A POSITIVE MODEL OF DEPARTURE TIME CHOICE
UNDER ROAD PRICING AND UNCERTAINTY

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ABSTRACT

This paper develops a novel positive model for departure time choice under road pricing and uncertainty at the individual levels, and analyzes the consequent system-level dynamic properties. The proposed modeling framework avoids assumptions of substantial rationality, and focuses on how individuals actually make decisions. Bayesian learning, knowledge updating, search, and decision-making under uncertainty are modeled in the framework. Then the time-dependent departure patterns along with other system performance are investigated in a series of agent-based simulation experiments. How individuals actually choose departure time under various supply- and demand-side uncertainty scenarios are explored as to their effect on system performance and its dynamic properties.

INTRODUCTION

An important dimension of decision-making process available to trip-makers is that of the time at which to depart from their origins. Nowadays, as commuting corridors are getting increasingly congested, more than half of which can be attributed to random incidents such as traffic accidents, severe weather conditions, travel demand fluctuation, etc., travelers’ departure time choice under uncertainty draws growing research attention. Understanding the factors and behavioral mechanisms that determine travelers’ departure time choices under uncertainty is a prerequisite to designing and evaluating policies aimed at mitigating congestion and improving system reliability.

Existing models either do not give adequate attention to the dynamic aspects or only considers risk-avoiding behavior in a random utility maximization manner. In the authors’ previous work (1), a novel positive approach to departure time choice modeling considering the steady-state traffic conditions is specified, estimated, and validated. It has also been demonstrated on a real-world network (2). This approach theorizes the role of search, information, learning, and knowledge in decision-making, and focuses on modeling how departure time decisions are actually made.

The main research objective of this paper is to extend the fully operational positive departure time model in order to understand individuals’ actual choice under various supply- and demand-side uncertainty levels and to analyze the day-to-day system performance. The proposed positive model tracks the departure time changes of each individual in the transportation system, and therefore is especially suitable for integration with microscopic traffic simulators, simulation-based dynamic traffic assignment models, and activity/agent-based travel demand models.

The remainder of the paper is organized as follows. A brief review of previous studies on departure time choice modeling and behavior theories are provided in Section 2. Section 3 presents the positive theoretical framework and quantitative modeling components for departure time and peak spreading analysis under uncertainty. Section 4 demonstrates the model in a numerical example where the heterogeneous behavior under various supply- and demand-side uncertainties is studied. Conclusions are discussions on future research are offered in Section 5.

LITERATURE REVIEW

Rational behavior theory assumes that individuals can identify all feasible alternatives, measure all of their attributes, and choose the alternative that maximizes their utility (3, 4). There have been extensive research efforts applying this approach to departure time choice analysis. In particular, some earlier studies have adopted the following utility function \( V(t) \) with respect to departure time \( t \):

\[
V(t) = \alpha T(t) + \beta \max \left(0, (PAT - t - T(t))\right) + \gamma \max \left(0, (t + T(t) - PAT)\right)
\]  

(1)
Where, $T(t)$ is the travel time associated with departure at time $t$; $PAT$ is the preferred arrival time at destination; $\alpha$, $\beta$, and $\gamma$ are parameters to be estimated. The second and third terms on the right hand side of Equation 1 are thus formulated as the deviation from one’s preferred schedule. In other word, they measure the disutility of schedule delays (i.e. being either too early or too late). Preferred arrival time and schedule delays in scheduling issues have been studied by many researchers (5, 6).

The main line of research based on rational behavior theory focuses on discrete departure time choice modeling. Small’s paper (7) adopted the multinomial logit (MNL) approach to model departure time decision-making. However, the underlying assumption of independence from irrelevant alternatives (IIA) in MNL may not hold for departure time choice analysis because adjacent departure time options tend to exhibit correlated unobservable factors. Nested logit (NL) models have been used to identify and address the correlated departure time intervals (8-10). Cross-nested logit (CNL) models, which allow more flexible substitution patterns than NL, were also explored (11-13). Steady-state transportation system performance is often assumed in most previous studies wherein the users choose departure time based on the expected travel time and the corresponding arrival schedule. Some recent publications have studied departure time choice under uncertainty (14-16). In these studies, the travel time uncertainty is often measured as the 95% confidence interval of the travel time duration and empirically induces significant disutility.

Most previous studies have adopted the utility maximization and perfect information assumptions of rational behavior theory. However, making departure time choice among a large number of alternatives sliced from the continuous time range makes the perfect information acquisition almost impossible. Researchers have long realized this point and thus devoted themselves to modeling learning process (17) and improving the behavioral realism of the choice set generation problem (18, 19). Zhang (20) developed a positive theoretical framework explicitly considering learning, knowledge updating, belief/expectation adjustment, and search process. His model has been applied to model the searching for alternative routes. In addition, search theory, originally developed in economics (21), may be applied for identifying the departure time choice set.

As individuals identify new departure time alternatives from the search process, they need to decide whether or not they will use the new alternatives. This requires a set of decision rules in departure time models (22, 23). While maximizing utility acts as the decision rule for rational behavior analysis, positive departure time models need to focus on how individuals actually make departure time choice decisions. Several knowledge representation methods, such as machine learning and logical programming, can estimate a set of decision rules based on observed decision outcomes and decision environment (24, 25).

**POSITIVE MODEL**

Theoretical Framework

Firstly, the theoretical framework is extended to consider departure time decision-making under steady-state and uncertainty scenarios. This positive theoretical model is based on the authors’ previous research (1) and provides the foundation for subsequent modeling work. It is interpreted as follows.

A traveler acquires information about travel conditions on the transportation network corresponding to different departure times from her/his prior travel experience or other sources (e.g. traveler information systems). Through a perception and learning process which may be biased, the individual forms a certain degree of spatial knowledge, which produces subject beliefs. The subjective beliefs form the mental cognition and expectation regarding the amount of benefit this particular person believes she/he can expect to obtain from an additional round of search. This benefit is theorized as subjective search gain and is determined by the person’s spatial knowledge and subjective beliefs. It is
therefore continually adjusted in the search process. The search cost is a personal characteristic that reflects the time, monetary, mental efforts, and/or risk involved in each round of search as perceived by the person herself/himself. The tradeoff between the subjective search gain and the perceived search cost determines when the search for alternative departure times starts and ends.

If a person decides not to search, repetitive/habitual behavior is executed. Otherwise, the person will employ a set of search rules to search from her/his spatial and temporal knowledge and identify a new departure time alternative. After a person identifies an alternative departure time, she/he needs to determine whether or not to switch departure time after experiencing traffic conditions associated with the new departure time. The decision rules constitute a mapping from spatial knowledge (especially experienced traffic conditions corresponding to different departure times) to a binary decision: choose the new departure time or retain the current departure time. The search rules and decision rules should be empirically estimated from observed search processes.

When searching under uncertain situations when non-recurrent congestion generates unexpected delay, the proposed search theory suggests that in general travelers are more willing to search for alternatives as the subjective search gain is significantly higher under uncertainty. And it is hypothesized that the search rules may systematically favor certain departure time alternatives. For instance, if a person currently departs at 8 am and is not satisfied with the resulting travel and/or schedule delay, the person may be more likely to try departing at 7:30 am and 8:30 am than 7 am and 9 am (i.e. an anchoring effect). Also, in search for alternative departure times for a fixed-schedule commuting trip, the search process may be biased toward earlier departure times.

Normative utility maximization choice rules suggest a negative impact from the travel time uncertainty (usually defined as the 95% confidence interval of the travel time duration). When making a decision under uncertainty, travelers are not always risk-avoiders. For instance, by rule of thumb, commuters with more flexible arrival schedules may be more willing to try riskier alternatives as long as the expected travel time (or, very likely, the expected monetary travel cost) will be lower. In other word, they trade off the uncertainty over the travel time and/or cost. The proposed positive theory allow for these psychologically more realistic mental rules and heuristics.

As aforementioned, the knowledge updating, subjective beliefs, departure time search rules, and decision under uncertainty are theorized. A quantitative model of departure time choice under uncertainty is thus developed in the remainder of this section, where the travelers’ learning processes and comparison between search gain and search cost are quantified, and departure time search rules and decision rules under uncertainty are empirically derived. This quantitative model is then executed iteratively in an agent-based simulation in order to study system-level performance measures when the day-to-day departure time dynamics is of concern.

**Bayesian Learning**

In this section, Polya’s Urn model sheds light in the modeling of the human knowledge and learning process. In Polya’s model, an urn containing balls of I different colors is considered ($a_1$ balls of color 1, $a_2$ balls of color 2, etc.). Then $N$ random draws from the urn are performed. The Ball is placed back into the urn with an additional ball of the same color after each draw. As $N$ approaches infinity, the proportions of different colored balls follow a Dirichlet distribution $Dir(a_1, \ldots, a_n)$. 

This model best illustrates the properties of the process that each individual forms and updates her/his knowledge. Knowledge about departure time is assumed to be stored in $I$ discrete categories. Let $n_i$ be the number of times payoff level $u$ has been experienced by a particular individual. Therefore, the individuals’ knowledge about a departure time $j$ can be quantified as a single-dimension vector $K(n_{t,j}, \ldots, n_{l,j}, \ldots, n_{l,t})$. According to Bayesian learning rules, when a new alternative departure time is experienced and the associated payoff falls into category $i$, the updated knowledge becomes: $(n_{t,j}, \ldots, n_{l,t}+1, ..., n_{l,t})$. Let vector $P(p_{t,j}, ... , p_{l,j})$ represent an individual’s subjective beliefs, where $p_{t,j}$ is the subjective probability that an additional search would lead to an alternative departure
time \( j \) with payoff level \( u_{i,j} \). We assume all individuals initially believe there is no congestion for any departure times that they have never tried. And we assume that individuals’ prior beliefs follow a Dirichlet distribution (which itself is the conjugate prior of the multinomial distribution) to establish a quantitative relationship between knowledge \( K \) and beliefs \( P \). The posterior beliefs will also be a Dirichlet distribution (21). This assumption is equivalent to assuming Equation (2), where \( N \) denotes the total number of observations (\( N = \text{Sum}(n_{i,j}) \)).

\[
P_{i,j} = \frac{n_{i,j}}{N} \tag{2}
\]

**Search Gain and Search Cost**

Based on the previous assumption of Bayesian learning and subjective beliefs, we derive individuals’ subjective search gain, i.e. the expected payoff improvement from an additional search. And starting from forming the subjective search gain, individuals compare it with their search cost and then make a decision about searching. Let an individual’s payoff on the currently used departure time be \( u \). The subjective search gain \( g \) is based on subjective beliefs, \( P \), and defined as the expected payoff improvement from an additional search on departure time \( j \) (note that this departure time alternative can be completely unknown to a particular traveler and thus he/she initially believes \( u_{i,j} > u \) with probability \( p_{i,j} = 1 \)):

\[
g = \sum_{i,j(u_{i,j} > u)} p_{i,j} \cdot (u_{i,j} - u) \tag{3}
\]

where \( u \) is the maximum of all observed (experienced) payoff levels \( (u_{\text{max}}) \) because individuals can selected from all tried departure times. Here the payoff function \( u(\cdot) \) itself is also empirically estimated based on Small’s multinomial logit specification (7). The function consists of four explanatory variables including travel time, schedule delay early, schedule delay late, and monetary cost. While this term is denoted in this paper as payoff, \( u \) is really a measure of the level of satisfaction associated with various alternative departure times. It is then used to quantify the subjective search gain and to describe the processes how individuals try to improve their satisfaction level subject to learning, limited information, perceptions and belief, and search cost.

In the theoretical model, searching and acquiring information about the alternative departure times is associated with search cost. Travelers start searching once their subjective search gain exceeds their search cost. Throughout the search process, search cost is assumed to be constant for the same individual. It represents both the variety-seeking propensity of individuals and the perceived mental/monetary cost associated with search. We empirically observe individuals’ search start and stopping conditions in a memory-recall survey, wherein each respondent was asked to recall the order of alternative departure times they had considered and actually tried, as well as the travel conditions corresponding to those alternatives. More details about the survey are documented in (1). Once a respondent stops searching after \( n \) rounds of search, the perceived search cost for that individual must be lower than the subjective search gain after \( (n-1) \) searches such that search \( n \) is meaningful, and must be higher than the subjective search gain after \( n \) searches such that search \( (n+1) \) does not occur. Thus, the lower and upper bounds estimated from the empirical survey data are used to approximate the search cost for each traveler in the survey data sample.

\[
c = \frac{1}{2} \left( g_{n-1} + g_n \right) \tag{4}
\]
Search Scopes

Once an individual decides to start searching for alternatives, Different stimuli makes this person search with different scopes. The search scopes are empirically extracted from the memory recall survey. The variables used in the search scope induction model include: arrival schedule delay early (ASDE), arrival schedule delay late (ASDL), travel time (TT), and free flow travel time (TT'). Equation 5, 6, and 7 define the arrival schedule delay variables (i.e. ASDE, ASDL, and Delay), which is consistent with the definition in previous research. PAT denotes the preferred arrival time, AT the actual arrival time, Delay the difference between actual travel time (TT) and free flow travel time (TT').

\[
ASDE = \max(0, PAT - AT)
\]
\[
ASDL = \max(0, AT - PAT)
\]
\[
Delay = \left(\frac{TT - TT'}{TT'}\right)
\]

The authors have tested various machine learning algorithms (26) on the memory-recall survey dataset. Methodologies tested include C4.5 (27), PRISM (28), PART (29), and RIPPER (30). Among all derived rule-sets, we select PART rules based on predictive accuracy on the validation dataset. The complete departure time search rule sets are presented below:

Search Scope = 60+ min earlier, if
[ASDL > 70] Rule 1

Search Scope = 30-60 min earlier, if
[45 < ASDL <= 70] Rule 2

Search Scope = 0-30 min earlier, if
[ASDL > 0 AND Delay > 0] Rule 3

Search Scope = 0-30 min later, if
[0 < ASDL <= 30 AND Delay > 40%]
OR [ASDL <= 10 AND ASDE <= 40 AND Delay <= 50% AND TT <= 65] Rule 4

Search Scope = 30-60 min later, if
[ASDL = 0] Rule 5

Search Scope = 60+ min later, if
[ASDE > 75] Rule 6

OR [ASDE > 45 AND Delay > 10%] Rule 7

Otherwise, search 0-30 min earlier. Rule 8

Decision under Pricing and Uncertainty

Once an individual found a new departure time alternative, the individual after experimenting with the new alternative will either change or not change departure time. This adjustment decision-making process can be modeled with a set of decision rules. The dataset employed here is collected from a stated-preference departure time survey, where seven different scenarios with various travel time duration and toll cost specifications are given to each respondent. The empirically derived decision rule set consists of 13 rules, presented below. RIPPER is chosen for its superior predictive performance on validation dataset, and the clear physical meaning of the derived behavioral rules.

The travel time uncertainty (RANGE) is specified here as the 95% confidence interval of the travel time duration. Other explanatory variables in the decision rules include: travel time (TIME), arrival schedule delay early (ASDE), arrival schedule delay late (ASDL), monetary cost (COST), household income (INCOME), gender (GENDER). The variable flex is a dummy variable that is equal to one if the trip maker’s preferred arrival schedule is flexible, and 0 otherwise. \(\Delta\) denotes percentage changes of the alternative departure time attributes from the attributes of current departure time choice.
Switch to the alternative departure time, if
\[\Delta R \leq -16.7\% \text{ and } \Delta T \leq -15.4\%\] Rule 1
\[\Delta T \leq -25\% \text{ and } \Delta R > 0\%\] Rule 2
\[\Delta R > 0\% \text{ and } \Delta C \leq -15.2\% \text{ and } flex = 1\] Rule 3
\[\Delta R \leq 0\% \text{ and } INCOME < 150K \text{ and } -8.3\% < \Delta C \leq 0\% \text{ and } \Delta T \leq 10\%\] Rule 4
\[\Delta R \leq 0\% \text{ and } INCOME < 150K \text{ and } \Delta C \leq -8.3\% \text{ and } \Delta ASDL \leq 35\%\] Rule 5
\[-16.7\% \leq \Delta R \leq 0\% \text{ and } INCOME \leq 50K\] Rule 6
\[\Delta ASDL \leq -38\% \text{ and } \Delta R > 0\% \text{ and } \Delta T > 17\%\] Rule 7
\[-66.7\% \leq \Delta R \leq -16.7\% \text{ and } -4.2\% \leq \Delta C \leq 10\%\] Rule 8
\[INCOME \leq 50K \text{ and } gender = \text{female} \text{ and } \Delta R \leq -70\%\] Rule 9
\[INCOME \leq 50K \text{ and } flex = 1 \text{ and } -22.7\% \leq \Delta T \leq 16.6\% \text{ and } \Delta C \leq 20\%\] Rule 10
\[INCOME \leq 100K \text{ and } gender = \text{female} \text{ and } \Delta T \leq 8.3\% \text{ and } \Delta R \leq -44.4\%\] Rule 11
\[-21\% \leq \Delta T \leq -10\% \text{ and } \Delta ASDL \leq 33\% \text{ and } \Delta R \leq -40\%\] Rule 12
Otherwise, continue to use the current departure time Rule 13

There apparently exist perception thresholds in travel time uncertainty. In general, the rules imply individuals are more likely to change departure times as long as the travel time uncertainty is lower. This risk aversion behavior is especially significant for certain travelers, such as those who are with lower income (Rule 6) and whose gender is female (Rule 9 and 11). While strongly risk-loving behavior (i.e., choose the riskier alternative given all other things equal) is not directly captured in the rule set, some travelers are implicitly risk-neutral or risk-loving and are willing to try more risky departure time alternatives as long as they are better off in other attribute(s). As shown by the Rule 2, 3, and 7, for instance, the travelers tend to sacrifice the travel time reliability for the improved travel condition, i.e., shorter expected travel time, lower travel cost, and less arrival schedule delay, respectively. These different attitudes toward risk and travel time uncertainty are thereby simulated in the agent-based system. Drivers’ heterogeneity towards pricing is also explicitly modeled (Rule 3 and 10). Rule 8 further suggests that drivers are willing to pay up to an extra 10% of the original travel cost for a more reliable alternative. These sensitivities potentially allow the model to analyze time-varying/dynamic pricing, flexible work hours, and other peak spreading incentives. While the following section presents a numerical example with natural peak spreading incentives, we leave the simulation of various pricing scenarios and peak spreading effects for future research.

Model Validation

Validating the rule sets is an important process proving the model’s credibility. A within-sample validation is conducted for each of the model developed. In particular, ten-fold cross-validation has been employed in the validation, which is typically seen in most practical limited-data situations (31). Future research may explore how innovative data collection and advanced survey methods, such as web-based interactive games, simulation-based group dynamics, GPS surveys, and smart-phone applications, can support and improve the validation.

In the ten-fold cross-validation, the original data sample is first randomly partitioned into ten sub-groups. One sub-group is retained as the test set. The rest nine sub-groups are used as the training set. Then the estimation and validation process is repeated ten times so that each data sample is used exactly once for validation. The aggregate cross-validation accuracy for the search scope modeling is 93.3%, while six search scopes have been specified in the rules set. And the validation of the decision rules can get 96.5% correctly classified instances.

From Micro to Macro

So far, this model is completely agent-based, focusing on individuals’ Bayesian learning, departure time search scope, and decision under uncertainty. Exploratory agent-based studies for other demand patterns, such as route choice, travel diversion, and policy-makers’ investment decisions, are also available among the literature (32-35). In real world, individuals realize and assess all these behavioral
decisions in the transport network. Thus, it makes sense that this positive model should be integrated with simulation-based network systems. The integrated modeling structure is illustrated in Figure 1.

**FIGURE 1 From Agent Rules to System Behavior, From Theory to Useful Models**

Currently, this system is coded in MATLAB. Starting from the agent behavior loop, travelers’ social demographic characteristics are first synthesized. By applying the positive departure time model, each agent in the system learns from its previous experiences and then searches and decides its departure time accordingly. By aggregating these agents’ departure times, the time-dependent OD matrices in the database are updated. These OD tables are then implemented in the simulation loop. Simulation-based network models calculate travel time, uncertainty, cost, etc. in order for agents to gain travel experiences and reevaluate their departure time decisions.

For the convergence of the system, a behavioral departure time equilibrium (BDTE) will be achieved when all individuals in the transportation system have subjective search gains lower than their respective perceived search costs, and therefore stop searching for alternative departure times. When system conditions change due to increasing level of congestion and/or policies such as dynamic pricing, flexible work hours, and other peak spreading incentives, an existing BDTE will be disturbed and certain individuals will restart the search process and potentially adjust their departure times until the system reaches a new BDTE.

The iterative execution of the model guarantees the existence of the BDTE, because subjective search gain decrease as number of searches increases. However, BDTE is not stable in that after an infinitesimally small disturbance. When the system uncertainty level increases, it takes a considerably large number of iterations for the model to equilibrate. This computational property of BDTE, along with supply- and demand-side uncertainty scenario test, is explored further in the next section.

**DEPARTURE TIME CHOICE UNDER SUPPLY- AND DEMAND-SIDE UNCERTAINTY**

**Base Case Scenario**

The computational feasibility to combine departure time model with various macro/meso/microscopic network traffic models for peak spreading analysis has been demonstrated in the authors’ previous work (1). In this section, we enhance the numerical test with supply- and demand-side uncertainty and demonstrate how the travelers’ actual departure time decision-making process under various
uncertainty scenarios. Since a large number of uncertainty scenarios are specified and at this moment only the departure time changes are considered in the model, a one-link highway commuting corridor with one OD pair and two lanes is selected here as the test example for simplicity. Other setups of the numerical example are listed as follows:

- Link capacity is 1,600 vehicles per lane per hour.
- Link length is 33 miles, with two lanes.
- The base-case scenario is characterized by an initial demand in 15-minute intervals from 4 a.m. to 11 a.m. A total number of 21,648 trips per day are simulated in each iteration.
- The testing policy assumes a uniform 10% increase in OD demand across all time intervals (see the thick dotted line in Figure 4), which is expected to cause significant increase in congestion (especially during the peak hours of the study period) and subsequently adjustment of departure times for certain commuters. And
- Commuters’ arrival times in the base case are assumed to be their preferred arrival times.

**Demand- and Supply-Side Uncertainty Scenarios**

In order to examine how travelers’ make departure time decisions under uncertainty, a number of demand-side uncertainty scenarios and a number of supply-side uncertainty scenarios are defined and simulated in this paper. In each run of the simulation, each traveler learns, makes departure time search, and adapts behavior under certain demand-side and/or supply-side uncertainty.

On the demand side, the uncertainty is introduced by randomness of the total travel demand from day to day. For instance, consider the case when a student commutes to campus on a daily base. She/he may encounter higher congestion caused by day-to-day demand fluctuation such as special events, graduation, etc. The coefficient of variation (CV, defined as the demand standard deviation divided by the mean travel demand) can be used to measure the demand-side fluctuation. In this study, 50 demand-side uncertainty scenarios are specified. The CV value varies from 0 to 0.3 in a uniform step size.

On the supply side, the uncertainty is defined by lane failure rate. It is defined as the probability that one lane loses the capacity due to certain events such as work zone and traffic incidents, etc. Since we only define one link in the numerical example for simplicity, the occasion that all the lanes on the same link fail at the same time is neglected. 50 supply-side uncertainty scenarios are specified. The lane failure rate varies from 0 to 0.0002 in a uniform step size.

Thus, a total number of 2,500 combinations of demand- and supply-side uncertainty scenarios is produced and tested in this agent-based simulation setup. 100 random seeds are selected in order to varying the simulation results. And in each uncertainty scenario, 100 iterations (simulated days) at maximum are conducted to allow system-level performance measures to converge to their true values for that particular scenario.

**Model’s Sensitivity to Uncertainty Scenarios**

Figure 2 verifies that as simulated by the numerical example, travelers actually experience worse travel time reliability as the level of uncertainty increases. The reliability is measured by the coefficient of experienced travel time variation (i.e. the standard deviation of the experienced travel time divided by the mean travel time). As shown in Figure 2, the reliability is approximately monotone with respect to both the supply-side and the demand-side uncertainty. A reasonable interpretation is that individuals are making one-dimensional departure time decisions. More dramatic reliability variation can be introduced by simultaneously considering together the routing and changing departure time in a more sophisticated and realistic road network.
Departure time search and switching behavior under uncertainty is illustrated in Figure 3. Overall, it agrees with the hypothesis that more travelers search for alternatives in response to non-recurrent congestion due to increasing uncertainty (contour color turns darker from the bottom-left to the upper-right). At the highest uncertainty level, about 16% of the travelers have searched for alternatives. Interestingly, we can observe that when both the supply-side and the demand-side uncertainty reach peak (the upper-right corner in Figure 3), the average percentage of travelers who have searched/changed departure time drops to the level of moderate uncertainty scenarios. This is because when the uncertainty level is too high, a small amount of travelers keeps searching and changing due to their extremely high subjective search gain. While most scenarios under low and normal uncertainty level take some 30 simulated days to converge, under the high-uncertainty scenario it takes significantly more iterations (about 90 iterations) for the travelers to satisfy and for the model to converge given the uncertain situation. Thus, the average percentage of travelers who have changed their behavior decreases in this occasion.

Figure 4 plots the ratio of travelers who have chosen more reliable departure alternatives among all travelers who have searched. This ratio is defined as the total number of travelers who have switched to or stayed in the less risky departure times (i.e. of lower coefficient of experienced travel time variation) divided by the total number of travelers who have searched for departure time alternatives.

**FIGURE 2 Experienced Travel Time Reliability (Measured by Coefficient of Travel Time Variation)**

**FIGURE 3 Daily Departure Time Search and Switching Behavior under Uncertainty**
As aforementioned, we observe a general trend of increased departure time searching and changing propensities with increased system uncertainty (see Figure 3). Here we further explore travelers’ decision under uncertainty by calculating the percentage of travelers who have chosen the less risky departure time alternatives when they are making the switching decision. As depicted in Figure 4, when the uncertainty level is relatively low, about 60% to 65% of the travelers are able to choose more certain alternatives. As the uncertainty grows to a certain level, as highlighted by the dash line, travelers become less successful in decreasing their experienced uncertainty and this percentage of choosing lower risk decreases to about 50%. In other word, travelers are almost indifferent between choosing riskier alternatives and choosing more reliable alternatives when uncertainty level grows to a certain level. When the system becomes even more unreliable, travelers’ decisions are strongly against more risky alternatives. Under the highest level of uncertainty scenario, about 75% travelers in the system prefers alternatives associated with lower travel time uncertainty.

Another interesting comparison when studying departure time searching and switching behavior is between searching/switching to earlier time alternatives or searching/switching to later time alternative. The ratio of travelers who searched for earlier departure times (calculated as the total number of people who have employed search rules to investigate earlier departure alternatives divided by the total number of people who have searched for alternatives) is presented in Figure 5a. Similarly, the ratio of travelers who switched to earlier departure times is calculated as the total number of travelers who have decided to choose the earlier departure alternatives divided by the total number of travelers who have decided to change their departure time. And this ratio is presented in Figure 5b.

As the system becomes more congested due to the demand growth, travelers generally arrive at their destinations later than their preferred schedule ($ASDL > 0$) and this dissatisfaction encourages them to search (often biased towards earlier alternatives). Interestingly, the numerical result suggests significant behavioral heterogeneity in this regard. Travelers are interested in earlier alternatives only when the system-level uncertainty is relatively lower. As depicted by the dark grey zone in the bottom-left corner of Figure 5a and 5b, about 55% to 60% of the travelers try earlier departure times when the supply- and demand-side uncertainty is low. And under these circumstances, about 65% eventually decide to depart earlier among those who have decided to change departure times.

Again, we observe a ribbon area in Figure 5a and 5b, showing that when the uncertainty increases to a certain level, the ratio of searching for earlier alternatives and the ratio of switching to earlier alternatives drop drastically to below 40% and below 55%, respectively. In other word, travelers in general are more likely to look into later departure times under these uncertainty scenarios, even when they have experienced schedule delay under the policy scenario that the total demand grows by 10%. This uncertainty zone is very consistent with the bounded dash line shown in Figure 5, which together
indicates that travelers are somewhat indifferent between earlier departures and later departures, and between lower risk and higher risk.

a. The ratio of searching for earlier alternatives

b. The ratio of switching to earlier alternatives

FIGURE 5 The Ratio of Travelers who Searched/Switched to Earlier Alternatives
CLOSING REMARKS

This paper has developed a positive theory for modeling departure time choice under uncertainty. Important cognitive processes which individuals actually employ to make a departure time decision have been specified and empirically modeled. And an agent-based simulation model has been developed based on the theory in order to analyzing the agents’ behavior and the consequent system-level dynamic properties.

The work presented in this paper differs from previous studies of the departure time choice in a number of significant aspects, including:

- The specification of learning mechanisms by which individual travelers adjust their subjective beliefs based on prior experience on a daily basis;
- The search and decision heuristics under uncertainty are empirically modeled, representing a rich behavioral foundation and the interaction between decision behavior and system-level performance measures is recognized;
- The numerical example successfully simulates the day-to-day dynamics of departure time decisions under various uncertainty scenarios.

It remains a first research effort as a departure from rational behavior assumptions and to dynamically model the departure time decision-making under uncertainty. This paper attempts to gain insights into travelers’ behavior variation in uncertain and dynamic environments. The implementation of the quantitative models indicates its capability to simulate travelers’ day-to-day departure time adjustment.

The travel time reliability plays a crucial role in the individuals’ decision-making processes as well as for the system to converge. The agent-based simulation confirms that more travelers search for alternative departure times in response to non-recurrent congestion caused by increasing uncertainty. And under extremely high uncertainty level, travelers need more iterations (simulated days) to exhibit satisficing behavior.

Another interesting result obtained in this paper is that travelers exhibit risk-neutral and slightly risk-loving behavior when the system-level uncertainty increases to a moderate level and become extreme risk averters when the uncertainty reaches a very high level. When the uncertainty level is extremely low and extremely high, the majority of users choose a particular departure time with lower variability in travel time. When the uncertainty level is moderate, an increasing number of travelers choose the alternative with lower expected travel time but higher variability in travel time.

This paper is primarily exploratory in nature. The principal aim is to introduce and illustrate a promising theoretical framework and explore the system performance under different uncertainty scenarios. Although the conclusions drawn here are plausible and consistent with casual observation, an essential ingredient in future research is the more comprehensive consideration of the actual departure time choice behavior under uncertainty. Advanced survey methodologies, such as GPS-based longitudinal travel survey and smartphone-based survey, collect day-to-day revealed behavior in a real-world context. It supplements the traditional survey with desired level of data richness and is worthy of further investigation. Another future research direction may be extending the model to consider multiple travel decision-making dimensions. The travel time reliability issue is not only associated with a more reliable departure time, but also with many other agent behavior aspects, including routes, modes, destinations, etc. The current research may be enhanced further by modeling the choice “bundles” and estimating dimension-specific search and decision heuristics in the future.
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