HUMAN FACTORS PERSPECTIVES ON MODELS OF TRANSIT DWELL-TIME VARIABILITY

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Abstract

Transit service design and planning relies largely on quantitative tools (e.g., statistical models, simulations) to characterize relationships between operational parameters on transit service scheduling and performance. However, few predictive models exist to quantify the influence of differences in passenger characteristics (like impairment, aging, mobility aid use) on transit planning and performance.

The extensive literature on transit dwell time variability provides a case example. This paper presents findings from a systematic research review performed to (i) identify factors affecting variability in bus-stop dwell time, and (ii) determine the extent to which prior dwell-time research acknowledges variability in passenger functional capabilities and limitations.

Preliminary results indicate that most studies consider passengers as being homogenous. This assumption limits the ability to identify and accommodate design needs across disparate groups of passenger groups (e.g., older adults, wheeled mobility users, persons with strollers), particularly in transit service planning and design. Some dwell-time models categorically exclude data on passengers in wheelchairs as ‘rare events’ or ‘outliers’ due to prolonged boarding/disembarking times.

The lack of quantitative tools to operationalize information about passenger variability into the operations and planning models impedes incorporating accessibility and usability as measures. On-board and on-person technologies (e.g., smartphones, smart card payment, computer vision) create new possibilities to gather information about diverse passengers and their interactions with the transit system for improving transit usability and service quality.

Keywords: dwell-time, systematic review, regression, usability, system performance, low-floor bus

1. Introduction

Measurement and monitoring of transit performance is critical to understanding how well service is being provided to customers. This information also serves as inputs
in decisions about unmet mobility needs and improvements to existing transit services. Transit service design and performance measurement rely on empirically-based quantitative tools (e.g., statistical models, simulations) to characterize relationships between operational parameters (e.g., passenger load, time of day) on scheduling and performance (e.g., dwell time, wait time, travel time).

Ensuring accessible and equitable transit services for diverse users presents a unique challenge due to technical design constraints and economic objectives in the operating environment (i.e., maximizing seating and standing capacity, generating revenue, off-setting operating costs). However, limited information is available on the extent to which variability in passengers affects transit system performance variability. Service performance reporting by transit agencies to the federal government concerning persons with disabilities pertains mostly to complementary paratransit service (e.g., missed trips) and not fixed route service.

The extensive literature on transit dwell time, particularly for low-floor buses, provides an excellent case example. Dwell time is defined as the amount of time a transit vehicle spends at stops and stations serving passenger movements, including boarding and alighting (Kittleson Inc., 2003). Dwell time at bus stops represents a significant portion of bus operating time and contributes to its variability in on-time performance and predicting travel times – which makes it an important measure transit capacity and service quality. The Transit Capacity and Quality of Service Manual (TCQSM) recognizes the importance of dwell time in capacity and service planning and provides suggested default values for passenger service times (e.g., 60s at a downtown stop; 30s at a major outlying stop; 15s at a typical outlying stop) or calculations based on expected volume of passengers (Kittleson Inc., 2003).

Statistical models of bus stop dwell time are a category of quantitative models used in scheduling fixed-route transit services, often represented as regression equations, to predict estimated service times at bus stops.

The objectives of this systematic research review were to:
1. Identify factors affecting variability in bus-stop dwell time for low-floor transit buses, and
2. Determine the extent to which prior dwell-time research acknowledges variability in passenger functional capabilities and limitations, particularly passengers that are elderly or have disabilities, and thus provide insights into design strategies for improving system usability.

2. Methodology

2.1 Literature Search

A literature search was conducted in transportation engineering research databases for scientific articles on transit bus stop dwell time. The databases searched included the Transportation Research Integrated Database (TRID), ScienceDirect, and Google Scholar. Keywords used in the search comprised “dwell time”, “dwell-time”, “bus dwell times”, “low-floor bus dwell”, “low floor bus dwell”.
2.2 Document Coding and Analysis

Research studies identified were reviewed to characterize key attributes of dwell time models based on significant predictor variables (e.g., number of passengers boarding/disembarking), design conditions (e.g., vehicle type, pre-boarding or on fare payment), statistical relationship to dwell time (e.g., linear, logarithmic, exponential), and data collection methodology (e.g., observational data, automatic passenger counts).

3. Results

The literature search yielded approximately 100 research articles on factors affecting bus stop dwell time. The following sections summarize some of the key observations across the different studies reviewed.

3.1 Definition of Dwell-time

The operational definition of dwell time was observed to be different across studies. This affected the methods used and data required for calculating independent and dependent measures. Fernandez (2010) defined bus dwell time as time duration that the public transit vehicle remains stopped while transferring passengers. Shen and Li (2013) divided dwell time into three parts, viz., ‘deceleration delay’—when the bus slows down to a stop, ‘stop delay’ defined as total passenger boarding and alighting time and the time of opening and closing doors, and ‘acceleration delay’—when the bus accelerates out of the stop. Most papers define dwell time as only the ‘stop delay’ but some (e.g., Shen and Li, 2013; Robinson, 2014) argue that deceleration and acceleration are reasonable inclusions for calculating the dwell time accurately. Sensor-based methods for vehicle tracking have made field-measurements of deceleration and acceleration delays much simpler as compared to manual data collection methods.

3.2 Data Collection Method

The review revealed a variety of methods used to collect empirical data for developing and validating predictive models of dwell times. One category of field studies has used manual methods to collect data. Fletcher (2013) uses manual observations of passenger movement, fare payment methods and crowding after consent from the transit provider. Rashidi and Ranjitkar (2013) and Khoo (2013) have used video surveys. Katz and Garrow (2012) conducted a survey by having an observer on board. A manual counting method is sometimes used to count boarding and alighting passengers to arguably minimize error (Widanapathiranage et al., 2013b). González et al. (2012) used 2 observers on board, stopwatch and data collection sheets to collect the necessary data for calculating the dwell time.

A second category comprises automatically collected data on dwell time. Transit agencies in most large cities in the U.S. have adopted Automatic Vehicle Location (AVL) technology that relies on GPS for automatically determining and transmitting the geographic location of vehicles across the transit system. These systems often form the back-end of bus dispatch systems and real time information systems for passengers. Zolfaghari et al. (2004) uses real time passenger information and AVL
Automatic Passenger Counting (APC) systems are electronic devices installed on transit vehicles that record the number of passengers enter, alighting and boarding times and other information that can be used to optimize the bus times. Multiple studies on dwell time have used data obtained from AVL and APC systems (e.g., El-Geneidy et al., 2011; Zhang and Teng, 2013; Dueker et al., 2004; Rajbhandari et al., 2003). Others have used smart card transaction data for estimating dwell times (Widanapathiranage et al., 2013a). Liao (2011) and Milkovitz (2008) combined data from multiple technologies, including automatic fare counting (AFC) data apart from AVL and APC. Newer methods have also relied on Vehicle Identification Technology (VID) for estimating bus travel times (Kieu et al., 2012).

These different methods vary in terms of type and quality of data, and constraints on personnel time and equipment. The different methods also have implications for what data is not collected. For instance, smart card transaction data may not record boarding of passengers that don’t pay fare such as seniors and persons with disabilities that sometimes can travel free on certain routes. AVL and APC data alone do not provide information on attributes of the passengers (e.g., elderly, passengers with a wheelchair or stroller) and may not explain variability in boarding times for identical volumes (number) of passengers boarding. Studies increasingly use a combination of methods such as a combination of both observational methods and AVL/APC data to obtain contextual information about passengers.

3.3 Person Variables Effecting Dwell-time

Dwell time is directly related to the number of passengers boarding and alighting which makes passenger volume a frequently used predictor variable in dwell time models. Quite understandably, boarding and alighting is further slowly when there is platform crowding and congestion present (Kittleson Inc., 2003). Thus significant number of studies have also accounted for effects of door crowding on operational performance and safety (Katz and Garrow, 2012; Tirachina et al., 2013). Tirachini (2013) specifically compared boarding times in older compared to younger passengers in developing a multiple regression of bus dwell time.

A sub-set of studies make deliberate efforts to separate dwell time into components attributed to person vs. design variables. Jaiswal et al. (2009; 2010) split the dwell time into two parts – bus side data and passenger side data. The bus side data includes queuing time, and door opening and closing time. The passenger side data includes platform density, walking time from waiting position to bus door, and queuing time. Li et al. (2006) include information about latitude and longitude of location where delay was encountered, bus arrival time, front door open time, number of passengers alighting at front door, ending time for alighting at front door, number of passengers boarding at front door, ending time for boarding at front door, number of passengers alighting at rear door, ending time for alighting at rear door, front door close time, and bus departure time. Dueker et al. (2004) includes lift operations, bus route and time and an indicator for low-floor bus in analyzing determinants of dwell time.
3.4 Design Factors Effecting Dwell-time

Prior research into dwell time has explored a multitude of design factors including type of vehicle (40 ft. low-floor bus, 60 ft. articulated bus), number of doors used in ingress/egress, fare payment location (pre-boarding vs. on-board), and fare payment method (e.g., coin vs. electronic fare payment such smart cards, swipe cards). Studying these factors helps quantify the impact of design and policy decisions on dwell time.

Human factors in fare payment have important implications for efficient and safe boarding. Choice of payment method and interface design can have a differentially impact different groups of users based on their functional abilities and consequently dwell time. Some agencies only accept cash while others accepts both cash and fare cards – each payment method having implications for the ease-of-use and time required for completing the fare transaction. Fernandez (2010) investigated on-board and pre-boarding fare payment methods for different combinations of platform height and door width. The TQSCM provides estimates for the incremental time per passenger based on fare payment method, e.g., 2.5s for pre-paid, 3.5 s with smartcards and 4.2 s with swipe tickets (Kittleson Inc., 2003). An underlying assumption of most dwell time models is that the effect of different design parameters is independent of user abilities, i.e., there is no interaction effect. The study by Tirachini (2013) was one example of a study that characterized effects of passengers’ age alongside different payment methods and bus floor level on the dwell time.

3.5 Dwell-time model formulation

Statistical models of bus stop dwell time use multiple regression to model the effects of different parameters like the number of passengers boarding and alighting and vehicle design attributes. These include linear regression approaches (e.g., El Geneidy and Vijayakuman, 2011; Rashidi and Ranjitkar, 2015) while others include non – linear statistical models such as multinomial logit model and error components model (Tirachini et al., 2013; Li et al., 2012). Gonzalez (2012) compares both linear and logarithmic models. Statistical simulation techniques are another category of approaches used in dwell time modeling (e.g., Dessouky et al., 2003; Chien and Qin, 2007; Li et al., 2006). Rashidi and Ranjitkar (2015) also include time series models such as moving average, random walk and exponential smoothing in predicting dwell time.

Researchers have differed on the statistical distributions that best model dwell time variability. Dwell times have been assumed to be normal, lognormal, Wakeby and ARIMA (Rashidi and Ranjitkar, 2013). Rashidi and Ranjitkar (2013) conclude that Wakeby distribution outperformed the most commonly used distribution function namely lognormal distribution to approximate the dwell time for both peak and off-peak periods while ARIMA performed reasonably well for a short-term prediction of the dwell time.

Criteria for data inclusion and exclusion can affect distributional properties and subsequent analysis of dwell time. Data on passengers with special needs (e.g.,
passengers in wheelchairs or with bicycles) are often categorically excluded as ‘rare events’ or ‘outliers’ due to prolonged boarding/disembarking times. Others take an approach where passengers on the tail of the dwell time distribution are categorized as ‘atypical’ and are separated from the data set for separate analysis. Milkovits (2008) uses a threshold value of 8s per passenger as the cutoff for dwell time per passenger categorized as ‘typical’ vs. ‘atypical’ for the purposes of dwell-time analysis. This resulted in excluding about 5% of all collected observations in their study. Another category of research studies these ‘atypical’ cases as part of the residual or error component of the statistical model. When representing the impact on dwell time caused by atypical passengers, it is best to have these records as a distribution, rather than just as part of the residual.

4. Discussion

Numerous statistical models have been developed to predict dwell-times for low-floor buses as a function of the number of passengers boarding and alighting, and other secondary factors such as crowding, fare type, and bus design. These models are critical to estimating service reliability, travel times and on-time performance. Few studies acknowledge and explicitly address the impact of passengers with special needs into dwell-time analysis and prediction.

Preliminary results from our review of the research on dwell-time models indicate that a majority of studies consider passengers as being homogenous. This assumption limits the ability to identify and accommodate design needs across disparate groups of passenger groups (e.g., older adults, wheeled mobility users, persons with strollers) in transit service planning and design. This approach stems from a general assumption that “unless these [wheelchair boarding] activities occur regularly at a given stop, they can be treated as random events” (TCQSM p.4-4, Kittleson Inc., 2003). Adjusting transit schedules for some dwell time variability is deemed sufficient to address these ‘rare events’.

The typical approach is to categorically exclude data on passengers with special needs e.g., in wheelchairs as ‘rare events’ or ‘outliers’ due to prolonged boarding/disembarking times. For example, an elderly passenger who is not able to stand while the bus is in motion may increase dwell time as the driver waits to move until the passenger has found a seat. Passengers using a wheeled mobility device also require considerably greater ingress and egress times due to the need for deploying an access ramp and on-board securement of the wheeled mobility device (Nelson/Nygaard, 2008; Goldman and Murray, 2011). Default values for dwell time when using access ramps in low-floor buses along with on-board wheelchair device securement are estimated to be between 30s to 60s (Kittleson Inc., 2003). Jayaprakash and D’Souza (2015) reported dwell times obtained from field studies of ingress to be in the range of 43.1s to 125.8s in passengers using wheeled mobility devices.

The lack of quantitative tools to operationalize information about passenger variability into the operations and planning models impedes incorporating accessibility and usability as measures of transit service quality and performance. Increasing use of on-person and on-vehicle sensors (e.g., smartphones, smart
cards, computer vision) provides new capability to automatically gather information about passengers and their interactions with the transit system (e.g., boarding, fare payment, travel preferences). The future potential for leveraging these technologies for improving transit usability and service quality is largely unexplored.

5. Conclusions

Variability in dwell time at bus stops represents a significant portion of variability in travel time and on-time performance. Variability in passengers, although an uncontrolled source of variation, is perhaps one of the largest sources of variability in dwell-time. However, few predictive models exist to quantify the influence of differences in passenger characteristics (like impairment, aging, assistive device use) on dwell time predictions, and subsequently on transit planning and performance.

The research literature acknowledges the benefits of low-floor bus designs, particularly for passengers with strollers, bags or luggage, or disabilities as they require less time boarding and alighting low-floor buses than corresponding high-floor buses. Though studies on dwell time often exclude wheeled mobility device users from the data set because of the high variability of dwell time associated with ramp operation and wheelchair securement.

This review indicates significant knowledge gaps in our understanding of the impact of variability in passengers and/or functional capabilities on dwell time predictions, and more broadly in transit service design and performance measurement. Closer attention to variability in passengers’ abilities and corresponding design accommodations could yield improvements to transit service usability and performance.

References


