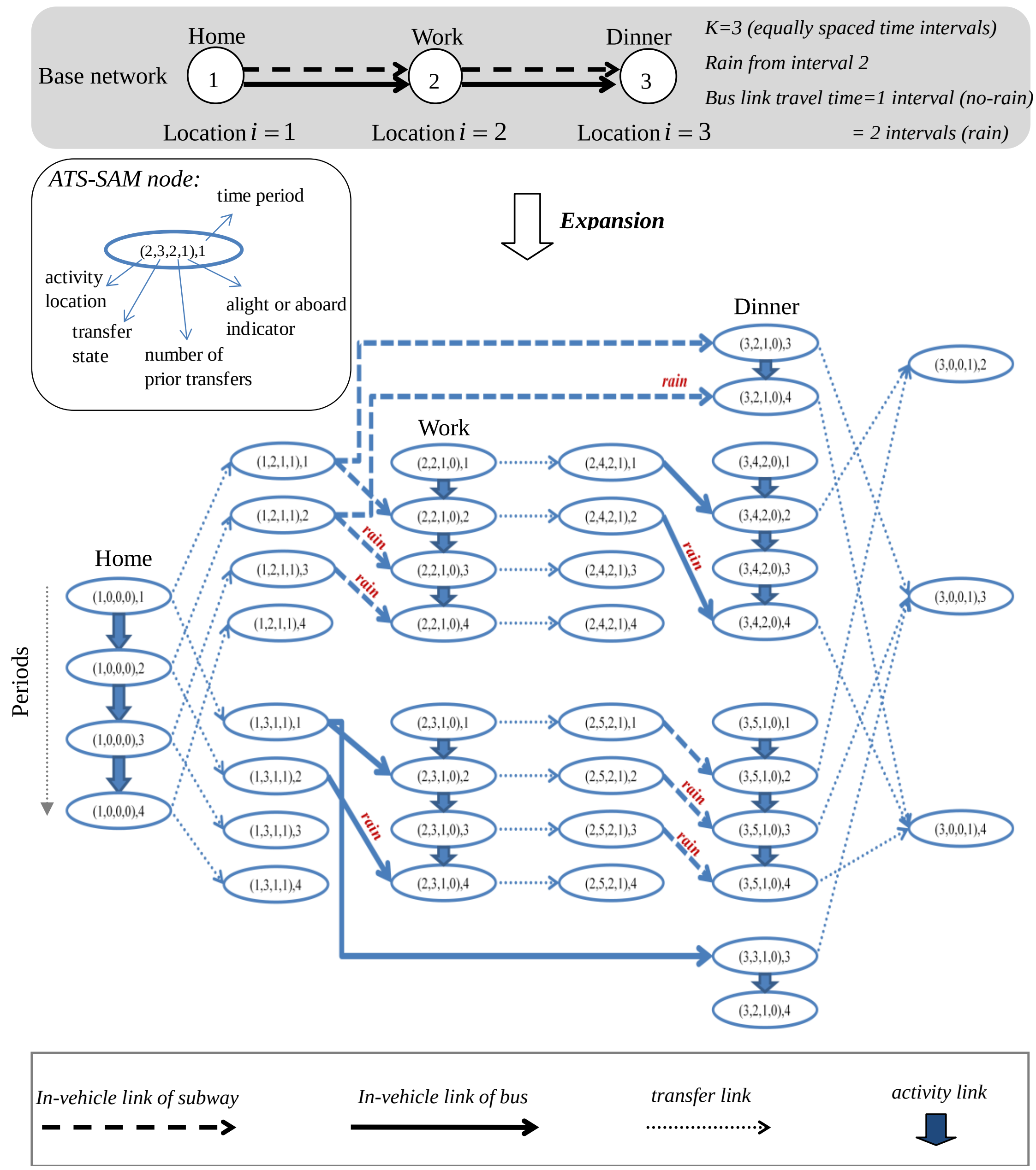


Figure 1. An illustrative example of the ATS-SAM super-network.

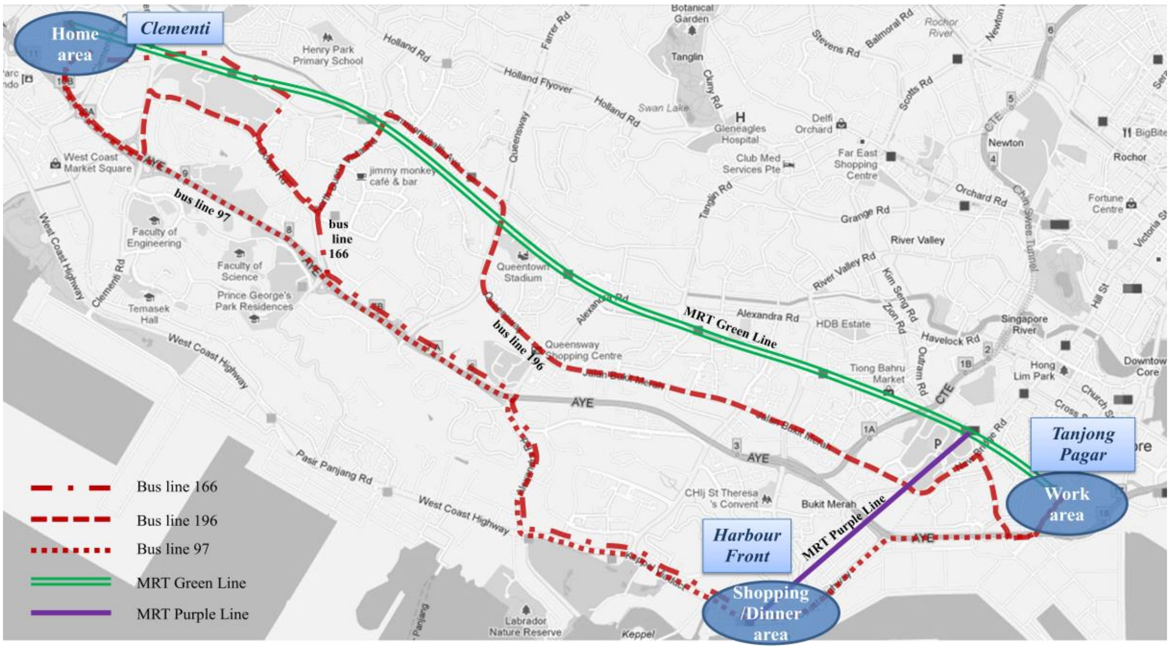


Figure 2. The multi-modal transit network in study area.

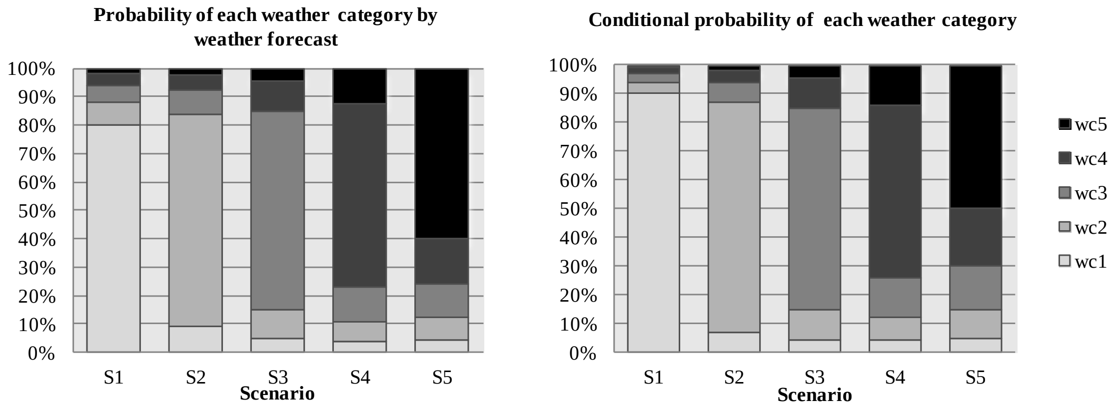
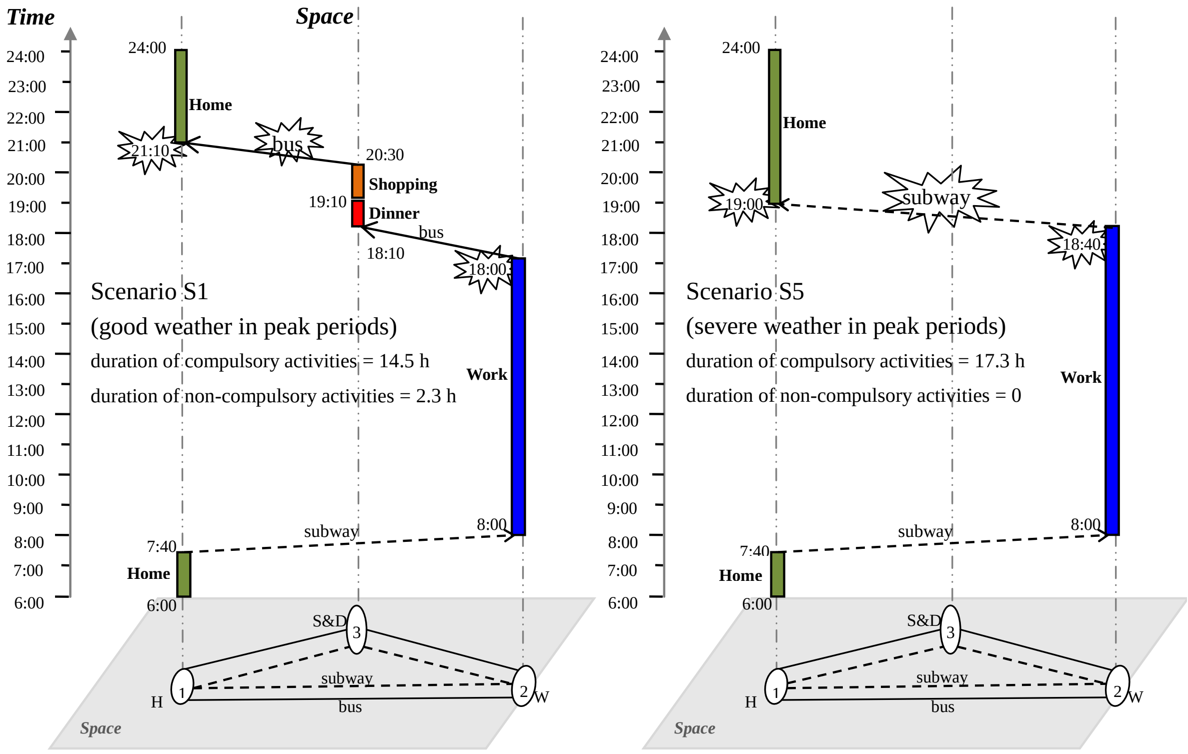


Figure 3. Scenarios for different weather forecast information.



(a) (b)

Figure 4. Results of daily activity-travel patterns under different weather scenarios.

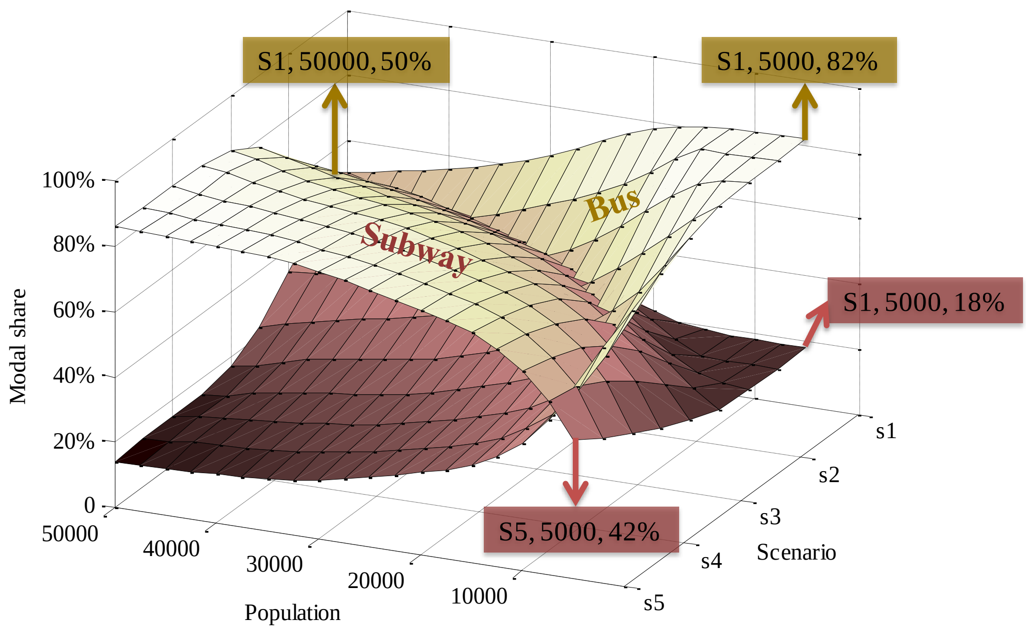


Figure 5. Modal shares under different weather scenarios and different population levels.