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A predictive-control framework to address bus bunching

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ABSTRACT

Busy bus routes often suffer from buses not arriving at regular intervals but in bunches at bus stops. In this paper we study this *bus bunching* phenomenon and address it by a combination of data-driven headway prediction and dynamic holding strategies, which allow to modulate buses' dwell times at stops to reduce the headway deviation. We formulate time headways as time series and compare several prediction methods by testing on data from a busy bus route in Dublin. Furthermore we review and extend an analytical model of an artificial bus route and discuss stability properties and dynamic holding strategies using both data available at the time and predicted headway data. In a numerical simulation we illustrate how the combination of two simple concepts lead to a promising strategy to reduce bus bunching.

1. Introduction

Public transportation is emphasized over private cars in urban centers to address growing traffic and congestion problems. To facilitate this, many bus service providers operate bus routes with a high frequency to ensure high mobility within the city area. One problem that comes along with highly frequent bus routes is called *bus bunching*, also known as *platooning*, which refers to the phenomenon when two or more buses of the same route arrive at the same time at a bus stop.

One of the main reasons for bus bunching is varying passenger boarding times and can be seen as a vicious cycle: If a bus arrives with a small headway to its predecessor at a stop, there will be fewer waiting passengers. This decreases the overall boarding time and the bus will depart earlier and further catch up to its predecessor, assuming this one drives with a constant average velocity. This repeats until the two buses finally bunch.

Bus bunching has negative effects for the passengers as well as for the service providers as it causes larger headways between separate bunches of buses. This leads on the one hand to longer waiting times for the passengers at the stops downstream and on the other hand to longer travel times for the passengers inside the bus due to longer boarding and dwell times at the stops. The disadvantage for the service providers is that the costs are those of a highly frequent bus route, i.e., they need to provide many vehicles and drivers, but the real frequency experienced by the passengers is much smaller due to the larger headways between the separate bunches, which results in a low cost efficiency.

The field of bus bunching has been studied for more than 50 years but got more attention recently due to modern GPS based techniques that provide online data on the bus positions. The two main areas of research based on the newly

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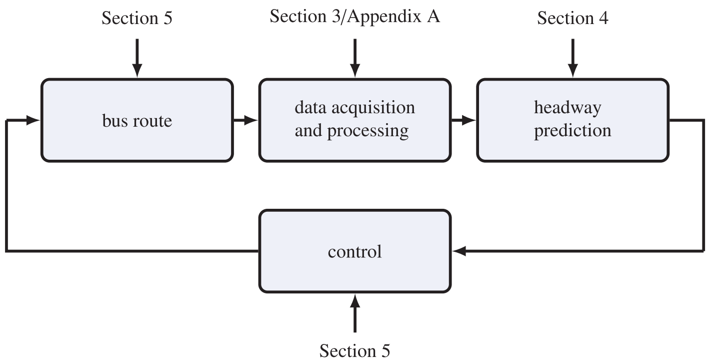

Fig. 1. Predictive-control framework and organization of this paper.

created data focus on the prediction of bunching events and on corrective control strategies. In this paper we present a predictive-control framework based on real data of a busy bus route in Dublin that combines these two main areas.

One of the two main contributions of this paper is the data-driven prediction of future headway values, which is performed by interpreting continuous-time headways as time series and predicting these directly, instead of predicting arrival times at stops as an intermediate step like done in previous works. As we will see in Section 4 the simple linear-regression method performs similarly to the more advanced techniques, e.g., based on artificial neural networks, so by using this we get a general data-driven prediction method that does neither depend on a statistical training performed on a (large) offline training-data set like in a classical machine-learning context nor on a specific underlying prediction model. The second main contribution is the combination of the headway prediction with the existing headway-based dynamic holding strategy. This includes an extension of the existing stability analysis as well as a numerical experiment of an illustrative example and a comparison to the classical holding strategy based on readily available data. In this paper *holding* refers to the alteration of buses' dwell times at stops after the boarding process is finished. The goal of the holding strategy is not to adhere to a schedule but to regularize the headway distribution and with that to improve the service provider's performance and the customers' experience, which will be explained more in detail in Section 5.

This paper is structured like the predictive-control framework shown in Fig. 1. We start in Section 3 and Appendix A where some preliminary topics like the concept of *continuous-time headways* and the acquisition of real data from the Dublin Bus route are discussed. In Section 4 we formulate the data-driven prediction of headways in the context of time-series forecasting and compare the predictive performance of several methods, namely linear regression, kernel regression, artificial neural networks and autoregressive models, as applied to the real data. In Section 5 we review an analytical model of an artificial bus route and a classical headway-based control strategy using directly available data. We extend this to a predictive-control strategy by including predicted headway values and we extend a known stability result according to this. We apply the concept of predictive control to an illustrative example. This is done by a numerical simulation and shows the advantage of predictive-control schemes compared to the ones that only employ directly available headway data. In Section 6 we summarize our findings and refer to starting points for future work. In the following subsection we give a literature review on topics related to bus bunching.

2. Literature review

We organize the literature review with respect to the two main topics of this paper: prediction and control.

2.1. Prediction

One of the main tools to investigate the bus bunching phenomenon is the *space-time diagram*, which is illustrated in Fig. 2 and describes the bus trajectories as offset distances, i.e., as the distances the bus traveled from the start of its journey until its current position along the path. By predicting future arrival times of buses one is able to predict the time headways for each bus pair and thus to predict bunching events.

A first general framework for the prediction of *transit vehicle arrival and departure times* based on AVL data has been presented by Cathey and Dailey (2003), using a tracker, filter and predictor element. Like Padmanaban et al. (2010) we could group the different types of methods for the arrival time prediction as follows:

- *schedule-based methods* (Manolis and Kwstis, 2004; Lin and Zeng, 1999).
- *statistical methods*, like *nonlinear time-series models* (D'Angelo et al., 1999; Ishak and Al-Deek, 2002), *regression models* (Frechette and Khan, 1998; Rice and Van Zwet, 2004; Patnaik et al., 2004), and *nearest-neighbor approaches* (Chang et al., 2010; Coffey et al., 2011; Tiesyte and Jensen, 2008).
- *machine-learning methods*, like *artificial neural networks (ANNs)*, optionally with exogenous inputs (Jeong and Rilett, 2004; Jeong, 2005; Jeong and Rilett, 2005), *support vector machines (SVMs)* (Bin et al., 2006; Vanajakshi and Rilett, 2007), and *kernel-regression methods* (Sinn et al., 2012; Nair et al., 2014; Lam and Bouillet, 2015).