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Research Article / Araştırma Makalesi

IMPACT OF COMMUTER FLUCTUATIONS ON THE HEADWAY REGULARITY OF PUBLIC BUSES IN SINGAPORE

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ABSTRACT

A phenomenon known as equal headway instability predicts that in the absence of explicit control, buses naturally bunch together. This adversely affects the consistency of waiting times for commuters which generally results in customer dissatisfaction. In 2014, the Land Transport Authority of Singapore (LTA) adapted from London a performance metric known as excess waiting time (EWT) that aims to monitor the regularity of arrival time of buses in selected stations. In this work, we report the performance results of selected bus services that have been monitored in the second half of 2014 calculated using historical automated vehicle location data. Based on these results, we show that fluctuations in commuting demand significantly impact the measured EWT. By collating the results of bus headway for different services, we also verify that given an adequate sample size, the difference between actual headway and scheduled headway for different services can generally be closely approximated by a normal distribution. Finally, we provide recommendations on the usefulness of EWT and how it can be improved in the context of Singapore's public bus system, which is primarily composed of high frequency bus service that experiences large fluctuations in commuter demand.
Keywords: Commuter waiting time, regularity, public bus, headway.

1. INTRODUCTION

The regularity of public buses is a major concern for public transport regulators and operators worldwide. By improving public bus service quality, regulators can thereafter encourage more people to adopt public transport as opposed to private transportation options in order to reduce the vehicle population and consequently congestion on roads. Transport operators are not just concerned about meeting regulatory standards, but also to improve profitability through improved commuter satisfaction.

The headway, which is defined as the amount of time between the arrivals of two consecutive buses for a specific service at a particular bus stop, is the essential component of bus operations that needs to be regulated in order to ensure bus service reliability. Unfortunately, studies in the

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past literature have shown that headway instability may occur even in the absence of traffic delays. Even with perfectly equal travel times between bus stops, a system which does not actively regulate headways will still produce bus bunching due to the presence of unequal numbers of commuters boarding between consecutive buses. This forms an inherently unstable system which quickly magnifies small changes in headways [1]. The resulting headway distribution will therefore have a high amount of variance and this poses a direct negative impact on the commuters since large increases in headway also typically increases the waiting time of commuters [2].

In 2014, the Land Transport Authority of Singapore (LTA) piloted the Bus Service Reliability Framework (BSRF) that aims to monitor and regulate the service reliability of buses. This is done through monitoring of a metric known as excess waiting time (EWT) that is calculated using the recorded values of headway of bus services at specific bus stops throughout the day [3]. Transport operators are then subsequently either provided incentives or penalised depending on the reported service performance over a month.

In this article, we present some initial results on the analysis of the EWT results of a selected ten services operated by SMRT Buses Ltd, which is currently one of the two major public bus transport operators in Singapore. This has resulted from the collation and analysis of a historical dataset that records automated vehicle location data for a period of 5 months. We first provide some aggregated results on the empirical headways indicating that despite intrinsic differences between various bus services, they display universal characteristics in their statistical headway distribution. We also present evidence to show the impact of commuting fluctuations on the EWT results and also provide other relevant spatiotemporal factors that are highly impactful on the regularity of buses.

2. CALCULATION OF EXCESS WAITING TIME (EWT) METRIC

We first provide the mathematical definition of the EWT metric as introduced in the BSRF Framework. The EWT score of a bus service for a particular time period is calculated from the Actual Waiting Time (AWT) and the Scheduled Waiting Time (SWT) as described by the following three equations.

$$EWT = AWT - SWT \quad (1)$$

$$AWT = \frac{1}{2} \times \frac{\sum (\text{actual headway})^2}{\sum (\text{actual headway})} \quad (2)$$

$$SWT = \frac{1}{2} \times \frac{\sum \text{scheduled headway}}{\text{number of trips}} \quad (3)$$

This EWT metric represents the average amount of additional time on top of the average scheduled waiting time that is spent by commuter waiting for their buses to arrive prior to boarding. The metric is derived from the mathematical model of the average commuter waiting time first introduced by Osuna and Newell in 1972 [4]. We also note that EWT has previously been used by London’s public bus services [5] and its introduction has been shown to have brought about significant improvements in the reliability of service in London’s bus system [6].

For the purpose of the BSRF framework introduced by Singapore’s LTA, about 3-6 bus stops for each service are taken into consideration when monitoring the headways. These are denoted as intermediate timing points (ITPs) and are typically uniformly spread across the service route. These bus stops are specifically identified by the LTA to characterise the headway performance throughout the service route. Several of the ITPs also represent specific bus stops which have been identified to have high commuting demand. Since the scheduled headway and SWT also changes throughout the day, separate EWT scores are calculated across different specified time periods covering different peak and off peak periods throughout the day. The EWT performance is currently only monitored for weekdays since they form a more crucial period where a large percentage of the commuting population utilise public bus services.

The final EWT average score for the service for the day is thereafter calculated as a weighted average of the EWT scores at individual ITP across different time periods.

3. CASE STUDY OF TEN PUBLIC BUS SERVICES IN SINGAPORE

In this study, we monitored the headway performance of ten bus services operated by SMRT Buses Ltd in Singapore for a period of 5 months from July till November 2014. The headway of every bus arrival during this period is calculated from a historical dataset that records the bus arrival events occurring throughout this period for the selected bus services. However, as mentioned earlier, only the headway performance of selected ITPs along the service route is calculated. Table 1 below provides a summary of the basic characteristics of the ten services analysed in this study.

Table 1. Summary of characteristics of ten bus services analysed in this study

Service Index	No of bus stops	No. of ITPs	Total distance (km)	Average daily ridership	Average peak headway (mins)	Average non-peak headway (mins)
S1	117	6	47.8	8878	8.3	11.4
S2	51	3	23.2	6540	7.8	9.4
S3	109	6	43.3	8646	8.9	11.6
S4	39	3	19.9	7825	8.1	9.7
S5	21	3	7.4	10327	4.3	6.0
S6	88	6	40.4	5013	12.4	15.4
S7	72	5	73.4	9940	8.4	9.9
S8	14	3	6.0	6686	4.1	5.1
S9	27	3	11.8	9031	5.5	7.1
S10	45	3	16.7	8267	7.3	11.3

It should be noted that all of the services analysed in this study can be classified as high frequency services since their average headways are mostly less than 15mins. Notably, although Services S5 and S8 are short distance services (<10km), they serve a considerably high amount of commuting population. This is because these services are intra-neighbourhood services which mainly serve to connect bus stops at residential areas to the neighbouring MRT stations. These bus services therefore act as essential bridges that connect commuters into longer travel routes that are more prevalent in Singapore's high throughput MRT systems.

3.1. Information Contained in the Dataset of Bus Arrival Times

The historical dataset records the following information for all of the bus arrival events that occur during the monitoring period:

a) Service Number
b) Vehicle Identification Number
c) ID of Bus Stop Visited
d) Time of Bus Arrival
e) Scheduled waiting time (SWT) for the particular bus service / stop for the time period.

As with many real-world datasets, this dataset is not without imperfections. Based on the observed errors found within the dataset, we believe that some of these imperfections may be caused by technical faults in the automated GPS systems collecting the arrival data. For example, the bus arrival data occasionally recorded multiple arrival times at the same bus stop within 10 minutes for the same trip. This reduces the recorded headway and therefore causes inaccuracies in the headway information. In order to ensure that the headway information closely represented reality, some of these superfluous data had to be removed while ensuring that the calculated service performance from the cleaned up data closely matched the EWT scores provided by LTA for validation purposes.

4. DISTRIBUTION OF EXCESS HEADWAY

In this section, we analyse the raw headway distribution that gives rise to the EWT scores from the bus operations. Since different bus services have different scheduled headways at different time periods, we introduce a generic variable termed as "excess headway" which is calculated as the difference between actual and scheduled headways for all the timing points in the dataset. This provides us with a means to compare between different services at different times and it also provides a simple measure of how early or late the bus arrives as compared to the scheduled headway. Monitoring excess headway also allows us to gauge how well bus drivers are actually adhering to their scheduled targets and monitoring individual drivers' excess headway allows for us to easily monitor whether the particular bus driver tends to be early or late in his or her arrivals.

Interestingly, we concluded that the overall distribution of excess headway can be closely modelled using a normal distribution with equivalent mean and variance (Refer to Figure 1). This reveals to us that in general, bus arrivals actually tend to be equally early (negative excess headway) as they are late. This also means that using the statistical information within this historical dataset, it is possible to construct a simulation model of the bus arrival events that closely match the performance of the actual empirical bus arrival data.

While negative excess headway (early bus arrivals) could be mistaken as something positive, this is not necessarily true because the scheduled headway is typically designed by equally dividing the period of operations with the number of available buses. This means that excessively early bus arrivals would cause subsequent buses to arrive later than required since the supply of buses would not be adequate to cover the full operational period according to the scheduled headway.

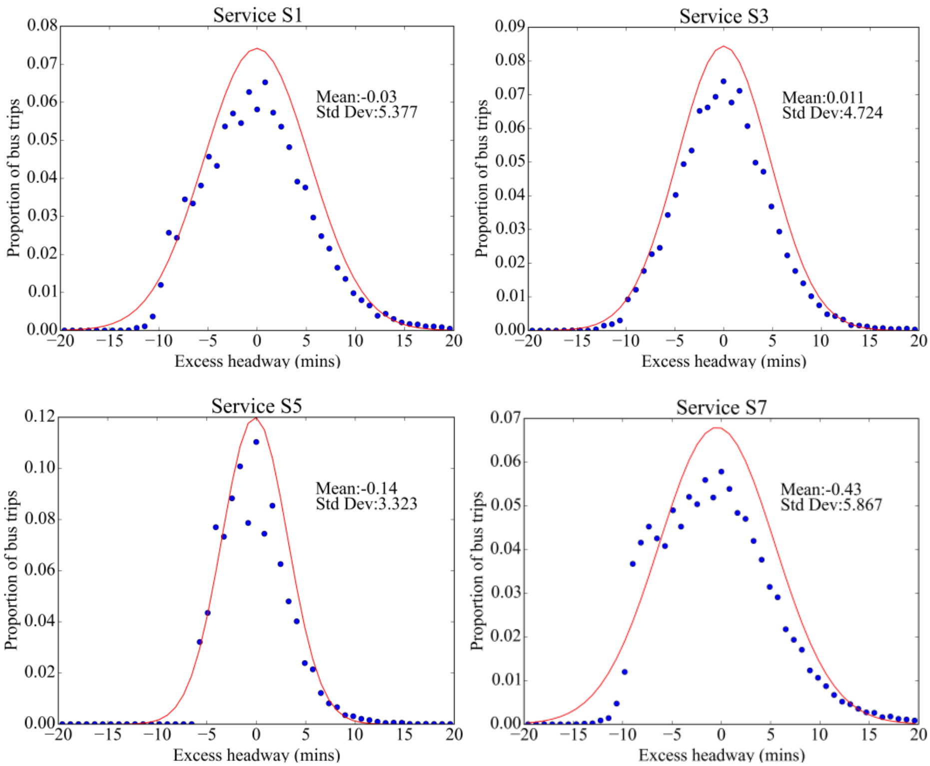


Figure 1. Plots of the distribution of excess headway obtained for 4 sample services, S1, 3, 5 and 7 in our analysis. Each plot is accompanied by a reference normal distribution curve (shown in red) with mean and variance equal to the calculated sample values. Service S5 and S7 show a slight left skew indicating that there is a higher amount of early bus arrivals as compared to late arrivals.

5. EXCESS WAITING TIME SCORES FOR THE MONTHS OF JUL – NOV 2014.

We present 3 samples of the daily service EWT performance across the 5 month period of Jul-Nov 2014 (Refer to Figure 2). It can be clearly observed that the daily scores are subjected to a high amount of fluctuations throughout the monitored period. Unfortunately, there are many contributing factors that may have caused these fluctuations including traffic, changes in ridership numbers, differences in bus driver behaviour, scheduling problems and even bus breakdowns. It is therefore correspondingly difficult and complex to pinpoint exactly which of these factors caused the resulting EWT. In the next few subsections, we attempt to explore some of these factors especially those which are essentially related to the ridership of the bus services.

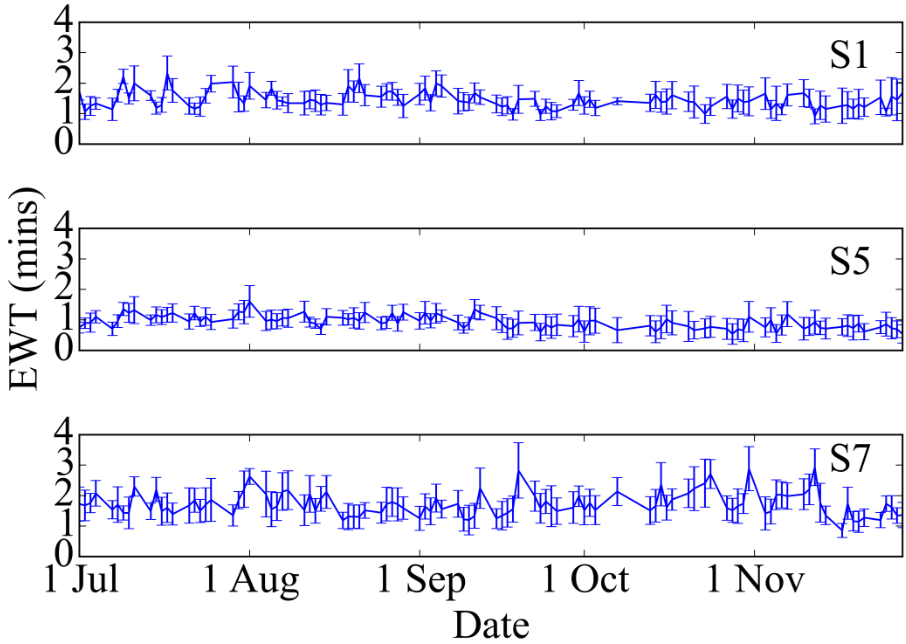


Figure 2. Sample daily EWT scores from July to Nov 2014 for 3 bus services S1, S5 and S7. The error bars represent the variation of EWT scores between the different ITPs selected for each service.

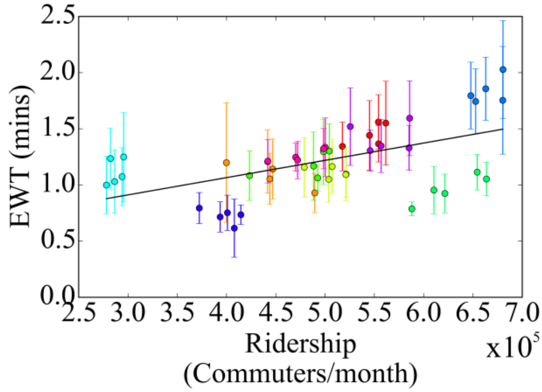
6. FACTORS AFFECTING EWT SCORES

We explore three main factors that have been observed to have an effect on the resulting EWT, they are:

a) Number of commuters using the particular service
b) Distance from First Bus Stop
c) Time of Day and Weekday

6.1. EWT as a Function of monthly ridership

While the patterns of commuter arrivals are typically consistent [8] on a weekly basis, small fluctuations do occur between different days and different months. By combining the EWT performance data against the recorded monthly average ridership, we observed that there is indeed a correlation between the monthly ridership and the corresponding mean EWT score (Refer to Figure 3). From the data, we can conclude that regularity of the service is generally correlated by the number of commuters utilizing the bus service. For example, the overall performance of the bus services have been found to have generally improved during the month of November but this is mainly due to a reduction in commuting demand due to the month coinciding with the school holiday period. It is noted that other corresponding factors such as an overall reduction in traffic may also have contributed to this performance improvement.



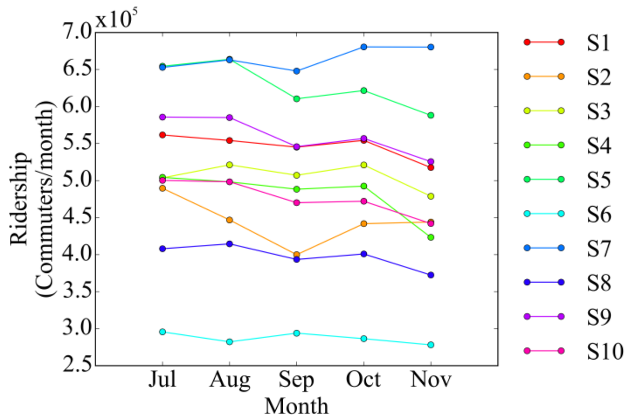


Figure 3. When the average monthly EWT is plotted against the total ridership per month, we can show that an increase in ridership generally correlates with a corresponding increase in EWT (left). The variation of monthly ridership for the ten services analysed in this article (right).

While ridership can be directly correlated to the corresponding EWT score, we are aware that the ridership values are widely different both spatially throughout the bus route as well as across different days and time periods. We therefore explore both factors in the subsequent subsections and observe their relationship with EWT.

6.2. Distance from First Bus Stop

By plotting the obtained EWT scores for different bus stops against their corresponding distances away from the first bus stop (Refer to Figure 4), we observe a gradual increase in both the mean and the variance of the EWT scores as a function of the distance from the first bus stop in the service. This is intuitive, as it can be expected that as the bus service progresses along the route, it is subjected to various different externalities such as fluctuations in traffic. Moreover, as the bus proceeds along its service route, it encounters an increase in the number of commuters boarding and alighting and these contribute increasing amounts of variability in the arrival patterns of the buses at subsequent bus stops further away. A similar result has also been previously reported for services operated in Beijing, China, where the reliability of the bus services has been shown to decrease with the length of the route [7].

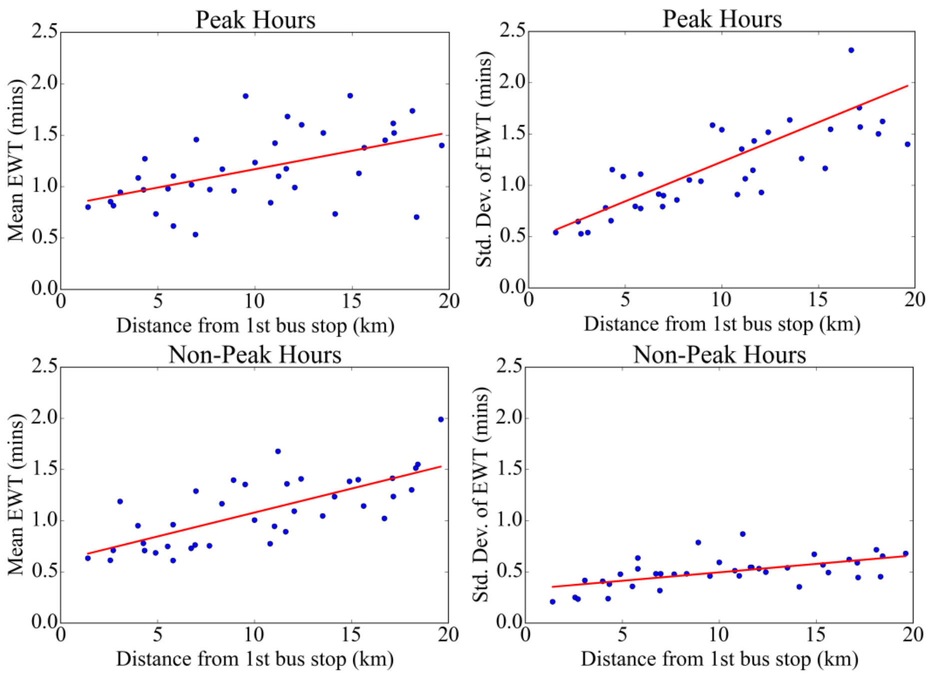


Figure 4. The variation of mean (left) and standard deviation (right) of EWT against the distance away from the 1st bus stop in the route. The data is split between the peak monitoring periods (0630h -0830h) (top) and the non-peak monitoring periods (bottom)

6.3. Time of Day and Weekday

By collating different EWT scores for different time periods, we can also deduce that the reliability performance of bus services is affected by the time of operation. Once again, we can relate this to the different ridership numbers experienced during the bus operations. The morning and afternoon peak periods generally translate to higher numbers of ridership and we observe that the service performance is correspondingly worse as compared to the off peak periods. It has also been previously shown that Fridays have a slightly different commuting pattern as compared to the earlier weekdays [8], and this is also shown to have a negative impact on the corresponding EWT performance (Refer to Figure 5).

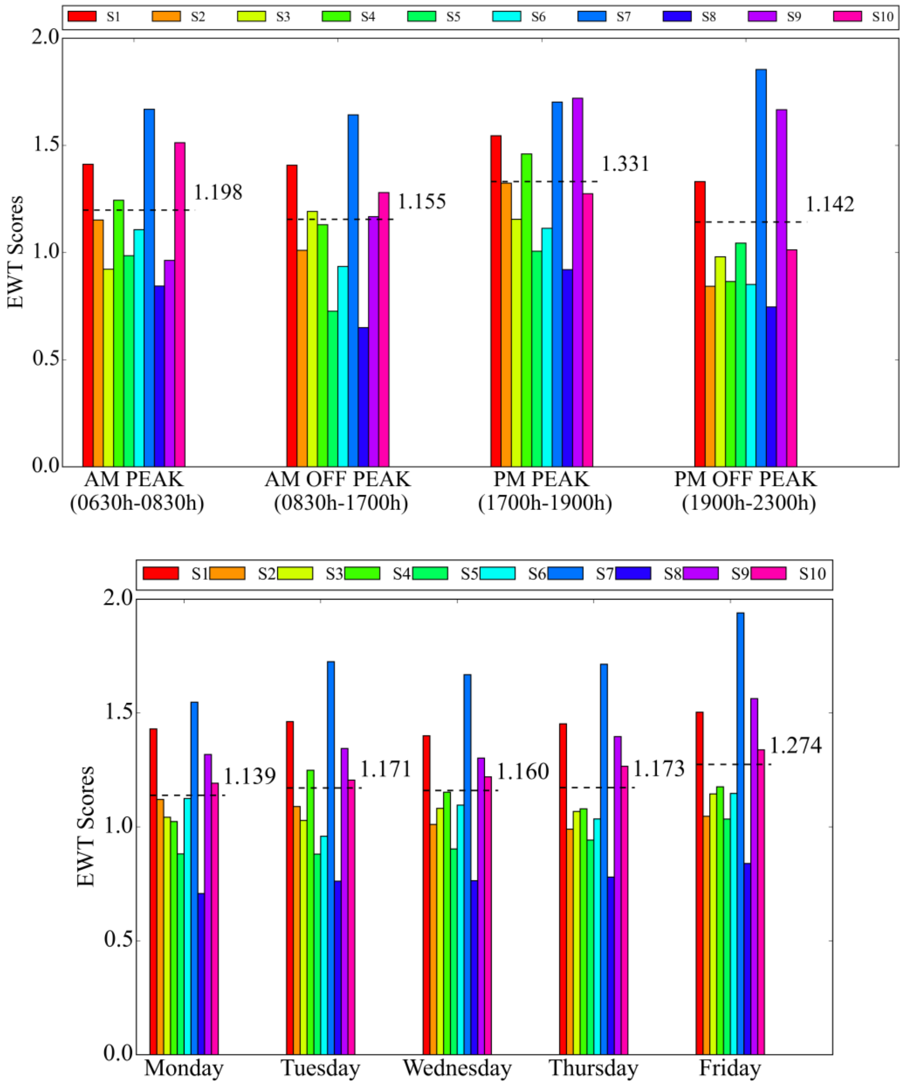


Figure 5. The average EWT scores for different services compared against different time periods (top) and weekdays (bottom). The overall average scores (labelled in black) for each time period and weekday are also indicated by the black dashed line.

7. DISCUSSION

It should be noted that although the measured reliability metric introduced here is denoted as excess waiting time, no actual measurement of the waiting time of commuters is actually used in the calculation. This is because data collection only occurs when commuters board the buses while there is a lack of available data on when commuters arrive at the bus stop. Since EWT calculation is derived from headway measurements, the metric should therefore strictly be considered as a measure of headway regularity as opposed to a measurement of commuter waiting time. We provide a simple example to illustrate this; given that there are absolutely no commuters waiting at a specific bus stop, the measured EWT using headways can still provide a positive measure as long as buses continue to visit the stop. However, the actual average amount of waiting time would correspondingly be zero since no commuters actually waited for a bus at that stop.

While EWT does model the excess waiting time of commuters, it does so based on several assumptions on the commuter arrival patterns. This includes a major assumption that commuters arrive randomly and uniformly at the bus stop [4]. Unfortunately, we have observed that the actual amount of commuters boarding varies and fluctuates widely throughout the day and across different days of the month. Moreover different bus stops and services experience different fluctuating commuting patterns especially in a densely populated city state such as Singapore [8]. We would therefore propose that an improved EWT measure should include the number of actual commuters that board and alight the buses so as to better model the actual waiting time dynamics experienced by the commuters.

It is however, still hoped that with improved regularity that is constantly monitored through the EWT metric, commuters would be better able to time their arrivals at the bus stop based on familiarity and thus decrease their actual waiting times accordingly. With the advent of real-time information on expected bus arrivals also made available to the commuters, this would further improve the reliability of bus services and provide direct impact to the service quality provided.

8. CONCLUSION

In this article, we report the performance variation of excess waiting time (EWT), a metric that reports the regularity of headways for public bus operations. It is also shown that EWT performance may be directly related to various external factors experienced during bus operations. These include the ridership of the bus service, various temporal factors such as the time of day and day of the week, as well as the location of the tested bus stop along the route.

We also show that the excess headway, defined as the amount of deviation of the actual headway from the scheduled headway observes a universal model throughout the ten services we analysed in this study despite the different characteristics of the services tested. We show that the empirical headway distribution is in fact closely related to a normal distribution with equivalent mean and variance.

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