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Demonstrating the feasibility of using Wi-Fi sensors for dynamic bus-stop queue length estimation

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Abstract We demonstrate that a Wi-Fi sensor located at a bus stop can be used to estimate the current queue length of passengers waiting for the bus. These crowdsourced data are hence a cost-effective source to obtain information on transit demand. Based on the observed queue lengths we further estimate the resulting waiting time for passengers for each line that serves the stop. This information can be used to evaluate the impact of operational strategies. Our experiments are conducted at a busy bus stop in Kyoto, Japan, during the peak tourist season. The estimated regression and machine learning approaches show that both randomised and non-randomised MAC addresses as well as the received signal strengths are important indicators for the queue length. We discuss the limitations of the approach if applied in other contexts with less organised crowding and more noise than in our experiment.

Keywords: Waiting time estimation · Bus stop · Passenger queue · Time-dependent arrival rates · Wi-Fi signal data

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1 Introduction

The existence of waiting times at boarding points is a key characteristic of mass public transport systems which one aims to minimize to make the service more attractive. Passengers' experienced waiting times can be a factor in evaluating the performance of a given bus line as well as a stop. Estimation of actual waiting times is, however, in most cases severely constrained by data availability. Therefore, often expected waiting times are constructed based on the assumption of an arrival time distribution. However, such an approach does not take into account demand irregularities. Furthermore, when several lines serve the stop the estimation gets more complex as passengers who intended to board one line might swap to another if it arrives first or if the preferred line is known to arrive late.

We suggest that in particular at crowded stops, served by partially overlapping lines, improved knowledge of how long and how many passengers wait for a specific or a set of lines can facilitate better service design. Both dynamic and statistical averages can be useful: Live queue estimates can help operational strategies such as adding services or, simpler, making appropriate announcements to waiting passengers. On average, historic information can support service design questions.

To identify the number of waiting passengers at a certain point in time and how long they stay at a bus stop, new data sources are required. With the exception of gated Bus Rapid Transit Systems (BRT), passengers do not “check in” at stops. Further, Automatic Passenger Counting and Automatic Fare Collection technologies are in most cases installed inside the vehicle and do not provide this information. To obtain continuous estimates of queues we therefore collect data with Wi-Fi sensors placed at bus stops and validate their accuracy with manual counts.

Wi-Fi-enabled devices (e.g., smartphones, game consoles, laptops) send probe request packets to connect to networks. The probe request packet can be captured by Wi-Fi packet sensors and contains a timestamp, Media Access Control (MAC) address, and Received Signal Strength Indicator (RSSI) which can be interpreted as an indirect representation of the distance between the device and the sensor. Due to privacy concerns, nowadays the traceability of Wi-Fi signal data is greatly weakened. A series of actions have been taken by mobile phone vendors to mask the MAC addresses. 89.9% of the MAC addresses are randomised in the data we collected. In this research, we therefore aim to estimate line-specific waiting times at bus stops, proposing a new model using Wi-Fi signal data with a high percentage of randomised MAC addresses.

We develop a two-step approach to estimate the waiting times. Firstly, linear regression and neural network models are established to estimate a function representing the relationship between total queue length at bus stops and observed Wi-Fi data as well as bus departure information. For estimation purposes, the queue length in each minute is taken as the dependent variable and is recorded manually by

investigators. Wi-Fi signal records, bus arrival times, and time-of-the-day dummies are used as independent variables. It is shown that Wi-Fi signal data can be a reliable and cheaper alternative to manually observed queues over time. In this paper, we present the advanced results of queue estimation and discuss the second step to estimate the waiting times from estimated queues based on the fitted model in the first step.

The remainder of this paper is organised as follows. After the literature review, we first explain the Wi-Fi data in further detail and then define how queues and waiting times can be estimated using such data. We discuss in particular how Wi-Fi data in conjunction with Automatic Vehicle Location (AVL) data are used. Section 4 presents the results performed on a case study. Finally, this paper is concluded in Section 5 with discussions for future studies.

2 Literature Review

Queue estimation has been carried out with data from fixed-location sensors and mobile sensors using counting and time series analysis. For road traffic, queue estimation is widely carried out based on loop detectors and video data analysis including number plate recognition and applying advanced analysis methods including machine learning (Luo et al., 2019). In contrast, identifying passenger queues is more difficult; for one, passenger queues are shorter and identifying a person is more difficult than identifying vehicles. To overcome this problem, Rajvanshi and Pramod (2021) estimate the number of trolleys and baskets for queue estimation in checkout counters using computer vision with deep learning algorithms. Also, Wi-Fi sensors have been used to identify queues and waiting times. For example, Bulut and Ferhatosmanoglu (2015) propose “LineKing” to observe waiting time based on smartphone Wi-Fi readings. Wu et al. (2017) analyse in detail whether a Wi-Fi-recorded mobile is likely to be waiting in a queue. They also consider queues at restaurants or shopping facilities. Wang et al. (2014) extract properties such as the RSSI to monitor the time a person spends in a queue and when he is likely served. They consider the performance of different queue types such as straight or snaking queues. Namulindwa et al (2023) measure the busyness and queues at a cafeteria with Wi-Fi data including RSSI information. We note an important difference compared to monitoring the length of queues at bus stops. In all the above examples, the server fairly continuously handles the person waiting in the queue. Instead, in the bus stop case, the server is discrete and serves many, possibly all, passengers at a time. This means the queue length at bus stops displays significant jumps whereas in restaurants, shops, and retail stores the queue changes tend to be more continuous.

There is a body of literature on estimating pedestrian crowding at stations and using image processing technologies such as “Minkowski fractal dimensions” (Marana et al., 1999), “grayscale edge histograms” (Dewei et al., 2013), or a generic “head

detector” (Subburaman et al., 2012). With respect to estimating person queues, Wu and Solmaz (2017) designed a system of queue estimation based on RSSIs using three Bluetooth Low Energy (BLE) sensors. Their experimental results indicated higher accuracy than the camera-based approach. Brockmann et al. (2018) created a prototype queueing system called Communication Utility Queue (CutiQueue) for counting devices passing through a series of links, similar to a loop detector, using BLE sensors. There is surprisingly little literature on estimating person queues at stops, possibly because of the aforementioned data collection difficulties.

Waiting times of passengers are often estimated “indirectly” by, for example, comparing vehicle arrival time information and schedule data. Also, approaches have used AVL data and Automated Fare Collection (AFC) data. Webb et al. (2020) established relationships between passenger waiting time and vehicle delay using AFC data, AVL data, and General Transit Feed Specification (GTFS) data and showed application results on an arterial Bus Rapid Transit line.

Closest to our study are the following studies that are also using Wi-Fi data but leverage the traceability function of Wi-Fi signals. Kusakabe et al. (2018) estimate bus waiting times using Wi-Fi signal data at a coach terminal and the estimation is verified with interview survey results. They imply that the observed data includes traffic as well as travellers. Oransirikul et al. (2014) aim to estimate the arrivals and departures of passengers at a bus terminal using Wi-Fi signal data. Shlayan et al. (2016) utilize unique Bluetooth IDs and Wi-Fi MAC addresses to track pedestrians using data from three sensors at a subway station and six sensors in a port in New York City. Wepulanon et al. (2019) propose a methodology to handle massive noise in Wi-Fi data and utilize Wi-Fi data to estimate average passenger waiting times as the average of the time difference between the entry time and exit time of the waiting passengers at a single bus stop by conducting experiments in Hong Kong.

In summary, though there have been a few studies using Wi-Fi sensors at bus stops, the focus of the studies differs partly from ours. In particular, we suggest this is the first study explicitly using RSSI and randomised MAC addresses to obtain the length of bus line-specific queues.

3 Methodology

We now introduce a two-step methodology to estimate passenger queues and waiting times from Wi-Fi signal data. The first step is to model the relationship between collected data and passenger queues. The capability to capture this relationship and estimate queue length is tested by a multiple regression model (LR) and an artificial neural network (ANN) approach. As will be discussed we confirmed an acceptable accuracy for both models. The second step is to obtain expected passenger waiting times from the estimated queues, using the output of the first step as the input. In both

steps, we distinguish the effects of different bus lines at the stop. Figure 1 illustrates the study flow.

In Section 3.1 firstly the basic data obtained from the Wi-Fi sensors are explained. The models for queue estimation are elaborated on in Section 3.2. This is followed by the approach for waiting time estimation in Section 3.3.

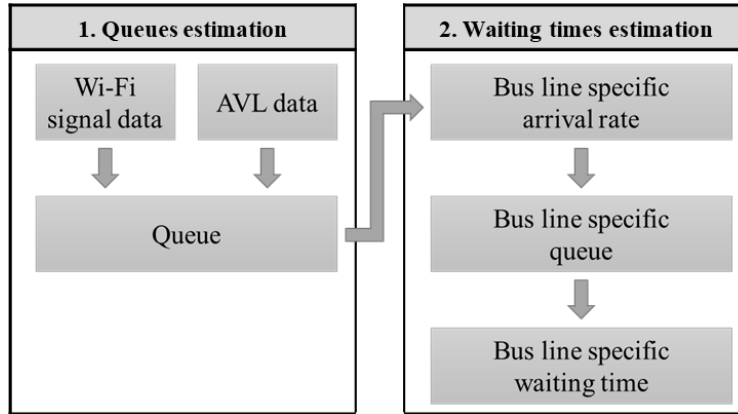


Fig. 1 Flowchart to estimate passenger queues and waiting times from Wi-Fi signal data

3.1 Wi-Fi data

The functions of Wi-Fi packet sensors are receiving probe request packets from Wi-Fi-enabled devices in the vicinity, converting the MAC address contained in the packet by a one-way hash function to anonymize the data, and uploading the captured packets to a cloud storage server. Although the number of devices around the sensor may not match the number of people carrying them, assuming that the average ratio of Wi-Fi emitting devices per person is constant over time, it can be expected that this data will provide an estimate regarding the number of passengers in the queue.

Further, before hashing, the device itself might randomise the broadcasted MAC address. MAC addresses consist of a total of 6 bytes, the first 3 bytes being Organizationally Unique Identifier (OUI). The OUI identifies a manufacturer or other organization and is registered in the database (<https://standards-oui.ieee.org/>). When the MAC address is randomised, this OUI is also randomised, it can be concluded that the MAC address with the OUI not in the database is randomised. If this is the case, even probe request packets transmitted from the same device cannot be traced because the MAC address continuously changes each time it is transmitted. In this research, the MAC address randomised by the device itself will be referred to as “randomised”, and the MAC address that is not randomised by the signal emitting device but hashed by the Wi-Fi sensor will be referred to as “non-randomised”. The Wi-Fi sensor furthermore records the RSSI. As noted in the introduction and literature, this can

indicate the distance between the emitting device and the Wi-Fi sensor (e.g. Wang et al, 2014; Wu and Solmaz, 2017). The closer the device the stronger the signal. Typically values of around -50 indicate strong signals and mean the device is within a few meters of the sensors. Devices up to around 40m distance are picked up by the sensor but their signal strength is likely to be less than -80. As we will discuss in the case study, clearly weak signals are important for our purposes, as only the strong signals will not give a good indication as to the queue length.

To estimate how long a person is staying in a queue we further have to estimate the period a single Wi-Fi recording refers to. For non-randomised signals, we can pick up the same (hashed) address several times so we can estimate the broadcasting frequency and hence estimate the period a single record represents. For randomised signals this is not possible as each time a different MAC address is broadcasted, meaning that it is not possible to distinguish whether two signals are from the same or different devices. Furthermore, the transmission period of the probe request packet varies depending on the device type and OS version. In our case study, as a result of the calculation based on the non-randomised MAC address of the data, the average reception period of the probe request packet from the same device observed within 30 minutes was approximately 219 seconds. Thus, 100 seconds before and after the reception of a signal are each added as the period for which we assume a person (or rather device) is part of the queue.

3.2 Queues estimation

Emerging technologies such as AVL, AFC, and Automatic Passenger Counting (APC) systems have been commonly adopted. The time since the last bus left a stop can be calculated by these bus arrival times. Assuming that passengers arrive at the bus stop at a constant rate (and that they do not leave the queue once they joined), the length of the queue is expected to increase monotonically from the time of departure of the last bus. The length of the queue is therefore the product of passenger arrival rate and the time since the last departure. Clearly the arrival rate does not have to be constant. In particular, if interarrival times are long and passengers have good information on the next arrivals, a higher arrival rate close to the scheduled departure time can be expected.

The two basic cases of Wi-Fi data with and without bus arrival time information deserve distinction in this discussion. Without bus arrival time information, the Wi-Fi sensors can give a direct estimate of the passenger queue though the noise in the Wi-Fi data can be substantial so that the queue estimates might not be good.

Information on bus departures or continuous AVL data are hence expected to improve the model fit and further can help estimate bus line-specific queues. The interpretation of the Wi-Fi records is, however, different in this case: For a bus stop served by

multiple bus lines, the proportion in a queue for each bus line is expected to increase monotonically by a line-specific arrival rate. Therefore, in the case of regular arrivals, a high goodness-of-fit of the queue estimation model can be expected if linear regression is performed using only the cumulative time from the departure of the last bus of each line as an independent variable. The estimated coefficient then indicates the arrival rate of passengers per unit time for each line. As this “ideal assumption” is not likely to hold for the observed data, we aim to pick up the variation in actual arriving passengers with the Wi-Fi records. In other words, controlling for the time since the last bus departed, the less regular the passenger arrival rate, the more significant we hypothesize the Wi-Fi sensor records to be in a regression model.

Furthermore, passenger boarding demand is usually varying depending on the time of day. To control for this, we add time-of-the-day dummy variables in our model that moderate the expected basic arrival rate for the corresponding period.

Finally, we add a range of variables corresponding to information received from our Wi-Fi sensors. For one, we group devices based on the RSSI of each probe request packet. For a non-randomised MAC address, the maximum value was extracted and used because the RSSI varied by each observation time for each observed data from the same device. The group was essentially divided into five groups, with two groups of greater than -50 dBm and less than -80 dBm, and three groups of less than -50 dBm and greater than -80 dBm at 10 dBm intervals.

We note that we take a minute as the base unit in our analysis for which we record and predict the queue. Since the timestamp of the Wi-Fi data is accurate to the second level, it is possible to calculate the number of probe request packets per second in the group, which is then converted to a minute-index by calculating the average value of the number in that minute. Finally, the number of non-randomised MAC addresses and the number of randomised MAC addresses per minute are calculated for each group classified by the magnitude of RSSI.

The data used as explanatory variables for the queue length are summarised in Table 1. We note that we do not have AVL data but only record the time a bus departs at the stop as part of our data collection explained later. In the table, the number in the bracket denotes the number of associated variables used in the model. The number of bus-related variables (“Time since the last bus left” and “Bus arrived at the time”) changes in line with the number of bus lines intersecting at the stop. In the models reported in Section 4, we select a subset of these variables that provide the best model fit. We firstly establish multiple linear regression models followed by neural network models that are expected to provide higher model fit if well trained due to their ability to consider the interaction between these independent variables. We choose a multilayer perceptron (MLP) approach which is a model that combines neural network and regression models. The parameter setting for this neural network is summarized in Figure 2 with the 22 input layer variables as those shown in Table 1.

We include three hidden layers for this MLP. For these hidden layers, we specify 1024, 512, and 4 neurons respectively. We also tried different types of layouts, simpler and more complex. Simple layouts provided worse results, but more complex layouts did not make a significant difference in the estimation accuracy, only increased computation time.

Table 1 Details of multiple linear regression

Dependent variable (1)	Independent variables (22)	
Length of total queue at a stop at time t	Time since the last bus left (2)	
	Bus arrived at the time (2)	Dummy variable
	Time of the day (8)	Dummy variable
	Non-randomised MAC addresses (5), Randomised MAC addresses (5)	$-50 \leq \text{RSSI}$
		$-60 \leq \text{RSSI} < -50$
		$-70 \leq \text{RSSI} < -60$
		$-80 \leq \text{RSSI} < -70$
		$\text{RSSI} < -80$

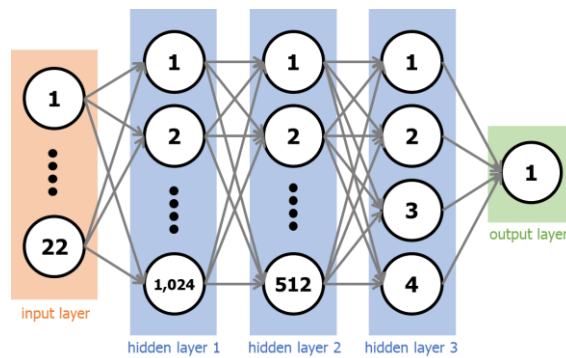


Fig. 2 Structure of the neural network model

3.3 Waiting times estimation

The notations used in this section are listed in Table 2.

Table 2 Notation

Symbol	Unit	Meaning
$Q(t)$	PAX	Length of the total queue at a stop at time t
i		Bus line
S		Set of bus lines, $i \in S$
t_i^*	min	The time when the last bus of line i left before time t , $t_i^* < t$
$\alpha_i(\tau)$	PAX/min	Arrival rate for passengers of bus line i in time period τ
$\alpha_i(h)$	PAX/min	Arrival rate for passengers of bus line i in hour h
t_h	min	Minutes in hour h
ξ_{i,t_h}	min	The last departure time of a bus of line i at minute t_h
$q_i(t)$	PAX	Length of the queue for a bus of line i at a stop at time t

Waiting time at a bus stop is defined as the time that a passenger spends waiting for a bus serving the stop in a passenger queue. Figure 3 illustrates the dynamics of a queue over time. The increase in queue length from the previous minute can be taken as the arrival rate of passengers in the current minute. With the arrival rate in each minute identified we can calculate the waiting times according to the arrival time points of the passengers, as distinguished by color in the right figure. This problem can be simplified if the arrival rate in a period is assumed to be constant.

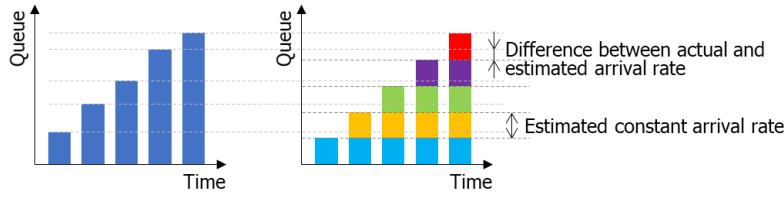


Fig. 3 Relationship between waiting time, queue and arrival rate, each bar denotes the queue length at the correspondent minute

Since demand varies over the day, it is assumed that passenger arrival rates are time-dependent. With arrival rate $\alpha_i(\tau)$ at time period τ , a length of the queue at a stop at time point t can be expressed with passenger arrival rates as follows:

$$Q(t) = \sum_{i \in S} q_i(t) = \sum_{i \in S} \sum_{\tau=t_i^*+1}^t \alpha_i(\tau) \quad (1)$$

Since obtaining bus line-specific passenger arrival rates within short time intervals is a challenge, it is assumed that these are constant over a predefined period, in our case study the period is one hour. The passenger arrival rate of each bus line can then be estimated with Equation (2) where the total queue length data will be estimated using

Wi-Fi signal data as described in Section 3.2 and the last departure time of a bus will be obtained from the bus arrival information provided for the public. Then, the length of the queue for a bus line can be estimated as in Equation (3) using the passenger arrival rate of each bus line estimated with Equation (2).

$$\min_{a_i(h) \forall i \in S} \sum_{t_h=0, \dots, 59} \left[Q(t_h) - \sum_i a_i(h) (t_h - \check{t}_{i,t_h}) \right] \forall h \quad (2)$$

$$q_i(t_h) = a_i(h) (t_h - \check{t}_{i,t_h}) \quad (3)$$

The average waiting time per bus run can be calculated by dividing the total waiting time by the number of bus runs arriving in a corresponding hour, as shown in Figure 4 (a). Similarly, the average waiting time per passenger can be calculated by dividing the total waiting time by the number of passengers boarding in a corresponding hour, as shown in Figure 4 (b).

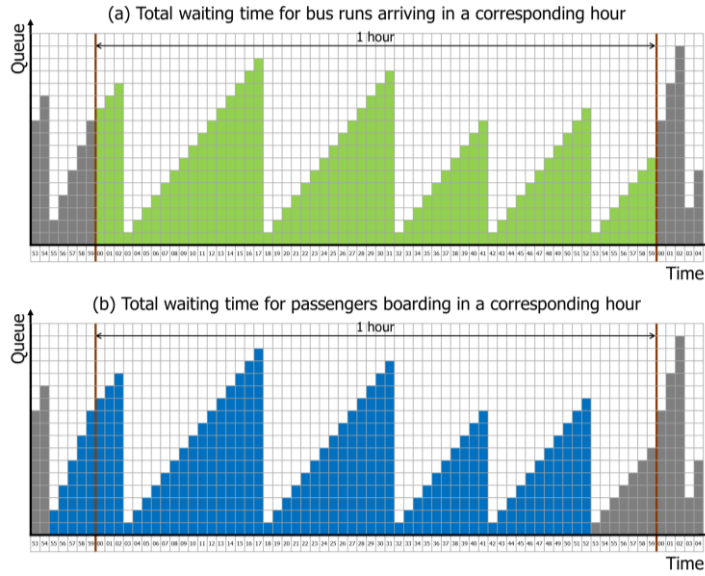


Fig. 4 Illustration of two types of total waiting time in a corresponding hour

4 Case study

The data used for this research was obtained from several experiments conducted in the peak tourist season for the fall foliage in 2019 in the area of “Ginkakuji” (Silver Pavilion), a famous tourist attraction in the northeastern part of Kyoto city, Japan. The Wi-Fi sensors are identical to those used in Ota et al. (2018) and Gao and Schmöcker (2021, 2022) where the goal was to estimate tourist numbers and their walking routes. Also, Nishida et al. (2014) use the same type of sensors and showed

that they are suitable to estimate traffic flows. Two handheld sensors with a portable power bank are located at a bus stop and on opposite sides of the stop. As the proxy of the AVL data introduced in the methodology, bus arrival times are recorded by the investigators. Furthermore, queue every minute and boarding numbers for every bus arrival are recorded as ground truth data.

Ginkakuji-mae bus stop in the Ginkakuji (“Silver temple”, world heritage site) area is selected to test the proposed model. At bus stops in Kyoto, passengers usually line up to wait for a bus. The Ginkakuji-mae bus stop often shows long, fairly tidy queues along the pavement. Figure 5 shows a picture of the bus stop when it has a queue of more than 20 passengers. The stops in this area can be busy and the queue length can exceed 40 passengers during peak sightseeing hours and in particular in the late afternoon when some of the sights are closing. The chosen stop is served by two bus lines (Kyoto City Bus Lines 32 and 100). The daytime frequency of Line 32 is 20 minutes and that of Line 100 is 10 minutes. Lines 32 and 100 overlap for only three stops after the Ginkakuji-mae bus stop so that only few passengers will be willing to board “whichever bus comes first” and hence the common line problem is not significant for our problem. To note is that there are relatively few points of interest (POIs) in the direct vicinity of 40m in which we pick-up up signals. Such POIs will create noise in terms of people staying at these points rather than at the bus stop. Only a restaurant behind the stop is a POI that will have created some disturbance to our records. Furthermore, road traffic is an obvious source of additional Wi-Fi records and creates more Wi-Fi records than the restaurant, even though traffic on this road is not as high as on some of the more major neighbouring roads. There is, however, often a queue of taxis on the other side of the road which will have created further additional signals. Finally, passing pedestrians will clearly also influence the number of records.



Fig. 5 Ginkakuji-mae bus stop, Kyoto, Japan

The counting and Wi-Fi data collection was carried out for three days with 8 hours each day and 4-hour counting on the last day as shown in Table 3. To note is that

there are some missing data at the beginning of each day. The number of probe request packets captured from the Wi-Fi packet sensor in this experiment for four days is also shown in Table 3. If the interval of the non-randomised MAC address is longer than or equal to 30 minutes, it is filtered as it is considered as noise since passengers are not likely to wait for such long periods with service frequencies being higher. Such a long-observed device is more likely located inside the nearby restaurant or it is a device that has passed the bus stop several times in the interval indicating that it is also unlikely to be a waiting passenger.

Table 3 Number of captured probe request packets

Date	Time	Number of non-randomised	Number of randomised
27 Nov 2019	10:00 - 18:00 (8 hours)	1,969	15,465
28 Nov 2019	10:00 - 18:00 (8 hours)	1,633	14,327
30 Nov 2019	10:00 - 18:00 (8 hours)	2,272	21,318
1 Dec 2019	11:00 - 15:00 (4 hours)	998	9,987

Using data from this experiment, the linear regression (LR) model described in Section 3.2 is fitted. A fairly acceptable overall model fit is achieved and the significance of the variables is confirmed. Table 4 shows the results of the fitted model. The adjusted R-squared is 0.676. Figure 6 shows the estimated length of queues by LR and the observed length of queues by investigators. It can be found that the dynamics in queue evolution are successfully captured by our proposed model. However, the peaks are less well predicted. When there are too many passengers waiting, it can be difficult to estimate the number of passengers because they are out of range of the Wi-Fi sensor or the signal strength is very weak. In further work, one might hence repeat our experiment with additional sensors placed in the direction of the queue and possibly at nearby POIs. A significant decrease in Wi-Fi readings at nearby POI is likely indicating the arrival of passengers at the stop in the near future.

We note that buses in general arrive in fairly regular intervals. At some periods the operator provided additional buses to serve the unusually large demand as our experiment was conducted during the peak tourist season. At those times bus bunching occurred a few times. For example at 10:47, 11:14, and 13:54 on November 28, 14:42 on October 30, and 14:20 on December 1, two buses of Line 100 arrived at the same time. When the bus bunching happens, we treat that there is only bus serving the passengers to board in our model. And we observed that few passengers boarded the back bus of the two as the passengers know that the back bus will not overtake the front one.

The coefficient for the independent variable of time from the departure of the last bus is 1.03 for line 100 and 0.227 for line 32, respectively, and the p-value indicates that these are significant. These coefficients are in line with our observation that Line 100

is more attractive to passengers since it is a circular line connecting several popular tourist attractions. This model therefore enables the estimation of the approximate arrival rate of passengers in a real environment. With the coefficient of the time of the day variable, it is possible to estimate that the length of the queue is relatively long from 15:00 to 16:59. As a bus stop close to a famous tourist attraction, the demand peak usually appears before the closure of this tourist attraction which is 17:00, therefore, the estimation result is in line with the observation. Bus arrival dummies indicate the line-specific boarding number of passengers per bus arrival, they thus have a negative sign. Although Line 100 attracts passengers at a higher rate, it loads fewer passengers than Line 32 per bus arrival. This may result from the fact that Line 100 provides more frequent service. Our field observations showed that capacity problems also come into play as in some cases the bus arrives already full and some passengers in the queue were denied boarding.

Negative coefficients are obtained for weaker signal groups of non-randomised MAC addresses. These MAC addresses are considered to be not in a queue and are excluded from the queue by the model. As noted, weak signals can be important to predict long queues since weak signals can indicate that passengers are far away from the stop sign and waiting in the rear of the queue. Especially for relatively weak signals with a strength of $-80 \leq \text{RSSI} < -70$ we obtain a large positive coefficient. We suspect that the negative sign for non-randomised signals indicates that at times with large queues the larger number of people around the stop block the repeated reception of the weaker signals from non-randomised further away. Ota et al. (2018) discuss some of the body-absorption effects in more detail. Few differences are found between the number of strong signals in long queues and short queues. Clearly in cases of less organized queues we would expect different results. If passengers wait without forming a queue we would expect the significance of the strong RSSI signals to be larger.

Table 4 Results of multiple linear regression

		Coeff.	p-value	t-value
Independent variables				
Time since the last bus left	Line 100	1.030	<0.001	24.519
	Line 32	0.227	<0.001	9.955
Bus arrived at the time (Dummy variable)	Line 100	-2.039	<0.001	-3.569
	Line 32	-3.281	0.001	-3.430
Time of the day (Dummy variable)	10:00~10:59	-0.992	0.080	-1.751
	11:00~11:59	-4.028	<0.001	-8.180
	12:00~12:59	-5.609	<0.001	-11.339
	13:00~13:59	-3.666	<0.001	-7.001
	14:00~14:59	-0.123	0.806	-0.246
	15:00~15:59	5.886	<0.001	10.620
	16:00~16:59	8.236	<0.001	13.554
	17:00~17:59	-2.563	<0.001	-4.450
Randomised MAC	-50≤RSSI	-0.061	0.226	-1.212
	-60≤RSSI < -50	0.090	0.003	2.927
	-70≤RSSI < -60	0.104	<0.001	3.688
	-80≤RSSI < -70	0.191	<0.001	11.380
	RSSI < -80	-0.019	0.100	-1.648
Non-randomised MAC	-50≤RSSI	1.026	0.071	1.806
	-60≤RSSI < -50	1.481	<0.001	7.280
	-70≤RSSI < -60	1.323	<0.001	6.966
	-80≤RSSI < -70	-0.248	0.045	-2.008
	RSSI < -80	-0.684	<0.001	-6.642
Intercept		-2.858	<0.001	-4.668

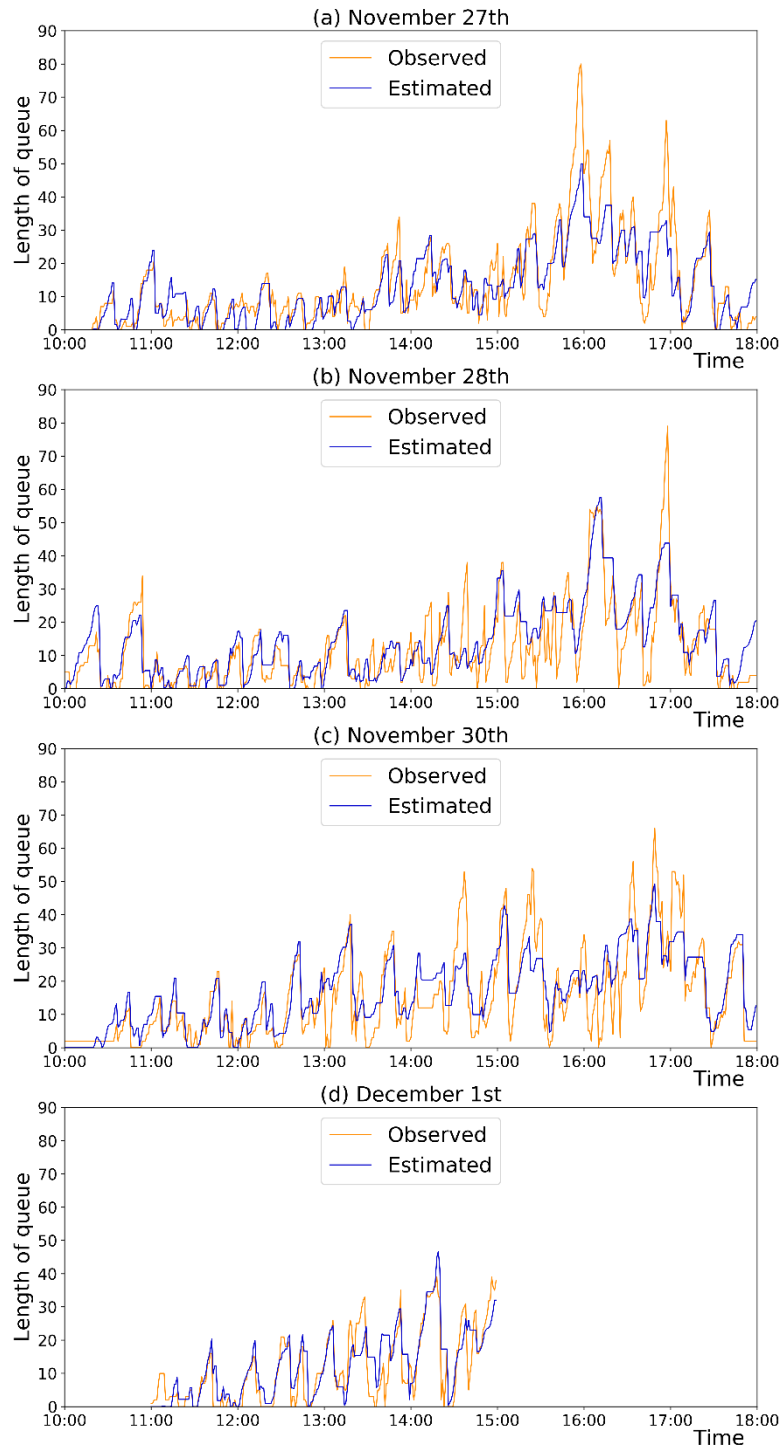


Fig. 6 Estimated length of queue by multiple linear regression

Next, we compared the results of the LR model with machine learning approaches. Model training and testing are conducted by "scikit-learn" which is a commonly used Python machine-learning library that provides an easy and efficient development environment (Pedregosa et al, 2011). We use an MLP regressor with the structure shown before in Figure 2.

The data are randomly split into a training dataset and a testing dataset at a ratio of 8:2. We run the model 100 times and take the average of the 100 runs as the final model fit. R-squared and Root Mean Square Error (RMSE) are used to evaluate the model performance. The same dataset with randomly splitting into training and testing at a ratio of 8:2 is also applied to the LR, in order to make these two models comparable. The results are shown in Table 5. The neural network model's goodness of fit of the test set has a higher value than that of the regression analysis although there is arguably some overfitting (higher model fit for the training than the test result).

Table 5 Results of 100 ANN model and LR model runs with training/test split

Model	Training		Test	
	R ² (Std Dev)	RMSE (Std Dev)	R ² (Std Dev)	RMSE (Std Dev)
ANN	0.949 (0.031)	2.871 (0.797)	0.779 (0.039)	6.152 (0.505)
LR	0.681 (0.008)	7.427 (0.105)	0.666 (0.031)	7.592 (0.413)

In Equation (3), we provide a method to obtain queue length using arrival rate and time since last departure for a single-line bus. For a stop having two bus lines, as our studied bus stop, we can combine Equations (1) and (3) to Equation (4) and calculate the queue length. If we consider Equation (4) as a regression model and use the queues $\hat{Q}(t_h)$ estimated from Wi-Fi signal data as the dependent variable, the passenger arrival rates of both bus lines in each hour of a day can be estimated as in Table 6. The passenger arrival rates indicate the demand of each bus line. Relatively high arrival rates of both bus lines in 15:00~16:59 and long observed queues in the same time period are well matched. Bus line-specific waiting time is hence calculated as in Table 7 by summing up the length of queues derived by passenger arrival rates in Table 6 and then dividing by the number of bus runs and the number of passengers. The estimated results for average waiting time per bus run show a similar trend with passenger arrival rate over hours of a day. The average waiting time per bus run of Line 100 is less than that of Line 32 although the passenger arrival rates of Line 100 are about 2 to 6 times higher than that of Line 32. This results from the difference in the bus headway. There is, however, no significant difference in average waiting time per passenger over hours of a day. Since average waiting time per passenger is expected to be highly related to the bus headway under the condition of a constant passenger arrival rate, the results indicate that the service is operating at appropriate frequencies and without significant delay differences during the operational hours. Only in the late afternoon, the waiting time exceeds 7min which is possibly due to some denied boarding cases. Nevertheless, overall, we conclude that these results

demonstrate that bus operators could fairly well control the passenger waiting times by regulating the bus headway.

$$\hat{Q}(t_h) = a_{100}(t_h - \check{t}_{100,t_h}) + a_{32}(t_h - \check{t}_{32,t_h}) + \varepsilon \quad (4)$$

Table 6 Results of passenger arrival rate estimation

Time of the day	Line 100 (PAX/min)	Line 32 (PAX/min)	Adjusted R ²	RMSE (PAX)
10:00~10:59	1.102	0.178	0.958	2.354
11:00~11:59	0.740	0.230	0.830	3.436
12:00~12:59	0.969	0.211	0.867	3.802
13:00~13:59	1.258	0.307	0.861	5.653
14:00~14:59	1.644	0.400	0.927	5.010
15:00~15:59	2.225	0.549	0.898	7.625
16:00~16:59	2.069	1.001	0.921	8.674
17:00~17:59	1.071	0.475	0.815	7.889

Table 7 Results of waiting time estimation

Time of the day	Average waiting time per bus run (min)		Average waiting time per passenger (min)	
	Line 100	Line 32	Line 100	Line 32
10:00~10:59	40.4	47.0	6.2	10.3
11:00~11:59	18.9	68.2	5.7	13.3
12:00~12:59	38.8	48.3	5.8	14.3
13:00~13:59	61.2	76.2	6.2	12.8
14:00~14:59	80.2	87.8	5.8	13.6
15:00~15:59	105.6	146.2	5.7	12.5
16:00~16:59	151.8	218.7	7.0	12.2
17:00~17:59	61.0	162.9	7.6	12.5

5 Conclusions

In this research, we show the feasibility to estimate passenger queue length and waiting time at a bus stop mainly from Wi-Fi signal data collected by a packet sensor installed at the stop sign. Additional data we use are records of the bus departure times which are helping to explain the jumps in the queue. A two-step methodology is developed.

Firstly, the length of a queue at a bus stop is inferred from Wi-Fi signal data and bus AVL data. Wi-Fi data provide information on passengers staying around a bus stop and bus AVL data provide information on bus arrival time and time since last

departure. We successfully obtain acceptable estimation accuracy for time-varying queue length, and estimate the line-specific proportion of boarding demand in the passenger queue using line-specific arrival rates as the independent variables for an LR model. We compare the accuracy with an ANN model using the same model input and find that the accuracy by LR is slightly lower than ANN. However, the LR provides more insights for bus operators as it quantifies the line-specific arrival rate, the effect of bus arrivals on the queue length, and the effect of time-of-day intervals. Signal strength as well as both randomised and non-randomised MAC address data are used in this research. Through this, it is possible to further increase the predictability. Due to increasing inbuilt randomisation rates by mobile phone producers we suggest utilising such data records will be even more important in the future. Clearly, since randomised data cannot be traced, these records are not suitable for “network flow models”, but it has been confirmed that the data contributes to the estimation of bus stop queues.

Secondly, using the prior estimated queues, the bus line-specific waiting time could also be estimated. For this estimation, the passenger arrival rate of each bus line was obtained first by assuming that the arrival rate pattern is constant for every hour. With this, the waiting time of each bus line was calculated.

The length of queues and bus line-specific waiting times are indicators of boarding demand and service performance at a bus stop. This research contributes, therefore, to the operation planning of bus systems with boarding demand estimation and can be taken as an early and initial step in the entire process of bus system planning and management. Bureaus of transportation, for example, can utilize this research for online operation strategies (e.g., flagging long queues or less demand than usual) and offline operation strategies (e.g., understanding demand and boarding patterns to optimize bus routes).

Alternative analysis approaches other than those presented here are also worth considering. For one, we could consider the queue as an autocorrelated time series or a “SARIMA” problem where seasons reflect the arrival of buses. We note, however, that in our model the time since last departure has a similar autoregressive effect in that it is a cumulative measure for an increasing queue. Furthermore, though the buses arrive fairly regularly, taking the actual bus arrival time instead of fixed intervals appears to be significant. In another future work direction, the total queue at a bus stop might be estimated by using data fusion with Wi-Fi signal data from additional sensors or using Bluetooth data. It could help in the data cleaning process and is expected to improve the goodness of fit.

We also consider additional experiments where we explicitly measure the waiting time of some passengers. In our case study, we obtained the average waiting time for passengers who intend to board each bus line. We noted that this is possible because bus lines do not serve many common stops. As for bus stops served by more lines,

this is often different, one might extend this research by conducting different case studies and aiming to distinguish passengers travelling within the common line section from those who can only use a specific bus line, by introducing the arrival rates of common line passengers as additional variables to the proposed model in this paper.

We also conducted similar, preliminary experiments on 4 stands at two other bus stops. More than two bus lines serve at these stops, and the surrounding traffic congestion is higher than the Ginkakuji-mae bus stop. Partly due to these reasons and partly due to the lower number of recorded data samples, the linear regression model proposed in the Ginkakuji-mae bus stop resulted in lower accuracy. It suggests the importance of appropriate data clustering and noise elimination for local conditions of the Wi-Fi signal data. It also emphasizes the need to repeat our experiments in cases where passengers form less tidy queues. We note that “chaotic waiting” does not necessarily mean a large reduction in demand estimation capability since more passengers will form a crowd near the bus stop and hence more people will be recorded with stronger RSSI at the stop.

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