Role of Day-to-Day Learning in Achieving Equilibrium after a Major Network Change: Application to New Jersey Turnpike Toll Road

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Abstract

This paper presents an experimental dynamic traffic assignment framework that incorporates a Bayesian-Stochastic learning Automata model previously developed by Yanmaz-Tuzel and Ozbay to study day-to-day updating mechanism of travelers’ learning and adaptation to major changes in transportation networks. The main objective of this paper is to examine the day-to-day evolution of travel patterns in a traffic network when major disturbances are introduced into the transportation system. The dynamic traffic flow evolution and network-level interactions of driver departure time and route choice decisions are captured within the traffic flow simulator. The proposed integrated learning and dynamic traffic assignment framework is tested using the NJTPK network. The case study investigates the impacts of the addition of a new interchange (15X) on the Eastern Spur on day-to-day departure-time and route choice behavior of NJTPK travelers, and the impacts of toll structure change on day-to-day departure-time behavior of the travelers. The calibration and validation results have shown that the proposed framework that integrates day-to-day learning with DTA can successfully capture day-to-day update of traffic flow after the imposed disruptions. The sensitivity analysis confirmed that proposed day-to-day learning framework is a crucial component of the DTA, particularly while investigating the traveler behavior during a transient period after a major disruption. Ignoring the impacts of travel experiences, and travelers’ learning behavior on the evolution of traffic conditions result in lower prediction capabilities, and failure to capture the day-to-day evolution of travel trends.
INTRODUCTION

Modeling of traffic flows and travel times on congested road networks is crucial for predicting, controlling or managing congestion, and analyzing the need for infrastructure provision or improvement. Dynamic traffic assignment (DTA) refers to the assignment process that incorporates the traffic flow dynamics varying over time. DTA approach is useful to analyze how congestion forms and dissipates under time-varying conditions. Currently, many analytical models and simulation-based models are under development in attempt to understand the evolution of traffic congestion over a given time period.

This paper has a unique objective of investigating the travelers' behavior during a transient period after a major disruption to the network equilibrium. This disruption may be the addition of a new road, interchange or a congestion pricing scheme. To achieve this goal an experimental DTA framework that incorporates a Bayesian-Stochastic Learning Automata (Bayesian-SLA) model previously developed by Yanmaz-Tuzel and Ozbay (1) is employed to study day-to-day updating mechanism of travelers’ learning and adaptation under major system disruptions. The availability of vehicle-by-vehicle trip data for before and after the disruptions has enabled us to build a unique experimental set up that can be used to evaluate the modeling capability of our proposed integrated framework for capturing time dependent learning behavior of travelers in the presence of a major event that disturbs network equilibrium.

The most common approach employed to capture the interaction between travel choice and network performance has been to solve an equilibrium DTA problem where a time-dependent yet pre-determined trip matrix for the design period to be evaluated is assigned onto a network. Under equilibrium conditions the travel choice is assumed to be governed by the Wardrop principle which states that all used routes have equal and minimum travel time costs. At this equilibrium point no user can decrease his/her travel time cost by switching to another choice since travel costs on all the used routes are equal.

Equilibrium DTA approaches assume that network conditions from day-to-day and within different periods of a day are in steady-state, predicate rigid behavioral tendencies a priori, and try to attain either User Equilibrium (UE) or System Optimum (SO) (3). Moreover, travelers are assumed to be rational, exploring each alternative’s relevant attributes and trading off the utilities derived from them. The decision strategy serves to generate a choice from a choice set for the alternative that provides the individual with the maximum utility. The question of whether equilibrium actually takes place or is a mathematical construct is a very old question (4). Horowitz (5) showed that day-to-day flow dynamics may oscillate around Stochastic UE (SUE), or may even converge to some non-equilibrium point. Chang and Mahmassani (6) and Friesz et al. (7) performed experiments for modeling transition of disequilibria from one state to another. The results lead to the conclusion that a day-to-day adjustment process can lead to an equilibrium state under fixed supply and demand conditions. However, the fact that there are always changes in supply, demand, and traffic propagation, in combination with the stochasticity of all the involved parameters and drivers’ day-to-day disequilibrium route choice behavior, makes the concept of equilibrium highly questionable (4). Moreover, these models exclude driver learning (based on past experiences and personal characteristics) which can significantly affect traveler choice behavior on a specific day. In reality, the natural mechanism of traveler choice is based on traveler’s behavioral tendencies, past experiences, and the traffic conditions encountered (1). This issue implies the need for day-to-day modeling of users' learning mechanism through a day-to-day traffic assignment model.
DTA models integrated with day-to-day learning framework aim to model traveler’s day-to-day learning and adaptation behavior and provide insight on how the traffic flow pattern evolves over time. In day-to-day modeling, behavioral approaches are integrated into the equilibrium paradigm, where the sequences of states that occur as the system reaches to equilibrium are linked through a learning model based on travelers’ past experiences. These intermediate stages are important for evaluation of the transportation system, because the transportation system is often in disequilibrium due to travelers’ gradual response to continuously changing conditions. These models predict travelers’ choices for any given day based on his/her experienced choices in the previous days. Day-to-day models thus reflect the travelers’ learning and forecasting mechanisms.

Several studies have focused on modeling drivers’ day-to-day route choice behavior adjustment (e.g., 7,8,9,10,11,12,13,14,15,16,17,18,19). An extensive review of these models can be found in Yang and Zhang (20). Moreover, several simulation tools have been proposed to model day-to-day learning behavior of travelers including DYNASMART which is based on a mesoscopic simulator that treats traffic individually but moves them according to macroscopic flow principles (11,12,21) and DRACULA (22,23) which is based on a microscopic simulator both on demand and supply levels.

This paper presents a new DTA framework to examine the day-to-day evolution of travel patterns in a transportation network when major disturbances are introduced into the transportation system. Proposed DTA framework integrated with day-to-day learning combines three main sub-models. The first sub-model namely, demand model represents the day-to-day variability in total demand. It takes the observed total demand values within the analysis period and simulates for each traveler the preferred departure time choice and route to be taken. This information is then passed to the traffic simulator, the second sub-model, which calculates macroscopic flow conditions for each simulation interval. At the end of each day, a new learning model proposed by Yannaz-Tuzel and Ozbay (1), the third sub-model, stores the experienced travel history, and updates each individual’s probability profile based on this experience.

The developed integrated day-to-day learning and DTA framework is tested using the NJ Turnpike (NJTPK) network. The case study investigates the impacts of the addition of a new interchange (15X) on the Eastern Spur (just south of EXIT 16E) on day-to-day departure-time and route choice behavior of NJTPK travelers, and the impacts of toll structure change on day-to-day departure-time behavior of the travelers. Next sections present the details of the application network, followed by the proposed DTA framework, and the results of the application.

**Data Sources**

The proposed integrated day-to-day learning and DTA framework is tested and verified on NJTPK network. NJTPK is a 148 mile-toll road extending from the Delaware Memorial Bridge in the South of New Jersey to George Washington Bridge in New York City. Currently, the road has 28 interchanges, commonly referred to as exits, with an average daily traffic that exceeds 700,000 vehicles. To minimize queuing delays, NJTPK has minimal number of toll plazas located at the exits. The interchanges connect to NJ’s major highways and vast transportation network, institutions, and economic hubs.

The database includes vehicle-by-vehicle traffic and travel time information for all the trips observed on NJTPK between December 2005 and December 2006. The data were collected
from E-ZPass recordings of each vehicle at each time of the day (2). This time period includes
the observed trips after two major disruptions imposed to NJTPK network, i.e. installation of
15X interchange on December 2005, and change in congestion pricing structure on January
2006. The calibration and verification of the proposed day-to-day learning model covers the
period between December 2005 and December 2006.

The first major disruption is the installation of 15X Interchange. After nearly three years
of construction, NJTPK Authority opened the $250 million Interchange 15X on the Eastern Spur
(just south of EXIT 16E) on December 1, 2005. The new interchange serves the Secaucus
Junction rail transfer station. Before opening of Interchange 15X, the only alternative traveling to
Lincoln Tunnel area was to travel through Interchange 16E. However, since December 2005,
Interchange 15X became a viable alternative for these travelers.

The second major disruption was imposed one month later. In January 2006, NJTPK
Authority eliminated the E-ZPass peak period discounts and E-ZPass peak users started to pay
the same amount of toll as the cash users. In this new toll structure, toll amounts were increased
by around 18% and 5% for E-ZPass peak and off-peak users, respectively; while cash tolls were
kept the same.

METHODOLOGY

The proposed integrated day-to-day learning and DTA framework makes use of the
concept of demand and supply submodels which interact with each other. Demand side is
modeled via microscopic simulation to describe individual decisions, and supply side is modeled
via macroscopic simulation to depict movement of vehicles and both sub models evolve over
time from one day to another. The travel costs experienced by the travelers are then re-input to
the demand model for the next day. Thus, there is no pre-determined requirement for the process
to converge to a stable “equilibrium” state. In fact, the transportation system never reaches to a
single state but continuously changes and evolves from one day to the next as the travelers learn
about the system and react to changes within the system. The proposed traffic simulator performs
for the time period between 6 am and 10 am. The demand entering to the transportation network
during this time period is obtained from observed O-D trip matrices. The general form of the
simulator is as follows:

1. Initialization: For each traveler in the network set individual characteristics, and an
initial departure time choice probability profile. Set day counter \( n = 0 \)
2. OD demand generation: Increment day counter \( n = n+1 \). Select the total am peak
demand for each origin-destination pair from observed O-D trip matrices.
3. Travel Choice: For each individual traveling on day \( n \) select a departure time period
(pre-peak, peak or post-peak) and/or route (interchange 15X or interchange 16E), based
on their choices, travel costs, and arrival time to their destinations on previous days.
4. Traffic Loading: Load the O-D matrix on day \( n \) depending on departure time and/or
route choice of each individual.
5. Simulation Results: For each time interval calculate travel time, traffic flow, speed and
density variables.
6. Individual Travel Experience: For each traveler calculate experienced travel cost and
determine whether the selected action is favorable or unfavorable.
7. **Learning:** Update the probability profile of each traveler using the learning parameters. In particular, increase the probability of selecting favorable actions, and decrease the probability of selecting unfavorable actions for the next day. Return to step 2.

The overall structure of the integrated DTA framework is presented in FIGURE 1. Our objective is to determine the probability distribution of individual day-to-day states as proposed and discussed in (e.g. 9,14,18,24,25,26).

![FIGURE 1 Flow chart of the day-to-day dynamic traffic assignment framework](image)

**Travel Choice**

Consider a transportation network \([M;L;S]\) with nodes \(m\), \((m=1,2,...,M)\), links \(l\), \((l=1,2,...,L)\) and OD pairs \(s = (i, j)\) \((s=1,2,...,S)\). The demand functions for each OD pair are time-dependent, given by \(G_t(s)\), \(s \in S\), and give rise to path flows \(h_p(t)\). The experienced travel time for a path \(p\) which carries a flow generated at time \(t\) is \(\tau_p(t,h)\). On any given day, each driver traveling from origin \(i\) to destination \(j\) maintains a probability profile for the available alternatives and updates his/her probability profile based on previous travel choices, exhibiting a tendency to search for satisfying choice rather than the best behavior.

Annual and daily traffic trends observed at NJTPK indicate that traffic demand continues to increase and shows similar behavior before and after the implementation of time-of-day pricing.
Based on the results of the same study by (27), it can be safely assumed that majority of the NJTPK users make departure time choices (between peak and off-peak periods), or route choice between interchanges 15X and 16E. This is in fact an expected outcome since NJTPK is practically the only alternative for a large number of trips to various important employment centers in and outside the state including New York City. NJ has an excellent rail system, but it does not provide a viable alternative to most of the NJTPK users who reside far from train and who want to travel at peak periods can shift to peak hours.

Thus in this study two different choice mechanisms are considered. Travelers exiting from interchanges 16E or 15X make both route (which interchange to take) and departure time (which period to travel) choice, while all travelers using the remaining interchanges only make departure time choice. Next sections provide in depth description of both choice models.

For the departure time choice model, an input set \(X\) composed of the explanatory variables is considered. Output set \(D = \{d_1,d_2,d_3\}\) includes actions composed of three choices (1: pre-peak from 6:00 am to 7:00 am, 2: peak from 7:00 am to 9:00 am, and 3: post-peak from 9:00 am to 10:00 am).

The viable options for travelers making simultaneous route and departure time choice consist of 6 choices. \(D = \{d_1,d_2,d_3,d_4,d_5,d_6\}\) includes actions composed of six choices (1: pre-peak Interchange 16E, 2: peak Interchange 16E, 3: post-peak Interchange 16E, 4: pre-peak Interchange 15X, 5: peak Interchange 15X, 6: post-peak Interchange 15X).

Each traveler has a probability profile for each travel choice. On day \(n=1\) it is assumed that the probability profile represents a random variation around the observed frequency on day \(n=0\):

\[
P_{i,j}^{k,n=1}(r) = (u_{i,j}^k) \ast p_{i,j}^{n=0}(r) \quad \forall i,j \text{ and } \forall k
\]  

where;

\(i\): Origin index (\(i=1,2, \ldots, 27\))

\(j\): Destination index (\(j=1,2, \ldots, 27\))

\(k\): Individual traveler index (\(k=1,2, \ldots, N_t\))

\(n\): Day index

\(r\): Travel choice index

\(p_{i,j}^{k,n=1}(r)\): Probability of selecting choice \(r\) at day \(n=1\) for individual \(k\) traveling from origin \(i\) to destination \(j\)

\(u_{i,j}^k\): Random variation for individual \(k\) traveling from origin \(i\) to destination \(j\)

\(p_{i,j}^{n=0}(r)\): Observed frequency of choice \(r\) from origin \(i\) to destination \(j\)

Depending on the individual probability profiles Monte Carlo simulation is used to generate discrete choices, and travel demand at each choice is generated.

**Traffic Loading**

Generated travel demand based on individual probability profiles at each departure time period is loaded to the transportation network. The traffic loading model is a mesoscopic simulation of vehicle movement on the network. The model uses a small time step so that congestion details can be accurately modeled. During each small time interval, vehicles keep
their variables constant (position, and speed). At time each interval, the variables are computed for all vehicles and the simulation proceeds to the next time step. The simulation is finished when all vehicles entering between 6 am and 10 am finish their journeys. The major steps of the traffic simulation on day \( n \) are as follows:

1. **Initialization**: Set simulation clock \( t=0 \), generate vehicle macro-particles by distributing travel demand at each departure time period equally within each time interval.
2. **Vehicle movement**: Load the macro-particles to the transportation network.
3. **Simulation Results**: Store aggregate measures of traffic volume, travel time, speed, density for each link and O-D pair.
4. **Termination**: If all drivers have finished their journey, terminate the day; otherwise increment the simulation clock and return to step 2.

The traffic simulation algorithm satisfies the following constraints:

1. **Flow conservation**: The flow conservation require that for any given time instant, the flow entering to any node, together with the demand generated at that node, must all exit from this node to the next link unless the node is a destination. Mathematically, this constraint can be expressed as:

\[
\sum_{l \in A(i)} \varphi^j_l(t) = G^j(t) + \sum_{l \in B(i)} v^j_l(t)
\]

(2)

In the above equation \( \varphi^j_l(t) \) denotes the inflow rate to link \( l \) to destination \( j \) at time instant \( t \), \( G^j(t) \) denotes the travel demand from node \( i \) to destination \( j \) at time \( t \), and \( v^j_l(t) \) is the exit flow rate from link \( l \) to destination \( j \) at time \( t \). Moreover, \( A(i) \) is the set of links whose starting nodes are \( i \), and \( B(i) \) is the set of links whose ending nodes are \( i \).

Then, total flow on link \( l \), \( h^ij_l(t) \), due to demand from origin \( i \) to destination \( j \) is the sum of vehicles entering to link \( l \) from previous link and demand generated at link \( l \) minus the number of vehicles exiting link \( l \):

\[
h^ij_l(t) = \varphi^j_l(t) - v^ij_l(t) + G^ij(t) \quad \forall l \in L, \quad \forall (i,j) \in S
\]

(3)

Then total flow on link \( l \) at time \( t \), \( h^i_l(t) \):

\[
\sum_{(i,j)} h^ij_l(t) = h^i_l(t)
\]

(4)

2. **FIFO constraint**: FIFO condition states that a traffic stream generated at time \( t'' \) cannot overtake another stream that has started earlier at time \( t \) \((t < t'')\). In order to satisfy FIFO condition when path costs are additive, certain conditions must be satisfied by the link cost functions. The FIFO condition may be stated as:

\[
t'' > t \Rightarrow t'' + \tau_i(t'') > t + \tau_i(t)
\]

(5)
At each time interval, link travel time function, $\tau_i^t$, is linked to instantaneous inflow $\varphi_i^t$, link volume $h_i^t$, density $k_i^t$ and speed $V_i^t$, and other link parameters $\bar{P}_i^t$ such as length and capacity:

$$\tau_i^t = f(\varphi_i^t, h_i^t, k_i^t, V_i^t; \bar{P}_i^t)$$ (6)

This mesoscopic description can also be seen as a cellular automata description where each link and node corresponds to a unique cell. Congestion occurs on link cells, and route decisions occur in node cells. Inside any given link, there is no underlying representation of the vehicles, except the fact that they follow FIFO rule. The vehicle interaction is described only by travel time function $\tau_i^t$. This approach implies vertical queuing since there is no restriction imposed on $\varphi_i^t$ or $h_i^t$.

Travel time at each time interval and link is calculated based on well-known speed-concentration relationship. The speed-flow relationships are (28):

$$k_i^{t+1} = k_i^t + \left(\frac{1}{y_l} \Delta x_i\right) (\varphi_i^{t+1} - V_i^{t+1} + G_i^{t+1})$$ (7)

$$V_i^t = (V_f - V_o) \left(1 - \frac{k_i^t}{k_o}\right) + V_o$$ (8)

$$\tau_i^t = \frac{\Delta x_i}{V_i^t}$$ (9)

where

- $k_i^{t+1}$ = Concentration on link $l$ at time interval $t+1$
- $y_l$ = Number of lanes
- $\Delta x_i$ = Length of link $l$
- $V_i^t$ = Mean speed at link $l$ during $t$-th time step
- $V_f$ = Free flow speed
- $V_o$ = Minimum speed on the facility
- $k_o$ = Maximum concentration
- $(\tau)_i^t$ = Travel time at link $l$ during $t^{th}$ time step
- $\alpha$ = a parameter to be calibrated
- $G_i^{t+1}$ = Demand generated at link $l$ at time $t+1$.

The observed travel times for NJTPK include the link travel times, as estimated in eqn-10, and service and waiting times at the exit toll plazas. To model the toll plaza delays at each interchange, we have used a macroscopic toll plaza delay model developed by Lin (27). Even though, this model is a relatively simple formulation, it has been validated by Özmen-Ertekin et al. (30) that macroscopic model results are comparable (within average error of 2.6% to 6.4%) with the PARAMICS microscopic model for the NJTPK toll plazas.

According to this macroscopic model total delay experienced at toll plazas by each vehicle can be expressed as follows:

$$d = d_d + d_l + d_p + d_a + d_q$$ (10)
where;

- \(d_d\): deceleration delay (s/veh)
- \(d_i\): incremental delay (s/veh)
- \(d_p\): service time (s/veh)
- \(d_a\): acceleration delay (s/veh)
- \(d_q\): initial queue delay (s/veh)

Deceleration delay is the extra travel time incurred while drivers decelerate before reaching a toll booth (27):

\[
d_d = \frac{(V - V_b)^2}{2dV}
\]  

where,

- \(V\): Speed of the approaching vehicle (m/s)
- \(d\): Deceleration rate (m/s^2)
- \(V_b\): Speed at toll booth (m/s)

Acceleration delay depends on the free flow speed and the acceleration characteristics of vehicles (27):

\[
d_a = \frac{(V - V_b)^2}{2aV}
\]  

where,

- \(a\): Acceleration rate (m/s^3)

Incremental delay experienced by each vehicle refers to the random variations in toll processing times and vehicle arrivals (27):

\[
d_i = 900T \left( (X - 1) + \sqrt{(X - 1)^2 + \frac{4X}{C \cdot T \cdot N}} \right)
\]  

where,

- \(T\): Analysis period (h)
- \(X\): Volume-to-capacity ratio
- \(C\): Capacity (veh/lane/hour)
- \(N\): number of toll lanes

Similarly, initial queue delay can be formulated as (27):

\[
d_q = \frac{1800Q_b(1+u)t}{cT}
\]  

where,
After determining the performance measures for each traveler, depending on the experienced utility and deviation from the desired arrival time, whether the action is favorable or not is determined. Using the explanatory variables obtained from traveler survey (31), a user-specific utility function is derived for each departure time choice based on the proposed Bayesian-SLA framework by Yaman-Tuzel and Ozbay (1). Eqn-15 shows parameters for each utility function. Each parameter, $\beta$, follows a normal distribution, with mean, $\mu_\beta$, and standard deviation values, $\sigma_\beta$, provided in (1). Thus, parameters of the utility function for each traveler are different. This departure time choice model considers travelers’ trip characteristics (travel time ($t$), toll), desired arrival time characteristics (departure time ($dt$), early ($ea$)/ late ($la$) arrival amount) and socio economic characteristics (income, education ($ed$), age, employment ($emp$), gender).

$$U^r_{k,n} = \beta_{tt}tt^r_{k,n} + \beta_{dt}dt^r_{k,n} + \beta_{ea}ea^r_{k,n} + \beta_{la}la^r_{k,n} + (\beta_{toll}toll)^r_{k,n} + (\beta_{income}income)^r_{k,n} + (\beta_{toll}toll * t)^r_{k,n} + (\beta_{ed}ed)^r_{k,n} + (\beta_{gen}gender)^r_{k,n} + (\beta_{emp}emp)^r_{k,n} + (\beta_{gender})^r_{k,n} + \varepsilon_{k,n}$$ (15)

The travel utility function for route choice, $U^r_{k,n}$, includes travel time, $tt^r_{k,n}$, departure time, $dt^r_{k,n}$, early arrival amount, $ea^r_{k,n}$, late arrival amount, $la^r_{k,n}$, inertia effect on choice $r$ for driver $k$, $I^r_k$ (takes value of 1 if choice $r$ is the current choice ; 0 otherwise); where $\beta_r$ are the coefficient for each corresponding variable.

$$U^r_{k,n} = \beta_{tt}tt^r_{k,n} + \beta_{dt}dt^r_{k,n} + \beta_{ea}ea^r_{k,n} + \beta_{la}la^r_{k,n} + (\beta_{toll}toll)^r_{k,n} + \beta_{I}I^r_k + \varepsilon_{k,n}$$ (16)

After calculating the experienced travel utility value and early/late arrival amount associated with each individual travel choice; whether the selected choice is favorable or not is determined. In particular, it is assumed that travelers exhibit a tendency to search for satisfying choices rather than the best behavior; thus they do not have the cognitive ability to process all the information simultaneously and are happy with a good solution. To incorporate this kind of behavior, bounded rationality (BR) approach (first introduced by (32) and used in many studies in transportation field including (33)) is included in the behavior updating mechanism. In particular, the travelers will switch routes and/or departure times if the difference between experienced costs on the selected choice and the travel cost on the best choice that day. If the difference is acceptable the traveler increases the probability to select the current choice for the next day, otherwise decrease the probability to select the current choice, and increases the probability to select the best choice of that day. The mechanism for the indifference threshold can be formulated as follows:
where $\delta_{k,n}$ is a binary variable that takes value of 1 if the difference between the utility of the current choice $r$, $U_{k,n}^r$, and the utility of the best choice, $U_{best,n}$, is acceptable for individual $k$ on day $n$, and 0 otherwise; $\Delta^k$ is the acceptability threshold. Behaviorally, small $\Delta^k$ value indicates less tolerance of small cost differences compared with large $\Delta^k$ value. If $\Delta^k$ takes zero value, traveler is intolerant of any difference in travel cost, and would switch for even the smallest cost difference. The acceptability threshold $\Delta^k$ reflects individual attitudes and preferences, and thus should vary across the population (33). In this study, a normally distributed acceptability threshold with mean $\mu_{\Delta^k}$ and standard deviation $\sigma_{\Delta^k}$ is assumed (33).

### Learning Model

In this paper, commuters’ day-to-day learning behavior on the basis of experienced travel choices and user-specific characteristics is modeled via Bayesian-SLA theory proposed by the authors (1). Specifically, each user updates his/her choice based on the rewards/punishments received due to selected actions in the previous days. At the end of each day, favorable actions are rewarded, while unfavorable actions are punished. After determining favorable and unfavorable actions, a linear reward-penalty reinforcement scheme is considered to update day-to-day learning behavior of NJTPK users, and to investigate commuters’ response to new route inclusion while selecting their departure times and routes. The parameters of the learning model are calibrated and validated using the same network and same system disruptions based on the real data collected as part of the NJTPK Value pricing study.

As discussed in (1), the learning parameters for departure time choice follow Beta distribution. Mean values for the parameters $(a, b)$ are $(0.062, 0.0067)$, and standard deviations are $(0.0046, 0.0021)$, respectively.

\[
p(a) = \frac{1}{B(2.29,1.73)} \frac{(a-0.003)^{1.29}(0.106-a)^{0.73}}{1.03^{3.02}}
\]

\[
p(b) = \frac{1}{B(49.35,4.75)} \frac{(b+0.041)^{1.29}(0.011-b)^{0.73}}{0.052^{3.11}}
\]

where;

$B(.)$: Beta distribution.

$a$: Reward parameter

$b$: Punishment parameter

Similarly, the learning parameters for departure time and route choice follow Beta distribution (34). Mean values for the parameters $(a, b)$ are $(0.029, 0.0029)$, and standard deviations are $(0.011, 0.00093)$, respectively.

\[
p(a) = \frac{1}{B(5.649,5.764)} \frac{(a+0.007)^{4.69}(0.066-a)^{4.764}}{0.0736^{10.413}}
\]

\[
p(b) = \frac{1}{B(47.56,35.18)} \frac{(b+0.0069)^{4.656}(0.0101-b)^{34.18}}{0.0178^{1.74}}
\]
CALIBRATION AND VALIDATION

Calibration and validation are important processes in the development and application of DTA models. These processes ensure that the models accurately replicate the observed traffic condition and driver behavior.

Model calibration is a process whereby the values of model parameters are adjusted so as to match the simulated model outputs with observations from the study site. It is usually formulated as an optimization problem to determine the best set of model parameter values in order to minimize the discrepancies between the observed and simulated values (35). The calibration process then modifies the values of the model parameters \{\beta\}, to find the best set of values which minimizes function $F$. The proposed objective function $F$ minimizes the difference between observed and simulated link volumes and travel times:

$$
\min_{\beta} F = \sum_{l} \sum_{t} \left[ w_1 \left( \frac{q_{l,t}^{\text{sim}} - q_{l,t}^{\text{obs}}}{q_{l,t}^{\text{obs}}} \right)^2 + w_2 \left( \frac{tt_{l,t}^{\text{sim}} - tt_{l,t}^{\text{obs}}}{tt_{l,t}^{\text{obs}}} \right)^2 \right]
$$

where;
- $\beta$: Set of parameters to be calibrated
- $t$: Time interval
- $l$: link index
- $q_{l,t}^{\text{sim}}$: Simulated link flows in $t$
- $q_{l,t}^{\text{obs}}$: Observed link flows in $t$
- $tt_{l,t}^{\text{sim}}$: Simulated link travel time in $t$
- $tt_{l,t}^{\text{obs}}$: Observed link travel time in $t$
- $w$: weight parameters

FIGURE 2 illustrates the solution algorithm for the calibration process. It is an iterative procedure to try to match the simulated results with those observed from the study site.
After determining the optimal set of parameters from the calibration process, a validation process is performed in order to determine whether the simulation model successfully replicates the real system. Two different measures were considered in the validation process:

1. Root mean square error (RMSE)
2. Mean percentage error (MPE)

The formulations of these measures are as follows:

$$RMSE = \sqrt{\frac{1}{N \cdot T} \sum_{t=1}^{T} \sum_{l=1}^{N} \left( \frac{q_{t,l}^{\text{sim}} - q_{t,l}^{\text{obs}}}{q_{t,l}^{\text{obs}}} \right)^2}$$ (21)

$$MPE = \frac{1}{N \cdot T} \sum_{t=1}^{T} \sum_{l=1}^{N} \left| \frac{q_{t,l}^{\text{sim}} - q_{t,l}^{\text{obs}}}{q_{t,l}^{\text{obs}}} \right|$$ (22)

where $q_{t,l}^{\text{sim}}$ and $q_{t,l}^{\text{obs}}$ are the simulated and observed measurements for link $l$ during aggregated time period $t$, $\bar{q}$ is the sample mean, $\sigma$ is the sample standard deviation, $N$ is the total number of
links and $T$ is the total number of time periods. RMSE measure penalizes large errors at a higher rate than small errors, while MPE indicates the existence of systematic under or over-prediction in the simulated variables (35).

**MODEL APPLICATION**

This section analyzes the effectiveness of the proposed day-to-day DTA framework in evaluating the impacts of major disruption on day-to-day traffic flows of real transportation networks. FIGURE 3 depicts the NJTPK network and the location of each interchange. The detailed results of the calibration and validation of the integrated day-to-day learning and DTA framework applied to NJTPK are presented in the next paragraph.

FIGURE 3 NJTPK network (36)

FIGURE 4 summarizes the MPE and RMSE plots for traffic volume calculations. The proposed integrated framework has a good performance with MPE values ranging around 0.107, and RMSE values ranging around 0.235 between December 2005 and December 2006. Similarly, FIGURE 5 summarizes the MPE and RMSE plots for travel time calculations. These
results are fairly consistent regardless of network congestion levels, and the simulation model and the real system show fairly good agreement. The relative magnitude of errors is similar to well accepted DTA simulation softwares, such as DynaMIT, developed for FHWA (37, 38) and AIMSUN (39). Both softwares obtained RMSE values between 0.2 and 0.3 when the DTA on real transportation networks was calibrated with observed day-to-day traffic and travel time data.

FIGURE 4 Mean percentage error and Root mean square error for traffic volume

FIGURE 5 Mean percentage error and Root mean square error for travel time
Convergence Properties

One major issue while investigating the day-to-day impacts of policy implications is to understand how long it takes for the transportation system to converge to a new steady state. This information is crucial in terms of understanding travelers’ behavioral responses to the major system changes that would help both researchers and policy makers in identifying expected impacts of future transportation management strategies.

To this extent, this section focuses on the overall system changes in terms of departure time and route choice after January 2006 toll structure change and December 2005 Interchange 15X installation, respectively. For each major disturbance, changes in the average traffic volume during peak and peak shoulder (pre-peak and post-peak) periods were analyzed. To evaluate the performance of integrated day-to-day learning and DTA framework in terms of predicting traveler departure time and route choice behavior, simulated and observed traffic volumes were compared. In order to reduce the impacts of seasonal changes each monthly average volume is normalized.

FIGURE 6 summarizes the behavioral changes (simulated and observed) after January 2006 toll structure change for peak and peak shoulder periods. Analysis results reveal that the DTA framework can successfully capture the trends in peak and peak shoulder periods after the disturbance. Furthermore, the observed and simulated traffic volume results show that February 2006 is the transient period where the travelers learn the prevailing conditions of the disturbed transportation system (fast-moving system). In this period, a rapid decrease for peak period and rapid increase for peak shoulder periods is observed. After February 2006, experienced and simulated traffic conditions exhibit a more steady state until November 2006. Between November 2006 and December 2006 the change in the traffic conditions exhibits an increased rate. This trend may be explained due to winter conditions and increased leisure trips due to holiday season. Since travelers are familiar with the transportation system this short transient period and rapid changes in this period is expected, and supported by larger learning parameters. Travelers being aware of the structure of the whole transportation system can adapt themselves to the new conditions and exhibit faster learning behavior.
A similar analysis is conducted to investigate the impacts of Interchange 15X installation. To determine the duration of the transient period and understand the convergence behavior to the new equilibrium, traveler choice behavior is analyzed by observing the changes in average traffic volume exiting interchanges 15X and 16E during am period in the northbound direction.

FIGURE 7 summarizes the behavioral changes (simulated and observed) at Interchange 15X and Interchange 16E. Analysis results reveal that proposed framework can successfully capture the trends in demand at interchanges 15X and 16E after March 2006. Furthermore, the observed and simulated traffic volume results show that the transient period after this major disturbance is much longer compared with January 2006 toll structure change. In fact, by September 2006, we observe that the demand for Interchange 15X is still increasing at a positive rate. Within this transit period, instead of a rapid change we observe slower responses from the travelers. As pointed out in (34), NJTPK users exhibit resistance to change their behavior.
resulting in slower learning and adapting rates to the new conditions. This type of behavioral pattern causes a longer transient period where no rapid changes in the demand is observed. After September 2006, the transient period diminishes and transportation system starts to reach to a new steady state. In particular, the demand for Interchange 15X still continuous to increase, however rate of increase diminishes resulting in reduced fluctuations in traffic flow conditions.

The overall convergence properties of observed and simulated traffic conditions reveal that, when the travelers are familiar with the form of the disturbance imposed to the system, such as changes in an existing pricing application, the transient period is rather short and we observe rapid changes and fast learning rates during this period. On the other hand, when the disturbance
is more significant, such as an infrastructural change in the transportation system, the transient period becomes longer, and we observe lower learning rates where travelers are hesitant to make drastic behavioral changes.

4 Sensitivity Analysis

In this section sensitivity analysis is conducted to investigate the impacts of changes in the model specifications on the validity of the proposed framework. In particular, in order to see the impacts of learning component on the performance of the proposed model, learning component is removed from the proposed framework.

FIGURE 8 and FIGURE 9 show the trend in MPE and RMSE values for traffic volume and travel time, respectively, when learning component is excluded from the simulation model. When learning component is removed from the integrated DTA framework, it is observed that both MPE and RMSE values increase compared with the error values calculated when day-to-day learning behavior of individuals is included into the model. Since the initial probability profile was assumed to be the observed frequency values, the estimated error values are smaller during first 10 days. However, as the transportation system evolves from day-to-day and drivers learn the new system conditions the error values start to increase. Moreover, neither MPE nor RMSE values show any tractable trend.

This sensitivity analysis confirms that proposed day-to-day learning framework is a crucial component of the DTA framework, particularly while investigating the traveler behavior during the transient period after a major disruption. Ignoring the impacts of travel experiences and travelers’ learning behavior on the evolution of traffic conditions results in lower prediction capabilities, and failure to capture the day-to-day evolution of travel trends.

FIGURE 8 MPE and RMSE for traffic volume, no learning component
FIGURE 9 MPE and RMSE for travel time, no learning component

Conclusions and Discussions

This paper presented a new experimental DTA framework to examine the day-to-day evolution of travel patterns in a traffic network when major disturbances are introduced into the transportation system. The dynamic traffic flow evolution and network-level interactions of driver departure time and route choice decisions are captured via a traffic flow simulator. The approach uses microscopic simulation to model the behavior of drivers on the demand side, and uses macroscopic simulation to obtain system variables such as link travel time, volume and density. Bayesian-SLA framework developed by the authors (1) is used to model day-to-day update mechanism of the transportation network.

The proposed model has been tested and verified on NJTPK. In particular, two major disruptions were considered. The first major disruption is the installation of 15X Interchange on December 2005. The second major disruption was imposed one month later. In January 2006, NJTPK Authority eliminated the E-ZPass peak period discounts and E-ZPass peak users started to pay the same amount of toll as the cash users.

The calibration and validation results have shown that the proposed integrated day-to-day learning and DTA framework can successfully capture day-to-day update of traffic flow after the imposed disruptions. The proposed framework performed reasonably well with MPE values ranging around 0.107, and RMSE values ranging around 0.235 between December 2005 and December 2006 for traffic. Similarly, the MPE values range around 0.118 and RMSE values range around 0.257 for the same time period.

In order to investigate the impacts of traveler learning behavior on capturing the day-to-day evolution of the travel trends, day-to-day learning component is removed from the DTA framework. The sensitivity analysis confirmed that proposed day-to-day learning framework is a crucial component of the DTA framework, particularly while investigating the traveler behavior...
during the transient period after a major disruption. Ignoring the impacts of travel experiences and travelers’ learning behavior on the evolution of traffic conditions resulted in lower prediction capabilities, and failure to capture the day-to-day evolution of travel trends.

The overall convergence properties of observed and simulated traffic conditions reveal that, when the travelers are familiar with the form of the disturbance imposed to the system, such as changes in an existing pricing application, the transient period is rather short and we observe rapid changes and fast learning rates during this period. On the other hand, when the disturbance is more significant, such as an infrastructural change in the transportation system, the transient period becomes longer, and we observe lower learning rates where travelers are hesitant to make drastic behavioral changes.

REFERENCES


