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Real-time bus route state forecasting using Particle Filter: An empirical data application

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Abstract

Buses on the same route tend to bunch when the system is uncontrolled. This lack of regularity leads to an increase in the average passenger waiting time, increases delays and makes travel times uncertain. A wide variety of solutions have been proposed to maintain accurate bus system performance. Unfortunately, if a strategy is applied permanently, it could detract from the entire transport system efficiency. That is why a transit operator needs an accurate forecast of the route in order to intervene before the bus route is too disrupted to be restored to regularity. This paper aims to predict critical situations in real-time forecasting of a bus route state. To accomplish this, we propose to take advantage of both theoretical and empirical information (model and data) using data assimilation (a particle filter). On one hand, a stochastic dynamic bus model forecasts future bus route states. On the other hand, archived data calibrates the model parameters while real-time data provides information about the actual route state. The methodology is applied to a real case study thanks to the quality data provided by TriMet (the Portland, Oregon transit district). Predictions are finally evaluated by an *a posteriori* comparison with real data. The results highlight that the method leads to a valid forecast of a bus route state with a 8 minutes time window. This duration is sufficient to predict critical situations, especially bus bunching. Further research would have to consider deterministic travel times from a traffic model instead of the distributions in order to maintain correlation between travel times on links. In that case, the assimilation process would focus on the surrounding traffic flow, also potentially available in the Portland data.

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Keywords: Bus route; stochastic bus model; probabilistic distributions; Portland transit data; model calibration; Particle Filter; forecast.

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Nomenclature

S	stop number
s	index of stops
l_s	length between stops s and $s+1$
I	bus number
i	index of buses
H	expected time headway between buses
$h_{i,s}$	effective time headway between buses $i-1$ and i at stop s
$B_{i,s}$	number passengers boarding the bus i at stop s
$A_{i,s}$	number passengers alighting the bus i at stop s
$L_{i,s}$	passenger of bus i at its arrival at stop s
$d_{i,s}$	dwell time of bus i at at stop s
$\pi_{i,s}$	travel time of bus i between stops s and $s+1$
$t_{i,s}$	arrival time of bus i at at stop s
$t_{i,s\|s_1}$	arrival time of bus i at at stop s from the knowledge of its real arrival time at station s_1
$\bar{t}_{i,s}$	real arrival time of bus i at at stop s provided by real data
λ_s	Mean passenger demand rate at station s
η_s	Mean alighting proportion at station s
a	individual alighting time
b	individual boarding time
c	time needed to open and close the doors
γ	time lost in acceleration
μ	mean of a normal distribution
σ	standard deviation of a normal distribution
λ	parameter of an exponential distribution
C	cycle of a signal between two stations
r	red time of a signal between two stations
L	number of particles for the Particle Filter
l	index of particles
$X^{(l)}$	variable referring to particle l
ε	acceptable time-error for a prediction
$\theta_{i,s}$	validity duration of a prediction
θ	validity duration of all predictions

1. Introduction

Bus routes are known to be naturally unstable. First uncovered and highlighted by Newell and Potts (1964), buses tend to bunch when the system is uncontrolled. The main causes of bunching are disruptions in transit operations, variations in passenger demand, and traffic congestion (McKnight et al., 2004). The bus route becomes unreliable, which tempts users to shift to other transport modes. This lack of uniformity in headways leads to an increase in the mean passenger waiting time in addition to longer and more uncertain travel times. A wide variety of solutions have been proposed to maintain reliable bus performance. A sampling of classical ideas includes: stop skipping (Sun and Hickman, 2005), boarding limits (Delgado et al., 2009), adding slack time into schedules, holding buses at control points or at a terminal (Dessouky et al., 1999; Xuan et al., 2011; Bartholdi and Eisenstein, 2012), regulating bus speed (Daganzo and Pilachowski, 2011), and implementing traffic signal priority (Stevanovic et al., 2008; Koehler and Kraus, 2010). However, if these strategies are applied permanently, then they could reduce overall transit system efficiency. For example, holding strategies and slack times increase bus travel times (Cats et al., 2011) which degrade system performance for passengers. Besides, when a bus that is ahead of schedule benefits from transit signal priority, it will more quickly catch its leader. It is also possible that recovery strategies are applied too late,