Travel modal choice analysis for traffic corridors based on decision-theoretic approaches

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Abstract The rapid development of multimodal transportation system prompts travellers to choose multiple transportation modes, such as private vehicles or taxi, transit (subways or buses), or park-and-ride combinations for urban trips. Traffic corridor is a major scenario that supports travellers to commute from suburban residential areas to central working areas. Studying their modal choice behaviour is receiving more and more interests. On one hand, it will guide the travellers rationally choose their most economic and beneficial mode for urban trips. On the other hand, it will help traffic operators to make more appropriate policies to enhance the share of public transit in order to alleviate the traffic congestion and produce more economic and social benefits. To analyse travel modal choice, a generalized cost model for three typical modes is first established to evaluate each different travel alternatives. Then, random utility theory(RUT) and decision field theory(DFT) are introduced to describe the decision-making process of how travellers make their mode choices. Further, some important factors that may influence the modal choice behaviour are discussed as well. To test the feasibility of the proposed model, a field test in Beijing is conducted to collect the real-time data and estimate the model parameters. The improvements in the test results and analysis shows new advances in the development of travel mode choice on multimodal transportation networks.

Keywords: modal choice analysis; traffic corridor modelling, decision field theory

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1. Introduction

Due to the rapid development of metropolis in China, excessive increase of vehicles, heavy traffic congestion, traffic safety and environmental pollution are becoming more and more serious. To alleviate the above problems, public transit has been encouraged to facilitate people's travels. Multimodal trips, which means of trips consisting of at least of two or more travel modes, are becoming more and more popular. Multimodal transportation systems are expected to become more important in the future due to their contributions to the sustainable urban transportation and traffic administrators are committed to increasing the share of multimodal trips in order to guarantee a high level of urban mobility [1]. The study on travel mode choice behaviour modelling and analysis in multimodal transportation system attracts more and more concerns, because travel mode choice of urban trips are significant determinants of urban travel demand [2].

Several measures had been developed in this last two decades to enhance the service level of multimodal transport network. Various studies could be roughly categorized into two kinds.

The first kind of studies focused on the dynamics of multimodal transport networks. Several models were proposed to characterize the traffic flow assignment in multimodal networks [25, 26]. By modelling the features of network nodes or links, these new models helped researchers to obtain the optimal equilibrium state of the multimodal network [27]. The achievements of such kind of studies contributes to increasing the efficiency of transport network.

The second kind studies focused on modelling the traveller's choice behaviour. Utility models and discrete choice models were involved to evaluate the different mode options [28, 29]. Their work effectively analysed and predicted the traffic sharing rates of different travel modes in multimodal networks and it must be beneficial to alleviate the traffic congestion problem.

The approach discussed in this paper belongs to the second kind. We attempt to model the travel cost of different travel modes based on real-time data and formulate the traveller's decision-making process. To characterize the travel mode choice issues, there are three problems that needs to be addressed.

The first one is how to select the appropriate studying scenario. Home-work commuting is considered as the most important daily travels of human beings. So, the analysis on mode choice behaviour of home-work commuting is very significant. In many Chinese metropolis, traffic corridors involving parallel roadways and transit lines are the main facilities to serve the commuters' travel demand from suburban residential areas to Central Business District (CBD) [3]. In this paper, we select a representative traffic commuting corridor in Beijing, which is equipped with an expressway (Jingtong Expressway) and a transit line (Beijing Subway Line 1). Graph theoretic model is applied to formulate the corridor scenario.

The second one is how to evaluate the options of different travel modes. Previous studies proposed the different models of multimodal transport network to characterize people's travelling behaviours [4~5], which includes logit-based choice models [6], multinomial probit models [7], dynamic assignment models [8] and so on. In our case, we adopt quantitative models to formulate the real-time generalized travel cost of different modes. It should be noticed that the choices of transportation costs combinations are based on factors other than just transportation costs, which are related to transit time, distance, money, intermodal transfers and etc.. A field test was conducted to collect real-time data and estimate the parameters of proposed models.

The third one is how to formulate the decision-making process when faced with different mode alternatives. In this paper, two typical decision-theoretic approaches were introduced to characterize the complex decision-making process. One is the static Random utility theory (RUT) [9~11] and the other is the dynamic Decision Field Theory (DFT) [12]. RUT is a classical discrete choice model that has the advantage of simple mathematical descriptions and easy computational process. Whereas, DFT is an advanced, stochastic and dynamic decision models involving the effects of the factors of deliberation time, attention on decision behaviour. Besides, several successful applications of RUT and DFT in other fields enlightened us to adopt the decision theories to travel modals choice. The comparison of RUT and DFT on travel modal choice would also be made as well.

To a give detailed description, the rest of paper is outlined as follows. *Section 2* first shows the scenario of traffic corridors and then constructs the mathematical formulations of choice models. In *Section 3*, we demonstrate how we collect the real-time data and estimate the parameters of proposed models. In *Section 4*, we analyse the effect of some important factors on travel modal choice. Conclusions are made and discussed in *Section 5* ultimately.

2. Mathematical formulation of travel mode choice model

In this section, a typical traffic corridor scenario in Beijing is selected and formulated into a graph network. And then a generalized travel cost model is proposed. At last, RUT and DFT are introduced to characterize the choice decision-making process.

2.1 Scenario representation

In a modern metropolis, there usually exists several main corridors for commuting from suburban areas to the Central Business District (CBD). The main corridors contains several major transportation modes and serve for commuters. **Fig.1** illustrates a representative traffic commuting corridor in Beijing, which serves residents who commutes from suburban Tongzhou District to Guomao CBD.

Fig.1 The scenario of a traffic commuting corridor in Beijing

The traffic corridor contains a transit line, called Beijing Transit Line 1, and an expressway, called Jingtong Expressway. Thus, the multimodal transportation system supports commuters to choose three types of travel modes: private vehicles (self-driving or taxi), public transit (subway or bus) and park-and-ride (P&R). We use a graph model to formulate the real scenario as a network with an expressway and a subway line; see **Fig.2**.

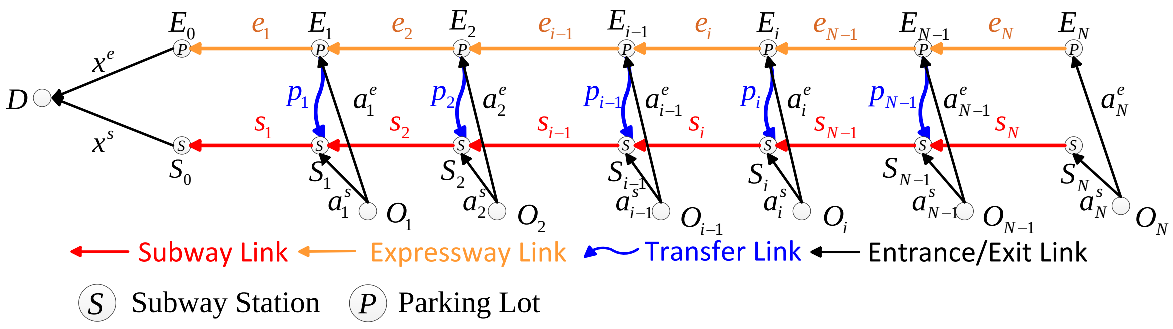


Fig.2 The formulated network of traffic corridors in Beijing

Suppose that the corridor network includes N subway links and the expressway is then divided into N roadway links as well. In this paper, we focus on the modal choice among the three following travel modes: subway mode for transit, expressway mode for private vehicles and P&R mode for park-and-ride combination. As illustrated in **Fig.2**, there are $N+1$ subway stations and $N+1$ parking lots nearby, which divides the corridor network into N consecutive segments. For the subway mode, the subway stations are denoted as S_i, and the subway links between S_i and S_{i-1} are denoted as s_i, $i=0,...,N$. For the expressway mode, the parking lots are denoted as E_i, and the expressway links between E_i and E_{i-1} are denoted as e_i, $i=0,...,N$. P&R mode is actually a combination of expressway mode and subway mode, we assume that commuters of P&R mode only transfers from expressway mode to the subway mode. The corresponding transfer links are denoted as p_i connecting the pairs (E_i, S_i), $i=1,...,N-1$. At last, the entrance links from the origin O_i to E_i and S_i are denoted as a_i^e and a_i^s, $i=1,...,N$; and the exit link from E_0 and S_0 are denoted as x^e and x^s, respectively.

In addition, it is assumed that the distance between the pairs (E_i, E_{i-1}) is equivalent to that between the pairs (S_i, S_{i-1}), which is denoted as d_i, $i = 1, ..., N$. The distance of entrance/exit links or transfer links are ignored, because commuters probably go on foot within these links. Thus, the total distance of commuting corridor can be calculated as

$$D = \sum_{i=1}^{N} d_i \tag{1}$$

2.2 Mathematical formulation of generalized travel cost

Researchers have proposed several quantitative models for urban transportation system to evaluate the transportation serviceability [13, 14]. It brings us much inspirations in travel cost modelling. Thus, we construct our models based on their innovative work.

It should be clarified that under different circumstances, the composition of travel cost varies significantly in different travel modes [15]. In this paper, we evaluate the general travel cost by involving the travel time, travel expense and travel comfort for expressway, subway and P&R modes accordingly.

For presentation simplicity, the symbols and notations are enumerated in **Table 1** below.

Table 1. Nomenclature List of Generalized Travel Cost Models

Parameters	Interpretations
The symbols below are variables of subway mode	
t_a^S	entrance time to the subway station
t_x^S	exit time from the subway station
t_0^S	in-metro travel time per unit distance
f_i^S	commuting passenger flow from S_i to CBD
C^S	the capacity of metro train
m_0^S	benchmark price of metro ticket
m^S	additional price of metro ticket per unit distance
$g^S(\cdot)$	comfort measure function of subway
T_i^S	total travel time from S_i to CBD
M_i^S	total travel expense from S_i to CBD
G_i^S	total comfort cost from S_i to CBD
V_i^S	generalized travel cost of subway mode from S_i to CBD
The symbols below are variables of expressway mode	
t_a^E	entrance time to the parking lot
t_x^E	exit time from the parking lot
t_0^E	free flow travel time per unit distance
t_i^E	congestion travel time from E_i to CBD
f_i^E	expressway traffic flow from E_i to CBD

C^E	the capacity of the expressway
m_t^E	expressway toll per unit distance
m_f^E	fuel charge per unit distance
m_0^P	parking fees in the CBD
T_i^E	total travel time from E_i to CBD
M_i^E	total travel expense from E_i to CBD
G_i^E	total comfort cost from E_i to CBD
V_i^E	generalized travel cost of expressway mode from E_i to CBD
The symbols below are variables of P&R mode	
t_i^P	park cruising and transfer time from E_i to S_i
m_i^P	parking fees in the E_i parking lot
T_{ij}^P	total travel time from E_i to S_j and then to CBD
M_{ij}^P	total travel expense from E_i to S_j and then to CBD
G_{ij}^P	total comfort cost from E_i to S_j and then to CBD
V_{ij}^P	generalized travel cost of P&R from E_i to S_j and then to CBD
The symbols below are universal variables of all three modes	
d_i	travel distance between (E_i, E_{i-1}) or (S_i, S_{i-1})
σ	transform coefficient of travel time
λ	transform coefficient of travel comfort

1) generalized travel cost of subway mode

The underground transit line is obviously escaping from the traffic congestion on road. Thus, the total travel time of subway mode T_i^S from S_i to CBD only involves the entrance time t_a^S, the exit time t_x^S and the travel time. It can be written as:

$$T_i^S = t_a^S + \sum_{k=1}^{i} t_0^S d_k + t_x^S \tag{2}$$

The travel expense of subway M_i^S contains two main components: the benchmark price m_0^S and distance-based additional price m_i^S, which can be written as:

$$M_i^S = m_0^S + \sum_{k=1}^{i} m^S d_k \tag{3}$$

Travel comfort in subway system relates with many kinds of factors [16]. Actually, most of them are influenced by the density of in-carriage passengers. So, we use a typical comfort measure function $g^S(\cdot)$, which is controlled by the passenger flow, to describe traveller's comfort. Accordingly, the travel comfort can be written as:

$$G_i^S = \sum_{k=1}^{i} g^S \left(\frac{f_k^S}{C^S} \right) \tag{4}$$

where $g^S(x) = \omega(1 - e^{-x/\theta})$, ω, θ are scaling and shape coefficients of comfort measure function. Giving the function $g^S(\cdot)$ for the comfort measurement, it is reasonable to assume that $g^S\left(f_k^S / C^S\right)$ increases with the increment of f_k^S, and if $f_k^S = 0$, $g^S\left(f_k^S / C^S\right) = 0$.

Summarizing the travel time, travel expense and travel comfort, the generalized travel cost V_i^S from S_i to CBD can be written as:

$$V_i^S = \sigma T_i^S + M_i^S + \lambda G_i^S \tag{5}$$

where σ, λ are transform coefficients of T_i^S, G_i^S. They represents the value of time (VOT) and value of comfort (VOC), respectively.

2) generalized travel cost of expressway mode

The travel time of expressway mode might be affected by traffic congestion. We use the well-known US Bureau of Public Roads function (BPR function) to calculate the travel time [17]. According to BPR function, the congestion travel time t_i^E involves the free flow travel time t_0^E and the traffic flow f_k^E, which can be written as:

$$t_i^E = \sum_{k=1}^{i} t_0^E d_k \left(1 + \alpha \left(\frac{f_k^E}{C^E} \right)^{\beta} \right) \tag{6}$$

where α, β are the coefficients of BPR function.

Then we should add the entrance t_a^E and exit time t_x^E, the total travel time T_i^E from E_i to CBD can be written as:

$$T_i^E = t_a^E + \sum_{k=1}^{i} t_0^E d_k \left(1 + \alpha \left(\frac{f_k^E}{C^E} \right)^{\beta} \right) + t_x^E \tag{7}$$

The travel expense includes three components: the distance-based expressway toll m_t^E, fuel charge m_f^E, the parking fees m_0^P, which can be formulated as:

$$M_i^E = \sum_{k=1}^{i} (m_t^E + m_f^E) d_k + m_0^p \tag{8}$$

Since taking vehicles is much more comfortable because of its escape from in-car crowding, we assume that the travel comfort cost in vehicle $G_i^E = 0$. So, the generalized travel cost V_i^E from E_i to CBD can be written as:

$$V_i^E = \sigma T_i^E + M_i^E \tag{9}$$

3) generalized travel cost of P&R mode

In P&R mode, the commuters may drive from origin O_i to parking lot E_i and transfer to subway station S_i and then take a transit line to CBD.

So, the travel time of P&R mode contains five components: entrance time t_a^E, travel time in vehicles t_i^E, transfer time t_j^P, travel time in metros t_0^E, exit time t_x^S. It can be written as:

$$T_{ij}^P = t_a^E + \sum_{k=j+1}^{i} t_0^E d_k \left(1+\alpha\left(\frac{f_k^E}{C^E}\right)^{\beta}\right) + t_j^P + \sum_{k=1}^{j} t_0^S d_k + t_x^S \tag{10}$$

For travel expense, it can be determined by summing up above-mentioned expense components as:

$$M_{ij}^P = \sum_{k=j+1}^{i} (m_t^E + m_f^E) d_k + m_j^p + m_0^S + \sum_{k=1}^{j} m^S d_k \tag{11}$$

Regarding to travel comfort cost of P&R mode, it actually involves the travel comfort of subway mode since that of expressway mode is assigned to zero. It can be formulated as:

$$G_{ij}^P = \sum_{k=1}^{j} g^S \left(\frac{f_k^S}{C^S}\right) \tag{12}$$

Similar to the former two modes, the generalized travel cost of P&R mode V_{ij}^P from E_i to S_j and then to CBD can be formulated as:

$$V_{ij}^P = \sigma T_{ij}^P + M_{ij}^P + \lambda G_{ij}^P \tag{13}$$

2.3 Mathematical formulation of decision-making process

To explore the modal choice behaviour, we use the choosing probability of one certain travel mode to characterize traveller's choice. It is assumed here that the traveller's may randomly choose their traffic modes to minimizing their commuting travel cost. We introduce two classical decision theories, Random Utility Theory (RUT) and Decision Field Theory (DFT).

1) choice modeling based on RUT

Logit model is adopted to characterize the choice behaviour. It has the advantage of fast computing speed, simplified mathematical expression and extensive applicability. RUT declares that decision makers make a choice between uncertainty and prospects by comparing the utility values of different options. The essential hypothesis of RUT is that we assume all the decision makers are characterized with absolute rationality.

The stochastic generalized travel cost U_η of travel mode η can be written as:

$$U_\eta = V_\eta + \varepsilon_\eta \tag{14}$$

where V_η is the actual observations of generalized travel cost for mode η, and ε_η is the stochastic error term for unobservable factors. So, the travellers may minimize their generalized travel cost by choosing a traffic mode with probability

$$\mathrm{Prob}_{RUT}^{\eta} = \frac{\exp(-\varsigma U^{\eta})}{\sum_{\eta'=\{E,S,P\}} \exp(-\varsigma U^{\eta'})} \tag{15}$$

where ς is a scaling parameter.

2) choice modeling based on DFT

Decision Field Theory is a dynamic and cognitive method to model the decision-making process for human-beings based on psychological principles [17]. Compared to the above classical static decision theory, DFT concentrates on the psychological deliberation process and the effects of deliberation time point. It also reflects the mechanism of how decision makers generate their preference. DFT describes the decision making behaviour from a psychological point of view. Different from those traditional decision theories, DFT is a stochastic and dynamic approach that uncovers the effect of cognitive ability, deliberation time and other psychological factors.

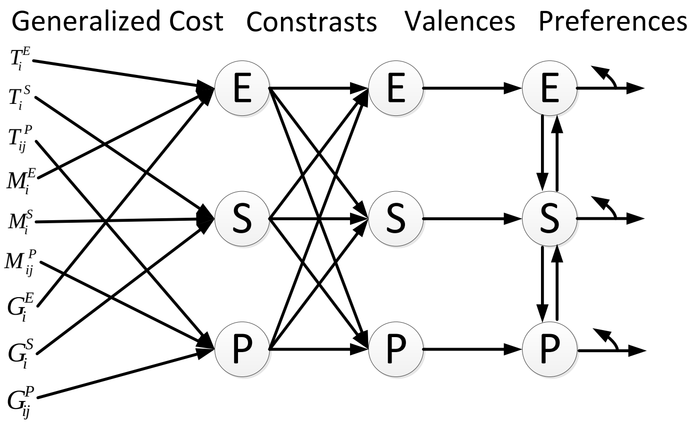


Fig.3 The three-layer network model of DFT

Several researchers [18, 19] utilized a three-layer network to illustrate how DFT works; see **Fig.3**. The first layer of the network computes the travel cost of different mode options, which has been formulated in *subsection 2.2*. We extend those static generalized cost models to dynamic ones by adding a temporal parameter τ, which denotes the deliberation time of decision-makers. So, the dynamic generalized travel cost of travel mode η can be written as:

$$U_{\eta}(\tau) = V_{\eta}(\tau) + \varepsilon_{\eta}(\tau) \tag{16}$$

The second layer of the network computes the differential valences which denotes the superiority and inferiority of each mode choice at deliberation time τ, which is described as:

$$v_{\eta}(\tau) = U_{\eta}(\tau) - U_{g}(\tau) \tag{17}$$

$$U_g(\tau) = \sum_{k\in\{E,S,P\}}^{k\neq\eta} U_k(\tau)/(m-1) \tag{18}$$

where $v_\eta(\tau)$ indicates the valence for traffic mode η, $U_g(\tau)$ represents the other $(m-1)$ mode options and m is the number of traffic modes. In our case, $m=3$.

The third layer generates the travel preference through a competitive recursive algorithm. The travel preference at a particular time point is integrated by the preference value at previous time points and the input valences. According to Qin's work [18], preference state can be formulated by a linear dynamic system as follows:

$$P(\tau+\Delta\tau) = S\cdot P(\tau) + \psi(\tau+\Delta\tau) \tag{19}$$

where $P(\tau)$ is the preference vector for all mode options at deliberation time τ. Each component of $P(\tau)$ actually indicates the choosing probability of different modes. $\psi(\tau)$ is the differential valence vectors and S is the feedback matrix.

Further, **Eq.(19)** can be expanded as:

$$P_\eta(\tau+\Delta\tau) = s^{\eta\eta}\cdot P_\eta(\tau) + \sum_{k\neq\eta} s^{\eta k}\cdot P_k(\tau) + \psi_\eta(\tau+\Delta\tau) \tag{20}$$

where $P_\eta(\tau)$ denotes the preference for mode option η at time τ. $s^{\eta\eta}$ is the self-feedback coefficient positive value and $s^{\eta k}$ is the negative mutual feedback coefficient value.

Busemeyer and Roe [21, 22] gave a detailed explanation for the reference value of $s^{\eta\eta}$. $s^{\eta\eta}=0$ suggests no impact of previous valences over time; $0<s^{\eta\eta}<1$ suggests weaken impact of previous valences; $s^{\eta\eta}=1$ suggests complete impact of previous valences; $s^{\eta\eta}>1$ suggests strengthen impact of previous valences. As for the mutual feedback coefficient , Duan and Li [23, 24] proposed two typical calculating methods as follows:

$$s^{\eta k} = s^{k\eta} = 0.042\cdot\frac{1}{1+e^{20*(d-2.4)}} \tag{21}$$

$$s^{\eta k} = s^{k\eta} = -0.10\cdot e^{-0.022*d^4} \tag{22}$$

where d can be calculated as

$$d = \sqrt{\sum_{k=\{E,S,P\}}^{k\neq\eta} (U^\eta - U^k)^2} \tag{23}$$

In our case, we choose the first calculating methods to determine the mutual feedback coefficient $s^{\eta k}$.

When implementing DFT model, a stopping criteria needs to be set to terminate the recursive algorithm. Roe proposed two kinds of stopping criteria respectively regarding deliberation time and preference value [22]. The first one is that decision makers will choose his/her option with the maximum preference state within a fixed deliberation time period. The second one is that, without a time limit, the deliberation process will not stop until any one of the preference states exceeds a threshold value.

3. Choice model parameter estimation and computation results

In this section, a field test is conducted in Beijing to collect the empirical real-time data of traffic commuting corridors. It should be clarified that the model parameters can be divided into two kinds: time-variant and time-invariant. Thus, we conduct our field measurements from 5:30a.m. to 11:00p.m. with a step of 30 minutes so as to get the whole day's travel cost.

3.1 Model parameter estimation

As illustrated in *Section II*, the scenario is chosen as a traffic commuting corridor serving residents who commutes from suburban Tongzhou District to Guomao CBD. The origin of the studied scenario is set as the residential area of Tongzhou Beiyuan and the destination is set as the Guomao CBD. There are $N=10$ subway stations along the corridors in length of $D=15.5$ km. The subway stations are Guomao CBD(1st), Dawanglu(2nd), Sihui(3rd), Sihui East(4th), Gaobeidian(5th), Chuanmei University(6th), Shuangqiao(7th), Guanzhuang(8th), Baliqiao(9th), Tongzhou Beiyuan(10th). In accordance, the studied corridors can be divided into 9 links. The distance of each link are illustrated in **Fig.4**.

Then, the field measurement results of travel cost model parameters for expressway mode, subway mode and P&R mode is presented respectively.

As for subway mode, the parameters are measured as $t_a^S=84s$, $t_x^S=170s$, $t_0^S=98s/km$, $m_0^S=3RMB$, $m^S=0.2RMB/km$, $C^S=1470$; the station-variant parameter f_i^S are illustrated in **Fig.5**; the scaling parameters of $g^S(\cdot)$, are chosen as $\omega=1,\theta=1$ [31]. As for the parameter of passenger flow f_i^S in subway, only the passenger who travels from suburban area to CBD is calculated. That is, the passengers who travels from CBD to suburban area will be ignored in our case.

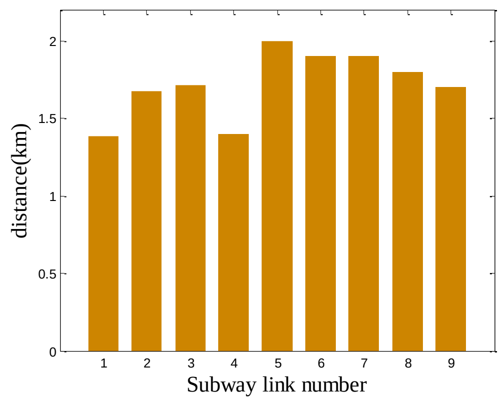


Fig.4 The distance d_i among any two stations

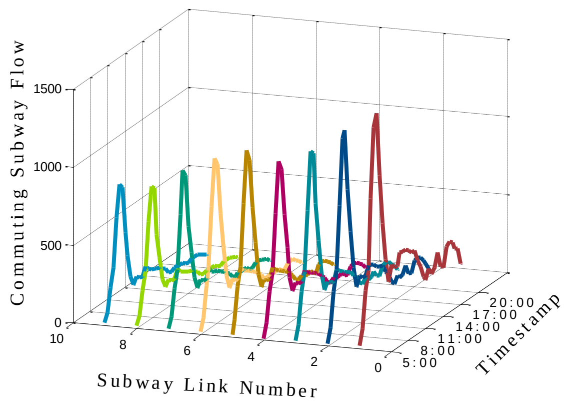


Fig.5 the distribution of passenger flow f_i^S

As for expressway mode, the parameters are measured as $t_a^E=59s$, $t_x^E=105s$, $t_0^E=85s/km$, $m_t^E=1RMB$, $m_f^E=0.7RMB/km$, $m_0^P=8RMB/\text{h}$; the time-variant and station-variant parameter t_i^E are illustrated in **Fig.6**. It is necessary to note that since the value of real-time traffic flow f_k^E and road capacity C^E is hard to attack, we directly measure the congestion travel time t_i^E.

As for P&R mode, the station-based parameters t_i^P and m_i^P are illustrated in **Fig.7**.

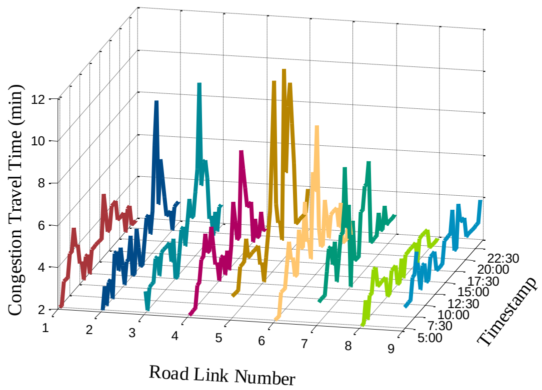


Fig.6 congestion travel time t_i^E

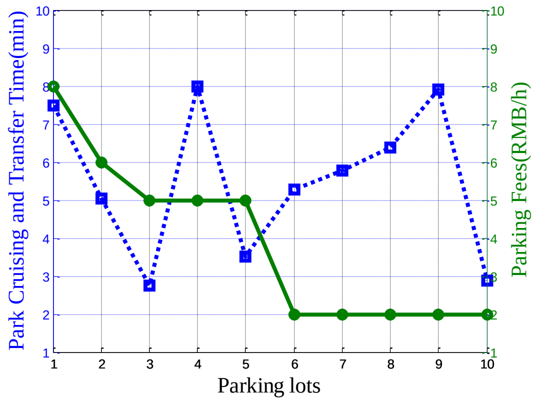
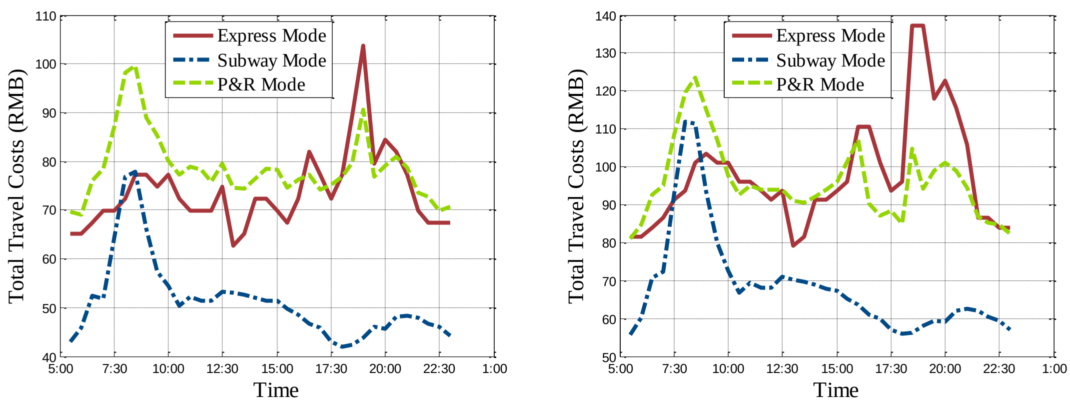


Fig.7 the parameters of t_i^P and m_i^P

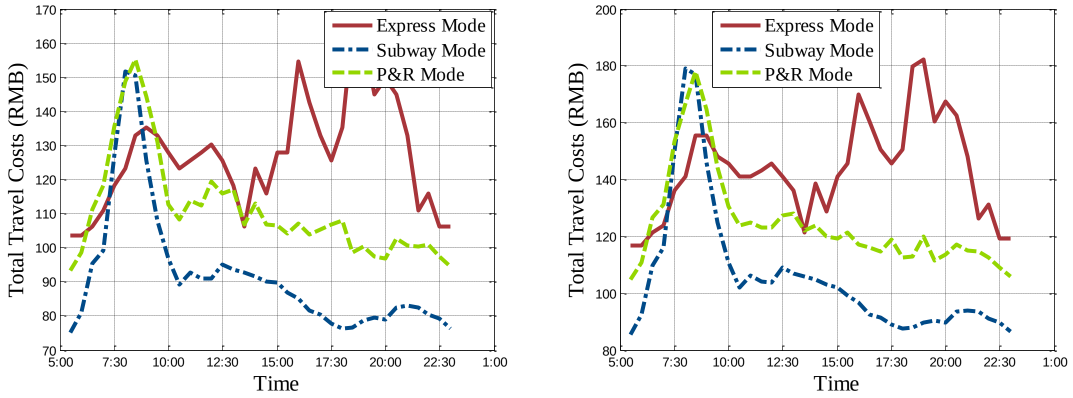
Besides, according to the statistics from Beijing Household Travel Survey, the VOT and VOC of Beijing residents is set to be $\sigma = 48\text{RMB}/h$ and $\lambda = 30RMB/unit$.

3.2 Generalized travel cost of subway, expressway and P&R mode

Based on the estimated model parameters in *subsection 3.1*, the real-time generalized travel cost of different travel modes can be calculated, accordingly. **Fig.8** illustrates the generalized travel cost from part of different origins to CBD.



(a) (b)



(c) (d)

Fig.8 The generalized travel cost of expressway, subway and P&R mode: a) generalized travel cost of the 3rd station; (b) generalized travel cost of the 6th station; c) generalized travel cost of the 8th station; d) generalized travel cost of the 10th station;

It should be clarified that P&R mode contains more than one generalized travel cost, due to the fact that travellers have multiple transfers to park-and-ride. We assume that all P&R travellers will choose the transfers with minimum generalized travel cost. **Fig.9** shows us a P&R traveller's generalized travel costs of different P&R transfers who departs from the origin of the 10th station at 9:00a.m.. According to our assumption, this P&R traveller will choose the 7th station to transfer from expressway mode to subway mode.

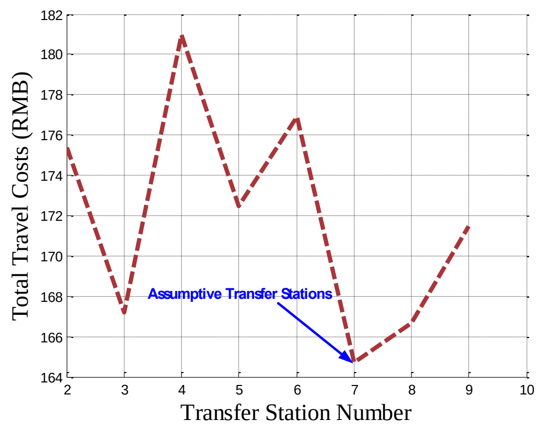


Fig.9 The assumptions of P&R travellers on the choice of P&R transfers at 9:00 a.m.

3.3 Computation results of RUT-based and DFT-based choosing probability

Based on the measured parameters, it is capable to estimate the choosing probability of travel modes via the proposed decision theories. Similarly, it is necessary to demonstrate the parameters of RUT and DFT at first.

In our case, the parameters of RUT are set as follows. The error term ε_η follows the normal distribution with mean of zero and variance of one. The scaling parameter ς is assigned to one. **Fig.10** illustrates the RUT-based choosing probability of subway, expressway and P&R mode from the origin of the 10th station.

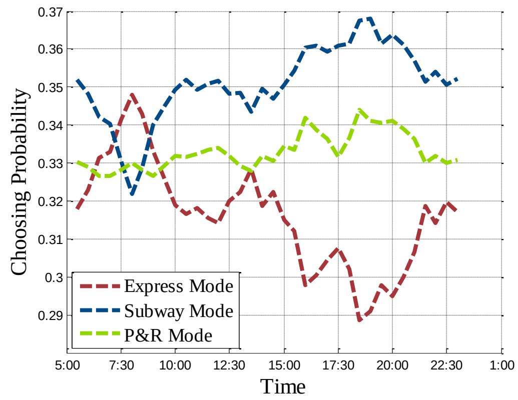
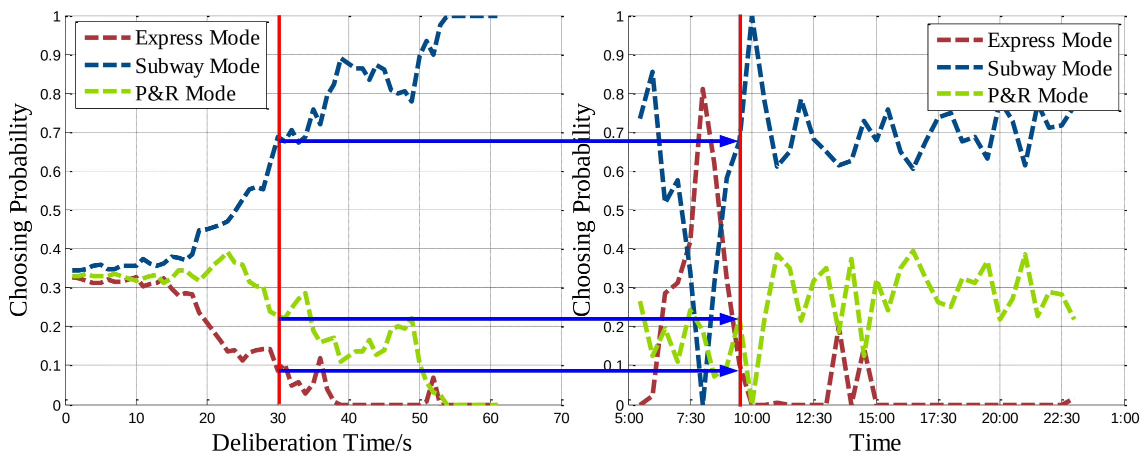


Fig.10 the illustration of RUT-based travel mode choice probability

Then we determine the parameters of DFT as below. The error term $\varepsilon_\eta(\tau)$ also follows the normal distribution with mean of zero and variance of one. The self-feedback coefficient $s^{\eta\eta}$ is set as 0.9115 based on Qin's work [18]. To make a comparison with RUT, the initial preferences $P_i(0)$ for subway, expressway and P&R mode are chosen as the corresponding RUT-based choosing probability. The first stopping criteria is selected to terminate DFT algorithm in our case. The maximum deliberation time is set as $T_d = 30s$.

Fig.11(a) first shows us the dynamic evolution of the DFT-based mode choice probability. We choose an example of the travellers who departs at 9:30a.m.. It actually reflects the psychological deliberation process of the decision maker. Similar to the RUT-based theory, **Fig.11(b)** then illustrates the DFT-based travel mode choice probability. Since the maximum deliberation time is set as 30s, the choosing probability at 30s in **Fig.11(a)** is chosen as the final DFT-based choosing probability at 9:30a.m. in **Fig.11(b)**.



(a) (b)

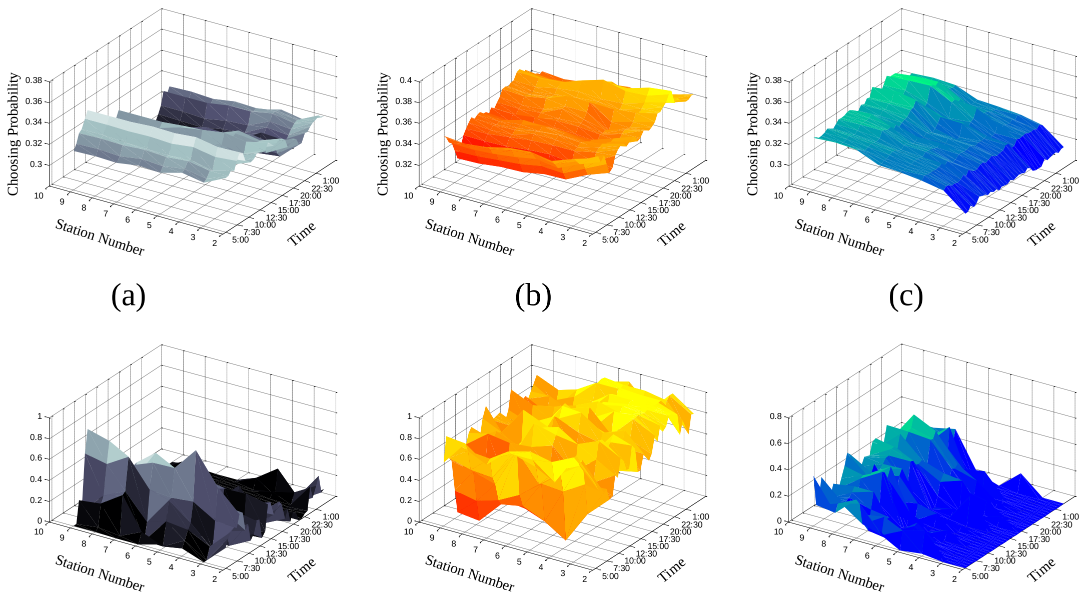
Fig.11 the illustration of DFT-based travel mode choice probability: a) dynamic evolution of deliberation process at 9:30 a.m.; b) DFT-based choice probability

4. Modal choice behaviour analysis in term of important factors

In *subsection 3.3*, we give an illustration of mode choice probability based on RUT and DFT. However, the modal choice behaviour is influenced by many considerable factors, such as trip distance, departure time, income levels. In this section, a set of computational results with the model is presented to illustrate the effects of considerable factors, including traveling distance, traffic flow, VOT and VOC.

4.1 The effects of trip distance

To check the effect of trip distance on corridor mode choice analysis, we measure the number subway stations that pass to CBD and then summing up the distance of each passing link. Since we have 10 stations in our traffic corridor network, the travel distance of commuting to CBD will increase from the 2nd station to the 10th station. Both RUT-based and DFT-based choosing probabilities of different stations are depicted in **Fig.12**.



(a) (b) (c)

(d) (e) (f)

Fig.12 the choosing probability distribution with different trip length based on RUT and DFT: a) RUT-based probability for Expressway Mode; b) RUT-based probability for Subway Mode; c) RUT-based probability for P&R mode; d) DFT-based probability for Expressway Mode; e) DFT-based probability for Subway Mode; f) DFT-based probability for P&R mode;

As for the results, we found that the choosing probability of P&R mode increases with the increase of trip length. Correspondingly, the probability of subway and expressway mode decreases. It indicates the fact that P&R mode is more attractive to longer distance commuters while the expressway mode and subway mode are suitable for shorter distance commuters. This findings may suggest us that subway service does not need to cover the rural areas along the traffic corridor, and the P&R mode may be a more suitable choice for long distance trip.

4.2 The effects of traffic flow

Usually, the traffic flow in the commuting corridors are mainly influenced by the departure time of travellers. In the morning peak hours, the traffic corridor suffers from heavy congestion due to high level of traffic flow. While in the non-peak hours, the commuting traffic flow decreases correspondingly. We choose the time point 7:30a.m. (peak hours) and 12:00a.m. (non-peak hours) as an representative to check the mode choice behaviour under different levels of traffic flow. Their RUT-based and DFT-based choosing probabilities are illustrated in **Fig.13**.

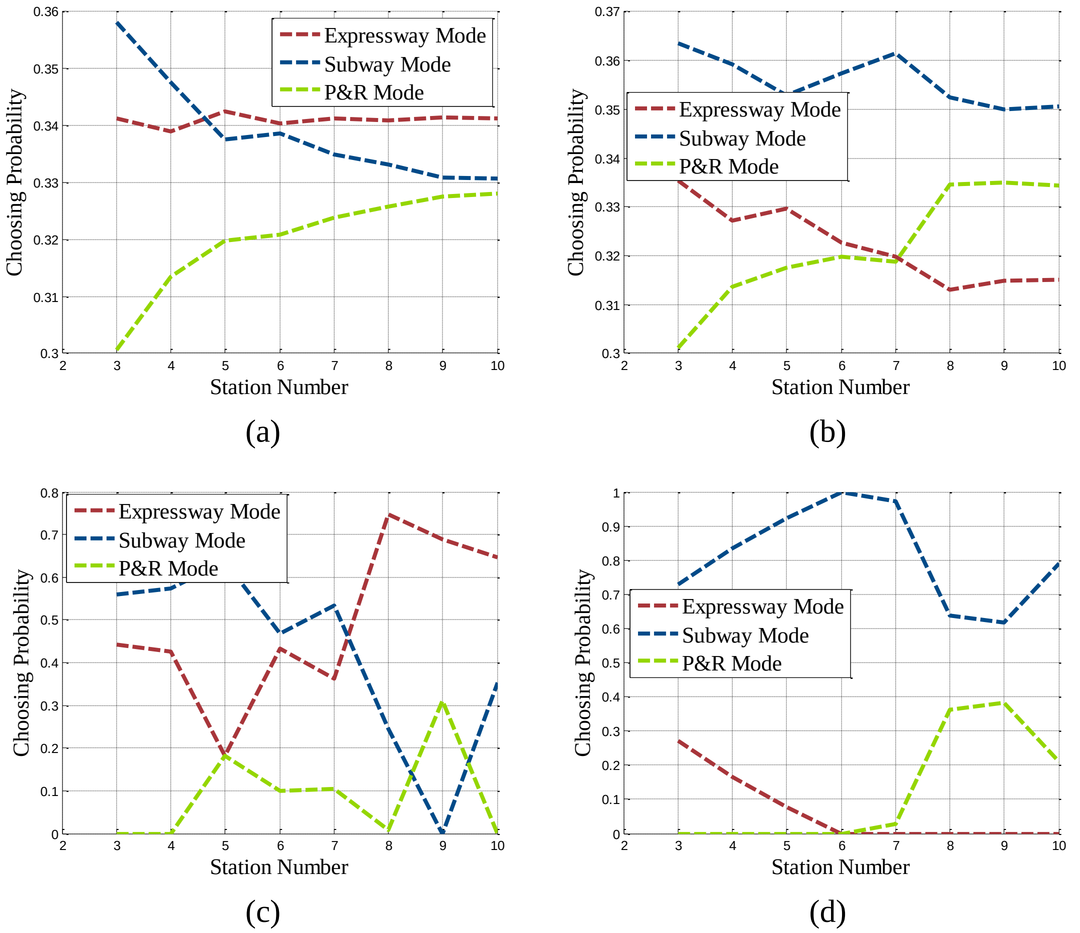


Fig.13 the choosing probability distribution with different time periods based on RUT and DFT: a) RUT-based probability for peak hours; b) RUT-based probability for non-peak hours; c) DFT-based probability for peak hours; d) DFT-based probability for non-peak hours

It can be seen that within peak hours, most travellers near the suburban area prefer to drive cars because of its high speed and comfort, while travellers in the downtown areas prefer to take a subway due to its congestion free property and the escape from high parking fees in the CBD. Whereas, within non-peak hours, the travellers prefer to take a subway because of its relatively low travel cost.

4.3 The effects of VOT and VOC

In our case, the effect of VOT and VOC is studied to characterize the modal choice behaviour of different income level travellers. It is assumed that the parameters of VOT and VOC have an approximate linear relation with traveller's income [30]. So, we set a scaling parameter r_V to represent this linear coefficient. **Fig.14** illustrates the choosing probabilities with different VOTs ($r_V\sigma, r_V = 1,2,3$) and VOCs ($r_V\lambda, r_V = 1,2,3$).

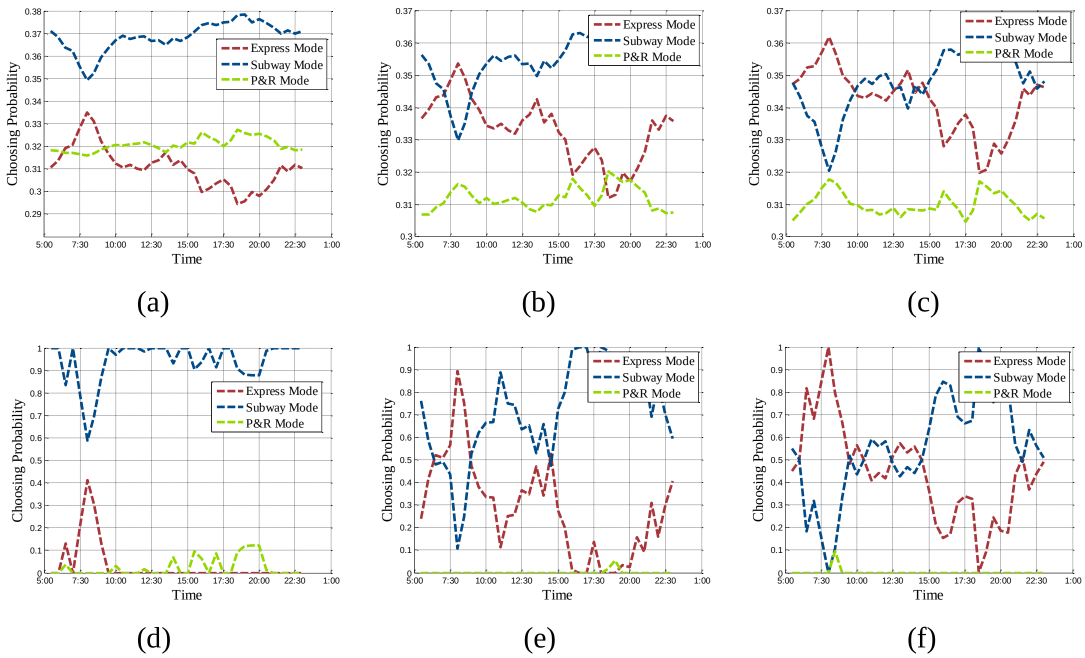


Fig.14 the choosing probability distribution with different VOT&VOC ratios r_V based on RUT and DFT: a) RUT-based probability for $r_V = 1$; b) RUT-based probability for $r_V = 2$; c) RUT-based probability for $r_V = 3$; d) DFT-based probability for $r_V = 1$; d) DFT-based probability for $r_V = 2$; f) DFT-based probability for $r_V = 3$;

It displays that with the increment of VOT and VOC, the choosing probability of expressway mode increases, whereas the probability of subway mode decreases. And the probability of P&R mode maintains at a low level. The results shows us that the high income level travellers are more sensitive to travel comfort issues and prefer to drive their private vehicles as long as possible to avoid the discomfort of subway mode.

5. Conclusions

In many cities with multimodal transportation systems, traffic administrators make efforts to enhance the sharing rate of public transit. They make various policies, such as road pricing toll, reducing public transit fares and support P&R parking facilities, to reduce the usage of private vehicles and encourage the usage of public transit. However, it is an urgent need to propose a theoretical model to evaluate how these polices influence the mode choice behaviour of different modes. Therefore, we propose a method to analyse and evaluate the travel mode choice via describing the travel cost of one certain transportation mode's status in a specific node, link, route or network within different time periods. Two typical decision-theoretical methods were introduced to formulate the traveller's decision-making process on travel mode choice. Effects on the mode split patterns for some important factors, such as trip length, traffic flow, VOT and VOC, were investigated as well.

The new method offers two significant contributions to multimodal transportation system:

First, by applying the quantitative models to depict travellers' generalized travel cost of different modes, we can capture the detailed variability of those modes. Further, the proposed model relied on real-time data is capable to identify the travel costs with different time periods, especially for peak hours and non-peak hours. It helps us to distinguish the diversified modal choice behaviour and then estimate the sharing rate of different travel modes.

Second, by applying the Decision Field Theory, we overcome the limitation of classical random utility based decision theories which cannot well depict the psychological deliberation process of human beings. It helps us to approach the more accurate decision making behaviour and explore the real choosing probability.

There are also some improvements that can be made to improve our research work. For example, the choosing probability estimated by our proposed model needs to verified by the real condition. A survey needs to be conducted in the near future to collect more real data so as to validate the correctness and effectiveness of our model.

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