Study of Drivers' Day-to-Day Route Choice Behaviors and Network Performance in Advanced Traveler Information Systems

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***Abstract*—The response by road drivers to traveler information is not well understood due to the heterogeneity in how drivers may react differently to provided information. In this study, we explicitly consider drivers' asynchronous response to information, by assuming that drivers have different decision intervals. Within this new modeling framework, we develop a simulation platform to study how people make use of information at disaggregate level and how drivers' day-to-day route choice behavior would impact the system performance at the aggregate level. In particular, we will study efficiency and stability under different distributions of decision intervals and information provision schemes. This model is different from existing ones, since it explicitly incorporates drivers' heterogeneous response frequencies, and is computationally more efficient. This study could lead to a better understanding on impacts of information provision on drivers' behavior in transportation networks and a better design of advanced traveler information systems.**

I. Introduction and Overview of the Study

An emerging direction in Intelligent Transportation Systems (ITS) would be to integrate vehicles and infrastructure in a network of information exchanges known as the Advanced Traveler Information Systems (ATIS). The basis of such a system is easy accessible and accurate traffic information from two different entities: drivers and network. For example, different traffic signals will help to distribute detailed, personalized, and decentralized real-time information about traffic flow, congestion, and other traffic conditions through such a medium as the Internet [1], [2]. In the future, drivers' behavior could be significantly impacted by information sources, available knowledge, processing power, and risk evaluation procedure (see Figure 1).

However, it has been argued that excessive information provision could cause over-saturation, over-reaction, concentration, and other problems [3]. It is also known that the decision maker has bounded rationality, since he has limited capabilities for gathering and treating information [4]. To have a better understanding of the potential impacts of rich and traffic information, it is important to understand how information provision schemes would impact drivers' decisions in route and other choices.

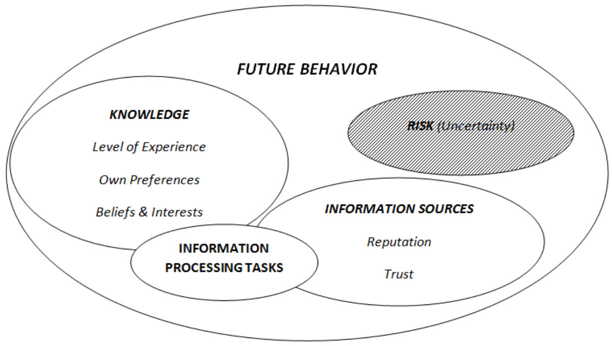

Fig. 1. Drivers' future behavior (extracted from [5]).

In the literature, there are many studies on drivers' day-to-day route choice behaviors and the corresponding dynamics of a transportation system in ATIS. On one hand, information provision is not explicitly considered, or all vehicles are assumed to have access to full information of a transportation system. In these studies, drivers choose their routes stochastically [6], [7], deterministically [8], or based on game theoretic evaluations [9]-[12]. On the other hand, information provision schemes and their impacts on drivers' choices are explicitly considered [13], [14]. Existing models of day-to-day route choice behaviors are usually based on utility maximization principle based on their perceptions of travel times on different routes [3], [7], [15]. In [15], drivers switch their routes if the improvements in travel time exceed some threshold level based on a bounded-rationality decision model. There have been many other studies on learning processes and decision rules [14], driver's perception updating schemes [16], drivers' compliance to guidance [17], and heterogeneous behaviors [18], [19].

In these and many other studies, however, it is generally assumed that drivers make synchronous decisions and evaluate their alternative route choices based on available information every day. But in reality, due to habits and other constraints (e.g. all vehicles don't have access to full information of a transportation system), drivers consult available traffic information and make a decision only infrequently. That is, different drivers can have different response frequencies to information provision, and their decisions are usually asynchronous. In [20], it was shown that different drivers can have different rhythms and habits.

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Such rhythms and habits can be related to drivers' socio-demographic characteristics, commitments to specific regular activities, and valuation of time. Therefore, it is also likely that different drivers have different temporal rhythms when choosing their routes from day to day. That is, different drivers can have different frequencies in consulting traffic information and making day-to-day route choices. In the literature, however, drivers' heterogeneous response frequencies to traffic information are not explicitly studied.

II. A New Model Of Day-To-Day Route Choice Behaviors

In this paper, we introduce a new model of day-to-day route choice behaviors, where players have different decision intervals and make asynchronous decisions. In some sense, drivers are considered to play asynchronous games with each other in a road network. Here we assume that there exists a distribution of the random variable of response frequencies or decision intervals. As in other driving behaviors, drivers' decision intervals could be affected by their socio-demographic characteristics, commitments to specific regular activities, and valuation of time [20]. In addition, their decisions intervals could be impacted by characteristics of available traffic information, including the availability, nature, and quality of information, as well as stability and other characteristics of road networks.

A. Model Description

Different from existing modeling frameworks, this model separates drivers' response process into two steps. In the first step, a driver decides whether to consult available information or not. In the second step, once a driver decides to consult available traffic information, s/he will make a choice of available routes. Here characteristics of drivers, road network, and information could impact both steps of drivers' response, including the distribution pattern of decision intervals and decision rules. In this study, we are interested in a simple model, where drivers always choose the shortest path, but their decision time intervals are stochastic.

Indeed, if a driver decides not to consult traffic information, it is equivalent to choosing the current route. Thus the model is consistent with existing one-step models in terms of route choices. Compared with existing frameworks, however, this method introduces more flexibility by introducing one more step. As shown in the following simulation results, even with the deterministic route choice rule, no over-reaction is observed due to the heterogeneity in drivers' decision intervals. In addition, the new framework is computationally more efficient by introducing decision intervals: drivers only evaluate their alternatives routes on their decision days.

In this simulation framework, we can further investigate the impacts on system performance of heterogeneous information sources, different perception updating schemes, market penetration rate of ATIS, accuracy of information, link performance functions, number of participants, and so on. At this point, we want to introduce a figure explaining how in our framework the aggregate behavior is the result of individual decisions (see Figure 2).

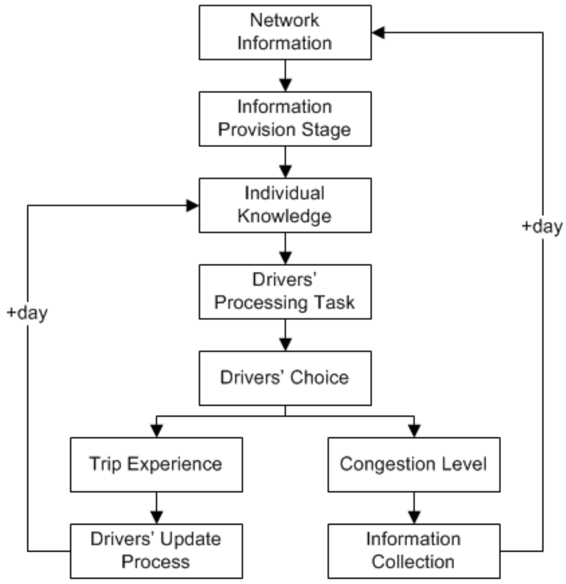

Fig. 2. System level versus individual level.

Our model could be used for a better understanding of ITS and the influence of the communicative process and the information provision stage, matters that are challenging to deal with.

B. Assumptions and Limitations

In addition to the fundamental assumption of heterogeneous decision intervals (A1), some other assumptions are made in this study:

- (A2) Each driver has a constant decision interval.
- (A3) Accurate pre-trip information is available to all drivers.
- (A4) Drivers only make pre-trip route decision choice. We do not consider en route decision in response to information received during the trip.
- (A5) Drivers choose the shortest route.
- (A6) Drivers make decisions based just on historical information, and no predictive information is used.
- (A7) Traffic congestion is simply described by static link performance functions.

In reality, these assumptions could be too limited, and the modeling framework can be easily extended to account for more realistic situations. But here we arbitrarily make these simplified assumptions, since this study is intended to understand basic impacts of heterogeneous decision intervals on system-level performances.

III. Simulation Study for a Two-Link Network

In this section, we discuss day-to-day route choices on a simple road network with different numbers of players, different distribution patterns of drivers' decision intervals, and so on.

A. Network and Congestion Model

Our simulation scenario consists of a two link network shown in Figure 3:

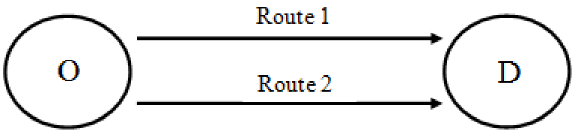

Fig. 3. Representation of the studied network.

This network represents one origin-destination pair connected by two alternative routes. Let $n_1(t)$ and $n_2(t)$ represent the numbers of drivers using routes 1 and 2 on day t, respectively. Here the total origin-destination flow Q is constant:

$$Q = n_1(t) + n_2(t) \tag{1}$$

Let $C_1(t)$ and $C_2(t)$ represent the travel time on routes 1 and 2, respectively. Here we assume that the corresponding performance functions considered are linear and given in the following:

$$C_1(t) = 0.4 \cdot \frac{n_1(t)}{Q} + 0.2 \tag{2}$$

$$C_2(t) = 0.6 \cdot \frac{n_2(t)}{Q} + 0.4 \tag{3}$$

Clearly route 1 is shorter than route 2 here.

In our simulations, we set an original input of Q=1,000 vehicles per day.

B. Information Provision Schemes

For drivers to make decisions on day t, information can be provided in three different information provision schemes:

- Previous day's information: average travel time on each route on the previous day when the decision has to be made.
- All historical information: average travel time on each route from day 0 to day $t-1$.
- Historical information since last decision time period: each driver is provided the average times on both routes since his/her last decision time step.

C. Distributions of Decision Intervals

In this study, we consider the following distribution patterns of drivers' decision intervals:

- Uniform distribution: decision time intervals follow a uniform distribution between 1 and the largest decision interval.
- Normal distribution: decision time intervals follow a normal distribution with mean μ and standard deviation σ.
- Exponential distribution: decision time intervals follow an exponential distribution with mean parameter μ.
- Power Law distribution: decision time intervals follow a power law distribution with parameters b (location parameter of Pareto distribution) and α (shape parameter). Note that the mean is infinite for $\alpha \leq 1$ and the variance is infinite for $\alpha \leq 2$.

D. Initial Route Choices

At the beginning of the simulation on day 0, drivers are assumed to choose their route considering the following possible scenarios (initial conditions):

- All random route choice.
- All choose route one (or alternatively all choose route two).
- Half and half: drivers redirected equally to each considered route.

E. System-wide Performance Measures

We measure the performance of the whole traffic system by both efficiency and stability. We measure the efficiency by the number of days for the system to converge to user equilibrium. In particular, we use the first day, on which C_1(t) = C_2(t), as the measure of efficiency. It can also be understood as a delay time measured in days. By stability, we mean the variance in route costs after user equilibrium is first reached. We will study the values of efficiency (delay) and the equilibrium oscillation frequency (stability) for different scenarios.

IV. Results

A. Convergence to User Equilibrium

In this subsection, we consider route choices of 1,000 drivers for 3,000 days. Initially all drivers use the side road 2, and their decision intervals are from 1 to 1,000 days. Here all drivers obtain average travel times on both routes since their last decision time step. In Figure 4, we demonstrate the fractions of drivers and travel times on both routes. From Figure 4, we can see that the system converges to user equilibrium after about 900 days, but it never settles down at the equilibrium. This confirms the observation in [21] that route choices based on historical knowledge can lead to oscillating behavior. Although the system oscillates around equilibrium, we do not observe serious over-reactions. Note that here we assume drivers always choose the shortest route. The non-existence of over-reaction is a significant difference between the new two-step model and existing one-step models.

B. Influence of the Number of Drivers, Q

In this subsection, we consider the impacts of the number of drivers Q on system performance. In Figure 5, we demonstrate the evolution of route choice fractions during 3,000 days for 1,000 and 100 drivers. Initially drivers equally split their choices. Here all drivers obtain average travel times on both routes since their last decision time step, and drivers' decision intervals follow a uniform distribution between 1 and 500.

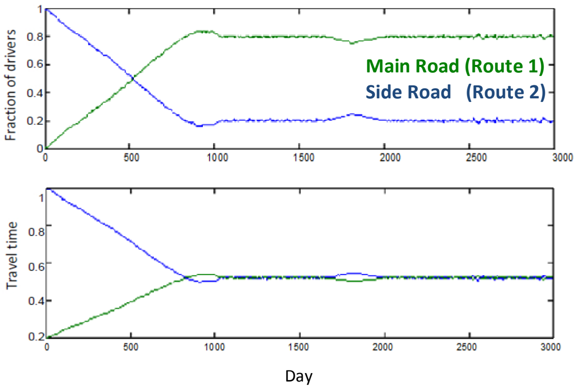

Fig. 4. Evolution of fraction of drivers and travel times on both routes

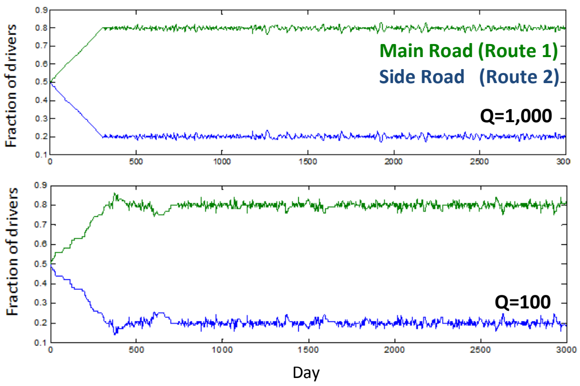

Fig. 5. Evolution of fraction of drivers on both routes for different number of vehicles: Q=1,000 (top) and Q=100 (bottom).

From Figure 5, we can see that the number of drivers barely impact the delay in reaching equilibrium. But more drivers would make the system more stable, as variances in fractions are smaller in the top figure.

C. Influence of Different Decision Interval Distribution Patterns

Considering a scenario where initially half of the drivers select route 1 and the other half choose route 2 and providing information since last decision point for each driver, we have introduced different decision time periods distributions in order to study the simulation results assuming different situations in terms of decision periods per each driver (Q=1,000).

The pattern drawn in Figure 7 is an example of how different parameters setting up the dissemination intervals distributions could affect the efficiency of the system. We should find a realistic balance among more spread out (heterogonous) decision times, delay and equilibrium.

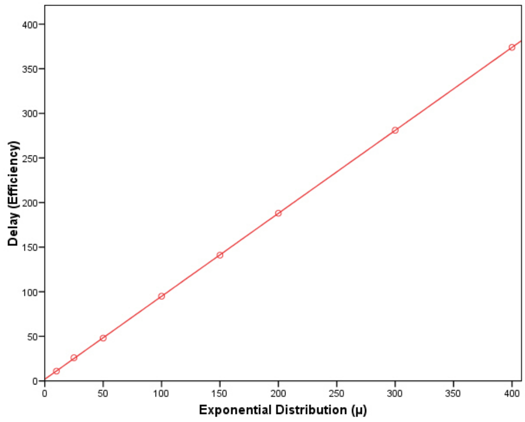

Fig. 7. Delay versus mean parameter μ. Exponentially distributed decision time periods (0.93x + 1.93, R^2=0.99). Information since last decision time period strategy provision.

We also have had interesting results (clustered curves following a power law relationship) when plotting the existing relationship between delay and stability.

Generally we can conclude that if we have a more spread out decision time periods (more heterogeneous) the convergence will be better (smaller standard deviation in the steady state), but it takes longer time to reach the equilibrium (efficiency issue). The obtained results reducing the decision time periods range are really interesting; we got better response in terms of efficiency (faster convergence to equilibrium) because more trip-makers decided their route at the same time, but at the risk of leading to an oscillating behavior.

D. Influence of Information Provision Schemes

One of the main contributions of this paper is the pattern that we have found between delay and stability (power law relationship) for scenarios that we have been run under different information provision strategies and decision time periods distributions (see Figures 8 & 9). The basic idea of this pattern is that larger values of delay leads to smooth equilibrium and vice versa, larger oscillatory behavior is often related to small delay values.

We have run the simulations considering different information provision strategies and a wide range of different distributions of decision time periods running the simulations for different parameters as follows:

- Power Law distribution: changing parameter alpha α (0.6, 0.9, 1.2) (setting b=1).
- Uniform distribution: testing different ranges of route decision dissemination intervals (days): [(1:1000), (1:500), (1:333), (1:200), (1:100), (1:50), (1:25)].
- Exponential distribution: testing different μ values (10, 25, 50, 100, 150, 200, 300, 400).
- Random distribution: testing different ranges of route choice decision dissemination intervals (days): [(1:1000), (1:500), (1:333), (1:200), (1:100), (1:50), (1:25)].

The results obtained under these circumstances (following a power law curve) are depicted in Figure 8:

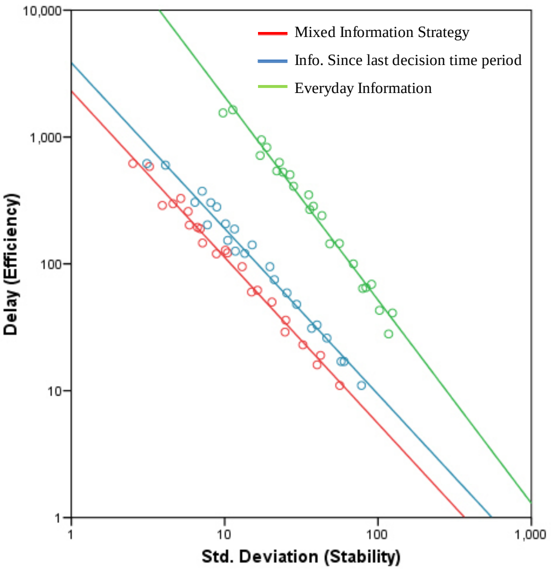

Fig. 8. Efficiency versus stability for each information strategy provision considered: mixed information strategy ($y=2301.3x^{-1.311}$, $R^2=0.986$), information since last decision time period strategy ($y=3846x^{-1.307}$, $R^2=0.978$), everyday information strategy ($y=82920x^{-1.602}$, $R^2=0.981$). Uniform, exponential & random distributions of decision time periods.

From Figure 8, we can see that the mixed information strategy which combines the three different types of information provision considered (this information strategy provision equally combines everyday information, information since last decision time period and one day information; the dissemination intervals of the traffic information are followed by the combination of four different probability distributions: uniform, power law, exponential and random) has shown the best system results in terms of both efficiency and stability and clearly outperforms the other information strategies provision.

Otherwise, the worst results are obtained under the scenario that provides everyday information (cumulative mean travel time) to each driver. In the upper top of the plot in Figure 8 we can see that this scenario leads to a system with the largest delay values and oscillations (efficiency and stability issues). This situation is due to the problem formulation that does not ensure good delay values if the drivers are not redirected equally to each considered route in the time step 0 of the simulation (initially all drivers travel the side road 2).

It is important to remark that we cannot introduce one day information strategy because the standard deviation once the equilibrium is reached equals zero in the most number of simulations.

It is observed that under a mixed information strategy provision and power law decision time periods we get the best results in terms of delay when we are looking for fast convergence to the equilibrium with small oscillations (see Figure 9). Besides, if we are looking for really small oscillations in the steady state and we do not care on larger delay values, the best strategy is a mixed information strategy combining uniform, random and exponential distributions of decision time periods.

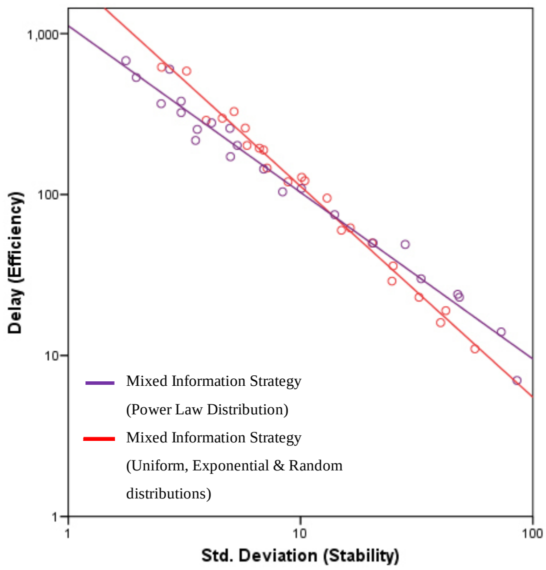

Fig. 9. Efficiency versus stability with mixed information strategy. Uniform, exponential & random ($y=2301.3x^{-1.311}$, $R^2=0.986$) and power law α (0.6, 0.9, 1.2) ($y=1117.6\ x^{-1.035}$, $R^2=0.976$) distributions of decision time periods.

V. Conclusion

The developed tools and gained insights could be helpful for understanding how such new technologies as inter-vehicle communications can help reduce congestion and emissions through proper route guidance.

In this paper we made several contributions. A major hypothesis is that different people have different decision intervals and preliminary results of the experiments support it. We will design further experiments to study the impacts of information provision on drivers' day-to-day route choices. We will develop experimental studies to realistically estimate and provide the distribution of drivers' response frequency in order to validate our study. This work is also our starting point to come up with an economic relationship that evaluates the efficiency/delay trade-off.

In the future, we will examine the impacts of predictive information, differential information provision, market penetration rate and inaccurate information, providing suggestions on how to improve and realistically evaluate ATIS services to make transportation systems more stable and efficient.

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