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Evaluating Bus Running Time Variability in High-Frequency Operation Using Automatic Data Collection Systems

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ABSTRACT

Bus services usually tend to be irregular and their level of irregularity depends on various factors, such as crowding level, terminal departure behaviour, passengers' behaviour, operator behaviour, traffic and weather condition and etc. High-frequency bus routes have shorter headways (usually headway less than 10 to 15 minutes) and higher passenger demand compared with normal routes. Therefore, level of irregularity can be even higher in bus service at high-frequency operation. Running time variability comes from both systematic changes in ridership and traffic levels at different times of the day, which can be accounted for in service planning, and the inherent stochasticity of homogeneous periods, which must be dealt with through real-time operations control. This study evaluated impact of ridership changes and traffic condition through time of the day on running time variability, using Automatic Vehicle Location system (AVL) and Automatic Fare Collection system (AFC). All data extracted and collected from RapidKL Company for route U32, which is a high-frequency route in downtown of Kuala Lumpur. Descriptive analysis on data showed a high variation in running times, especially in morning peak hours. A liner regression model also proved than crowding level (extracted from AFC data), number of stops and congestion zones have relatively high impact on running time variation.

Keywords: AFC, AVL, bus service, high-frequency, running time, variability

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INTRODUCTION

Malaysia has high private vehicle ownership and only urban travel is by public transport (Kamba et al., 2007). Thus, providing a productive and sufficient service that is reliable for the public is an important challenge for transport authorities and agencies (Lee & Vuchic, 2005). One of the most significant features of transit service quality is reliability. In addition, it is a major concern for transit agencies and passengers (Daganzo & Pilachowski, 2011). Running time variability is one the indicators of bus service reliability and the essential resources to a high-frequency route reliably (Diab & El-Geneidy, 2013). Automated data collection systems, such as AVL, which provide very large observation samples at low marginal costs, enable the development and use of new data-driven analysis tools that can potentially enhance performance monitoring abilities, and ultimately lead to improved resource allocation and effectiveness.

Running time is the amount of time that a bus spends travelling from one point to another on a chosen route in the service of travellers. One important factor that can worsen transit service reliability is increase in the variation in run time for a given mean run time (El-Geneidy et al., 2011). Higher levels of variation in service for travellers are directly related to increases in waiting time at bus stops, which intensify travellers' stress levels and diminish their perceived ease and comfort, lessening the appeal of bus service (Bates et al., 2001; Berrebi et al., 2015; Perk et al., 2008). Previous studies have shown that the value commuters place on travel time and travel time variation are nonlinear (Pinjari & Bhat, 2006). The cost of travel time variation might actually be higher than the cost of standard travel time (Chen et al., 2003; Perk et al., 2008), significantly impacting decision making and day-to-day time scheduling procedures (Nam et al., 2005; Noland & Polak, 2002). Studies have shown that commuters are more interested in reliable service with fewer deviations than in services with shorter headway (Balcombe et al., 2004; Daskalakis & Stathopoulos, 2008). Researchers have found that improving reliability of service in terms of running time and running time variation is strongly related to increasing passenger satisfaction levels and responding to demand (Boyle, 2006; Hollander, 2006).

Passenger behaviour variables such as boarding and alighting percentages influence run-time variation (Lin & Bertini, 2004; Tirachini et al., 2013). Moreover, studies have identified various factors that can impact bus running time, including the distance involved, geometric conditions (such as the number of signalised intersections), tardiness at the beginning, time of day, number of real stops made, environmental factors (such as rain and snow), and traffic conditions (El-Geneidy et al., 2011; Mahudin et al., 2012). In this study, descriptive analysis on running times was carried out to determine current situation of route and level of variability. A linear model was developed to evaluate and understand the factors which significantly impact running time variation.

MATERIALS AND METHODS

RapidKL is owned by Prasarana Berhad, a government-owned company. It was established in 2004 as a provide solution to public transport woes affecting Kuala Lumpur and its surrounding cities. For reporting and analysis purposes, RapidKL uses automatically collected data to estimate the route ridership per hour. This data can be used to predict total route ridership to be distributed at each key stop (schedule time points and stops with high passenger demand). The primary data source for evaluating this study is the raw automatically collected data from Automatic Vehicle Location (AVL) and Automatic Fare Collection (AFC) systems. Data is stored at the RapidKL database, when the bus refuels, which is useful to identify running times and terminal departure behaviour (in response to schedule deviation). The AFC system creates a record for each fare transaction using smart media or magnetic stripe fare media; cash paying and non-paying passengers (e.g. children) are not recorded. This study uses Route U32 as a case in point. It is a high-frequency route due to high passenger demand in downtown Kuala Lumpur (Figure 1). This route has 59 bus stops (almost 30 stops in each direction). Table 1 shows route U32 specifications and table 2 shows list of key stops in each direction. The study duration was between October and November 2015 (including weekends and holidays). As described in Table 2, this route has four key stops in each direction. Therefore, each direction consists of three segments (segment is the distance between two key stops). Accordingly, segment 1 is between HUB TMN DANGANG and BLTN KG PANDAN, segment 2 is between PANDAN and Majestic and segment 3 is between Majestic and HSBC/ 7 ELEVEN.

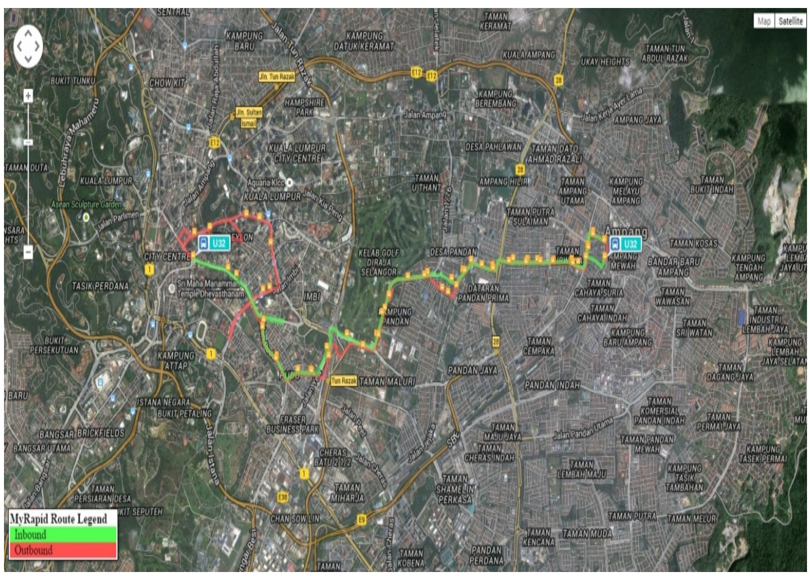


Figure 1. Route U32 layout and location

Table 1
Route U32 specifications

Route	Origin	Destination	Distance	No. of Buses	No. of bus stops
U32	TAMAN DANGANG	BUKIT BINTANG	20.565 Km	9	59

Table 2
Route U32 key stops (Outbound)

Stop ID	Stop Name	Order	Zone	Distance
1000970	HUB TMN DAGANG	1	3	0
1000360	BLTN KG PANDAN	21	3	5347
1001846	MAJESTIC/LRT PUDU	24	3	7561
1000958	HSBC/7 ELEVEN	28	2	9375

RESULTS AND DISCUSSION

Running time variability is one of the main causes of unreliability in bus routes (Moosavi et al., 2015). A descriptive analysis was used in this study. When examining variability by segment, the time range of data for analysis must be consistent across segments (figure 2). Similarly, when examining variability by time of day, data must be spatially consistent across times of day. Based on the scope of this study, only one direction of route U32 is considered for further analysis. Figure 3 illustrates running time variability by time of day. All running times are demonstrated in seconds.

Running time variability differs based on time. As Figure 3 shows, this variability reaches its maximum during morning and afternoon peak hours. The analysis will measure variability within homogeneous periods, aggregating observations from different days of the week and weeks of the year only if they are considered to represent the same operating environment.

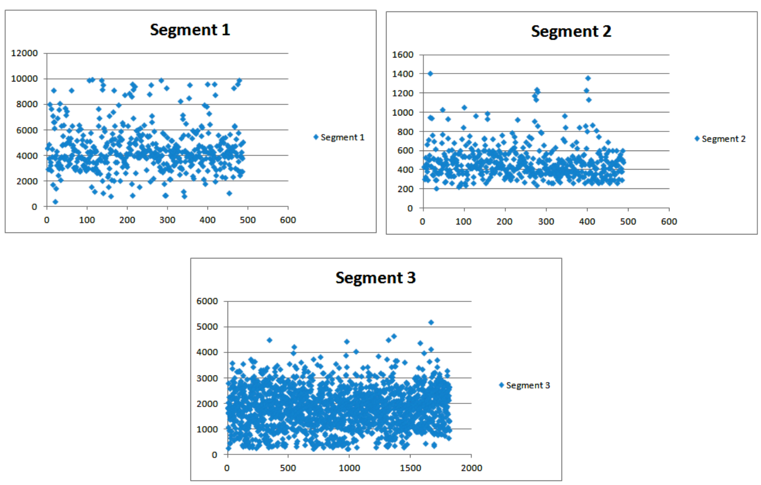
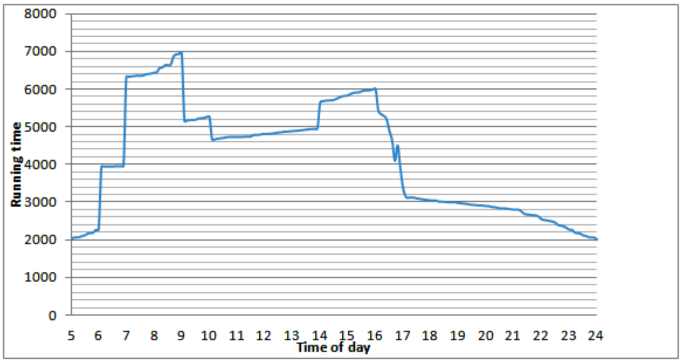


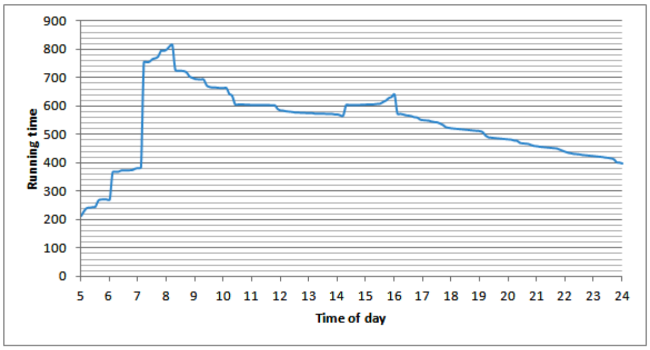
Figure 2. Running time variation for each segment separately

Table 3
Route U32 running time records

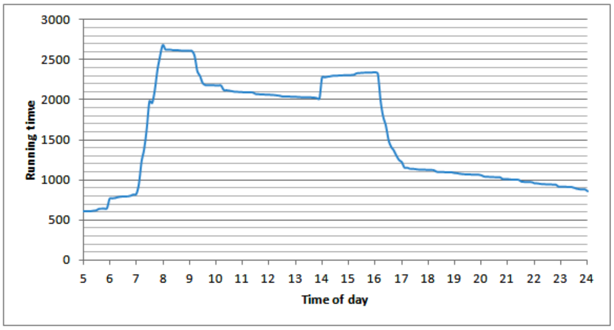
	Morning peak				Afternoon peak			
	Min	Max	Mean	Stdev	Min	Max	Mean	Stdev
Segment 1	0:08:58	1:31:50	0:57:17	0:029:47	0:07:24	1:12:43	0:46:32	0:27:33
Segment 2	0:03:31	0:23:20	0:07:21	0:3:32	0:03:45	0:23:32	0:07:32	0:3:11
Segment 3	0:04:04	1:09:07	0:21:06	0:5:43	0:04:53	1:09:08	0:39:12	0:4:56



(a)



(b)



(c)

Figure 3. Running time variability (sec) by time of day: (a) Segment 1; (b) Segment 2; and (c) Segment 3

Linear Model of Median Running Time

A linear model is specified with median running time as a function of distance, number of stops, average crowding level, and dummy variables for segments entering the congestion zone in down town of Kuala Lumpur. In this study, areas around Kuala Lumpur, especially streets and area around BUKIT BINTANG, are considered as congestion zone. Automatic Fare Collection

(AFC) data was used to obtain the average crowding level at key stops. Table 4 shows the regression results for this model. The signs of all the parameter estimates agree with general experience: longer running times are related to segments going through the congestion zone, greater run distances, greater number of stops, and greater ridership. The statistical significance of the estimates is very high, and the overall fit, with $R^2 \approx 0.81$, is moderately high. The average number of boarding per trip is a better characterisation of how busy the operating environment is in comparison with morning peak and afternoon peak dummy variables (not included in this model) because it captures pattern-specific characteristics.

Table 4
Linear regression on running time

Coefficient	Estimate	Std. Error	T value	Pr (> |t|)
Distance	1.52E-3	1.93E-4	8.01	1.64E-9
No. of stops	3.53	0.91`	3.67	7.04E-3
Average crowding level	0.18	0.03	8.64	8.68E-9
Congestion zone	3.68	0.99	3.88	1.43E-2

Residual standard error: 7.409 on 236 degrees of freedom
R^2: 0.81
F-statistic: 126.8 on 6 and 246 DF, p-value: < 2.3E-15

CONCLUSION

A descriptive analysis carried out to understand current situation of route U32 in term of running time variability. The results showed a very high variation in running times in this route. In order to gain better insights on running time variation, homogeneous sets of running time were prepared (morning peak, afternoon peak and off-peak hours). Results showed that morning peak hours (6am to 9am) has the highest variation with standard deviation of almost 30 minutes. A linear model was developed with the goal of finding general patterns of route characteristics leading to higher or lower typical running times and running time variability. Segments entering central Kuala Lumpur tend to have higher and more variable running times. Distance, number of stops, and ridership all contribute to higher and more variable running times as well. Obviously, there are other factors not explored here such as driving running time variability. Variables such as traffic, weather conditions, corridor characteristics, road work, ridership patterns (at a disaggregate level), operator behaviour at the terminal and mid-route, and even fleet size itself could have significant impact on variability.

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