DEMAND SIMULATION FOR DYNAMIC TRAFFIC ASSIGNMENT

Constantinos Antoniou, Moshe Ben-Akiva, Michel Bierlaire, and Rabi Mishalani

Massachusetts Institute of Technology, Cambridge, MA 02139

Abstract: This paper presents a pre-trip demand simulator with predictive capabilities and an explicit simulation of the response of travelers to real-time pre-trip information. The demand simulator is an extension of dynamic OD estimation models aimed at explicitly capturing the effect of information on demand. This is achieved by explicitly simulating driver behavior in response to both descriptive and prescriptive information at the disaggregate level.

Keywords: estimation, prediction, simulation, behavior, information

1. INTRODUCTION

Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS) are being developed to address traffic congestion problems. Dynamic Traffic Assignment (DTA) – a component of ATIS and ATMS – uses historical and real-time data to estimate and predict traffic conditions. The ability to accurately predict demand is critical, because if future conditions are not taken into account for guidance generation, then the guidance will likely be outdated and irrelevant by the time it reaches the travelers. Moreover, an estimate of current condition is a key input for prediction, hence the importance of its accuracy.

One of the key components of a DTA system is the quantification of pre-trip demand – the demand that enters the network and thus reflects the effect of pre-trip information on drivers' decisions. The pre-trip demand can be represented by the following:

$$d^* = d_H + \Delta d_I + \Delta d_F + \varepsilon \qquad (1)$$

where:

d^* = true demand,

d_H = historical demand,

Δd_I = systematic deviation reflecting the effect of pre-trip information on the demand,

Δd_F = systematic deviation reflecting the effect of daily demand fluctuations on the demand, and

ε = random error term.

In Equation 1 the true demand is constructed from the historical demand with the addition of two systematic and one random deviations. True demand corresponds to the demand that actually enters the network. Historical demand is the average of the demand over previous days.

Pre-trip demand is commonly represented by Origin-Destination (OD) matrices. Real-time OD estimation models (Ashok and Ben-Akiva, 1993) update the historical demand to reflect actual network demand, thus capturing drivers' travel patterns and demand deviations at the OD level. The models start from a historical OD matrix and observed link counts and estimate an OD matrix that is consistent with these link counts. Therefore, these models do not explicitly take into account the systematic deviation due to pre-trip information.

This paper presents a *pre-trip demand simulator* with predictive capabilities and an explicit simulation of traveler response to real-time pre-trip information. For a more detailed presentation, the reader is referred to Antoniou (1997). This simulator is developed and implemented as part of DynaMIT (Dynamic Network Assignment for the Management of Information to Travelers) – a DTA system that simulates pre-trip demand (using the presented demand simulator), en route demand and supply (using a supply simulator) to estimate and predict traffic conditions and consequently generate traveler information and guidance (Ben-Akiva et al., 1997).

The next section presents the design of the demand simulator. The framework is outlined and the two main functions are described. Section 3 summarizes the implementation of the system and Section 4 presents conclusions.

2. DESIGN OF THE DEMAND SIMULATOR

The methodology combines aggregate and disaggregate models. An OD estimation model is applied on aggregate dynamic OD matrices, and the individual choices of drivers are captured by disaggregate behavioral models. This allows the simulator to use individual driver characteristics to accurately capture travel behavior. To be able to use disaggregate models, however, the demand simulator must disaggregate the historical OD matrices into a population of drivers, which will be updated and subsequently aggregated to produce the updated OD matrices that will be used as input to the OD estimation model.

This methodology, characterized by the explicit representation of pre-trip travel decisions in response to information, differs from existing approaches. To the best of the authors' knowledge and based on published literature, existing DTA models either do not capture pre-trip travel decisions (e.g. Mahmassani et al., 1993), or when they do, assume complete knowledge of future traffic conditions (e.g. Ran et al.,1992; Friesz et al., 1993).

2.1 Framework

The functionality of the pre-trip demand simulator can be separated in two main functions:

- Travel behavior update in response to information, and
- Dynamic OD estimation and prediction.

The overall structure of the pre-trip demand simulator is presented in Figure 1. The travel behavior model is disaggregate and is applied to individual drivers. On the other hand, historical demand is available as aggregate OD matrices. In order to use the disaggregate behavioral model, the demand simulator transforms the aggregate OD matrices into a disaggregate population of drivers, to which the behavioral model is applied. The behavioral model then uses the available real-time information to update the travel choices of each traveler, to determine if they will adhere to their initial travel pattern or will change departure time, mode or route, or cancel their trip. After the travel behavior of each driver has been updated to reflect the available information and guidance, the population of drivers is aggregated to a set of updated OD matrices (one OD matrix is generated for each departure time interval).

At this stage, the OD estimation model accepts as input the updated OD matrices and uses traffic counts, along with a series of other inputs, to estimate aggregate demand for the current interval. The OD prediction model makes an assumption about time evolution of demand to predict OD matrices for a given number of future intervals.

The pre-trip demand simulator is capable of being used in a wide range of applications. Depending on the nature and the requirements of each application, the output can be either:

- Aggregate demand, or
- Disaggregate demand.

If aggregate demand is required as output, then no further operation is performed and the estimated and predicted OD matrices are the desired output. Alternatively, if disaggregate demand is required, then the estimated and predicted OD matrices are disaggregated to a list of drivers by an additional disaggregation component. This procedure uses the previously generated updated population of drivers as a basis, and generates new or removes existing drivers to reflect the OD estimation results.

The presented demand estimation process takes the form of a *discrete step* simulator, i.e. the state of the system is updated in a series of steps, each corresponding to some fixed time interval. The demand simulator uses two time discretization intervals:

- Departure time interval, and
- Estimation interval.

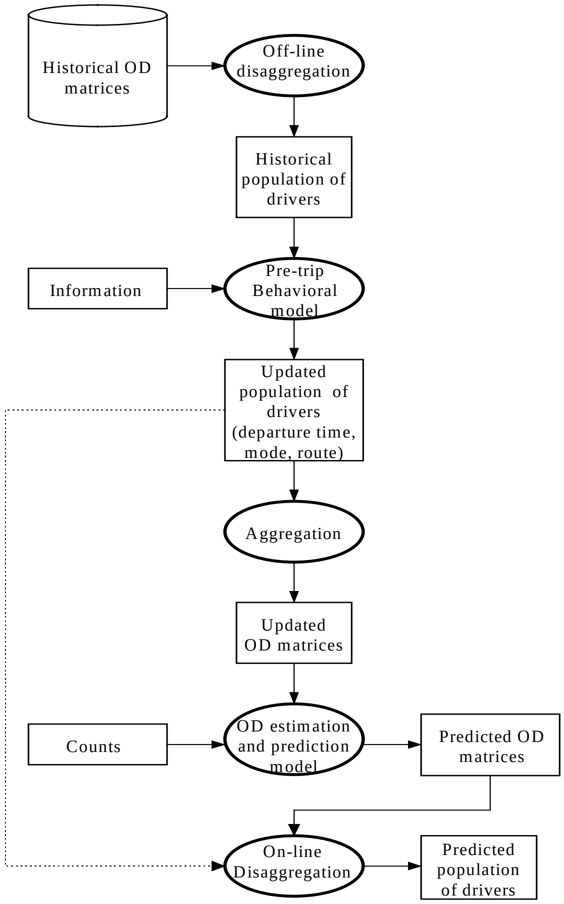

Fig. 1. Pre-trip Demand Simulator.

The departure time choice is modeled as a discrete choice. Therefore, a time discretization is used to define the choice set. Similarly, the OD estimation is performed for discrete intervals of time. Therefore, an interval referring to the time period for which the demand is estimated is also necessary. The two time intervals need not coincide; a mapping from one time discretization into the other is applied if they do not.

2.2 Pre-trip Behavior Update

The *off-line disaggregation* component's role is to generate a population of drivers from the historical OD matrices. A number of socioeconomic characteristics required by the behavioral models, such as value of time, trip characteristics, and trip purpose, are generated and assigned to each driver. Origin, destination, departure time interval and mode are assigned to the drivers using information from the OD matrices. The origin and destination are the particular OD pair for which the driver is generated, the departure time interval is the interval to which the OD matrix corresponds, and the mode is the car (since the OD matrices contain only car trips). Furthermore, a habitual behavior model is applied to each driver in order to generate via historical information a habitual path.

The behavioral model that is used to provide choice probabilities for each path is the C-logit model, a modified multinomial logit (MNL) model, proposed by Cascetta et al. (1996). The model specification of the C-logit is that of a MNL with a modified utility to account for overlapping paths. The model overcomes the main shortcoming of MNL: unrealistic choice probabilities resulting from paths sharing a number of links. Once the probabilities are computed for each path, Monte Carlo simulation randomly selects one which is assigned as the habitual route choice of the driver.

The pre-trip behavior update applies to each individual driver in the generated historical population a behavioral model to capture their travel behavior in response to available pre-trip information. The drivers may decide to change departure time, path, mode, a combination of these, or cancel their trip. It is assumed that the drivers' destination does not change in response to available information.

Two types of information are modeled:
- Descriptive, and
- Prescriptive.

Descriptive information reflects traffic conditions on the network; it is the driver's responsibility to use this information in making a travel choice. On the other hand, prescriptive information provides specific recommendations to the user about travel decisions (e.g., change path to a specific route) and the user decides whether to comply or not. Two model structures have been specified depending on the type of information.

For the descriptive behavior model, the choice set is first defined. Regarding mode, the alternatives are to drive or to switch to another mode. Similarly, for the trip cancellation choice, the driver may choose whether or not to make the trip. Regarding departure time choice, the feasibility of the time intervals is bounded on one side by the decision time, since an individual can not decide to depart earlier than the decision time. The feasibility of the time intervals is also bounded in the future, since the drivers usually need to complete the trip within some time frame. The habitual departure time interval is captured by the *do not change* alternative. In the case of path choice, the choice set of an individual is comprised of all paths connecting the origin and destination of interest. The habitual path, again, is the *do not change* alternative. Finally, in the case of both departure time and path change, the choice set is comprised of all possible combinations of the time intervals in the departure time choice set with the paths in the path choice set.

Given the choice set, the descriptive behavioral choice model is formulated as a nested logit model. The choice tree for the descriptive model is presented in Figure 2. At the first level, the traveler decides whether to change mode, departure time, path, both departure time and path, or cancel trip. The mode change and trip cancellation alternatives do not require any further decisions. In the case of departure time change, the lower level alternatives are the departure time intervals in the choice set of the individual. Similarly, in the case of path change, the lower level alternatives are the paths in the choice set of the individual. However, in the case of both departure time and path choice more than one tree structure can be used. Here it is assumed that the individual driver makes both choices simultaneously. Therefore, only one subsequent level is required and the lower level alternatives are the combinations of intervals and paths as mentioned above. This approach is selected mainly due to the lack of data and relative ease of estimation.

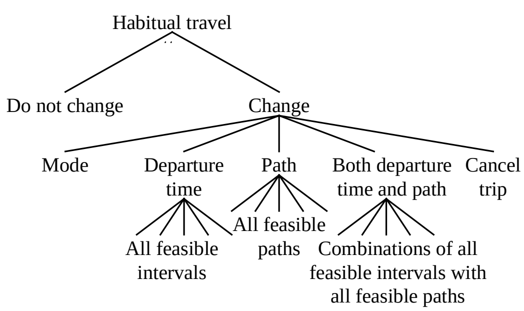

Fig. 2. Pre-trip choice tree in the case of descriptive information.

In the case of prescriptive information, the behavioral model simplifies to a compliance model. It is assumed that the travelers decide whether or not they will change their habitual travel behavior. If they decide to change, it is assumed that they follow the suggested alternative. The model is assumed to apply only to route choice. This is due to the fact that, given current technological constraints, no prescriptive guidance for departure time or mode choice can be generated based only on information derived from the prevailing network conditions.

The variables used in the behavioral models are classified into the following:

- Travel time information, both historical and actual,
- Deviation in arrival time from the habitual arrival time of the individual,
- Information reception time,
- Individual’s value of time (low-medium-high),
- Trip purpose (work, leisure, other),
- Length of path,
- Length of path on highways,
- Out-of-pocket monetary cost for path,
- Number of signalized intersections in path, and
- Number of left turns in path.

Once the choice probabilities for all alternatives are computed using the appropriate behavioral model, Monte Carlo simulation is used to select an alternative. The updated departure time interval, mode and path are then assigned to the driver, according to the choices made.

2.3 OD Estimation and Prediction Model

The role of the aggregation component is to generate updated OD matrices by aggregating the updated population of drivers. The updated OD matrices are used as input for the OD estimation model. The aggregation is based on the departure time interval, the origin and the destination of the drivers.

The formulation of the real-time dynamic OD matrix estimation problem based on a Kalman Filtering framework is described by Ashok and Ben-Akiva (1993) and Ashok (1996). The basic idea of this approach is to use all the information contained in historical OD data in conjunction with data on traffic counts to generate OD estimates in real-time. The OD matrices that are used in this procedure have already been updated so that they reflect the response to information available to the travelers at the pre-trip stage. Unlike other approaches in the literature, the adopted model is based on deviations from historical values rather than the values themselves, as proposed by Ashok and Ben-Akiva (1993). Estimated and predicted deviations are finally added to an updated historical OD matrix to get estimated and predicted OD matrices. The solution to the model formulation is given by a *square root* Kalman Filtering algorithm (Chui and Chen, 1987).

The input to the OD estimation and prediction model for an estimation time interval consists primarily of the following matrices:

- An updated OD matrix of drivers departing in that interval.
- A number of assignment matrices, equal to the number OD flows of prior intervals that contribute to the link flow of the current interval.
- A link flow table, containing information about the traffic conditions on the links of the network.

The output is estimated and predicted OD matrices.

The OD estimation and prediction has three main components. The first is called *initialization*. It takes place only once, prior to the estimation for the first interval. The second step is the *estimation*, where OD demand for the current interval is estimated. The last step is the *prediction*, in which the model makes assumptions about the evolution of demand to predict future demand based on the estimates in the previous intervals.

3. IMPLEMENTATION AND PRELIMINARY TESTING

The demand simulator is implemented using the Object Oriented (OO) paradigm (Rumbaugh et al., 1991) and the programming language C++ with the Standard Template Library (STL).

The general objectives of the implementation were the following:

- Design flexibility,
- Data management efficiency,
- Computational efficiency, and
- Numerical robustness.

Preliminary results were obtained from a series of evaluation exercises that focused on specific aspects of the performance of the demand simulator. These results provide indicative evidence that the simulator's performance is compliant with its design. The following observations are worth reporting:

- Behavioral update plays a stronger role in the demand simulation, when adverse traffic conditions are observed in the network.
- Stochasticity inherent in the simulator's behavioral update is indeed reflected at the aggregate output level. Nevertheless, its impact does not seem unreasonable.
- Small changes in the inputs of the demand simulator reflecting input inaccuracies are not reflected significantly in its outputs.

It is important to emphasize, however, that further testing is needed to validate the simulator.

4. CONCLUSIONS

In this paper a pre-trip demand simulator for DTA applications has been presented. The demand simulator takes pre-trip information explicitly into account and, therefore, the OD estimation is based on the updated demand. Thus, the simulator explicitly takes into account both systematic components of variations in the demand – namely the effect of information and the daily demand fluctuations – and, potentially, provides a better estimate than an OD estimation based directly on historical demand. The design of the simulator is presented. Preliminary results are promising, indicating that the performance of the demand simulator is consistent with its design. Further evaluation of the demand simulator is required in order to assess its overall performance and its ability to replicate true demand.

5. REFERENCES

Antoniou, C. (1997). *Demand Simulation for Dynamic Traffic Assignment*. SM Thesis, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology.

Ashok, K. (1996). *Estimation and Prediction of Time-Dependent Origin-Destination Flows.* Ph.D. Thesis, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology.

Ashok, K. and M. Ben-Akiva (1993). Dynamic O-D Matrix Estimation and Prediction for Real-Time Traffic Management Systems. In: *Transporation and Traffic Theory* (Daganzo, C.F., (Ed.)). Elsevier Science Publishing Company Inc.

Ben-Akiva, M., M. Bierlaire, J. Bottom, H. N. Koutsopoulos, R. Mishalani (1997). Development of a Route Guidance Generation System for Real-Time Application. *Proceedings of the IFAC Transportation Systems 97 Conference*, Chania, Greece.

Cascetta, E. (1996). A Modified Logit Route Choice Model Overcoming Path Overlapping Problems. Specification and Some Calibration Results For Interurban Networks. *Proceedings of the Thirteenth International Symposium on Transportation and Traffic Theory (ISTTT)*, Lyon, France.

Chui, C.K., and G. Chen (1987). *Kalman Filtering with Real-Time Applications*. Springer Verlag.

Friesz, T.L., D. Bernstein, T.E. Smith, R.L. Tobin, and B. Wie (1993). A Variational Inequality Formulation of the Dynamic Network User Equilibrium Problem. *Operations Research*, Vol. 41.

Mahmassani, H. et al. (1993). *Development and Testing of Dynamic Traffic Assignment and Simulation Procedures for ATIS/ATMS Applications.* Technical Report DTFH61-90-R-00074-FG, Center for Transportation Research. University of Texas at Austin.

Ran, B., D.E. Boyce, and L.J, LeClanc (1992). Dynamic User-Optimal Route Choice Models Based on Stochastic Route Travel Times. *Presented at the 2nd International Capri Seminar on Urban Traffic Networks*, Capri, Italy.

Rumbaugh, J., M. Blaha, W. Premerlani, F. Eddy, W. Lorensen (1991). *Object-Oriented Modeling and Design*. Prentice Hall.