ASSESSMENT OF TRAFFIC INFORMATION WITH STOCHASTIC ASSIGNMENT

Yongtaek Lim Research Associate Department of Urban Transportation Seoul Development Institute San4-5, Yejang-dong, Chung-ku Seoul 100-250, KOREA Fax:+82-02-726-1291 E-mail: limyt@plaza.snu.ac.kr

Seungkirl Baek Researcher Department of Urban Transportation Seoul Development Institute San4-5, Yejang-dong, Chung-ku Seoul 100-250, KOREA Fax:+82-02-726-1291 E-mail: bsktrans@chollian.net

Kangwon Lim Professor Department of Environmental Planning Graduate School of Environmental Studies Seoul National University Seoul, 151-742 Korea Fax:+82-02-887-6905 E-mail: kangwon@plaza.snu.ac.kr

abstract : A simulation-based day-to-day stochastic assignment model and solution algorithm are developed in order to reflect the driver's daily route choice behaviour according to the traffic information. Driver's route choice mechanism are based on the past experience of the road traffic conditions which they took previous days. A numerical example is presented to illustrate the application and assessment of the developed day-to-day traffic management model. The results of this paper show that the effect of provision of traffic information exist under the condition of proper demand, compliance with information, and the variance of travel time perception.

1. INTRODUCTION

Higher vehicle ownership and usage have led to heavy traffic congestion on urban road network. The traffic management schemes in order to reduce the urban congestion and to make best use of available road capacity are introduced. Some of them are traffic demand management, network operation and provision of information. The usage of real-time traffic information systems within the framework of ITS(Intelligent Transportation System), in particular, has become a powerful tool as a possible solution to the ever-growing congestion problem on urban area. Traffic information also enables driver to avoid the traffic accident area and reduce the congestion to some extent.

One of the basic assumptions in conventional traffic assignment approaches is that the drivers' attributes are identical, or they are not different among others. However, this assumption is not realistic in urban traffic conditions. There exist differences or perception errors among drivers. Stochastic approaches of traffic assignment include the variability in driver's perceptions of costs and seek to minimize disutility. In stochastic equilibrium models, costs perceived by drivers are considered different from actual costs. The perceived cost is modelled as a random variable. Several approaches have been proposed to fomulate and solve the stochastic assignment. But simulation-based and proportion-based methods are relatively widespread accepted.

Recently various methods have been developed to the traffic information systems within the ITS. In terms of providing information, the approaches are classified into individual in-vehicle route guidance system and collective system such as VMS(Variable Message Sign). The in-vehicle system may be considered to fall into autonomous navigation aids, one-way or two-way communication systems. In the collective system, drivers may receive information from VMS distributed at a key location in the network. In contrast to the in-vehicle systems, the message content will have general value which individual drivers must interpret. The subsequent driver's decision will vary with their level of knowledge of the network and their ability so as to determine the implications of the message for their own journey.

Breheret et al.(1990) used the heuristic dynamic assignment model as a tool for evaluation of traffic information effects. They assumed unguided drivers to follow an approximate stochastic user equilibrium(SUE) based on prevailing conditions, whilst guided drivers follows user optimum routes based on current conditions. They reported that total travel time decrease until proportions of guided drivers is 20% and benefits of guided drivers is greater than one of unguided. Smith and Russam(1989) also reported average journey time saving of 6-7% for guided, which actually decreased with an increase in take up and unguided is also benefited with travel time reductions of up to 3%.

Koutsopoulos and Lotan(1989) assumed that route guidance would reduce the perception errors in link travel time estimates, so that their model consists of a SUE assignment of two classes with different variances in the normal distribution in perceived link costs. An increase in the quality of information resulted in a reduction in perception errors by guided drivers, and therefore in a reduction in their travel times.

Van Vuren and Watling(1991) assumed the unguided user were expected to follow a SUE, whilst equipped drivers were guided via UE(User Equilibrium) or SO(System Optimal) routes. They reported that SO routing benefited the unguided drivers - at the expense of guided drivers - at the levels of take up. However, equipped drivers stated benefiting too when their numbers increased: at the highest levels of take up(higher than 50-70%)the results revealed how guided drivers under SO routing might benefit even more than that of the unguided ones.

The results of these various model studied are obviously rather ambiguous. Hypotheses about the route choice and interaction of guided and unguided driver strongly influence the model outcomes. Often the models used in these studies are heuristic, or they are only valid under rather strong assumptions. this is not to

Assessment of Traffic Information with Stochastic Assignment

belittle the importance of all these model studied: it merely shows the current problems in understanding and anticipating the expected behaviour of future route guidance systems.

The objective of this paper is to assess the effect of the traffic information according to the various information providing strategies with stochastic assignment. For this purpose, simulation-based day-to-day stochastic assignment is developed to reflect the driver's daily behavior. Driver's route choice mechanisms are based on the past experience of the road traffic conditions which they took previous days. Some information provision strategies are also developed in order to use the systems effectively. An example of contrived network is used to evaluate day-to-day stochastic traffic assignment model and to assess the effect of information provision strategies.

2. STRUCTURE OF THE DAILY STOCHASTIC ASSIGNMENT MODEL

The developed model in this paper consists of two models that are daily stochastic assignment and traffic information. Traffic information is used to provide route following information in order to avoid traffic congestions ahead of some alternative routes. Two routines calculate interactively until mutually consistent traffic flows are obtained. The systematic framework of the model is shown in Figure 1 below.



Figure 1. Systematic diagram for the model

2.1 Day-to-day stochastic assignment model

Day-to-day stochastic assignment model is developed in order to reflect the driver's daily route choice behaviour according to the traffic information. Driver behaviors are varied with the travel cost which is consisted of mean link travel time and variation which come from drivers' perception errors. The errors are supposed to be normally distributed. Driver's daily route choice rules are based on the previous experiences and information provision strategies also cause the switching of driver's daily route choice behaviour.

Stochastic network loading models are a special case of discrete choice models. To apply these models, the probability distribution function of the (perceived) travel time on each path has to be known so that the path choice probability can be calculated. Generally route-choice model is divided into multi-nominal logit-based model and probit-based one. In this research probit model with Burrell's method which assume that the random error of each utility is normally distributed is used. And the computation of the probit choice probabilities used in here is a Monte Carlo simulation procedure.

SUE is more general statement of equilibrium than the UE conditions. In other words, the UE conditions are a particular case of SUE; when the variance of travel time perception is zero, the SUE conditions are identical to the UE conditions.

Link travel time function is developed as follows:

$$T_a(w) = (1-\delta)t_a(w) + \delta S_a(w) \tag{1}$$

Where $T_a(w)$ is the total travel cost on link *a* at day w, comprising of actual travel cost $t_a(w)$ and predicted cost, $S_a(w)$. δ is a parameter reflecting driver's behaviour. $t_a(w)$ and $S_a(w)$ are the function of traffic flow in day w as follows.

$$t_{a}(w) = t_{0} + a[c_{a}(w) - t_{o}]$$

$$S_{a}(w) = \beta_{1} t_{a}(w) + \beta_{2} t_{a}(w-1) + \beta_{3} t_{a}(w-2)$$
(2)
(3)

where, $c_a(w)$ is BPR cost function and t_0 is free flow travel time.

2.2 Provision of information

Traffic information plays an important role in drivers' route choice behaviors and it is classified into individual system and collective system. The paper selects VMS as a collective information system and provide the predicted travel time information to drivers. Sensitivity of drivers' following to the routing information is tested, as the drivers' compliant parameter δ increases incrementally. The predicted travel cost is formulated as a linear polynomial equation:

$$S_{a}(w) = \beta_{1}t_{a}(w) + \beta_{2}t_{a}(w-1) + \beta_{3}t_{a}(w-2)$$
(4)
$$\sum_{i=1}^{n} \beta_{i} = 1 , \quad i=1, \dots, n$$
(5)

Where $S_a(w)$ is the predicted travel time on link *a* at day w, which is based on weighted averages of the travel times on current and previous days by moving average method. On the other aspect, the provision of traffic information is also to fall into two parts; minimizing travel cost for driver(user equilibrium) or network as a whole(system optimality).

2.3 Solution Algorithm

The solution algorithm in the paper is the method of successive method(MSA) which is based on a predetermined move size along the descent direction.. MSA algorithm used in the paper can be summarized as follows :

[step 0] Initialization.

- Perform a stochastic network loading based on a set of initial travel times $\{t_a^{\,0}\}.$
 - (0) Initialization : l = 1
 - (1) Sampling : sample $T_a^{(l)} \sim N(t_a, \theta t_a)$ from each link a
 - (2) All-or-nothing assignment based on $[T_a^{(l)}]$
 - \cdot assign $[q_{rs}]$ to the shortest path connecting O-D pair r-s.
 - · yields the set of link flows $\{X_a^{(l)}\}$
 - (3) Flow averaging : $X_a^{(l)} = [(l-1) X_a^{(l-1)} + X_a^{(l)}]/l$
 - (4) Stopping test

$$\sigma_{a}^{(l)} \sqrt{\frac{1}{l(l-1)}} \sum_{m=1}^{l} [X_{a}^{(m)} - x_{a}^{(l)}]^{2}, \quad \forall z$$

If max $[X_a^{(l)}] \le k$, stop. The solution is $\{X_a^{(l)}\}$. Otherwise,

set l = l + 1 and go to step 1.

- Set n=1.
- [step 1] update. set $t_a^n = t_a(x_a^n)$, $\forall a$
- [step 2] Direction finding. Perform a stochastic network loading based on the current set of link travel times $\{t_a^n\}$.
- [step 3] Move. Find the new flow pattern by setting $x_a^{n+1} = x_a^n + (1/n)(y_a^n x_a^n)$
- [step 4] Convergence criterion. If convergence is attained, stop. If not, set n=n+1 and go on step 1.

3. NUMERICAL EXAMPLE

3.1 A test network

A numerical example is presented to illustrate the application and assessment of the developed day-to-day stochastic traffic assignment model. The example network

shown in Figure 2, includes one variable message sign. The input data such as link capacity, free-flow cost and the parameters of compliance, variance are shown in Table 1. It is assumed that there is one origin-destination pair from node 1 to node 6 with different trip demand of 500vehicles/day(undersaturation), 1,000vehicles/day(saturation) and 1,500vehicles/day(oversaturation) respectively.



Figure 2. Example Network

Table 1. Input data

 network data capacity(veh/day) free flow time(sec) 	1000 60	at all at all	link link
 others degree of information compliance (δ) the variance of travel time perception(θ) total trip demand(veh/day) study period 	0.0 0.0 500 1	0.5 0.5 1000 5 days	1.0 1.0 1500

3.2 Numerical results

1) The transition of traffic flow

Figure 3 and figure 4 show the evolution of traffic flow as day go by. In the case of no variance of perception error, traffic flows are stable as day elapse in figure 3. With the perception variance value of $\theta=0.5$, traffic flows are ,however, fluctuated over days as shown in figure 4 but as the compliance of information, δ , increase, the range of fluctuation become lesser. This results show that traffic information make traffic smooth and give benefits to drivers.



Figure 3. transition of traffic flow(d=1000, θ =0.0) Figure 4. transition of traffic flow(d=1000, θ =0.5)

As you see figure 5, at the low demand level, the range of traffic fluctuation is very high but in the case of higher demand level in figure 6, traffic fluctuation decrease.





Figure 5. transition of traffic flow(d=500, δ =0.5)

Figure 6. transition of traffic flow(d=1000, δ =0.5)

2) The transition of the total travel time

Figure 7 and figure 8 show the evolution of the total travel time. In the case of 1000 vehicles and the value of $\delta = 0.5$ or 1.0 in Figure8, total travel time are lower in early days as the compliance of information increase. However as days elapse they also converge to a certain value and show that no more benefits provide.



Figure 7. transition of travel time(d=500, θ =1.0)



From the viewpoint of θ , the UE conditions are a particular case of SUE; when the variance of travel time perception(θ) is zero, the SUE conditions are identical to the UE conditions.

Figure 9, 10 shows that at demand=500(under-saturation) and θ =0.0(UE condition), despite different compliance(δ), travel time is constant. But at θ =0.5 or 1.0(SUE condition) the travel time is fluctuate severely.



Figure 9. transition of travel time(d=500, δ =0.0)

Figure 10. transition of travel time(d=500, δ =0.5)

Compared with demand=500vehicles in Figure 10, in the case of demand=1000 vehicles(saturation) and 1500vehicles(over-saturation) the transition of travel time is very different. At demand=1000vehicles and delta=0.5, 1.0, the travel cost is low in early days, especially at θ =1.0. But as day goes on, the travel cost is moving up and similar at all conditions.



Figure 11. transition of travel time(d=1000, δ =0.5) Figure 12. transition of travel time(d=1500, δ =0.5)

The results of this paper show the effect of provision of traffic information is influenced by many things such as trip demand level, compliance with the information, variance of travel time perceptions, etc.

4. CONCLUSION

The important results of this research is as follows:

First, the results of this paper show that the effect of traffic information is influenced by many factors such as demand condition, compliance with the information, variance of travel time perceptions, etc. Second, the effect of provision of traffic information exist in under the condition of proper demand, compliance of information and the variance of travel time perception.

Daily stochastic assignment model with traffic information developed in this paper is useful to assess the various traffic information strategies. The model also enable to simulate the network conditions more precisely than deterministic traffic assignment models in that the model is more available to reflect the driver's behaviour.

Future researches relating to this paper is as follow.

1) Considering strategies of traffic information provision

The main object of traffic management is how control the traffic for the purpose of decreasing traffic congestion and how to provide traffic information. Therefore in the next paper the provision of traffic information strategies such as minimizing travel cost for driver(user equilibrium), network as a whole(system optimality) and mixed type strategy are studied.

2) Including Multi-User Class(MUC)

The day-to-day stochastic assignment requires a modelling of users' dynamic adjustment behavior, of users' learning and forecasting mechanism, and of users'

reactions according to the traffic information. Driver's dynamic route choice rules are based on the experienced travel time and information provision strategies.

Multi-Class model is required to take differences among drivers or among vehicles into account. To capture the behavioral differences of various types of travelers in information gathering and compliance with traffic information, traffic model should incorporate these factors by classifying drivers into different types.

ACKNOWLEDGEMENTS

Funding for this research has been provided by S.N.U Korea Electric Power Corp. Research Fund.

REFERENCES

Ben-Akiva, M., De Palma, A., Kaysi, I. (1991). Dynamic network models and driver information system, Transportation Research 25A, 251-266

Boyce, D., B. Ran, L.J. LeBlanc. (1995). Solving on Instantaneous Dynamic User-Optimal Route Choice Model, Transportation Science, 128-142

Horowitz, J.L. (1984). The stability of stochastic equilibrium in a two-link transportation network, **Transportation Research**, 18(B), 13-28

Janson, B.(1991) Dynamic traffic assignment for urban road networks, **Transportation Research 25B**, 143-161

Mahmassani, H. and Chang, G. (1987). On boundedly rational user equilibrium in transportation systems, Transportation Science 21(2), 89-99

Mahmassani,H. and Mouskos,K. (1988). Some numerical results on the diagonalization algorithm for network assignment with asymmetric interactions between cars and trucks, **Transportation Research 22B**, 275-290

Vuren.T.V., Watling,D.P. (1991). A multiple user class assignment model for route guidance, TRR 1306, 22-32

Vythoulkas, P.C. (1990). A dynamic stochastic assignment model for the analysis of general networks, Transportation Research 24(B), 153-169

Lee, S. Lim,K., Kim,G. and Lim,Y.(1996) Assessment of dynamic traffic management schemes of responsive signal control and variable message sign, the 3rd Intelligent Transport Systems World Congress, Oct. 14-18, Orlando,USA

Lim, Y.T.(1997) Development of the dynamic traffic management models with signal control and variable message sign, Ph.D dissertation, Seoul National University

Ran, B. and Boyce, D. (1994). Dynamic Urban Transportation Network Models, Lecture Notes in Economics and Mathematical Systems, Springer-Verlag.

Sheffi, Y. (1985). Urban transportation networks: equilibrium analysis with mathematical programming methods, Prentice Hall, New Jersey.

Vuren, T.V., Vliet, D.V. (1992). Route Choice and Signal Control, Ashgate Publishing Limited.