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Doubly dynamics for multi-modal networks with park-and-ride and adaptive pricing

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ABSTRACT

This paper models and controls a multi-region and multi-modal transportation system, given that the travelers can adjust their mode choices from day to day, and the within-day traffic dynamics in the network also evolve over days. In particular, it considers that the city network can be partitioned into two regions (center and periphery). There are park-and-ride facilities located at the boundary between the city center region and the periphery. Travelers can either drive to the city center, or take public transit, or drive to the park-and-ride facilities and then transfer to the public transit. Travelers can “learn” from their travel experience, as well as real-time information about traffic conditions, thus will adjust their choices accordingly. It follows that the dynamic traffic pattern (within-day) in the city network will evolve over (calendar) time (day-to-day). To improve traffic efficiency in the network, an adaptive mechanism, which does not need detailed travelers' behavioral characteristics, is developed to update parking pricing (or congestion pricing) from period to period (e.g., one period can be one month). The developed doubly dynamics methodological framework coupled with a feedback pricing mechanism unfolds and influences equilibrium system characteristics that traditional static day-to-day models cannot observe. The proposed adaptive pricing approach is practical for implementation in large-scale networks as the variables involved can be observed in real life with monitoring techniques. Also, it can contribute to reduce total social cost effectively, as shown in the numerical experiments.

1. Introduction

The notion of user equilibrium in transportation systems was first proposed by Wardrop (1952), and then extended by Daganzo and Sheffi (1977) (stochastic user equilibrium), and Mahmassani and Chang (1987) (bounded rational user equilibrium) and many other works. Considerable efforts in the literature have analyzed the equilibrium states when travelers have no incentive to switch mode, and/or departure time, and/or route, and have provided insightful ideas for both transportation planning and traffic management. However, in reality, it is often observed that traffic flows can fluctuate from time to time, due to the interference of external factors and change of the network itself (see, e.g., Guo and Liu, 2011). This raises the interests to analyze the day-to-day flow evolution in a transportation system with various models (for single-mode systems with either fixed or elastic demand, see, e.g., Smith, 1984; Friesz et al., 1994; Cantarella and Cascetta, 1995; Nagurney and

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Zhang, 1997; Watling, 1999; Watling and Hazelton, 2003; Bie and Lo, 2010; He and Liu, 2012; Smith and Watling, 2016; Xiao et al., 2016; and for multi-modal systems, see, e.g., Cantarella et al., 2015; Li and Yang, 2016). Also, in recent years, more and more efforts have been dedicated to pricing or control strategies given that traffic pattern can change from day to day (e.g., Sandholm, 2002; Yang et al., 2007; Smith and Mounce, 2011; Ye and Yang, 2013; Xiao and Lo, 2015; Tan et al., 2015; Ye et al., 2015; Guo et al., 2015).

However, most of the previous studies on the day-to-day flow evolution often simplify the traffic dynamics within a day, i.e., static traffic models are adopted to describe the traffic conditions within a day. This is often necessary to make these day-to-day models analytically tractable, but important features of the congestion patterns are missing. The traditional static network models (average travel cost/time vs. input demand level) are not always consistent with the physics and dynamics of traffic. It is known that the transportation networks are not memoryless, since the same inflow will create higher travel times in a more congested state, compared to an initially less congested (or uncongested) state. This is because for a given average flow (i.e. given demand rate over a period of time) the total cost (expressed in delay terms) depends on the initial state of the system (the initial level of congestion). Therefore, the estimated congestion toll based on idealized versions of these supply/performance curves (usually based on steady states) may not be optimal and accurate, and the system may be either still congested (if underpriced) or very uncongested (if overpriced) (see for example Tsekeris and Geroliminis, 2013).

A few studies have attempted to address the dynamic features of traffic under the day-to-day framework. Ben-Akiva et al. (1986) numerically analyzed the dynamic evolution process of departure rate in the single bottleneck (point-queue) model. Recently, Guo et al. (2017) made a solid effort to show the non-convergence of the conventional proportional swap system when applied to the single bottleneck model with departure time choice. However, their analytical analysis, while insightful, relies on the simplified (within-day) traffic dynamics under the bottleneck model and ignores that real-time information could also affect travel choices in the context of within-day dynamics. Different from the above, the current study incorporates more realistic within-day traffic dynamics when considering travelers can adjust their mode choices from day to day, and traffic pattern (in a day) evolves over days. The complexity of the within-day dynamics generally leads to non-tractability (analytically) and no closed-form formulation. More importantly, besides travelers' day-to-day experience, real-time traffic condition (e.g., accessible through advanced traffic information platform, smartphone navigation apps) can affect travelers' choices, and thus will affect the day-to-day traffic evolution. This further complicates the dynamical system, which has been rarely modeled and explored in the literature.

To deal with the foreseen complexity of a model with many behavioral characteristics and degrees of freedom, we propose instead an aggregated traffic model. Specifically, we consider that the city network can be partitioned into two regions: the city center and the periphery (the extension to consider more regions is straightforward but more tedious).[1] A large-scale network traffic model expressed by the Macroscopic Fundamental Diagram (MFD) is adopted to capture the regional traffic dynamics (within a day) on the roadway network. The MFD of a network describes the relationships among network vehicle density, network average speed, and network space-mean flow (or travel production). This aggregated modeling approach enables and eases the dynamic modeling of large-scale transportation networks (for MFD-based modeling of multi-modal transportation system, see some initial attempts at Geroliminis et al., 2014; Chiabaut, 2015 and others). The aggregated dynamic MFD model to capture the within-day dynamics is then integrated with (1) a discrete choice model to capture users' mode choices; (2) a day to day learning and evolution model to capture the variations of users' choices and traffic flows over calendar time; and (3) an adaptive aggregated pricing mechanism that affects travelers' mode choices and thus to improve system efficiency. The relevant assumptions regarding the coupled models are discussed in the following sections.

For the demand side, this study models two types of travel demands, i.e., traveling from periphery to city center and traveling within city center (trips from the city center to the periphery are neglected in this study). There are park-and-ride facilities located at the boundary of the city center, which has been implemented in many cities around the world, such as Munich, Stockholm, Amsterdam, and Glasgow. There are quite some studies looking into the park-and-ride problem with static traffic models, e.g., Wang et al. (2004), Liu et al. (2009), Liu et al. (2014), and Pineda et al. (2016). For travelers living in the periphery, they can either drive to the city center, or take public transit, or drive to the park-and-ride facilities and then transfer to the public transit; while for travelers living in the city center, they can either drive or take public transit. For those who drive, they have to park their cars either at their final destinations or at the park-and-ride facilities.

Travelers can learn from both their travel experience and the real-time traffic information, and adjust their mode choices over time through a learning mechanism and consequently this influences the (within-day) dynamic traffic patterns in the city network (the day to day learning and evolution model). We assume that travelers have access to the real-time traffic information before starting their trips. In the literature, there is a branch of studies adopting "learning behavior" models (e.g., Horowitz, 1984; Watling, 1999; Bie and Lo, 2010) to capture people's behavior in a day-to-day dynamical system. Specifically, travelers rely on their perceived travel cost (or utility/disutility) of different options to make decisions. Furthermore, the perceived travel cost is a convex combination of previous day's perceived cost and experienced (or actual) cost. However, as one may tell, real-time information provision as well as its potential impacts are ignored in this type of learning models. Differently, we include the "predicted cost" (beyond past perceived and experienced costs) in the learning model to cap-

[1] Partitioning of a city network into multiple regions where each region exhibits a well-defined Macroscopic Fundamental Diagram (MFD) is discussed in, e.g., Saeedmanesh and Geroliminis (2016).