Modeling the effect of subway strikes on bus operations using Automatic Vehicle Location Data

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Extended Abstract

1. Introduction

Efficient operation of public transport systems is vital for urban congested areas. Reliability problems cause increased waiting time on stops, travel time uncertainty, bus bunching (BB) events and decreased passenger satisfaction (Moreira-Matias et al., 2015). To achieve a high level of service while keeping operating costs as low as possible, public transport companies should be able to estimate route duration under different external and internal (controllable by the companies) conditions. To this end, the factors that dynamically affect travel times such as traffic, weather conditions and unpredictable events should be identified. New technologies allow for easy and efficient collection, storage and processing of data at a low cost (Chen et al., 2016), and increase the power of analytic procedures used to determine travel time variations at a microscopic level. Big data play a decisive role in the way smart cities use intelligent transport systems to improve the performance of public transport operation and services (Tao et al., 2014). On the supply side, the data collected by Automatic Vehicle Location (AVL) systems, are used to increase the efficiency of management and operations, by analyzing travel times, headway distribution and bus bunching events. Decrease in bus travel time improves utilization of available capacity and enhances transit users' satisfaction (Hensher et al., 2003) and thus, public transport demand by attracting users to the system (Vuchic, 2005).

2. Background

Both demand and capacity factors are closely related to travel time variation (Rahman et al., 2018). According to Tetreault and El-Geneidy (2010), the capacity and demand factors that have been found in the literature to affect bus travel time can be divided into those which can be controlled by the transit operator such as route design and behavior of drivers (Strathman and Hopper, 1993) and, those which can not be controlled such as weather conditions, traffic flow and traffic collisions (Hofmann and O Mahony, 2005; Mesbah et al., 2015). Several estimation methods have been applied in the literature to analyze the factors affecting bus travel times, including multiple regression (Mesbah et al., 2015), K nearest neighbor (k-NN) (Chang et al, 2010) artificial neural network and support vector machine approaches (Yu et al, 2011). The advantages and disadvantages of these methodological procedures are described in detail by Soriguera and Robuste (2011). Mesbah et al. (2015) applied ordinary least squares regression to analyze tram travel time using AVL data for ten randomly selected tram routes and concluded that precipitation significantly affect travel time. Malzoumi et al., (2010) used regression with a stepwise selection method to analyze weather effects on travel time and found that precipitation was only a significant variable in peak hours. Although there are few papers investigating the effects of strikes on public transport use and car travel time (Adler and van Ommeren, 2016), we found no research investigating the effect of subway strikes on bus operations by analyzing travel time and headways distribution.

The aim of this paper is thus to analyze the effect of factors which cannot be controlled by the operator, such as weather conditions and special events (strikes) on bus travel time using Automated Vehicle Location data. The analysis is based both on descriptive analytics and also on the application of multiple regression, using a variety of continuous and discrete variables. Additionally, the effect of strikes on headway distribution and on the number of bus bunching events is also investigated.

3. Data collection and processing

Three classes of data were collected and used for the analysis and development of the econometric models: AVL data, weather data and data regarding subway and tram strikes for the respective time period. The AVL data was extracted for two bus routes for a period of three months from September 2017 to December 2017. The AVL trip record data includes the following fields: timestamp, vehicle code, bus route id and name, direction of the route, starting and ending point of the route, longitude and latitude, and type of incident (departure from starting point/arrival to ending point/arrival to bus stop) with the respective recorded time of arrival and departure. The following steps were followed for data processing: First, the data were split by route direction and non-normal trips flagged as “out of the route” were removed. Incomplete trips that did not have records in all bus stops were also removed from the final database. Total travel times for each route and headways for each stop were calculated, removing anomalies and missed trips which resulted in extremely large values in some cases.

Historical weather data were collected from the Hydrological Observatory of Athens, operated by the National Technical University of Athens. Six weather observation stations located in the Athens area were selected, measuring parameters of hydro meteorological interest such as rainfall, temperature and relative humidity. For the purpose of this study, data on air temperature and precipitation in 10-minute intervals were collected between September and December 2017. For each observation, data from the nearest station are considered for the analysis.

Information on public transport strikes was obtained from the Athens operator (OASA), while information on special events was extracted through internet research. For each strike, mode type, date/time of day and duration were recorded, while days with bus strikes were excluded from the analysis. About 14 days of public transport (subway and tram) strikes were observed in the period examined, while there are 7 days referring to special events or holidays.

4. Preliminary Results and Conclusions

Preliminary analysis results are presented in Figures 1 and 2. Figure 1 presents the mean scheduled headway, as well as the mean actual headway per hour on a regular day and on a day with a 24 hour subway strike for the southbound direction of Route 608. As expected, the mean headway for the day with subway and tram strikes is significantly higher compared to regular days with no strikes and the peak is observed between 11.00 am – 15.00 pm and between 20:00-21:00pm. Most notably, the deviation from scheduled headways is much larger during these times, while the overall distribution of headways during the day is entirely different for a 24-hour strike day, indicating the unsuitability of regular schedules for these conditions.

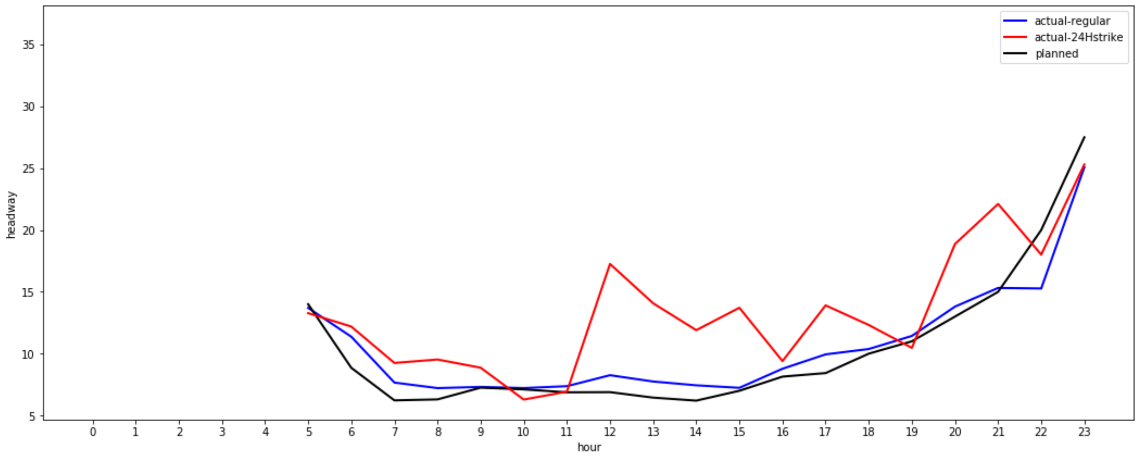

Figure 1. Mean headway during the different hours of the day compared to a day of a 24- hour subway strike (608 Route- southbound direction).

With respect to running time, results indicate notable differences for days where strikes take place. Figure 2 below shows the comparison of the average running time between regular days and days with strikes. Evidently, the existing schedule is not appropriate for the latter, as running times are significantly higher throughout the day. In fact, a very large deviation occurs during the morning peak period (8.00-10.00 AM), where mean actual running time exceeds the corresponding regular-day value by more than 25% and the respective scheduled trip time by 16%.

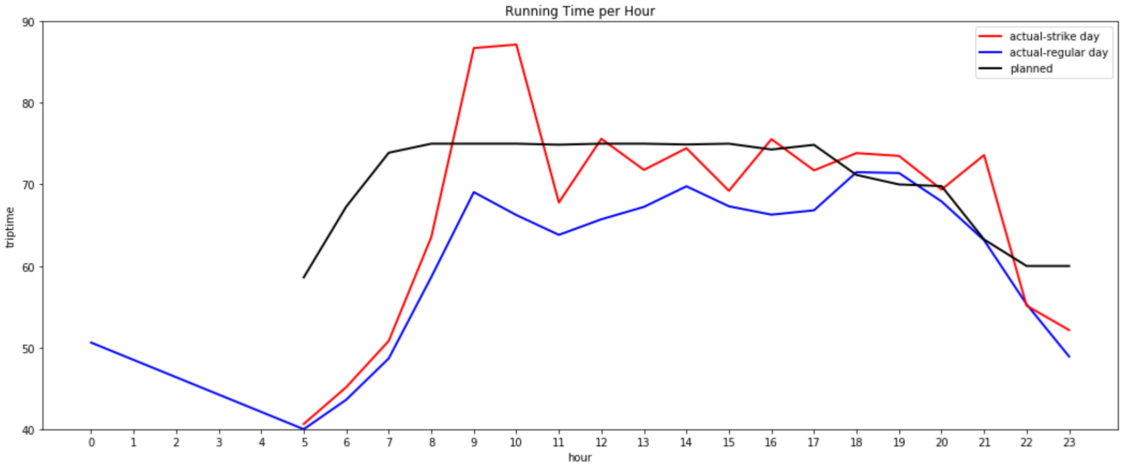

Figure 2. Mean running time during the different hours of the day (608 Route-southbound direction).

The next step after the exploratory data analysis is the specification of the appropriate running time models. The remaining step is to select the best model based on the chosen goodness of fit measures. Overall, the results of the study are expected to provide useful information for transit authorities to improve the level of service provided to passengers by designing robust travel schedules that are considerate on weather and strike effects. The analysis can also help to support real-time operational decisions when such events are likely to occur and minimize passenger discomfort.

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