DECOMPOSITION AND SENSITIVITY ANALYSIS OF BUS TRAVEL TIMES

Yuxuan Wang, Corresponding Author
Department of Civil, Geology and, Mining Engineering
Polytechnique Montréal, Montréal, Québec, Canada, H3T 1J4
Email: yuxuan.wang@polymtl.ca
ORCID: 0000-0002-1512-8846

Catherine Morency, Ph.D.
Department of Civil, Geology and, Mining Engineering
Canada Research Chair in Mobility
Polytechnique Montréal, Montréal, Québec, Canada, H3T 1J4
Email: cmorency@polymtl.ca
ORCID: 0000-0002-3211-4243

Martin Trépanier, Ph.D.
Department of Mathematics and Industrial Engineering
Interuniversity Research Center on Enterprise Networks, Logistics and Transportation
Canada Research Chair in Transportation Transformation
Polytechnique Montréal, Montréal, Québec, Canada, H3T 1J4
Email: mtrepanier@polymtl.ca
ORCID: 0000-0001-8408-8035

Word Count: 7395 words + 0 table(s) × 250 = 7395 words

Submission Date: August 11, 2024

ABSTRACT
Transit service reliability is important for transit planning and operations as well as passenger experience. Large travel time variations increase operating costs and negatively affect passenger satisfaction. Existing literature focuses on specific aspects of transit travel times but less on how these aspects interact with each other. This paper proposes to combine previous research efforts by further decomposing observed trip travel times. Then, we identify important trip elements affecting the overall travel time reliability, as well as how much variation can be attributed to each trip element. More specifically, variance-based and one-at-a-time sensitivity analyses were used to answer these questions.

The analyses show that the overall travel times and red light waiting times are more affected by interaction effects between trip elements, whereas the overall inter-stop times and dwell times are mainly affected by large individual variations of inter-stop speeds and ridership respectively. Trip departure time, even when changed by a few minutes, can greatly affect the overall trip travel times and red light waiting times for most routes analyzed. This is mainly due to the varying cycle lengths in our fixed signal timing plans as well as their interactions with inter-stop and ridership variations. The results suggest that planners must consider potential chain reactions where small variations in one trip element can lead to significant changes in the overall trip times.

These findings will help planners better pinpoint the elements affecting travel time variation on each route, which will help create strategies to improve travel time reliability.

Keywords: Transit Planning, Transit Travel Times, Travel Time Variations, Sensitivity Analysis

INTRODUCTION

Reliable travel time is important for both transit agency operations and passenger satisfaction. Transit agencies and planners have been striving to achieve better reliability. From the agencies' perspective, travel time reliability affects both vehicle and operator scheduling. Transit planners typically add schedule padding or layover times to account for potential travel time variations, which will, unfortunately, increase the operating costs (*1*). Missing a layover will also propagate delays to downstream trips and cause driver dissatisfaction issues (*1*). Unreliable travel times will also force passengers to budget additional times in order to arrive at their destination on time, which in turn affects their satisfaction and mode choice (*2*). Some passengers value reliable service more than service frequency and faster travel times (*3, 4*).

Many studies have looked at the reliability of transit travel times from specific perspectives, such as travel times on various analysis levels (e.g. timepoint to timepoint) (*5*), dwell times at stops (*6*), as well as signal priority measures at intersections (*7*). However, little attention has been paid to how these different elements interact with each other. For example, due to signal synchronization, if the vehicle always arrives at the stop during the red light, maybe dwell time variation becomes less critical. On the other hand, if the vehicle always arrives during the green light, the previous inter-stop traffic and dwell time can become more critical when the driver tries to cross the intersection before the light turns red. Thus, it is still important to consider the interactions between different trip elements as well as to quantify the sensitivity of each trip element.

This paper aims to combine the previous research efforts and answer the two following questions. Where do travel time variations come from? How much travel time variation can be attributed to each trip element, i.e. departure time, inter-stop speed, ridership change, and traffic signal timing change?

We propose to answer these two questions by further decomposing observed trip travel times using 3 months of archived transit data from various sources in Montréal, Canada. More specifically, we obtain the departure time and inter-stop speed from the automatic vehicle location system. The dwell time model is estimated based on 25,000 on-board observations and the model is applied to the ridership data obtained from automated fare collection where there are no on-board observations. The traffic signal timing plans, including the timing plan changes, offset, red length, and cycle length, are also estimated based on the vehicle location observations using the methodology proposed by Fayazi et al. (8). Since traffic signal timings are not under the agency's control, we treat them as a fixed input and analyze the variations in red light waiting times as a result.

Finally, we conduct two sensitivity analyses on these decomposed times to demonstrate the importance of each trip element. First, we propose to use the variance-based analysis, followed by the one-at-a-time analysis. The variance-based analysis is a global method that can handle interaction effects and non-linearity among different variables (*9*). The results provide two indices regarding the proportion of variation that can be attributed to each trip element, one with the interaction effects and one without. We also perform some example one-at-a-time analyses to demonstrate the non-linearity observed between the variation of a trip element and the overall variation in trip travel times.

The results will enhance our understanding of travel time variations and help planners identify certain locations or trip elements affecting travel time variations. In turn, these insights could help agencies target specific issues, choose the appropriate strategy to improve the reliability of a given route, develop more robust transit schedules, and thus improve passenger experiences.

This paper is structured as follows. We will summarize existing research contexts in section 2. The research framework, data sources, and detailed methodology are explained in section 3. Section 4 shows the result of our case study using data from Montréal. Finally, we conclude this paper in section 5.

LITERATURE REVIEW

Transit reliability measures are commonly used by transit agencies in their planning and operations. Academics have also studied specific elements of transit reliability and proposed numerous additional measures. The focus of current literature is typically on different levels of travel times variations, ridership variations which relate to dwell times, and transit priority measures.

Research has focused extensively on transit travel times since the implementation of Automated Vehicle Location systems. Travel time variations are important for transit agencies because they serve as a key scheduling input to determine the schedule padding and layover times needed, which affect vehicle requirements (*10*). The variations are typically analyzed at four different levels, line, trip, timepoint to timepoint, and stop to stop levels according to an agency survey (*1*). The analyses for travel time variations have focused on typical variation measures such as the standard deviation, coefficient of variation, or a predefined percentile (*10*).

Common factors affecting transit travel times are typically route length, passenger activity, and number of signalized intersections dating back to 1984 from Abkowitz and Engelstein (11). Researchers also show the number of stops, direction, time-of-the-day, dwell time, and weather variations also have significant effects on route run time (*12*). Some researchers have also observed mixture travel time distributions in recent years (*13*), which have more than one peak in the distribution shape, unlike the Normal distribution with one single peak. These underlying components in mixture distributions can relate to different traffic states, such as congested state and free flow state (*13*).

In addition, even the smallest scale so far, namely the stop-to-stop scale, consists of the travel time between the two stops, dwell time at one stop, and potentially multiple traffic signal waiting times. Buses routinely wait for traffic signals and higher ridership at a stop could also contribute to buses missing a green light. A much finer analysis scale with the ability to better isolate various trip elements and handle interaction effects among these elements is needed to attribute the travel time variation to a specific issue or a combination of issues.

Dwell times have also received high coverage in previous studies. It is defined as the time a vehicle spends at stops for passenger boarding and alighting, typically the time between the door opening and closing (*10*). Similar to travel time studies, dwell time studies have also focused on typical variation measures such as the standard deviation, coefficient of variation, or a predefined percentile (*10*). Some studies analyzed stop-level dwell times, which can be compared with vehicle load to understand the source of dwell time variability. The variability could be due to passenger boarding and alighting activities, existing crowding in vehicles which makes boarding and alighting difficult, fare payment methods, and ramp usages (*6, 14, 15*). However, there is less attention in the existing literature on how dwell times might impact the overall travel times.

The Transit Capacity and Quality of Service Manual (*10*) does not consider the time a vehicle remains stationary at the stops after passenger boardings and alightings as dwell time, such as red light waiting time. Most traffic signal-related studies in the transit context are related to transit signal priorities for transit vehicles. Many studies show positive impacts of transit priority signals on reducing transit travel times (*16*). However, some other studies failed to show any significant travel time gains from signal priority (*17*).

For some cities, the majority of the signalized intersections still use a fixed timing plan. Researchers have suggested that good arrival time predictions are important in these cities for transit priority signals to be effective at reducing travel times (*18*). Better inter-stop and dwell time estimations are needed to improve the arrival time predictions. Scheduling strategies can also be adapted to take advantage of transit priority signals (*19*). However, these previous studies tend to focus on one specific intersection or a few consecutive intersections on a given corridor, which would have similar base timings. Similarly, some studies only included the number of priority signals to model their effects which essentially assumes these signals behave similarly. Since buses can make turns and travel through multiple corridors, the signal synchronization and cycle lengths may all be different in reality. Smaller intersections typically have shorter cycle lengths, while large intersections have longer cycle lengths. There is still a need to consider how the travel time and red light waiting times are affected by various trip elements.

Overall, the literature mostly focused on the travel time impacts from one specific element of the transit system, namely the variation in travel times, dwell times, and signal priorities. There is still less attention on combining these various elements to examine how these travel time elements affect and interact with each other. For example, given a signal synchronization, if the vehicle always arrives at the stop during the red light, dwell time variation can become less critical since the bus is stopped by the signal anyway. On the other hand, if the vehicle always arrives during the green light, the previous inter-stop traffic and dwell time can become more critical when the bus tries to rush through the intersection before the light turns red.

In addition, since transit agencies have limited resources, there is still a need to help planners prioritize their resources. Thus, it is important to determine which trip element is more important on a given route to reduce the overall travel time variations. By evaluating the importance of each trip element, planners can select a good and effective strategy to improve the reliability of a specific route.

Thus, in this paper, we propose a framework to further decompose transit travel times so that the variation of each trip element along the route can be isolated. Given the limitations of earlier studies, we also conduct a sensitivity analysis to rank the importance of each trip element for their potential impacts on the overall travel times. We aim to provide better tools to help planners diagnose and improve transit reliability.

METHODOLOGY AND DATA

Figure 1 shows our research framework. The basic idea is to decompose the trip travel times into the sum of a sequence of times. For this paper, we decompose the trip travel times into three categories, inter-stop times, dwell times, and red light waiting times. To reconstruct the arrival times at each stop, we also need to include departure times in our analyses.

To get these detailed times, we use the General Transit Feed Specification (GTFS), GTFS Real Time (GTFS-RT), OpenStreetMap, Automated fare collection, and some ride-check observation data. The departure times and inter-stop speeds are directly obtained or calculated from the GTFS-RT feed. Due to the lack of door-closing times, we estimate a simple dwell time model at the stop level using ride-check observation data and apply the model to the fare transaction data. The traffic light settings are also estimated following the methodology proposed by Fayazi et al. (8).

Then the decomposed travel times are grouped by route direction and three different time-of-the-day and used for sensitivity analyses. Here we focus on both the variance-based analysis (*9*) which is a global method that quantifies the proportion of variance that can be attributed to each variable, and one-at-a-time sensitivity analysis to better illustrate the non-linearity between the input variables and the overall travel times. Since sensitivity analyses require varying one or more variables, we can adjust the inter-stop and dwell time variables given the observations. However, since signal timings are not within the agency's control, we calculate the resulting red light waiting times given arrival time and the signal timing plan as input.

We use the data provided by Société de Transport de Montréal on the island of Montréal in Canada as a case study. The system currently has 222 bus lines in operation, about 2000 buses in the fleet, and more than 17,000 published bus trips on average weekdays. More detailed information regarding the methodologies and data used in each step can be found in the subsections below.

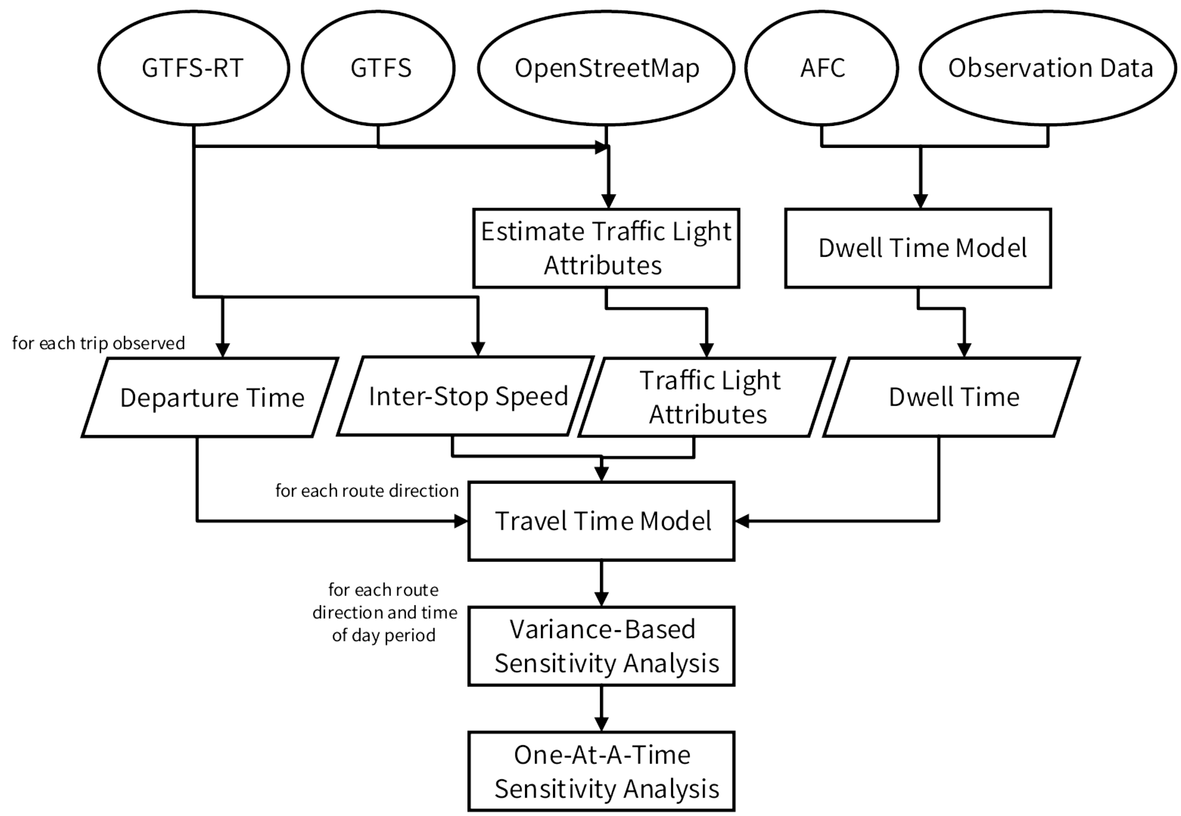

FIGURE 1 Research Framework

Defining the Trip Elements

The GTFS file provides detailed information on the planned services, such as schedules and geographical information for the routes and stops. Since it only publishes transit-related information based on stop arrival and departure times, we need to add more detailed information to better isolate each trip element for our analysis.

To reconstruct the travel and arrival times, we need to calculate four categories of information, the departure time, a series of inter-stop times, a series of dwell times, and a series of red light waiting times. The sequence of these times is ordered as follows, first, we depart from stop

1 at a given departure time, followed by the inter-stop time to stop 2, then the dwell time at stop 2 if applicable, and finally the red light waiting time at stop 2 if applicable. The pattern then repeats itself for the following stop-to-stop pairs until the service destination. Thus, we define our input variables following the same logic for every trip.

Since there may or may not be traffic lights between two scheduled stops, we will consider these traffic lights as a stop with no ridership for simplicity. If there is a traffic light at the near-side stop, we will merge them to have a single stop point at the stop line. If there are traffic lights in between two stops, we will split the original stop-to-stop segment into two to better isolate the potential red light waiting time variations and inter-stop variations. To split the routes into these sections, we used the route shape from GTFS and matched traffic light positions from OpenStreetMap, so that we can estimate the red light waiting times in later steps using the vehicle location information.

Estimating Traffic Signal Settings

To estimate the traffic signal settings, we mainly followed the methodology proposed by Fayazi et al. (8) with some minimal modifications to handle a few particularities of our local vehicle locations feed. The basic idea is to overlap stop times at a given traffic light observed over a given time-of-the-day, then test out various cycle lengths and signal offsets to see which combination fits the observations the best. Then, using a moving window, we can detect changes in traffic signal schedules, such as peak schedule vs off-peak schedule. Readers interested in the details can refer to the original paper cited here.

To verify the estimated signal settings, we conducted ride-checks on board buses and point-checks at intersections. The estimation errors are typically around 3 to 5 seconds. We consider this acceptable, as it is similar to the length of yellow lights. As mentioned in the original paper, drivers have different risk tolerances towards yellow lights, some may treat it as a green light and some may treat it as a red light, thus causing some slight discrepancy in the estimated timing (*8*). For Montréal, we mainly use fixed signal timing plans with very little flexibility which allows this estimation method to function well. Unfortunately, the sensitivity for more flexible timing plans and more aggressive transit signal priorities have to be left for future research.

Getting Departure Times and Inter-Stop Speeds

This step mainly uses the GTFS-RT data, which provides the actual bus arrival and departure times at stops, as well as detailed bus location and speed information around every 5 to 20 seconds. Using this information, we can directly obtain or calculate the departure times and inter-stop speeds needed for our analyses. Here, we used 3 months of archived data from Jan 8, 2024 to March 24, 2024.

The sensitivity analyses require changing and swapping variables from the original observations. If the analysis includes a change to make an extra stop, the inter-stop times cannot be directly applied due to the extra slowdown and acceleration time needed. Thus, we decided to calculate the inter-stop speed from the original observation, and then convert it back to inter-stop time to include the time changes due to additional or skipped stops.

Since this project focuses on travel times, outlier observations, such as major detours, might greatly affect the sensitivity of travel time, and agencies are typically aware of these types of travel time variations. Thus, we will remove these outliers from the analysis using Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (*20*), which is a density-based algorithm to identify clusters and outliers in the data. For each trip, we compare the similarities of the trip departure, travel time and delay observation for all trips. The outliers, such as significant delays and unusually long or short travel times, are identified where the observations are less similar to the others and are removed from the analysis.

Estimating Dwell Times

The dwell time is defined as the time for passengers boarding and alighting the bus (*10*). However, due to the lack of door-closing times and some drivers leaving the door open while waiting for the red lights, we will estimate a dwell time model using ride check observation data.

The ride check observations include detailed door opening times, number of boardings, and number of alightings. The end of dwell time is defined as either the door closing times collected on-board, or 5 seconds after the last passenger boarding or alighting in case the driver leaves the door open. Then, using roughly 25,000 dwell time observations over two years, we estimated a simple dwell time model using linear regression using these observations following the example from Dueker et al. (6). For trips without on-board observations, we used the origin-destination from fare transaction data to obtain the passenger counts at each stop, and applied the estimated dwell time model for decomposition.

We acknowledge that the dwell time model is in no way perfect, and dwell time variations deserve more research on their own. However, due to the time limit, we will settle with these imperfections for the moment, and leave improving dwell time models and understanding its variations as a future research task.

Example of decomposing a stop-to-stop travel time observation

Finally, to sum up these detailed time breakdowns, Figure 2 shows an example time distance diagram for one stop-to-stop travel time observation. The stop-to-stop travel time is split first into the inter-stop time where the bus travels to the next at the given departure time. Then, as the bus stops at the second stop, the stopped times are split into dwell times according to the dwell time model and red light times according to the traffic signal model mentioned above. The decomposition is performed for every stop-to-stop observation.

Sensitivity Analyses

Sensitivity analyses are typically used to attribute the variation of model outputs to the input space. In this paper, we analyze the sensitivities by route direction and by three time-of-the-day periods, since the signal synchronization, ridership pattern, and traffic conditions may be different. There are typically two main categories of sensitivity analyses, one-at-a-time and global analyses (*9*). We will provide a quick introduction to both methods in this subsection.

Variance-Based Sensitivity Analysis

Due to the complexity and non-linearity typically observed in previous travel time studies, we first consider the variance-based sensitivity analysis, which is a global method that can handle non-linearities between input and output results. A quick summary of the method is that it varies all input variables at the same time. Then, it sends the inputs to the model, which is considered a black box. Next, it decomposes the total variance of the model output into partial variances and attributes the partial variances to individual input variables. Readers who are interested in more detailed derivations and explanations can refer to Saltelli et al. (9).

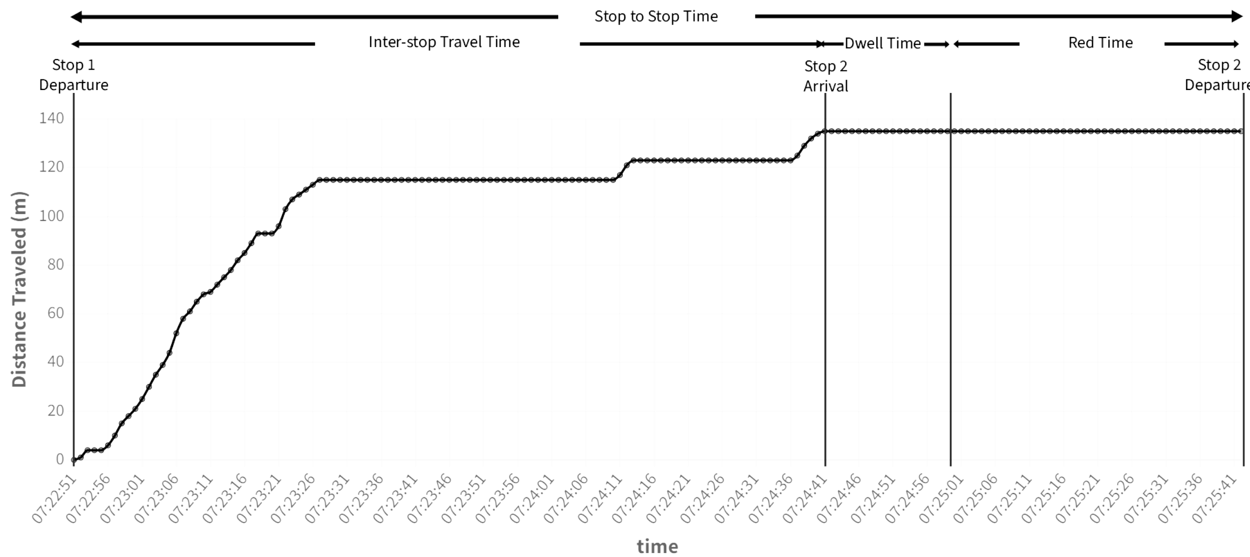

FIGURE 2 Example: Splitting a Stop to Stop Travel Time Observation

The model produces two indices, the first-order index and the total-order index. The first-order index shows the percentage of the total variance caused by the variation of a given input variable, without interaction effects (*9*). It is formulated as

$$S_i = \frac{Var[E(Y|X_i)]}{Var(Y)} \tag{1}$$

Similarly, the total-order index shows the percentage of the total variance caused by the variation of a given input variable, with interaction effects (*9*). It is calculated as the complement of the variance produced by varying all but one variable, normalized by the total variance.

$$S_{Ti} = 1 - \frac{Var[E(Y|X_{j\neq i})]}{Var(Y)} \tag{2}$$

These indices lie between 0 and 1, since they represent a percentage of total variance. These indices can also be used for ranking purposes according to the share of total variance attributed to each input.

To generate the samples needed to calculate these indices, researchers typically conduct a Monte Carlo simulation (*9*) to uniformly sample all input space. However, given the various travel time distributions observed from previous studies (*13*), we decided to focus on the empirical data distribution observed here. To analyze the sensitivity, we use one observed trip as a base case, then gradually replace different sections of the trip using the observations from a different trip to calculate the overall travel time changes.

One-At-A-Time Sensitivity Analysis

One-at-a-time sensitivity analysis is a typical direct approach to see the effect of changing one input on the output (*21*). The steps are incrementing one input variable while keeping the others constant, then returning the changed input to its original value, and repeatedly changing the other variables in the same way. Sensitivities are typically measured by the partial derivatives, i.e. the amount of changes observed in the output by changing the input by 1.

Due to its simplicity, the method does not examine the entire input space like the variance-based method from above, and thus the results do not show the interaction effects and non-linearity (*21*) between variables. Due to its easy-to-understand nature, we decide to include this method to better illustrate the sensitivity results and non-linearity between trip travel times and various trip elements. However, we will not aggregate the results into one number in this paper due to the limitations mentioned above.

CASE STUDY: MONTRÉAL

In this section, we present the sensitivity results using the data from Montréal. First, we will provide a quick overview of the variance-based global analysis results, and some examples of the one-at-a-time results to demonstrate the non-linearity observed. The data and conclusions may be specific to Montréal, but the readers can nevertheless adapt the methodology for their cities and draw their conclusions.

Variance-Based Sensitivity Results

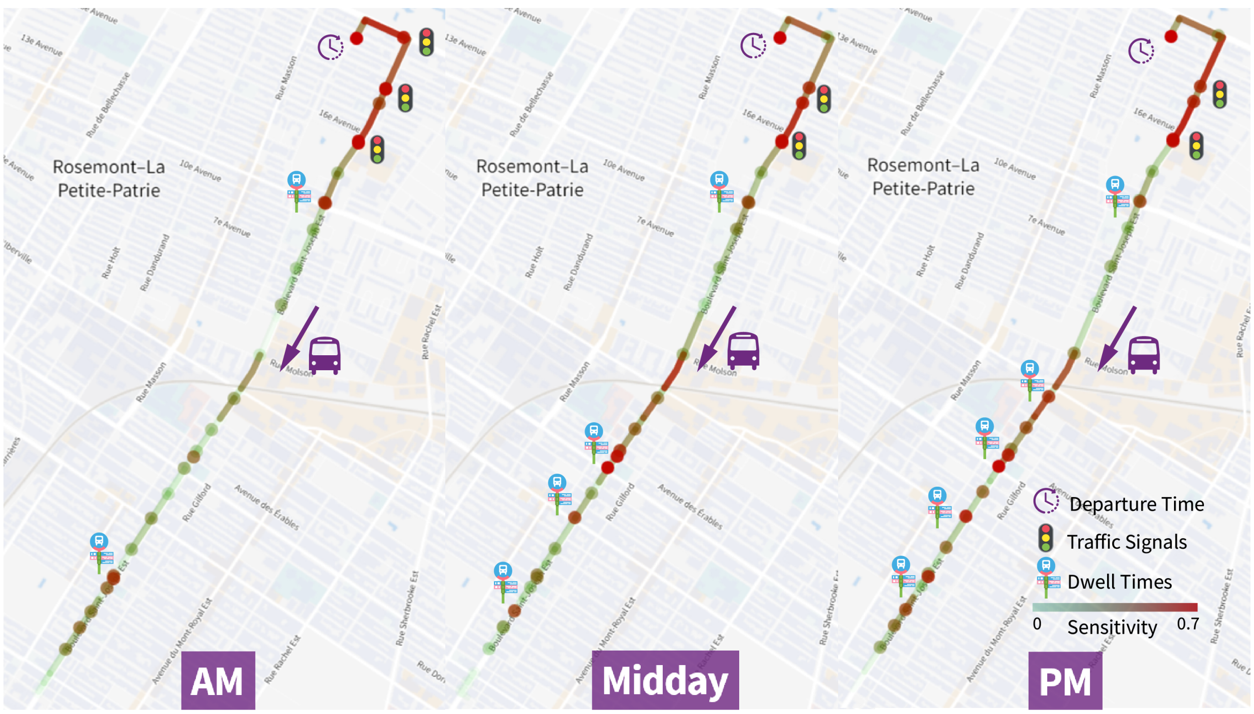

FIGURE 3 Example: Sensitivity Indices for Westbound Route 27, where relatively red colours show more importance and relatively green colours show less importance

Here, we first present the global results using westbound route 27 as an example, then we will summarize the global sensitivity results for 20 selected routes we have analyzed in the subsections. Route 27 is relatively short and straightforward. The 4.1 km route operates on a secondary corridor Saint-Joseph Boulevard through a densely populated neighbourhood on the eastern side of the city. Its daily ridership is an average of 2400 passengers, mainly feeding passengers into the metro service which is its western terminus.

Since we decomposed each stop-to-stop segment into 4 variables, departure time, inter-stop time, dwell time, and red light waiting time, the 22-stop service has 83 input variables. Due to the length, we try not to include a detailed table showing every single result. Instead, we will include a map highlighting the most important variables (Figure 3) and we will include examples of more detailed numbers in the explanations.

For this route direction, the most important factor for both the first-order and total-order indices is the departure time for all three time-of-the-day periods, shown as a dark red circle on top of the figures. 8% of the total variance during the AM peak can be attributed to the departure time without interaction effects (first-order). In terms of standard deviation for context, it is roughly 5 seconds. If we include the interaction effects (total-order index), the departure time attributes 67% of the total variance during the AM peak (roughly 40 seconds in terms of standard deviation). However, the sensitivity for departure time changes slightly later in the day. The first-order indices for the midday and pm peak periods are 6% and 18%. The total-order indices for the midday and pm peak periods are 47% and 42%.

The second most important factor for the trip travel times is the traffic light timing changes, shown in the sections and points near the top of the maps. During the study period, there was a traffic light timing plan change due to a newly implemented bike lane as well as improved pedestrian crossings. The change in signal timing contributed on average 2% of the total variance without interaction effects (1 second in terms of standard deviation), but 20% of the total variance with interaction effects (12 seconds in terms of standard deviation) for all three time-of-day periods. Thus, a change in traffic light timing may not cause a significant variation in travel times locally, but planners must consider the potential chain reaction it has with other sections of the route when evaluating the impacts of signal timing plan changes.

As for the overall red light waiting times, we can observe the same pattern. For the departure times, the first-order sensitivities are still around 8% and the total-order indices remain around 60% to 70%. Thus, there is a strong correlation between the sensitivity of red light waiting times and the overall trip travel times. We therefore emphasize the need for transit planners to pay more attention to the base timing of traffic signals and their interactions with transit vehicles.

The sensitivity results for the overall inter-stop and dwell times are similar. The most important variable for the inter-stop time variation is the segment at the top of the maps which has the largest variance. Similarly, the most important factor affecting the overall dwell time variation is the stop with the largest ridership variance, located in the lower part of the map for the AM peak, and the middle of the maps for the midday and PM peak.

To summarize, the above observations show strong interaction effects between input variables for the overall trip time and the overall red light waiting times, given the larger differences between first-order and total-order sensitivity indices. Thus, the result emphasizes the need to include and better understand interaction effects in transit travel time studies. The results also show little interaction effects for the inter-stop times and dwell times given our assumptions, which makes it easier for planners to improve reliability for times in these two categories.

We will try to demonstrate the potential variations caused by different variables and the non-linearity relationship by applying the one-at-a-time analysis on this route as an example in later sections.

Factors Affecting Trip Travel Time

Figure 4 shows the most important factors contributing to overall trip time variations for 20 routes at various time-of-the-day periods. As we can observe from the figure, the most important factor

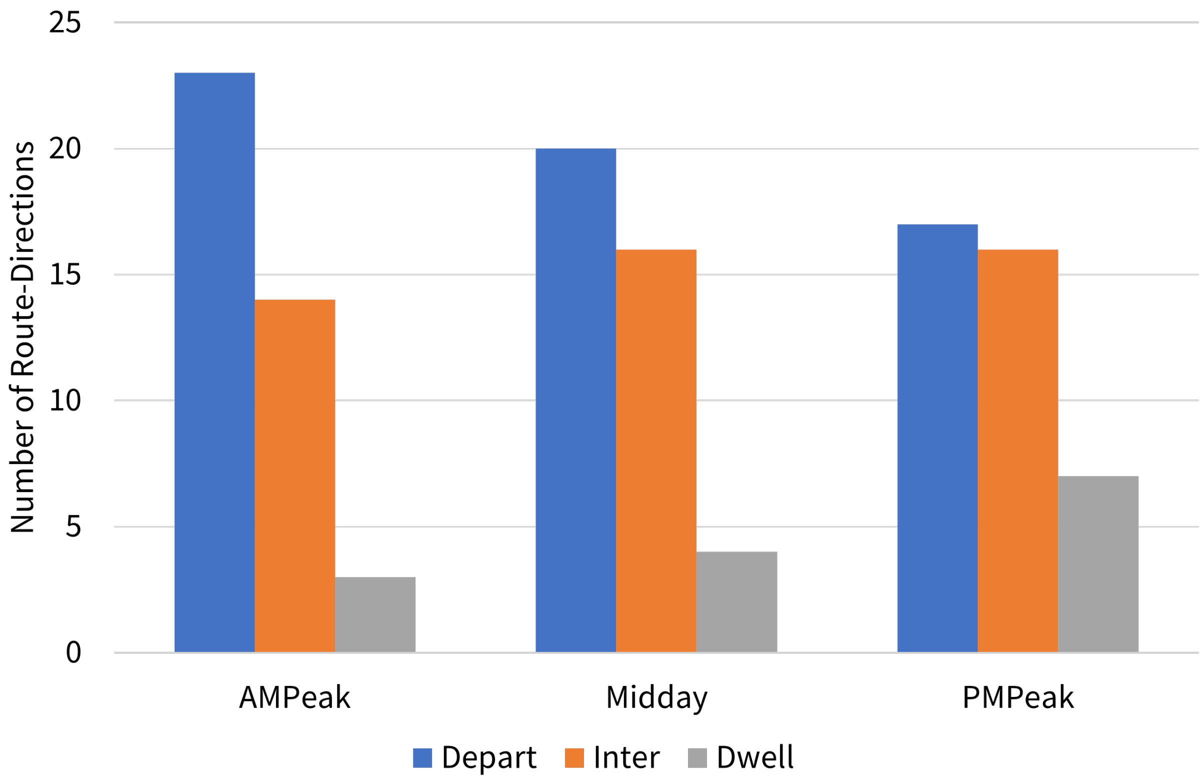

FIGURE 4 Most important factors contributing to overall trip time variations for 20 routes at various time-of-day periods

can change throughout the day. Thus, planners may need to consider different strategies to improve transit reliability at various time-of-the-day periods.

The departure time contributes the most to the trip travel time variations for most of the routes analyzed. However, the number of route directions with departure time as the most important factor decreases as the day goes on, decreasing from 23 routes during the AM peak to 20 routes during midday to 17 routes during the PM peak. The number of routes having inter-stops as their most important factor grows from 14 to 16 from AM peak to midday. The number of route directions with dwell time as their most important factor grows from 3 to 7 throughout the day.

We believe this could be correlated to the travel pattern changes or signal timing plan changes. For the AM peak, the traffic patterns and ridership patterns are relatively stable, mostly people going to work or school as shops and other destinations are not yet open. As the day goes on, more shops and restaurants begin to open, the traffic and ridership variations become more important to some routes.

In addition, the changes may correlate to the three signal timing plan changes during the day as well. During the off-peak hours, such as midday, midnight, and weekends, the signals typically use the same timing plan. During the two peaks, the timing plan is changed to facilitate the travel towards downtown in the morning or away from downtown in the evening. Therefore, we need to consider how these factors might potentially affect the overall red light waiting times.

Red Light Waiting Time

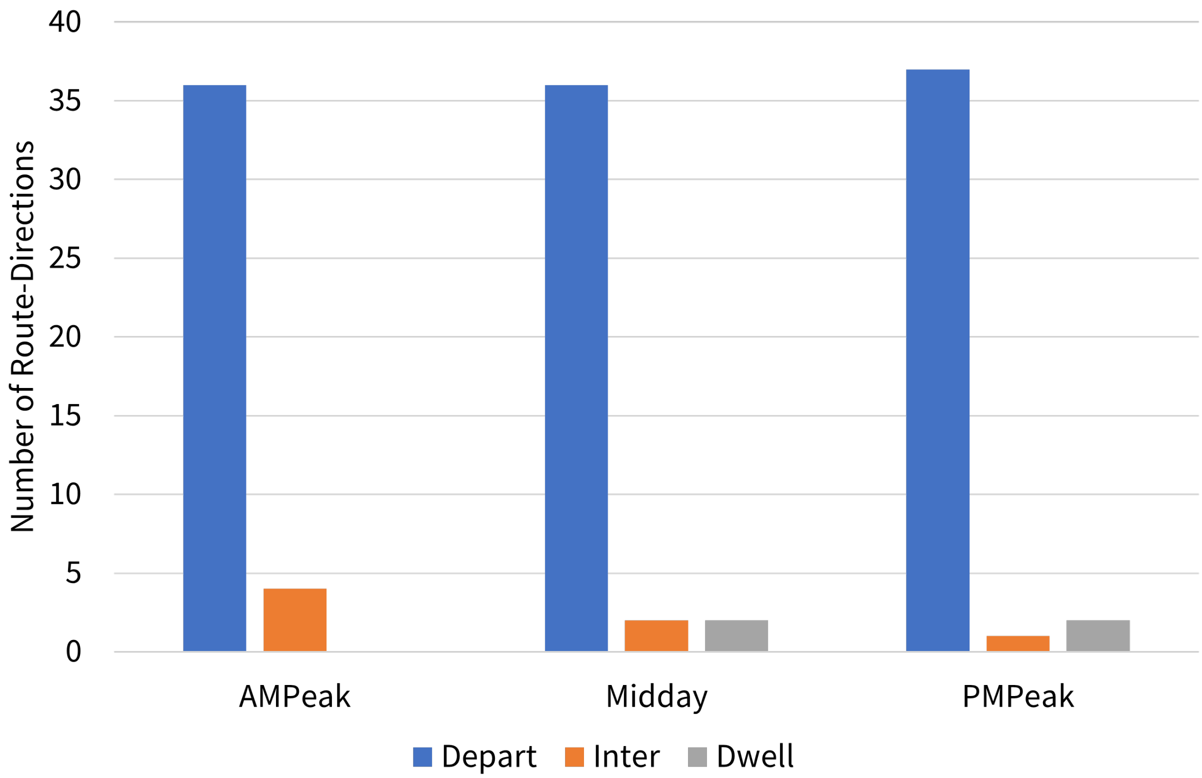

FIGURE 5 Most important factors contributing to overall red light waiting time variations for 20 routes at various time-of-day periods

Figure 5 shows the most important factor contributing to the overall red light waiting time variations. The most important factor for 20 routes is almost all departure time changes, and the pattern remains stable throughout the day. The 20 routes analyzed in this paper are all located near the center of the city, thus having a higher density of traffic lights. The red light waiting time counts towards 20% to 25% of trip travel times for these 20 routes, and it is the category with relatively high variance. This observation shows that it is really important to choose the right departure time. If the planners want to reduce the red light waiting time variations, there is a need to consider how departure time changes affect red light waiting time variations when adjusting the schedules.

Currently, the signals follow a fixed timing plan with varying cycle lengths given the importance of an intersection. Larger intersections have longer cycle lengths, and quieter intersections have shorter cycle lengths. Thus, green waves do not necessarily line up perfectly for the entire bus route at all times. The importance of departure time arises from how synchronized or desynchronized the signals are. Given the importance of departure time on red light waiting times, a potential strategy to reduce the red light waiting time variations could be a more aggressive signal priority that is applied more in advance.

In addition, a common assumption used when creating schedules and optimizing vehicle assignments is to assume travel times remain the same within a few minutes. Intuitively, traffic congestion levels may stay similar and ridership may remain similar if we change the departure time by a few minutes. However, as it is shown here, the red light waiting times may be significantly affected by departure time changes. Thus, planners need to be careful when optimizing for bus schedules that the constant travel time assumption may not be applicable everywhere.

Inter-stop Travel Time and Dwell Time

The differences between first-order and total-order sensitivities are very small for the overall inter-stop and dwell times. Therefore, the results suggest little interaction effects contributing to the variation of inter-stop times and dwell times.

The important factors affecting the overall inter-stop times are all inter-stop variables. As we categorized the trips by time-of-day periods, the inter-stop travel times are relatively similar. Therefore, they are not as sensitive to the departure times as the overall trip times and red light waiting times. The overall inter-stop time is also not very sensitive to the signal timing plan changes, since the vehicles would still need to travel to the next stop in similar traffic conditions.

Similarly, the most important factors affecting the overall dwell times are all ridership variables for the stops. This makes sense since we do not consider the ridership variations caused by vehicle interactions or schedule adherence issues in this paper. Therefore, we emphasize the future research need to better understand ridership variations caused by vehicle interactions.

One-At-A-Time Sensitivity

In this subsection, we will attempt to demonstrate the non-linear relationship between each trip step and the trip travel time. As mentioned before, due to the limitation of one-at-a-time analysis, we will not aggregate the results into one number. Like the previous section, we will again use a westbound route 27 trip during the AM peak as an example. Similar analyses can be carried out for the other routes.

Changing Departure Time

One of the important variables discussed previously is the departure time. It was shown to contribute a lot of variations to trip travel times and the red light waiting times. Here, we use a median observation on the westbound route 27 trip departing at 6:30 as an example to demonstrate the impacts of departure time by imposing the same inter-stop speed, same dwell time at stops, and keeping the same traffic signal settings.

Figure 6 shows the trip travel time and red light waiting time variations given various departure times. From the figure, we can observe that the trip travel time and red light waiting time follow the same trend, which is not surprising as we kept the same inter-stop speeds and dwell times. This result shows the correlation between the overall travel times and the overall red light waiting times.

A 4-minute difference can be observed on this 20-minute route between 6:33 and 6:39 departures if we keep all other variables the same. This once again highlights the impact of departure time changes on the overall trip and red light waiting times. Given the on-time window is 4 minutes, small departure time changes on this route could also have a huge impact on the on-time performance. In addition, in reality, drivers may speed up to rush through the intersection before the light turns red (the interaction effects), which may or may not be a desired behaviour. Therefore, planners need to carefully consider the departure time choice when scheduling for this route or optimizing for inter-linings.

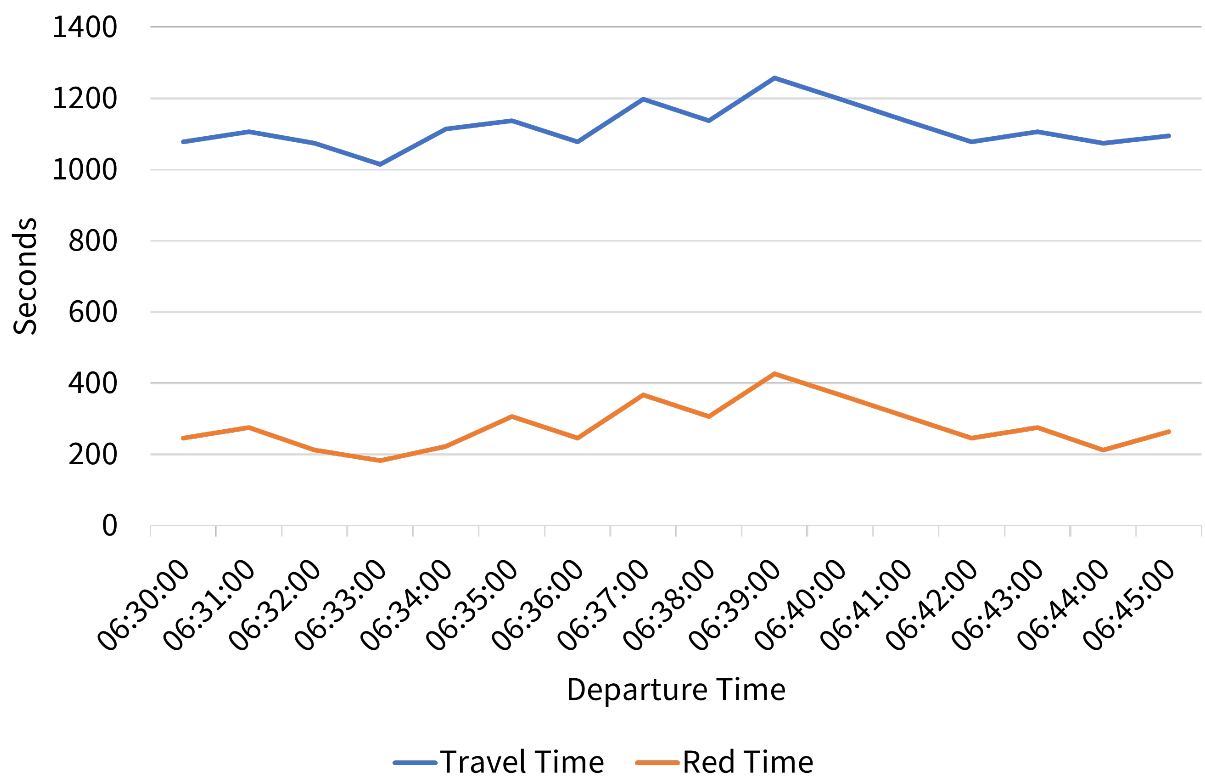

FIGURE 6 One-at-a-time analysis for departure time changes

Changing Traffic Light Settings

As seen from previous sections, the traffic signal timing changes were the second most important factor for this route. During the analysis period, there was a change in the traffic light timing plan for a newly implemented bike path as well as an improved pedestrian crossing. Three consecutive signals were affected by this change (the 3rd, 4th, 5th signals from the start of the route in Figure 7). In the new timing plan, there is a dedicated bike and pedestrian signal phase, a shortened green light duration for car traffic, and a shorter overall cycle length. More notably, the cycle lengths were modified from all 100 seconds to 80, 100, and 90 seconds respectively for the three signals.

Figure 7 shows an observed trip before the timing plan change (green line). The orange line in the figure shows the potential impact on the trip travel time if we impose the same departure time, the same inter-stop speed, and the same dwell time on the newly implemented signal timing plan with the red phases shown in red.

From the figure, we can observe a potential 3-minute increase in overall trip travel times due to the timing plan change. If we analyze the impacts locally at the spots with changed traffic signals, the difference between the two lines is only 1 minute. However, this 1-minute delay would cause the vehicle to potentially delay 2 additional minutes, due to missing one more green light later in the route. Also, from the figure, the bus very nearly misses a few signals after the changed signals. Thus, the inter-stop speeds or dwell times would also become more important if we consider the interaction effects.

Once again, the cycle lengths are not necessarily the same on the entire route, and the green

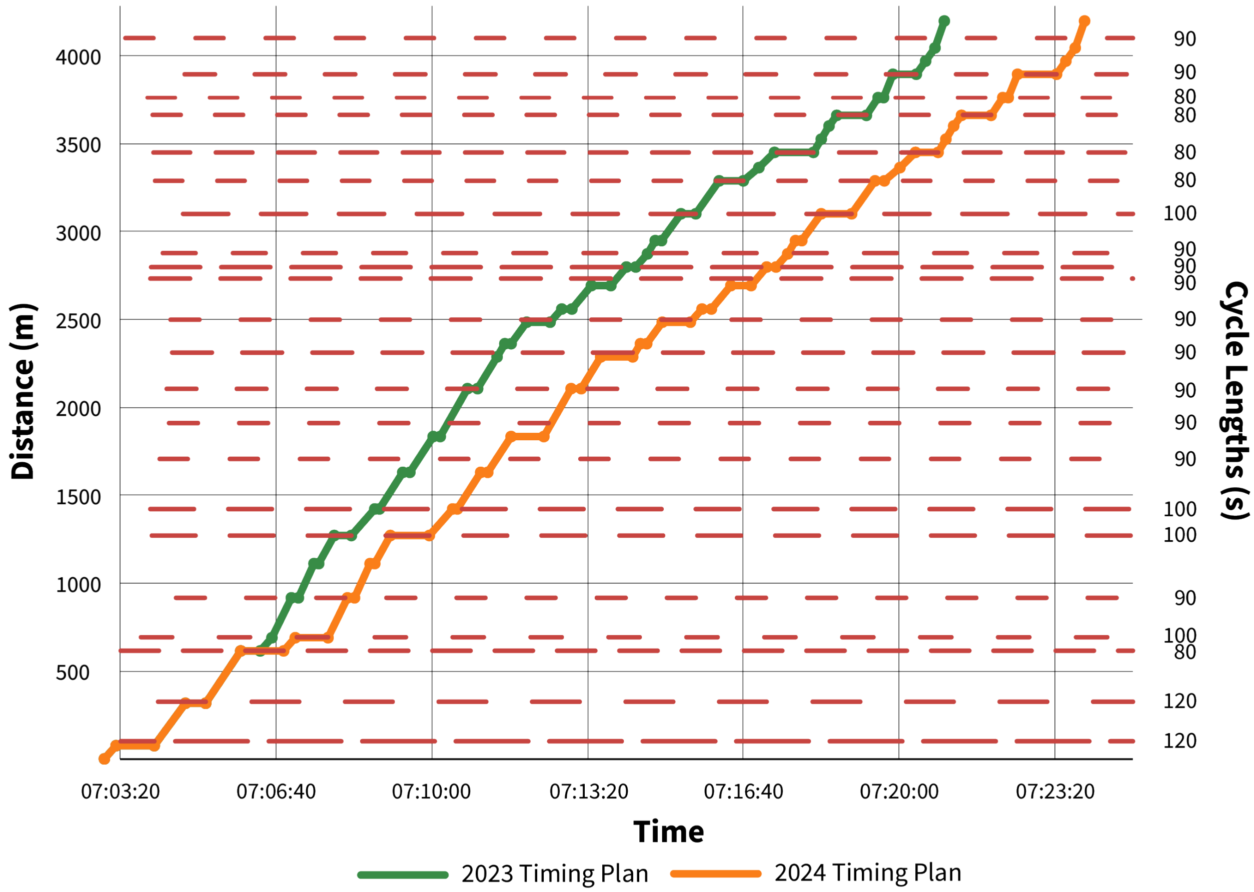

FIGURE 7 One-at-a-time analysis for traffic signal changes

waves may not be aligned everywhere along the route. Planners must consider the potential chain reaction effect after the signal changes to the end of the route rather than analyzing the impacts of traffic signal changes locally. Thus, we highlight once again the importance of including more detailed traffic signal configurations and interaction effects in the transit travel time studies.

Changing Dwell Time

Similar to previous sections, we can also examine the potential impact of ridership variation or inter-stop time variation on trip travel times while keeping the same departure time and traffic signal settings from the same median observation.

As shown in the previous section, the importance of dwell time and inter-stop speeds are high for a stop at the western half of route 27. Figure 8 shows the relationship between a time increase in either dwell or inter-stop times and the resulting red light waiting time and trip travel times.

We can observe that the differences are similar but not the same. The overall travel time stays the same if we add less than 10 seconds, the overall trip time stays the same. However, if we spend an additional 10 seconds either on the inter-stop segment or at the stop, we face an increase of 89 seconds in travel times, similar to one traffic light cycle.

For red light waiting times, if we add less than 10 seconds, the overall red light waiting

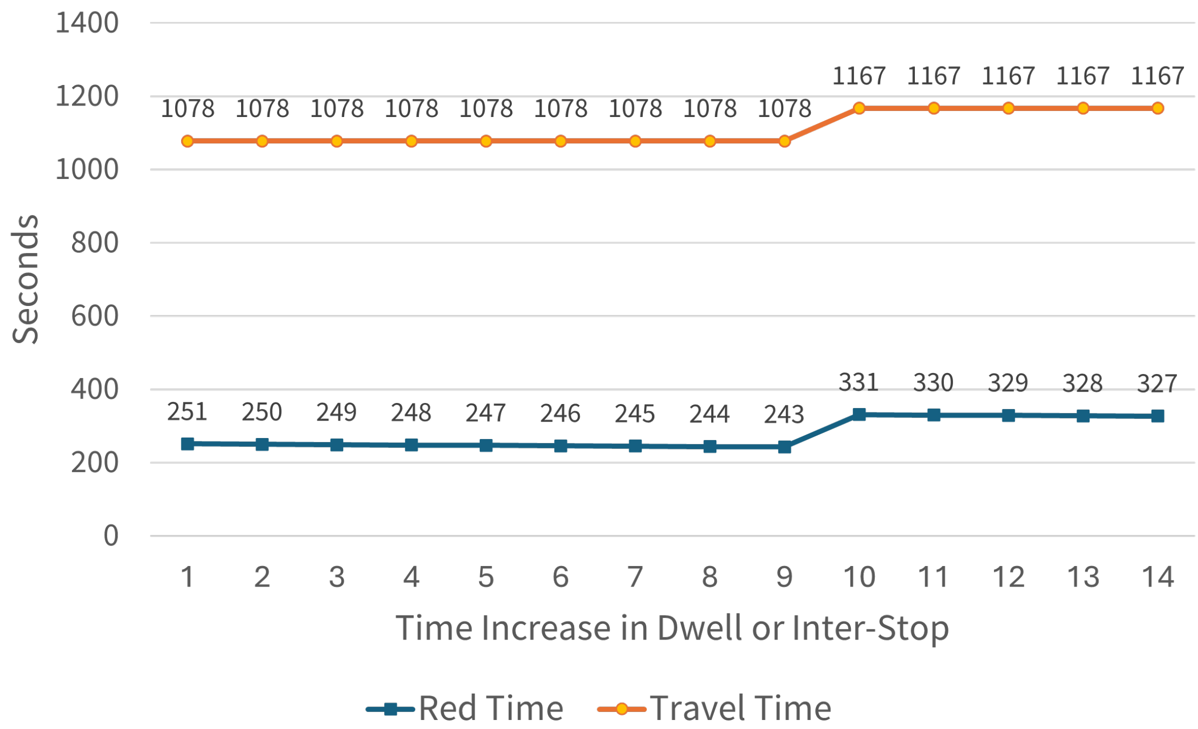

FIGURE 8 One-at-a-time analysis for dwell time or inter-stop time changes

times decrease. This makes sense because we will wait less at the next red light given the longer time spent on this specific section. If we add 10 seconds, we would not be able to pass the intersection, resulting in an 88-second increase in red light waiting times, again similar to one traffic light cycle. After 10 seconds, the red light waiting times gradually decline again. Planners can potentially look at the risks of not going through an intersection when evaluating the sensitive elements on a given route.

However, a limitation of our study is that the vehicle delays also cause ridership variations. If the vehicle is delayed, the vehicle may pick up additional passengers that are supposed to catch the next trip. Similarly, delays on the previous trips might affect the ridership on this trip. Therefore, we need further research into the interaction effects between ridership and delays as well as the interaction between transit vehicles.

CONCLUSION AND FUTURE RESEARCH

To summarize, transit reliability is important for both transit agencies and passengers. Larger travel time variations affect the scheduling process for transit agencies and trip planning decisions for passengers.

Previous studies mostly focused on either the variation of trip travel times or the variation of specific elements in trip travel times. The main focus on travel time variation has been the contributing factors and the overall distribution of travel times. Dwell time variation has also been studied though not directly related to the overall travel times. Traffic signal studies are mostly focused on giving priority to buses with mixed results. We identified that there is still a need to better isolate the variation in each trip element, further decompose the travel time, examine the interactions between these trip elements, and rank the impact of each element on the overall travel time variation.

Aiming to create more comprehensive evaluations of transit travel time variations and to help prioritize the resources for transit planners, we conducted both a variance-based sensitivity analysis and a one-at-a-time analysis for observed transit travel times. More specifically, we further decomposed recorded transit travel times from 20 routes in Montréal into several trip elements, i.e. departure time, inter-stop times, dwell times, and red light waiting times. Departure time and inter-stop times can be obtained directly from the vehicle location data. However, due to the data limitation, the traffic signal settings and dwell times are estimated using various combinations of vehicle location data, fare transaction data, and ride-check observation data.

The results show that we can better decompose the travel times by adding more details on traffic signal settings and ridership variations, and that the variations in specific trip elements can be better isolated. From the variance-based analyses, we quantified and ranked the contribution of each trip element to the overall trip travel time variations. The red light waiting times contributed the most variation to the trip travel time variations for most of the routes analyzed in our case study. The most important element observed in our case study is the departure time, which determines how synchronized the traffic signals are given the fixed timing plan. In addition, most of the variation in the overall travel time and red light waiting time came from the interaction effects. The inter-stop travel times and dwell times, however, are affected less by the interaction effects and can mostly be ranked by the individual variations.

The one-at-a-time analysis also demonstrated the non-linear relationship between the variation of each trip element and the trip travel time variation. We demonstrated a potentially large travel time variation caused by slightly changing the departure time. Thus, the historical vehicle location and travel time observations are conditional given our fixed signal plan and the varying cycle lengths. Planners need to be more careful when adjusting scheduled departure times for optimizations, such as slightly modifying the departure time to facilitate interlining or transfer synchonization. Similarly, small changes in signal timing plan changes can have a chain-reaction effect on the overall travel times. The travel time variations in the affected area can be small, but the impact on the whole trip can be large due to the interaction effects. Thus, we emphasize on including more detailed signal timing information in transit travel time studies.

However, there are many limitations and potential future research that are needed. The first is related to our analysis scale. We have only analyzed three months of recent data, yet we would need more observations to better reduce the confidence intervals for less frequent routes during off-peak times. There is also a need for a longitudinal study to discover potential trends and changes in the sensitivity results to better inform transit planners on the changes in the system. With more data on more routes, it will also be possible to examine potential temporal and spatial patterns affecting transit travel time reliability, which may in turn help the planning process for new schedules or routes.

Our methodology does not currently consider the interaction between buses, since delays can affect the number of boardings and alightings, where the vehicle may pick up additional passengers that are supposed to take the following vehicle. The interactions between vehicles, such as vehicles on the same route, common trunk sections served by various routes, as well as local and express services running parallel, should be better understood to improve the accuracy of the model, as well as to inform planning and operation decisions.

In addition, since our traffic signals mainly use fixed timing plans, there is a need to better understand the interaction between buses and non-fixed timing signals using empirical data as the majority of the current literature is based on simulations. This way, we could potentially compare various transit systems to identify pros and cons in various configurations to help improve transit reliability.

ACKNOWLEDGEMENTS

The authors would like to thank the Société de Transport de Montréal and Autorité Régionale de Transport Métropolitain for providing data access. This research is funded by the Natural Science and Engineering Research Council of Canada, the Canada Research Chair in Mobility, and the Canada Research Chair in Transportation Transformation.

AUTHOR CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: study conception and design: Yuxuan Wang, Catherine Morency, Martin Trépanier; data collection, analysis and interpretation of results: Yuxuan Wang, Catherine Morency, Martin Trépanier; draft manuscript preparation: Yuxuan Wang, Catherine Morency, Martin Trépanier. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. Danaher, A., J. Wensley, A. Dunham, T. Orosz, R. Avery, K. Cobb, K. Watkins, C. Queen, S. Berrebi, M. Connor, et al., *Minutes Matter: A Bus Transit Service Reliability Guidebook*. Washington, DC: The National Academies Press, 2020.
2. Carrel, A., A. Halvorsen, and J. L. Walker, Passengers' perception of and behavioral adaptation to unreliability in public transportation. *Transportation Research Record*, Vol. 2351, No. 1, 2013, pp. 153–162.
3. Balcombe, R., R. Mackett, N. Paulley, J. Preston, J. Shires, H. Titheridge, M. Wardman, and P. White, *The demand for public transport: a practical guide*. Transportation Research Laboratory, 2004.
4. Daskalakis, N. G. and A. Stathopoulos, Users' perceptive evaluation of bus arrival time deviations in stochastic networks. *Journal of Public Transportation*, Vol. 11, No. 4, 2008, p. 2.
5. Muller, T. H. and P. G. Furth, Trip time analyzers: key to transit service quality. *Transportation Research Record*, Vol. 1760, No. 1, 2001, pp. 10–19.
6. Dueker, K. J., T. J. Kimpel, J. G. Strathman, and S. Callas, Determinants of bus dwell time. *Journal of public transportation*, Vol. 7, No. 1, 2004, pp. 21–40.
7. Altun, S. Z. and P. G. Furth, Scheduling buses to take advantage of transit signal priority. *Transportation research record*, Vol. 2111, No. 1, 2009, pp. 50–59.
8. Fayazi, S. A., A. Vahidi, G. Mahler, and A. Winckler, Traffic signal phase and timing estimation from low-frequency transit bus data. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 16, No. 1, 2014, pp. 19–28.
9. Saltelli, A., M. Ratto, T. Andres, F. Campolongo, J. Cariboni, D. Gatelli, M. Saisana, and S. Tarantola, *Global sensitivity analysis: the primer*. John Wiley & Sons, 2008.
10. National Academies of Sciences, Engineering, and Medicine and others, *Transit Capacity and Quality of Service Manual, Third Edition*. Washington, DC: The National Academies Press, 2013.
11. Abkowitz, M. and I. Engelstein, Methods for maintaining transit service regularity. *Transportation Research Record*, Vol. 961, 1984, pp. 1–8.
12. Berkow, M., A. M. El-Geneidy, R. L. Bertini, and D. Crout, Beyond generating transit performance measures: visualizations and statistical analysis with historical data. *Transportation Research Record*, Vol. 2111, No. 1, 2009, pp. 158–168.
13. Ma, Z., L. Ferreira, and M. Mesbah, A framework for the development of bus service reliability measures. In *Proceedings of the 36th Australasian Transport Research Forum (ATRF), Brisbane, Australia*, 2013.
14. Rashidi, S., S. Ataeian, and P. Ranjitkar, Estimating bus dwell time: A review of the literature. *Transport Reviews*, Vol. 43, No. 1, 2023, pp. 32–61.
15. Currie, G., A. Delbosc, S. Harrison, and M. Sarvi, Impact of crowding on streetcar dwell time. *Transportation research record*, Vol. 2353, No. 1, 2013, pp. 100–106.
16. Lin, Y., X. Yang, N. Zou, and M. Franz, Transit signal priority control at signalized intersections: a comprehensive review. *Transportation letters*, Vol. 7, No. 3, 2015, pp. 168–180.
17. Diab, E. I. and A. M. El-Geneidy, Variation in bus transit service: understanding the impacts of various improvement strategies on transit service reliability. *Public Transport*, Vol. 4, No. 3, 2013, pp. 209–231.

18. Li, J., W. Wang, H. J. Van Zuylen, N. N. Sze, X. Chen, and H. Wang, Predictive strategy for transit signal priority at fixed-time signalized intersections: Case study in Nanjing, China. *Transportation research record*, Vol. 2311, No. 1, 2012, pp. 124–131.
19. Altun, S. Z. and P. G. Furth, Scheduling buses to take advantage of transit signal priority. *Transportation research record*, Vol. 2111, No. 1, 2009, pp. 50–59.
20. Ester, M., H.-P. Kriegel, J. Sander, X. Xu, et al., A density-based algorithm for discovering clusters in large spatial databases with noise. In *kdd*, 1996, Vol. 96, pp. 226–231.
21. Czitrom, V., One-factor-at-a-time versus designed experiments. *The American Statistician*, Vol. 53, No. 2, 1999, pp. 126–131.