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An agent-based choice model for travel mode and departure time and its case study in Beijing

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ABSTRACT

Aiming to alleviate traffic jams, many traffic management strategies/policies are adopted to nudge travelers to re-arrange their departure time or switch from driving to public transit or non-motorized mode. Analytical travel behavior model is needed to predict travelers' departure time choice and mode switch under such strategies. In this paper, we developed an agent-based model for travellers' choices of mode and departure time. Departing from the traditional utility maximization theory, this model focuses on the decision-making process based on imperfect information, bounded and distinctive rationalities. In the modeling framework, travelers accumulate experiences and update their spatial and temporal knowledge through a Bayesian learning process. Before making a trip, travelers decide whether to search for alternative departure time and/or travel mode according to their expected search gain and cost. When an additional search happens, travelers decide whether or not to switch to the new departure time and travel mode according to a series of decision conditions. Both the search and decision processes are represented by production (if–then) rules derived from a joint revealed/stated-preference survey data collected in Beijing. Then the agent-based model is applied to evaluate congestion charge policies with various demand scenarios in the 2nd ring road of Beijing. Results suggest that the model can display the peak spreading and mode switch process practically.

1. Introduction

As the rapid development of the economic, the number of private cars has expanding quickly in China, thus cause serious traffic congestions in many big cities (such as Beijing and Shanghai). Many traffic management policies and strategies (e.g. vehicle usage restriction, public transit priority) have been taken to solve this problem, but the result is not as good as expected. One of the most important reason is that the decision makers cannot know exactly how the travelers will switch their travel behavior after the policies and strategies are implemented, so the policies and strategies may not meet the actual requirement. Mode choice and departure time choice are important components of travelers' decision behavior during a trip. At macro level, mode and departure time have a direct bearing on the number and temporal pattern of vehicle trips on urban roadways; at micro level, mode and departure time have great influence on travel time and travel cost. It is necessary to build

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effective behavior model to predict travelers' departure time shift and travel mode switch and evaluate the effect of traffic management policies and strategies.

There are many researches to study travel behavior. Traditional theory based on utility maximization assumes substantial rationality and complete information. The logit model derived from the traditional theory is widely used in transportation planning and management. Some researchers suggests that the assumptions of substantial rationality and complete information are not reasonable and do not conform to human behavior character. Then a new travel behavior theory which considers human beings' bounded rationality and incomplete information appears. Zhang (2006) developed a SILK theory which considers Search, Information, Learning, and Knowledge for travel decision-making analysis and he applied the new theory in route choice. Xiong (2011) extended the SILK theory into departure time choice. But there are no applications in mode choice and no research in departure time choice joint with mode choice, especially in developing countries. Both the details of the two theories will be showed as following literature review section.

This paper develops an agent-based joint travel mode and departure time choice model which considers human beings' bounded rationality and incomplete information, and focuses on the travelers' real decision-making process. Travelers are regarded as a group of agents which make decision in the traffic system according to a series of behavior rules. Each agent retrieves spatial, temporal and travel cost information and accumulates travel experience from every single trip. Then agent will update its knowledge through a Bayesian learning process. When a new trip occurs, each agent will make travel mode and departure time choice on the basis of search gain, search cost, search rules and decision rules.

A joint revealed/stated-preference survey was conducted in Beijing to calibrate and validate the search gain function, search cost function, search rules and decision rules. In practice, the agent-based model can be used to analysis the result of travel mode shift and departure time switch for different kinds of policies and strategies which may nudge travelers to change their travel mode and departure time, such as gasoline tax, road pricing, bus and metro fare, and vehicle usage restriction. For example, if we increase the road price during peak period, the proposed agent-based travel behavior mode could be adopted to forecast the peak spreading and mode switch process. This paper takes the road network within the Second Ring Road of Beijing to conduct case study and analyzes the influence on departure time shift and travel mode switch of the different congestion charge policies and the sudden increasing of trip number.

The remainder of the paper is organized as follows. The traditional theory based on utility maximization and agent-based modeling that considers bounded rationality and incomplete information are contrasted and reviewed in Section 2. Section 3 presents the survey design and data collection. Section 4 introduces the agent-based joint travel mode and departure time choice model in detail, then the model is calibrated and validated by using the survey dataset. Section 5 demonstrates the application of the model for policy and scenario analysis in Beijing Second Ring Road. Conclusions and discussions on future research are presented in Section 6.

2. Literature review

The theory of travel behavior is one of the most important theories in traffic management and control area. Travel behavior refers to the complicated decision making process what travelers make during a trip about travel mode choice, route choice, departure time choice, destination choice and so on (Wen and Koppelman, 2000; Arentze et al., 2001).

Traditional behavior theory assumes that human beings are perfect rationality and perfect information. Before making a decision, individuals can identify all the feasible alternatives. Each alternative consists of a set of attributes that can describe the certain alternative. And travelers derive a level of utility from that alternative based upon those attributes and the characteristics of the travelers, then they choose the alternative which can maximize their utility. This is called the utility maximization theory (Von Neumann and Morgenstern, 2007).

The most widely used travel behavior model based on the maximization theory is discrete choice model. This is operationalized in the modeling structure by making the choice process a function of both the alternative attributes and the characteristics of the traveler. The study of discrete choice model in modal share and modal split has a long history. Luce (2012) deduced the Logit model which is the typical representative of discrete choice model. On the basis of the research results on theory by McFadden (1973) and Ben-Akiva and Lerman (1985) get the discrete choice model into application in practical project. In order to estimate the probabilities, various forms of logit and probit models are invented.

While most of these models have the problem of independence of irrelevant alternatives (IIA) and are criticized for their inability to consider decision makers' computational capacity and information availability (Hausman and McFadden, 1984). A large number of researchers have made great efforts to eliminate the IIA property and develops a series of nested logit models and generalized nested logit models (Koppelman and Wen, 1998; Bekhor and Prashker, 2001; Wen and Koppelman, 2001). In addition, several researches have been taken to study the mode switching behavior based on the theory of utility maximization (Hunecke et al., 2001; Srinivasan and Mahmassani, 2003; Wang and Chen, 2012).

Departure time is another important component of travel behavior. Multinomial logit (MNL) approach was first adopted to model departure time choice by Abkowitz (1981) and Small (1982). Just the same as the application in mode choice, the multinomial logit departure time choice model also suffers from the problem of irrelevant alternatives (IAA). In order to avoid IAA, nested logit (NL) models are adopted to analyze correlated departure time intervals (Ben-Akiva and Bierlaire, 2003). Bhat (1998) adopted a nested logit model for departure time choice.

The rational travel behavior theory based on the assumptions of utility maximization and perfect information depicts how travelers should behave but not they actually do (Banister, 1978; Zhang, 2006). Some researchers argues that human beings are bounded rationality and incomplete information. When an individual make a choice, the information is often incomplete and biased and they will pay money and time to search the alternatives and compare them, so they just choose the relatively satisfying alternatives rather than the best one in theory under most cases (Tversky and Kahneman, 1974; Acquisti and Grossklags, 2005; Weber, 1987; Kim et al., 1999; Wei, 2010).

Agent-based modeling which considers the bounded rationality and incomplete information of decision makers is adopted to model travel behavior. Agent-Based Modeling (ABM) focuses on naturalistic (or descriptive) representation of individual behavior and seeks to capture emergent global (or system-wide) patterns resulting from the local interactions and decisions of individual agents (Zou et al., 2013). Compared to equation-based modeling (EBM), ABM give more realistic results than EBM in many domains (Parunak et al., 1998).

Previous researchers have conducted some studies in applying ABM to the field of traffic. Arentze et al. (2010) proposed an agent-based approach to model activity generation and allocation decisions of individuals and households. Vaněk et al. (2013) developed an agent-based simulation model of maritime traffic that explicitly models pirate activity and piracy countermeasures. Schelenz et al. (2014) applied agent based simulation for evaluating a bus layout design from passengers' perspective. Yin et al. (2014) presented an agent-based travel demand model system for hurricane evacuation simulation. While these models just emphasize the learning process of individuals and have not relax the assumption of rationality in decision-making.

Then the fuzzy set theory is adopted to model travellers' decision-making process (Vythoulkas and Koutsopoulos, 2003). Fuzzy set theory is a framework that assumes that decision-making is based on a number of simple "IF, THEN" rules of the form "if ... (system perceptions) ... then ... (preferences toward alternatives) ... " (Zimmermann, 2010). Zhang (2006) developed an agent-based model of spatial learning and route choice based on SILK theory. The search for alternatives and choose among alternatives are represented by production (if–then) rules. Wehinger et al. (2010) developed an agent-based model to study adoption of plug-in hybrid vehicle (PHEV) technology under a variety of scenarios using a set of "if–then" rules. McDonnell and Zellner (2011) developed a stylized agent-based model which recreates the decision-making process of choosing a mode though "if–then" rules. Zhang and Xiong (2012) applied the SILK theory on departure time choice. Chong et al. (2013) proposes a rule-based neural network model to simulate driver behavior in two driving situations, namely car-following situation and safety critical events. Beykaei et al. (2014) developed a hierarchical rule-based land-use extraction system.

While the agent-based models which use fuzzy set theory as the behavior rules of agents are relatively infrequent in mode choice research, and no research has been taken to study in departure time choice joint with mode choice by using this theory. In order to meet this gap, this paper develops an agent-based joint mode choice and departure time choice model based on the SILK theory. The model is calibrated and validated by using the data from a joint revealed/stated-preference Pad-based and Web-based survey in Beijing. Then the model is applied to analyze the effect of the different congestion charge policies and the sudden increasing of trip number within the Second Ring Road of Beijing.

3. Travel behavior data collection

In order to calibrate the model, we conducted a joint revealed/stated-preference panel computer-based and web-based survey in Beijing. The survey questionnaire consist of three parts. The first part is revealed-preference (RP) survey which contains the respondents' personal attributes and their socio-economic status. The second part is the survey about the information of respondents' most recent trip and the purpose of this part is to know the current travel behavior of respondents. The third part is the stated-preference (SP) experiment which gives the values of different attributes to respondents according to the answers of the first and second part of the questionnaire.

3.1. Revealed preference survey

This part consist of 16 questions which are designed to achieve the socioeconomics and part of the current travel information of respondents. The collected information is displayed as following:

- Socioeconomics information of respondents: age, gender, education, occupation, number of people per household, number of children needing shuttling for school per household, income of the respondent per year, income of the whole household per year, family address.
- Travel information: number of vehicles per household, whether have a driving license, whether have a public transit card (can make public transit travel more cheaper), average time out of vehicle (e.g. the time for waiting, transferring) for a bus trip, average time out of vehicle for a metro trip, average time out of vehicle for a taxi trip.

3.2. Last trip survey

The purpose of this section is to collect the basic information about travellers' commuting and non-commuting trips and the commuting and non-commuting scenario will be given to the respondent with the probability of 50% individually according to *Beijing Transport Annual Report 2013*. The last trip is chosen considering that respondents can remember the details of this trip so that the information will be more reliable. The collected information includes travel mode, departure time, arrival time, expected arrival time, travel distance and travel cost (fuel cost, parking fee and toll).

3.3. Stated-preference experiment

The last part of this questionnaire is a stated-preference experiment which can achieve the travel behavior switching result of the respondent under different scenarios and polices. There are five kinds of policies and scenarios: (1) increasing of road pricing for car travellers; (2) conducting congestion charge; (3) changing of traffic congestion extent; (4) changing of bus fare; (5) changing of metro fare. The logic design of this is shown in Fig. 1.

Firstly, informations including travel mode, travel time and travel cost of the respondents' most recent trip are recorded. Secondly, a policy or scenario is given randomly, then the travel cost and travel time are updated by multiplying a series of random parameters on the basis of most recent trip information. Thirdly, the respondent is asked to decide whether to change behavior or not. If the respondent chooses "*NO*" or "*I will cancel the trip*", then the survey is stopped; if chooses "*YES*", then the respondent will be asked to decide changing what and the alternatives including changing travel mode, changing departure time and changing route (only for traveler by car and taxi). Lastly, the travel time, travel cost and travel mode will be updated and displayed to the respondent, then another iteration begins. The interface of the stated-preference experiment is shown in Fig. 2.

3.4. Data collection

The travel information presented to the respondents in the part of stated-preference experiment are calculated according to the answers collected in part 1 and part 2, but the traditional static questionnaire cannot update the travel information dynamically, so we design a questionnaire which can meet the requirement. The questionnaire was coded in JAVASCRIPT and JAVA as an APP to conduct a Pad-based survey and coded in HTML to conduct a Web-based survey. The survey used simple random sampling method and the data collection process contains two steps and began on December 10, 2013. First, we send out the link to the Web-based survey to respondents though E-mail, Tencent QQ, Tencent Wechat, and Fetion. In addition, the link was displayed on the website of *Renren* and *Sina Weibo*. We collected a total number of 162 effective samples though the Web-based survey in two weeks.

After comparing the gender ratio and age distribution of the 162 samples with the Sixth Nationwide Population Census Data of Beijing, we conducted the supplement survey by using Pad-based questionnaire which can aim at specific samples on December 25, 2013, thus making the whole survey data more reasonable. Another 81 effective samples were collected though the Pad-based survey. At last, we get 241 effective samples in total. The comparison of the gender ratio between the survey data and the Sixth Nationwide Population Census Data is shown in Figs. 3 and 4.

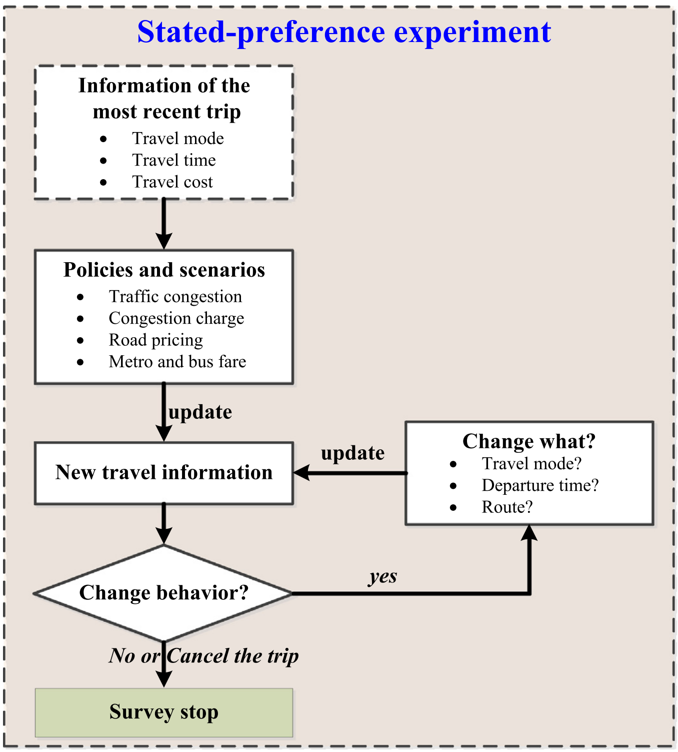

Fig. 1. Design of the stated-preference experiment.

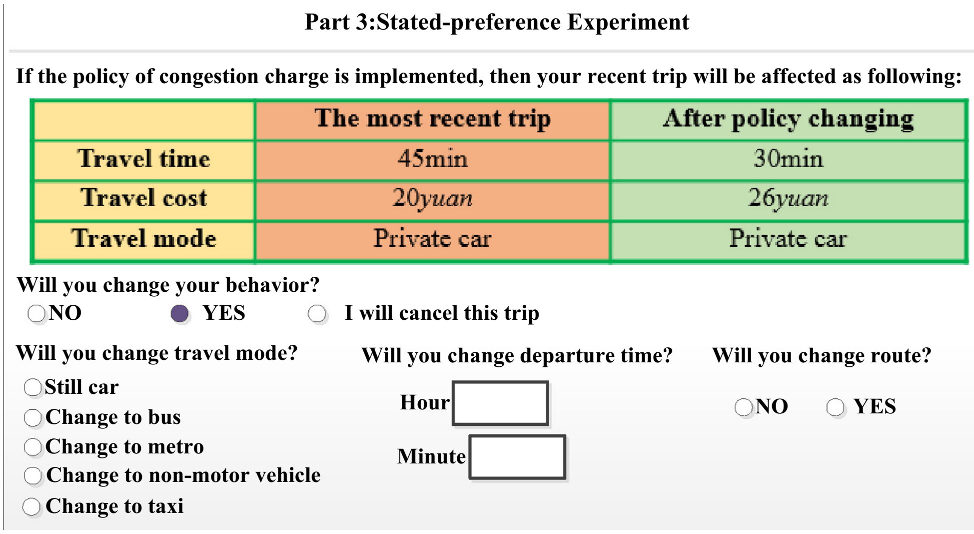

Fig. 2. The interface of the stated-preference experiment.

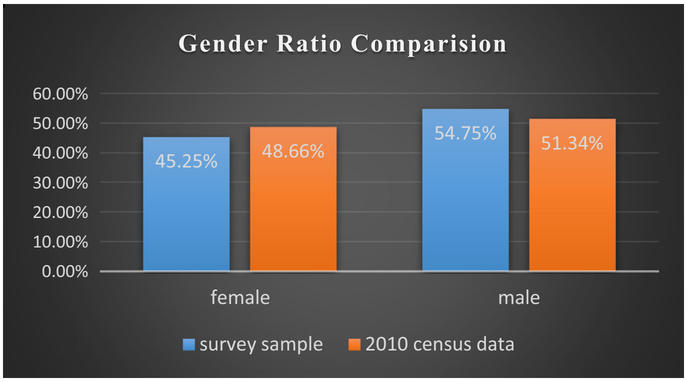

Fig. 3. Comparison of the gender ratio.

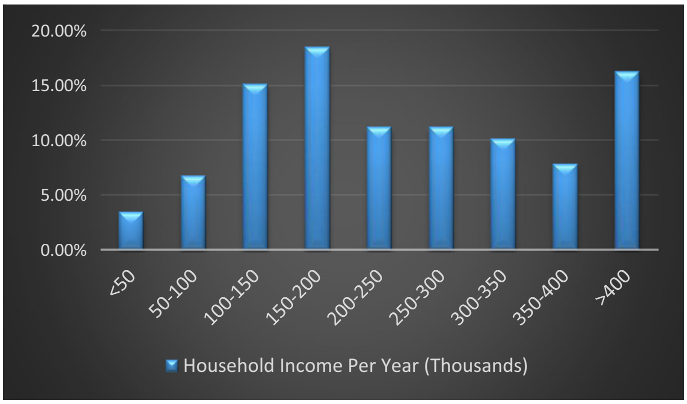

Fig. 4. Household income distribution.

As shown in Fig. 5, the departure time distribution achieved in this survey is slightly different from the result of the Sixth Nationwide Population Census Data. The morning peak hour is 7:00 am–9:00 am, the evening peak hour is 17:00–19:00.

Fig. 6 shows that mode share of public transit (Metro, 12% and Bus, 28%) in Beijing is nearly the same as the driving mode (car, 40%). The total share of car, bus and metro is about 80%.

4. Model development

4.1. Model framework

According to the typical structure of an agent, we develop the framework of the agent-based choice model as shown in Fig. 7. Individuals accumulate travel experience though the performance informations of the road network and other conditions, such as traffic management policies and strategies. Then each traveller will achieve spatial and temporal knowledge through a Bayesian learning process.

Travelers typically face two types of pre-trip choices: mode selection and departure times selection. For a repeating trip, travellers might choose to keep the current mode and departure time or search for new options. In order to model when a traveler will begin and stop searching, the theory of search gain and search cost with imperfect information is adopted. The

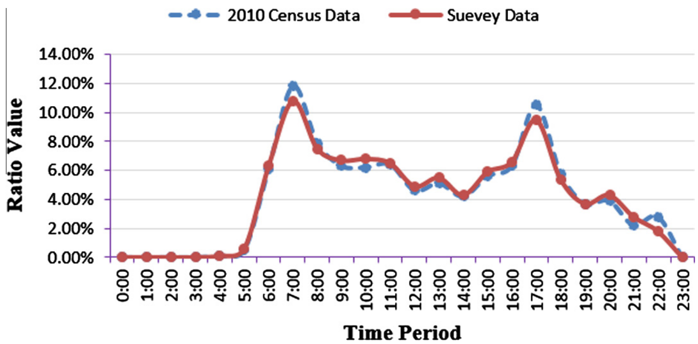

Fig. 5. Departure time distribution.

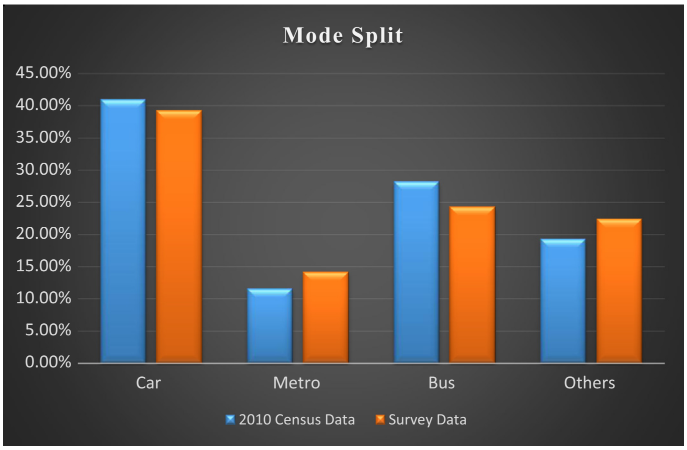

Fig. 6. Mode split.

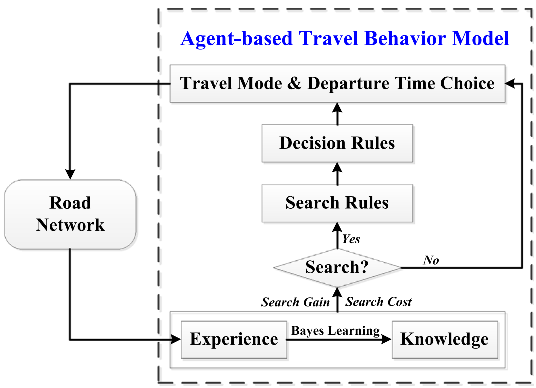

Fig. 7. Framework of the agent-based choice model.

search gain is the individuals' subjective benefits form an additional search. For example, if the current travel mode is car and the alternative mode is metro, then possible travel cost savings predicted by the traveler is the search gain. The search cost is the time, money and energy paid for an additional search by the traveler.

If the search cost is bigger than the search gain, travelers will decide not to search, then repetitive learned behavior or habitual behavior is executed. Otherwise, travelers will search for alternative modes according to a series of heuristics search rules. When a feasible alternative mode or departure time is searched out, a group of decision rules are adopted by travelers to decide whether to switch to the new mode and departure time or not.

4.2. Knowledge learning process

An individual's spatial knowledge for travel mode choice is based on experienced utility from previous learning and trials. Assume that there are I kinds of travel modes (or departure times) based on prior perception, and that mode m_i with utility u_i has been experienced n_i times by a particular individual. Therefore, the individual's knowledge about travel modes can be quantified as a vector $\boldsymbol{K}(n_1,\ldots,n_i,\ldots,n_I)$. According to Bayesian learning rules, the perceived weights of past observations are the same. Let vector $\boldsymbol{P}(p_1,\ldots,p_i,\ldots,p_I)$ represent an individual's subjective beliefs, where p_i is the subjective probability that an additional search would lead to an alternative travel mode with utility u_i.

We assume that individuals' prior beliefs follow a Dirichlet distribution to establish a quantitative relationship between knowledge $\boldsymbol{K}$ and beliefs $\boldsymbol{P}$. Since the Dirichlet is the conjugate prior of the multinomial distribution, the posterior beliefs will also be a Dirichlet distribution (Rothschild, 1974). This assumption is equivalent to Eq. (1), where N denotes the total number of observations ($\boldsymbol{N} = sum(n_i)$).

$$P_i = n_i/N \tag{1}$$

The knowledge learning process for departure time can be seen in Zhang and Xiong (2012).

4.3. Search gain and search cost

The decision to search for a new alternative travel mode is based on the relationship between subjective search gain and search cost. We assume that an individual's utility associated with the current travel mode is u. The subjective search gain (g) is the expected utility improvement from an additional search:

$$g = \sum_{i(u_i>u)} p_i(u_i - u) \tag{2}$$

Define the theoretically maximum utility as u^*. Then after N searches, the probability of finding a travel mode with utility u^* is $1/(N+1)$. Thus we can simplify Eq. (2) as follows:

$$g = (u^* - u_{\max})/(N+1) \tag{3}$$

Furthermore, perceived search cost needs to be estimated and then compared with subject search gain in order to initiate the search process. The perceived search cost is assumed to be constant for the same individual throughout the process. If an individual stops searching after n rounds of search, the perceived search cost must be lower than the subjective search gain after the $(n-1)$th search so that the nth search is meaningful, and must be higher than the expected search gain after the nth search so that the $(n+1)$th search does not occur. The lower bound c^- and upper bound c^+ can be calculated though Eq. (4) and (5), then we can estimate the search cost as shown in Eq. (6).

$$c^- = g_n = (u^* - u_{\max,n})/(n+1) \tag{4}$$
$$c^+ = g_{n-1} = (u^* - u_{\max,n-1})/n \tag{5}$$
$$c = (c^- + c^+)/2 \tag{6}$$

The utility function adopted in this paper is a linear function, which contains five variables: Travel time, travel cost, a dummy variable, TDE and TDL defined in 4.4. The utility function is estimated with the survey data in part 1 and part 2 of the questionnaire. Because the search times of each respondent are recorded in the stated-preference experiment, so the search cost distribution is easily achieved.

4.4. Search rules

There are many methods to signify human knowledge storage and application process. Production (if–then) rules are selected to represent the search process of human beings for several reasons. (1) They are shown to be capable of replicating various types of human heuristics decision-making processes in previous studies on expert systems. (2) They can be implemented to predict search results with minimum computational resources which is important for mode and departure time choice models often involving millions of independent decisions agents. (3) Production rules can express the knowledge of human beings naturally and conform to the cognition process. (4) Models based on production rules have fast calculating speed.

The data set collected from the Pad-based and Web-based travel behavioral survey in Beijing was used to derive the search rules. Because mode switching between metro, bus and non-motorized (walk and bike) is not so meaningful for traffic policies and strategies, we just study the mode switch between car and other modes. In addition, taxi and private car have the similar influence on the traffic system, so we regard them as the same mode: car.

After analyzing the survey data, we find out that there are only 0.85% travellers will switch to car and there are few switches between car and non-motorized modes, so we just study the search process from car to bus and metro. The search process contains two dimensions: travel model and departure time search. The variables used in the search rules include: age (AGE), personal income per year (PI), household income per year (HI), travel distance (TD), outside metro time (OMT), outside bus time (OBT), DTL, DTE, D-TIME, D-COST.

OMT (OBT) means the time travelers spend for going to the metro (bus) station, the time for waiting and transferring. DTL and DTE means the difference value between preferred arrival time (PAT) and actual arrive time (AAT). D-TIME means the increment of travel time, D-COST means the increment of travel cost. As shown Eqs. (7)–(10)

$$DTL = AAT - PAT \quad AAT \geqslant PAT \tag{7}$$

$$DTE = PAT - AAT \quad PAT > AAT \tag{8}$$

$$D - COST = COST^1 - COST^0 \tag{9}$$

$$D - TIME = TIME^1 - TIME^0 \tag{10}$$

AAT is the actual arrival time, PAT is the preferred arrival time, $TIME^1$ and $COST^1$ are the travel time and travel time after changes, $TIME^0$ and $COST^0$ are the values before changes. Machine learning algorithm PART (Frank et al., 2005) is adopted to derive the search rules. The search rule sets for travel mode and departure time are shown below.

The current travel mode is car:
Search bus, if
Rule 1: [AGE > 45 AND D-COST > 5yuan AND PI < 50,000yuan] (12.0/1.0)
Rule 2: [AGE > 37 AND D-COST > 40yuan AND OMT > 30 min] (15.0/1.0)
Rule 3: [150,000yuan < HI ⩽ 200,000yuan AND 100,000yuan < PI ⩽ 150,000yuan AND D-COST > 10yuan AND OMT > 20 min] (3.0)
Rule 4: [OMT > 30 min AND 10 < D-COST ⩽ 45yuan] (5.0/1.0)
Search metro, if
Rule 5: [D-TIME > 25 min AND 50,000yuan < PI ⩽ 100,000yuan] (10.0)
Rule 6: [D-COST > 40yuan AND 300,000yuan < PI ⩽ 350,000yuan AND AGE > 28] (7.0/1.0)
Rule 7: [D-TIME > 25 min AND HI > 400,000yuan AND OMT ⩽ 30 min AND D-COST > 0] (8.0/1.0)
Rule 8: [50,000yuan < PI ⩽ 100,000yuan AND OBT > 10 min AND D-COST > 20yuan] (14.0/2.0)
Rule 9: [150,000 < PI ⩽ 200,000yuan AND D-COST > 5yuan AND OBT > 10 min] (10.0/1.0)
Rule 10: [AGE ⩽ 28 AND OBT ⩽ 30 min AND 150,000yuan < HI ⩽ 200,000yuan AND D-COST > 40yuan] (5.0)
Rule 11: [HI ⩽ 50,000yuan AND DTE < 15 min AND AGE ⩽ 26 AND D-COST > 0] (6.0/1.0)
Rule 12: [21 < AGE ⩽ 28 AND 200,000yuan < HI ⩽ 250,000yuan AND D-TIME > 10 min] (5.0/1.0)
Rule 13: [35yuan < D-COST ⩽ 60yuan AND OBT > 30 min AND OMT ⩽ 20 min] (8.0/1.0)
Rule 14: Otherwise, continue to use car and begin to search departure time (108/20)
Rule 15: Search 0–20 min earlier, if:
[0 < DTL ⩽ 20 min] (4.0)
Rule 16: Search 20–30 min earlier, if.
[10 min < DTL ⩽ 20 min AND TD > 20 km] (16.0/4.0)
Rule 17: Search 30–40 min earlier, if
[20 min < DTL ⩽ 45 min AND TD ⩽ 15 km] (15.0/3.0)
Rule 18: Search 40–60 min earlier, if
[30 min < DTL ⩽ 50 min AND TD > 15 km] (20.0/3.0)
Rule 19: Search 60+ min earlier, if
[DTL > 50 min] (24.0/4.0)
Rule 20: Search 0–20 min later, if
[20 min < DTE ⩽ 40 min AND TD ⩽ 20 km] (34.0/6.0)
Rule 21: Search 20–40 min later if
[30 min < DTE ⩽ 60 min AND TD ⩽ 30 km] (43.0/5.0)
Rule 22: Search 40+ min later, if
[DTE > 60 min] (15.0/2.0)
Rule 23: Otherwise, keep the current departure time as the alternative of the next trip (42.0/0)

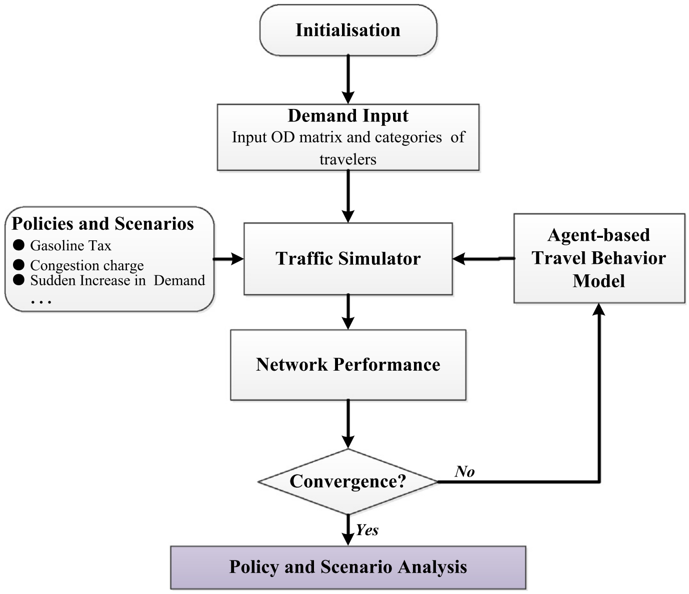

Fig. 8. Policy and scenario analysis framework.

There are 23 rules in the search rule sets are just for the car travelers. Rule 1 means that if an individual's age is bigger than 45, and the travel cost has an increase 5yuan (i.e. congestion charge), and the personal income is below 50,000yuan per year, he will search for bus as the alternative travel mode. It is reasonable, because bus is cheaper than metro in Beijing. When a traveler will not search for alternative mode according to the rules from 1 to 13, then he will continue to use car as the travel mode and begin to search for alternative departure time according to rules from 15 to 22.

4.5. Decision rules

After each round of search, a new travel mode and departure time is identified by the search rules. The traveler then should decide whether to stick to the current travel mode and departure time or switch to the new mode and departure time according to decision rules. Similar to search process, if–then rules are selected to represent the decision-making process of human beings. The machine learning algorithm JRip (Frank et al., 2005) is adopted to derive the decision rules. The decision variables used in rule set include: AGE, PURPOSE, GENDER, $\Delta TIME$, $\Delta COST$, INCOME.

$$\Delta TIME = (TT^1 - TT^0)/TT^0 \tag{11}$$

$$\Delta COST = (C^1 - C^0)/C^0 \tag{12}$$

TT^1 is the travel time with the alternative travel mode or departure time, TT^0 is the travel time before switch. C^1 is the travel cost with the alternative travel mode or departure time and C^0 is the travel cost before switch. The decision rules are presented below.

Decision Rules:
The Current Mode is Car, Switch to the alternative mode, if
Rule 1: [$\Delta TIME \leqslant -0.066667$ AND AGE $\leqslant$ 30 AND PURPOSE = non-commute] (51.0/6.0)
Rule 2: [$\Delta TIME \leqslant 0.105263$ AND $\Delta COST \leqslant -0.022727$ AND age $\leqslant$ 30 AND GENDER = female) (13.0/1.0)
Rule 3: [$\Delta TIME \leqslant -0.1$] (15.0/4.0)
Rule 4: [INCOME $\geqslant$ 400,000 AND AGE $\leqslant$ 33] (19.0/4.0)
Rule 5: [$-0.287129 \leqslant \Delta TIME \leqslant -0.066667$ AND $\Delta COST \leqslant -0.75$ AND AGE $\geqslant$ 32] (8.0/0.0)
Rule 6: Otherwise, continue to use the current mode (523.0/45.0)
The Current Mode is Car, Switch to the alternative departure time, if
Rule 7: [$\Delta COST \leqslant 0$ AND $\Delta TIME \leqslant -0.1$] (125.0/15.0)
Rule 8: Otherwise, continue to use the current departure time.

Eight rules are derived from the survey data. Rule 1 indicates that if the travel time decreases by more than 6.67%, and the age is less than 30 years old, and the trip is non-commute travel, then the traveler will switch to the new mode. Rule 7 shows

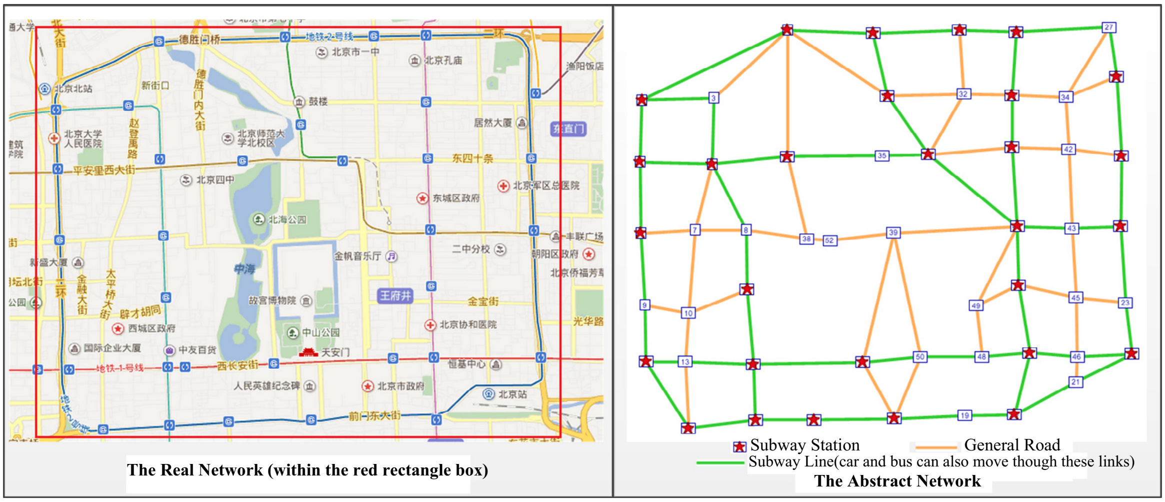

Fig. 9. Simulation network (2nd ring road of Beijing).

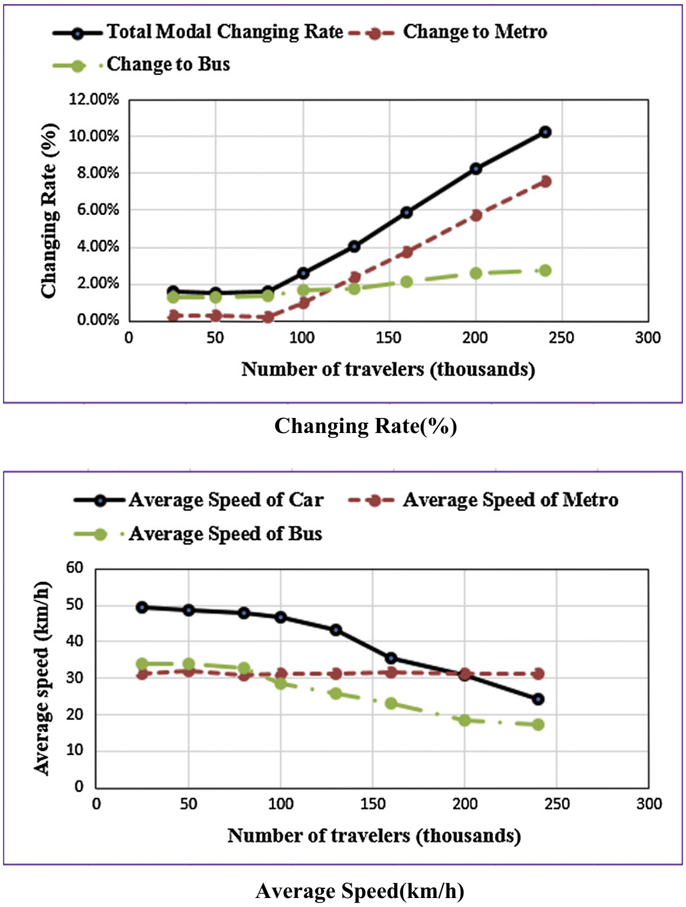

Fig. 10. Various demand scenarios.

that if the travel cost can be reduced and the travel can be reduced by at least 10%, then the traveler will switch to the new departure time.

5. Policy and scenario analysis

5.1. Analysis framework

The agent-based joint travel mode and departure time choice model can be combined with macro-/meso/micro-scopic network traffic models to analyze the modal shift and peak spreading process under different policies and scenarios. As shown in Fig. 8, at first, an initial OD matrix and an initial dynamic network user equilibrium are given. Then policies and scenarios (e.g. gasoline tax, congestion charge and sudden increase in demand) are taken to the network, then the equilibrium state is disturbed and travelers will conduct modal shift and departure time switch following the agent-based travel behavior model until the Behavior Equilibrium (BE) is obtained.

5.2. Simulation setup

In this section, the model is applied to estimate the modal shift and peak spreading effects due to congestion charge and increased level of congestion (caused by sudden increase in demand) on a road network The simulation details is set up as follows:

- The topological structure of the network is derived from the Second Ring Road of Beijing which contains 52 nodes and 186 links and the size of the area is about 7 km × 7 km. The free flow speed is 50 km/h link (2lanes) capacity is 4000 vehicles per hour. As shown in Fig. 9, the metro lines are arranged according to the real situation. There are 29 metro stations and 82 metro links (see Fig. 10).
- The simulation program is coded in MATLAB. Dijkstra algorithm is adopted to search for the shortest route between any two nodes for car and bus. The search process for metro travelers is *Origin--Metro Station--Metro Station--Destination* and the distance function is *walk-distance* $*$ *10 + lengh of metro line* for those not departure or arrival at a metro station.
- Bureau of Public Roads (BPR) volume-delay function is chosen to compute traffic congestion for simplicity. Considering morning peak period only, the subjective arrival time is assumed to be a Normal Distribution whose average value is 8:20, and variance is 20 min. The departure time equal to arrival time minus travel time.
- The travel cost of car is proportional to travel time, and the cost for bus is 1yuan, for metro is 2yuan on the basis of the current situation in Beijing.

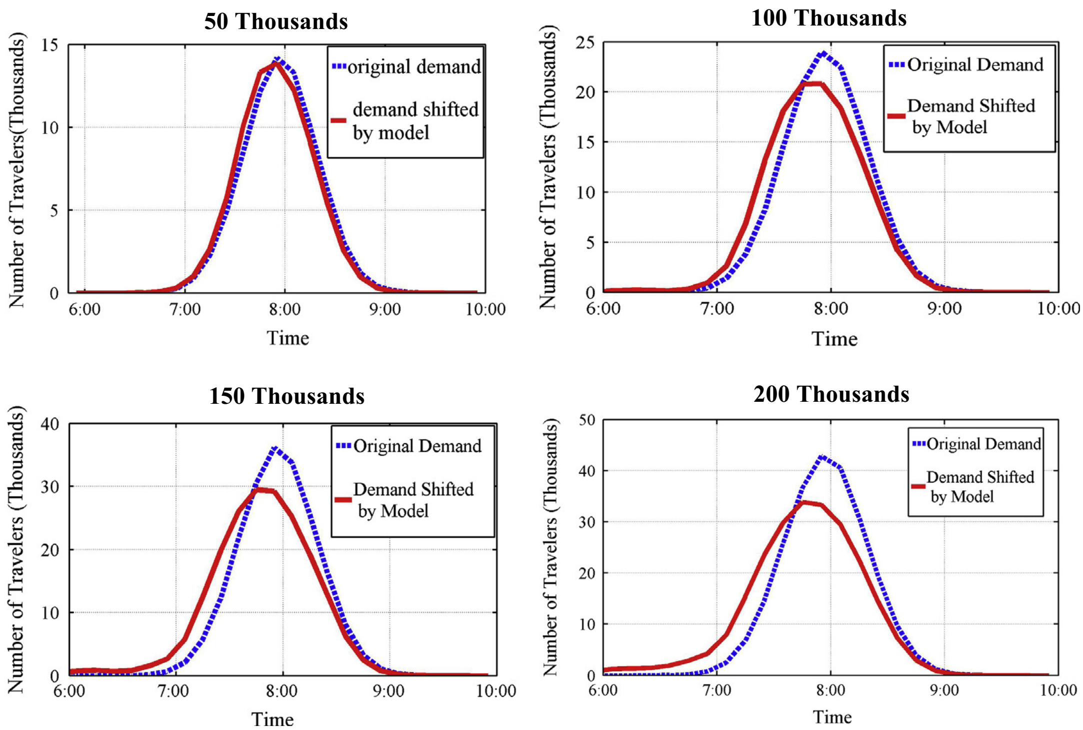

Fig. 11. Peak spreading effect.

The simulation contains 4 steps:

Step 1: Input the initial OD matrix whose distribution proportion is achieved from the Sixth Nationwide Population Census Data, while the number of trips is achieved though assumption, then distribute gender, age, personal income, household income, travel purpose, outside bus time and outside metro time to each agent according to survey data. The original travel mode is car for most agents.
Step 2: Conduct the first round of simulation, then record the travel time and travel cost of each agent, and the average speed of each mode.
Step 3: Put the policy and scenario into effect, and calculate the D-TIME, D-COST, DTL, and DTE of each agent after simulation. Then travelers then decide whether or not to search for alternative mode or departure time according to the search rules.
Step 4: Conduct another simulation round to calculate the $\Delta TIME$ and $\Delta COST$ for travelers to make decision according to the decision rules.
Step 5: Continue iteration until Behavior Equilibrium.

5.3. Analysis of demand increase

We assume that there are 24 thousands agents on the network at first, and their initial mode is all by car. We increase the demand gradually to observe the changing process of average speed, modal changing rate (the percentage of traveler switch to bus and metro) and departure time.

As shown in Fig. 11, when the total number of travelers is below 80 thousands, the changing rating nearly keep the same and the value is only about 1.50%; the average speed (consider outside vehicle time) of car, bus and metro also remain unchanged. When total number exceeds 80 thousands, the changing rate ascends gradually along with the increase of travelers; the average speed of car and bus decrease at the same time. While the average of metro almost remain the same

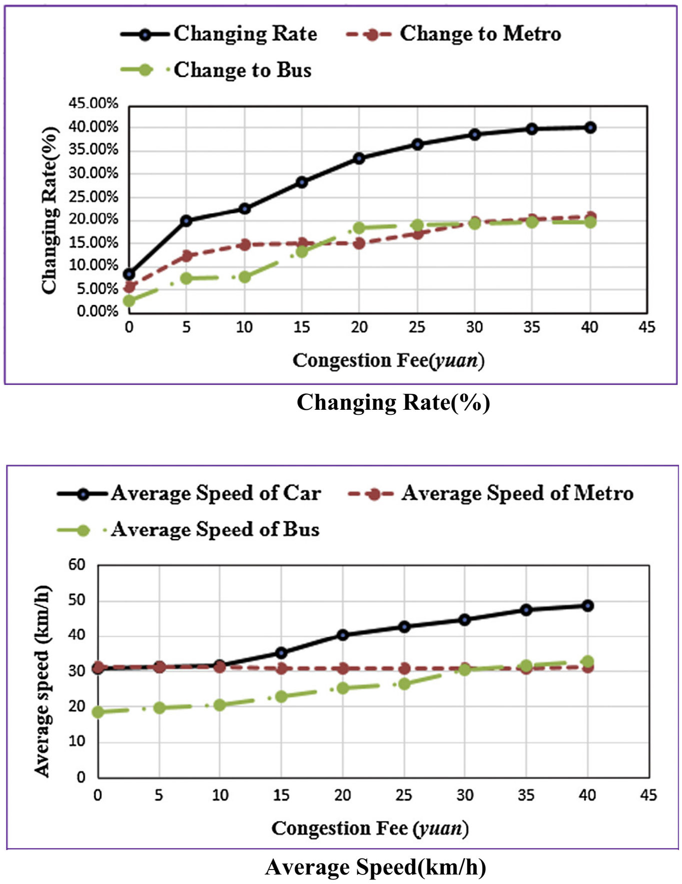

Fig. 12. Congestion charges scenarios.

because of the low sensitivity to volume. When the total number is 200 thousands, the changing rate is 8.29%, among which 5.73% travelers shift to metro, 2.56% shift to bus. The effects of peak spreading is shown in Fig. 12.

Fig. 11 shows that travelers who do not shift mode will switch their departure time due to the increase of demand to reduce congestion. The more increase in demand, the more significant of the peak spreading phenomenon. When the total number of travelers is 200 thousands, there are about 23.31% travelers switching their departure time from 8:00 am to other alternatives.

5.4. Analysis of congestion charge with various demands

Now we assume that the policy of congestion charge is implemented to all of the car travelers when the demand is 200 thousands. We set the congestion fee to be 5yuan, 15yuan, 20yuan, 25yuan, 30yuan, 35yuan and 40yuan. When the Behavioral Equilibrium is obtained after simulation, the changing rate and average speed is displayed in Fig. 12.

As shown in Fig. 12, the changing rate is constantly improved with the increase of congestion fee. Without congestion charge, the changing rate is only 8.29% when the demand is 20 thousands; when the congestion fee is 10yuan, the changing rate increases by 14.27%, reaches 22.56%, which means another 14.27% of the travelers will change to metro and bus; when the congestion fee is 30yuan, another 17.40% of the travelers will shift to public transit compared to 20yuan. The average speed of car and bus rise gradually along with the increase of congestion fee due to the improvement of the road congestion, while the average speed of metro change a little because of the low sensitivity to volume. The peak spreading process is presented in Fig. 13.

We can conclude from Fig. 13 that congestion charge has significant impact on the effect of peak spreading. Without congestion fee, there are about 14.70% travelers will switch their departure time at 8:00 am, while the switch percentage decreases along with the increase of congestion fee. When the congestion fee is 40yuan, there are only 8.24% travelers switching departure time. The results indicate that congestion charge can urge travelers shift from car to public transit, thus improve the performance of the network and ease the traffic congestion, so that fewer travelers will switch departure time when demand increase.

The scenario analysis in 5.3 shows that travelers will both shift travel mode and departure time to make the situation better when demand increase, but the effect is not significant because the mode changing rate is not so high. The analysis in 5.4 proves that congestion charge can increase the changing rate to a large extent so that this policy is an effective way to alleviate traffic jams.

The simulation result in 5.3 and 5.4 shows that the agent-based mode choice and departure time choice model can predict the mode shift and peak spreading behavior effectively. On the basis of the result given by the model, we can develop other

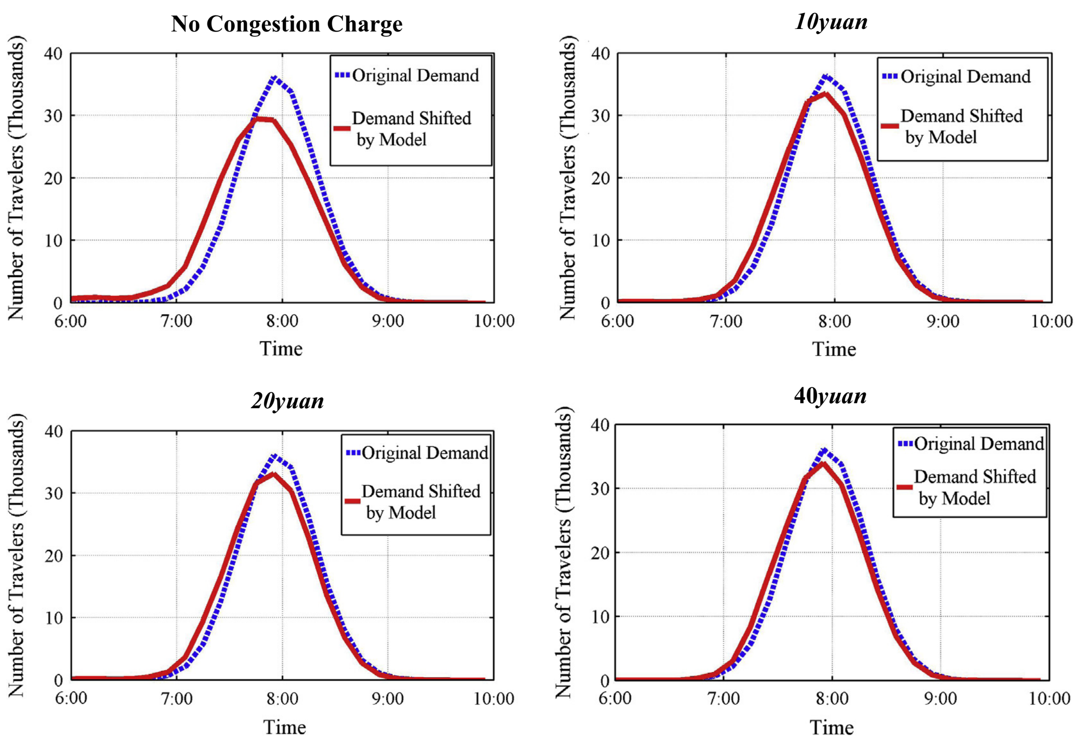

Fig. 13. Effect of peak spreading under different fees.

evaluation model to assess the benefit and cost of different policies (i.e. congestion fee), thus helping the government to make more scientific traffic management policies and strategies.

6. Conclusions and future work

On the basis of the SILK theory, we developed an agent-based based choice model for travel mode and departure time according to the behavior survey conducted in Beijing, China. This research is an extension of the model proposed in Zhang (2006) and Xiong (2011), and focuses on the issues in developing countries where the travel behavior is different from that in developed countries. Different from the traditional utility maximization based model, this model considers the bounded rationality of human beings and focuses on the knowledge learning, search and decision making process of agents. In addition, this joint model take the effect of interactions between travel mode shift and departure time switch into consideration and try to evaluate the combined influence on the network. Production (if–then) rules based on Fuzzy Set Theory are adopted to represent the search and decision process of travelers. In order to calibrate and validate the model, a joint revealed/stated-preference Web-based and pad-based survey which contain 3 parts was conducted in Beijing to obtain the behavior data.

In the aspects of application, the joint model can be combined with traffic simulators to analyze the change of road network under different scenarios. In the case study, we took the network within the Second Ring Road of Beijing as the study case. Three modes (car, metro, bus) are considered and a hypothetical initial OD matrix is given. We analyzed the process of mode shift and departure time switch under two scenarios, i.e. various demands with and without congestion charges. The results shows that the model is capable of modeling the interaction of mode and departure time and can be used to estimate the changes of mode shift and peak spreading process of the network.

The future work may be conducted toward two directions. First, a comprehensive agent-based travel behavior model can be expanded to the whole decision-making process of a traveler, such as destination choice, route choice, departure time choice and mode choice. Second, a real network with actual traffic demand in Beijing can be further studied by the proposed model in order to evaluate potential management strategies or policies.

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