The Effect of Real-Time Information on Travelers' Route Choice Behaviors

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ABSTRACT

Non-recurring disruptions to traffic systems caused by incidents or adverse conditions can result in uncertain travel times. Real-time information allows travelers to adapt to actual traffic conditions. In a behavior experiment, subjects completed 120 "days" of repeated route choices in a hypothetical, competitive network submitted to random capacity reductions. One scenario provided subjects with real-time information regarding a probable incident and the other did not. A reinforcement learning model with two scale factors, a discounting rate of previous experience, and a constant term is estimated by minimizing the deviation between predicted and observed daily flows. The estimation combines brute force enumeration and a subsequent stochastic approximation method. The prediction over 120 runs has a root mean square error of 1.05 per day per route and a bias of 0.14 per route.

1. INTRODUCTION

Every traveler makes route choices in an inherently uncertain environment. The uncertainties in a traffic network come from either unpredictable disturbances (incidents, vehicle breakdowns, inclement weather, special events, and work zones), or, more frequently, the unpredictable behavior of other travelers. By acquiring real-time traffic information from information communication technologies (ICT), a traveler can make more confident decisions even in uncertain environments.

Behavior studies with experimental data can help provide a better understanding of travelers' learning and choice behavior under uncertainty. We distinguish between two types of experimental settings: competitive and non-competitive. In a non-competitive experiment, the experimenter generates the alternative attribute values which subjects have no knowledge of and cannot influence, such as route travel times, through an underlying sampling process. In a competitive experiment, subjects make decisions simultaneously and the behavior of the group determines alternative attributes. For example, in a route choice experiment, the experimenter sets up volume-delay functions for each link, but calculates the actual travel times by applying the total number of subjects choosing a particular route as an input to the delay functions.

Barron and Erev (2003) and Erev and Barron (2005) find the effects of payoff variability and recency to be robust across a large number of non-competitive experiments on binary choices with uncertain payoffs. Recency effect is a cognitive bias, indicating more recent outcomes having a larger effect in decision making. Selten et al. (2007) find that, in a competitive experiment with a hypothetical two-route network, subjects' choices reveal sequential dependencies. They capture this effect by defining contingent decision strategies in a

reinforcement learning model. The aforementioned studies do not use real-time information. However, they provide insights into repeated decisions under uncertainty.

Avineri and Prashker (2006), Bogers (2006), Ben-Elia et al. (2008), Ben-Elia and Shiftan (2010), and Razo and Gao (2010, 2011) analyze the effects of real-time traffic information, travel time variability, and feedback mechanisms in non-competitive environments. Avineri and Prashker (2006) find that providing static information on the mean travel time on risky and fast routes makes subjects more likely to choose another route. Ben-Elia et al. (2008) find that accessing real-time information on the travel time range increases risk-seeking behavior, and that this effect increases when the subject lacks long-term driving experience. Razo and Gao (2010) find that some subjects plan ahead in anticipation of future real-time information.

Mahmassani and Liu (1999) conduct competitive experiments in a three-route highway network with connectors between the routes. They find that pre-trip or en-route real-time information on prevailing traffic conditions increases the route switches at the point of information provision. Lu et al. (2011) introduce en-route real-time information on the occurrence of an incident and feedback information on non-chosen routes in a pilot competitive experiment. En-route real-time information improves network travel time and reliability; but extra feedback on non-chosen alternatives has the opposite effect. However these results have no statistical significance due to the small sample size.

We refine the experimental setup of Lu et al. (2011) by increasing the sample size and providing feedback only on chosen alternatives. An experiment with both random capacity reductions and competitive route choices captures the sources of random travel times from both the supply and demand sides. To the best of our knowledge, no other travel behavior researchers have explored this type of experiment. We fill the gap, and provide insights through both

non-parametric statistical analysis and modeling.

2. EXPERIMENTAL DESIGN

Recruited subjects were students at the University of Massachusetts Amherst. Each session had sixteen participants. Figure 1 shows the experimental network screenshot. We asked subjects to make work-to-home trip on a "day-to-day" basis. The map of the network showed the free flow travel time of each road. Participants were expected to have preferences among highways, arterials, and local roads from their long-term driving habits. We asked the subjects to make choices solely based on a particular network condition, so as to best track and model their habit-forming process. The risky route (Interstate 99) has a one out of four chance of having an incident. We notified the subjects of the incident odds and its potential consequence. We randomly generated the position of an incident in each 4-day block. All subjects' route choices collectively determined the travel time, and they were made aware of the actual travel time of the chosen route after the trip. We presented the information of the route traveled on the previous day for all sessions. Subjects made route selections for a total of 120 days. We did not notify the subjects of the total number of runs, but only a rough estimate of the duration of the experiment, in order to reduce the likelihood that the participants would make "rushed" choices during final runs.

There were eight sessions in total, with four using real-time information (information scenario) and four that did not (incident scenario). In the information scenario, a variable message sign (VMS) just before the second bifurcation informed drivers whether there was an incident on I-99 or not. This piece of information was only available for those choosing the lower bifurcation. To allow for comparison, we used the same incident profile for each pair of incident and information scenarios.

2.1 Equilibrium design

We use the following notation:

y : name of link

i : index of path (routing policy)

x_y : flow on link y

f_i : flow on path (routing policy) i

$C_y(x_y)$: link travel time as a function of flow on link y.

The travel time (in minutes) on a given link is a function of the link flow specified as follows Eq. (1):

$$C_{\text{Park Avenue}}(x_{\text{Park Avenue}}) = 33.5 + 2x_{\text{Park Avenue}}, \quad C_{\text{Local 1}}(x_{\text{Local 1}}) = 0.5x_{\text{Local 1}},$$

$$C_{\text{local2}}(x_{\text{Local 2}}) = 36.5 + 3.82x_{\text{Local 2}},$$

$$C_{\text{I-99}}(x_{\text{I-99}}) = 20 + 0.5x_{\text{I-99}}, \quad \text{with probability 0.75 (normal condition)}$$

$$20 + 27.5\, x_{\text{I-99}}, \text{with probability 0.25 (incident condition).} \tag{1}$$

Starting from the uppermost one in the map, we define the three paths as:

Path 1: Park Avenue (safe branch or route)

Path 2: Local 1 followed by Local 2 (detour, as part of the risky branch)

Path 3: Local 1 followed by I-99 (risky route, as part of the risky branch).

A routing policy is to describe a strategic route choice, which defines condition-action pairs with different traffic conditions revealed by the VMS (Gao et al., 2009). A fixed path is a special routing policy where any action is independent of traffic conditions. In the experimental network, the three fixed paths are also routing policies 1 through 3. The two additional adaptive

policies are Routing Policy 4: "First take Local 1, and if the incident has occurred, take detour Local 2, otherwise take the risky route I-99." The policy will result in Path 2 under the normal condition and Path 3 under the incident condition. Routing Policy 5 states, "Take the detour when no incident is present, otherwise choose the risky route." Such strategies exist only in the information scenario. In the incident scenario, only three fixed paths are available.

We develop the user equilibrium principle in a static and deterministic network assuming risk neutral travelers. Traffic conditions under such equilibrium conditions can serve as a benchmark for analyzing the results of the experiment.

In the incident scenario, the user equilibrium condition is such that all used paths have the same and minimum mean travel times. The equilibrium path flows are: $f_1=9, f_2=3, f_3=4$, where the corresponding path travel time is 51.5 minutes.

In the information scenario, the routing policy-based user equilibrium condition is such that all used routing policies have the same and minimum mean travel times. There are five possible routing policies in the network, including the three fixed paths and two adaptive paths. The equilibrium flows are: $f_1=4, f_2=0, f_3=2, f_4=10, f_5=0$. Splitting the flow on Routing Policy 4 onto Path 2 with probability 0.25, and Path 3 with probability 0.75, obtains the mean path flows: $f_1=4, f_2=2.5, f_3=9.5$. The equilibrium mean travel time is 41.5 minutes.

3. EXPERIMENT RESULTS

3.1 Route Flows

Figure 2 shows the average total number of subjects on each of the three routes for both scenarios over five days. The dots indicate days with incidents. Table 1 summarizes the average flow on each route over 120 days and their standard deviations (SD) for all sessions. The route

flows in both scenarios fluctuate towards the end, and there are no steady states (constant flows). The fluctuation is more obvious in the information scenario, where subjects can change routes based on real-time information. At a more aggregate level, the average route flows in the information scenario are close to the equilibrium solutions, likely due to the significant reduction of uncertainty by real-time information. In contrast, the average route flows in the incident scenario differ significantly from the equilibrium solutions; for example, the average flow on the safe branch is 6.98 and the equilibrium value is 9. Figure 2 shows the safe branch flow gradually increasing, although it is still lower than 9. These findings are expected, as an uncertain environment lacks that perfect network knowledge required for both homogeneous risk neutrality and a functioning equilibrium model.

With the Wilcoxon-Mann-Whitney test, we reject the null hypothesis of no route share difference between the incident and information scenarios at the 5% level for both the safe branch and risky route. This suggests that the potential of real-time information availability downstream influences travelers' decisions at the origin (when the information is not yet available). A network traffic prediction model should incorporate such look-ahead behavior. However, most conventional traffic assignment models under real-time information assume myopic behavior.

With the Wilcoxon–Mann–Whitney test, we reject the null hypothesis, which states that there is no difference in route flow SDs between the incident and information scenarios at the 5% level for the two routes of the risky branch. Subjects can change their route based on real-time information, and the resulting flows have more fluctuations than when no real-time information is available. Selten et al. (2007) also find that information increases flow fluctuations, although in their experiment information is a feedback on un-chosen routes.

3.2 Route Switches

Figure 3 shows the 5-day average total number of route switches at the origin and branch nodes for the same pair of incident and information sessions in Figure 2. Table 2 presents the averages over all days for all sessions. Route switches at the origin node are significantly more frequent in the incident scenario than in the information scenario. The trend is opposite at the branch. With the Wilcoxon–Mann–Whitney test, we reject both null hypotheses at 5% (one-sided). This suggests that real-time information significantly reduces the level of uncertainty and helps subjects learn about the decision environment more quickly.

In the information scenario, 90% of subjects follow Routing Policy 4 (taking the risky route in a normal situation and the detour if an incident is revealed). In Information Session 4, 94.8% of subjects follow Routing Policy 4. This indicates that when provided with real-time information, travelers will trust the information they receive and apply it to their decision-making.

3.3 Average Trip Time

Table 3 shows the average trip times for all sessions. The incident scenario has an average length of 60 minutes, while the information scenario has an average length of 42 minutes. With the Wilcoxon–Mann–Whitney test, we reject the null hypothesis of no difference at 5% (one-sided), and confirm the positive effect of real-time information in reducing average network travel time.

We measure the reliability of the network by the standard deviation of the network travel time for each session. With the Wilcoxon-Mann-Whitney test, we reject the null hypothesis at 5% (one-sided). The trip time reliability of the information scenario is significantly higher than that

of the incident scenario, both statistically and numerically. The results are similar to Lu et al. (2011).

The value of information in improving network efficiency and reliability cannot be independent of the network context, including network topology, road characteristics, and information type (Arnott et al., 1991; Gao, 2005). Lu et al. (2011) have shown that where the Braess Paradox exists, extra feedback information on non-chosen alternatives has negative effects on the network performance, including increased trip travel time and variability.

4. SIMULATION OF THE LABORATORY EXPERIMENTS

We developed a reinforcement learning model with an exponential probabilistic response rule similar to that in Brown (1951), Erev and Roth (1998), and Barron and Erev (2003). As our primary focus is the effect of real-time information on route choice behavior and network-level conditions, we only modeled the information scenario.

4.1 The Reinforcement Learning Model

4.1.1 Strategies at the Origin and Branch

At the origin, a subject does not necessarily choose a single path to the destination. The incident indicator at the branch allows the subject to make a secondary route choice at the branch. We simulate each subject's route choice as a two-stage process.

We define an action as a physical link from a decision node, and a strategy as a set of rules specifying the action to take under each condition. The condition can be the outcome of the real-time information or the subject's previous choice.

Initially, the subject takes one of the two branches. There are four strategies at the origin, which are similar to Selten et al. (2007); the first two are unconditional and the remaining two are conditional on the subject's previous day's experience.

1) Safe Branch (SB): take the safe route, Park Ave.;

2) Risky Branch (RB): take the risky branch, Local 1;

3) Direct: compare the travel time from the last chosen branch to median travel time from all previous periods. If it is lower than the median, change to another branch. Otherwise, continue on the same branch.

4) Contrary: if the travel time of a subject from the last chosen branch is lower than the median, stay on the same branch. Otherwise, change to another one.

The Direct and Contrary Strategies are conditional strategies capturing the sequential dependencies of choices according to Selten et al. (2007), who find that positive outcomes can result in both positive and negative responses. The contrary strategy might seem to violate the win-stay, lose-change dependency in reinforcement learning; however, in a competitive environment, a subject might expect many others to take the best route, and attempt to counter with the opposite strategy. Rapoport and Budescu (1992) articulate similar findings in their competitive experiment. As both of these strategies require travelers to have prior knowledge and experience, they are only possible after the first day of the experiment.

At the branch, a subject takes an action by choosing one of the two continuing routes. There are four strategies at the branch; the first two are unconditional and the remaining two are conditional on the outcome of the real-time information:

1) Risky Route: take the risky highway, I-99;

2) Detour: take the detour route, Local 2;

3) Avoid Incident (the same as Routing Policy 4 in the equilibrium design): take the detour if the real-time information indicates that an incident has occurred. Otherwise, take the highway;

4) Ignore Incident (Routing Policy 5): take the highway if an incident has occurred and take the detour otherwise.

4.1.2 Travel Time Updating Mechanism

On each day *t*, a subject chooses among the strategies based on $C_j(t)$, the weighted average (or perceived) travel times of strategy *j* from the current decision node to the destination based on experience. We update the weighted average travel times of related strategies after the subject takes an action and is made aware of the travel time. The result of an action influences the perception of two strategies: conditional and unconditional. For example, if a subject takes the detour and an incident occurs, the perception of both Strategy Avoid Incident and Strategy Detour might change, as they involve the same action (taking the detour on that day). As long as a strategy *j* is to take the actual action $A(t-1)$ on day *t* - 1, we update it on day *t*, regardless of whether strategy *j* is chosen. If strategy *j* leads to $A(t-1)$, $\theta_j(t-1)$ is 1, otherwise zero.

Define $c(t-1)$ as the experienced travel time of the action $A(t-1)$ and $Q(i)$ as a set of strategies at a given decision node *i*. Weighted average travel time update equations for strategies at either the origin or branch are in Eq. (2).

$$C_j(t) = \begin{cases} \gamma C_j(t-1) + (1-\gamma)c(t-1), \text{ if } \theta_j(t-1) = 1 \text{ and } A(t-1) \neq \text{RB} \\ \gamma C_j(t-1) + (1-\gamma)c(t-1) + \min_{j' \in Q(\text{intermediate})} C_j(t), \text{ if } \theta_j(t-1) = 1 \text{ and } A(t-1) = \text{RB} \\ C_j(t-1), \text{ otherwise} \end{cases} \quad (2)$$

where γ is a discounting factor applied to previous experience, ranging between 0 and 1. The effect of previous experience decreasing at an exponential rate (with more recent outcomes having a larger effect) is a cognitive bias known as recency.

The experienced travel time of the action of taking the risky branch has two components. One is the experienced travel time of the action itself, which is the travel time of Local 1 on the

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previous day, $c(t-1)$. The other component is the best-perceived travel time from the branch to the destination, $\min_{j' \in Q(\text{intermediate})} C_{j'}(t)$, as we assume that the subject is aware that she could have another chance at the branch. We update strategies in a backwards fashion. That is, we first derive the perceived travel times of the four strategies at the branch on day t, and then use the minimum perceived travel time among the four strategies at the risky branch to update strategies at the origin. $\min_{j' \in Q(\text{intermediate})} C_{j'}(t)$ already includes the latest experience from the intermediate node to the destination, and there is no need to multiply it by a discounting factor γ.

The travel time variability, $S(t)$, of the subject in Eq. (3) and (4) accounts for the payoff variability effect, where high payoff variability seems to encourage random choice and occasionally reduces the effects of very high travel time. Travel time variability $S(t)$ measures a subjects' overall experience with the decision environment, rather than with any particular strategy.

$$S(t) = \gamma S(t-1) + (1-\gamma)|d(t-1) - D(t)| \tag{3}$$

$$D(t) = \gamma D(t-1) + (1-\gamma)d(t-1) \tag{4}$$

$d(t-1)$ is the experienced origin-destination (OD) travel time from the previous day and $D(t)$ is the weighted average experienced OD travel time.

4.1.3 Exponential Probabilistic Response Rule

Similar to Erev and Barron (2005), we assume an exponential probabilistic response rule. At the origin, the probability that a subject takes strategy j on day t is

$$P_j(t) = \begin{cases} \dfrac{\exp\left(-\alpha \dfrac{C_j(t)}{S(t)}\right)}{\sum_{j \in Q(\text{Origin}), j \neq RB} \exp\left(-\alpha \dfrac{C_j(t)}{S(t)}\right) + \exp\left(-\alpha \dfrac{C_{RB}(t)}{S(t)} + \omega_{RB}\right)}, except\ Strategy\ \text{RB} \\[2em] P_{RB}(t) = \dfrac{\exp\left(-\alpha \dfrac{C_{RB}(t)}{S(t)} + \omega_{RB}\right)}{\sum_{j \in Q(\text{Origin}), j \neq RB} \exp\left(-\alpha \dfrac{C_j(t)}{S(t)}\right) + \exp\left(-\alpha \dfrac{C_{RB}(t)}{S(t)} + \omega_{RB}\right)} \end{cases} \tag{5}$$

where α is an exploitation-exploration parameter at the origin, where low values imply more exploration, such as random choice, and we need to calibrate a positive scale from the data; ω_{RB} is a constant that captures the bias of subjects on the risky branch.

At the branch, the probability of choosing strategy j on day t is:

$$P_j(t) = \frac{exp\left(-\beta\,\frac{C_j(t)}{S(t)}\right)}{\sum_{j \in Q(\text{intermediate})} exp\left(-\beta\,\frac{C_j(t)}{S(t)}\right)} \tag{6}$$

where β is a scale parameter at the branch.

Initial Travel Times and Variability

On the first day, the subject has no prior experience, so the calculation of travel times and variability depends solely on the free flow travel times (FFTT). The subject is aware of a probable incident on the risky highway route. To reflect this effect, we add a positive number to the travel time of strategies that involve the risky route. The number is set manually to match the average predicted route flows with observed flows.

The initial S is the same for all strategies and the calculation is in Eq. (7).

$$\text{Initial S} \;=\; \sum_{\text{route}=1}^{3} |\text{AverageFFTT} - \text{FFTT}(\text{route})|/3 = 6.78 \tag{7}$$

4.1.4 The Simulation Procedure

As in the experiment, each simulation run includes sixteen participants who interact for 120 trial periods, using a given incident profile with real-time information. On each day and for each subject, we update the weighted average travel time and travel time variability for strategies using Eq. (2), (3), and (4) and calculate the strategy probabilities using Eq. (5) at the origin. For

each day, we draw a strategy at the origin at random, and then again at the branch based on the strategy probabilities calculated in Eq. (6). After processing all sixteen subjects and obtaining route flows, we calculate the travel times for the day using the link performance functions. Then we switch to the next day.

4.2 Model Calibration and Simulation Results

α and β are the scale coefficients in the exponential probability function, which indicate the subject's sensitivity to travel time in making route choice decisions. γ is the weight of previous experience. ω_{RB} is the constant term in the utility function of Strategy RB. We first conduct a brute force enumeration varying α from 0.5 to 3.5 with a step size of 0.5 (7 values), β from 0.5 to 10 with a step size of 0.5 (20 values), γ from 0.1 to 0.9 with a step size of 0.1 (9 values) and ω_{RB} from -4 to 4 with a step size of 1 (9 values). We select the ranges of parameters α, β and ω_{RB} through trial-and-error to ensure that the optimal values fall within the ranges. For each session and parameter combination, we carry out 1,000 simulation runs. There are two measures to evaluate the simulation results. The first is root mean square error (RMSE) at the day level.

RMSE

$$= (\sum_{route} \sum_{trial} \left(\frac{(\Sigma_{simulation} \text{ Predicted Flow })}{\#of \text{ simulations}} - \text{Observed Flow}\right)^2 \Big/ (\text{No. of routes} \times \text{No. of trials}))^{1/2} (8)$$

The other measure is the bias, or the distance between predicted and observed flows averaged over all 120 days:

Bias

$$= \frac{\sum_{\text{simulation}} \sum_{\text{route}} |\text{Average Predicted Flow} - \text{Average Observed Flow}|}{\text{No. of simulations} \times \text{No. of routes}} \qquad (9).$$

The calibration problem is to find the parameter values minimizing RMSE+Bias. The current model provides predictions which reduce the discrepancy to less than 1.05 per route and day.

After applying the brute force method, we apply a simultaneous perturbation stochastic approximation (SPSA) method to solve the minimization problem, using starting values generated with the brute force method. SPSA is suitable for optimization problems where the objective function evaluation involves considerable complexity, such as in a simulation. Spall (1998) has a detailed discussion on the subject, and Balakrishna (2006) reports applications in traffic model calibration. In our case, SPSA does not provide significant improvements, largely because the parsimony of the model provides adequate starting values. Table 4 shows the final calibration results, with an average RMSE of 1.05 and a bias of 0.14.

At the final branch, the average combined percentage of choosing the risky route and avoid incident strategies is over 98%, providing more evidence of the significant influence of real-time information on route choice behavior.

Figure 4 shows an example of flow comparison between the observed and calibrated simulation results. The route flows are five-day averages, where the dashed line represents observed data and the solid line represents the simulation result. Simulation results capture both the fluctuations and trends on the two routes of the risky branch.

Cross-validation shows that the model estimated from one session gives accurate predictions of flows in each of the other sessions. This suggests that the parameter estimates are robust, and the model has good transferability over subjects.

5. LIMITATIONS AND MODEL APPLICABILITY

Our experiment is a simplified representation of a real-life traffic scenario. The simplifying flow-delay functions control all external influences such as traffic lights, intersection delays, route characteristics, and so forth, as our primary goal is to understand how subjects learn and deal with the flexibility of downstream information. This allows for the observation of human behavior under a clearly specified environment. Accordingly, in the later simulation model, we only calibrate parameters capturing travelers' learning and decision making procedures.

Secondly, the experimental network contains only three routes, allowing for a focused examination of the factors influencing subjects' decision-making processes, and the development of a model to describe how they learn and form travel habits. Although the simplicity of the network topology restricts its general use, it provides an excellent starting point to incorporate strategic behavior in a more realistic experiment environment.

In a simulation experiment, subjects do not have to bear the real-world consequences of their behaviors, such as arriving late to an appointment due to traffic congestion or becoming lost on an unfamiliar route. In order to gain more accurate experimental data, we asked participants at the beginning of each session not to treat the experience as a game or test. Nevertheless, we suspect that subjects are generally more risk-seeking in the laboratory, making the calibrated parameters inappropriate for general use.

Despite the simple design of the experiment, it has significant implications. Most notably, it verifies the need to include strategic behaviors in route choice modeling. In the experiment, over 90% of participants chose Routing Policy 4. Moreover, the significant difference between scenarios in route flows on the safe branch indicates that travelers do consider the flexibility of information downstream. In the simulation, the high percentage of subjects choosing the avoid incident strategy also supports that finding.

6. CONCLUSION

With the emerging application of Information Communication Technologies (ICT) in transportation, there is a growing need to understand and assess the possible effects of real-time information on user behavior and network performance. We obtained experimental observations on a day-to-day traffic pattern variation in a simple congested network with random disruptions. Comparing the traffic patterns with and without real-time information, we found that real-time information significantly reduces network travel time and its variability. However, we did not observe equilibrium in any of the experiment sessions. Participants switch more often in the information scenario at the branch than in the incident scenario. However, this trend is reversed at the origin. It is plausible that route switching may permit information gathering when real-time information is unavailable. The significant difference in route flows on the safe branch between scenarios verifies the need to consider travelers' long-range planning behaviors in a traffic assignment model.

These results have particular relevance for the future development of smart traveler information systems. Over 90% of participants chose Routing Policy 4, which suggests a route switch at the branch in response to an incident alert. We also performed simulations based on an exponential probabilistic reinforcement learning model and compared to daily and overall

prediction flows with the observed experiment data in the information scenario. Despite its relative simplicity, the simulation model performed well when compared to observed experiment data.

As the simulation model captures participants' travel characteristics under specific conditions, we cannot yet apply it directly to a general network traffic assignment model. However, the qualitative trends in route flows and switches, the methodology of updating perceived travel times of conditional and unconditional strategies, and the discovery that some travelers use strategic thinking when making route choices, provide important insight into the use of real-time information.

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TABLE 1: Route Flows Mean and SD for All Sessions

Scenario	Session	Safe Branch		Detour		Risky Route	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Incident	1	7.48	1.92	1.72	1.12	6.80	2.08
	2	7.19	1.65	2.08	1.45	6.73	1.72
	3	6.27	1.83	1.85	1.21	7.88	1.83
	4	6.98	1.77	2.56	1.42	6.46	1.61
	Average	6.98	1.79	2.05	1.30	7.02	1.81
	Equilibrium	9		3		4	

Scenario	Session	Safe Branch		Detour		Risky Route	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Information	1	4.2	1.66	2.43	3.73	9.37	4.50
	2	3.75	2.39	1.8	3.10	10.45	4.86
	3	4.79	1.51	2.15	3.37	9.06	3.93
	4	4.09	1.73	2.70	4.47	9.21	4.62
	Average	4.21	1.83	2.27	3.67	9.52	4.48
	Equilibrium	4		2.5		9.5	
Statistic Analysis	Null hypothesis (5% one sided)	Rejected	Not rejected	Not rejected	Rejected	Rejected	Rejected

TABLE 2: Route Switch Mean and SD for All Sessions

Scenario	Session	Origin		Branch	
		Mean	**SD**	**Mean**	**SD**
Incident	1	4.04	1.87	0.83	1.09
	2	4.13	1.75	2.17	1.40
	3	5.54	2.20	0.75	1.18
	4	6.08	2.20	1.08	1.20
	Average	4.95	2.01	1.21	1.22

Scenario	Session	Origin		Branch	
		Mean	**SD**	**Mean**	**SD**
Information	1	4.79	1.99	3.37	3.50
	2	3.63	2.73	3.50	3.19
	3	3.79	2.09	3.04	3.16
	4	3.17	2.27	4.54	4.16
	Average	3.84	2.27	3.61	3.50
Statistic Analysis	Null hypothesis (5% one sided)	Rejected		Rejected	

TABLE 3: Average Trip Time Mean and SD for All Sessions

Scenario	Session	Average Trip Time (min)	
		Mean	SD
	1	58.17	39.23
	2	58.77	39.76
Incident	3	64.66	51.99
	4	57.52	34.62
	Average	59.78	41.40

Scenario	Session	Average Trip Time (min)	
		Mean	SD
	1	42.16	18.10
	2	40.92	19.31
Information	3	42.36	17.86
	4	43.08	18.85
	Average	42.13	18.53
Statistic Analysis	Null hypothesis (5% one sided)	Rejected	Rejected

TABLE 4: Simulation Results for All Information Sessions

Session	Scale α	Scale β	Discounting Factor γ	Constant ω_{RB}	RMSE	Bias
1	1.00	7.03	0.81	1.01	1.18	0.21
2	0.49	2.50	0.89	1.00	0.99	0.11
3	1	3.01	0.90	0.50	0.84	0.10
4	0.50	2.00	0.91	1.00	1.19	0.11
Average	0.75	3.63	0.88	0.88	1.05	0.14