Day-To-Day Evolution Of Network Flows Under Departure Time Dynamics In Commuter Decisions

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Abstract
This paper investigates day-to-day dynamics in urban traffic network induced by departure time dynamics in commuter decisions. This investigation relaxes some key restrictions regarding fixed departure time and equilibrium assumptions to analyze the stability and performance of urban traffic networks over a multiple day planning horizon. A simulation-based framework is developed to analyze day-to-day dynamics by integrating an empirically calibrated model of dynamic departure time decisions with a dynamic network assignment model.

Computational experiments are used to investigate the effect of the following experimental factors, recurrent network congestion level, time-dependent loading profile, and users' sensitivity to commute experience and trip-time volatility on network performance and reliability. The findings provide evidence of considerable day-to-day variations and stochasticity in network flows and performance, even under the assumption of fixed routes and in the absence of information. The results indicate that: 1) the network performance under departure time dynamics can deviate significantly from equilibrium, 2) the departure time adjustment process is remarkably stable and reaches stationarity, although the departure time choices do not appear to be at equilibrium, 3) departure time dynamics introduces significant volatility in trip-times from day-to-day, and 4) increasing the sensitivity of users to commute and network performance attributes (schedule delay, trip-time variability) can lead to more stable system behavior and reliability. These results have important implications for estimation of time-dependent O-D matrices, dynamic network analysis, and effective congestion management strategies.

Key words: day-to-day dynamics, departure time dynamics, network flow evolution, stationarity, disequilibrium
1. INTRODUCTION

Dynamic traffic assignment models aim to describe network flow dynamics, and form a core component in the evaluation and operation of Intelligent Transportation Systems. Three principal time-dimensions are of interest in dynamic traffic modeling: real-time, within day and day-to-day dynamics. Real-time dynamics relates to dynamics that arises due to the effect of real-time traffic information on user decisions (particularly en-route and associated flow changes) and system performance. Within-day dynamics refers to variations in trip-time due to variation in O-D patterns across different departure times (1). Day-to-day dynamics refers to variation in network flows from one day to the next due to internal and external system perturbations. A large body of network modeling studies has focused on the first two dimensions of dynamics, given the interest in modeling routing decisions under information. These studies have sought to characterize steady-state conditions and equilibrium flows, typically under the assumption of known but time-dependent demand (O-D) distribution (2). Fewer studies examine day-to-day dynamics in real-world networks (2-3), particularly, dynamics that results from variation in departure time decisions of trip-makers, despite significant empirical evidence of such variability (4-8).

This paper investigates day-to-day dynamics in network flows induced by departure time dynamics. In particular, three major objectives are of interest in this study. First, the influence of recurrent congestion levels on day-to-day evolution in network flows is analyzed. The second objective investigates the effect of time-dependent loading profiles on day-to-day dynamics in departure time decisions, and consequent stability and variability in network performance. The third objective examines the role of users’ responsiveness to network performance measures on the stability of trip times and performance of network from day-to-day. This study specifically examines network dynamics in the commuting context due of the repetitive nature of commute patterns, fixed arrival time constraints, and their significant contribution to peak period congestion.

Addressing these objectives has important implications for the: a) design of transportation control measures to reduce congestion since departure time decisions of commuters significantly influence peak-period traffic flow distribution and congestion patterns; b) developing robust models of time-dependent (departure-time varying) origin-destination inputs, needed for accurate real-time assignment methodologies; c) improved planning capabilities and evaluation of departure time-based demand management measures such as flexible and staggered work hours etc. and d) analysis of travel time reliability and stability (an emerging thrust in network operations, e.g. FSHRP makes travel time reliability a key national priority).

Due to these motivating considerations, the three objectives are addressed by developing a simulation-based framework to model day-to-day dynamics in network flows. The proposed framework accounts for the day-to-day variation and stochasticity in departure time decisions through an empirically calibrated user behavior model. This framework combines within-day and day-to-day dynamics in an integrated framework by embedding a within-day network simulation assignment model (DYNASMART) within this day-to-day user decision framework (as noted in Section 3). This integrated simulation model is used to conduct a series of computational experiments to analyze the effect of departure time dynamics on network flow evolution. The experimental factors varied in the experiments include: recurrent congestion level, time-dependent loading profile, and users’ sensitivity to commute experience. By systematically
varying the levels of these factors, the following performance measures are observed and analyzed: system performance evolution (average network trip time and its variability), commute performance (average early/late schedule delay), and departure time response (average switching rate and switching magnitude).

This study is distinct from the prior research efforts in the following respects. This study aims to analyze network flow evolution, stability, and reliability when the system may not necessarily be at user equilibrium. Furthermore, network flow evolution induced by departure time dynamics is of interest here, since commuters are more likely to switch departure times than routes (1, 7, 9). In contrast, earlier day-to-day studies have focused on route-choice dynamics, partly due to lack of empirical data and models on departure time dynamics. To address this limitation, this study uses an empirically calibrated model of dynamic departure time adjustment process, which provides a richer stochastic representation of user decisions. This dynamic model was found to be superior to static departure time choice models (used in planning) as it explicitly accounts for dynamics in network and commute performance, users’ past experience, and users’ departure time switching history (10). At a substantive level, the interactions between recurrent congestion levels, departure time dynamics and network flow evolution are analyzed in this study. Further, the role of behavioral factors such as sensitivity to schedule delay and trip-time volatility on network flow evolution and stability are also systematically investigated.

The rest of the paper is organized as follows. Section 2 reviews related literature on within-day and day-to-day dynamics. In Section 3, the simulation framework is described, and the experimental design procedures are described in the next section. The results from the computational experiments and their significance are discussed in Section 5, followed by concluding remarks and directions for further research, presented in Section 6.

2. BACKGROUND REVIEW

This section briefly reviews prior studies on within-day and day-to-day dynamics in network flows. Many researchers have investigated within-day dynamics using the equilibrium framework. Several types of ‘dynamic’ equilibria (11-12) have been proposed and currently form the basis for network design, operation and control decisions. Although, the assumptions underlying these equilibria vary across different studies, one common feature is that at equilibrium no user can improve his/her cost by switching (choices) unilaterally. Thus, these equilibria are ‘dynamic’ in the sense that the travel times of users departing at different times vary on a given-day. However, the equilibria are essentially ‘static’ in a day-to-day sense, since travel times do not vary from day-to-day for a given route and departure time. Therefore, it is assumed that once equilibrium is reached, it continues to persist from day-to-day. For instance, significant day-to-day variations in network flows have been reported by observational studies of traffic in several cities in the U.S, the Netherlands and England (4-6). However, due to their focus on characterizing steady state conditions, equilibrium models do not adequately account for these day-to-day variations and stochasticity.

To account for these day-to-day variations, a few researchers have investigated the evolution in network flows over many days. Cantarella et al. (13) used a stochastic process model and found that system flows may deviate significantly from equilibrium due to the effect of information and past experience on route choice decisions. Horowitz (14), in one of the earliest studies in this area, demonstrated that traffic flow can exhibit non-convergence, or convergence to non-equilibrium
states, even when stochastic user equilibrium was unique, due to the role of learning effects on user decisions. In a related finding, Nakayama et al. (15), indicated that network may converge to a deluded equilibrium state which may be considerably worse than equilibrium conditions, due to heterogeneity (differences across drivers) of perception (of trip-times and paths). More recently, Peeta et al. (3) question whether real-world flows are at or near equilibrium conditions, given the numerous sources of random shocks (demand, supply, incidents, weather, construction etc.).

In most studies cited above, route choice decisions have been the main source of day-to-day variability in network flows. In contrast, the role of departure time decisions on network flow evolution has received little attention, although several empirical studies have found that commuters are more likely to change their departure time than route (16). For instance, departure time switching rates of 56% and route switching rates of 23% were observed in commute trips (based on travel-diary surveys for 2 weeks) in Dallas and Austin (7-8). Due to the focus on the effect of routing decisions in current models, the influence of departure time dynamics on network performance, stability and reliability are not well understood. Furthermore, due to tractability considerations, many day-to-day studies do not account for within-day dynamics (with a few exceptions, e.g., 13).

A few studies try to address these shortcomings by combining within-day and day-to-day dynamics through an integrated framework. Among these studies, Cascetta (17) used a modified version of within-day departure time choice model (18) and evaluated system performance under alternative control strategies. However, the departure time adjustment process is modeled at an aggregate level by assuming that a pre-specified fraction of users will reconsider the previous day’s choices. Hu and Mahmassani (19) used a dynamic traffic assignment framework (DYNASMART) to evaluate day-to-day network dynamics under real-time information and responsive signal control system. The results showed that the departure time patterns convergence to a peaked flow pattern which had the same mode (peak), regardless of the control strategies that were considered. Although this study uses a more disaggregate and empirically calibrated behavioral model, adjustment decisions are only partially accounted for through an empirical binary departure time switching model (switch / not). Further, due to the focus on the role of information market penetration and on-line control in this study, few insights are obtained on day-to-day dynamics and stability.

A common feature in these day-to-day studies is their use of simulation-based experiments for analysis. This approach is necessitated by the complexity and nonlinearity of this problem (stochasticity and dynamics), which precludes the use of analytical approaches (20) for realistic networks. Further, the direct use of empirical real-world data for analysis is also inadequate, since it is difficult to control experimental factors, observe user response at the desired temporal resolution. Further, the observed evolutionary path (in the real-world) is only one possible sample from a set of possible stochastic realizations. Due to these difficulties with other approaches, this study will also use a simulation-based approach, described in Section 3, to model network flow evolution due to departure time dynamics.
3. DAY-TO-DAY DYNAMIC SIMULATION ASSIGNMENT FRAMEWORK

3.1 Departure Time Decision Model

Given the focus on departure time dynamics, it is essential to represent departure time adjustment decisions from day-to-day at a sufficiently disaggregate level and rich temporal resolution. Toward this end, an empirically calibrated model of dynamic departure time choice (21) has been integrated with a dynamic network assignment framework (DYNASMART) in this study. As noted earlier, this dynamic departure time adjustment model provided a significantly better fit to empirical data than alternative static departure time choice models (used in planning, 21).

To represent commuting constraints, each commuter is assumed to have a target or preferred arrival time (PAT) at the work place, and the user selects departure times to reach his/her workplace by this time. In the proposed model, the departure time adjustment takes place in two stages. First, a user ‘reviews’ whether the current departure time is satisfactory for the next day’s commute (based on current and past traffic experience). In the second stage, if the current choice is satisfactory, it is retained. Otherwise, the user determines the magnitude of departure time switch based on past experience, network performance, and failure to meet arrival time goals. Empirical results (21) indicate that the alternatives are considered in aggregate intervals (bins) of five-minutes, and alternatives closer to current choices are evaluated preferentially ahead of farther alternatives. In other words, a user is more likely to consider adjustment by five minutes first before considering a switch by over fifteen minutes. The user continues to evaluate alternatives sequentially until a satisfactory and sufficient alternative is found.

Accordingly, the adjustment process is represented as a sequence of binary decisions. This model is operationalized through a set of corresponding binary alternatives and utilities shown in Figure 1. The utility values U1,... U5, correspond to the utility of no adjustment, adjustment by more than 1 minute, adjustment by more than 5 minutes and so on. The specification of these random utilities, U1,... U5, are given below, and the coefficients and parameters of the error-terms are based upon the empirical model reported in Srinivasan (21). In this model, a user will change departure times if U1 < U2, and by 5 minutes if U2 > U3 and U1 < U2.

\begin{align*}
U_1 &= 0 \\
U_2 &= \alpha_1 + \alpha_2 \times \text{Dtratio} + \varepsilon_1 \\
U_3 &= \beta_1 + \beta_2 \times \text{Dtratio} + \beta_3 \times \text{SDE} + \beta_4 \times \text{SDL} + \varepsilon_2 \\
U_4 &= \gamma_1 + \gamma_2 \times \text{Dtratio} + \gamma_3 \times \text{SDL} + \varepsilon_3 \\
U_5 &= \chi_1 + \chi_2 \times \text{Dtratio} + \chi_3 \times \text{SDL} + \chi_4 \times \text{NSEP} + \chi_5 \times \text{NSLP} + \chi_6 \times \text{Triptimet}_{t-1} + \varepsilon_4
\end{align*}

where:

- \( U_i \) = total utility for i-th switching alternative
- \( \alpha, \beta, \gamma, \chi \) = the coefficients of utility functions calibrated empirically
- \( \varepsilon_i \) = correlated random error for each switching alternatives
- \( \text{Dtratio} \) = trip-time volatility ratio
- \( \text{SDE} \) = early schedule delay
- \( \text{SDL} \) = later schedule delay
- \( \text{NSEP} \) = cumulative percentage of switching to early departure times
- \( \text{NSLP} \) = cumulative percentage of switching to late departure times
Triptime_{t-1} = trip time for previous day

The departure time adjustment alternative for each individual is determined according to this model on each day. (The actual adjustments are assumed to be uniformly distributed within the chosen bin, i.e. the departure time shift could be 7 minutes for a 6-10 minute adjustment bin). These individual departure time adjustment decisions are aggregated to form the time-dependent O-D matrix for the following day.

Based on this time-dependent O-D matrix, within-day traffic flows can then be simulated on the network according to alternate routing rules. The corresponding network performance and associated variables used in departure time utility computations (e.g. schedule delay) are recorded. The systematic utility of the alternatives are also updated accordingly for the next day. Monte-Carlo simulation is used to generate the random error terms in the utility for the next day. The new adjustment decisions are obtained by evaluating the random utilities of the adjustment alternatives sequentially. These decisions collectively form the time-dependent O-D input to the within-day dynamic component for the next day, and the cycle continues.

### 3.2 Dynamic Simulation Framework

The within-day network assignment model used in this study is based upon the well-established dynamic network assignment model (DYNASMART) developed at the University of Texas at Austin (22). This model has been chosen for this study in view of its capability to represent user decisions at a highly disaggregate level. The network simulation assignment model consists of three main components: the traffic simulator, the network path processing component, and the user decision-making components. Based on the time-dependent O-D matrix, the traffic performance simulator (a fixed time-step 'mesoscopic' simulation) moves vehicles on network links according to prevailing macroscopic speed-density relations (e.g. modified Greenshield's model) and capacity constraints. In each time step (6 seconds resolution), the simulator also updates the time-dependent network performance measures including link and path trip times, density, and queue lengths. These level-of-service measures, in turn, affect users’ decisions of alternate routes and experienced travel times. These capabilities are adapted in this study to compute measures affecting departure time utilities such as schedule delay, and trip-time volatility. In addition, DYNASMART also provides the capability to simulate information supply to drivers, although this is disabled in the current study to avoid confounding between information, route choice, and departure time dynamics. Therefore, users are assumed to have no access to information and consequently follow habitual (pre-specified) paths. Further details of the dynamic network assignment model are available elsewhere (16).

### 4. EXPERIMENTAL DESIGN AND SYSTEM PERFORMANCE MEASURES

Due to the inherent fluctuations in actual traffic systems, and lack of critical data, the simulated environment becomes the only possible way to systematically examine these effects while controlling others to avoid confounding. Therefore a series of computational experiments are conducted in this study to investigate network flow evolution. Specifically, in these experiments, three experimental factors are analyzed: recurrent congestion level, initial time-dependent O-D profile, and user behavior factors. In each experiment, the corresponding treatment levels (described below) are varied systematically, while other experimental factors are held fixed to avoid confounding. In each experiment, the performance measures pertaining system, commute, and
departure time response metrics (noted below) are recorded. Network flow evolution is recorded for a period of 55 days for each experiment, but the first five days are discarded from the analysis to avoid potential initialization and simulation biases.

4.1 Experimental Factors

4.1.1 Recurrent Congestion

The first experiment focuses on the effect of recurrent congestion on network flow evolution. Four levels of recurrent congestion are considered in this experiment: mild, moderate, high and severe congestion. Under moderate (severe) congestion, 12596 (22146) vehicles are simulated in the network, with average travel speed of 19 (9.8) mph. By examining the effect of varying congestion levels on system performance and stability from day-to-day, this experiment seeks insights for developing congestion control and reliability improvement strategies.

4.1.2 Initial Time-dependent Loading

In contrast, the second experiment examines the role of initial time-dependent loading profile (first day’s O-D loading pattern) in system performance and stability. This factor consists of the following three levels of initial departure time (loading) profiles: uniform demand profile, peaked demand profile, and an extended peak demand profile. Although the uniform demand is unrealistic, it provides a useful benchmark (lower bound) to compare the day-to-day dynamics with more realistic demand pattern (peaked demand) and extended peak demand pattern. The extended-peak case maintains the peaking characteristics of the peaked demand pattern, but reflects a longer loading horizon during the rush hour (rush hour is extended). The influence of various loading patterns on network dynamics is of interest in developing and evaluating departure-time based demand management strategies (such as staggered work policies), and to understand the stability of the departure time decision process.

4.1.3 Behavioral Factors

The third experimental treatment pertains to user behavior factors affecting departure time dynamics. In particular, three behavioral factors are considered: i) sensitivity to early schedule delay, ii) sensitivity to late schedule delay, and iii) sensitivity to trip-time volatility. For each factor, three experimental levels (low, moderate, and high) are analyzed. The baseline, moderate level, corresponds to the coefficients as per the empirically calibrated model. The higher (lower) sensitivity level is simulated by increasing (decreasing) the coefficients of departure time adjustment utility (by 50% from the baseline). Increased user sensitivity leads to a larger effect on the switching process, by affecting the aforementioned utilities. Insights into the role of these behavioral factors on network dynamics can support the development of more effective demand management strategies and accurate planning models.

4.2 Network Characteristics

The three experiments are conducted using a real-world traffic network representing part of the Dallas Fort Worth metropolitan area (figure 2). This network consists of 13 Origin-Destination zone pairs, 178 nodes and 441 links. This corridor network consists of two parallel freeway facilities (I-35 corridor), with the associated frontage roads. Free flow speeds of 55 mph and 30 mph respectively, are assumed for the freeway and arterials on this network. In these
experiments, the preferred arrival time for each commuter is drawn (using Monte-Carlo simulation) from an empirical PAT distribution (obtained using commuter surveys, 21). The PAT, for each commuter, is assumed to be fixed for the duration of the study (55 days). Commuters are assumed to have no access to en-route information. Therefore, their routing decisions are simulated as following habitual (pre-specified) paths.

4.3 Performance Measures

In these experiments, network flow evolution is characterized by recording and analyzing the following performance measures on each day. The effect of the experimental treatment is assessed by comparing the performance measures across treatment levels.

4.4.1 System Performance Measures

- Within-day travel time represents the average trip time of all vehicles on a given day. The deviation and evolution of within-day trip-time average is analyzed.
- Trip time volatility ratio (on day t) is defined as the ratio of trip-time change (min.) to departure time shift (min.), averaged across users who changed departure times between days t-1 and t. A greater volatility ratio implies that a small departure time shift can lead to large trip-time changes (e.g. five minute departure time shift can lead to ten minute trip-time change).
- Trip time reliability is defined in terms of the probability that the deviation of within-day trip times on successive days (t and t-1) exceeds a pre-specified threshold. This is captured by the fraction of days on which the discrepancy between the mean trip-times (day t and t-1) exceeded a pre-set threshold (0.8 minutes is chosen here, approximately five times the standard deviation of the mean within-day trip-times).
- Deviation of mean day-to-day trip time from user equilibrium (obtained for initial day’s time-dependent O-D demand) is measured in percentage terms.

4.4.2 Commute Performance Measures

- Late/early schedule delay represents the discrepancy between the actual work arrival time and the users’ preferred arrival time on the late/early side respectively.

4.4.3 Departure Time Response Measures

- Switching magnitude to later/earlier departure times reflects the magnitude of departure time adjustment from previous day’s departure time
- Cumulative percentage of switches to later/earlier departure times:

Let \( NSEP_i / NSLP_i \) denote the cumulative proportion of switch to earlier/later for user i at day

These are computed as: 

\[
NSEP_i^t = \frac{NSE_i^t}{t-1} \quad \text{and} \quad NSLP_i^t = \frac{NSL_i^t}{t-1}
\]

where: \( NSE_i^t / NSL_i^t \) Cumulative number of switches to early/later side made by user i from day 1 to day t

These measures reflect the cumulative switching history of a commuter.
Switching rate, on day $t$, measures the fraction of users who switched departure times compared to the previous day ($t-1$).

5. EXPERIMENTAL RESULTS AND DISCUSSION

As noted earlier, three sets of experiments were conducted using the simulation model described previously. The results from this study are shown in Tables 1-3 and are discussed below. Note that all the results for experiments one and two are discussed in terms of percentage deviation from the baseline case (moderate congestion level, experiment one). The baseline in experiment 3 corresponds to the low-sensitivity case for each factor. Due to space limitations, the evolution of a few key performance metrics are displayed in Figures 3 and 4, only for experiment one. The evolution of system travel time, departure time measures, and commute performance metrics over the 50 day horizon are depicted elsewhere (23), and salient trends discussed here.

5.1 Experiment 1: Role of Recurrent Network Congestion Level on System and Departure Time Dynamics

5.1.1 System Performance

With increasing network congestion, average network travel time increases significantly (by 34%, see Figure 3a) as expected, whereas, its variance increases at an even faster rate (roughly 41%). System variability captured through travel time volatility ratio (defined in Section 4) also increases from 0.47 min. to 2.2 min. per min. of departure time shift (Figure 3b). For all loading levels considered, the average system travel times deviate significantly from user equilibrium (20.6% to 35.3%). Further, the system performance does not converge to a steady state value even for mild congestion and varies considerably from day-to-day (reliability = 79.6%). This day-to-day variability increases with increasing network loads indicating the importance of travel time reliability and variability under highly congested conditions. Note that the dynamic system evolution of average trip-times varies qualitatively across different congestion levels suggesting that network evolution patterns are sensitive to initial conditions.

5.1.2 Time-dependent Network Loading Profile

The difference in trip-time evolution over days is due to differences in time-dependent network loading across the three scenarios. Although for each scenario the actual loading pattern converges in all four cases (Figure 4), the resulting steady state profile varies across the three congestion levels. With increasing network loads, the peak of the loading pattern shifts to the left (earlier), and results in an extension of the peak period, consistent with real-world network demand profiles under congested conditions (24). Time-dependent loading pattern can converge even though individual departure time decisions do not appear to converge to a fixed value. As a result although the aggregated loading profile converges, the network trip-times and volatility varies form day-to-day.

5.1.3 Commute Performance

Under moderate congestion, people accept a greater early schedule delay (about 4.3 minutes) and a smaller late schedule delay (4.1 minutes) reflecting a stronger aversion to lateness in
commuting trips. Under very high recurrent congestion, however, commuters accept a much larger schedule delay on both sides (7.9 minutes on the late side and 7.1 minutes on the early side) in order to accommodate the increased trip time and its variability in the network (Figure 3c).

5.1.4 Departure Time Response to Network Performance and Commute Performance

Users’ departure time decisions under day-to-day network dynamics is captured through three related performance measures: i) average departure switching rate over the study period (50 days) ii) average magnitude of departure time shifts (for those who changed departure time), and iii) distribution of departure time shifts. It is observed that all three of these measures converge to steady state values over 50 days for each congestion level, suggesting that the departure time adjustment process is stationary.

- Average departure switching rate
  The asymmetry between early and late schedule delay noted above is also seen in switching rates to earlier and later departure times. Under moderate congestion, switches to later departure times are more likely (29%) than switches to earlier departure times (23%, see Figure 3d). In contrast, users display a more conservative switching behavior under high congestion levels, with increased switches to earlier departure times (30%), which dominates the shifts to later times (27%)

- Average Switching magnitude
  For each congestion level, larger shifts were observed for earlier departure times than switches to later times. With increasing congestion, the magnitude of shifts also increases, but only marginally.

- Distribution of departure time shifts
  Not only does early switching rate increase with increasing congestion, the overall switching rate also increases significantly from 50 to 59%. It is interesting to observe that the characteristics of switching distribution at convergence also vary with congestion levels. At low congestion, the switching distribution is symmetric on the early and late sides (22% users switch by 1-5 minutes on early and late, and 3% each for 11-15 minute adjustment). However, with increasing congestion, switches to early side increase (24% users switch by 1-5 minutes, 7% switch by 11-15 minutes), and shifts to later departure times decreases (20% switches in 1-5 minute range, 4% switches in 11-15 minute range)

5.1.5 Switching Rate and Convergence

With increasing recurrent congestion, switching rate increases nearly linearly (non-linearly) from 50% to 59% under very high congestion. The departure time switching rate converges for each loading case reaches a steady state switching rate; however, the departure time choices themselves are not at equilibrium. In other words, the system dynamics is such that all users do not converge to desired departure times. This conclusion is also supported by the constant rates of switches to early and late departure times (cumulative percentage of switches to earlier/later departure times reaches steady state after about 25 days). Further, the absence of convergence in travel times indicates that stationarity and stability in the underlying choice process does not guarantee similar desirable properties for the system dynamics and network performance. On the
other hand, the absence of smooth and desirable properties in network performance and trip-times does not negatively affect the stability of the behavioral process.

Note that with increasing trip-times users accept both increased travel times and schedule delays. In other words faced with increased congestion and variability, more users switch to earlier departure times resulting in worse schedule delay and travel time. This together with the substantial gap from UE suggests that departure time adjustment may lead to inefficient and volatile flows, which may not be desirable from a system performance standpoint. Therefore, some form of coordination or information to drivers may be needed to steer the system to more desirable travel time and schedule delay characteristics.

5.2 Experiment 2: Effect of Initial Time-dependent Loading (Initial Departure Time) Profile

5.2.1 System Performance

The uniform demand pattern leads to a lower network trip time, more stable evolution, and lower trip time variance. In contrast, the system performance deteriorated considerably under peaked demand profile. For instance, the highest trip time corresponded with peaked demand and the highest variance corresponded with an extended peak profile. The trip-time volatility ratio is also higher for the peaked and extended peak profiles (11-18%) than the baseline case. In fact, in the extended peak case, the volatility ratio does not converge even after 50 days but continues to increase, in contrast to the other two cases which stabilize to a steady state.

5.2.2 Time-dependent Network Loading Profile

It is observed that the aggregate loading pattern converges in each case to a unimodal loading pattern with a well-defined peak. The steady state profile although qualitatively similar, differs across the three experimental levels (uniform, peaked, and extended peak initial distribution). The difference is that the peaked initial demand leads to a greater percentage of pre-peak (mode of the demand profile, not the peak hour) users and lower fraction of post-peak users. The extended peak, on the other hand, leads to a lower percentage of pre-peak users and a higher percentage of users departing in the post-peak. However, the duration of the peak period is not affected by initial demand profile, unlike in the previous experiment.

5.2.3 Commute Performance

The presence of peaking in the initial demand profile increases the average early and late schedule delay by 6.5% and 12.6% respectively. Further, it also induces less variability in early (17.3%) and greater variability in late schedule delays (33.9%) than the uniform profile. Although the average schedule delays do not appear to converge for any of the initial demand patterns considered, they appear to remain stably bounded between 4-5 minutes.

5.2.4 Departure Time Response to Network Performance and Commute Performance

- Average departure switching rate
The departure time switching rates converge to a steady state as in experiment 1, and in fact, to nearly the same steady state value (nearly 53%) independent of the initial conditions. This suggests that the stationary steady state is more dependent on network congestion level than initial demand distribution. However, the rate of convergence depended on initial demand profile, with a faster convergence seen under peaked profiles. There are also hardly any discernible differences between early and late switching rates (steady-state) across various initial demand profiles.

- Average switching magnitude
  Compared to the uniform initial demand level, a small but statistically significant increase in magnitudes is seen for earlier departure shifts, which is consistent with the increase in trip times and late schedule delays in these cases noted above. It is noteworthy that in both experiments, the average magnitude of shifts to earlier departure times is larger than shifts to later departure times, indicating the role of lateness avoidance in commuters’ departure time decisions. Interestingly, the magnitude of departure time switches is stable (4-5 minutes) and is consistent with switches reported in other empirical studies (24).

- Distribution of departure time shifts
  There were hardly any discernible differences in switching distribution across various initial demand profiles.

5.2.5 Switching rate and convergence
Regardless of the initial demand profiles, the switching rate reaches steady state. These results suggest also support the earlier findings that stationarity in switching rates does not imply travel time equilibrium.

5.3 Experiment 3: Effect of Behavioral Factors on Day-to-day System Dynamics

5.3.1 System Performance
In the results that follow, the percentage changes are computed relative to low sensitivity level. As users’ sensitivity to late schedule delay increases, both trip time and trip-time volatility are found to decrease (by 11 and 28.5% respectively). Increased sensitivity to early schedule delay results in increased travel time (1.9%) and volatility (12%). However, if users react to increased volatility in trip-times by switching departure times aggressively, the system performance deteriorates in terms of both trip-times (5.9% increases) and volatility ratio (40.7% increase).

5.3.2 Time-dependent Network Loading Profile
The actual time-dependent loading pattern (aggregated across all O-D pairs) is also found to converge for each scenario. However, the resulting steady state profile varies across each behavioral factor. With increasing sensitivity to late schedule delay, the peak of the loading pattern starts earlier and shifts to the left, leading to the spreading of traffic over the peak-period. In contrast, with increasing sensitivity to early schedule delay, users switch to later departure times, resulting in a more concentrated peak period. Once again the stationarity of departure time adjustment decisions is observed.
5.3.3 Commute Performance

With increasing sensitivity to late (early) schedule delay, both early and late schedule delays increase. With increasing sensitivity to late (early) schedule delay, a larger magnitude of earlier (later) switches is observed. In contrast, in response to increased sensitivity to trip-time fluctuations, users exhibit more conservative departure switching behavior, leading to an increase in the early schedule delay and a decrease in the late schedule delay.

5.3.4 Departure Time Response to Network Performance and Commute Performance

- Average departure switching rate
  With increasing sensitivity of users to late schedule delay, the proportion of late switches decreases (to 22%) whereas, the early side switching rate increases (to 30%). In contrast, as users become more sensitive to early side delays, However, if users are more sensitive to trip-time volatility, the switching rates increase by 5.6 and 9% respectively, as users attempt to select more efficient paths.

- Average switching magnitude
  When increasing sensitivity to late (early) schedule delays, the magnitudes of departure time shifts increases on both side, more so on the early (late) side. On the other hand, the magnitude of departure time shift reduces when users are more sensitive to trip-time volatility, although the switching rate increases.

- Distribution of departure time shifts
  With increasing sensitivity to late schedule delay, the overall user-switching rate decreases, particularly in the five to ten minute adjustment category. However, the frequency of switches in the 10-15 minute adjustment category increases.

5.3.5 Switching Rate and Convergence

With increasing sensitivity to late schedule delay, switching rate decreases from 54.2% to 52.6%, whereas, increased sensitivity to early schedule delay only has a marginal effect on the switching rate. In contrast, as sensitivity to trip-time volatility ratio increases, switching rate increases considerably from 50.9% to 55.7%. The departure time switching rate, was found to converge to steady state values, for each treatment level (high, low, moderate).

5.4 Significance of Findings

The findings from the three experiments have several important implications for dynamic network analysis, design of transportation control strategies to enhance system performance, and travel time reliability. The results indicate that in response to increasing recurrent congestion, users switch departure times aggressively, leading to increased system cost, and lower reliability, which further accentuates departure time switching. Thus, system evolution is governed by the mutual interdependency between departure time dynamics and network performance (particularly trip time volatility). Consequently, measures to reduce congestion must not only address system costs (trip-time) but also system volatility and departure time response to be effective.
The results from the second experiment provide evidence that certain departure-based demand strategies may result in cost reduction, but may induce instability and volatility in day-to-day flows (e.g., extended peak demand profiles). Therefore, care must be exercised in the selection of congestion reduction strategies through peak spreading (e.g. staggered work strategies) to ensure that travel time reliability is not adversely affected. The findings also provide guidelines to enhance system performance, stability, and reliability through measures that influence user decisions. For instance, measures that increase users’ sensitivity to late schedule delay and trip-time volatility are generally conducive towards improving system performance and reliability. An interesting implication of this finding is that, measures such as flexible work hours, under some conditions may actually lead to an increase in system costs (long-run) and instability by reducing users’ sensitivity to schedule delays.

From a theoretical perspective, the system performance under realistic departure time dynamics deviates considerably from equilibrium conditions (even if initial path choices are at equilibrium, though not shown in this study). Although, the system trip-times do not appear to reach equilibrium in these experiments, the departure time decision process appears to be remarkably stable, with the switching rates reaching stationarity in all cases. Furthermore, the departure time choices do not appear to reach equilibrium. This suggests that evaluating control measures under the assumption of fixed departure time in equilibrium analysis may result in misleading conclusions. Note that although, the temporal loading patterns aggregated across O-D pairs converge over time, there is considerable departure time switching even after 55 days. Given the relatively high rates of departure time switching, and its influence on longer-term network evolution, control strategies that influence both route and departure time decisions will likely be more successful than purely routing-based strategies. The results also highlight the need for more general network analysis frameworks since equilibrium-based approaches cannot account for day-to-day stochasticity in network flows.

Due to the nature of the experiments, simulated conditions, and the assumptions regarding experimental factors used in this study, caution is advised in interpreting these findings. In particular, two important caveats are noteworthy regarding the experimental conditions. In this study it is assumed that 1) users do not have access to real-time information 2) users select pre-specified paths. Although restrictive, these assumptions are necessitated by the lack of empirical data and insights, and to avoid potential confounding due to complex interactions between routing and departure time decisions. Further, a few commuter-behavior studies show that the day-to-day variability from habitual routes (most frequently selected paths) is relatively smaller than the variability in departure time decisions (8).

Despite these restrictions, the results appear to be robust with empirical data and consistent with other simulation-based studies. The average departure switching rate of 53-56% observed under moderate congestion in these experiments are consistent with day-to-day departure time switching rates from commuter diary studies (7-8) in Austin (52%) and Dallas(54%). The average late and early schedule delay are 4.1 and 4.3 minutes respectively, which is consistent with the average late schedule delay of 2.0-5.0 minutes reported by Liu, 1998 (24). The aggregate distribution of preferred arrival time keeps consistent with the peak distribution from previous empirical study, with average PAT before work start 15.1 min. and 61% of commuters prefer to reach workplace at least 15 min. before work start time (12.7 min. and 44%
respectively, 25). The unimodal and left-skewed pattern of time-dependent loading profile has been noted in several previous studies (26-27).

The trends of day-to-day evolution were tested for various sets of pre-specified paths, and appeared to be robust across various (pre-specified) path sets. However, in view of the importance of jointly modeling route and departure time decisions, analysis of information and en-route choice decisions are important directions for continuing research.

6. CONCLUDING COMMENTS

This paper investigates day-to-day evolution in network flows induced by dynamic departure time adjustment decisions of commuters. This investigation relaxes some key restrictions regarding fixed departure time and equilibrium assumptions to analyze the stability and performance of urban traffic networks over a multiple day planning horizon. In addressing day-to-day dynamics, attention is restricted to commuting trips, and evolution of departure time decisions.

In view of the complex and analytically intractable network dynamics, the day-to-day evolution in network flows is analyzed by developing a simulation-based framework. This framework integrates a recently calibrated behavioral model of dynamic departure time decisions with a dynamic traffic simulation assignment model (DYNASMART). Computational experiments are conducted using the simulation framework, by systematically varying the following experimental factors: recurrent network congestion level, time-dependent loading profile, and users’ sensitivity to commute experience and trip-time volatility. The influence of these factors on day-to-day evolution is studied by observing and tracking the evolution of various network (trip-time, volatility, day-to-day reliability) and commute performance measures (early, late schedule delays, switching rate, switching magnitude etc.).

The findings provide preliminary evidence of considerable day-to-day variations and stochasticity in network flows and performance, even under the assumption of fixed routes and in the absence of information. The results indicate that: 1) the network performance deviates significantly from equilibrium under heuristic departure time adjustment rules, 2) user equilibrium flows may be unstable due to departure time adjustment decisions 3) departure time decisions do not converge to an equilibrium, although the switching rate attains stationarity in all cases considered here, 4) commute characteristics, network supply conditions (recurrent congestion level), and user responsiveness to network and commute characteristics are strong determinants of network performance and travel time stability, and 5) While the departure time adjustment process exhibits remarkable stability across experimental treatments (average switching is about five minutes, and average switching rate close to 50%), the travel time process is relatively unstable, and strongly dependent on initial conditions (network loading pattern, congestion level etc.). These results have important implications for estimation of time-dependent O-D matrices, dynamic network analysis, and development of congestion management strategies.

The results and insights from this study raise several important questions on day-to-day network flow evolution. While this study focuses on the role of departure time decisions, exploring network flow evolution induced by real-time information and route choice is a promising
direction of current and continuing research. Furthermore, investigating the impact of non-recurrent congestions levels on day-to-day dynamics will lead to valuable practical insights to improve travel time reliability. In contrast to the focus on commuter decision dynamics in this study, the role of non-commuting traffic on network dynamics is of particular interest during the evening peak period.
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TABLE 1  Performance Measures for Different Recurrent Congestion Levels

<table>
<thead>
<tr>
<th>Network and User Performance Measures (averaged over 50 days)</th>
<th>Mild Congestion</th>
<th>Moderate Congestion (Base Line)</th>
<th>High Congestion</th>
<th>Severe Congestion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>Std Dev</td>
<td>Average</td>
<td>Std Dev</td>
</tr>
<tr>
<td>System Performance</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip Time (min.)</td>
<td>13.208</td>
<td>0.459</td>
<td>17.959</td>
<td>0.516</td>
</tr>
<tr>
<td>Trip Time Volatility Ratio (min. / min.)</td>
<td>0.474</td>
<td>0.074</td>
<td>0.935</td>
<td>0.102</td>
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<tr>
<td>Reliability (%)</td>
<td>95.920</td>
<td>79.590</td>
<td>57.140</td>
<td>46.940</td>
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<tr>
<td>Deviation above UE Solution (%)</td>
<td>29.053</td>
<td>22.686</td>
<td>35.254</td>
<td>20.610</td>
</tr>
<tr>
<td>Commute Performance</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Late Schedule Delay (min.)</td>
<td>2.892</td>
<td>0.300</td>
<td>4.106</td>
<td>0.382</td>
</tr>
<tr>
<td>Early Schedule Delay (min.)</td>
<td>3.518</td>
<td>0.583</td>
<td>4.317</td>
<td>0.253</td>
</tr>
<tr>
<td>Departure Time Response</td>
<td></td>
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<tr>
<td>Cumulative Percentage of Switches to Later Departure Times (%)</td>
<td>29.429</td>
<td>2.634</td>
<td>28.936</td>
<td>1.370</td>
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<td>Cumulative Percentage of Switches to Earlier Departure Times (%)</td>
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<tr>
<td>Average Switching Magnitude to Later Departure Times (min.)</td>
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<td>0.220</td>
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<td>0.155</td>
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<td>Average Switching Magnitude to Early Departure Times (min.)</td>
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<tr>
<td>Switching Rate (%)</td>
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<td>0.504</td>
<td>53.338</td>
<td>0.558</td>
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<tr>
<td>Performance Measures for Different Initial Departure Time Profiles</td>
<td>Uniform Demand (Base Line)</td>
<td>Peaked Demand</td>
<td>Extended Peak Demand</td>
<td>Last Day's UE Solution Path</td>
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<td><strong>Network and User Performance Measures</strong> (averaged over 50 days)</td>
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<td><strong>Std Dev</strong></td>
<td><strong>Average</strong></td>
<td><strong>Std Dev</strong></td>
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<td>Late Schedule Delay (min.)</td>
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<td>Cumulative Percentage of Switches to Later Departure Times (%)</td>
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<td>Switching Rate (%)</td>
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</table>
TABLE 3 Performance Measures Under Different Sensitivity Levels to Behavioral Factors

<table>
<thead>
<tr>
<th>Network and User Performance Measures (averaged over 50 days)</th>
<th>Low Sensitivity to Trip-time Volatility Ratio</th>
<th>High Sensitivity to Trip-time Volatility Ratio</th>
<th>Low Sensitivity to Early Schedule Delay</th>
<th>High Sensitivity to Early Schedule Delay</th>
<th>Low Sensitivity to Late Schedule Delay</th>
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<td>Trip Time (min.)</td>
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<td>18.677</td>
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<td>Deviation above UE Sol'n (%)</td>
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<td>Late Schedule Delay (min.)</td>
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<tr>
<td>Switching Magnitude to Later(min.)</td>
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<td>0.170</td>
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<td>Switching Magnitude to Early(min.)</td>
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<td>Switching Rate (%)</td>
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<td>55.736</td>
<td>0.768</td>
<td>53.533</td>
<td>0.614</td>
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</table>
FIGURE 1
Sequential greedy search adjustment model of departure times
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FIGURE 4   Loading profile at convergence (last day)