ESTIMATING EFFECTS OF PASSENGER DWELL AND NON-PASSENGER DELAY ON OVERALL BUS TRIP TIME: A HIERARCHICAL MODELING APPROACH

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Word count: 4,764 words text + 10 tables/figures x 250 words (each) = 7,264 words

Submission Date: 8/1/2018

ABSTRACT

For local bus service, in-vehicle travel time is composed of time spent in motion and time stopped. Time in motion is dependent on factors common to general traffic travelling on a road segment, while time stopped has some features in common with general traffic (i.e., traffic signals) and some unique to buses such as passenger dwell time. In addition to passenger dwell, there are multiple sources of delay from serving a bus stop, such as deceleration, acceleration, and signal delay. To improve overall travel time, transit agencies can attempt to reduce dwell and delay, but the relative improvements resulted will depend on the contribution of the various components of the bus “time budget.” This paper attempts to quantify the contribution of passenger dwell time, non-passenger delay and in-motion time to total travel time. Using a stop-level data source, passenger dwell time and non-passenger delay are calculated per stop within each trip. A hierarchical probabilistic model is then used to estimate the effects of these components on overall travel time. We demonstrate that for a local, high-frequency route, the fraction of total travel time that a bus spends on stop-associated non-passenger delay is about twice as much as what it spends on passenger dwell. Additionally, the contribution of passenger dwell time is additive to total travel time, whereas non-passenger delay around bus stops is multiplicative. Thus, when transit agencies consider techniques to improve travel time with limited resources, the modeling approach can suggest prioritization of efforts.

Keywords: Public Transit, Stop Crossing Records, Bus Time Budget, Bayesian Hierarchical Model

INTRODUCTION

Transit agencies are faced with the challenge of improving the speed and reliability of bus service, and often focus efforts on reducing stop-associated delays. As a transit vehicle approaches a pre-assigned stop location, it can experience different sources of delay such as deceleration, bus stop failure (bus arrives at a bus stop to find all loading areas occupied by other buses), dwell time due to passengers boarding and alighting, passenger service, traffic signal delay, reentry delay and acceleration *(1)*. Out of these sources, dwell time and traffic signal delay are usually thought to be the largest contributors to the total delay.

Delay at signalized intersections for general traffic has been estimated using regression models based on traffic flow, signal timing and signal geometry *(2, 3)*. Signal timing, specifically red signal phase duration, has been found to be linearly correlated with signalized intersection delay for transit vehicles *(4)*. The physical location of a bus stop also appears to have a statistically significant impact on signal delay and passenger boarding time, as the interaction between the two types of delay can compound overall travel time *(4)*.

Instead of using overall traffic flow and traffic signal features, Ko et al. *(5)* estimated signalized intersection delay for private vehicles based on information collected from the vehicles. Select private vehicles were equipped with Global Positioning System (GPS) devices that provide locations at one-second intervals. The authors developed speed profiles for the vehicles by using the high-frequency location records to estimate deceleration delay, stopped delay and acceleration delay *(5)*.

In recent years, many transit agencies have adopted Automatic Vehicle Location (AVL) technology on transit vehicles. AVL provides the location of a transit vehicle at a pre-defined time interval, ranging from five-second to one-minute intervals. AVL data have been used to estimate signalized intersection delay. Hellinga et al. *(6)* used AVL data to identify the locations of and time spent on unscheduled delays, i.e. stopping due to traffic signal or traffic congestion. Each estimated delay was assigned to its corresponding downstream traffic signal. Wang et al. *(7)* applied a piecewise constant deceleration model and a simple platoon advancement model with some modification on AVL data in order to extract signal delay.

There has been extensive study on passenger dwell time estimation and modeling. Decision tree-based methods *(8)*, linear and non-linear regression models *(1, 9, 10)*, time series models including random walk, exponential smoothing, moving average (MA) and auto-regressive integrated moving average (ARIMA) *(11)*, machine learning methods such as k-Nearest Neighbors (KNN) *(12)*, and prediction algorithms *(13)* have been adopted to model bus dwell time. In these models, the most common independent variables are the number of boardings and alightings. The time series models only consider historical dwell time. Additional independent variables include number of standees or crowdedness and capacity limits.

High-frequency AVL data have been used to measure time lost due to a bus serving a bus stop *(14)*. Peak speeds immediately before and after serving a bus stop are identified, and the time between these peaks is considered the actual time it takes to serve the bus stop. This is then compared to free-flow travel time interpolated from the calculated peak speeds. The free-flow travel time is used as a proxy for travel time through the bus stop without stopping. Speed along a bus route segment can also be derived from high-frequency AVL data. Slow-speed areas can then be compared to signalized intersections where there is expected significant delay to find whether slow speed is a result from signalized intersection delay *(15)*. This approach is useful for granular exploration of individual locations, but it is difficult to generalize to examine an entire route or network.

Despite the extensive research into these sources of dwell and delay individually, fewer studies have examined how they act when integrated at the trip level, examining their relative impact to total travel time of a given trip on a route. The construction of such a bus “time budget” would contribute to understanding the relative influences of the different types of dwell and delay, and thus lead to a better indication of where a transit agency might act to improve speed and reliability along a given route. This is especially critical in a time of limited financial and other resources at transit agencies across North America.

In order to better understand the relative contributions of these bus behaviors to overall travel time, we model bus total travel time at the trip-level as a function of in-motion time; dwell time due to passenger activities; and delay due to signalized intersections, deceleration before, and acceleration after serving a stop. We use a hierarchical probabilistic model to quantify the relative contributions of these sources to the overall travel time of a trip, nested within each trip pattern and time of day. This approach allows a coherent evaluation of the entire trip as a function of its individual dwell and delay components, and allows comparisons across routes and times of day.

DATA

Metro Transit is the primary public transit provider in the Minneapolis/St. Paul, Minnesota metropolitan area. Metro Transit operates over 140 bus routes, 2 light rail lines, and one commuter rail line, providing nearly 270,000 rides on an average weekday.

In early 2018, Metro Transit upgraded its CAD/AVL operational data system (TransitMaster; Trapeze, Ontario, Canada) so that at each bus stop, the bus generates a record with a series of timestamps: time of arrival at stop, time doors open, time doors close, and time of departure from the bus stop. Hereafter we refer to these records as stop crossing records. These records represent a rich source of stop-level information, especially as compared to historical datasets at Metro Transit, which only included arrival time and departure time at time points.

Stop crossing records are generated through a combination of GPS and odometer information, and are based on arrival and departure zones which are set for each stop. For example, consider a bus that travels from stop A to stop B (see Figure 1). The distance between A and B is 2,000 feet. The departure zone for stop A is 150 feet and the arrival zone for stop B is 200 feet. For simplicity in this example, the odometer is at 0 feet when the bus is at stop A. As the bus moves along the route and the odometer reader hits 1,800 feet, the bus detects the arrival zone of stop B. These records are then validated by its GPS (Global Positioning System) location. If, in this example, the bus’s odometer reader is at 1,800 feet but the GPS location is not within reasonable distance to the actual location of the corresponding bus stop, this record will be flagged and can be excluded. At Metro Transit, arrival zone is usually 200 feet from stop location, and departure zone 150 feet past the stop.

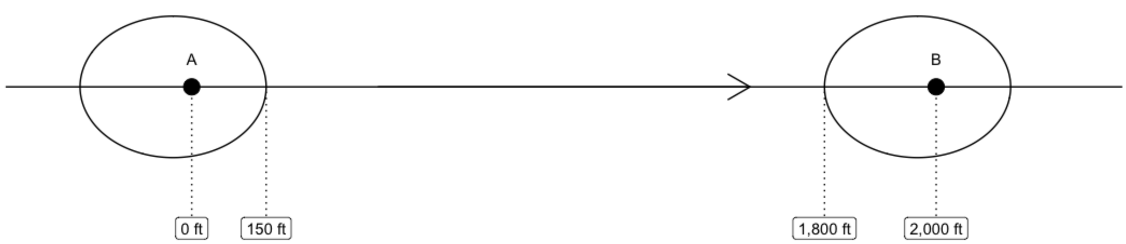

FIGURE 1 Bus travels from stop A to stop B.

As a bus approaches a bus stop, there can be three scenarios:

(1) It stops and opens the doors to serve passenger boarding and/or alighting
(2) It stops but does not open the doors (e.g. stopping at red traffic signal)
(3) It neither stops nor opens the doors

The data generated in scenario (1) are different from those in scenarios (2) and (3). In scenario (1), each stop crossing record consists of arrival time as the bus approaches the arrival zone, time it first opens the doors, time it last closes the doors, and departure time detected as the bus leaves the departure zone. In scenarios (2) and (3), only zone arrival time and departure time are recorded.

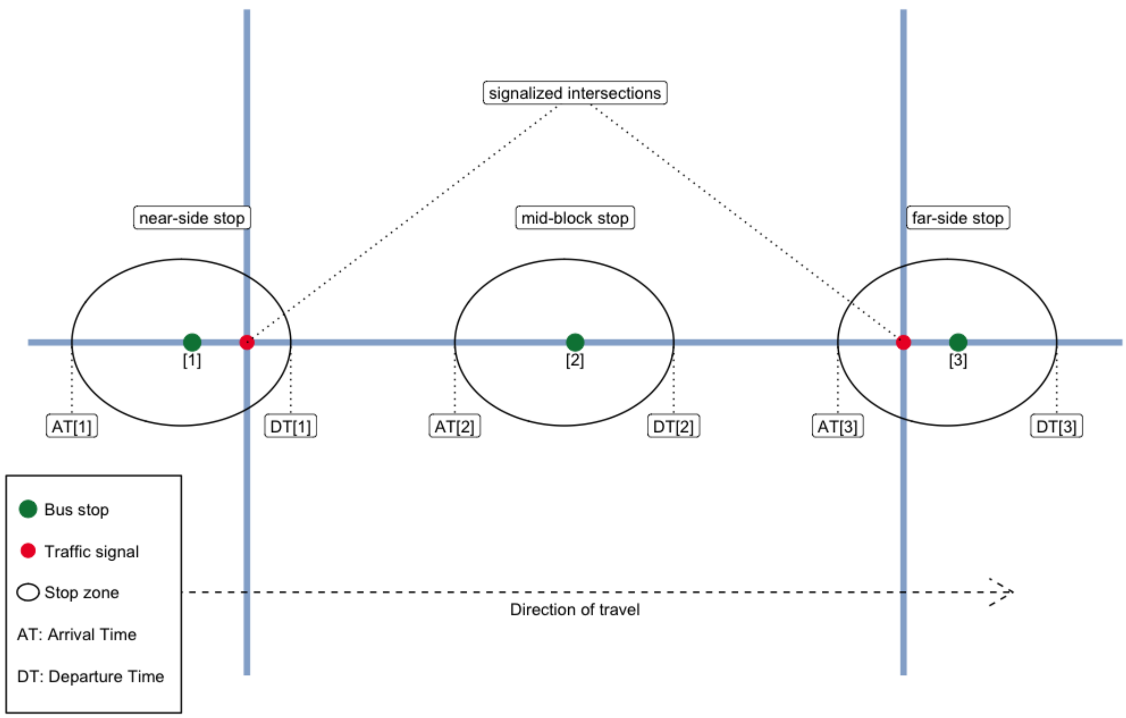

FIGURE 2 Bus stop locations in relative to street intersections.

The interpretation of the time segments can depend on the geometry of the stops, especially with respect to signalized intersections. Figure 2 illustrates three possible locations for bus stops: near-side, mid-block and far-side. For near-side stops, door-close-to-departure time includes any delay caused by the signalized intersection that is within its corresponding stop zone in addition to acceleration delay. For far-side stops, signalized intersection delay is included in arrival-to-door-open time in addition to deceleration delay. For mid-block stops, assuming free-flow traffic, arrival-to-door-open time and door-close-to-departure time can be considered as delay due to deceleration and acceleration, respectively. Regardless of the geometry, the estimation of the contributions of passenger dwell and stop-associated non-passenger delay can be evaluated separately. However, in order to effectively quantify these contributions in the midst of trip-level variation, we turn to a statistical modeling approach.

We apply our statistical methods described below to stop crossing data from Metro Transit's Route 2. Route 2 is an east-west local route serving the University of Minnesota and Franklin Ave south of downtown Minneapolis (see Figure 3). Route 2 serves over 40 stops in each direction along a 7-mile (11.5-kilometer) route. On a typical weekday, Route 2 runs about 180 trips (90 trips in each direction) providing about 5,000 rides. Stop crossing records for Route 2 between July 2 and July 20, 2018, excluding weekends and holidays, are used in this analysis.

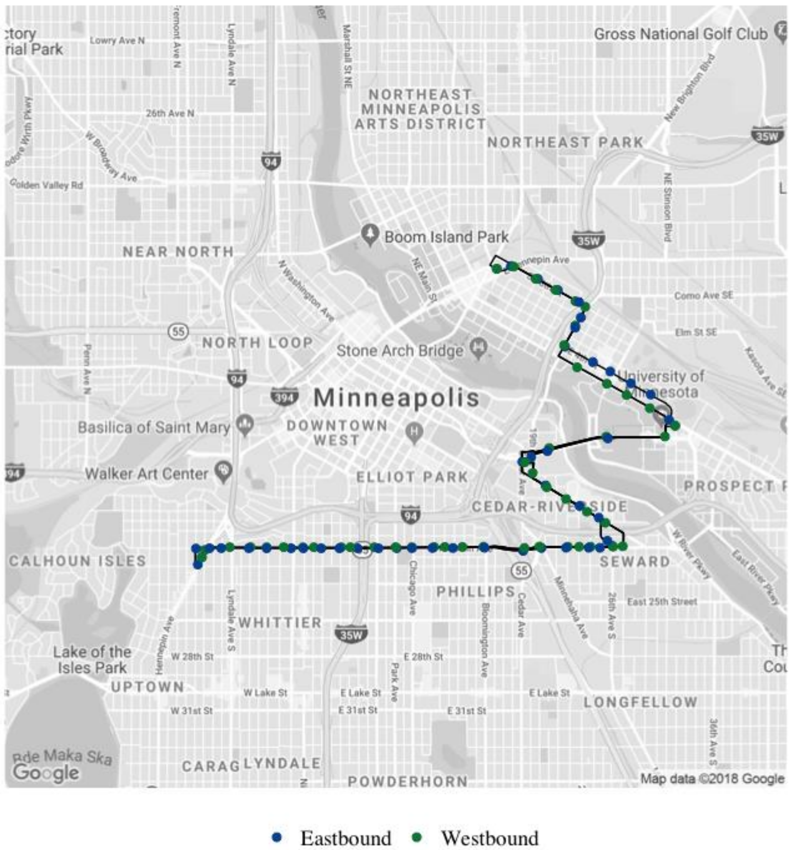

FIGURE 3 Metro Transit Route 2.

STATISTICAL METHODS

Our purpose in this study is to evaluate the relative contributions of in-motion time, non-passenger delay, and passenger dwell time to overall trip travel time. We decompose bus total travel time from one terminal to the other into passenger dwell time (PDT), non-passenger delay (NPD), and in-motion time (IMT). The following four subsections detail how each metric is estimated. Table 1 lists notations and acronyms used in the rest of this paper.

TABLE 1 Notations and Acronyms

Notation/Acronym	Description
I	set of all stops for a given bus route
T	set of all trips in a given day for a given bus route
PDT	Passenger Dwell Time (sec)
NPD	Non-Passenger Delay (sec)
IMT	In-Motion Time (sec)
TT	Total Time: total travel time (sec)
DC	Door Close: time bus closes its door (HH:MM:SS)
DO	Door Open: time bus opens its door (HH:MM:SS)
ATD	Arrival to Departure: time between arriving and departing a bus stop less PDT (sec)
AT	Arrival Time (HH:MM:SS)
DT	Departure Time (HH:MM:SS)
FFT	Free-Flow Time: time it takes a bus to pass through a stop zone without stopping at bus stop or hitting a red light (sec)
TOD	Time of Day. one of: Early (2am to 6am); AM Peak (6am to 9am); Midday (9am to 3pm); PM Peak (3pm to 6:30pm); Evening (6:30pm to 2am).

Passenger Dwell Time (PDT)

PDT is delay due to passenger activity at stops including boarding and/or alighting, mobility ramp cycling, and other customer service activities. It is calculated as time between door opening and door closing:

$$PDT_i = DC_i - DO_i; \quad \text{for } i \in I. \tag{1}$$

Non-Passenger Delay (NPD)

NPD includes any delay that is associated with serving a bus stop, excluding PDT. Importantly NPD can be non-zero when there is no passenger activity at a stop for a particular trip (for instance, a bus slowing to ensure waiting passengers can board if they desire, but none do). NPD includes, but is not limited to, delay due to traffic signals, traffic, deceleration and acceleration. NPD is calculated for every stop along a trip except the terminals (first and last stops of a trip).

Let $ATD_{i,T0}$ denote the distribution of ATD_i from all trips in T where the bus does not stop at stop i, and P_5 denote the fifth percentile. The arrival to departure time can be computed as:

$$ATD_i = (DT_i - AT_i) - PDT_i; \quad \text{for } i \in I, \tag{2}$$

and FFT can be estimated as:

$$FFT_i = P_5\left(ATD_{i;T0}\right); \quad \text{for } i \in I. \tag{3}$$

Then NPD can be estimated as:

$$NPD_i = ATD_i - FFT_i; \quad \text{for } i \in I. \tag{4}$$

The estimation of an FFT is critical to measuring delay as opposed to simple travel time through a stop zone area. We use the fifth percentile of ATD when bus does not stop at the bus stop as a proxy for FFT instead of, for example, minimum ATD to avoid accidentally picking an anomaly as the baseline FFT. This proxy works well when buses do not hit a red light at a signalized intersection or get delayed due to heavy traffic near stop i for at least 5 percent of the trips.

Total Travel Time (TT)

TT is the time elapsed between when a bus departs its first stop and when it arrives at its final stop for a given trip. It can be measured directly as:

$$TT_t = AT_{li;t} - DT_{fi;t}; \qquad \text{for } t \in T, \tag{5}$$

where $AT_{li;t}$ is the arrival time at the last stop, and $DT_{fi;t}$ is the departure time from the first stop, for trip t.

In-Motion Time (IMT)

IMT is the total time, estimated at trip-level, where the bus travels between stops. For a given trip, TT is the sum of IMT, PDT and NPD. Since TT can be measured for each trip, and PDT and NPD can be estimated from stop crossing data, we can estimate IMT as well as effects of PDT and NPD on TT using the probabilistic functional form:

$$TT \sim IMT_{pattern} + PDT_{TOD} + NPD_{TOD} + \varepsilon_t. \tag{6}$$

A hierarchical multilevel model (also known as a mixed model) is used in order to incorporate the grouping effects of variables such as patterns and time of day that are not the main variables of interest but encode significant effects on total travel time. For bus routes with multiple branches, i.e. start at the same location and share most of the same route but end at different locations, each branch has a different pattern. Since some patterns are shorter or longer for the same bus route, it is important to account for different patterns when analyzing total travel time. Time of day is included in part as a proxy for traffic congestion but also implies varying ridership levels. Importantly, the effects of passenger dwell and non-passenger, stop-associated delay can vary in their contributions to overall travel time across the different levels of TOD.

The equation system below depicts the priors and likelihoods used in the Bayesian implementation of the hierarchical model (6). The overall travel time is modeled as a normally distributed random variable centered on the sum of the three time components. These components are in turn drawn from parent distributions which reflect the influence of different patterns and times of day. Finally, those parent distributions themselves have priors on the parameters including the variances.

$$\mathrm{TT} \sim \mathrm{N}(\hat{\mu}_t, \sigma^2) \tag{7}$$

$$\hat{\mu}_t = \mathrm{PDT_{TOD}} + \mathrm{NPD_{TOD}} + \mathrm{IMT_{pattern}} \tag{8}$$

$$\mathrm{PDT_{TOD}} \sim \mathrm{N}(\overline{\mathrm{PDT}}, \sigma^2{}_{\mathrm{PDT}}) \tag{9}$$

$$\mathrm{NPD}_{\mathrm{TOD}} \sim \mathrm{N}(\overline{\mathrm{NPD}}, \sigma^2{}_{\mathrm{NPD}}) \quad (10)$$

$$\mathrm{IMT}_{\mathrm{pattern}} \sim \mathrm{N}(0, 2) \quad (11)$$

$$\overline{\mathrm{PDT}} \sim \mathrm{N}(0, 2) \quad (12)$$

$$\overline{\mathrm{NPD}} \sim \mathrm{N}(0, 2) \quad (13)$$

$$\overline{\mathrm{IMT}} \sim \mathrm{N}(0, 2) \quad (14)$$

$$[\sigma^2, \sigma^2{}_{\mathrm{PDT}}, \sigma^2{}_{\mathrm{NPD}}] \sim \mathrm{N}[0,2) \quad (15)$$

We fit the hierarchical model in the probabilistic modeling language Stan *(16)*, interfaced through the R statistical programming language *(17)* using the *rstanarm* package.

RESULTS

Passenger Dwell Time

Using equation (1), we calculate dwell time for each stop across each trip. The estimated stop-level dwell time can then be visualized on a map as shown in Figure 4. For westbound trips, stop 51533 at Franklin Station, which is a transfer point from Route 2 to Route 9, Route 67, and Metro Blue Line (light rail), has the highest median PDT of 24 seconds. For eastbound trips, stop 13325 at Franklin Ave and Nicollet Ave, which is a transfer point from Route 2 to Routes 11, 17 and 18, has the highest median PDT of 38 seconds.

FIGURE 4 Passenger dwell time at stop for westbound trips (top) and eastbound trips (bottom) for Route 2. Terminals not included.

Non-Passenger Delay

Using equations (2), (3) and (4), we can estimate stop-level non-passenger delay per stop for each trip. For westbound trips, stop 41248 at Oak St and Washington Ave has the highest median NPD of 36 seconds. For eastbound trips, stop 13325 at Franklin Ave and Nicollet Ave has the highest median NPD of 22 seconds. Of note, while the eastbound trips experience the highest median NPD and PDT at a single stop, for westbound trips these two components of delay are highest at separate locations. The estimated NPD means and ranges for westbound and eastbound trips for Route 2 are 14 [2, 36] seconds and 12 [2, 22] seconds, respectively.

Total Travel Time

Using equation (5), we can measure TT for each of the trips in our dataset. Figure 5 shows the distribution of travel time by time of day for Route 2 during weekdays (excluding holidays) between July 2 and July 20. Trips during PM Peak are more variable than other times of day in terms of travel time, as indicated by the greater spread of observations. Part of the variability is the different patterns that are run at different times of day; this is accounted for explicitly in the model.

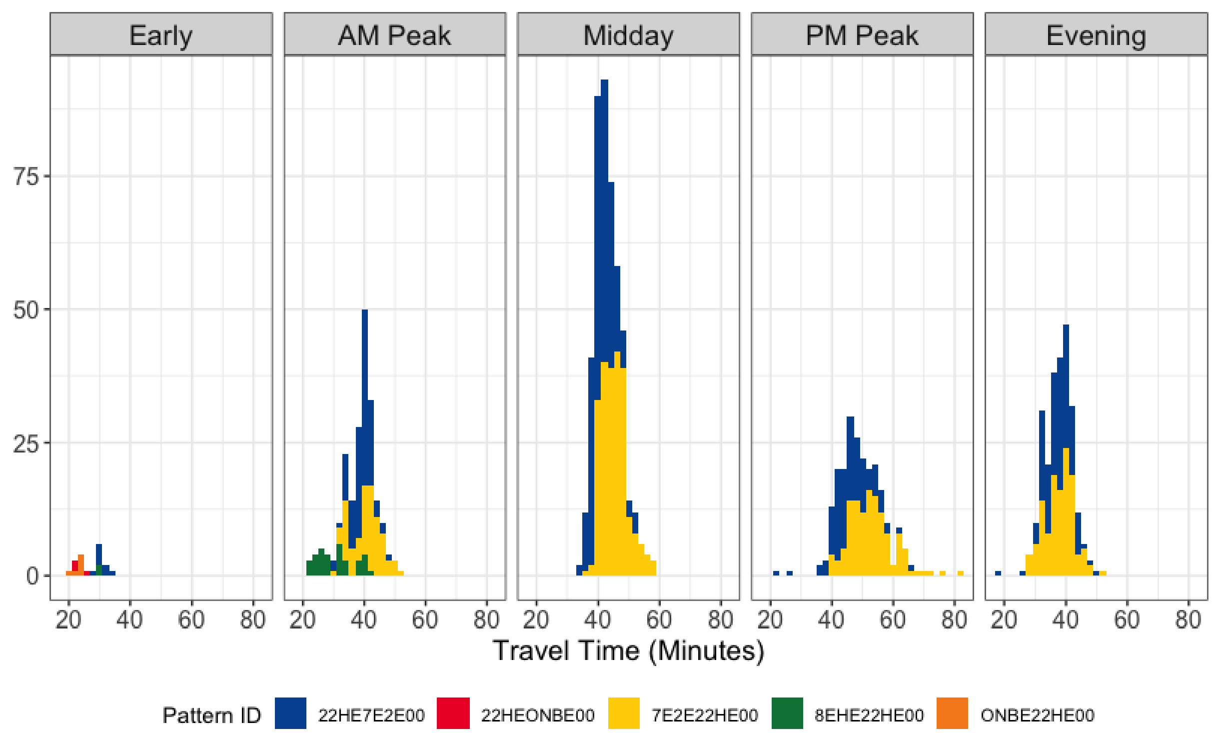

FIGURE 5 Histogram of total travel time for Route 2 by time of day.

Modeling Components of Travel Time

The model was checked for convergence, and for fit. Convergence was established by visual inspection of chain mixing, all Gelman-Rubin statistics < 1.1, and by the lack of divergent transitions in the Stan sampling process. The model was checked for reasonableness of fit by a posterior-predictive check, whereby the model is used to generate a distribution of values from the posterior probabilities and then compared against the observed data.

Figure 6 shows the distributions of parameter estimates of NPD_{TOD} and PDT_{TOD}. In each time period, non-passenger, stop-associated delay is more influential on total travel time than is passenger dwell. For example, during the PM Peak, on average a one-second increase in PDT causes a one-second increase in TT, but a one-second increase in NPD causes a 1.25-second increase in TT. PDT parameter estimates center between 0.9 and 1 across different times of day. In general, any additional time buses spend serving passengers at a stop is additive to total travel time. However, additional time due to non-passenger delay around bus stops is scaled up by a factor of 1.2 to 1.5. In other words, the passenger dwell is additive to total travel time, while the non-passenger stop associated delay is multiplicative to total travel time.

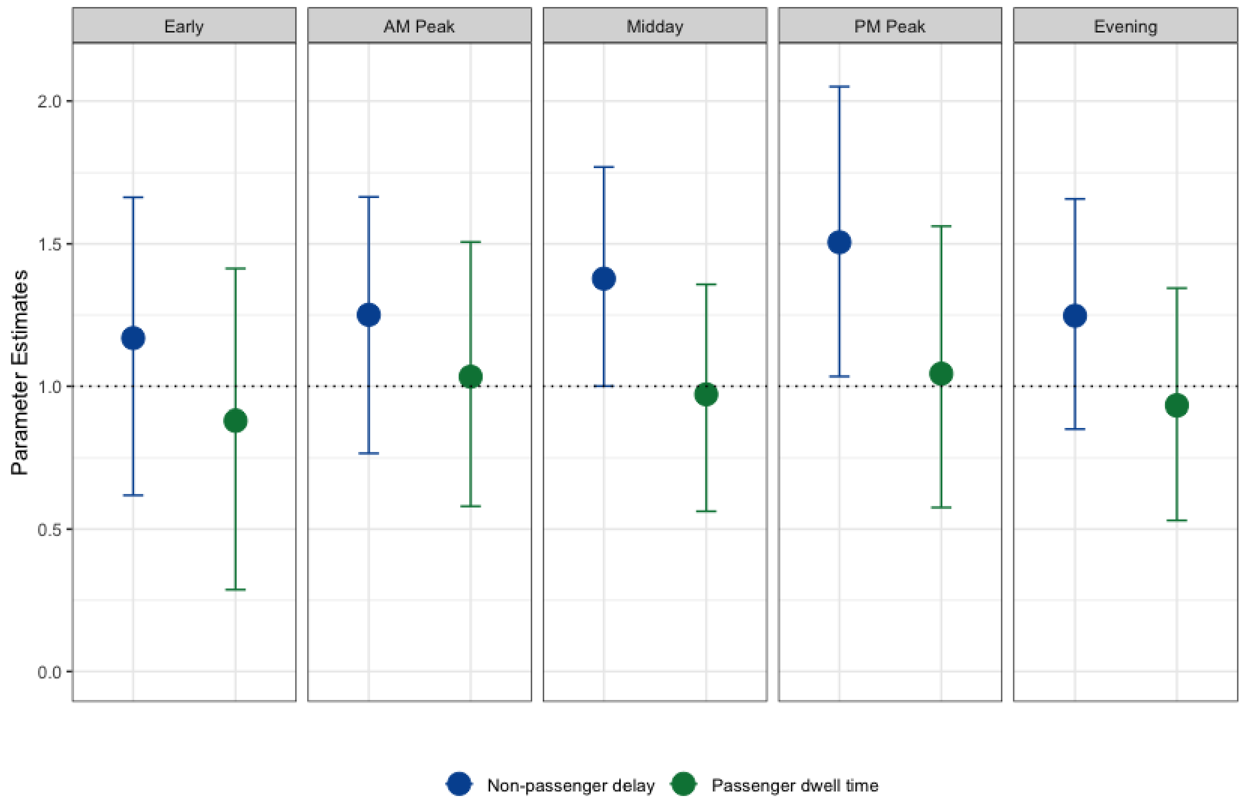

FIGURE 6 Parameter estimates, means and 90% confidence intervals, for NPD and PDT by time of day

Figure 7 demonstrates how the larger effects of non-passenger delay impact total travel time, compared to the effects of passenger dwell time, with increasing levels of each. As passenger dwell is added, total travel time increases along the 1:1 line, emphasizing its additivity, while increasing non-passenger delay results in a more disproportionate increase in total travel time.

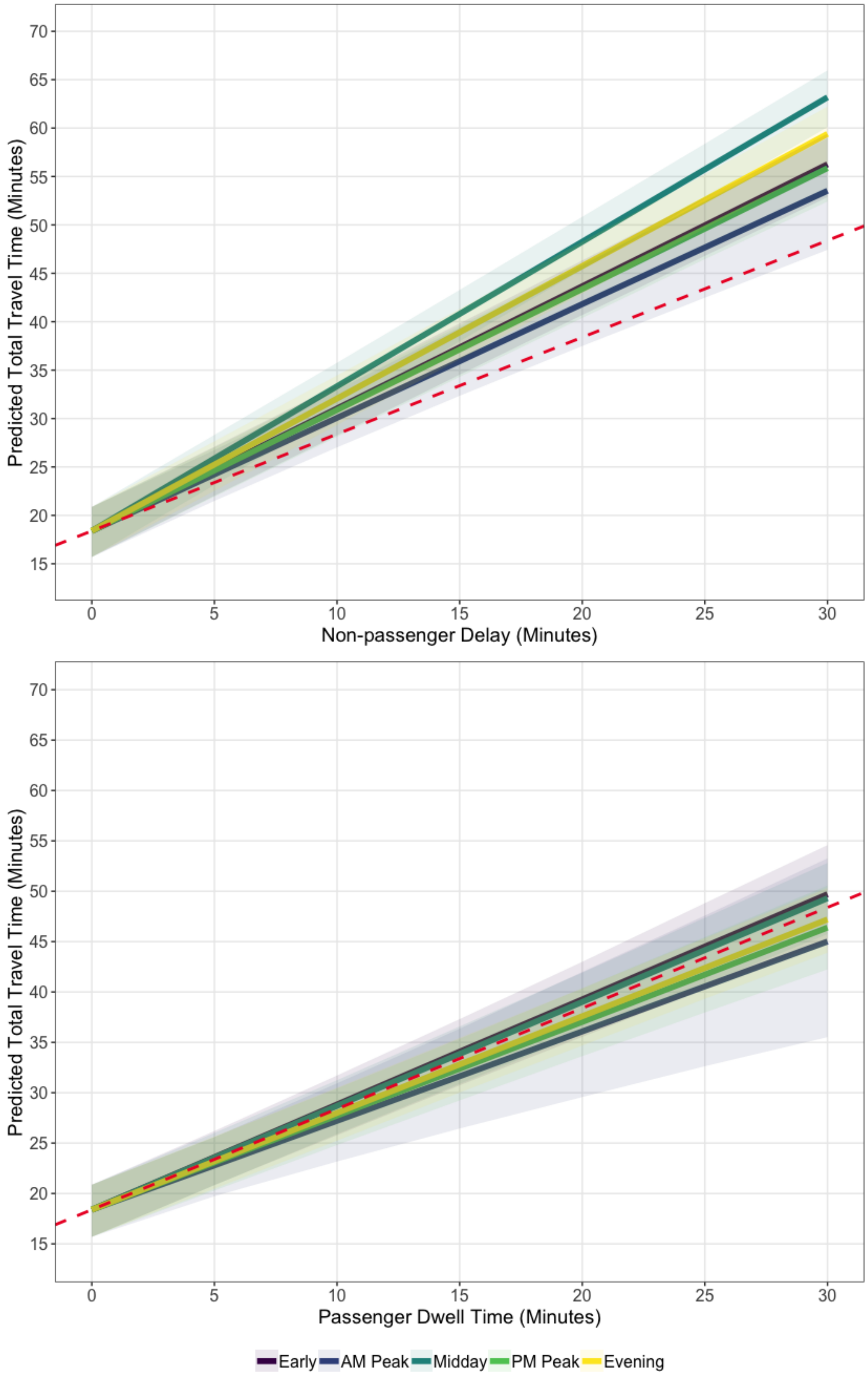

FIGURE 7 (top) Effects of non-passenger delay on total travel time, holding passenger dwell time at 0. (bottom) Effects of passenger dwell time on total travel time, holding non-passenger delay at 0. Red dashed lines are lines with slope of one.

Bus Time Budget

To estimate bus time budget for each time of day, we input typical NPD and PDT values into the model. We define the typical values as the median of each variable, which are shown in table 2.

TABLE 2 Median NPD and PDT by time of day

Time of Day	NPD (sec)	PDT (sec)
Early	411	130
AM Peak	660	270
Midday	744	380
PM Peak	882	421
Evening	627	274

Figure 8 shows time budget for Route 2 for different times of day. The error bars reflect the variability in estimated TT given uncertainty in the effect of NPD and PDT. On average, passenger dwell time accounts for 8%, 13%, 15%, 17% and 13% of total travel time for Early, AM Peak, Midday, PM Peak and Evening, respectively. Non-passenger delay accounts for 22%, 30%, 27%, 33% and 27% of total travel time for Early, AM Peak, Midday, PM Peak and Evening, respectively. Although the percent of total travel time varies across time of day, it is consistent that NPD is a significantly larger fraction of TT compared to PDT.

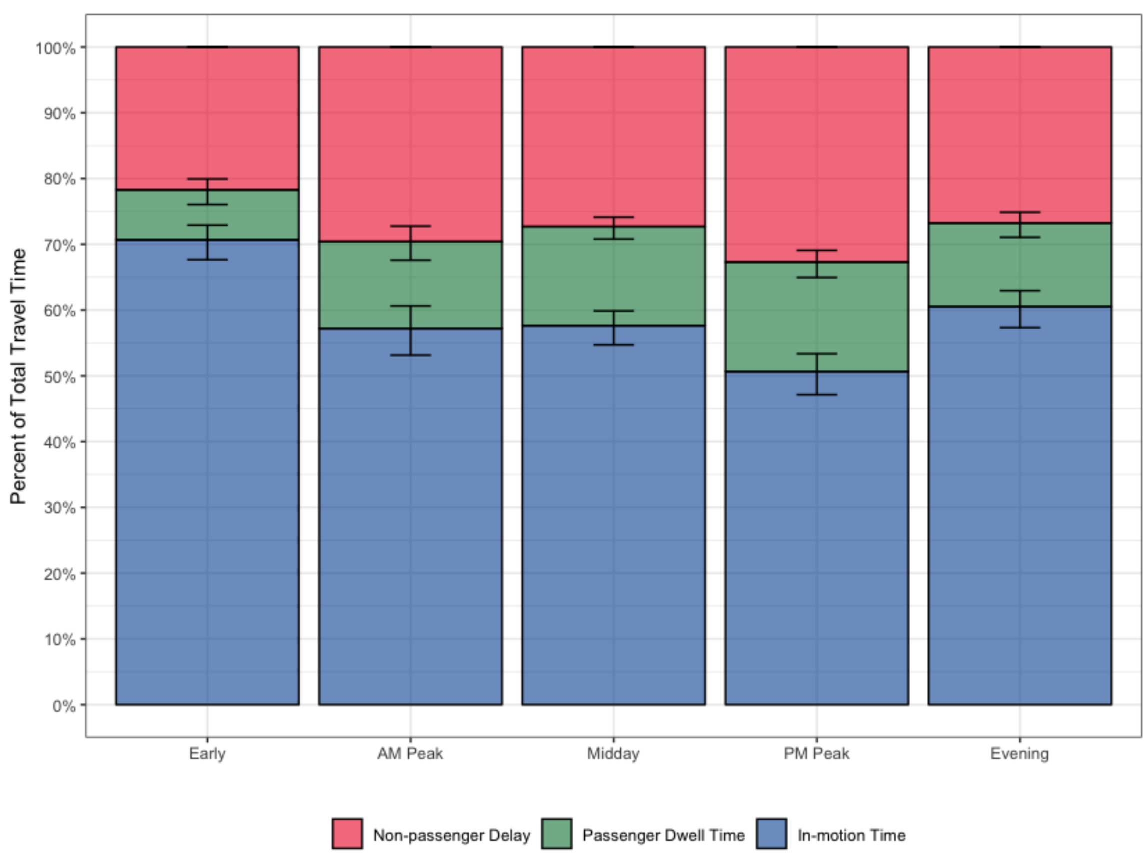

FIGURE 8 Route 2's time budget by time of day.

DISCUSSION AND CONCLUSION

We use a fine-resolution stop activity dataset to evaluate the effects of independent components of bus trip travel time using a hierarchical, probabilistic model. This approach distinguishes between additive and multiplicative components of overall travel time, as well as quantifying the relative size of the component time pools. Based on the example of Metro Transit's Route 2, non-passenger delay accounts for a larger fraction of total travel time than passenger-related delay, and has a multiplicative effect on overall travel time.

The bus activities of leaving, and merging back into traffic, are most likely not confined to the 350-foot buffer around the stop location for which we have high-resolution stop activity data. This is the most likely reason that the coefficients for NPD were multiplicative: the delay extended beyond the measured zone. In contrast, the boarding and alighting activity which comprises the bulk of passenger delay is by definition captured between the first door open and last door closed timestamps we used. Thus passenger dwell is well captured by the data source, while the non-passenger delay is not. The full coherent picture is thus only revealed in the modeling approach we used.

Motivated in part by time savings in passenger dwell, transit agencies across North America have invested in new and improved technology for fare payment (e.g. smart card and off-board payment), and in at least some places instituted all-door boarding on regular route service. This study shows that there are similar if not greater opportunities for transit agencies to improve their travel time by minimizing the non-passenger delay.

Unlike the boarding experience, non-passenger delay includes phenomena beyond the direct control of the transit agency, such as traffic congestion and traffic signal timing. However, by demonstrating the outsized impact of these components on overall travel time, agencies may be able to partner with municipalities to explore creative solutions. For instance, from the stop-level non-passenger delay calculation, transit agencies can target specific stops where there is significant non-passenger delay, and explore transit advantages such as bus-only lanes or transit signal priority.

Although the focus of this study was on total trip travel time, the concepts explored here can help at finer resolution as well, for instance by focusing on the stop-level estimation of NPD. In the example studied here, stops with larger NPD tend to be those with a nearby signalized intersection. Transit agencies can use this information to act to improve speed and reliability. In the example of Route 2, on average, stop 41248 has the highest NPD compared to other stops. The traffic signal associated with this stop does not allow turns on red light. So, although it is a right turn for Route 2, the bus has to wait until the signal light turns green. This particular intersection also experiences heavy pedestrian traffic. Hence, when the light is green, buses still have to wait until the crosswalk is clear before they make a right turn. In this case, Metro Transit may consider requesting a transit-only signal for this intersection in order to minimize its significant delay at this particular stop. In the cases where delay is mainly from hitting a red light, Metro Transit can minimize the delay by collaborating with the city of Minneapolis to establish transit signal priority for transit vehicles, so that buses can flow through signalized intersections more smoothly. NPD calculated at the stop-level can be especially useful if applied to the whole bus network, to identify particular stops that contribute to delay across multiple routes. Knowing where to target transit signal priority, Metro Transit can improve its buses' travel time while minimizing time and resources.

A further expansion of our approach is to separate the contributions of acceleration and deceleration to NPD from the contributions of signal delay. By incorporating high-frequency AVL records, delay at signalized intersections could be isolated and separated from deceleration and acceleration. Transit agencies again may be able to be creative with decreasing delay due to such activities, for instance establishing bus-only lanes around stops found to have high non-passenger delay. These would allow the bus to return to general traffic speed and merge more quickly, especially during congested times when the impact of NPD is highest. In all, the modeling approach used here can be used to support a diversity of improvements to local route bus travel time, and provide concrete evidence for agency prioritization of those improvements.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Kim Eng Ky, Eric Lind, Madeline Handschy; data collection: Kim Eng Ky; analysis and interpretation of results: Kim Eng Ky, Eric Lind; draft manuscript preparation: Kim Eng Ky, Eric Lind, Madeline Handschy. All authors reviewed the results and approved the final version of the manuscript.

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