

**Relaxing the User Equilibrium
Assumptions and its Effects on Traffic
Pattern and Network Behavior**

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Relaxing the User Equilibrium Assumptions and its Effects on Traffic Pattern and Network Behavior

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ABSTRACT

This study examines the traffic pattern and the network behavior after relaxing the fundamental assumptions in the user equilibrium concept— perfect information, rationality, and homogeneity. Employing a day-to-day evolution approach, we develop simulation-based models that include drivers' learning model, preference model and preference sensitivity to relax these assumptions. Through simulation experiments, network performance and the evolution of drivers' route choice behavior are investigated. Among three assumptions, the perfect information assumption is the most influencing and the basis of the other assumptions. A learning model replacing the perfect information assumption reveals that drivers' ability of predicting the travel time is limited to the route they use through their learning process. The preference model replacing the rationality assumption shows how drivers' habitual route choice behavior is developed in their leaning process. Lastly, the replacement of the homogeneity assumption with drivers' preference sensitivity shows that drivers with a high sensitivity value develop strong habitual route choice behavior if the initial congestion perception is not realistic.

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INTRODUCTION

Drivers' route choice behavior in a network has been described with user equilibrium (UE) based on the Wardrop's first principle (1) during the past decades. The UE principle has been accepted as a general rule and widely applied to estimating and predicting network traffic patterns. The popularity of the equilibrium principle is mainly because of its mathematical clarity though it lacks of the ability to capture the process and the evolution of drivers' route choice behavior. The UE state in which "the travel times of all used routes are same and less than those of unused routes" is somewhat normative rather than descriptive, so the UE state is often regarded as a target state to achieve rather than a representation of current traffic pattern. It stems from three fundamental assumptions behind the UE principle. The assumptions are that 1) drivers have perfect information and knowledge; 2) they are rational decision makers; and 3) they are all homogeneous. During the past decades many researchers have pointed out that the unrealistic assumptions are sources of inaccuracy in UE model, and have strived to develop models relaxing these assumptions. This paper take a fresh look at how these assumptions affect the performance of traffic assignment and the evolution of drivers' route choice behavior.

That the drivers have perfect information is the most important and fundamental assumption in mathematically interpreting the user equilibrium behavior; however, in reality, drivers do not have perfect information for their route decision mainly due to the limitations of information sources. Even when advanced traveler information systems (ATIS) are available to drivers, it is difficult to reach the perfect real-time information situation. One may argue that commuters acquire good knowledge on their routes from their long experience and reach close to the perfect knowledge. In such circumstances, however, the traffic pattern may fall into an equilibrium state (2).

The assumption of drivers' rationality can also be interpreted similar to the assumption of perfect information. The rational drivers are assumed to select the minimum travel time or cost route based on their information. However, when drivers do not have perfect information, drivers will rely on their previous experience, and their preference on a certain route acquired from their experience will affect their route decision. For example, drivers may avoid the shortest route if they had a bad experience on the route. Drivers may not just try to minimize the expected travel time, but also consider their preference accumulated from their experience.

The last assumption of homogeneity is that all travelers have the same travel characteristics. However, obviously each traveler has different background in terms of age, income, education, preference, etc. Although the homogeneity assumption is essential in simplifying the network problem, the effect of drivers' heterogeneous characteristics on network traffic condition should not be neglected. Multi-class approaches have been applied in order to consider such heterogeneity, but these are mostly to investigate the difference between classes of users than across individual users.

This study relaxes these three assumptions by employing a day-to-day evolution modeling approach and investigates how each assumption affects traffic assignment results and how driver's route

1
2 choice behavior evolves under different settings. The new features of the model in this paper are to
3 incorporate a drivers' preference model into the drivers' learning process and to apply such a process
4 model to a network traffic assignment problem.
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7 8 **TRAVELER BEHAVIOR AND DAY-TO-DAY EVOLUTION APPROACH**

9 One representative effort to relax such assumptions in the network problem, was the stochastic user
10 equilibrium (SUE) model (3). The SUE model was further developed for departure time choice and day-
11 to-day variation (4). The SUE model transforms a link travel time into a random variable (a perceived
12 link travel time) by adding a random error term, and seeks an equilibrium state in which the perceived
13 travel times of all used paths are same. That is, the SUE model incorporates drivers' perception error in
14 its equilibrium. However, in SUE model, all travelers confront the same level of uncertainty for a specific
15 link regardless of their origin and destination. In a general network, between an origin and destination
16 pair, some routes are frequently used by drivers while some routes are rarely chosen. This means that the
17 perceived error of link travel time should be modeled independently by OD pair and the error term cannot
18 be represented by a single value. Criticizing that the uncertainty modeling in SUE model cannot
19 reasonably represent the uncertainty, Nakayama et al. (2) suggests that the error terms be modeled to
20 decrease as drivers get experiences to reflect the situation of imperfect information.
21

22 As a different approach, Horowitz (5) first developed a drivers' information acquisition process
23 through their own experiences, and Ben-Akiva et al. (6) and Cascetta (7) proposed a stochastic process
24 approach for analyzing day-to-day dynamics in a transportation network. This approach models the
25 evolution of drivers' route choice behavior as a stochastic process. Since then, many researchers have
26 applied the day-to-day evolution approach to route choice behavior studies. The day-to-day dynamic
27 approach in Mahmassani and Chang (8) considers the choice of departure time and route according to the
28 schedule delay governed by traveler's daily learning process. Iida et al. (9) tested driver's route choice
29 behavior with laboratory experiments, and demonstrated that the route choice pattern could be stabilized
30 without decreasing the sensitivity of route choice by the indifference band. Cascetta and Cantarella (10)
31 combined a day-to-day route choice model to a within-day formulation, and Cantarella and Cascetta (11)
32 showed that drivers' individual experience could stabilize the network flow pattern and the dissemination
33 of information would make the network flow pattern unstable. Watling (12, 13) models the variation of
34 traffic flow by a stochastic process and then suggested an "ergodic state" in which a stochastic process is
35 stabilized. The simulation program DYNASMART (14) was extensively used for simulating these types
36 of processes under several conditions. Hu and Mahmassani (15) investigated the day-to-day evolution of
37 network flows under real-time information and responsive signal control. Oh et al. (16) applied this
38 approach to investigate the effect of less-equilibrated data on model estimation by incorporating a nested
39 logit model in the process.
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2 Unlike other analytical equilibrium models, the day-to-day dynamic framework enables the
3 analysis of traveler choice changes over a time horizon based on traveler's updated knowledge. Most
4 studies in this approach have focused on investigating the impact of information on route choice behavior.
5 Previous studies (2, 5, 9, 11) found the drivers' route choice could be affected by their experiences in
6 early times. Recently, Nakayama et al. (2, 17, 18) developed a rule-based model to study drivers' route
7 choice behavior. However, their process is rather complicated and their route-based if-then rules cannot
8 consider the overlapped attributes between routes. The common findings are 1) the initial traffic condition
9 plays an important role in resulting route choices; 2) drivers' route choices become unstable if they
10 receive the travel time information on unused routes; and 3) drivers' route choices might be easily
11 stabilized if they choose their routes based on their own experiences.
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16 **MODEL DEVELOPMENT**

17 **Model Concept and Framework**

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19 The main purpose of this paper is to compare how the network traffic changes as the assumptions in the
20 UE are relaxed. To achieve the objective, we develop three models. Table 1 summarizes the underlying
21 assumptions and their relaxations.
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29 **Figure 1** describes the general model framework. The framework consists of five stages including
30 initialization, network loading, learning process, route choice, and checking convergence. The main
31 feature of the model is to integrate the route preference model in drivers' learning process through
32 individual driver's post evaluation, and assumptions in the UE are relaxed in this cognitive process. The
33 first assumption, perfect information, is relaxed by modeling the drivers' perceived travel time that is
34 updated only through their experience. That is, drivers' information source is limited only to their
35 previous experience. The second assumption, rational behavior, is relaxed by incorporating a preference
36 update process in the inductive learning process. In the process, drivers' preference on their routes is
37 modeled by considering the travel time difference between expected and experienced, and the route
38 preference plays a major role in making their next route decision along with their expected travel time.
39 The third assumption, homogeneity, is relaxed by assigning a different sensitivity parameter in the path
40 preference model for each driver at the demand generation stage.
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Model Details

Initialization of Network Condition

The model starts by stochastically initializing network condition for individual drivers. Each driver's initial perceived link travel times are determined by his/her initial perception on the level of network congestion and random perception error on each link. Drivers' prior perceived link travel times are expressed as:

$$\bar{t}_{m,i}^0 = \alpha_m \cdot (t_i^f \pm \beta_{m,i} \cdot t_i^f) \quad (1)$$

where

$\bar{t}_{m,i}^0$: the initial perceived travel time of link i by driver m

t_i^f : free-flow travel time of link i.

α_m : the parameter for driver m's perceived congestion level.

$\beta_{m,i}$: the parameter driver m's random perception error on the free-flow travel time of link i.

The parameter for driver's initial perceived congestion level, α_m , is also regarded as the level of information. This parameter plays an important role in developing drivers' reference on their routes. The parameter, $\beta_{m,i}$, is randomly assigned for each driver makes each drivers perceive different travel times on the same link and choose different routes. Each driver's initial perceived travel times (prejudice) are determined by combining the systematic perception error, α_m , and the link-driver-specific random perception error, $\beta_{m,i}$. In this paper, we use 1.3 as α_m and randomly assign a value of $\beta_{m,i}$ between -0.3 and +0.3 for each driver and each link.

To find feasible routes between an original and a destination, we develop path enumeration algorithm. The algorithm is based on conventional tree building algorithms. While general tree building algorithms only store the shortest paths or specific paths from an origin node to all other nodes, the scheme here is to store all paths from an origin to all other nodes. The algorithm is divided into two sub-algorithms: 1) spanning the branches and 2) sorting and storing the paths. Since this path enumeration algorithm searches all feasible paths, the number of paths drastically increases as the network size increases. Obviously the scheme is not viable for large networks, but for the purposes of this paper, it suffices. In this study, the number of feasible paths is constrained by the relative path length compared to

1
2 the shortest route. In other word, the algorithm searches all paths that are shorter than α times the shortest
3 path. Here, α is specified by users. The detail algorithm is not included in this paper due to the space
4 limitation.
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7 *Travel Time Perception in Learning Process*

9 In the model, drivers update their expected link travel times based on their previous experience. The
10 expected link travel time for next day is updated by the recursively equation as follow.
11

$$12 \quad \bar{t}_{m,i}^{d+1} = (1-s)\bar{t}_{m,i}^d + s \cdot t_{m,i}^d \quad (2)$$

14 where

16 $t_{m,i}^d$ = the experienced travel time on link i on day d by driver m

18 $\bar{t}_{m,i}^d$ = the expected travel time on link i on day d by driver m

20 s = a learning rate ($0 \leq s \leq 1$)

22 The expected travel times are updated only on links that the driver m used on day d-1. A learning
23 rate of 0.05 is applied. Note that we do not update the route travel time, but travel times on links that the
24 driver used unlike other studies on day-to-day route choice behavior in which drivers' alternative routes
25 are assumed independent. These route-based procedures have a shortcoming in that a driver could not
26 update his/her knowledge on an unused route even if the route is substantially overlapped with the used
27 route. However, the link-based approach in this paper allows the partial update for the unused routes that
28 share some links with the used route. Especially when there are numerous alternatives, it is necessary to
29 consider an indirect inference model to update driver's knowledge based on the limited experience.
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32 After updating link travel times, the expected route travel time is computed by summing travel
33 times on links that are part of the route.
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$$35 \quad \bar{T}_{m,p}^d = \sum_i \delta_{m,p,i} \cdot \bar{t}_{m,i}^d \quad (3)$$

37 where

38 $\bar{T}_{m,p}^d$ = the expected travel time on route p on day d by driver m

40 $\delta_{m,p,i}$ = an incident indicator between route and link (1 if link i is part of route p; 0 otherwise).
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Route Preference in Inductive Learning Process

In this study, we introduce the concept of route preference. Drivers evaluate their routes by comparing their experienced travel time with their expectation. If their experienced travel time on the route is shorter than they expected, their preference on the route will increase and vice versa. Through this process, each driver will build his/her own route preference map. The process of route preference is modeled as an inductive learning process, expressed as:

$$\Phi_{m,p}^{d+1} = \Phi_{m,p}^d + \gamma(T_{m,p}^d, \bar{T}_{m,p}^d) \quad (4)$$

where

$\Phi_{m,p}^d$ = driver m's preference on route p on day d,

$T_{m,p}^d$ = the experienced travel time on route p on day d by driver m

$\bar{T}_{m,p}^d$ = the expected travel time on route p on day d by driver m

$\gamma(\cdot)$ = is a function of the travel time difference between expected and experienced.

The preference function, $\gamma(\cdot)$, is formalized as in Figure 2 and equation (5) by incorporating the indifference band, ε . That is, a minor travel time difference within the band (5% in this study) does not affect their preferences. The changes in preference is calculated by the product of the travel time difference and the value of driver's sensitivity, σ_m , when the travel time difference is greater than the indifference band, ε . In the model, if the actual experienced travel time is longer than expected, the value of the preference function becomes greater than 1.0, which means the driver loses his preference on the route. On the other hand, the driver's preference value on the route becomes smaller than 1.0 when the actual travel time was shorter than expected.

$$\gamma(T_{m,p}^d, \bar{T}_{m,p}^d) = \begin{cases} 0 & \text{if } \left| \frac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d} \right| \leq \varepsilon \\ \sigma_m \cdot \left(\varepsilon - \frac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d} \right) & \text{if } \frac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d} > \varepsilon \\ -\sigma_m \cdot \left(\varepsilon + \frac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d} \right) & \text{if } \frac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d} < -\varepsilon \end{cases} \quad (5)$$

The preference sensitivity could vary by driver. In this paper, drivers' heterogeneity is represented by assigning different sensitivity parameters to drivers for the case of Model 3 while the same sensitivity is applied in other cases. While drivers with a high σ tend to change their route preference quickly,

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2 those with a low σ change their preferred route slowly. The sensitivity value reflects driver's route
3 switching characteristics. Drivers with high σ values are regarded as "sensitive drivers," and those with
4 low σ values are regarded as "insensitive drivers," respectively. In Model 3, each driver's preference
5 sensitivity parameter is randomly assigned within a bounded range in order to model heterogeneous
6 drivers in the context of route choice behavior.
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10 << Insert Figure 2 here >>
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12 *Route Choice Model*

13 Route choice decision is made simultaneously considering both driver's perceived travel time and their
14 preference on alternative routes.
15
16

$$17 \text{ Driver } m\text{'s route on day } d = \arg \min_p \Phi_{m,p}^d \cdot \bar{T}_{m,p}^d \quad (6)$$

18 where the arg is an operator which chooses the route with the minimum value of $\Phi_{m,p}^d \cdot \bar{T}_{m,p}^d$ among
19 alternatives.
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22 According to the equation (6), each driver selects the best route based on his/her travel time
23 expectation and preference. This route choice routine is repeated every day for their next trip. This
24 iteration stops when drivers' choice behavior is converged. In this study, we use the "perceived user
25 optimal state" as a stopping criterion. We regard that the convergence is reached when most drivers (more
26 than 99% of driver) do not change their route for the predefined number of days (5 days).
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32 NUMERICAL EXPERIMENT

33 **Test Scenario and Network**

34 Simulation experiments are implemented on a test network with 9 nodes and 13 links as shown in Figure
35 3. There are two types of links in the network: one with high capacity and the other with low capacity.
36 The links depicted by thicker line are high capacity links with the capacity of 220 vehicles per hour; this
37 other links are low capacity link with the capacity of 180 vehicles per hour. Three origin-destination pairs
38 are included, traveling from nodes, 1, 3, and 6 to destination node 9. The OD demands, 1→9, 3→9, and
39 6→9, are assumed to be 300, 200, and 100 vehicle per hour, respectively. Using the all-feasible-path
40 enumeration algorithm, we identified 9 routes between 1 and 9, 7 routes between 3 and 9, and 5 routes
41 between 5 and 9.
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<< Insert Figure 3 here >>

Comparison of Network Equilibrium

While the UE provides the same travel time among route for a given OD pair thanks to the assumption of drivers' perfect information and knowledge, other models show different travel times among alternatives as shown in Figure 4. Especially, the travel times are highly variable among alternatives in Model 2 and 3 where drivers' route preferences are included in their route choice. In Model 1, even though drivers are acquiring network information from their experience, they could not reach the UE condition mainly because of the limited information.

<< Insert Figure 4 here >>

In order to compare models in terms of the level of travel time equilibrium, the level of equilibrium (LOE) is defined as a standard deviation of travel times used routes. In the true UE state, travel times among used paths should be same. As compared in Table 2, Model 2 shows the greatest travel time variability among routes. Although it is not conclusive, the heterogeneous characteristics in Model 3 may have led to the network traffic dispersion and the lower LOE than Model 3.

$$LOE = \sqrt{\frac{\sum_{p \in P} (T_p - \bar{T})^2}{N_p}} \quad (7)$$

where T_p = the travel time on path p

\bar{T} = the mean travel time of routes used for a given OD pair

P = a set of paths used for a given OD pair

N_p = the number of paths used for a given OD pair

Table 2 also compares average travel times between OD pairs and the total network costs. Although UE shows the lowest LOE, but its travel times are not the lowest. Model 1 results in the lowest travel costs in our experiment. As known, the UE pattern does not provide the lowest network cost, implying that dissemination of travel information is not always beneficial as many other studies (5, 9, 11) identified. The system optimum traffic pattern always results in lower cost than the UE, and some stochastic user equilibrium patterns may give lower costs than the UE. This implies. Model 1 in our experiment is regarded as such a SUE pattern.

<< Insert Table 2 here >>

Investigation of Learning Behavior

This section investigates drivers' leaning effect in predicting route travel times. Until reaching the convergence, Model 1 takes 69 days, and Model 2 and Model 3 take 97 and 100 days, respectively. Unlike the UE model, these models move toward convergence by updating information only from drivers' limited experience. Figure 5 compares expectation errors of all routes and those of used routes. While the average expectation errors of the all routes are still large (around 15% for all cases), those of used routes are almost zero. This reflects drivers' incapability in predicting travel times in unfamiliar area and drivers' inertia in switching to new routes. This also manifests that limited knowledge is the main reason that drivers are not capable of finding alternatives when they face with non-recurrent congestion.

<< Insert Figure 5 here >>

Effect of Prior Information Accuracy on Network Performance

In this section, we investigate how the drivers' prior perception (prejudice) affects the network flow pattern and the drivers' route choice habit. The drivers' prior perception is represented by the α_m value in equation 1. In this analysis, we increase the α_m value representing network congestion level from 1.0 to 1.8, and investigate network performances. In the UE state, the overall flow level is about 1.5 times higher than its capacity.

<< Insert Figure 6 here >>

Figure 6 shows variations of network performance by the drivers' initial perception on overall congestion level, α_m . When the initial perception of network congestion is lower than the actual congestion level ($1.00 \leq \alpha_m < 1.5$), there are fluctuations in network performances, while the performances show smooth pattern when $\alpha_m > 1.5$. The drivers may be considered *optimistic* when α_m is in the low range. When drivers are optimistic, they would switch routes more often because they would think there are other routes better than those they used. This tendency however makes the system unstable. Conversely, when α_m is greater than 1.5, the *pessimistic* drivers would think that their routes are better than they thought, which results in less route switching and makes the system stable. The total cost increases as the value α_m goes up from 1.5 to higher. It is because more drivers do not expect other alternative routes would be any better when higher α_m is applied. Such tendency results in inefficiency of network performance. Figure also depicts the system cost could be the lowest when drivers' prior perception is realistic (when α_m is in between 1.4 and 1.6). Learning the network condition from their day-to-day experience, drivers make reasonable efforts to optimize their travel. This result emphasizes the importance of drivers' prior perception on congestion level especially when drivers' information is limited.

Effect of Prior Information on Route Preference

In this section, we examine drivers' route preference with respect to their initial network perception. This investigation is limited only to Model 2 and Model 3 where the drivers' route preference model is applied; however, this explains how the initial perception on network congestion influences drivers' learning behavior. As defined before, the lower values in route preference ($\Phi_{m,p}$) indicate higher preference. The route preference models drivers' habitual behavior as opposed to the assumption of drivers' rationality.

<< Insert Figure 7 here >>

Figure 7 shows both maximum preference values and minimum preference values by the initial congestion perception. Drivers' preference behavior can be classified into two categories by the level of initial perception, α_m of 1.5. When drivers initially perceive the network congestion is better than actual (α_m is less than 1.5), the preference values ($\Phi_{m,p}$) range between 0.9 and 1.3. In such circumstances, drivers' route decisions are affected by their aversion behavior. On the other hand, route decisions are influenced by their characteristics to choose preferred routes when α_m is greater than 1.5. In this case, drivers are less motivated in switching their routes, and they choose their routes habitually. That is, drivers initially optimistic tend to develop their aversion on specific routes, while drivers initially pessimistic tend to develop their preference on specific routes. This investigation shows how drivers' habitual route choices are developed.

Another interesting point is that the difference between the maximum preference and the minimum preference is minimal when the initial perception is close to the actual congestion level. The small difference between max and min preference values means that route preferences are not significantly developed and drivers' route choices could be more rational than habitual. That is, providing accurate information helps drivers develop rational behavior, which is intuitively appealing. Considering that drivers' strong habitual route decisions could cause inefficiency in network utilization, providing accurate information to drivers is important for efficient network management.

Effect of Preference Sensitivity on Travel Time

As described before in Figure 2, the preference sensitivity (σ) affects drivers' route preference and routing decision. In order to evaluate the preference sensitivity, we first calculate relative travel time indices for all routes.

$$\text{Relative Travel Time Index} = \frac{\text{Route Travel Time}}{\text{Mean Travel Time between Origin and Destination}} \quad (8)$$

$$\text{Relative Route Travel Time Index} = \text{Slope} \times \text{Preference Sensitivity} + \text{Constant} \quad (9)$$

Based on the relative travel time indices, regression analyses are conducted with respect to the route preference sensitivity averaged for all drivers on the route. The regression analysis results are reported in Table 3. Interestingly, the slope of the regression model varies also by the initial perception on congestion level. When the initial congestion perception is lower than 1.5, drivers with a high sensitivity value tend to use routes with high travel time. It is because sensitive drivers end up using longer routes by quickly excluding routes from their alternatives at the beginning stage, which results in irrational route choice. On the other hand, when the initial congestion perception is higher than 1.5, the slope in the regression model becomes a negative sign. This means that, unlike the previous case, sensitive drivers end up taking better routes by developing strong preference on the routes that they used. In either case, if the initial congestion perception is not realistic, drivers with a high sensitivity value develop strong habitual route choice behavior although the way of habitual choice is the opposite each other. As in Table 3, the values in slope gradually change as the initial congestion perception increases, and the slope is close to zero when the initial congestion perception is in between 1.5 and 1.6. That is, the unreasonable perception of congestion level is the main source of the irrational route choice behavior and causes different route choice by drivers' heterogeneous characteristics.

<< Insert Table 3 here >>

CONCLUSION AND DISCUSSION

This study has examined effects of assumptions in UE that have taken for granted in conventional traffic assignment problems. Employing the day-to-day modeling approach, we relaxed each assumption and investigated effects on traffic pattern and network behavior. This study shed light on the route choice behavior associated with three assumptions-- perfect information, rationality, and homogeneity.

The relaxation of the perfect information has greatly influenced the traffic assignment result and the performance of the network. Although the system could not reach the equilibrium in drivers' learning process when only limited information is available, drivers' expected travel times could be quite accurate and the overall network performance is dependent on the initial perception of network congestion. In drivers' learning process, the initial perception played important role especially when information sources were limited.

This study relaxed each assumption to investigate drivers' network behavior and factors influencing their route choice decisions. The assumption of perfect information is the most influencing in route choice behavior. This assumption affects realization of the other assumptions as a basis of the other assumptions. An inductive learning model was applied to relax the perfect information assumption. The learning model in this study reveals that drivers accurately predict travel times on used routes from their

1
2 learning process although the average expectation errors of the all routes are still large. This reflects
3 drivers' incapability in predicting travel times in unfamiliar area and drivers' inertia in switching to new
4 routes.
5

6 The relaxation of perfect information assumption also raises the importance of accurate prior
7 information. The accuracy of prior information greatly influences drivers' route choice behavior. If
8 drivers have accurate congestion perception, they tend to choose their routes more rationally rather than
9 developing habitual route choice behavior. However, inaccurate drivers' initial congestion perception
10 leads to optimistic or pessimistic driver behavior. While the optimistic drivers would switch routes more
11 often and cause the unstable system unstable, the pessimistic drivers tend not to switch their routes.
12

13 Route preference was included to relax drivers' rationality assumption. This analysis shows how
14 drivers' habitual route choices are developed. Drivers initially optimistic tend to develop their aversion on
15 specific routes, while drivers initially pessimistic tend to develop their preference on specific routes. This
16 study also found that providing accurate information helps drivers develop rational behavior by
17 narrowing the range of their preference.
18

19 Lastly, the homogeneity assumption was relaxed by introducing drivers' preference sensitivity.
20 From this preference sensitivity analysis, it was found that drivers with a high sensitivity value develop
21 strong habitual route choice behavior if the initial congestion perception is not realistic. As asserted by
22 Nakayama et al. (2001), driver's "habitat segregation (path dependence)" could be dependent on driver's
23 personal preference.
24

25 This study investigated the evolution of drivers' route choice behavior and network performance
26 using a process model. Although there have been many studies on drivers' route choice behavior,
27 relatively less effort has been made to understand drivers' route choice behavior as a process. We believe
28 that such an approach is advantageous in understanding the drivers' learning mechanism and could be an
29 alternative to tackle the traffic assignment problem from another aspect.
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33 REFERENCES

- 34 1. Wardrop, J. G., Some Theoretical Aspects of Road Traffic Research, Proceedings of the Institute of
35 Civil Engineers, Part II, 1952, pp. 325-378,
- 36 2. Nakayama, S., R. Kitamura and S. Fujii, Drivers' Learning and Network Behavior: A Dynamic
37 Analysis of the Driver-Network System as a Complex System. Transportation Research Record, No.
38 1676, 1999, pp. 30-36.
- 39 3. Daganzo, C. and Y. Sheffi, On stochastic models of traffic assignment model, Transportation Science,
40 1977, pp 253-274.
- 41 4. De Palma, A., M. Ben-Akiva, C. Lefevre, and N. Litinas, Stochastic equilibrium model of peak
42 period traffic congestion, Transportation Science 17, 1983, pp 253-274
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5. Horowitz, J. L., The Stability of Stochastic Equilibrium in a two-link Transportation Network, Transportation Research part b., 1984. pp. 13-28
 6. Ben-Akiva M, M. Cyna, and A. de Palma, Dynamic models of peak period traffic congestion, Transportation Research, 18 B, 1984, pp 339-355.
 7. Cascetta, E., A stochastic process approach to the analysis of temporal dynamics in transportation networks, Transportation Science 29, 1989, pp 305-329.
 8. Mahmassani H., and G. Chang, Experiments with departure time choice dynamics of urban commuters, Transportation Research, 20 B, 1986, pp 297-320.
 9. Iida, Y., T. Akiyama, and T. Uchida, Experimental Analysis of Dynamic Route Choice Behavior, Transportation Research, 26 B, 1992, pp. 17-32
 10. Cascetta, E., and G. E. Cantarella, A Day-to-Day and Within-Day Dynamic Stochastic Assignment Model, Transportation Research, 25 A, 1991, pp. 277-291.
 11. Cantarella, G. E., and E. Cascetta, Dynamic Processes and Equilibrium in Transportation Networks : Towards a unifying theory, Transportation Science 25, 1995, pp. 305-329
 12. Watling, D., Asymmetric Problems and Stochastic Process Models of Traffic Assignment, Transportation Research, 30 B, 1996, pp. 339-357
 13. Watling, D., Stability of the stochastic equilibrium assignment problem : a dynamic systems approach, Transportation Research, 33 B, 1999, pp. 281-312
 14. Jayakrishnan, R., H. Mahmassani, and T. Hu, An evaluation tool for advanced traffic information and management systems for urban networks, Transportation Research, 2 C, 1994, pp 25-36.
 15. Hu, T. and H. Mahmassani, Day-to-day evolution of network flows under real-time information and reactive signal control, Transportation Research, 5C, 1997, pp 51-69.
 16. Oh, J-S, C. Cortes, and W. Recker, Effects of Less-Equilibrated Data on Travel Choice Model Estimation, Transportation Research Record: Journal of Transportation Research Board, No. 1831, 2003, pp 131 – 140
 17. Nakayama, S. and R. Kitamura. A Route Choice Model with Inductive Learning, Transportation Research Record: Journal of Transportation Research Board, No. 1725, 2000. 63-70
 18. Nakayama, S., R. Kitamura and S. Fujii, Driver's Route Choice Rules and Network Behaviour: Do drivers become rational and homogeneous through learning?, Transportation Research Record: Journal of Transportation Research Board, No. 1752, 2001, pp 62-68

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Figure Index

- Figure 1 General model framework
- Figure 2 Driver's preference function
- Figure 3 Test network
- Figure 4 Comparison of route travel time by model
- Figure 5 Reduction of expected travel time errors
- Figure 6 Effect of prior information accuracy on network performance
- Figure 7 Route preference ($\Phi_{m,p}$) with respect to drivers' initial perception on network condition

Table Index

- Table 1 Summary of Models
- Table 2 Model Comparison
- Table 3 Regression Analysis: Relative Route Travel Time v.s. Preference Sensitivity

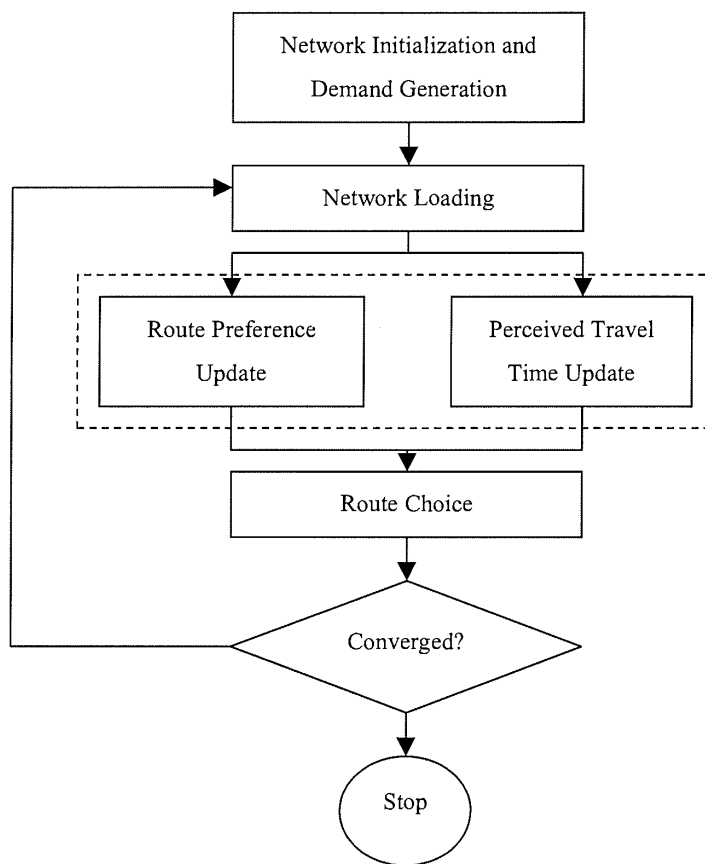


Figure 1 General model framework

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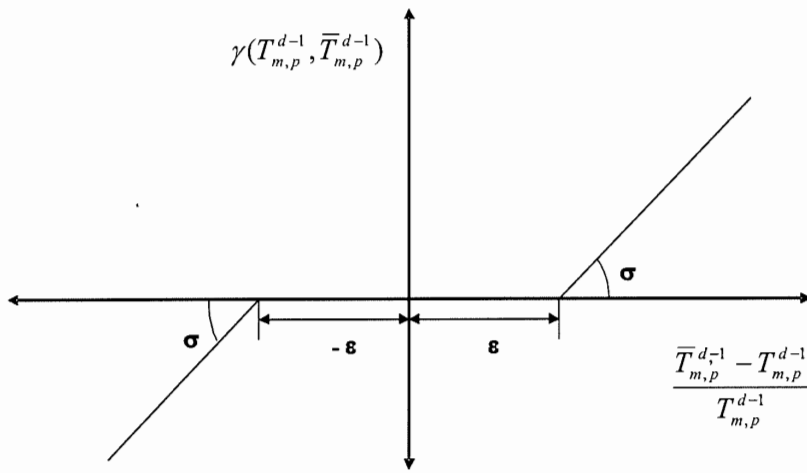


Figure 2 Driver's preference function

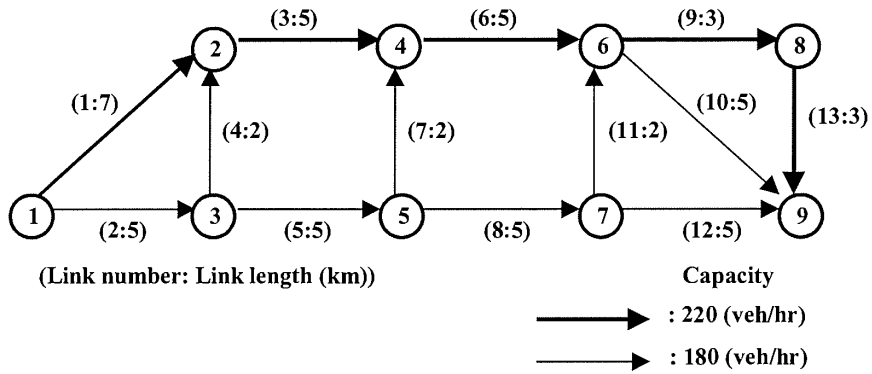
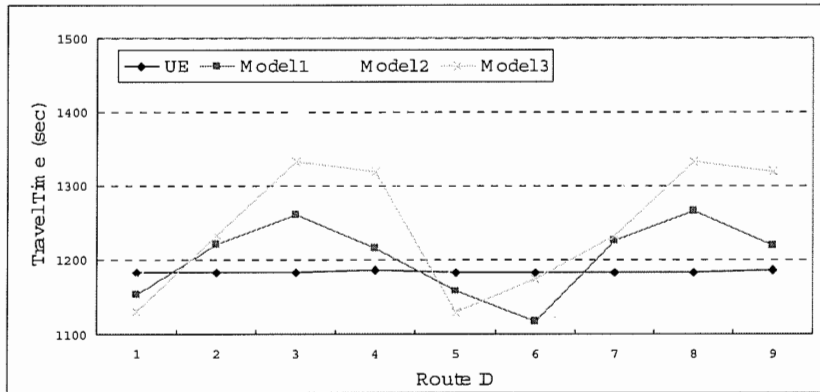


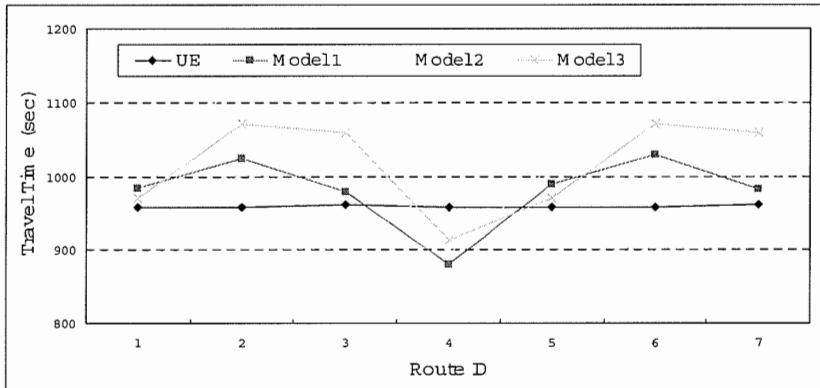
Figure 3 Test network

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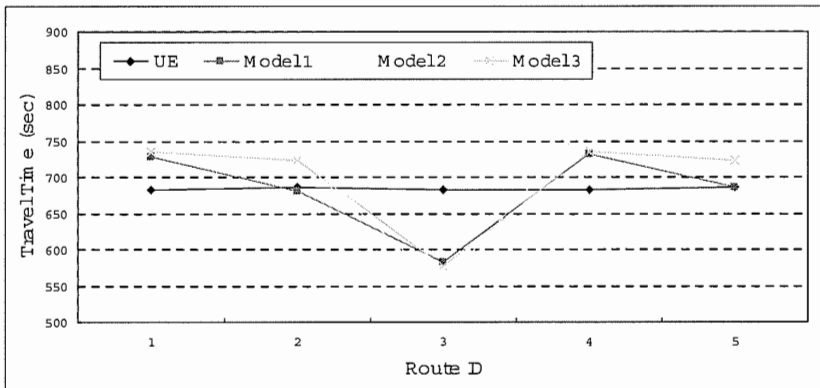
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(a) Route travel time between 1 - 9



(b) Route travel time between 3 - 9



(c) Route travel time between OD 5-9

Figure 4 Comparison of route travel time by model

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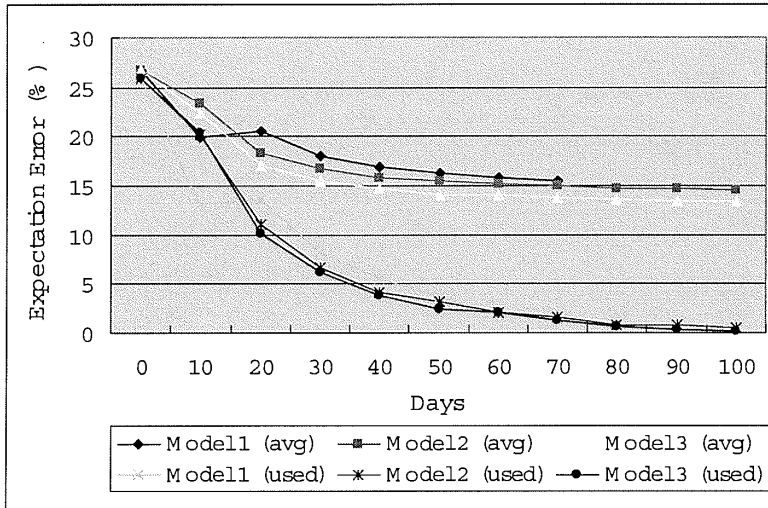


Figure 5 Reduction of expected travel time errors

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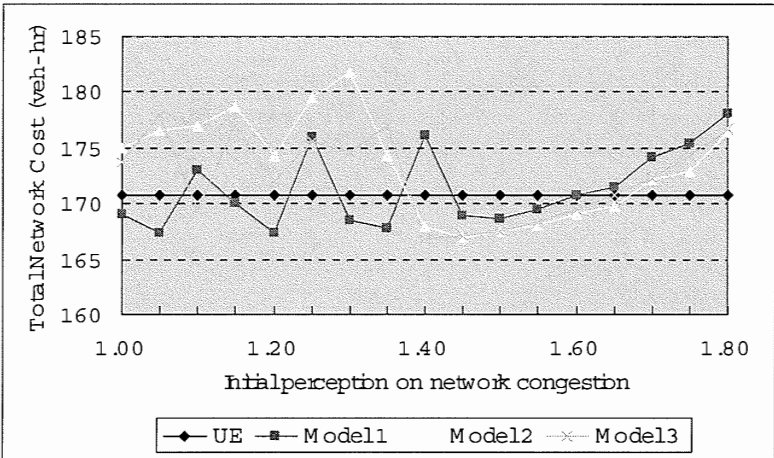


Figure 6 Effect of prior information accuracy on network performance

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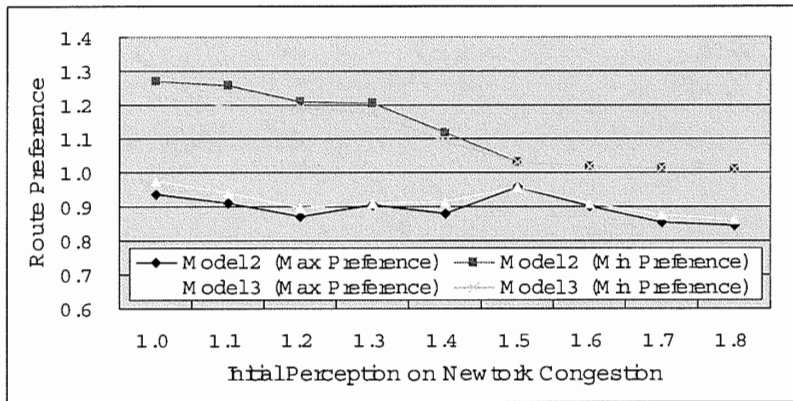


Figure 7 Route preference ($\Phi_{m,p}$) with respect to drivers' initial perception on network condition

Table 1 Summary of Models

	Perfect information	Rational behavior	Homogeneous drivers
UE	Assumed	Assumed	Assumed
Model 1	Acquire information on from their previous experience	Assumed	Assumed
Model 2	Acquire information on from their previous experience	Route preference is included in route choice model	Assumed
Model 3	Acquire information on from their previous experience	Route preference is included in route choice model	Each driver has a different preference sensitivity.

Table 2 Model Comparison

	Level of Equilibrium			Average Travel Time (sec.)			Total Network Travel Time (veh-hr)
	1 → 9	3 → 9	5 → 9	1 → 9	3 → 9	5 → 9	
UE	0.12	1.30	1.44	1182.6	957.6	682.5	170.7
Model 1	47.72	45.50	53.67	1156.9	960.5	674.9	168.5
Model 2	89.92	74.05	84.94	1239.5	1068.4	683.1	181.7
Model 3	80.31	58.81	60.72	1198.3	1008.3	671.7	174.6

Table 3 Regression Analysis: Relative Route Travel Time v.s. Preference Sensitivity

Initial Perception on Network Congestion	Slope	Constant	R-sq
1.3	0.6749	0.8568	0.3542
1.4	0.5895	0.8706	0.3454
1.5	0.1825	0.9594	0.2623
1.6	-0.1177	1.0258	0.0231
1.7	-0.3078	1.0677	0.0349
1.8	-0.6138	1.1342	0.0712