MULTI-CLASS DAILY ASSIGNMENT MODEL FOR TRAFFIC INFORMATION STRATEGY

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Abstract: A simulation-based multiple user class daily stochastic assignment models and its solution algorithm is developed. The developed model can depict the driver's day-to-day route choice behavior according to several traffic information. Driver's route choice mechanism is based on the past experience of the road traffic conditions that they took on previous days. A numerical example is presented to illustrate the application and assessment of the developed model. The results of this paper show that the effect of provision of traffic information exists under the condition of compliance with information and the variance of travel time perception.

Keywords: multiple user class, stochastic assignment, information strategy, traffic management

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 recently 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 Intelligent Transportation System (ITS), 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 to reduce the congestion to some extent.

Urban traffic management consists of an interaction between the traffic manager and the individual drivers. They have somewhat different traffic behaviors and may pursue different objectives respectively. While the traffic manager represents the community interests and pursues its goal, the driver seeks only his own benefit. Given demands for travel in an urban area and a fixed supply of transportation facilities, the traffic manager must consider a variety of management strategies to induce a traffic flow pattern that will meet the overall objectives of the community. The manager's criteria for evaluating his actions may include public interest measures of performance such as travel time, energy consumption, noise and pollutant emissions, etc. On the other hand, the individual driver is assumed to selfishly strive to minimize only his own travel costs, subject to the constraints imposed by the physical system supply, the manager's intervening actions and the interactions resulting from other drivers' decisions. Thus the traffic management problem can be set as system-optimization for flows that result from user-optimization. This leads to a traffic assignment model capable of simulating traffic measures of traffic manager and behaviors of drivers.

In order to implement the strategies of ITS, it is needed to predict the temporal evolution of traffic pattern on a congested transportation network where travel demands and travel cost vary over time and space. In urban area dynamic model is mainly considered as one, which describes how commuters adjust their travel decisions concerning route and departure time. Moreover to model the impact of ITS' information provision, it is necessary to develop multiple user class model considering of the fact that there are different classes of users in the transportation network and that they respond differently to traffic information.

The objective of this paper is to develop a multiple user class daily stochastic assignment model and to assess the effect of the traffic information according to the various information providing strategies with the model. For this purpose, multi-class stochastic model is developed to reflect the behaviors of drivers who have different perception error and different route choice behavior each other. Driver's route choice mechanisms are based on the past experience of the road traffic condition, which they took on previous days. Some information provision strategies are also developed in order to use the systems effectively. This paper, which extends from static single user class assignment to multiple one, shows the results of the applications of the model with information to an example network.

2. EXISTING STUDIES

One of the basic assumptions in conventional traffic assignment approaches is that the drivers' attributes are identical, or they do not different from 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 modeled as a random variable. Several approaches have been proposed to formulate and to solve the stochastic assignment (see Sheffi, 1985). But simulation-based and proportion-based methods are relatively widespread accepted.
There are also two kinds of stochastic models: a non-equilibrium based stochastic and an equilibrium based stochastic assignment models. In the first case a short-run spread of routes between two points are produced without learning process whilst in the second case, a long-run spread of routes with learning process. Both models reflect on variability in the perceived routes cost. In particular, the second case is called stochastic user equilibrium. The stochastic user equilibrium (SUE) model seeks an equilibrium condition where: Each user attempts to choose his/her route with the minimum 'perceived' travel cost through day-to-day learning process; in other words, under SUE condition no user has a route with lower 'perceived' costs and therefore all the users stay with their current routes. By using these stochastic user equilibrium assignment models we could assess the effect of traffic information provided by traffic manager.
Breheret et al. (1990) used the heuristic dynamic assignment model. They assumed unguided drivers to follow an approximate stochastic user equilibrium based on prevailing conditions, whilst guided drivers follow user optimum routes based on current conditions. They reported that total travel time decrease until proportions of guided drivers is 20% and the 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.

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.

Recently Baek et al. (1997) and Lim et al. (1997) suggested a multiple user class day-to-day stochastic assignment model and it solution algorithm in order to reflect the driver's daily route choice behavior regarding traffic information. A numerical example is also presented to illustrate the applications and the assessment of the model.

In conjunction with traffic information, Ta-Yin Hu et al (1997) have simulated daily traffic evolution under real-time information and reactive signal control. They described a day-to-day dynamic simulation-assignment framework to study the interaction among individual decisions, traffic control strategies and network flow patterns under real-time information systems.

On the other hand, Ben-Akiva et al. (1991) showed some adverse effects of traffic information. They explained that if drivers would respond to providing information too sensitively, potential adverse impacts could occur. Thus information may lead to increase travel time and to worsen road network.

The results of previous researches above are obviously rather ambiguous. Hypotheses about the route choice and the interactions between the guided and the unguided might influence the outcomes. Often the models have, however, used heuristic approaches and they are only valid under rather strong assumptions. In spite of that, this is not to belittle the importance of all these models' results: it merely shows the current problems in understanding and anticipating the expected behavior of future route guidance systems.

3. STRUCTURE OF THE MODEL

The developed model in this paper consists of two models that are multi-class daily stochastic assignment model and traffic management model for optimal routing. The multiple user class daily stochastic model describes the traffic flow on the road network and drivers' behavior in detail. The traffic management model is setting traffic information for certain control purpose. In the paper some traffic management strategies can be considered regarding information and then tested in a contrived network. The multi-class daily stochastic model evaluates the effects of these information schemes. These two routines calculate interactively until mutually consistent traffic flows are obtained.

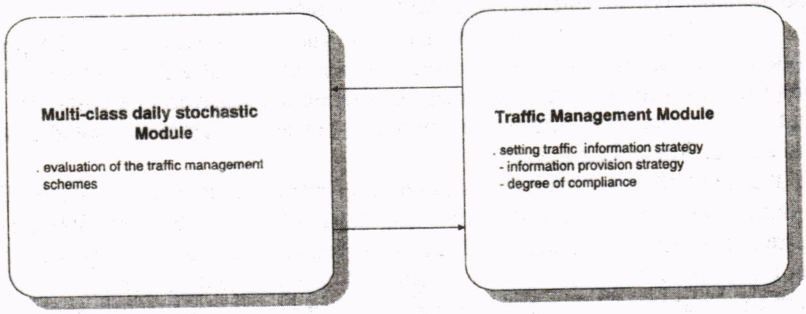

Figure 1. Basic framework of the model

3.1 Multiple user class daily stochastic assignment model

Multiple user classes (MUC) has more than one class of user, where class may be defined on the basis of vehicle type, driver's cost functions, the sections of the network available, etc. 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.
Each class of user is assumed to choose a minimum cost route in accordance with his own definition of cost. MUC would also allow an approximation to the effects of traffic information within Intelligent Transport System. Guided class can be assumed to have perfect knowledge of network conditions, thus the guided class is assumed to follow user-equilibrium (UE) behaviors. But unguided class group has uncertainty of network states, so this group is assumed to follow stochastic user-equilibrium (SUE) principle. We may also classify the group by the degree of guidance. In this research to take account of MUC, we divide travelers into three groups by using a parameter of θ which is the variance of guidance with the specific values. One class is the guided and the others unguided, these three classes are loaded on network one by one.

Stochastic user equilibrium is more general statement of equilibrium than that of the user equilibrium 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. SUE models look particularly attractive in terms of the theory. There are, however, operational and practical difficulties in applying them. The difficulty of the model lies in the convergence properties for its conventional solution algorithm based on the convex combination method. The reason is twofold. First, the determination of the descent direction requires, at every iteration, a stochastic network loading. In this step, the link flows are approximately estimated using the law of large numbers rather than computed accurately. The second difficulty with the application of a standard descent algorithm to the minimization of the SUE model is that the move size cannot be optimized since the objective function itself is difficult to calculate. To avoid these difficulties, iterative Monte Carlo simulation and Method of Successive Average (MSA) are used widely to solve the stochastic user equilibrium problem. MSA is based on a predetermined move size along the descent direction. In other words, optimal move size is determined prior instead of attaining it from minimizing the objective function.
On the other hand, conventional route-choice models are divided into multi-nominal logit-

based model and probit-based. In this paper probit model (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.

The day-to-day stochastic assignment requires a modeling of users' dynamic adjustment behavior, of users' learning and forecasting mechanism, and of users' reactions 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. In this paper driver's dynamic route choice rules are based on the experienced travel time and the predicted travel time come from information provision strategies. Link travel time function is developed as follows:

$$T_a^w(f_a) = (1-\delta)t_a^w(f_a) + \delta s_a^w(f_a) \tag{1}$$

Where $T_a^w(f_a)$ is the total travel cost on link a at day w, comprising of actual travel cost $t_a^w(f_a)$ and predicted cost, $s_a^w(f_a)$. f_a is the flow of link a and δ is a parameter reflecting driver's behavior. Sensitivity of drivers' following to the routing information is tested with the incremental increase of the value of δ . $t_a^w(f_a)$ is BPR (Bureau of Public Roads) function as shown in equation (2) and $s_a^w(f_a)$ is the function of traffic flow in equation (3) and equation(4).

$$t_a^w(f_a) = t_{ao}^w[1+0.15(\frac{f_a}{c_a})^4] \tag{2}$$

$$s_a^w(f_a) = \beta_1 t_a^w(f_a) + \beta_2 t_a^{w-1}(f_a) + \beta_3 t_a^{w-2}(f_a) \tag{3}$$

$$\sum_{i=1}^{3} \beta_i = 1 \tag{4}$$

where, t_{ao}^w, c_a are free flow travel time and capacity on link a at day w, predicted link travel cost $s_a^w(f_a)$ is calculated by the moving average method of current and previous link travel times with weighting factor β_i, $i=1,2,3$.

3.2 Traffic management scheme for information provision

Traffic information plays an important role in drivers' route choice behaviors and it is classified into individual system and collective system. On the other aspect, the provision of traffic information is also fall into two parts; minimizing travel cost for driver (user equilibrium guidance) or network as a whole (system optimality guidance). It is recently a key issue to traffic manager on which route guidance strategy selects and provides for drivers. There exist several strategies in respect of the management purposes and also exist conflicts of interest between the equipped drivers who want to improve their travel time, and the traffic managers, whose objectives is reducing overall traffic congestion. One of the solutions to this problem would seek a strategy, which combines the objectives of the user and the system. Three information strategies are, in the paper, introduced such as 'User Optimality [UO] strategy', 'System Optimality [SO] strategy' and 'Mixed Optimality [MO] strategy'. The first strategy, UO routing, is implemented by performing user equilibrium assignment with an average travel cost on link as follows.

[UO strategy] $\quad s_a^w(f_a)$ (5)

In order to implement the second strategy, SO routing, system optimal assignment is performed with a marginal link travel cost as the same above.

$$\text{[SO strategy]} \quad s_a^w(f_a) + f_a \frac{\partial s_a^w}{\partial f_a} \tag{6}$$

And lastly, the Mixed optimality strategy is to be considered as follows.

$$\text{[MO strategy]} \quad s_a^w(f_a) + \gamma f_a \frac{\partial s_a^w}{\partial f_a} \tag{7}$$

Where γ is a parameter between 0 and 1. In the case of 0, the MO routing strategy is equivalent to the UE routing strategy, and 1 then to the SO routing strategy.

Another important parameter in traffic information system is the degree of information guidance. Guided travelers determine their route and mode by expected travel time and almost no perception error. Otherwise, unguided travelers get much more inaccurate travel conditions. In the paper we assume that guided driver follows user-equilibrium (UE) principle and the unguided follow stochastic user equilibrium (SUE) principle with some variance of travel time. Thus link travel time of unguided driver can be formulated as

$$C_a^{w,unguid} \sim N(T_a^w, \theta T_a^w) \tag{8}$$

Where $C_a^{w,unguid}$ follows normal distribution with mean travel cost of link a, T_a^w, and variance θT_a^w. θ is a constant and may be interpreted as the variance of perceived travel time over link a.

3.3 Solution Algorithm

The solution algorithm in the paper is based on the method of Vuren et al. (1991), originally proposed by Vliet et al. (1986) for solving the multi-class user equilibrium assignment and on the method of successive average (MSA) for stochastic network loading with probit model which assumes that the random variable is normally distributed with mean link travel time and the variance as shown in equation (8). MSA is based on a predetermined move size along the descent direction. Vliet et al. proved the algorithm to be converged Wardrop equilibrium for each class. The solution algorithm used in the paper can be summarized as follows:

[step 0] Initialization

Set Iteration numbei n=

Day w=

Information strategy γ

Degree of information compliance δ

Dispersion parameter of link travel time for each user class i, θ_i

For each user class i, perform all-or-nothing assignment based on initial link travel time, yielding link flow f_{ai}^n

[step 1] Calculate $F_a^n = \sum_i f_{ai}^n$ and

link cost $t_a^{w,n}$ corresponding to F_a^n

[step 2] Traffic information strategy

2.1 Calculate predicted link cost $s_{ai}^{w,n}(f_{ai}^n)$ based on information strategy

2.2 Calculate link travel cost for each user class i

$$T_{ai}^{w,n}(f_{ai}^{n}) = (1-\delta)t_{ai}^{w,n}(f_{ai}^{n}) + \delta s_{ai}^{w,n}(f_{ai}^{n})$$

[step 3] For each user classes i

3.1 Sample a set of link error terms ε_{ai} from the normal distribution, by pseudo-randomization process and set

$$C_{ai}^{w,n} = T_{ai}^{w,n}(f_{ai}^{n}) + \varepsilon_{ai}$$

where, $\varepsilon_{ai} \sim N(T_{ai}^{w,n}(f_{ai}^{n}), \theta_{ai} T_{ai}^{w,n}(f_{ai}^{n}))$

3.2 Perform an all-or-nothing assignment for this user class using the randomized cost $C_{ai}^{w,n}$, yielding a set of user class link flows y_{ai}^{n}

3.3 Update the flows for this user class

$$f_{ai}^{n+1} = f_{ai}^{n} + (1/n)(y_{ai}^{n} - f_{ai}^{n})$$

3.4 Set

$$F_{a}^{n+1} = F_{a}^{n} + f_{ai}^{n+1} - f_{ai}^{n}$$

[step 4] Convergence criterion.

If convergence is attained, stop.

Otherwise, set $n=n+$ and go on step 1.

[step 5] if $w \geq days$, stop

otherwise, $w=w+1$ and goto step 1.

4. NUMERICAL EXAMPLE

4.1 A test network

The traffic information strategy for multiple user class is implemented in the section with an example network. The network considered is that of Sioux Falls, consisting of 24 nodes and 76 links. The link impedance is BRP (Bureau of Public Roads) cost function with the parameters of α (0.15) and β (4).
The effect of information strategies are evaluated under following scenarios:

Three classes of users: The first is guided driver and the others unguided drivers, each of them aims to minimize his own cost of travel. Guided drivers are provided with perfect information. They adhere totally to the guidance systems, thus they follow UE behavior. Unguided drivers, however, in general fail to do so because of imperfect knowledge of the traffic conditions, therefore they follow SUE behavior. In SUE, the effects of existing errors of journey time prediction or of drivers do not adhere completely to the guidance. From the viewpoint of parameter θ , the variance of perceived travel time, the UE condition is identical to SUE condition at the value of θ with zero. In the paper three user classes are assumed to have the value of θ with 0.0, 0.4 and 0.8 respectively.

Six different degrees of compliance: To assess the effect of information according to the degree of compliance, six different levels are implemented such as δ = 0%, 20%, 40%, 60%, 80% and 100%

Five different information provision strategies: γ is a parameter representing information strategy between 0 and 1. In the case of 0.0, User Optimal routing is adopted. In γ =1.0

System Optimal routing. Mixed Optimal routing strategy has the values from 0.0 to 1.0

4.2 Numerical results

Figure 2 and Figure 3 show the evolution of the total travel time in considering multiple user classes who have specific values of θ . With the guidance the first class, cls1 in Figure 2, has a perfect knowledge of the traffic conditions and second class, cls2, follows with some variance of travel time. Thus the third class has a high degree of uncertainty on the network. For each user class there exist some fluctuations in early days. As days elapse, however, they converge to a steady state. As we expect, the first user class has the lowest value of total travel time and the others follow, not significant difference between them. From the point of the change of total travel time, shown in Figure 3, the second user class improves his travel time more than others. 2 or 4 percentages of travel times are reduced as a whole. This benefit comes from the decrease in perception error of travel time.

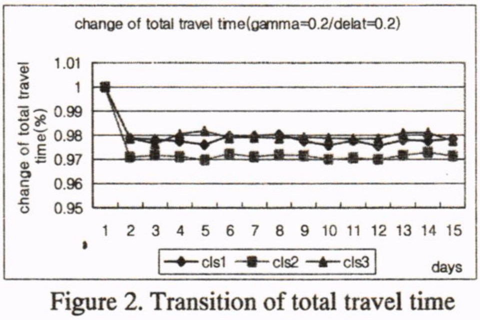

Figure 2. Transition of total travel time

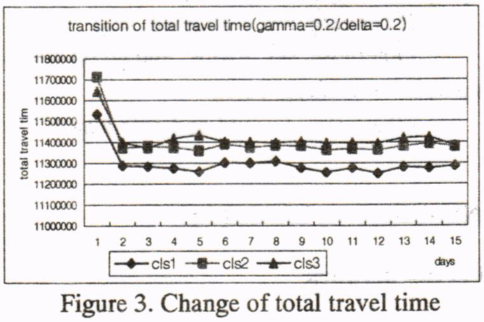

Figure 3. Change of total travel time

Figure 4 and Table 1 depict the relation between the compliance of traffic information (δ) and the total travel time for each routing strategy. Note that the effect of routing is expressed as a ratio of the total travel time under the no compliance of information base case; thus values below 1.0 correspond to a improving of system performance compared to the do-not information following case.
As the value of δ increases shown in Figure 4, there exist reduction of total travel times but not big differences among information strategies which is considered as a value of gamma (γ); γ =0.0 for UO strategy and γ =1.0 for SO strategy. This result implies that each routing strategy leads to improve the system. In conjunction with the information effect, Lim, et al. (1998) show the adverse impact of traffic information in the case of en-routing information provision. When traffic manager provide UO strategy for drivers and they follow the providing information absolutely, the change of total travel time even increase above the value of 1.0. Such worsening occurs when drivers switch their routes and then may occurs another traffic congestion on that alternative route. This phenomenon is a new 'Braess Paradox' with providing information to driver. The paradox may happen when traffic manager provides UO strategy and drivers take routes only for minimizing their travel time with no consideration of other network users. These worsening cases are also found in some other researches; Mahmassani el al. (1991), Ben-Akiva et al. (1991) and Emmerink et al. (1995). Ben-Akiva et al. mentioned this kind of adverse effect in more detail. They explained that it might occur on the condition that drivers who receive common information may tend to make similar route and departure time decisions, thereby increasing congestion. Fortunately, such worsening cases did not occur in this paper as shown in Figure 4.

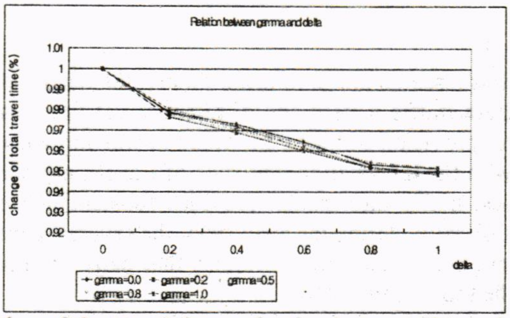

Figure 4. Relation of the travel time reduction by compliance for each strategy

Table 1. Change of total travel time for each routing strategy and compliance

Delta	Gamma=0.0	Gamma=0.2	Gamma=0.5	Gamma=0.8	Gamma=1.0
0	1	1	1	1	1
0.2	0.978742	0.978298	0.97642	0.980238	0.976377
0.4	0.972921	0.971633	0.970558	0.972052	0.968887
0.6	0.964496	0.961651	0.960782	0.963235	0.960098
0.8	0.953447	0.952067	0.9514	0.954563	0.952074
1	0.951523	0.949395	0.949141	0.951771	0.94855

With the different level of demand, evolutions of total travel time are shown in Figure 5 in the case of

γ =0.5 and MO strategy. Generally the magnitude of information effect depends on the degree of values of parameter δ, the degree of compliance. As the Figure explains, the more drivers follow the traffic information provided by traffic center, the more benefit we have. There, however, exist difference of information effect with the increase of congestion levels. The reason is that when traffic congestion becomes heavier, more routes will be used for minimizing travel cost. Figure 6 illustrates the evolution of travel time for each user class due to increasing congestion level in γ =0.5 and δ =0.6. Similar to Figure 5, in all cases the travel time saving becomes greater as the level of congestion increases. However, as we expect there are also differences between user classes, although not significant.

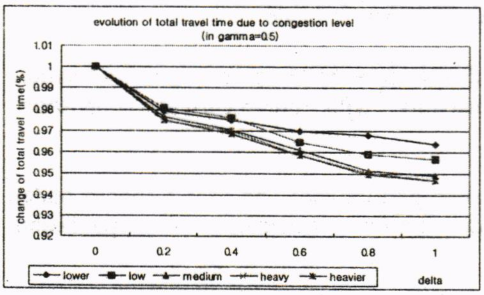

Figure 5. Evolution of total travel time due to congestion levels

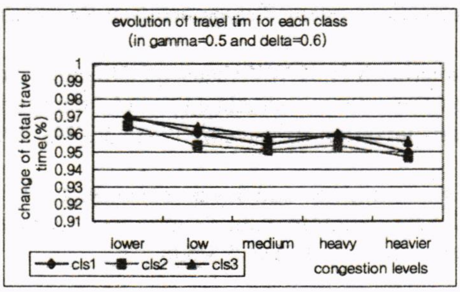

Figure 6. Evolution of total travel time for each user class

5. CONCLUSION

The important results of this research are as follows. Firstly, the results of the paper show that each user class has different traffic pattern and different travel time respectively. Secondly, we found that the effect of provision of traffic information was influenced by some variables such as the compliance with the information, variance of travel time perceptions and routing strategies. But in all cases, traffic information provides substantial benefits for drivers, no matter how they follow it. Finally, during the analysis of the several scenarios set in the paper, the adverse impacts do not occur. This result implies that daily information prior to trip is very effective to reduce the traffic congestion.
Further studies related to this research include the following issues. Firstly, the effects of traffic information are tested in normal condition, not incident. Therefore it is necessary to evaluate the effect under incident condition. Secondly, elastic demand should be considered for representing departure time and route choice behavior.

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