Extended Abstract for ISTDM2020

Quantifying day-to-day evolution of choice patterns in public transit system with smart transit card data

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1 INTRODUCTION

Reliability of transport service significantly affects the attractiveness of the service and the travel demand. For public transit system, the discrepancy between transit schedule and the realized schedule yields uncertain waiting times and trips times (Bates *et al.* , 2001), which can substantially affect transit demand pattern. In particular, to accommodate this uncertainty, travelers may depart earlier for a certain length of time. This additional time can be regarded as a safety margin. A series of studies proposed the "effective travel cost" when considering reliability-based travel choice, which consists of the expected travel time and the safety margin (Lo *et al.* , 2006; Szeto *et al.* , 2011). To capture the effect of transit service uncertainties on users' travel choice behavior, a number of studies establish stochastic models within the framework of reliability-based stochastic user equilibrium (Jiang & Szeto, 2016). Owing to the day-to-day variability of travel demand and traffic conditions, users' perception of unreliability in public transit services also varies. However, there are very limited studies examining how transit service reliability/unreliability could affect the day-to-day evolution of travel choices.

This study models the impacts of unreliability of public transit service on the day-to-day evolution of time-dependent transit travel demand. Specifically, we consider two dynamical processes that incorporate transit service unreliability, i.e., travelers' learning and perception updating process (LPUP) and proportional-switch adjustment process (PSAP). The conditions for the existence, uniqueness and stability of the fixed point of each model are analytically derived. These conditions are then examined using real-world public transit data from Sydney. The study period is 61 days. With some aggregations and approximations, we find that the system stability conditions at the fixed point are satisfied in both models. The observed weighted average flow change between two successive days is around 6.5% over the observation period, which may reflect the system stochasticity rather than instability. Among a series of empirical findings, it is noteworthy that the value of waiting time while the service is delayed is worth around 2.5 times of the in-vehicle time. Moreover, we find that the LPUP model more closely approximates real day-to-day travel choices than PSAP model, which is partially due to its stronger capability of capturing nonlinear effects.

2 Methodology

2.1 Problem description: commuters' day-to-day departure time choice

We take one OD pair in Figure 1 as an example, where d commuters or travelers go from A to B every day, using the only transit line L. On each day, commuters have to choose a departure time, which is between the earliest time

t_b and the latest time t_e. Note that, we discretize the departure time horizon into multiple time intervals, therefore, the travelers indeed choose a time interval.

Figure 1: The setting of the problem

2.2 Experienced travel cost

We assume that the travel cost of departing at the time interval m on day q is a function of travel demand within this time interval x_m^q i.e., $\mathrm{c}_m^q = \mathrm{c}(\mathrm{x}_m^q)$. Later on, the derivation of the existence, uniqueness and stability conditions at the fixed point in the proposed dynamical systems is built upon the properties of the cost function $\mathrm{c}(\mathrm{x}_m^q)$. We also define the experienced cost $\mathrm{C}_m^{e,q}$, which is the observed experienced cost from the dataset. It is utilized for the model calibration, which is given as follows

$$\mathrm{C}_m^{e,q} = \omega \delta_m^q + T_m^q \tag{1}$$

where δ_m^q is the experienced service schedule delay at the departure stop on day q and T_m^q is the experienced in-vehicle time on day q. δ_m^q and T_m^q are both obtained from the real dataset. Since the monetary value of the waiting time and that of in-vehicle time are often different, a coefficient ω (> 0) is added to the service schedule delay.

2.3 Effective travel cost

We consider that travelers have information regarding the in-vehicle time distribution and service schedule delay distribution, which may come from information services and their long term experience. Then, we propose the effective travel cost E_m with respect to departure time interval m as follows:

$$\mathrm{E}_m = \delta_m^H + \eta_1 \sigma_m^H + T_m^H + \eta_2 s_m^H \tag{2}$$

where δ_m^H is the mean service schedule delay, σ_m^H is the standard deviation of service schedule delay, T_m^H is the mean in-vehicle time, s_m^H is the standard deviation of in-vehicle time, and η_1 (≥ 0) and η_2 (≥ 0) are two parameters to capture the size of the safety margin, which reflect how risk-averse the commuters are. The effective travel cost intends to capture frequent transit commuters' general understanding of the level of service of the public transit system based on their long-term user experience or information provision. Regarding a certain period H, the effective travel cost E_m is a constant. It serves as a reference point for travelers when considering service uncertainty.

2.4 Day-to-day evolution models

2.4.1 Learning and perception updating process (LPUP)

We propose the following LPUP dynamical system in Eq. (3) and (4), which is similar to that proposed by Cantarella & Cascetta (1995). However, we incorporate the effective travel cost concept in the day-to-day model. In particular,

$$\tilde{\mathrm{c}}_m^q = \tilde{\mathrm{c}}_m^{q-1} + \kappa \left(\mathrm{c}(\mathrm{x}_m^{q-1}) - \mathrm{E}_m \right) \tag{3}$$

$$\mathrm{x}_m^q = d(1-\rho)\mathrm{P}_m(\tilde{\mathbf{c}}^q) + \rho \mathrm{x}_m^{q-1} \tag{4}$$

where $\tilde{c}_m^q$ is the perceived travel cost of the departure time interval m on day q, x_m^q is the number of travelers departed at time interval m, $\kappa > 0$ is the parameter associated with the previous day's experienced travel cost and the effective travel cost i.e., $c(x_m^{q-1})$ and E_m, $\rho \in (0, 1]$ is the ratio of travelers repeating the choice made on the previous day, d is fixed travel demand between an OD pair, and $P_m(\tilde{\mathbf{c}}^q)$ is the choice probability estimated by the multinomial logit function. The term $c(x_m^{q-1}) - E_m$ reflects that travelers will compare their experience on yesterday with the effective travel cost based on information provision or a certain period of travel experience.

2.4.2 Proportional-switch adjustment process

The proportional-switch adjustment process (PSAP) is established by Smith (1984). Similar to the LPUP model, we assume that travelers tend to favour the time interval m more on the next day (day q) if the previous day's experienced cost $c(x_m^{q-1})$ is less than the effective travel cost E_m, and vice versa. Again, we consider only a proportion of $(1 - \rho)$ travelers will re-consider their choices. The PSAP system can then be formulated as Eq. (5).

$$x_m^q = \rho x_m^{q-1} + (1 - \rho)\, x_m^{q-1} \left(1 + \alpha \left(E_m - c(x_m^{q-1})\right)\right) \tag{5}$$

where $\alpha > 0$.

3 Results

We examine the two proposed dynamical models both analytically and empirically. The analytical properties are omitted here to save space. In order to evaluate to what extent the two dynamical models can approximate the observed results, we compute percentage errors between the observed flows and the estimated flows based on the proposed models. The distributions of percentage errors are displayed in Figure 2 for both models. It is evident that LPUP outperforms the PSAP in terms of the percentage error.

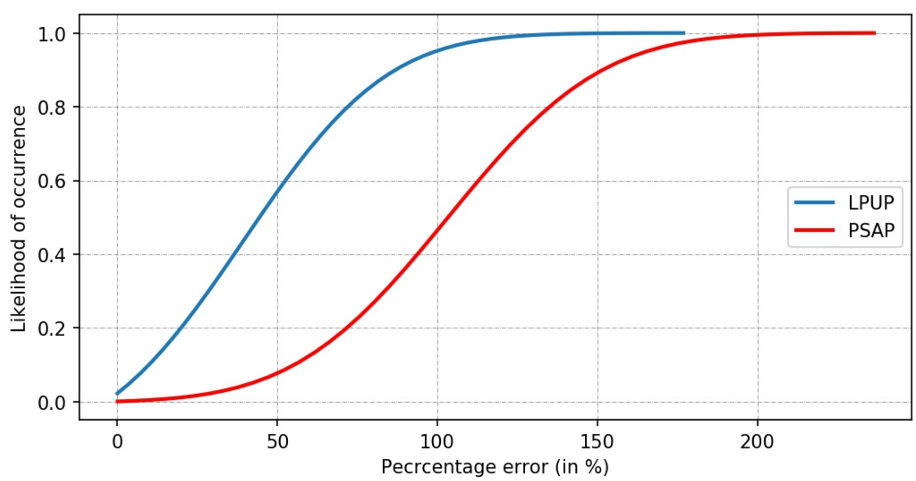

Figure 2: Comparison of the proposed dynamical models

A series of empirical insights are generated based on the calibration results. Firstly, the relative value of service delay against in-vehicle time ω is around 2.5. Secondly, the sizes of safety margins in relation to service schedule delay η_1 and in-vehicle time η_2 are 1.83 and 2.09 times the standard deviation of service delay and in-vehicle time, respectively. Thirdly, a significant amount of travelers do not re-consider their travel choices day-by-day ($\rho = 0.418$). Fourthly, the perception updating parameter in the LPUP model is relatively small ($\kappa = 0.026$), indicating that travelers do not sharply change their long term perceptions.

The analytical characteristics of the two proposed models are investigated. Our results show that the system stability conditions at the fixed point are satisfied in both models. This implies that the Sydney public transit system may already be in a stable state but with day-to-day randomness. We further examine the weighted average percentage flow discrepancy between two successive days $\Delta^{q,q-1}$. Figure. 3 visualizes the variation of $\Delta^{q,q-1}$ over the entire 61-day observation period. It is obvious that $\Delta^{q,q-1}$ fluctuates around 6.5%. Since the stability conditions of the two dynamical system hold, this 6.5% system variation from day to day may be due to uncertainty related to human activities and demand conditions.

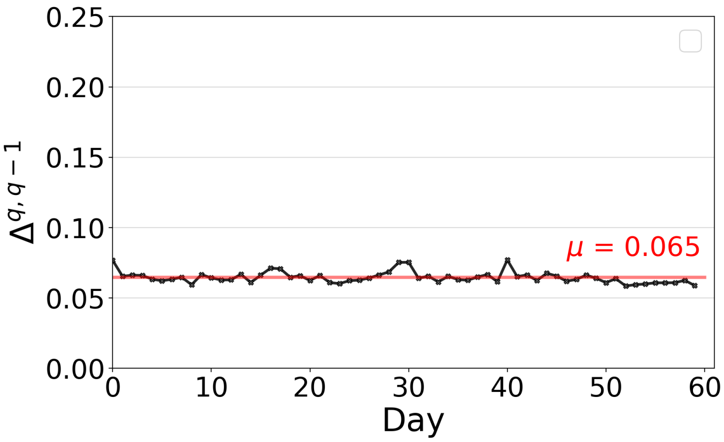

Figure 3: Average percentage flow changes from day to day

4 Conclusion

This study explores the day-to-day travel choices in public transit systems, with an emphasis on service reliability. Two dynamical systems are proposed and analytical proprieties of the two systems are examined. The proposed day-to-day reliability-based models are calibrated by using real-world smart transit card data from Sydney. This study illustrates the potential of smart transit card data to help uncover public transit service reliability and how it has affected travelers' day-to-day travel choices.

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