A Parametric Framework for Route Guidance in Advanced Traveler Information Systems with Endogenously Determined Driver Compliance

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ABSTRACT: This study develops a framework to parametrically evaluate networks under user equilibrium route guidance (UERG) and system optimal route guidance (SORG) assuming the unguided traffic to be in stochastic user equilibrium (SUE). The framework can determine in what condition ATIS performs well and which route guidance state performs better as the market penetration of guidance system increases. Unlike other studies that assumed fixed number of complied drivers, this study explicitly considers compliance rate as an endogenous variable in a general parametric nonlinear programming framework. Under endogenously determined compliance rate, SORG may result in higher total system cost than UERG due to lower compliance rate even though SORG is aiming to minimize total system cost. In contrast, even though UERG is generally preferable because of higher acceptance, UERG may result in increase of total system cost under certain conditions. Using a simple network, we illustrate the application of the framework and show that route guidance performance is highly dependent on the level of unguided driver's familiarity. A significant part of the framework is the scheme to find "sustainable" compliance rates under assumed compliance function.

Key Words: Advanced Traveler Information Systems, Route Guidance, User Equilibrium, System Optimum, Stochastic User Equilibrium

INTRODUCTION

Advanced Traveler Information Systems (ATIS) are considered as a promising technology to improve traffic condition by helping travelers to use efficiently existing transportation facilities. Recently there has been plenty of research on this field, and ATIS are in transition moving from laboratory to real world. It is expected to improve travel times for the drivers and reduce the total cost for the system under ATIS environment. Unlike other components of advanced management systems, however, the effectiveness of traveler information technology is determined by the traveler's awareness of the information and traveler's evaluation of its usefulness.

Research evaluating the effect of ATIS takes a multiple user class traffic assignment approach (Kanafani *et al.*, 1991; Ben-Akiva *et al.*, 1991; Van Vuren et al, 1991; Peeta *et al.*, 1995). For the evaluation of ATIS, the crucial part is modeling route choice behavior for both guided and unguided drivers. Previous research using static analysis methods have used user equilibrium (UE), system optimal (SO), and stochastic user equilibrium (SUE) traffic assignment for this problem. In most studies, guided drivers are modeled to use the UE routes or the SO routes and the route guidance strategies are assumed to be available to achieve SO or UE driving pattern. Kanafani and Al-Deek (1991) estimated the benefits of ATIS by comparing costs of UE and SO. Peeta and Mahmassani (1995) classified drivers into classes, and used a dynamic traffic assignment framework to study drivers under three different types of guidance information-- instantaneous, UE, and SO. Ben-Akiva *et al.* (1991) and Koutsopoulos and Lotan (1990) employed a mixed UE and SUE traffic assignment in which the guided drivers follow the UE routes while unguided drivers follow the SUE routes.

Though in static analysis of ATIS the above two basic routing objectives (UE and SO) have been considered, many studies argued that ATIS should not be viewed as a way of achieving a system optimum (Arnott *et al.*, 1991; Hall, 1993). It is mainly because drivers will not trust the information systems if they recognize that they have been guided to use longer routes than other drivers. However, no research has shown how much the SO routes deteriorate overall performance due to reduced compliance to the guidance.

Most previous studies focused on the evaluation of ATIS benefits. One of the most important findings in these studies is that higher market penetration might lead to overreaction and lower performance (Mahmassani and Jayakrishnan, 1991; Arnott et al., 1991; Ben-Akiva et al., 1991). Even though drivers' compliance is the most important factor in ATIS evaluation, most studies have investigated the benefits of ATIS by various levels of market penetration with 100% compliance assumption. Emmerink et al. (1994) first showed a framework for analyzing market penetration and Al-Deek et al. (1998) developed an evaluation framework by combining a probabilistic route diversion model and a system performance model. Recently Yang (1998) treated the market penetration of ATIS as an endogenous variable. He proposed a convex programming model and an algorithm to solve a mixed behavior equilibrium problem with endogenous market penetration that is determined by a continuous increasing function of the information benefit.

This study evaluates two different route guidance objectives (UE and SO) by employing driver's compliance model with varied level of unguided drivers' perception error and market penetration. We formulate the problem as a general parametric nonlinear programming problem. Traffic pattern and performance of route guidance system are obtained by solving the mixed equilibrium problem while demands by user class are fixed by the endogenously equilibrated compliance rates. The logit-type compliance model is based on drivers' travel time savings. The problem seeks "*sustainable*" compliance rates under given perception error for unguided drivers and given market penetration. Using such compliance rates, two route guidance objectives are evaluated. This study takes both guided drivers' travel time savings from the drivers' point of view and the total system cost from the system manager's point of view into consideration as measures of effectiveness (MOE) of ATIS. In fact, these two MOE's should be considered while evaluating the success of ATIS. Under endogenous compliance, UE route guidance can be expected to show higher rates than SO route guidance. However, it is not certain which route guidance state will show higher total system cost saving. Even though SO route guidance aims at minimizing the total system cost, SO route guidance may or may not show lower total system cost than UE route guidance due to deterioration of driver's compliance. In total system costs, the performance of SO and UE route guidance compared to current traffic condition represented as a SUE state is interesting to examine. This paper develops a framework for such analysis.

This paper is outlined as follows. The next section explains about problem formulations and solution procedure including a driver's compliance model and a mixed equilibrium assignment model. Section 3 depicts the numerical experiments. Finally Section 4 presents conclusion and future research.

FORMULATION AND SOLUTION ALGORITHM

The compliance problem is an intrinsic problem in evaluating route guidance strategies. It shares many common features with the endogenous market penetration problem with multiple equilibrium behaviors formulated by Yang (1989). Here we develop a similar framework to study the compliance issue in routing.

Performance of ATIS and Driver's Compliance

While Yang (1998) endogenously calculated market penetration via travel time saving, all equipped drivers were assumed to follow the guided route, thus ignoring the compliance issue. Here we assume the market penetration for ATIS to be known and treat compliance rate (i.e., decision to follow the advice or not) as a function of expected travel time saving. From driver's point of view, the expected travel time saving represents the quality of information. That is, if drivers are equipped, their compliance can be expressed as a function of travel time saving over the unguided case.

The problem is formulated in a similar manner to (Yang, 1998). The mixed demand is regarded as a vector of parameters and the mixed equilibrium traffic assignment problem is written as a general parametric nonlinear program problem as follows:

$$\underset{\mathbf{x}}{\text{minmize}} \quad Z(\hat{\mathbf{q}}, \mathbf{q}) \tag{1}$$

subject to

$$\mathbf{q} = \overline{\mathbf{q}} \cdot \rho\left(\Delta(\mathbf{x})\right) \cdot m \tag{2}$$

$$\hat{\mathbf{q}} = \overline{\mathbf{q}} - \mathbf{q} \tag{3}$$

where

$\mathbf{q}$ = guided demand
$\hat{\mathbf{q}}$ = unguided demand
$\overline{\mathbf{q}}$ = total demand
$\mathbf{x}$ = link traffic flow pattern
m = market penetration
$\Delta(\cdot)$ = guided driver's travel time saving over unguided
$\rho(\cdot)$ = driver's complaince function
$Z(\cdot)$ = objective function for traffic assignment

Compliance Model and Demand Split

A schematic of the classification of user classes is proposed in Figure 1. In this paper, the split between guided and unguided drivers is obtained directly by analyzing driver's

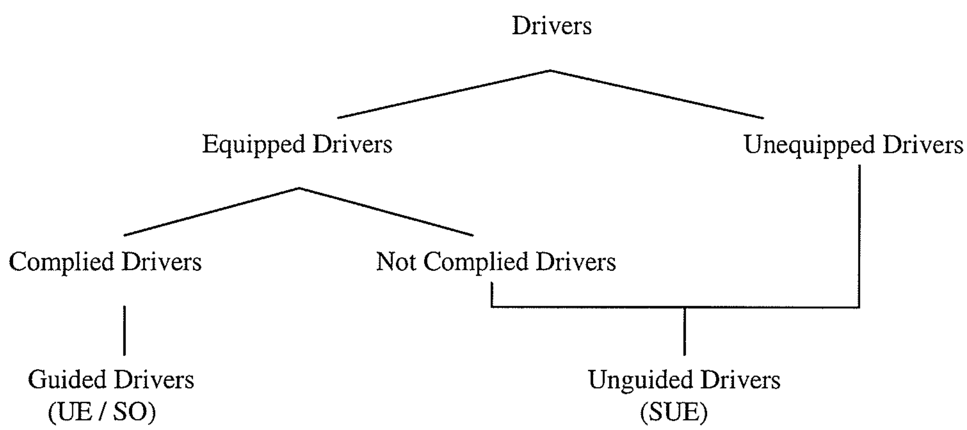


Figure 1. Classification of User Classes

compliance behavior given market penetration. That is, the fraction of guided drivers is obtained from the endogenous compliance rates and given market penetration. This study further classifies the equipped drivers into two groups: one is complied (guided), the other is not complied (unguided). Of course, the unequipped drivers fall in the unguided group. The number of guided drivers is modeled as a function of expected benefit (travel time saving) in this study. That is, the compliance rate is endogenously determined by the travel time difference between guided and unguided drivers. A logistic function is used for the model to reflect other factors affecting driver's compliance behavior.[1] Given market penetration for ATIS, the number of guided drivers is determined as follows:

$$q_{rs} = \frac{\bar{q}_{rs} \times m}{1 + \exp(\alpha + \beta \cdot \Delta_{rs})}, \quad \forall r \in R, s \in S \tag{4}$$

where, α, β = parameters which are common for all O-D pair

q_{rs} = guided demand from origin $r \in R$ to destination $s \in S$

$\bar{q}_{rs}$ = total demand from origin r to destination s

Δ_{rs} = travel time saving for guided demand from origin r to destination s

m = market penetration

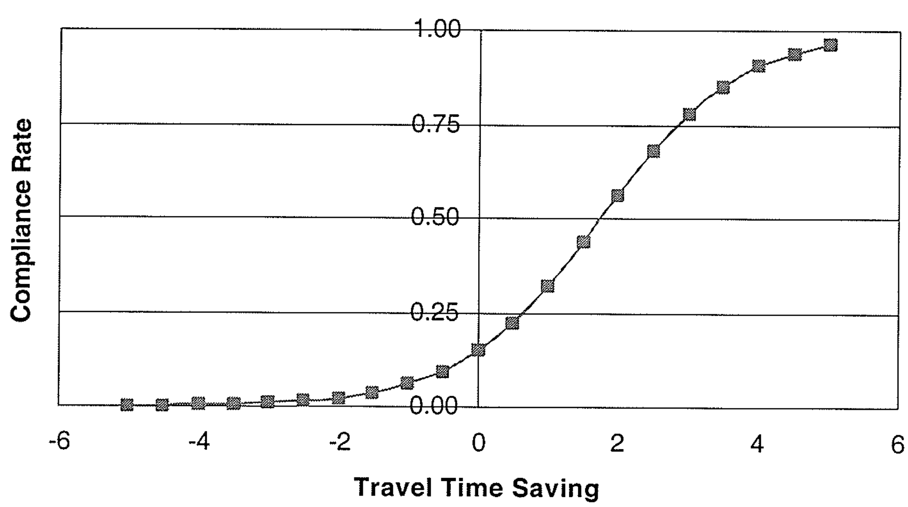


Figure 2. Compliance Model

This type of compliance model also leaves out other factors such as inequities between route travel times experienced by drivers being guided under SO. This is a rather strong assumption. More complicated compliance models to handle any inaccuracy from this are possible, but the complication from such models were deemed outside the scope of this paper.

[1] Other functional forms are possible, but we chose the simple function as in standard discrete choice models.

Mixed Behavior Equilibrium Traffic Assignment Problem

Readers familiar with the mixed equilibrium formulation and solution techniques may skip this section. The formulation discussed here is solved in the inner iterations of the solution procedure in the next section. The thrust of the paper is not on mixed assignment, but rather in incorporating it in a framework with endogenous compliance, which is handled in the outer iterations of the solution procedure.

We assume that unguided drivers make routing decisions based on perceived variables and hence their route choice behavior is assumed to result in stochastic user equilibrium. Guided drivers' travel pattern is according to user equilibrium (UE) or system optimum (SO) depending on the applied routing scheme. Therefore, the assignment problem is a mixture of either UE or SO with SUE.

Mixed behavior equilibrium formulations can be found in several previous studies (Harker, 1988; Hicks, 1992; Yang 1998). For the case of user equilibrium route guidance (UERG) where UE behavior and SUE behavior are mixed in the network, Yang (1988) formulated an optimization problem for the problem as:

(UE + SUE)

$$\text{minimize } Z_{US}(\hat{\mathbf{q}},\mathbf{q}) = \sum_{a\in A}\int_0^{x_a} t_a(w)dw + \frac{1}{\theta}\sum_{r\in R,s\in S}\sum_{k\in K_{rs}} \hat{f}_k^{rs}\ln \hat{f}_k^{rs} \tag{5}$$

Subject to

$$\sum_{k\in K_{rs}} f_k^{rs} = q_{rs},\ \forall r\in R, s\in S \tag{6}$$

$$\sum_{k\in K_{rs}} \hat{f}_k^{rs} = \hat{q}_{rs},\ \forall r\in R, s\in S \tag{7}$$

$$f_k^{rs} \geq 0,\ \ \forall k\in K, r\in R, s\in S \tag{8}$$

$$\hat{f}_k^{rs} \geq 0,\ \ \forall k\in K, r\in R, s\in S \tag{9}$$

$$x_a = \sum_{r\in R,s\in S}\sum_{k\in K_{rs}} \left(f_k^{rs} + \hat{f}_k^{rs}\right)\cdot\delta_{ak}^{rs},\ \ \forall a\in A \tag{10}$$

where t_a = travel time on link a

θ = parameter of driver's perception

f_k^{rs} = flow on route k connecting r to s for the guided drivers

$\hat{f}_k^{rs}$ = flow on route k connecting r to s for the unguided drivers

x_a = flow on link a

δ_{ak}^{rs} = 1 if the route k between r and s uses the link a, or 0 otherwise.

Unlike the mixed behavior equilibrium model for the UERG case, the equivalent optimization formulation for the mixed SO and SUE case (system optimal route guidance, SORG) cannot be obtained due to the nonseparablility of the cost function. Instead, a variational inequality approach is employed (Harker, 1988; Hicks, 1992). Harker (1988) showed a single variational inequality (VI) formulation for a mixed behavior network equilibrium problem (UE + SO). By replacing UE behavior with SUE, the VI formulation can be employed for the SORG case as follows:

(SUE + SO)

$$c^u(x^*)\cdot(x^u - x^{u*}) + c^g(x^*)\cdot(x^g - x^{g*}) \geq 0 \qquad (11)$$

or

$$\sum_{a\in A}\left[c_a^u(x_a^*), c_a^g(x_a^*)\right]^T \cdot \left[(x_a^u; x_a^g) - (x_a^{u*}; x_a^{g*})\right] \geq 0 \qquad (12)$$

where x_a^g = the link flow of guided drivers on link a

x_a^u = the link flow of unguided drivers on link a

x_a^* = the optimal link flow of the problem

c_a^u = the perceived travel cost for unguided drivers

c_a^g = the marginal travel cost for guided drivers

Both the above formulations fit the class of formulations for which diagonalizations have been found applicable. For the UE/SUE problem, Yang (1998) used a diagonalization type algorithm with convex combinations. We employ this solution algorithm for SO/SUE also. While we have not established convergence of this algorithm to the SO/SUE state due to the lack of an equivalent mathematical program for the VI formulation, we have found that the solutions obtained were indeed in SO/SUE by evaluating the marginal costs across used paths at convergence. The algorithm forms the inner iterations in the solution procedure given next.

Solution Procedure

The procedure for solution is classified into two routines. The outer routine is to find equilibrated compliance rate and corresponding demand by user class-- guided and unguided. The outer routine iterates until achieving equilibrated compliance rates. The inner routine is to solve a mixed equilibrium traffic assignment problem. In inner routine traffic flows are updated by using method of average success (MSA). Figure 3 depicts overall procedure of the solution algorithm.

Outer Iteration: Compliance update and demand determination.

Step 0: Initialization.

Set iteration number i = 0.

Set an initial value of compliance rate, $\rho_{rs}^{(0)}, \forall r \in R, s \in S$, and determine demand for both guided and unguided.

$$q_{rs}^{(i)} = \overline{q}_{rs} \cdot \rho_{rs}^{(i)} \cdot m \, , \ \forall r \in R, \ s \in S$$

$$\hat{q}_{rs}^{(i)} = \overline{q}_{rs} - q_{rs}^{(i)} \, , \ \forall r \in R, \ s \in S$$

Step 1: Mixed equilibrium traffic assignment.

Obtain average travel times $\hat{c}_{rs}^{(i)}$, $c_{rs}^{(i)}$, $\forall r \in R, \ s \in S$ for both guided and unguided by performing traffic assignment algorithm.

Step 2: Update demand.

Update compliance rate and demand for both guided and unguided using guided driver's travel time saving $\Delta_{rs}^{(i)}$.

$$\rho_{rs}^{(i+1)} = \frac{1}{1+\exp(\alpha + \beta \cdot \Delta_{rs}^{(i)})}, \ \forall r \in R, s \in S$$

$$q_{rs}^{(i+1)} = \bar{q}_{rs} \cdot \rho_{rs}^{(i+1)} \cdot m \text{ , } \forall r \in R,\ s \in S$$

$$\hat{q}_{rs}^{(i+1)} = \bar{q}_{rs} - q_{rs}^{(i+1)} \text{ , } \forall r \in R,\ s \in S$$

Step 3: Convergence check.

Stop if convergence is achieved, otherwise set i = i + 1 and go to Step 1.

<u>Inner Iteration: Mixed UE (SO) and SUE equilibrium assignment algorithm</u>

Step 0: Initialization.

Set iteration number i = 0.

Generate a set of link flows $x_a^{(i)}$, $a \in A$ by performing all-or-nothing assignment for $\mathbf{q}$ and a stochastic network loading for $\hat{\mathbf{q}}$ based on a set of initial free-flow time t_a^0.

Step 1: Update.

Update link cost $t_a^{(i)} = t_a(x_a^{(i)}),\ a \in A$.

Step 2: Direction finding.

Find auxiliary link flow pattern $y_a^{(i)},\ a \in A$ by performing all-or-nothing assignment for $\mathbf{q}$, based on the current set of (marginal) link flow time $t_a^{(i)}(\tau_a^{(i)}),\ a \in A$ and a stochastic network loading for $\hat{\mathbf{q}}$ based on the current set of link travel time $t_a^{(i)},\ a \in A$.

Step 3: Move.

Find the new flow pattern by setting $x_a^{(i+1)} = x_a^{(i)} + \alpha^{(i)}(y_a^{(i)} - x_a^{(i)}),\ a \in A$.

Step 4: Convergence check.

Stop if convergence is achieved, otherwise set i = i + 1 and go to Step 1.

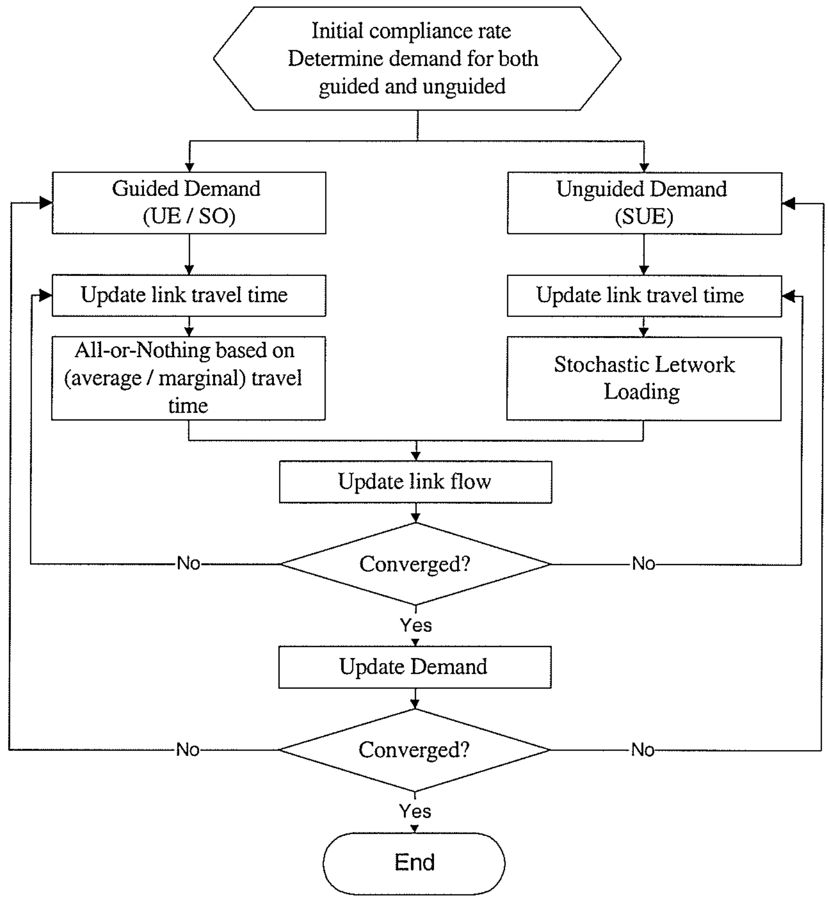


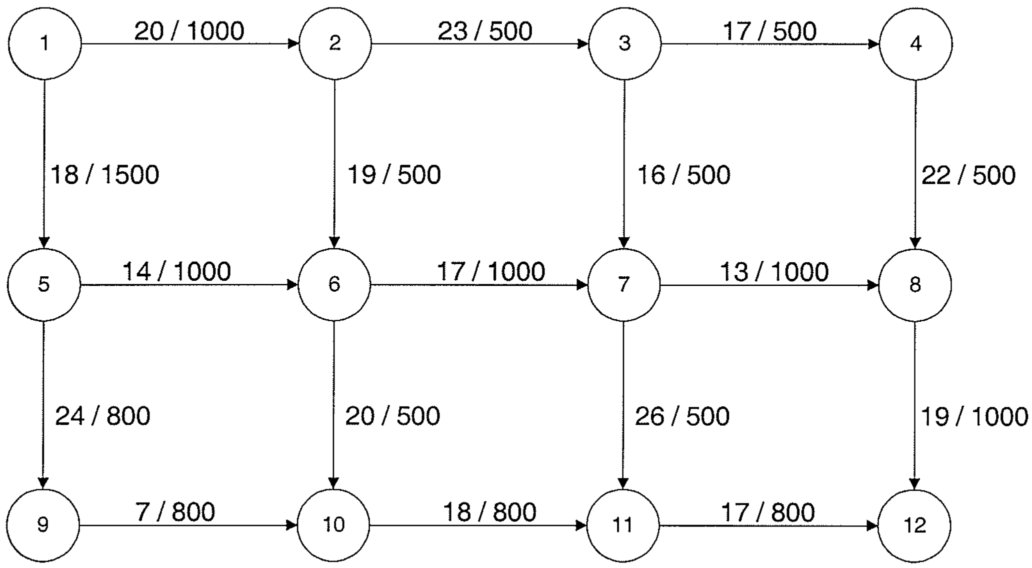
Figure 3. Solution Procedure

NUMERICAL EXAMPLES

Test Network

We use a simple network with 12 nodes and 17 links as shown in Figure 4 for the simple test. The BPR (Bureau of Public Road) link performance function is used as shown in equation (13), and network input data including free-flow travel time (t_a^0) and link capacity (c_a) are shown in Table 1. Here we assume that there is only one commodity connecting origin 1 to destination 12, and total demand is 1500. The parameters for the compliance model (equation 4) are assumed to be $\alpha = 1.75$ and $\beta = -0.50$.

$$t_a = t_a^0 \cdot \left[1 + 0.15 \cdot (x_a / c_a)^4\right],\ a \in A \tag{13}$$



(Free-Flow Travel Time / Capacity)

Figure 4. Test Network

Comparison of Total System Costs

First, we compare total system costs of three route choice behavior models. This analysis is not yet the mixed equilibrium case but with single driver groups (SUE, UE and SO). Total system cost of the stochastic user equilibrium behavior model is varied depending on level of drivers' perception error (θ in equation 5) while UE and SO are independent from the perception error. Here smaller values mean higher perception error; so the SUE model with very large θ value is equivalent to the UE behavior model. As shown Figure 5, the system cost of the SUE approaches that of UE. The figure also shows that the total system cost from UE routing could be higher than that of unguided traffic (SUE) when unguided drivers' perception error is smaller than certain level. From this comparison, we learn that the UERG may lead higher system cost, which the system manager does not want. This implies that route guidance for users may not be an effective way of improving the total system for some cases, especially when driver's perception error is small. That is, we get a conclusion, which is not surprising, that an important factor affecting the benefit from information is the level of the unguided drivers' perception error. It is, however, not easy to measure θ from a practical point of view.

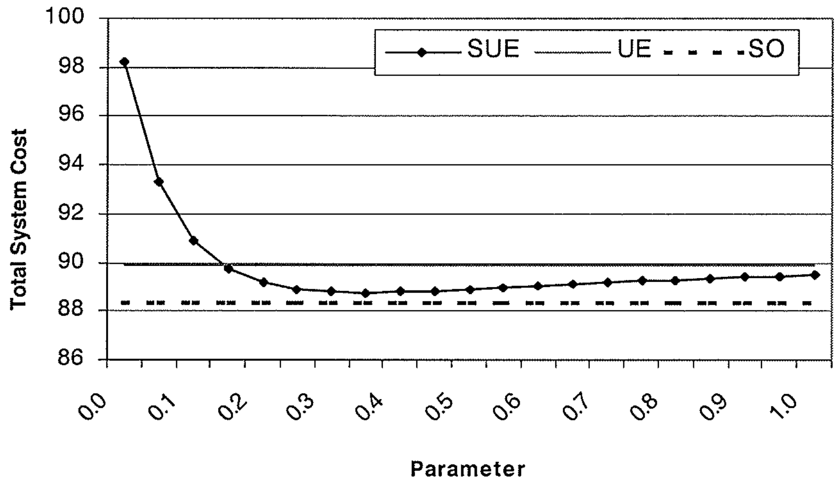


Figure 5. Comparison of Total System Cost
Parameter (θ) is unguided drivers' perception error (higher θ means smaller perception error).

Performance of ATIS and Driver's Compliance Behavior

Secondly, we investigate the user travel time and total system cost by varying fractions of guided drivers and different levels of perception error. In this test, 100% market penetration is assumed, so the fraction of guided drivers is same as the compliance rate. Figure 6 shows changes of user travel time and total system cost. This investigation expands the results from the previous section by introducing a compliance curve into the analysis. Note that we select three value of θ (0.1, 0.15, and 0.3) which are essentially values at and on both sides of where the SUE curve intersects the UE line in Figure 5.

- Guided drivers' travel time savings over unguided drivers (upper figure in Figure 6)

First, consider the curves excluding the superposed compliance line. Guided drivers' travel time savings are decreasing as their fractions increase except for the case of SORG with SUE perception error parameter θ = 0.3 (i.e., base-case drivers know network conditions well) as shown in the upper figure. When the driver's perception error is higher, the larger user travel time saving is obtained as expected. It is found that the level of driver perception error is the dominant factor affecting the guided drivers' travel time saving.

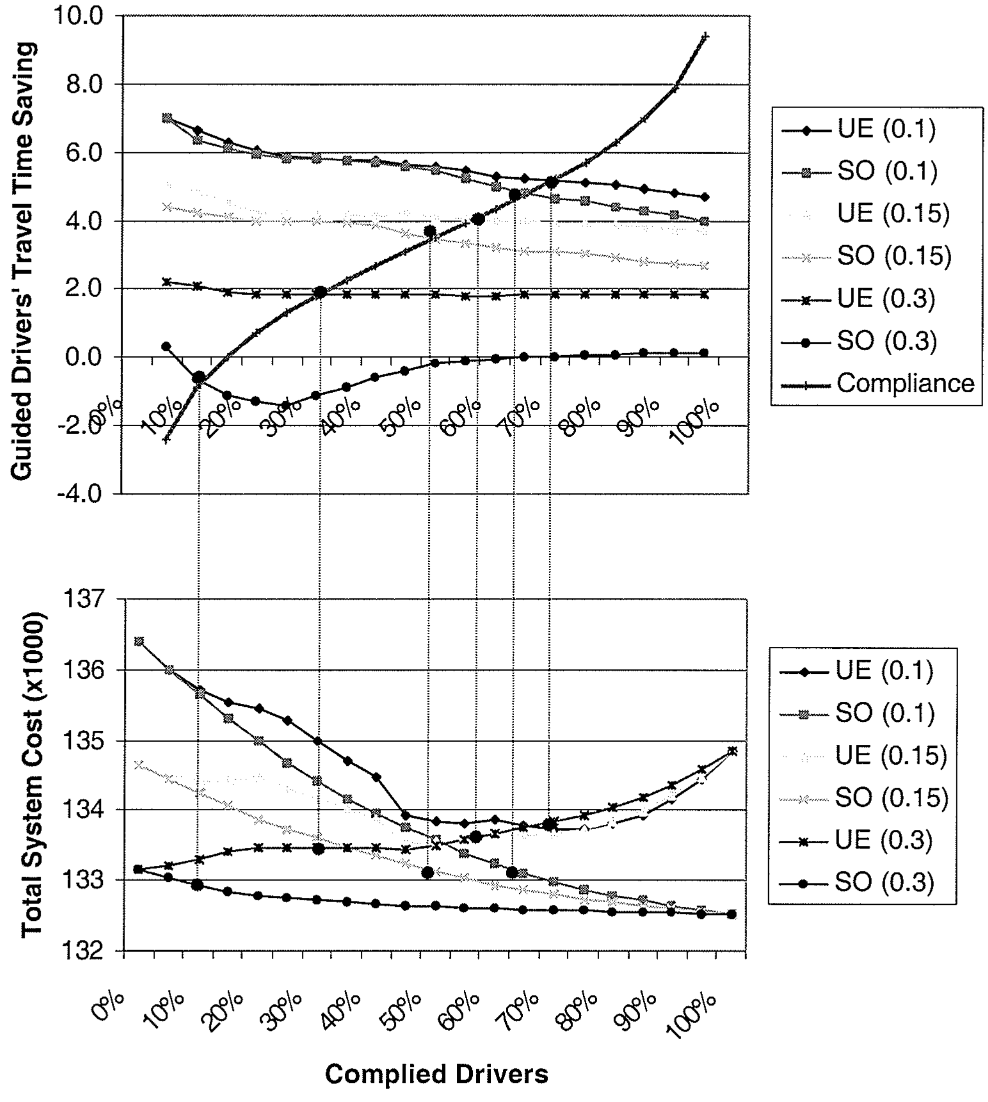


Figure 6. Comparison of User Cost and System Cost by Fraction of Guided Drivers.
* The values in the brackets represent level of driver's perception error (θ). A smaller value means higher perception error.

Interestingly, guided drivers' travel time saving for SORG with perception parameter of 0.3 reveals that drivers need to sacrifice substantial amount of individual travel time to improve the total system especially at low compliance rates. The amount of individual drivers' sacrifice decreases as compliance rate increases since more drivers share the burden for the total system.

- Total system costs (lower figure in Figure 6)

The lower figure shows changes of total system costs. As expected, SORG with 100% compliance results in the lowest total system cost. In all SORG cases, total system costs are decreasing as fraction of guided drivers increases regardless of levels of driver's perception error. In the cases of UERG, however, total system costs increase from when guided drivers are more than certain amount even though guided travel times are reduced. Especially for the case of $\theta = 0.3$, the total system cost increases as guided drivers increase. This result shows that the UERG may result in increase of total system cost, thus showing that the results in figure 5 for higher θ hold for various fraction of guided traffic as well. That is, if the unguided drivers are well-versed with the network, higher guided fractions may only make it worse.

- Endogenously determined compliance rate

Next we take driver's compliance behavior into consideration using the superposed compliance curve. An endogenous compliance rate can be found as follows. There is only one compliance rate satisfying the guided travel time saving shown for each of the six curves in Figure 6 (top). The fractions of guided drivers (or compliance rate at 100% market penetration) are determined by the six points where the compliance curve intersects the other six curves. Other points on the six curves cannot be achieved under the endogenous compliance framework. The total system costs corresponding to the compliance rates are found from the corresponding six points in the lower graph.

Interestingly, this experiment shows that SORG can result in lower total system cost when the compliance rate is endogenously found. The driver's compliance rate of SORG is lower than that of UERG, but not as low as we expected. This result conflicts with the general consensus that the information should not be used for achieving system optimum.

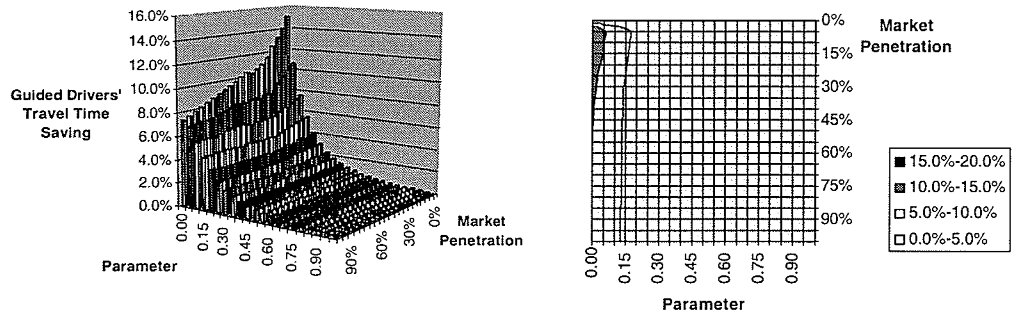
Instead, this result shows that SORG may in some cases be used for lower total system cost, though it will still be under low compliance rates.

Here we get three points for SO and three for UE (for the three θ values). It is easy to compute a continuous set of points for each case for a full range of θ values which give the complete set of cost values for "sustainable" compliance rates. This technique of endogenously finding compliance rates based on a compliance curve is a significant part of the analysis framework that we propose. Other forms of the compliance curve may be used if such curves are calibrated with real data, and the framework still applies.

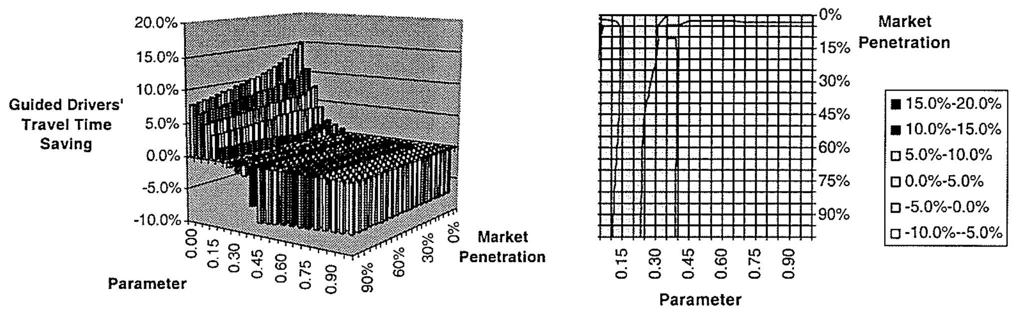
Performance Comparison under Endogenously Determined Compliance Rate

While the previous two sections analyzed the problem by fixing the market penetration and compliance rates at first and then superposed the compliance rates endogenously to find sustainable compliance rates, the next task is to include market penetration also into the framework. That is, the guided traffic fraction is now the fraction of *equipped* drivers who complied. Sustainable compliance rates can be formed in the same manner as above for various market penetrations.

Figure 7 compares guided travel time savings for the selected network under UERG and SORG states with sustainable compliance. As shown in the Figure 7-a, the UERG always gives positive travel time saving, showing highest benefit at the low market penetration and higher perception error (smaller θ). The SORG shows negative values in guided travel time saving when θ is greater than 0.3 - 0.4 as in Figure 7-b. This is the case where guided drivers sacrifice for the system benefit. Note that the number of such drivers is very low, which would be clear from examining the compliance rates corresponding to these cases. We have left out those results here.



(a) User Equilibrium Route Guidance

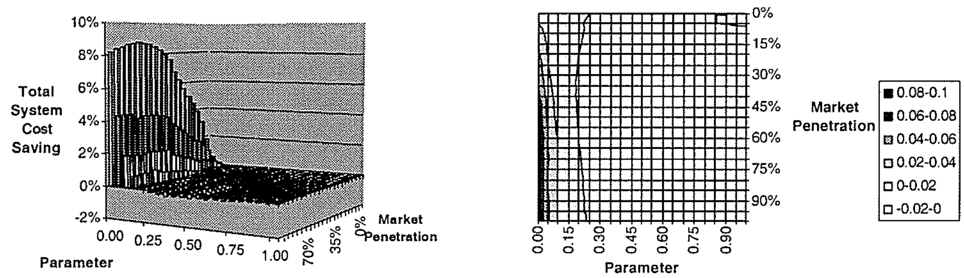


(b) System Optimal Route Guidance

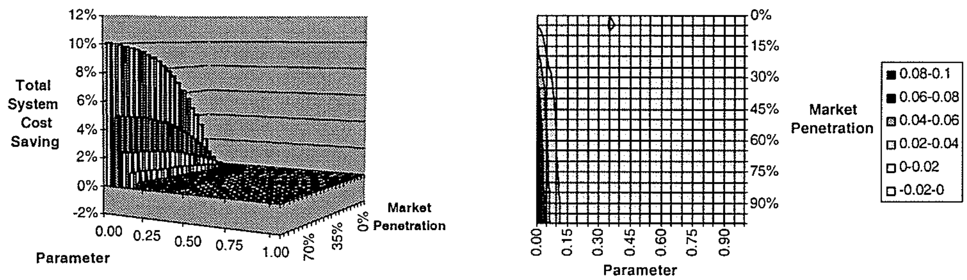
Figure 7. Comparison of Guided Drivers'Travel Time Saving at the Sustainable Compliance Rate
*The right side figure shows contour map of the left-side 3 dimensional graph

Figure 8 shows a comparison of total system cost saving. In contrast to the comparison of guided travel time saving, UERG results in negative values in total system cost saving when the level of perception error is higher than 0.2 while SORG shows positive saving. Unlike guided travel time saving, the total system cost saving increases as the market penetration increases.

It is possible to look further using this framework into measures such as percentage differences between SORG and UERG travel time saving, etc, for various levels of market penetration and SUE perception errors. We leave out such analysis, as the network used is just an illustrative one, and the results may not be generalizable anyway.



(a) User Equilibrium Route Guidance



(b) System Optimal Route Guidance

Figure 8. Comparison of Total System Cost Saving at the Sustainable Compliance Rate
*The right side figure shows contour map of the left-side 3 dimensioal graph

CONCLUSION

This study has developed a framework to parametrically evaluate traffic networks under various converged states: the user equilibrium route guidance (UERG) and the system optimal route guidance (SORG), both with unguided traffic in stochastic user equilibrium (SUE) state. The framework explicitly models sustainable compliance by drivers. It is capable of evaluating in what condition ATIS performs well and which route guidance state performs better as the market penetration increases.

Unlike previous studies that evaluated ATIS based on externally assumed number of guided drivers with perfect compliance, this study has taken drivers'compliance behavior into consideration by treating it as an endogenous variable. The route guidance system provides prescriptive information, and drivers make their decisions whether or not to follow the route guidance based on travel time savings over unguided travel. This paper has defined the problem as a general parametric nonlinear programming problem by using a logit-type model for compliance behavior. For the traffic assignments under route guidance, we have used two mixed equilibrium traffic assignments: one for UERG and the other for SORG.

This paper has pointed out that unguided drivers'perception error is an important factor affecting the performance of the route guidance system; however, it is not easy to observe such perception errors under recurrent congestion. In fact, understanding current traffic condition is a key for the better route guidance system. Results of the illustrative study in this paper should not be viewed as general results applicable to other cases because they are drawn from a simple network example. Also the results will be different under different compliance models. Therefore, further investigations with the different networks and compliance models are needed to draw generalized conclusions.

It needs to be stressed that this investigation was conducted under the static assumption. So the route guidance strategies evaluated in this study are somewhat abstract. Under dynamic framework, the evaluation of route guidance strategies can be performed more concretely and realistically, including studies of the exact details of routing dynamics if states, such as UERG or SORG, are to be achieved. More factors can be included for the evaluation in dynamic framework, such as information update interval, accuracy of information, types of information (instantaneous or predictive) as well as route guidance strategy. As a final comment, note that the paper focuses on evaluating UERG and SORG primarily because analytical models can yield these states. There is no presumption that route guidance needs to necessarily lead to these states, nor are these states best to achieve.

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