# Simulating the Travel Time Impact of Missed Transit Connections

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For Presentation and Publication:
91st Annual Meeting
Transportation Research Board
January 2012
Washington, D.C.

Submitted: August 1, 2011

Word count: 4,473 (excluding Figure and Tables)
Plus 8 Figures and 4 Tables: 3,000
TOTAL: 7,473

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## ABSTRACT

It is well established that transit passengers dislike transferring. This is partially due to the inherent risk that the connecting vehicle will be missed, which can increase overall travel time. Despite the problems they cause, missed transfers across a system are rarely tracked in transit performance monitoring programs. The likelihood of a missed transfer having occurred depends on combinations of several factors and thus is hard to estimate. In practice, transit systems are most often evaluated according to the performance of individual vehicles, stops, and routes, not the interactions between them. This paper describes a systems approach to quantify the effects of travel time reliability, schedule adherence, and schedule design on missed transit connections, and the resulting travel time distributions.

To determine the effects of vehicle interactions on transfers, and the role that transfers play in travel time, a series of simulations based on APC data from San Diego's bus system is carried out. Travel times on two transfer trips in downtown San Diego are simulated. The effects of passenger arrival rate, on-time vehicle performance, and schedule design on the likelihood of a transfer being missed are investigated in a sensitivity analysis. It is expected that this research will lead to a better understanding of the passenger effects of schedule adherence on transfer trips. Practically, this methodology could aid in the identification of a pair of buses whose chronic schedule deviations at a particular location are likely causing missed transfers.

*Keywords: transit performance monitoring, transit travel time, transit travel time reliability, performance measurement, travel time estimation, intelligent transportation systems, transfers*

# INTRODUCTION

For the passenger, missing a transfer that should have been available according to the schedule is costly in terms of increased travel time. Trip planners almost exclusively route passengers across transfers based on the schedule, not real-time data. Furthermore, trip planners may recommend a trip that transfers at an untimed transfer point. This means that any time a transfer is missed (i.e., the scheduled arrival order of two buses at a stop is reversed due to schedule deviations), passengers may be affected, even if the transfer was untimed. Any efforts to reduce passenger travel times across the system must consider the effects that missed transfers can have on overall system travel times and travel time reliability.

To understand and improve on-time performance, transit performance monitoring systems track vehicle travel times between points and schedule adherences at stops. This is done so that troublesome components of the system (e.g., individual stops, links, or routes) can be identified and improved, decreasing travel times and increasing reliability at those locations (or on those links). Transit performance measures are generally computed and reported at three levels: system-wide, across links or routes, and at nodes [1]. System-wide performance reports include metrics such as cost per vehicle mile. Route-based performance reports describe travel time and travel time reliability. Node-based performance reports may summarize schedule adherence at a particular stop. The effects of interactions between vehicles as presented in this paper are rarely considered in transit performance monitoring.

A missed transfer can never be the result of the performance of a single vehicle, or the on-time characteristics of an individual stop. Strictly speaking, to miss a transfer requires that both the arriving and departing vehicles interact in such a way that the connection is not achieved. This is not just a matter of late arrivals. If both vehicles are late, the transfer may still be possible. Any performance monitoring system that hopes to detect and reduce missed transfers must carefully consider the relationships between vehicle arrivals at the transfer stop.

The ever-increasing adoption of APC and AVL systems allows for the effects of missed transfers on travel times to be explored based on actual data from transit vehicles. This data is typically rich, containing vehicle arrival times at stops along a route often accompanied by contextual geographic information to relate records from multiple vehicles. This paper takes advantage of APC data from San Diego buses to conduct a series of travel time simulations across two transit trips with transfers. Based on these simulations, this study evaluates the risk of missed transfers on the two trips and the effects of those missed transfers on total trip travel times.

This paper first presents a literature review of existing efforts to relate schedule adherence, missed transfers, and travel time. It then gives an overview of the trips to be studied and discusses the characteristics of the APC data used. Next follows a description of the simulation method for obtaining transit travel time distributions over these trips, along with a discussion of the effects of transfers on travel time. Finally, we present sensitivity analyses between various on-time performance metrics and the simulated travel time distributions. This leads to a probabilistic understanding of how the passenger's arrival time, the schedule adherence of the connecting buses, and the schedule-based transfer time affect travel time.

# EFFORTS TO RELATE MISSED TRANSFERS AND TRAVEL TIME

As transfer time is simply one component of travel time, this study draws from several efforts to understand transfer time in terms of schedule adherence. Most notably, Muller and Furth developed a theoretical probability-based model to find transfer times that minimize expected passenger wait time [2]. Their model considers the standard deviations of the schedule adherences of the connecting buses. A key finding from this model is that the expected transfer time grows with increases in headway (past a point), as well as with increases in the standard deviations of arrival and departure time. Additionally, Knoppers and Muller characterized mean transfer waiting time in terms of scheduled transfer time and found it to be periodic, with a period directly related to the headways of the buses [3].

Literature from the modeling community explores the effect that transfers have on the passenger experience in terms of the "transfer penalty" [4]. Transit trips involving a transfer are assessed a "transfer penalty" to represent the passenger's reluctance to travel on such a trip. In terms of the relationship between the transfer penalty and system performance, stated preference data reveals that the transfer penalty grows with the headway of the vehicles involved in the transfer [4]. Some models go on to quantify the effect of transfers, for example by assigning a weight of 10 minutes of door-to-door travel time to trips involving a transfer [5].

In terms of the applications of this study, previous work argues for the potential of advanced control techniques to manage transfers plagued by poor connectivity. Control systems can better coordinate transferring buses in order to decrease transfer time and prevent missed transfers, reducing overall travel time. The effects of such control systems on travel times and on-time performance are reviewed in [6]. This sort of active transfer coordination could be paired with the methodology for identifying missed transfers described in this paper.

# DATA AND SETTING

San Diego's transit network is extensive and well connected, containing many transfer points. It includes 88 bus routes and several light rail lines. Most importantly, many buses in this system are equipped with APC equipment to monitor on-time performance. Two trips containing transfers through San Diego were selected for this analysis and are described in Table 1. These trips were chosen for their popularity with riders as well as their high data coverage rates. Maps of the trips are shown in Figure 1. Trip #1 is from the Gaslight District to the San Diego Zoo and has a predicted travel time of 39 minutes. Trip #2 is from Sea World to the Birch Aquarium, and is predicted to take 55 minutes.


Figure 1: Trips #1 (left) and #2 (right), with origins in black and transfer points in white.

The simulation of travel times is conducted over APC data on these buses. This data originates from GPS devices installed directly in the buses themselves. Each APC device keeps a detailed event-based record of the vehicle's performance as it drives along the route. A data point is created every time the vehicle makes a stop. For this study, the relevant elements in each data point are:

- The name of the route that the bus was on (e.g., Route 30).
- A unique ID corresponding to the individual run being made.
- A unique ID corresponding to the stop at which the record was made, enabling stops across routes to be cross-referenced.
- The time when the doors opened at the stop.
- The time when the doors closed at the stop.
- The scheduled time when the stop was supposed to be made.

Table 1: Trip characteristics

| Trip | Bus A Distance | Bus B Distance | Total Distance | Transfer Location | Estimated Time* |
|---|---|---|---|---|---|
| #1: Gaslight to the Zoo | 3.7 miles | 1.0 miles | 4.7 miles | Park Blvd. and University Ave. | 39 minutes |
| #2: Sea World to Birch Aquarium | 3.7 miles | 6.4 miles | 10.1 miles | Mission Blvd. and Felspar St. | 55 minutes |

**Estimated Time is from the San Diego MTS trip planner for a trip departing at 10:00AM on a weekday.*

# DATA PREPARATION

In order to relate travel times on these transfer trips to the on-time performance of the buses serving them, several APC data issues must first be addressed. Most critically, the data is not a complete record of all vehicle activity throughout the system. Only a portion of the vehicle fleet is instrumented with APC equipment, and certain routes have higher coverage rates than others. With data available on only a fraction of the runs, gaps in data coverage become problematic when looking at missed transfers. Because of the missing data, the number of directly observed transfers between two buses at a given stop and time is relatively low, as either the arriving or departing bus will often have been uninstrumented. This means that in this setting it is impossible to simply compute the travel times of all observed trips and compare them with the on-time performance of the buses at the transfer point.

To circumvent this problem of nonconsecutive instrumentation, a simulation-based method is used. This method works on the assumption that the on-time performance of the runs for which APC data exists is representative of the on-time performance of all trips. Rather than directly observing on-time performance that would result in a missed transfer, a large number of virtual passenger trips on Trips #1 and #2 are simulated based on APC data, an empirical passenger arrival distribution [7], and the schedule.

The APC data contributes distributions of arrival schedule adherence, departure schedule adherence, and travel times for the relevant buses and stops. In order to construct these distributions accurately, only data from runs that serve both the origin and transfer (or transfer and destination) stops should be included. Grouping the data into service patterns facilitates this. A service pattern is a finer unit of organization than a route and represents a grouping of trips that share the same stops in the same order. Route variations with alternate termination points or express service are examples of service patterns. To detect service patterns in the data, repeating patterns of stops made by different vehicles within a single route were identified. Runs were then labeled according to the service pattern they represent. Considering APC traces at the service pattern level instead of the route level allows data from trips that do not serve the desired stops to be discarded.

The inclusion of the passenger's arrival time at the origin in the simulated trips means that there are actually two transfers on each trip (from walking to Bus A and from Bus A to Bus B). Thus, the simulated passenger can either catch both buses, miss Bus A, miss Bus B, or miss both buses. The passenger arrival time distribution is based on one empirically derived by Bowman and Turnquist, scaled to the 15-minute headway of Bus A (on both Trips #1 and #2) [7].

The distribution of schedule-based transfer times was constructed based on the daytime weekday schedule for Buses A and B on each trip. The transfer times for both trips are irregular as they are untimed. However, despite their irregularity, in each there was some correlation between consecutive transfer times. For example, if one transfer time was short, the following transfer time was scheduled to be longer. Because of this, missed connections at the transfer point were assessed a travel time penalty corresponding to the transfer time immediately following the one that was missed (without another independent sample). This additional travel time is the same as Bus B's headway at that time of day. The relevant distributions used to simulate travel times on Trip #2 are shown in Figure 2.

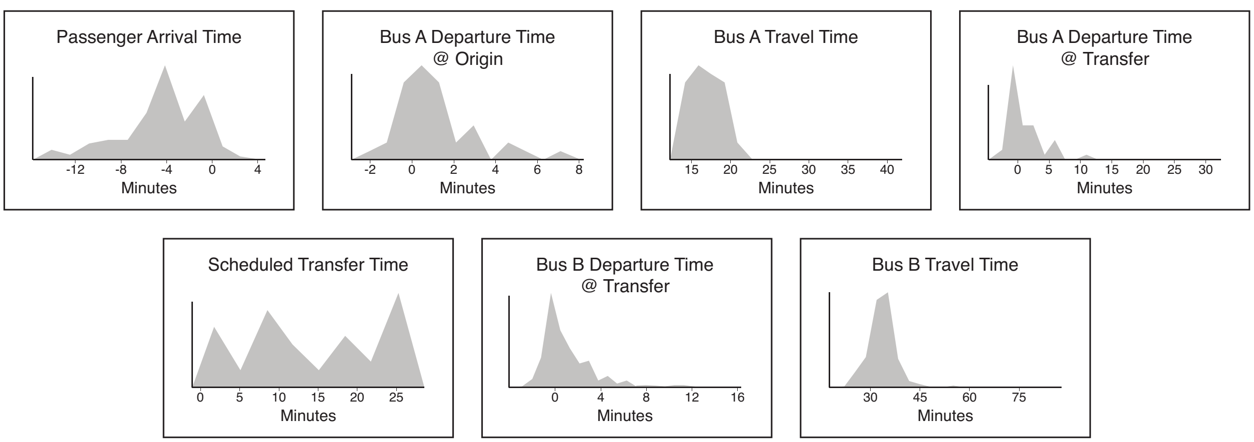


Figure 2: Distributions used to simulate travel times on Trip #2.

Several of these distributions correlate with each other, affecting how the samples are drawn in each simulation (see Figure 3, for example). On both trips, there was found to be some correlation between Bus A's departure time at the origin, Bus A's travel time, and Bus A's departure time at the transfer point. That is to say, a bus that departed late from the origin was more likely to be late when it left the transfer point. Correlation between Bus B's departure time at the transfer point and Bus B's travel time was also found. Because of these relationships between the distributions, simulated trips must not sample values from these related distributions independently. In a single travel time simulation, the values sampled from correlated distributions must come from the same APC trip record because they are related.

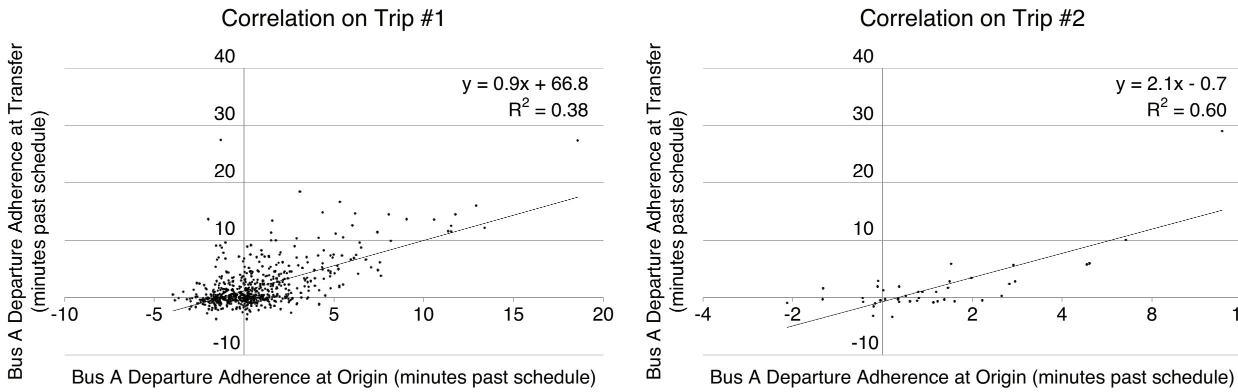


Figure 3: Positive correlation between Bus B's departure time at the transfer stop and its arrival time at the destination on Trips #1 and #2.

# APPROACH TO OBTAIN TRAVEL TIMES

The procedure for determining a single travel time can be seen in Figure 4. To begin, values are randomly sampled from the Bus A departure and passenger arrival distributions. These values (both relative to Bus A's scheduled departure at the origin) are then compared to determine whether or not Bus A is caught. If the departure time for Bus A is greater than the passenger's arrival time, the first bus is caught. Otherwise, the first bus is missed (as a result of the passenger's late arrival, the bus departing early, or some combination of the two). If the bus is missed, a single Bus A headway is added to the total travel time to represent the time spent waiting for the next bus. For both Trips #1 and #2, Bus A maintained regular 15-minute headways during the daytime on weekdays.

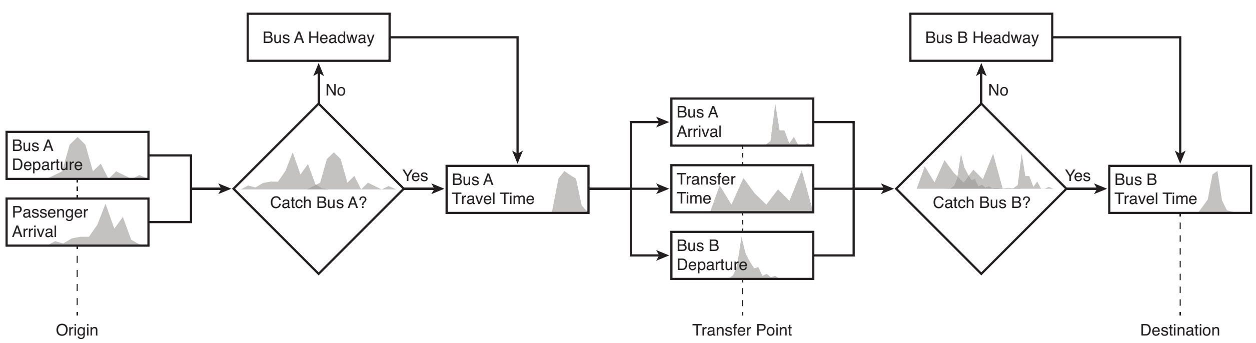


Figure 4: Procedure followed to simulate travel times

After Bus A has been caught, the Bus A travel time value from the same data point as Bus A's departure from the origin is added to the total travel time bringing the passenger to the transfer point. Whether or not the transfer is made depends on Bus A's departure from the transfer point relative to the schedule, the scheduled transfer time, and Bus B's departure from the transfer point relative to the schedule. In order to be conservative and to acknowledge the time required by the passenger to move between buses, the time that Bus A departs from the transfer point is actually used to construct the distribution of Bus A's arrival time at the transfer point. This represents a worst-case scenario. If Bus A's departure adherence is earlier than the sum of Bus B's departure adherence and the scheduled transfer time, Bus B is caught. Otherwise, Bus B is missed. Because of their correlation, the value used to represent Bus A's arrival at the transfer point is taken from the same run in the APC data as Bus A's schedule adherence at the origin and Bus A's travel time.

If Bus B is missed, a penalty of one Bus B headway is assessed to the travel time. For both Trips #1 and #2, Bus B's headways were irregular. Because of this, the actual time until the arrival of the next scheduled Bus B is taken, as opposed to simply sampling another transfer time value, or a headway from Bus B. After the transfer, the Bus B travel time value from the same run as the sampled Bus B transfer point departure is applied to the total travel time.

This completes the simulation, and the total travel time is computed as the sum of its components. The arrival and departure adherence distributions (passenger arrival time, Bus A's departure time at the origin, Bus A's departure time at the transfer point, and Bus B's departure time at the transfer point) are all in terms of schedule adherence: *actual time – scheduled time*. The other travel time and transfer time distributions are magnitudes of time. This process was repeated one million times for each trip in order to obtain travel time distributions that accurately reflect the sample distributions.

# RESULTS

**Trip #1: Gaslight to the San Diego Zoo**

A simulation of one million trips on Trip #1 produces the histogram for travel time shown on the left in Figure 5. The dashed lines indicate the trip planner's travel time prediction, the solid lines mark the average simulated travel time, and the dotted lines show the 95$^{th}$ percentile travel time. The shortest travel time is 21 minutes and the longest is 99 minutes. The 50$^{th}$ percentile is reached at 46 minutes and the 95$^{th}$ percentile is reached at 62 minutes. The average is 47 minutes. The longest travel time is 111% longer than the mean and 371% as long as the shortest time. Guidance to potential passengers might be that they should expect the trip to take 47 minutes but in one out of every 20 trips takes longer than 62 minutes.

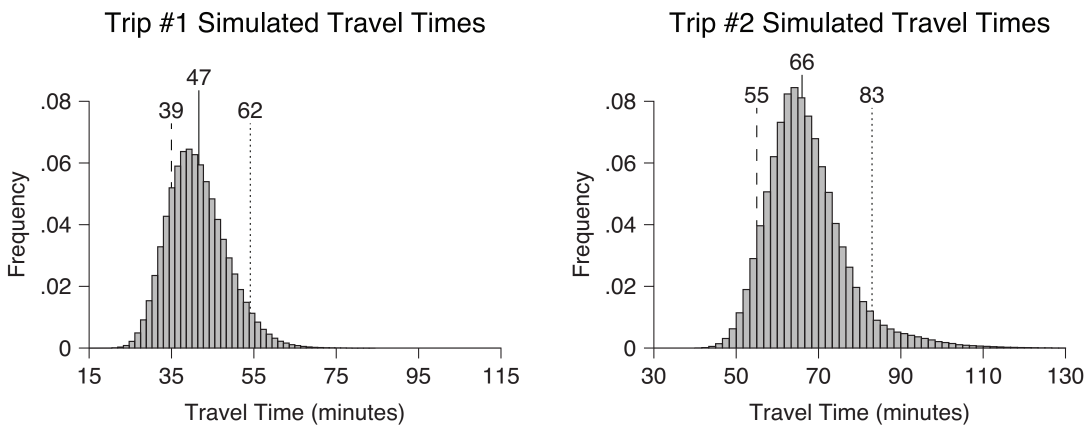


Figure 5: PDFs of one million simulated trips on Trips #1 and #2

The PDF of travel times appears to be normally distributed with a portion of the simulated travel times skewed to the right. These trips represent times when a very long in vehicle travel time was sampled for one of the legs of the trip, not necessarily trips where a connection was missed. Further insight into travel times on this trip can be gained by dividing the simulated trips into those that made or missed each bus.

Table 2 presents a breakdown of the simulations by scenario, with distributions shown in Figure 6. Four out of five simulated trips were able to catch both buses and enjoyed shorted travel times on average. The median travel time increased by roughly 9 minutes for each bus that was missed. Surprisingly, the travel time distribution for trips that missed buses were more tightly grouped (and thus had greater reliability) than those that made both buses. This is discussed in further detail in the following section.

Table 2: Travel time distributions under different trip scenarios

| | Percentage | Minimum (min) | Median (min) | 95$^{th}$ Percentile (min) | Maximum (min) | Mean (min) | Standard Deviation (min) |
|---|---|---|---|---|---|---|---|
| Make Both | 80.8% | 21 | 44 | 58 | 98 | 45 | 7.6 |
| Miss A, Make B | 7.9% | 35 | 56 | 68 | 99 | 56 | 6.8 |
| Make A, Miss B | 10.3% | 22 | 52 | 66 | 96 | 52 | 8.0 |
| Miss A, Miss B | 0.9% | 34 | 63 | 76 | 96 | 63 | 6.9 |
| Total | 100.0% | 21 | 46 | 62 | 99 | 47 | 8.5 |

**Trip #2: Sea World to the Birch Aquarium**

A simulation of one million trips on Trip #2 produces the histogram shown on the right in Figure 5. The shortest travel time is 38 minutes and the longest is 155 minutes. The $50^{th}$ percentile is reached at 66 minutes and the $95^{th}$ percentile is reached at 85 minutes. The average is 67 minutes. Thus, the longest travel time is 131% longer than the mean and 308% as long as the shortest time. Guidance to potential passengers might be that they should expect the trip to take 67 minutes but in one out of every 20 trips takes longer than 155 minutes. The distribution of travel times is approximately normal with a longer tail of high travel times.

On Trips #1 and #2, whether or not Bus A and/or Bus B were missed was tracked for the purposes of exploring the effects of missed transfers on travel time. Travel time distributions corresponding to each scenario are plotted in Figure 6 and described in Table 3. Clearly, missing one or more buses led to increases in travel time on this trip, although (as with Trip #1) the travel time reliability actually increased as well.

This apparent improvement in reliability may be unexpected but according to Figure 4, simulated trips that miss Bus A or Bus B are subjected to no or little additional randomness. If Bus A is missed, a predetermined 15-minute headway is added to the travel time. If Bus B is missed, a Bus B headway (ranging between 13 and 16 minutes) is added to the travel time (note that the standard deviation is greater when missing Bus B than when missing Bus A). Thus, the smaller standard deviations when missing buses are attributed to the smaller sample sizes and the presence of outliers in the "make both" case.

The presence of a few extremely long travel times for Bus A and Bus B on each trip contributed to these patterns. With a greater number of simulations catching both buses on each trip, more "make both" simulated trips had the opportunity to experience an extremely long in vehicle travel time. Thus, the rare occurrence of an extremely long travel time (roughly twice as long as the average travel time in this data) can have a greater effect than the occasional missed bus. However, it is important to note that trips that miss one or more buses do so unexpectedly, so even though the reliability in those scenarios is improved, the passenger can not plan for them, and their existence diminishes the reliability of the trip as a whole.

Table 3: Travel time distributions under different trip scenarios

| | Percentage | Minimum (min) | Median (min) | $95^{th}$ Percentile (min) | Maximum (min) | Mean (min) | Standard Deviation (min) |
|---|---|---|---|---|---|---|---|
| Make Both | 86.8% | 38 | 65 | 82 | 150 | 66 | 9.2 |
| Miss A, Make B | 3.4% | 51 | 73 | 88 | 147 | 74 | 7.9 |
| Make A, Miss B | 9.4% | 54 | 75 | 92 | 155 | 76 | 8.9 |
| Miss A, Miss B | 0.4% | 66 | 83 | 97 | 136 | 84 | 7.3 |
| Total | 100.0% | 38 | 66 | 85 | 155 | 67 | 9.7 |

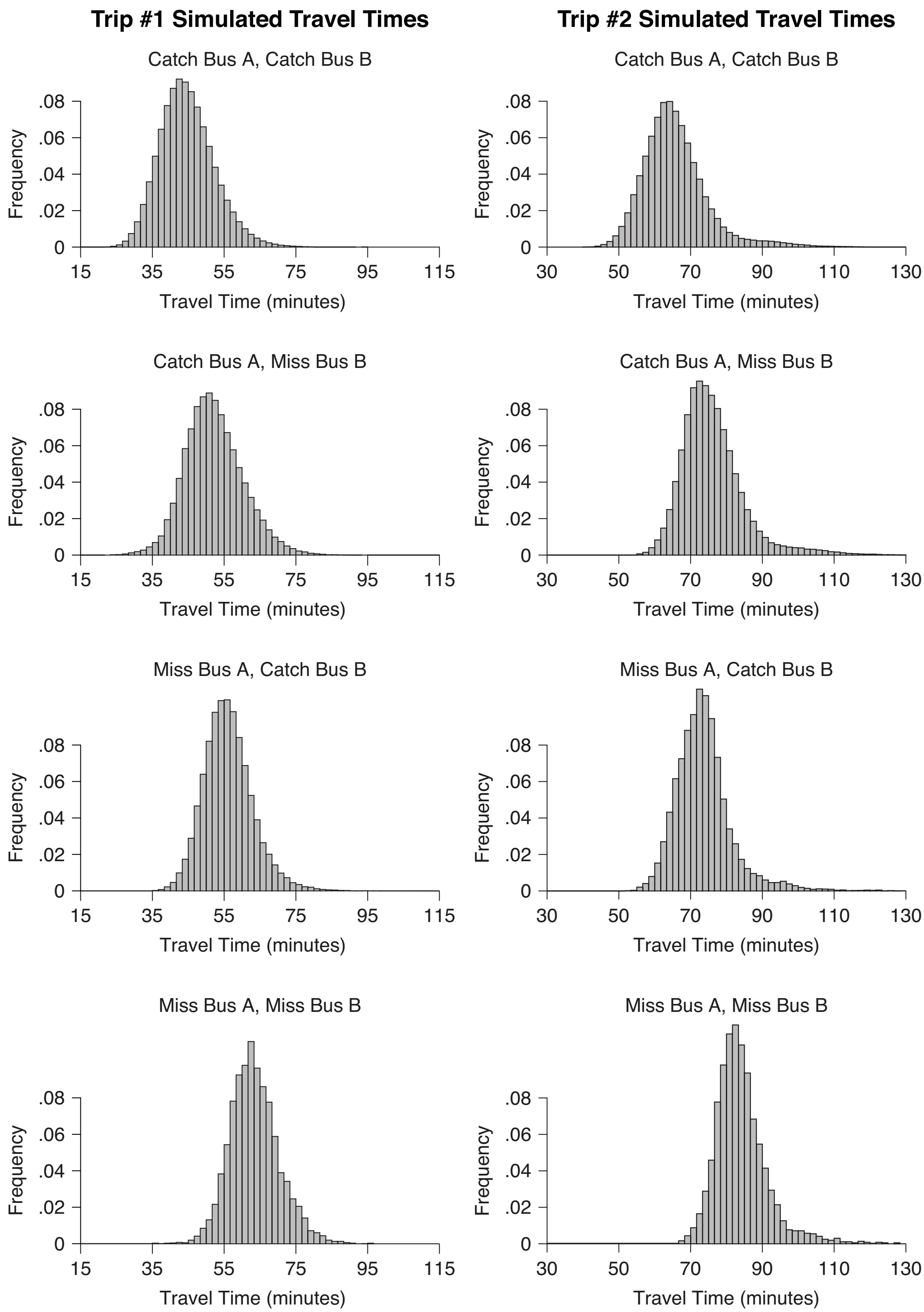


Figure 6: Travel times when catching or missing buses on Trips #1 and #2.

# DISCUSSION

A sensitivity analysis comparing the effects on various measures of travel time (as well as the percentages of simulated passengers who miss one or more buses) on Trip #2 is presented in Table 4. The baseline case represents the results of the simulation with all distributions unaltered. The passenger arrival distribution, Bus B's departure adherence at the transfer stop, and the scheduled transfer time are then each incrementally shifted or scaled to determine their effect on travel time. The scheduled transfer time was held at zero instead of allowing it to go negative.

Table 4: Sensitivity analysis

| | Mean (min) | Median (min) | 95th Percentile (min) | Standard Deviation (min) | Make Both | Miss A, Make B | Make A, Miss B | Miss A, Miss B |
|---|---|---|---|---|---|---|---|---|
| Baseline | 67.0 | 65.8 | 84.6 | 9.7 | 86.8% | 3.4% | 9.4% | 0.4% |
| Pax Arrival + 1 min | 66.9 | 65.5 | 84.9 | 9.9 | 82.2% | 7.9% | 9.0% | 0.9% |
| Pax Arrival + 2 min | 67.1 | 65.8 | 85.4 | 10.1 | 75.1% | 15.1% | 8.1% | 1.7% |
| Pax Arrival + 3 min | 67.6 | 66.5 | 86.1 | 10.2 | 66.4% | 23.7% | 7.3% | 2.6% |
| Pax Arrival * 1.2 | 68.0 | 66.7 | 85.8 | 10.0 | 86.8% | 3.6% | 9.3% | 0.4% |
| Pax Arrival * 1.4 | 68.9 | 67.6 | 87.2 | 10.2 | 86.8% | 3.24% | 9.3% | 0.4% |
| Bus B Departure – 1 min | 66.6 | 65.3 | 84.3 | 9.8 | 83.7% | 3.3% | 12.6% | 0.5% |
| Bus B Departure – 2 min | 66.3 | 65.1 | 84.0 | 9.9 | 78.8% | 3.0% | 17.5% | 0.7% |
| Bus B Departure – 3 min | 66.2 | 65.0 | 83.6 | 9.8 | 73.1% | 3.0% | 23.0% | 0.9% |
| Bus B Departure * 1.2 | 67.3 | 66.0 | 85.3 | 9.8 | 86.8% | 3.5% | 9.4% | 0.4% |
| Bus B Departure * 1.4 | 67.6 | 66.2 | 86.1 | 10.0 | 86.6% | 3.5% | 9.6% | 0.3% |
| Scheduled Transfer Time – 1 min | 66.5 | 65.2 | 84.2 | 9.8 | 83.8% | 3.2% | 12.5% | 0.5% |
| Scheduled Transfer Time – 2 min | 66.2 | 64.9 | 83.5 | 9.7 | 79.6% | 3.2% | 16.6% | 0.7% |
| Scheduled Transfer Time – 3 min | 65.8 | 64.5 | 83.2 | 9.8 | 76.4% | 3.0% | 19.9% | 0.8% |
| Scheduled Transfer Time * 0.8 | 65.5 | 64.3 | 82.3 | 9.3 | 84.9% | 3.2% | 11.4% | 0.4% |
| Scheduled Transfer Time * 0.6 | 64.1 | 62.8 | 80.3 | 9.0 | 81.0% | 3.3% | 15.2% | 0.6% |

Each of these fifteen alternative scenarios is designed to disrupt transfers. However, even a transfer is disrupted there may be no change to in-vehicle travel time, which makes up the bulk of the total travel time. For example, when Bus B's departure was shifted 3 minutes earlier, the number of passengers missing the second bus increased by 144%, with each of those passengers experiencing a delay of one Bus B headway. However the mean travel time in this scenario only increased by one minute. This could be because the length of the transfer is a relatively small part of the total travel time on Trip #2 due to its length. Also, shifting departures earlier makes all trips in which the bus is not missed start sooner, decreasing wait times overall and offsetting increases in the mean and median due to missed connections. This suggests that traditional performance metrics (even reliability-based metrics) may not capture the effects of missed transfers on a small proportion of the ridership.

When the scheduled transfer time is confined to a tighter range, travel time reliability (as measured by standard deviation) increases. This is because the distribution of transfer times has such a wide range on this trip (from 1 to 26 minutes) that when those long transfer times are cut nearly in half (as in the *Scheduled Transfer Time * 0.6 case*), each simulation benefits equally from reduced transfer times, even though the percentage of passengers who miss Bus B rises.

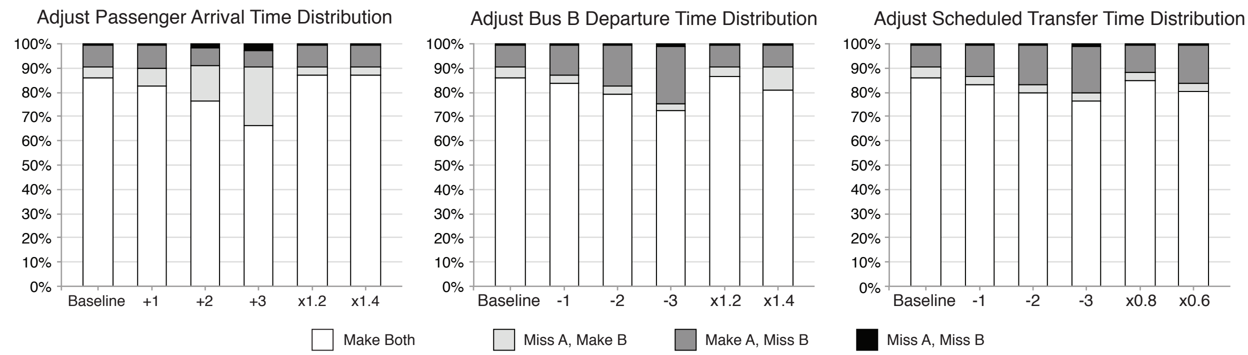


Figure 8: Sensitivity analysis

# CONCLUSION

This paper has leveraged a simulation-based approach to demonstrate the possibility of determining the percentages of passengers who could be missing transfers on a trip. These missed transfers could be due to late passenger arrivals, mistimed vehicle arrivals at the transfer point, or a transfer time that is too short as scheduled. The impacts of these missed transfers on travel time and travel time reliability are explored through a sensitivity analysis. It is concluded that unusually long in vehicle travel times can have a larger effect on traditional reliability measures than missed transfers, potentially hiding the existence of missed transfers on a trip.

# ACKNOWLEDGEMENTS

This work was sponsored by the second Strategic Highway Research Program (SHRP2). The authors would especially like to thank Alixandra Demers and Isaac Kumar for their help and feedback. The members of the SHRP2 L02 team also provided valuable feedback on developed methodologies. The authors would also like to thank SANDAG for providing access to the APC data.

# REFERENCES

[1] Kittleson; Urbitran; LKC Consulting; MORPACE International; Queensland University. *Transit Cooperative Research Program Report 88: A Guidebook for Developing a Transit Performance-Measurement System.* Transportation Research Board of the National Academies, Washington, D.C., 2003.

[2] Muller, Theo H.J., and Furth, P.G. *Transfer Scheduling and Control to Reduce Passenger Waiting Time*. Transportation Research Record, No. 2112. pp.111-118, 2009.

[3] Knoppers, P., and Muller, T. *Optimized Transfer Opportunities in Public Transport*. Transportation Science. Vol. 29, No. 1. February 1995.

[4] Liu, R., Pendyala, R.M., Polzin, S. *Assessment of Intermodal Transfer Penalties Using Stated Preference Data*. Transportation Research Record, No. 1607. pp. 74-80.

[5] Pursula, M., and Weurlander, M. *Modeling Level-of-Service Factors in Public Transportation Route Choice.* Transportation Research Record, No. 1669. pp. 30-37.

[6] Levine, J., Hong Q., Hug, G. E., and Rodriguez, D. *Impacts of an Advanced Public Transportation System Demonstration Project.* Transportation Research Record, No. 1735.

[7] Bowman, L.A., and Turnquist, M.A. *Service Frequency, Schedule Reliability and Passenger Wait Times at Transit Stops*. Transportation Research*,* 15A:6, pp. 465-471, 1981.