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Multiple User-Class Dynamic Stochastic Assignment for a Route Guidance Strategy

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1. Introduction

Traffic information systems have become a major issue in many countries as a modern technology for alleviating traffic congestion in urban areas. Pre-trip or en-route real-time travel information regarding traffic conditions can enhance drivers' knowledge of the situation in road networks and may assist in drivers' decisions such as the choice of departure time, route, and destination. In fact, several papers have shown that traffic information yields benefits to drivers such as travel-time reduction and the avoidance of traffic accidents, among others.

In considering the potential benefits of alternative driver information systems, it is also necessary to evaluate the potential of adverse impacts that improved information may have. Ben-Akiva et al. (1991) explained this phenomenon in terms of three elements: oversaturation; overreaction; and concentration. Among them, overreaction and concentration are the principal causes of adverse effects. Overreaction occurs when drivers' reactions to traffic information cause congestion to transfer from one road to another. It may also generate fluctuations in road usage. Overreaction may occur if drivers respond too sensitively to information on current traffic conditions. Concentration may occur when drivers choose a specific route in a very short period.

In order to implement the strategies of an Intelligent Transportation System (ITS), it is necessary to predict the temporal evolution of the traffic pattern on a congested transportation network, where travel demands and travel costs vary over time and space. For urban areas, dynamic models are mainly considered as they describe how commuters adjust their travel decisions concerning routes and departure times. Moreover, to model the impact of information provision by an ITS, it is necessary to develop a multi-class model given there are different classes of users in a transportation network, who respond in differing ways to traffic information.

In this chapter, a multiple-user-class dynamic stochastic assignment (MDSA) model is introduced to reflect drivers who have varying perceptual errors and varying dynamic traffic behaviors. MDSA is an extended version of a static single-user-class assignment. The driver's route-choice mechanism is based on his/her past experience of the road traffic conditions during prior days of travel. Some information-provision strategies that are involved in a route-guidance system are also introduced for the effective use of the systems.

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2. Literature review

One of the basic assumptions in conventional approaches to traffic assignment is that drivers' attributes are identical, i.e., drivers are homogeneous in terms of their attributes. However, this assumption is not realistic in urban traffic conditions: there do exist differences or perceptual errors across drivers. Stochastic approaches to traffic assignment include the variability in drivers' perceptions of costs and seek to minimize the disutility. In stochastic equilibrium models, the costs that are perceived by drivers are considered to be different from the actual costs. The perceived cost is modeled as a random variable. Several approaches have been proposed for formulating and solving the stochastic assignment problem (see Sheffi, 1985). However, simulation-based and proportion-based methods (i.e., methods that are predicated on the proportions of various types of driver, e.g., guided, unguided, etc.) are relatively widespread and accepted in practice.

There are also two kinds of stochastic assignment model: a non-equilibrium-based stochastic assignment model and an equilibrium-based stochastic assignment model. In the first case, a short-run spread of routes between two points is produced without a learning process, whereas, in the second case, a long-run spread of routes is produced with a learning process. Both models reflect the variability of the perceived cost of the routes. In particular, the second case is referred to as a 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 a day-to-day learning process; in other words, under the SUE condition, all users stay with their current routes that they perceive to offer the lowest 'perceived' cost to them. By using these stochastic user equilibrium assignment models, we can assess the effect of the traffic information that is provided by the traffic manager.

Breheret et al. (1990) developed a heuristic dynamic assignment model. They assumed that unguided drivers follow an approximate stochastic user equilibrium that is based on the prevailing conditions, whilst guided drivers follow user-optimal routes that are based on current conditions. They reported that the total travel-time decreases until the proportion of guided drivers is 20% and that the benefits for guided drivers are greater than those for unguided drivers. Smith and Russam (1989) also reported a saving of 6-7% in the average journey time for guided drivers, which actually decreased with an increase in the uptake of guidance; unguided drivers also benefited through travel-time reductions of up to 3%. Koutsopoulos and Lotan (1989) assumed that route guidance would reduce the perceptual errors in estimates of the travel times for links; therefore, their model consists of an SUE assignment for two classes with differing variances in the normal distributions with regard to the perceived link costs. An increase in the quality of information resulted in a reduction in the perceptual errors of guided drivers and therefore in a reduction in the travel times. Vuren and Watling (1991) assumed that unguided users were expected to follow an SUE route, whilst equipped drivers were guided via UE (User Equilibrium) or SO (System Optimal) routes. They reported that SO routing benefited unguided drivers at the expense of guided drivers at the levels of uptake that they considered. However, equipped drivers started benefiting as well when their numbers increased: at the highest levels of uptake (greater than 50-70%), guided drivers under SO routing could benefit more than unguided drivers. Baek et al. (1997) and Lim et al. (1997) also suggested a multiple-user-class day-to-day stochastic assignment model and a solution algorithm for reflecting drivers' daily route choice behaviors in the light of 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) 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 between individual decisions, traffic control strategies, and network-flow patterns under real-time information systems. On the other hand, Ben-Akiva et al. (1991) demonstrated some adverse effects of traffic information. They explained that if drivers respond too sensitively to the information provided, potential adverse impacts could occur. Thus, information may lead to an increased travel time and worsen the road network.

The results of prior research, as described above, are obviously rather ambiguous. Hypotheses about route choice and the interactions between guided and unguided drivers might influence the outcomes. However, often the models have used heuristic approaches and they are only valid under rather strong assumptions. These remarks are not intended to belittle the importance of the findings from extant research; they merely show the current problems in understanding and anticipating the behavior of drivers under future route-guidance systems.

3. Model formulation

The model described in this chapter actually consists of two models: a multiple-user-class daily stochastic assignment model and a traffic information model for optimal routing. The multiple-user-class daily stochastic model describes in detail the traffic flow on the road network and drivers' behaviors. The traffic information model sets traffic information for certain control purposes. In this research, some traffic management strategies can be considered with regard to information and then tested in contrived networks. The effects of these information schemes are evaluated through the multiple-user-class daily stochastic model. These two routines execute interactively until mutually consistent traffic flows are obtained.

For the model formulation, we assume the conditions of information provision and travelers' behaviors to be as follows. First, pre-trip and en-route information are provided, the output of which is the optimal route. Second, we define the characteristics of guided and unguided travelers in terms of the size of the perceptual errors. Lastly, guided travelers decide their daily mode and route through information on the projected travel costs.

3.1 Multiple-user-class daily stochastic assignment model

Multiple user-classes (MUC) have more than one class of user, where a class may be defined on the basis of the vehicle type, driver's cost functions, the sections of the network available, etc. A multi-class model is required to take into account differences across drivers or vehicles. To capture the behavioral differences between various types of traveler in terms of information-gathering and compliance with traffic information, a 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 its own definition of cost. MUC would also allow an approximation of the effects of traffic information within an Intelligent Transport System. The guided class of drivers can be assumed to have perfect knowledge of network conditions; thus, the guided class is assumed to follow user-equilibrium (UE) behaviors. However, the unguided class manifests uncertainty with regard to the network states; therefore, this group is assumed to follow the 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 segment travelers into three groups with respect to the values of a parameter, θ , which is the variance of the guidance. One class is the guided group of drivers, while one of the other two classes is the unguided group of drivers. For the third class of drivers, the variance of the perceived travel time is a fraction of that of the unguided drivers. The three classes are loaded on to the network, one by one.

A stochastic user equilibrium is a more general statement of equilibrium than the conditions of a conventional user equilibrium. In other words, the UE conditions are a particular case of SUE: when the variance in the perception of the travel time is zero, the SUE conditions are identical to the UE conditions. SUE models look particularly attractive in terms of the underlying theory. There are, however, operational and practical difficulties in applying them. The difficulty of an SUE model lies in the convergence properties of a conventional solution algorithm that is based on the convex-combination method. The reasons are twofold. First, the determination of the direction of descent 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 compute. To avoid these difficulties, iterative Monte Carlo simulation and the Method of Successive Averages (MSA) are widely used to solve the stochastic user equilibrium problem. MSA is based on a predetermined move size along the direction of descent. In other words, the optimal move size is determined beforehand instead of being attained from the minimization of the objective function.

On the other hand, conventional route-choice models are segmented into multi-nominal logit-based models and probit-based models. In this research, a probit model (Burrell's method), which assumes that the random error of each utility is normally distributed, is used. The computation of the probit choice probabilities used here involves a Monte Carlo simulation procedure.

The day-to-day stochastic assignment requires a modeling of users' dynamic adjustment behaviors, learning and forecasting mechanisms, and reactions to traffic information. Drivers' behaviors vary with the travel cost, which consists of a mean link travel time and variance, which arises from drivers' perceptual errors. In this research, drivers' dynamic route-choice rules are based on the experienced travel time and the predicted travel time that stems from information-provision strategies. The link travel time function is developed as follows.

$$T_a^w(f_a) = (1 - \delta)t_a^w(f_a) + \delta s_a^w(f_a) \quad (1)$$

In Eq. (1), $T_a^w(f_a)$ is the total travel cost on link a at day w and comprises of the actual travel cost, $t_a^w(f_a)$, and the predicted cost, $s_a^w(f_a)$. f_a is the flow along link a and δ is a parameter that reflects drivers' behaviors. The sensitivity of drivers to the routing information is tested through an incremental increase in the value of δ . $t_a^w(f_a)$ is the BPR (Bureau of Public Roads) function as shown in Eq. (2) and $s_a^w(f_a)$ is the function of traffic flows in Eqs. (3) and (4).

$$t_a^w(f_a) = t_{a0}^w \left[1 + 0.15 \left(\frac{f_a}{c_a} \right)^4 \right] \quad (2)$$

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

$$\sum_{i=1}^3 \beta_i = 1. \quad (4)$$

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

3.2 Provision of traffic information

Traffic information plays an important role in drivers' route-choice behaviors and is classified into individual system information and collective system information. Equally, the provision of traffic information also falls into two categories: minimizing the travel cost for the driver (user equilibrium guidance) and minimizing the travel cost for the network as a whole (system optimality guidance). The selection of a route-guidance strategy and its provision to drivers has recently become a key issue for traffic managers. There exist several strategies with respect to management purposes and also exist conflicts of interest between the equipped drivers, who want to improve their travel times, and traffic managers, whose objective is to reduce the overall traffic congestion. One of the solutions to this problem is a strategy that combines the objectives of the user and the system. The three information strategies that are considered in this research are the 'User Optimality [UO] strategy', 'System Optimality [SO] strategy', and 'Mixed Optimality [MO] strategy'. The first strategy, UO routing, is implemented through user equilibrium assignment with an average travel cost on each link as follows.

$$\text{[UO strategy]} \quad s_a^w(f_a). \quad (5)$$

For implementing the second strategy, viz., SO routing, a system optimal assignment is performed with a marginal link travel cost as above.

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

Lastly, the mixed optimality strategy that is considered is as follows.

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

In the above, γ is a parameter between 0 and 1. When γ is 0, the MO routing strategy is equivalent to the UE routing strategy; when γ is 1, it is equivalent to the SO routing strategy. Another important parameter in a traffic information system is the degree of information guidance. Guided travelers determine their routes and modes by the expected travel times and almost no perceptual errors. In contrast, unguided travelers get much more inaccurate information on travel conditions. In the research, we assume that a guided driver follows

the user-equilibrium (UE) principle and an unguided driver follows the stochastic user equilibrium (SUE) principle with some variance in the travel time. Thus, the link travel time of an unguided driver can be formulated as:

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

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

3.3 Solution algorithm

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

[step 0] Initialization.

Set the iteration number, $n=1$.

Day: $w=1$.

Initialize the following.

Information strategy, γ .

Degree of information compliance, δ .

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

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

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

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

[step 2] Traffic information strategy.

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

2.2 Calculate the 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-class, i :

3.1 Sample a set of link error terms, $\{\varepsilon_{ai}\}$, from the normal distribution by a 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 costs, $\{C_{ai}^{w,n}\}$, which yields 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 $n = n + 1$ and go to step 1.

[step 5] If $w \geq \text{days}$, stop.

Else, $w := w + 1$ and go to step 1.

4. Numerical calculations

In order to evaluate the model and information strategies suggested, two example networks are used. The first example involves a simple network with one origin-destination pair that is connected by two routes. The second example is a medium-sized network with several origin-destination pairs; it considers various information strategies in detail.

4.1 A simple network

A numerical example is presented to illustrate the application and assessment of the developed MDSA model. The example network is shown in Figure 1. The input data, such as the link capacity, free-flow cost, and the parameters of compliance and variance, are also shown in Table 1. It is assumed that there is one origin-destination pair from node 1 to node 4 with trip demands of 1500.

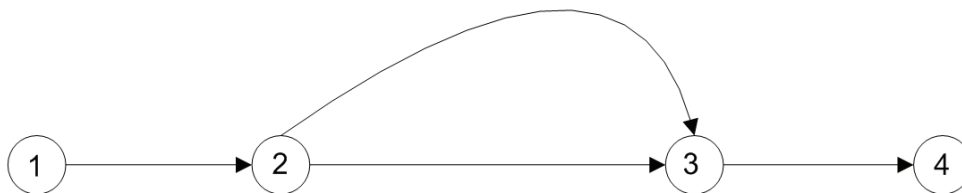


Fig. 1. Simple example network.

Network specification	
Capacity	1000(vehicle/hour)
Free-flow time	60 (sec)
User-class data	
Information compliance (δ)	0.0~1.0 by 0.2
Variance of perception (θ)	0.0/ 0.5/ 1.0
Trip demand (veh/h)	1500
Study period	15 days

Table 1. Input data for the example.

Figures 2 and 3 show the evolution of the total travel-time in the consideration of multiple user-classes in which the parameter, θ , represents the user class. The total travel-time is lower in the early days as the compliance with information increases, that is, as the

perceptual error decreases. However, as days elapse, the total travel-time converges to a certain value and no more benefits are realized.

Figure 3 and Table 2 show the variation of the total travel-time with the guidance level and the perceptual error on the first day. It is worth noting that the total travel-time is affected significantly by the perceptual error (θ) and does not decrease as the compliance (δ) with information increases. These results that are derived from the present research show that the effect of the provision of traffic information is influenced by many variables, e.g., the trip-demand level, compliance with information, variance of travel-time perceptions, etc.

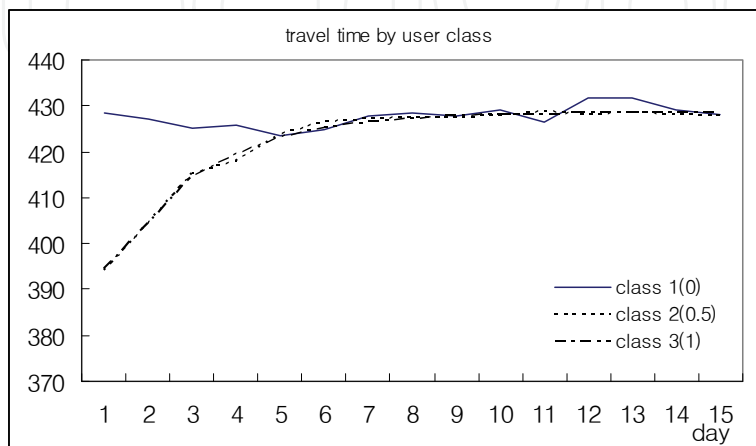


Fig. 2. Variation of the travel time by user class.

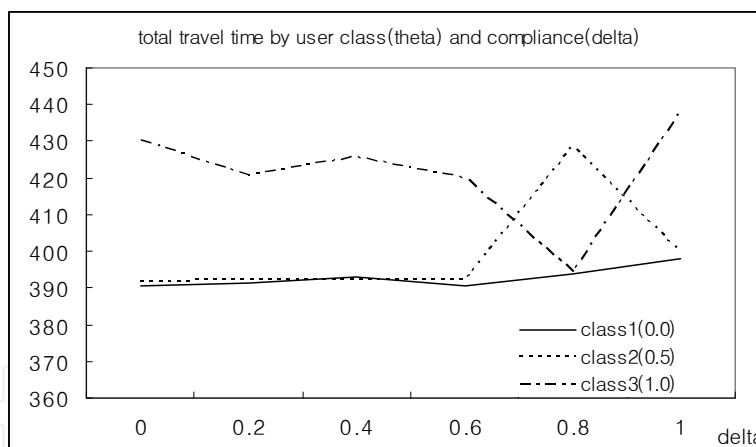


Fig. 3. Variation of the travel time by compliance.

δ	Class 1 ($\theta=0.0$)	Class 2 ($\theta=0.5$)	Class 3 ($\theta=1.0$)
0	390.6	391.7	430.1
0.2	391.3	392	420.8
0.4	392.9	392	425.6
0.6	390.7	392	419.9
0.8	394	428.4	394.3
1	398	399.6	438.1

Table 2. The total travel-time for varying degrees of compliance (δ) for each user-class.

4.2 A large network

The traffic information strategy for multiple user-classes is implemented in more detail with a larger network than in the first example. The network considered is Sioux Falls, SD, USA, which consists of 24 nodes and 76 links. The link impedance is the BPR (Bureau of Public Roads) cost function with the parameters of α (0.15) and β (4).

The effects of information strategies are evaluated under the following scenarios.

Three classes of user: The first class comprises guided drivers. The third class is that of unguided drivers, while the second class refers to drivers who are partially guided/unguided. Each class of drivers aims to minimize its own cost of travel. Guided drivers are provided with perfect information. They totally adhere to the guidance systems; thus, they follow UE behaviors. Unguided drivers, however, in general, fail to do so because of their imperfect knowledge of the traffic conditions; therefore, they follow SUE behaviors. In SUE, the effects of existing errors in journey-time prediction or of drivers imply the lack of complete adherence to guidance. From the viewpoint of the parameter, θ , viz., the variance of the perceived travel time, the UE condition is identical to the SUE condition when θ equals zero. In this research, the three user-classes are assumed to have values of θ of 0.0, 0.4, and 0.8, respectively.

Six different degrees of compliance: To assess the effect of information in terms of the degree of compliance, six different levels are implemented for δ : 0%; 20%; 40%; 60%; 80%; and 100%.

Five different information-provision strategies: γ is a parameter that represents information strategies that range from 0 to 1. When γ is 0.0, User-Optimal (UO) routing is adopted. When γ is 1.0, System-Optimal (SO) routing is adopted. A Mixed-Optimal routing strategy has values that range between 0.0 and 1.0.

Figures 4 and 5 show the evolution of the total travel-time in the consideration of multiple user-classes that have specific values of θ ; Figure 4 shows the absolute values, while Figure 5 shows the values normalized with respect to the initial value (at day 1). With guidance, the first class, cls1 in Figure 4, has perfect knowledge of the traffic conditions and the second class, cls2, comes next with some variance of the travel time. Thus, the third class has the highest degree of uncertainty in the network. For each user-class, there exist some fluctuations in the early days. As days elapse, however, their travel-times converge to

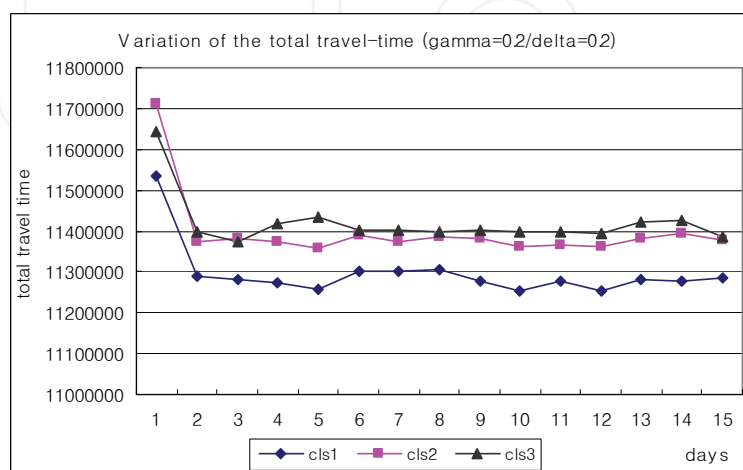


Fig. 4. Variation of the total travel-time.

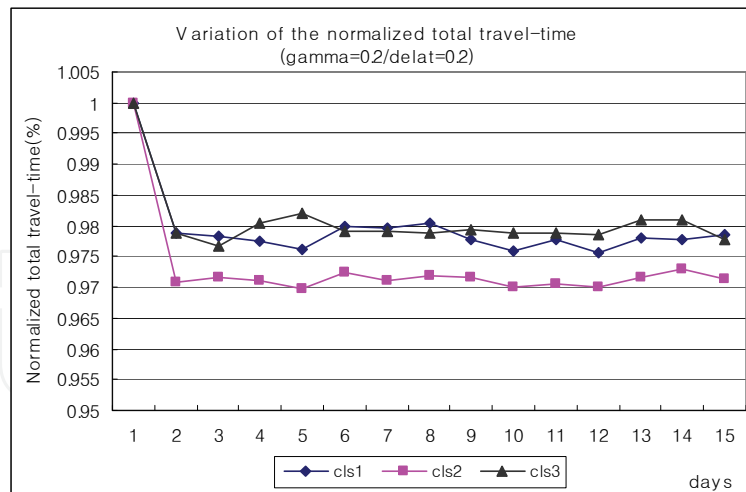


Fig. 5. Variation of the normalized total travel-time.

steady-state values. As one would expect, the first user-class has the lowest value of the total travel-time and the others follow behind with rather insignificant differences between them. After day 1, as shown in Figure 5, the second user-class, relatively speaking, improves its travel time more than the others. Across the three classes, the total travel-time is reduced by 2~4 percentage points with the lapse of time. This benefit comes from the decrease in the perceptual error with respect to the travel time.

Figure 6 and Table 3 depict the relationship between the compliance with traffic information (δ) and the total travel-time for each routing strategy. Note that the effect of routing is expressed as a ratio with respect to the total travel-time under the base case of no compliance with information; thus, values below 1.0 correspond to an improvement in the system performance in comparison with the case of no compliance with traffic information.

As the value of δ increases, as shown in Figure 6, the total travel-times reduce but the differences are not large across information strategies, which are captured as values of gamma (γ): $\gamma=0.0$ for the UO strategy and $\gamma=1.0$ for the SO strategy. This result implies that

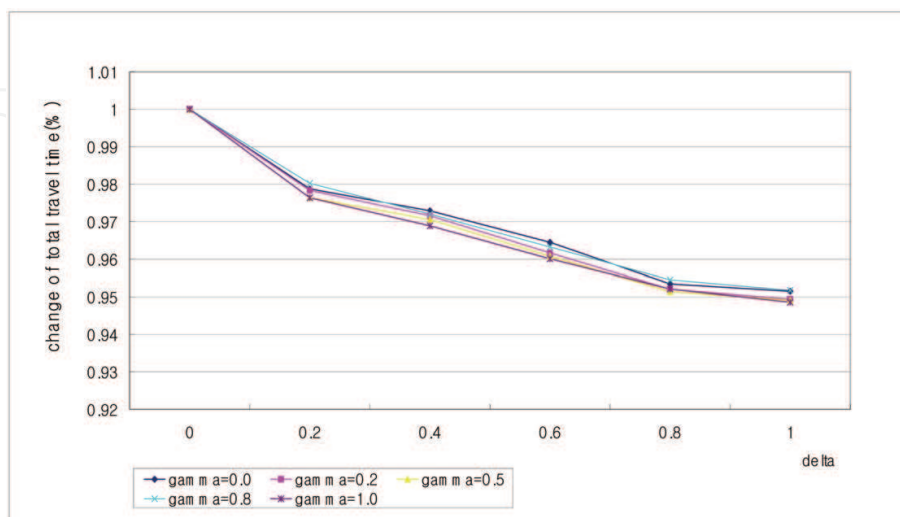


Fig. 6. Relationship of the travel-time reduction to compliance for each strategy.

each routing strategy helps to improve the system. In conjunction with the information effect, Lim et al. (1998) established the adverse impact of traffic information in the case of en-route information provision. When a traffic manager adopts the UO strategy for drivers and the drivers absolutely follow the provided information, the total travel-time even increases above the normalized value of 1.0. Such worsening occurs when drivers switch their routes, which can result in traffic congestion on the alternative route. This phenomenon is a new 'Braess Paradox' that results from the provision of information to drivers. The paradox may arise when traffic managers adopt the UO strategy and drivers take routes for only minimizing their travel times with no consideration of other network users. These worsening cases are also found in some other studies, e.g., Mahmassani et 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 may occur on the condition that drivers who receive common information may tend to make similar route-decisions and departure-time decisions, thereby increasing congestion. Fortunately, such worsening did not occur in this research, as shown in Figure 4.

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

Table 3. Variation of the total travel-time for each routing strategy and level of compliance.

For different levels of demand, evolutions of the total travel-time are shown in Figure 7 in the case when $\gamma=0.5$ and an MO strategy is adopted. Generally, the magnitude of the

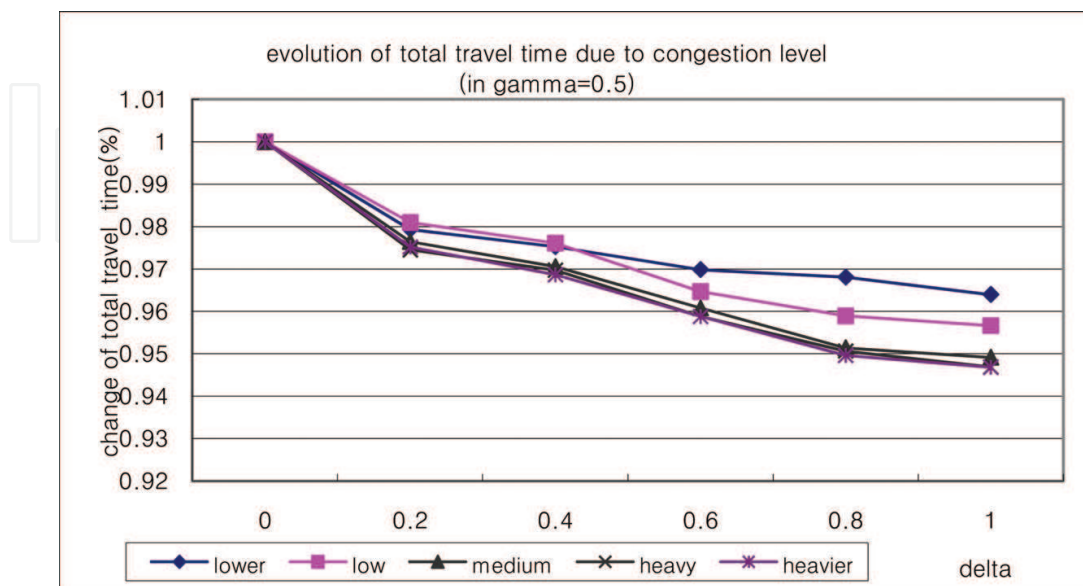


Fig. 7. Evolution of the total travel-time for various levels of congestion.

information effect depends on the value of δ , the degree of compliance. As the figure explains, the more are the drivers who follow the traffic information that is provided by the traffic center, the more benefits we will realize. There, however, exist differences in the information effect as the level of congestion increases. The reason is that when traffic congestion becomes heavier, more routes will be used for minimizing the travel cost. Figure 8 illustrates the evolution of the travel time for each user-class with rising levels of congestion when $\gamma=0.5$ and $\delta=0.6$. Similar to Figure 7, in all cases, the travel time saving becomes greater as the level of congestion increases. However, as we would expect, there are also differences between user-classes, although they are not significant.

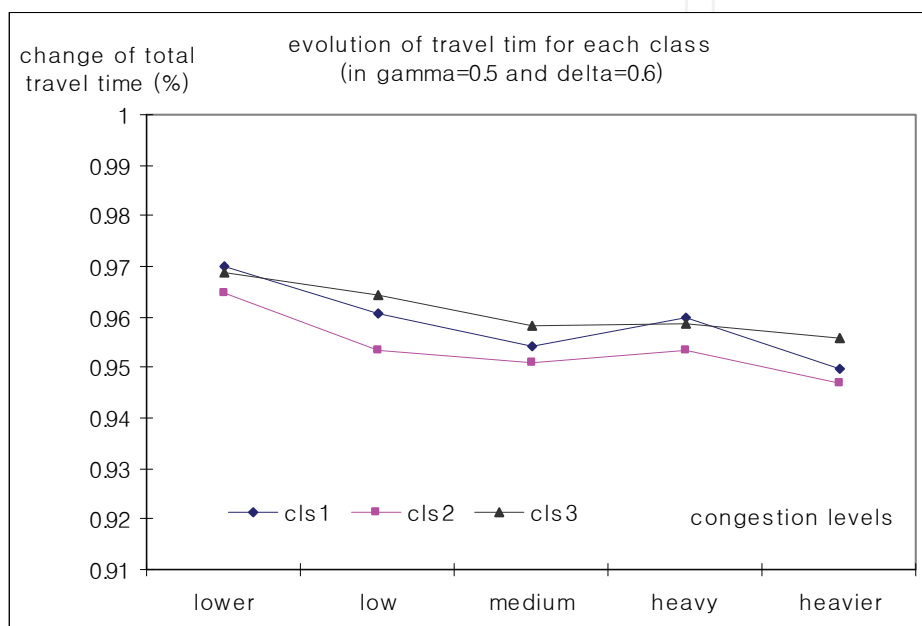


Fig. 8. Evolution of the total travel-time for each user-class.

5. Conclusions

This chapter presents an MDSA model and assesses the effect of traffic information according to the level of information. The MDSA model that is based on previous experiences considers the varying perceptual errors and varying dynamic traffic behaviors of users. Although it may not fully describe the behaviors of travelers, it is accepted here as a reasonable approximation to the long-term average route-choice of travelers under steady-state conditions. The model is also able to more precisely simulate the network conditions than deterministic traffic assignment models in that it is more flexible in reflecting drivers' behaviors. The important results that arise from this study are as follows. Firstly, the results show the traffic patterns of multiple user-classes (MUC) on a link, wherein each class has a unique travel-time. Secondly, this research also shows that the effect of traffic information is influenced by some factors, such as demand conditions, compliance with information, variance of travel-time perceptions, etc. Lastly, the effect of the provision of traffic

information exists under the conditions of proper demand, compliance with information, and the variance of travel-time perceptions.

Further studies related to this field of research would include the following issues. Firstly, the effects of traffic information are tested here in normal conditions, not those of traffic incidents. Therefore, it is necessary to evaluate the effects under traffic incidents. Secondly, elastic demands should be considered for representing departure-time and route-choice behaviors.

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Starting a journey on the new path of converging information technologies is the aim of the present book. Extended on 27 chapters, the book provides the reader with some leading-edge research results regarding algorithms and information models, software frameworks, multimedia, information security, communication networks, and applications. Information technologies are only at the dawn of a massive transformation and adaptation to the complex demands of the new upcoming information society. It is not possible to achieve a thorough view of the field in one book. Nonetheless, the editor hopes that the book can at least offer the first step into the convergence domain of information technologies, and the reader will find it instructive and stimulating.

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