M. Meng, C. Shao, J. Zeng, C. Dong: A Simulation-Based Dynamic Traffic Assignment Model with Combined Modes

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# A SIMULATION-BASED DYNAMIC TRAFFIC ASSIGNMENT MODEL WITH COMBINED MODES

#### ABSTRACT

This paper presents a dynamic traffic assignment (DTA) model for urban multi-modal transportation network by constructing a mesoscopic simulation model. Several traffic means such as private car, subway, bus and bicycle are considered in the network. The mesoscopic simulator consists of a mesoscopic supply simulator based on MesoTS model and a time-dependent demand simulator. The mode choice is simultaneously considered with the route choice based on the improved C-Logit model. The traffic assignment procedure is implemented by a time-dependent shortest path (TDSP) algorithm in which travellers choose their modes and routes based on a range of choice criteria. The model is particularly suited for appraising a variety of transportation management measures, especially for the application of Intelligent Transport Systems (ITS). Five example cases including OD demand level, bus frequency, parking fee, information supply and car ownership rate are designed to test the proposed simulation model through a medium-scale case study in Beijing Chaoyang District in China. Computational results illustrate excellent performance and the application of the model to analysis of urban multi-modal transportation networks.

#### **KEY WORDS**

dynamic traffic assignment, combined modes, mesoscopic simulation, time-dependent shortest path algorithm

## 1. INTRODUCTION

The modelling of simulation-based dynamic traffic assignment (DTA) has witnessed a growing amount of research attention recently as the management of the time-dependent traffic flow becomes more and more important. Most of the simulation-based DTA literatures are concentrated on the single mode modelling, usually private car or bus. In metropolitan areas, however, the combined travel mode is becoming more and more common, where travellers often transfer more than one time to complete a trip by using at least two different traffic modes. The ignorance of the transfer behaviour limits the existing research used in the realworld application.

Traffic assignment with combined modes is more complicated than the assignment of a pure mode trip. Especially, dynamic combined trip assignment needs to focus on the mode-route choice problem in the time-dependent network. It involves mode and route choice simultaneously in the traffic demand simulator in which travellers choose not only the routes but the traffic mode at the transfer nodes. The existing simulation-based DTA models are still limited by the pure mode trip assumption [1-5]. For instance, the mainstream traffic planning software DYNASMART and DYNAMIT regard buses as part of the vehicular mix, which follow a pre-specified route and departure schedule. The travel mode assignment is exogenous to the model which neglects the interaction between mode choice and trip assignment. Few DTA studies have been developed with considering the combined mode problem. Abdelghany [6] proposed an analytical stochastic DTA model with combined mode in the multi-modal networks. The model is formulated as minimization mathematical program with a set of descriptive constrains. Meanwhile, Abdelghany and Mahmassani [7] presented a simulation-based DTA model with combined mode. They captured the interaction between mode choice and traffic assignment in a multi-modal network. However, these two models just focus on the motor vehicles and regard travel time as the only factors in road impedance function model. A simulation-based DTA model with combined modes is closer to realistic behaviour in mode choice and assignment procedures, which should be the future direction of the research.

Four different traffic modes are considered in this paper including private car, bus, subway, and bicycle. A simulation-based approach to the dynamic assignment problem is adopted in this work in an attempt to combine mode and route choice with more realistic travel time function. The paper is organized as follows. The simulation framework is presented in Section 2. Section 3 elaborates about the components of the mesoscopic vehicle movement simulator. After the travel time analysis, Section 4 proposes the assignment algorithm and the mode-route choice procedures. Five sets of simulation experiments are designed in Section 5. Computational results illustrate the validity of the model and provide the basis for management policies. Finally, the concluding remarks are given in Section 6.

## 2. SIMULATION FRAMEWORK

In general, traffic simulation models can be categorized into three classes: macroscopic, mesoscopic, and microscopic models [8-10]. A mesoscopic model is more flexible than macroscopic models for modelling travel behaviour, such as route choice, and coarser than microscopic models for modelling the entity movement, such as lane changing. This can effectively reduce computational complexity and ensure the results with certain accuracy. Therefore, if the precision is not very high while dealing with a large-scale network, a mesoscopic simulation model would be the best choice for the traffic simulation.

The mesoscopic simulation framework is shown in *Figure 1*. The inputs in the system are the network information and available OD demand. The demand simulator separates the multimodal transportation network into several traffic layers to represent individual traffic modes. In addition, the demand simulator updates the traffic disutility at the start of each simulation run. The supply simulator moves the vehicles on the lane of the network until the end of simulation time. When the simulation process is complete, the output is the distribution of traffic flows which can be used in the traffic analysis.

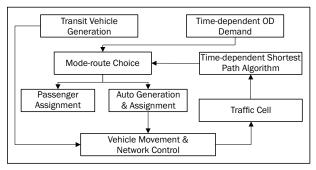


Figure 1 - Simulation framework

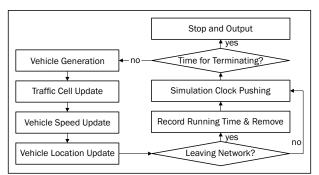


Figure 2 - Flowchart of the mesoscopic traffic simulator

## 3. MESOSCOPIC TRAFFIC SIMULATOR

The flowchart of the mesoscopic traffic simulator is shown in *Figure 2*. The vehicle simulator is composed of five modules: vehicle generation module, traffic cell module, vehicle speed update module, vehicle location update module, and vehicle movement module.

#### 3.1 Vehicle generation module

Time-dependent OD demand is considered in the simulation. The transit vehicles (bus and subway) follow the pre-determined timetable and routes, while

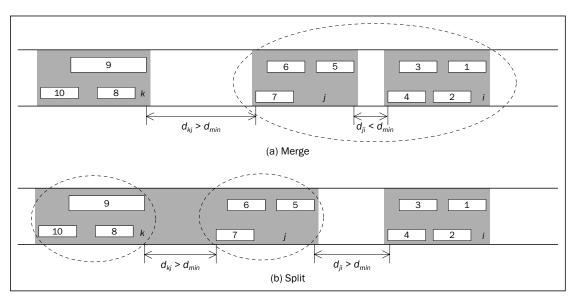


Figure 3 - Merging and splitting of traffic cells

the generation of cars and bicycles is a stochastic procedure. A Poisson distribution is used to represent the traffic arrival statistical regularity so that the time headway follows a negative exponential distribution.

#### 3.2 Traffic cell update module

Vehicles are formed into many groups in the simulation, which are called traffic cells in MesoTS (Mesoscopic Traffic Simulator) [11]. Each traffic cell is composed of vehicles which have the same traffic dynamics, such as traffic speed, vehicle position. The composition of the traffic cell varies with the changes of vehicle speed or position. The model defines first a standard distance DD (e.g. 60 m) to control the merging and splitting of traffic cells. The judge distance is the gap distance between the last vehicle in the leading traffic cell and the first vehicle in the following traffic cell (see  $d_{kj}$  and  $d_{ji}$  in Figure 3). When the vehicles are on the same segment, if the distance between two traffic cells is less than DD, these two traffic cells are merged into a larger traffic cell as shown by cell i and j in Figure 3-(a). Otherwise, if the distance between two vehicles in a traffic cell is greater than DD, this traffic cell is split into two cells as cell j in Figure 3-(b), where these two vehicles are the lead vehicle and the tail vehicle, respectively.

#### 3.3 Speed update module

The speed update module updates the speed of each vehicle in the traffic cells by two traffic modes [12-13]: cell-following model calculates the speed of the lead vehicle in a traffic cell; speed-density model calculates the speed of the tail vehicle in a traffic cell. The lead vehicle speed in the traffic cell can be obtained as follows:

The vehicle position in the next time step is the current position plus the travelled distance. If a bus sta-

$$v_{ij} = \begin{cases} v_{\max} & d_{ij} \ge DD, \\ \lambda_i v_{\max} + (1 - \lambda_i) v_{j0} & d_{ij} < DD, \end{cases}$$
(1)

where  $v_{ij}$  is the cell-following speed of the lead vehicle in traffic cell *i* travelling in direction *j*;  $v_{max}$  is the free flow speed in the segment;  $v_{j0}$  is the speed of the tail vehicle in the leading traffic cell *j*;  $\lambda_i$  is a scalar equal to  $d_{ij}/DD$ .

The tail vehicle speed in the traffic cell can be obtained as:

$$V_{i0} = V_{\min} + \left(V_{\max} - V_{\min}\right) \left[1 - \left(\frac{k_i}{k_{jam}}\right)^{\alpha}\right]^{\beta}, \qquad (2)$$

where  $v_{i0}$  is the speed of the tail vehicle in traffic cell *i*;  $k_i$  is the vehicle density in traffic cell *i*, which is equal to the total vehicle length in the traffic cell divided by the total segment length occupied by the traffic cell;  $k_{jam}$ is the jam density of the segment, which is usually set to 1;  $v_{min}$  is the minimum traffic speed of the segment, which is usually set to 0;  $\alpha$ ,  $\beta$  are the indefinite parameters, usually set as  $\alpha = 1.8$ ,  $\beta = 5.0$  [11].

The others vehicles in the middle of the traffic cell are calculated by a linear interpolation based on their speed:

$$v_{ij}^{n} = \min\left\{v_{ij}, v_{\min} + (v_{\max} - v_{\min})\left[1 - \left(\frac{k_{n}}{k_{jam}}\right)^{\alpha'}\right]^{\beta'}\right\}$$
(3)

where 
$$v_{ij}^n$$
 is the speed of the N<sup>th</sup> vehicle in traffic cell *i* towards direction *j*;  $k_n$  is the traffic density from the N<sup>th</sup> vehicle to the end of the road. In order to make sure that  $k_i > k_n$ ,  $\alpha'$ ,  $\beta'$  are different with  $\alpha$ ,  $\beta$  in Equation (1), typically set as  $\alpha' = 1.5$ ,  $\beta' = 3$  in the normal traffic condition.

tion is located along this link, after leaving the station the bus may clash with the last vehicle. To avoid this, the model takes the minimum position between the last vehicle position and the simulation position as the updated position.

A channelized section of a certain length is set for each segment in the simulation. Each channelized lane corresponds to a different turning direction, where a specific mode-route choice is determined. Once a vehicle moves near the intersection and into a channelized lane, it is not allowed to change its turning direction until it is in the downstream section. Vehicles in different lanes have no influence on each other.

### 3.5 Capacity constraints

The model calculates the average time headway in each update phase. The average time headway determines the time at which vehicles can move into the segment:

$$t_n = t_{n-1} + \frac{1}{Q} \tag{4}$$

where  $t_n$  is the earliest time for the next vehicle entering the segment;  $t_{n-1}$  is the time for the last vehicle entering the segment; Q is the real capacity of the segment,  $Q = q\bar{Q}$ , in which  $\bar{Q}$  is the traffic capacity in one direction; if the intersection is control-signalized, g is the green/cycle ratio; if the intersection is unsignalized, g is the delay coefficient [14]. If a bus stop is located along a particular segment,  $\bar{Q}$  for this segment should be reduced in order to represent the bus stopping effect.

A vehicle is allowed into a link only if the simulation time is greater than or equal to  $t_n$ ; otherwise, the vehicle queues at the node. Meanwhile, the model will check the vehicle count in the network while updating. If the end of the last traffic cell reaches the link boundary, no vehicle is allowed into this segment.

## 4. TIME-DEPENDENT SHORTEST PATH ALGORITHM

The total simulation time is divided into several time intervals. Each time interval is also divided into certain iterative phases according to the system initialization. The model updates the path travel time at the beginning of each iterative phase, finds the shortest path with the k-shortest path algorithm, and finally assigns the traffic flow based on an improved C-Logit model.

#### 4.1 Travel utility function

To facilitate the interface of the mode choice model with the shortest path calculation, the generalized cost is expressed in units of time (minutes). The resulting systematic utility equations are:

$$U_{\rm Sin} = -0.04722 \, C_k^{od}(s) \tag{5}$$

$$U_{Com} = -2.169 - 0.04722 C_k^{od}(s)$$
(6)

$$U_{Tra} = -0.598 - 0.04722 C_k^{od}(s) \tag{7}$$

where Sin = single-car travel mode, Com = combinedcar and transit travel mode, Tra = Transit travel mode; U is the travel utility;  $C_k^{od}(s)$  is the generalized traffic cost of path k in time s. Parameters in the above equations are calibrated by the survey results from the Beijing Huilongguan residential area.

The travel cost is updated only in the new time interval to reduce the calculation. The generalized travel cost contains many factors like travel time, travel cost, travel distance, and so on. Assuming these factors are independent for each link, the generalized traffic cost can be expressed as

$$C_k^{od}(s) = \delta_{ak} C_a^{od}(s) \tag{8}$$

where  $\delta_{ak}$  equals 1 if link *a* lies on path *k*, otherwise 0;  $C_a^{od}(s)$  is the traffic cost of the link *a* in time s. The considered travel time and travel cost,  $C_a^{od}(s)$  can be expressed as:

$$C_a^{od}(s) = \omega_t T_a(s) + \omega_m M_a(s)$$
(9)

where  $T_a(s)$  is the travel time of link *a* in time s;  $M_a(s)$  is the travel cost of link *a* in time s;  $\omega_t$  and  $\omega_m$  are the weights respectively. The details about the two components are discussed further in the text.

Running in an independent space, a subway link is affected little by external circumstances. Travel time for a subway is regarded as a deterministic value equalling the subway's runtime adding the waiting time. The travel time for a bus includes the bus run time and the delay time at the bus station which is determined by the number of travellers getting on and off the bus.

The link travel time for the bicycle and the private car is the mean time for many vehicles passing through. Let  $t_n^k$  denote the mean travel time for all vehicles passing through the link at iterative phase *n* in time interval *k*, and let  $T_{n-1}^k$  denote the mean travel time after the previous iterative phase *n*-1 in the same time interval. The link travel time for the bicycle and the private car can be updated by:

$$T_n^k = T_{n-1}^k + \frac{1}{n} (t_n^k - T_{n-1}^k)$$
(10)

The model decides the set of alternative moderoute choice at the beginning of the next iterative range according to the updated link travel time  $T_n^k$ . If no vehicle has passed through the link in a certain iterative phase, the link travel time is not updated; if there are vehicles passing through the link, the mean link travel time equals the total travel time for all passing vehicles on the link divided by the total number of vehicles. Moreover, one case that may arise at the onset of the simulation is that no vehicle arrives at a link in the whole time interval, and then the link travel time is equal to the link length divided by the link freeflow speed.

#### 4.2 Mode-route Choice Model

The nodes in the multi-modal networks can be of two types: route-choice node and non-route-choice node. Route-choice nodes are the nodes which connect several downstream nodes, in which the moderoute choice may be changed. Non-route-choice nodes are the nodes which connect only one downstream node with the same traffic mode, in which the travel route cannot be chosen. Therefore, the model only needs to make mode-route choices at the route-choice nodes in the simulation, thereby reducing the calculation process. Moreover, the route-choice node can be manually set in a large network for increasing efficiency.

After calculating the shortest path in the network, the travel route can be determined by a nested logit model. Mode-route choice in the simulation is assumed to follow the Stochastic User Equilibrium (SUE) principle. The mode-route choice probability is determined by absolute deviation of the path travel time in the C-Logit model as follows:

$$P_{k}^{od}(s) = \frac{\exp[-bU_{k}^{od}(s) - CF_{k}]}{\sum_{k \in K^{od}} \exp[-bU_{k}^{od}(s) - CF_{k}]}$$
(11)

where  $P_k^{od}(s)$  is the probability for choosing path k in time s;  $U_k^{od}(s)$  is the traffic utility of path k in time s; b is a non-negative parameter;  $CF_k$  is the common factor of path k, and the formulation from Cascetta [15] is introduced herein as follows:

$$CF_{\kappa} = \rho \ln \left[ \sum_{q \in K^{od}} \left( \frac{C_{\kappa}^{od} + C_{q}^{od}}{\sqrt{C_{\kappa}^{od} C_{q}^{od}}} \right)^{\sigma} \right]$$
(12)

where  $\rho$  and  $\sigma$  are non-negative parameters.

In the real world, however, travellers are more concerned about the relative deviation of the path travel time. Therefore, the C-logit model is modified as follows:

$$P_{k}^{od}(s) = \frac{\exp\left[-b\frac{U_{k}^{od}(s)}{U^{od}(s)} - CF_{k}\right]}{\sum_{q \in K^{od}} \exp\left[-b\frac{U_{q}^{od}(s)}{U^{od}(s)} - CF_{k}\right]}$$
(13)

where  $U^{od}(s)$  is the average traffic utility.

#### 4.3 Time-dependent K-shortest path algorithm

The assignment procedure in each iterative phase is achieved by a multi-objective shortest path algorithm. The k-shortest path algorithm [16] is an extension of the typical Dijkstra algorithm to calculate the set of the shortest travel time paths between every origin-destination pair. The primary advantage of this approach is that it can obtain more than one shortest path, and determine the distinct set of the shortest path numbers according to different criteria. The procedure proposed herein is extended by Kihara et al. [17] as follows:

- Step 0: Initialization. Set time interval TI=1, iterative phase IP=1;
- Step 1: Calculate the shortest path which has the least travel time between the original node and the destination node by Dijkstra's Algorithm;
- Step 2: Remove all links which belong to Step 1 from the network;
- Step 3: Repeat Step 1 and Step 2 k-times, and then k link-disjoint paths are obtained. If the Dijkstra's algorithm cannot be executed as the links are all removed, the shortest path in this IP is founded. The traffic flow can be assigned based on the mode-route choice model;
- Step 4: If the iterative phase matches the final iterative phase in this time interval, TI=TI+1, else IP=IP+1 and go to Step 1;
- Step 5: If the time interval reaches the final time interval, the algorithm is terminated, else TI=TI+1 and go to Step 1.

#### 5. EXPERIMENTS AND ANALYSIS

Five sets of simulation experiments were designed to illustrate the performance and application of the model. A medium-scale network was used in these experiments as shown in Figure 4, which is an area in the Chaoyang District in Beijing. The network consists of 5 subway lines (as bold blue lines) with 39 stations (as yellow nodes), and 188 road links with 122 nodes. The subway lines overlap with the roads on the same locations, but in two different layers. A bus line is taken into consideration only if it has at least four stations in the study area. Hence, 18 bus lines with 51 stations were selected as shown in Figure 5. As explained before, a bicycle link is the road link between an origin /destination node and a subway station. The bicycle and bus networks are introduced here for illustrative purposes only, and do not correspond to available service (which does not affect the examination of the model).

It is assumed that no traveller would be willing to transfer more than twice in one trip. Five travel modes are available for all travellers: private car, park and ride (P&R), one bus line, bus to transit (bus or subway), bicycle to transit (bus or subway). The proportions for five travel modes and the average travel time (minute) are recorded as the output results. Travellers head to the CBD area (the upper part of the network) from all other zones. All travellers are generated over 20 minutes of the peak period between 12 zones. The iterative phase is 0.5 seconds, and the time interval is 5 minutes. All travellers are assumed to have pre-trip information on available alternatives, and have the access to use a car and a bicycle (own or rent). The free flow speed and minimum speed of the road are set as 60 km/h and 15 km/h;62 signalized intersections are assumed to operate under vehicle-actuated two-phase control, the green ratio is set as 0.45; 60 unsignalized intersections), stop sign control (25 intersections) and yield sign control (15 intersections). The frequency of the subway is 15 vehicle/hour. The bus ticket is 1 yuan. Other parameters are:  $\xi = 18$  yuan/hour, b = 3.3,  $\omega_t = 0.5$ ,  $\rho = 1$ ,  $\sigma = 2$ .

The first set of experiments studies the effect of the different congestion levels. Four OD demand levels are considered in the experiments with regard to the spatial distribution, the OD trip desires, morning peak travel pattern. In this experiment, the traffic information is fully provided, the bus frequency is 12 buses/hour, and parking fee is 6 yuan. *Table 1* shows the effect of the network congestion on mode split and average travel time. With the increase in network congestion, more travellers will prefer the transit travel mode and the combined travel mode. For example, the

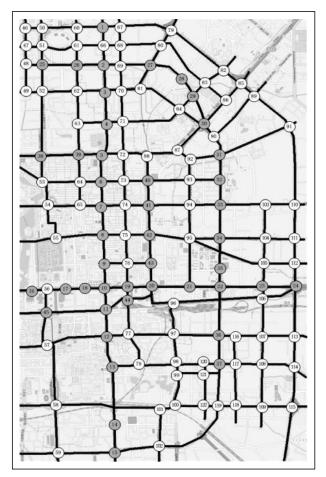


Figure 4 - Road network

proportion of car travel trips decreases from 63.0% for 9,000 OD demand to 60.6% for 15,000 OD demand. Similarly, the one bus line travel mode increases from 3.5% for 9,000 OD demand to 4.6% for 15,000 OD demand. With the increase of OD demand, transit travel trip is more attractive than car trip. Meanwhile, the increase of OD demand also adds the average travel time nearly in a linear pattern. The average travel time for the highest OD demand increases by 48.5% compared to the lowest level.

The effect of imposing parking fee on private car travellers is examined in the second set of experiments. The parking fee which ranges from  $\pm 0$  to  $\pm 12$  is applied to all final destinations in the network. In this experiment, the traffic information is fully provided, the bus frequency is 12 buses/hour, and the OD demand is 13,000, the parking fee at transfer node is  $\pm 2$ . A private car traveller who transfers to subway or bus to complete their trip must pay the parking fee and the transit ticket. Parking fee is assumed to charge for the entire parking time in one day. The simulation results are listed in *Table 2*. It shows that with the increase of the parking fee, the proportion of park and ride rises in a certain range, and other travel modes have

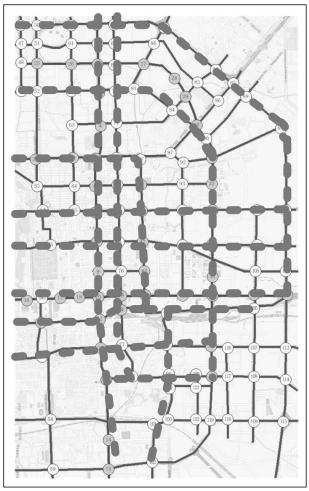


Figure 5 - Bus network

| OD demand                 | 9,000 | 11,000 | 13,000 | 15,000 |
|---------------------------|-------|--------|--------|--------|
| Private Car               | 63.0% | 62.7%  | 61.5%  | 60.6%  |
| Park and Ride             | 24.0% | 24.1%  | 25.3%  | 25.5%  |
| One Bus Line              | 3.5%  | 3.7%   | 3.9%   | 4.6%   |
| Bus to Transit            | 3.0%  | 3.2%   | 3.1%   | 3.2%   |
| Bicycle to Transit        | 6.4%  | 6.3%   | 6.2%   | 6.1%   |
| Average travel time (min) | 16.01 | 19.34  | 20.55  | 23.78  |

Table 1 - Effect of OD demand on travel mode split and traffic assignment

not changed much. When the parking fee is ¥0, the proportion of cars is the highest (75.8%); when the parking fee is ¥9, the proportion of cars is about 50%, when the parking fee is ¥12, the proportion of cars to subway is nearly 40%. Therefore, in this case, if the management objective for the proportion of cars is less than 50%, the parking fee should be set at more than ¥9.00, fewer travellers will choose the car trip because of high money cost at the destination. On the other hand, the increase of the parking fee at the final destination adds to the attractiveness of transit trip and the combined trip as the advantage of the traffic cost. Travellers would avoid high parking fees at their destination to change their travel mode. For example, the proportion of park-and-ride rises more than twice from 13.4% to 29.7%, and one bus line trip rises more than three times from 3.6% to 14.5%. Meanwhile, the increase of parking fee also adds to the average travel time as the transfer time and the delay time of transit increase.

The effect of bus frequency is examined in the third set of experiments. The bus frequency which ranges from 3 buses/hour to 15 buses/hour is assumed to apply to all bus lines in the network. In this experiment, the traffic information is fully provided, the parking fee is ¥6.00, and the OD demand is 13,000. The simulation results listed in Table 3 show that with the increase of the bus frequency, a slight increase in the transit share is observed. For example, when the bus frequency increases from 3 buses/hour to 12 buses/hour, the private car trips drop by 15.0%, the park-and-ride trips double to 25.3%, and the one-bus line trip increases almost 3 times to 3.9%. The increase in bus frequency to 15 buses/hour does not lead to a significant change in the travelling mode share, but most of the shift trips choose the one-bus line as the advantage of saving the transfer time. Therefore, considering the invested funds, the best bus frequency should be set at about nearly 12 buses/hour. Meanwhile, the increase of bus frequency reduces the average travel time as both the transfer time and the delay time of transit become smaller.

The fourth set of experiments examines the effect of traffic information on the travel mode choice. Five cases are considered in the experiments: full information, no car transfer information, no bus transfer information, no bicycle transfer information, and no all-transfer information. The traffic information is assumed as the only accessibility for travellers to other traffic modes. Without transfer information, travellers

| Parking Fee               | 0     | 3     | 6     | 9     | 12    |
|---------------------------|-------|-------|-------|-------|-------|
| Private Car               | 75.8% | 70.2% | 61.5% | 51.3% | 40.3% |
| Park-and-Ride             | 13.4% | 17.5% | 25.3% | 26.6% | 29.7% |
| One Bus Line              | 3.6%  | 3.8%  | 3.9%  | 8.9%  | 14.5% |
| Bus to Transit            | 2.1%  | 2.8%  | 3.1%  | 6.8%  | 8.9%  |
| Bicycle to Transit        | 5.1%  | 5.7%  | 6.2%  | 6.4%  | 6.6%  |
| Average travel time (min) | 20.29 | 20.38 | 20.55 | 20.87 | 21.21 |

| Table 3 - Effect of bus | frequency on travel | mode split and tr | affic assignment |
|-------------------------|---------------------|-------------------|------------------|
|                         |                     |                   |                  |

| Bus Frequency             | 3     | 6     | 12    | 15    |
|---------------------------|-------|-------|-------|-------|
| Private Car               | 76.5% | 63.5% | 61.5% | 59.0% |
| Park-and-Ride             | 14.0% | 24.2% | 25.3% | 25.9% |
| One-Bus Line              | 1.3%  | 3.4%  | 3.9%  | 5.5%  |
| Bus to Transit            | 2.0%  | 2.4%  | 3.1%  | 3.5%  |
| Bicycle to Transit        | 6.2%  | 6.4%  | 6.2%  | 6.1%  |
| Average travel time (min) | 20.86 | 20.75 | 20.55 | 19.97 |

| Traffic Information       | Full  | No Car Transfer | No Bus Transfer | No Bicycle Transfer | No All Transfer |
|---------------------------|-------|-----------------|-----------------|---------------------|-----------------|
| Private Car               | 61.5% | 86.5%           | 62.5%           | 64.2%               | 94.7%           |
| Park-and-Ride             | 25.3% |                 | 25.4%           | 27.7%               |                 |
| One-Bus Line              | 3.9%  | 4.3%            | 6.2%            | 4.4%                | 5.3%            |
| Bus to Transit            | 3.1%  | 3.4%            |                 | 3.7%                |                 |
| Bicycle to Transit        | 6.2%  | 6.0%            | 5.9%            |                     |                 |
| Average travel time (min) | 20.55 | 21.07           | 22.98           | 22.14               | 21.72           |

Table 4 - Effect of information supply strategies on travel mode split and traffic assignment

have no opportunity to change their travel mode. The parking fee is ¥6.00, the bus frequency is 12 buses/ hour, and the OD demand is 13,000. The simulation results listed in Table 4 show that full information ensures the best performance of the network. When the car transfer information is not provided, the traveller who drives the car has no opportunity to transfer to other traffic mode; the private car trip increased from 61.5% to 86.5%, and the average travel time increased from 20.55 minutes to 21.07 minutes. Similarly, when the bus transfer information is not provided, the onebus line trip will immediately increases from 3.9% to 6.2%; other travel modes do not change so much. The average travel time will increase more than the case in which there is no car transfer information from 20.55 minutes to 22.98 minutes. The case in which no bicycle transfer information is provided, other mode shares also increase a little. Finally, if no transfer information is provided, most of the travellers choose the private car trip, and the average travel time increases as the traffic congestion aggravates.

The last set of experiments examines the effect of car ownership ratio on the travel mode choice. Five cases of car ownership ratio are considered in the experiments: 100%, 80%, 60%, 40%, and 20%. The travellers who do not have a car can only choose the bus or bicycle trip. In this experiment, the traffic information is fully provided, the parking fee is ¥6.00, and the OD demand is 13,000. The simulation results listed in *Table 5* show that as the car ownership ratio decreases, the public travel trips rise sharply. With the decrease of car trips, the degree of traffic congestion is reduced, which leads to the conclusion that the travellers who have cars will prefer car trips over public trips. Moreover, the decrease in car ownership will save the average travel time at first, as the car travel

time decreases. However, when the car ownership ratio decreases to a certain level, the average travel time will increase with the limitation of the public running schedule. In our case, the average travel time is the least when the car ownership ratio is 80%.

# 6. CONCLUSION

DTA is an important issue in ATMS (Advanced Traffic Management System) and ATIS (Advanced Traveler Information Systems). Detailed research into DTA problem is helpful for traffic planning and management. This paper presents a simulation-based DTA model considering combined travel modes. The framework consists of a multi-modal supply network and a mesoscopic demand simulator. On the supply side, four traffic modes are included in the urban transportation network: private car, subway, bus and bicycle. On the demand side, the interaction between mode-route choice and traffic assignment is taken into account in a nested improved C-Logit model. The traffic assignment procedure is achieved by a time-dependent shortest-path algorithm.

Five experiments were designed to illustrate the performance and application of the model in the transportation management. These experiments illustrate the significance of combining the mode choice and route choice in the DTA framework and also verify the efficiency of the time-dependent-shortest path algorithm in the dynamic traffic assignment problem. Five sets of experiments show that the increase of OD demand makes the transit trip more attractive, but increases the average travel time; imposing high parking fee contributes to improving the proportion of transit trip; the frequency of the bus service will appeal to the travellers to shift their travel mode, but not in

Table 5 - Effect of car ownership ratio on travel mode split and traffic assignment

| Car Ownership Ratio       | 100%  | 80%   | 60%   | 40%   | 20%   |
|---------------------------|-------|-------|-------|-------|-------|
| Private Car               | 61.5% | 52.6% | 42.6% | 29.6% | 15.6% |
| Park-and-Ride             | 25.3% | 19.2% | 13.4% | 8.5%  | 4.1%  |
| One-Bus Line              | 3.9%  | 8.3%  | 13.3% | 18.6% | 24.8% |
| Bus to Transit            | 3.1%  | 6.4%  | 10.4% | 14.7% | 18.9% |
| Bicycle to Transit        | 6.2%  | 13.6% | 20.4% | 28.5% | 36.6% |
| Average travel time (min) | 20.55 | 20.04 | 21.25 | 23.14 | 25.22 |

the-more-the-better way; the traffic information service level influences the traffic assignment which should be provided completely and timely; the car ownership ratio has direct impact on the travel mode split, and proper car ownership ratio would contribute to saving the travel time. All the sets of experiments are well applied in the real traffic management with the proposed simulation-based DTA model.

Further research is planned for improving the algorithm efficiency in large-scale networks and calibrating the parameters with real data. Time-dependent shortest path algorithm tends to run fairly slowly, especially when a large network is involved. Intelligent algorithms (IA) have an excellent ability in searching for the globally optimal solution, and can be a direction in later studies. The use of the model to examine the application of APTS/ATIS and management measures are worth continuing the study.

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