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Quantifying out-of-station waiting time in oversaturated urban metro systems

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ABSTRACT

Metro systems in megacities such as Beijing, Shenzhen, and Guangzhou are under great passenger demand pressure. During peak hours, it is common to see oversaturated conditions (i.e., passenger demand exceeds network capacity) and a popular control intervention is to restrict the entering rate by setting up out-of-station queueing with crowd control barriers. The *out-of-station waiting* can make up a substantial proportion of total travel time but is often ignored in the literature. Quantifying out-of-station waiting is important to evaluating the social benefit and cost of metro services; however, out-of-station waiting is difficult to estimate because it leaves no trace in smart card transactions of metros. In this study, we estimate the out-of-station waiting time by leveraging the information from a small group of transfer passengers—those who transfer from nearby bus routes to the metro station. Based on the transfer interval of this small group, we infer the out-of-station waiting time for all passengers by a Gaussian Process regression and then use the estimated out-of-station waiting time to build queueing diagrams. We apply our method to the Tiantongyuan North station of Beijing metro; results show that the maximum out-of-station waiting time can reach 15 min, and the maximum queue length can be over 3000 passengers. We find out-of-station waiting can cause significant travel costs and thus should be considered in analyzing transit performance, mode choice, and social benefits. To the best of our knowledge, this paper is the first quantitative study for out-of-station waiting time.

1. Introduction

As the backbone of transportation systems in megacities, metro systems play a critical role in meeting the increasing demand of urban mobility. For example, the Beijing metro—a network consists of 22 lines and 391 stations—has an average daily ridership of more than 10 million by the end of 2019 (Wikipedia contributors, 2019a). To better satisfy the massive passenger demand, numerous measures have been taken to maximize the operational capacity, such as reducing peak-hour headway, increasing train speed, and removing seats for more standing space. In addition to these engineering practices, recent research also shows increasing interest in developing optimization strategies for the operation of large-scale metro systems, such as designing better timetables and schedules (Niu and Zhou, 2013; Sun et al., 2014; Yin et al., 2016), synchronizing different lines to reduce transfer time (Kang et al., 2015), and integrating the metro network with the bus network to minimize the impact of service disruptions (Jin et al., 2014, 2015).

Despite the tremendous efforts in increasing operational capacity, some metro systems are still operated in an oversaturated condition (Shi et al., 2019), which is purely due to the fact that even the optimized capacity cannot satisfy the burst of passenger demand. As a result, it is common to see overcrowded platforms with left-behind passengers who have to wait for more than one train to get on board during peak hours (Zhu et al., 2018). In these extreme scenarios, safety measures need to be taken to prevent overcrowdedness on the platform and operational risks and ensure the smooth operation of the system. Flow control is also a measure to keep safe social distance to prevent the spread of infectious disease in public transit (Hörcher et al., 2021). A common flow-control measure is *out-of-station* queueing—passengers are compelled to queue outside of a metro station before entering the metro station (see Guo

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et al., 2015; Bueno-Cadena and Muñoz, 2017; Jiang et al., 2018; Zou et al., 2018; Xu et al., 2019). It is reported that the out-of-station waiting time of a few metro stations in Beijing, Guangzhou, and Shenzhen can be up to more than 10 min at peak hours (Lin, 2021; Li, 2015).

Quantifying passenger waiting time in metro systems is crucial for evaluating service quality/performance and understanding passengers' choice behavior. In terms of the economic evaluation of public transport services, waiting time is also a critical component in assessing the social benefit/cost of different planning and operation strategies. In the literature, many methods have been developed to estimate the in-station waiting time or transfer time of metro systems using individual-based smart card transactions (Sun et al., 2012, 2015; Sun and Xu, 2012; Zhu et al., 2018; Qu et al., 2020). However, despite that out-of-station waiting may cover a substantial proportion of overall travel time and the experience is much more unpleasant than waiting inside the train station (e.g., under bad weather (Zhang et al., 2021)), it has received little attention in the research. This is primarily due to that out-of-station waiting time cannot be inferred directly from smart card transactions of metro systems, since out-of-station waiting happens before a passenger taps into a metro station. Although one can conduct field surveys to measure out-of-station waiting, the survey approach is very time-consuming and it cannot collect data continuously for long-term monitoring.

The goal of this research is to develop a data-driven method for quantifying out-of-station waiting time using smart card data. To address the aforementioned challenges, we propose an accessible and accurate method by combining the smart card data from both bus and metro systems. Our key idea is to consider those passengers who transferred from a nearby bus stop to the metro station as a proxy, whose transfer time can be estimated as the time interval from the first tapping-out on the bus to the next tapping-in at the metro station. In detail, we first identify these transfer passengers using smart card data. Next, the time interval between the bus tap-out and the metro tap-in is used to estimate the out-of-station queueing time. To handle the noise in the data and to extend the estimation to all passengers, we assume the latent true out-of-station waiting time is a continuous function of time and estimate it with a Gaussian Process regression with a Student-*t* likelihood. Moreover, the estimated out-of-station waiting time is used to build queueing diagrams for further analysis. We present a case study for the Tiantongyuan North station of Beijing metro. We find the maximum out-of-station waiting time is around 15 min, and the maximum queue length can reach 3000 passengers. Lastly, we use a simulation to test the accuracy of the proposed method.

To the best of our knowledge, this is the first quantitative study for out-of-station waiting time estimation. The contribution of this paper is three-fold. First, there is a lack of research on quantifying out-of-station waiting time in metro systems; we use transfer passengers from the bus to the metro as a proxy and apply Gaussian Process regression to estimate the metro out-of-station waiting time. Our data-driven method can be used for large-scale and long-term monitoring. Second, we combine out-of-station waiting time with a queueing diagram to estimate more criteria like queue length and arrival rate, supporting better service adjustments. Lastly, we show by real-world data that out-of-station waiting is a non-negligible part of the total travel time for over-saturated metro stations; more attention should be paid on this underestimated phenomenon. We also summarize potential solutions for out-of-station queueing.

The rest of the paper is organized as follows. Section 2 reviews relevant works and presents the research gap. Section 3 introduces the background and the problem. Section 4 presents the modeling framework of out-of-station waiting time estimation. In Section 5, we present a case study of the Tiantongyuan metro stations in Beijing; a simulation is conducted to test the accuracy of the proposed model. Next, we discuss potential solutions for the out-of-station waiting in Section 6. Finally, Section 7 summarizes the paper and provides future research directions.

2. Literature review

Most modern metro systems adopt a fare gantry-based smart card system, which generates a continuous flow of transactions registering when and where passengers start their trips (Pelletier et al., 2011). Given the rich information collected, smart card data has been widely used in understanding individual travel behavior and enhancing the planning and operation of metro systems (e.g., Niu and Zhou, 2013; Sun et al., 2014; Jin et al., 2014; Kang et al., 2015; Jin et al., 2015; Yin et al., 2016). In the following, we review the application of smart card data in estimating waiting time and inferring route choices in metro systems.

The waiting time of a metro system is a crucial indicator for transit service quality, and it is also a key determinant for passenger route choice behavior (Wardman, 2004). Many methods have been developed to estimating waiting times from smart card data. Typically, these methods decompose the time interval between tapping-in (at origin) and tapping-out (at destination) into waiting time, onboard time, and transfer time using certain regression techniques and side information (e.g., timetables of trains). In the meanwhile, these methods usually also output the route choice of each trip. For example, Kusakabe et al. (2010) combined smart card data with train timetables to estimate which train is boarded by each individual traveler. Sun et al. (2012) proposed a linear regression model to decompose travel time and applied this model to estimate the spatiotemporal loading profile of trains. Sun and Xu (2012) used smart card data to study travel time reliability and proposed a probabilistic mixture model to infer passenger route choice. Sun et al. (2015) developed a probabilistic generative model of trip time observations characterizing both the randomness of link travel time and route choice behavior. This model can be used as a passenger flow assignment framework for service planning and operation. Krishnakumari et al. (2020) developed a linear regression method that estimates the delay at each metro station, link, and transfer.

There is also research on the waiting time for buses and transfers. Early researchers estimated the average bus waiting time as a function of bus headway (e.g., Osuna and Newell, 1972; Newell, 1974; Hickman, 2001) by assuming uniform passenger arrival and independent bus headway. Amin-Naseri and Baradaran (2015) relaxed the assumptions regarding the passenger arrival and the independence of headway to improve the formulation-based method. Wepulanon et al. (2019) utilized the first and last observation by Wifi detectors installed at bus stops to estimate the average waiting time at bus stations. In terms of multi-modal trips, most studies focus on evaluating the transfer time or walking time. For example, Chang and Hsu (2001) proposed a mathematical model to analyze the waiting time at intermodal transit stations. Hsu (2010) found the transfer waiting time is mainly determined by the capacity and the headway of connected services by a simulation. (Guo et al., 2011) developed a mathematical model to calculate the average waiting time for passengers transferring from rail to buses. (Wahaballa et al., 2021) used a stochastic frontier model to estimate the transfer walking time and waiting time distributions between bus stops and rail stations. Eltved et al. (2021) used smart card data to estimate the walking time distributions for transfers from bus to rail platform with the consideration of possible intermediate activities.

The waiting time and route choice in an oversaturated metro system are more complex. For instance, passengers may travel backward to an uncrowded station to find a seat and then travel forward. Tirachini et al. (2016) investigated this interesting backward traveling phenomenon and estimated the disutility of sitting and standing (and also level of crowdedness) in metro trains. Besides, passengers often have to wait for multiple trains to get on board. Zhu et al. (2018) and Ma et al. (2019) developed data-driven methods to estimate the number of left-behind passengers in metro systems. Qu et al. (2020) also studied the waiting time of left-behind passengers; they found passengers' waiting time in peak hours is much longer than the metro headway. Mo et al. (2020) proposed a performance monitoring framework that incorporates the number of left-behind passengers.

The aforementioned studies have proposed various methods to estimate the waiting time, transfer time, or route choice from various data sources. However, the out-of-station waiting time in metro trips is a special phenomenon caused by oversaturated demand and in-flow control, which is not evaluated in the literature. And most above models (e.g., walking time estimation models) do not work under this special scenario. Therefore, we developed a new approach that combines the smart card data from bus and metro systems to infer the out-of-station waiting time in the metro system.

3. Background

Beijing Metro is one of the busiest metro systems in the world. During rush hours, the ridership at a few stations is extremely high that passengers have to queue for quite a long time outside the station before entering the metro station (see Fig. 1). For example, the Tiantongyuan area of Beijing is one of the largest residential hubs in China; it has a total population of 700 000 in 2019 (Wikipedia contributors, 2019b). There are three metro stations, Tiantongyuan North (TTY-N), Tiantongyuan (TTY), and Tiantongyuan South (TTY-S), in this area. Due to the large number of commuting passengers, all three stations are oversaturated during morning peak hours on weekdays. In this paper, we use the TTY-N station as an example to demonstrate our proposed solution to quantify out-of-station waiting time. The location of the TTY-N station is shown in Fig. 2. Because the TTY-N station is the northern terminus of Metro Line 5, the boarding rate in the morning peak is controlled to alleviate the overcrowdedness on the platform and to prevent the service at downstream stations be overwhelmed; this is also one of the reasons for the out-of-station queueing. Without this flow-control intervention, the trains will be fully loaded at departure, leaving no capacity for passengers waiting at the subsequent/downstream stations.

The public transit system in Beijing uses a distance-based fare scheme. Therefore, passengers need to tap their smart cards or tickets when getting on and off a bus and when entering and leaving a metro station. Useful information in smart card data includes anonymous IDs, origin/destination, and timestamps of tapping-in/-out. For bus trips, the transactions also record the ID of the bus. Note that user IDs are consistent in both metro and bus systems, so that we can link trips from both systems for a particular user. Next we show how to estimate the out-of-station waiting time by combining the smart card data from both bus and metro systems.

As illustrated in Fig. 3, we separate all the incoming passengers at a metro station into two groups: (G1) direct passengers who do not have a previous bus transfer and (G2) transfer passengers that coming from a nearby bus stop. For a direct passenger i, we only know the tap-in time $t_{\text{in},i}$ at the metro fare gantry, but we have no information about the out-of-station queueing. For a transfer passenger i, we can know the metro tap-in time $t_{\text{in},i}$, the bus tap-out time $t_{\text{out},i}$, and the transfer duration $d_{\text{transfer},i} = t_{\text{in},i} - t_{\text{out},i}$ (we use t for a timestamp and d for a time duration/interval). In addition, we can estimate the out-of-station waiting duration for a passenger in G2 by subtracting the walking time $d_{\text{walk},i}$ between the bus stop and the metro station from the transfer duration.

Typically, G2 only accounts for a small percentage of the total boarding passengers. Therefore, we regard G2 as a small sample set drawn from total passengers and use it to estimate the out-of-station waiting profile for all boarding passengers. In doing so, we need to (1) accurately estimate the out-of-station waiting time for all boarding passengers and (2) develop a method to analyze queueing profile. We introduce the methodologies for these tasks in Section 4.

4. Modeling framework

This section elaborates the methods for profiling the out-of-station waiting time using smart card data. First, in Section 4.1, we illustrate the impact of noise in the data and propose a Gaussian Process regression for the out-of-station waiting time estimation. Then, in Section 4.2, we introduce the idea of using a queueing diagram to analyze the out-of-station waiting.

4.1. Gaussian process for waiting time estimation

The out-of-station waiting time of a passenger i in G2 can be roughly estimated by $d_{\text{transfer},i} - d_{\text{walk},i}$, and we refer it as the *observed* waiting time for simplicity. Fig. 4 shows the observed waiting time at different metro tap-in times, where we regard the walking time d_{walk} as a constant and determine it by the median value of all d_{transfer} during 12:00–4:00 p.m. (observing that no out-of-station waiting at off-peak hours). We can see the observed waiting time is much higher in the morning peak. However, there is substantial noise in the observed waiting time. Even in a short period of time, there are significant discrepancies between different observations. Sources of noise include different walking speeds, unsynchronized clocks between smart card readers, intermediate

Fig. 1. The queue outside the Tiantongyuan metro station. Photo taken at 8:14 on Thursday, October 31, 2019.

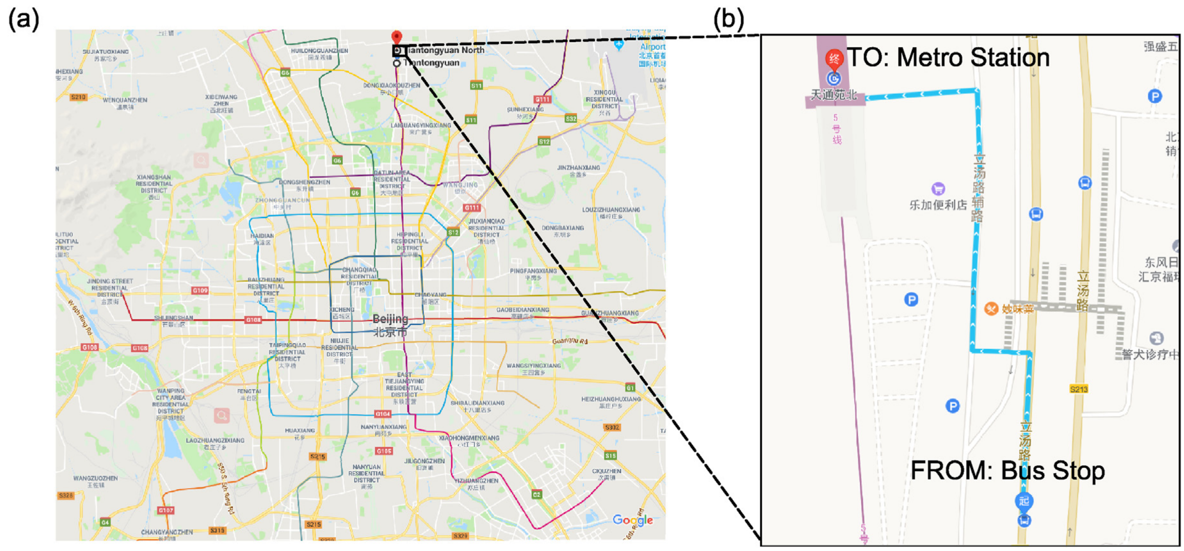

Fig. 2. The location of the Tiantongyuan North metro station and a nearby bus stop.

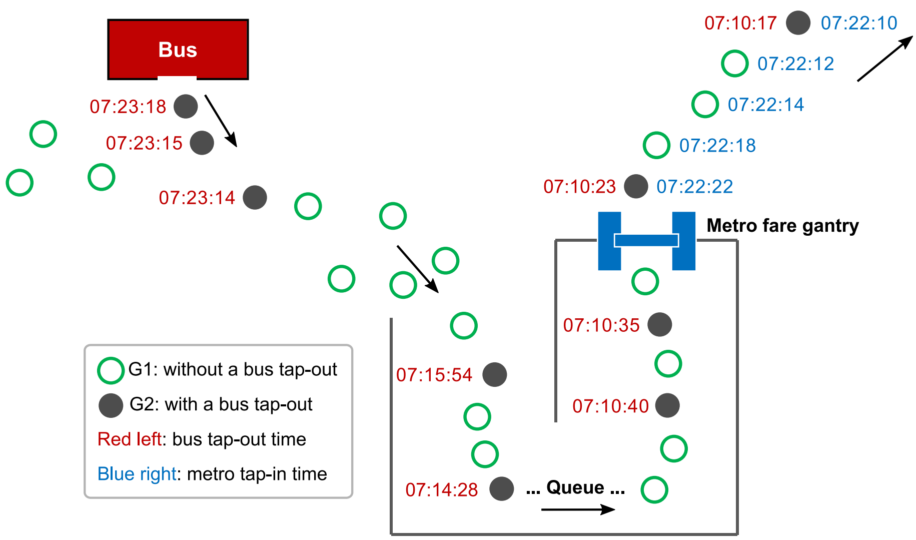

Fig. 3. An illustration of out-of-station queueing of a metro station. G1 means direct passengers without a previous bus trip. G2 represents transfer passengers coming from a previous bus trip. Red numbers to the left side give the bus tap-out time t_{out}, and blue numbers to the right side give the tap-in time t_{in} of the metro station. We estimate the out-of-station queueing time for both G1 and G2 based on the t_{in} and t_{out} of G2. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

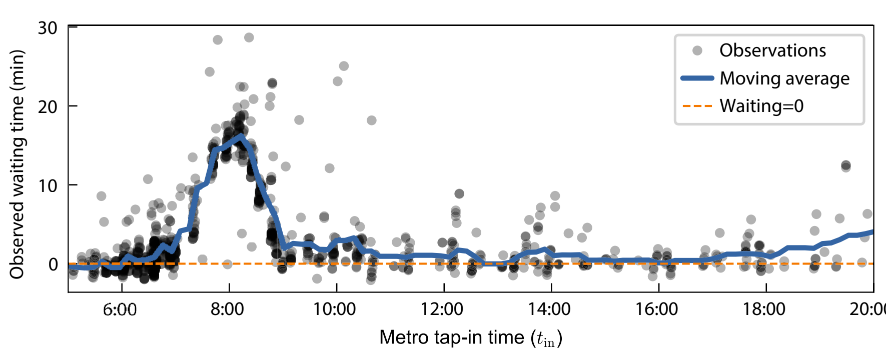

Fig. 4. The observed out-of-station waiting time (i.e., $d_{transfer} - d_{walk}$) and the moving average of nearest 30 data points at different metro tap-in times in a workday.

activities, and some passengers may "tap-out" before the bus arrives at the bus stop to speed up the alighting. A moving average (MA) estimation of out-of-station waiting is shown in Fig. 4, we can see the curve is jagged (affected by the bus timetable), and the off-peak hours have significant out-of-station waiting (not in line with the actual situation). Therefore, moving average is not a good estimation because of the noise; a well-founded method is required for out-of-station waiting time estimation.

We use a Gaussian Process (GP) regression (Williams and Rasmussen, 2006) to estimate the out-of-station waiting time. A GP is a non-parametric Bayesian model that defines a distribution over functions. Gaussian processes are very flexible and can approximate complex functions using various kinds of kernels and likelihoods. Most importantly, a GP is a probabilistic approach that also gives confidence intervals for the estimated values. In the presence of such a high level of noise, the confidence intervals given by the GP are particularly useful for judging whether the out-of-station waiting time estimation of a certain period is reliable; this is why we choose GP for this task instead of other machine learning models. We refer readers to the book by Williams and Rasmussen (2006) for more information about Gaussian Processes.

Let $y(t)$ be the observed waiting time for a passenger with metro tap-in time t. For ease of description, the time t in here and after means the metro tap-in time if not otherwise specified. The observed waiting time can be decomposed into a latent "true" waiting time $f(t)$ and a noise term ϵ:

$$y(t) = f(t) + \epsilon. \tag{1}$$

We assume the "true" out-of-station waiting time $f(t)$ is a continuous function of time. We need to infer the latent "true" waiting time given the observed waiting time. In doing so, we impose a GP prior to $f(t)$, meaning the function's values $f(\mathbf{t}) = [f(t_1), f(t_2), \ldots, f(t_n)]^\top$ for any finite collection of inputs $\mathbf{t} = [t_1, t_2, \ldots, t_n]^\top$ have a joint multivariate Gaussian distribution. We will write

$$f(t) \sim \mathcal{GP}(\mu(t), k(t, t')), \tag{2}$$

where $\mu(t)$ is the mean function and $k(t, t')$ is the covariance/kernel function. By convention, the mean function is set to zero, i.e., $\mu(t) = 0$. For the covariance function, we choose the commonly used squared-exponential (SE) kernel:

$$k(t, t' | \ell, \lambda^2) = \lambda^2 \exp\left(-\frac{(t - t')^2}{2\ell^2} \right), \tag{3}$$

where the length scale ℓ and the variance λ^2 are two hyperparameters that should be calibrated by data. This simple SE kernel (only two parameters) works pretty well for approximating continuous functions (Micchelli et al., 2006). The covariance in Eq. (3) is larger for two closer t and t', indicating passengers that enter the metro station at a closer time are more likely to have more similar waiting time. We can see a GP is fully specified by the mean and covariance functions and does not impose any assumption on the form of the function $f(t)$.

When using an i.i.d. Gaussian distribution for the noise term ϵ, the posterior of the latent variable $f(\mathbf{t})$ can be solved analytically. However, this convenient approach is very sensitive to outliers and is not appropriate for our data. To make a robust estimation for the "true" waiting time, we assume the noise is a zero-mean i.i.d. Student-t distribution with a long-tail probability density function (Jylänki et al., 2011):

$$p(\epsilon | \nu, \sigma) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{\pi\nu}\sigma} \left(1 + \frac{\epsilon^2}{\nu\sigma^2}\right)^{-\frac{\nu+1}{2}}, \tag{4}$$

where ν is the degrees of freedom and σ the scale parameter (Gelman et al., 2013).

Eqs. (1)–(4) describe the GP regression with a Student-t likelihood. Given a set of observed waiting times $\mathbf{y}$ at metro tap-in time $\mathbf{t}$, the four hyperparameters $\theta = \{\ell, \lambda^2, \nu, \sigma\}$ can be optimized by maximizing the log marginal likelihood

$$\log p(\mathbf{y} | \mathbf{t}, \theta) = \log \int p(\mathbf{y} | \mathbf{f}) p(\mathbf{f} | \mathbf{t}, \theta) d\mathbf{f}. \tag{5}$$

The log marginal likelihood cannot be explicitly obtained when the noise is a Student-t distribution. Therefore, approximate inference methods (Neal, 1997; Vanhatalo et al., 2009; Jylänki et al., 2011) were developed to fit hyperparameters. We use the Laplace approximation (see Williams and Rasmussen, 2006, Section 3.4; Vanhatalo et al., 2009) as implemented in GPy (GPy, since 2012) for the approximate inference. Next, for new passengers with metro tap-in times $\mathbf{t}^*$, we can calculate the posterior distribution $p(\mathbf{f}_* | \mathbf{y}, \mathbf{t}, \mathbf{t}_*)$ of their "true" out-of-station waiting time. The posterior distribution $p(\mathbf{f}_* | \mathbf{y}, \mathbf{t}, \mathbf{t}_*)$ is a multivariate Gaussian, but whose mean and variance can only be approximated obtained (e.g., using the Laplace approximation, see Vanhatalo et al., 2009; Jylänki et al., 2011). We use the posterior mean as a point estimation $\hat{f}(\mathbf{t}_*)$ for the out-of-station waiting time, referred to as the *estimated* waiting time in the following. And the posterior variance is used to calculate confidence intervals for estimated waiting time.

4.2. Queueing diagram

The out-of-station waiting phenomenon at a metro station is a queueing process with varying arrival rate and service rate. To better analyze the reason and the impact of the out-of-station queue, we further establish a queueing diagram based on the estimated waiting time, as illustrated in the virtual example of Fig. 5.

We used the virtual example in Fig. 5 to illustrate how to establish a queueing diagram from the estimated out-of-station waiting time. Fig. 5 (a) shows the queueing diagram, where the departure curve indicates the service rate at the metro gantries. Because the smart card data in Beijing contain passengers' tap-in times, the departure curve is directly reconstructed from passengers' metro tap-in records. The passenger arrival curve is not directly available from the data but can be inferred from the metro tap-in time and the out-of-station waiting duration. For example, the point B in Fig. 5 represents a passenger that tapped in the metro station at t_B; we can estimate his/her out-of-station waiting duration $\hat{f}(t_B)$ by the GP model described in Section 4.1, as shown in Fig. 5 (b). The segment $|AB|$ in the queueing diagram means the out-of-station waiting duration, we can thus calculate the arrival time for this passenger (point A) by $t_B - \hat{f}(t_B)$. The arrival curve can thus be obtained by connecting the estimated arrival times of all passengers. Note we use the estimated waiting time instead of the observed waiting time for both G1 and G2 to avoid the impact of noise in the data.

The queueing diagram provides important information much more than just a visualization. For example, the slope of the departure curve represents the service rate at the metro entrance, the slope of the arrival curve means the arrival rate. The horizontal distance (e.g., $|AB|$) and vertical distance (e.g., $|AC|$) between the two curves represent the waiting time and the queueing length, respectively. Moreover, the area between the two curves represents the total waiting time of all passengers. Next, we will build queueing diagrams to analyze the out-of-station queueing at the TTY-N station.

5. Results

In this section, we present the results for the out-of-station queueing at the TTY-N metro station. Firstly, the data and the demand pattern at the TTY-N station are introduced in Section 5.1. Next, Section 5.2 exhibits the out-of-station waiting time estimated by GP regressions. Finally, we analyze the queueing process in the morning peak and discuss possible solutions in Section 5.3.

5.1. Data description

Based on the available data, we select a five-day period from August 3rd to 8th, 2015, to analyze the out-of-station queueing at the TTY-N metro station. This five-day period reflects a typical weekday demand pattern. We have full smart card data for the TTY-N station in this period. The tap-in/out information for all metro passengers, including those who use tickets, is registered in the data. Besides, we also have smart card data from three different bus routes that pass through the TTY-N bus stop (next to the TTY-N subway station). The walking time from the bus stop

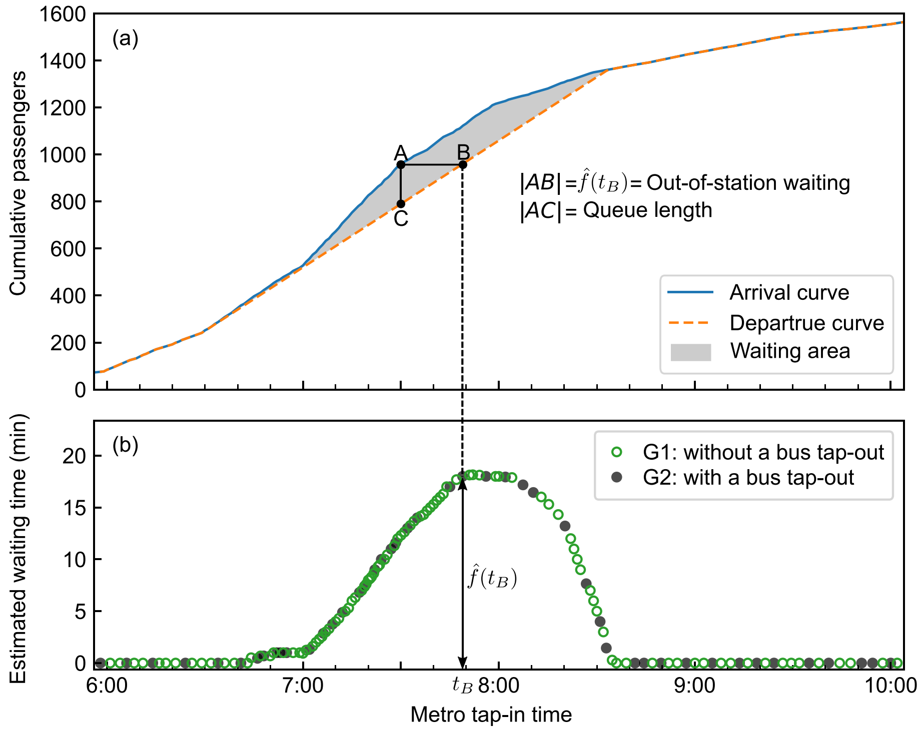

Fig. 5. Establishing a queueing diagram by the estimated out-of-station waiting time – A virtual example. (a) The queueing diagram. (b) The estimated out-of-station waiting time (only shows 10% of passengers for clarity).

to the metro station is the same for the three bus routes. The whole analysis is based on the tap-out at the TTY-N bus stop and the tap-in at the TTY-N metro station.

If we detect the same smart card ID has an immediate metro trip after a bus trip, and the interval between the bus tap-out and the metro tap-in is within 30 min, we regard this ID as a passenger in G2. After separating passengers into G1 and G2, the boarding demand of G1 and G2 at the TTY-N station on a typical weekday is shown in Fig. 6. We can see the TTY-N station services more than ten thousand passengers per hour in the morning peak (7–8 a.m.), and the demand is very low in the afternoon and evening, showing TTY-N is a typical residential-type station. On the other hand, the number of passengers in G2 is much smaller than that in G1. This is because only a small portion of passengers are transferred from the bus stop. We use G2 as a small sample drawn from all passengers to recover the out-of-station waiting profile at the TTY-N station. There are around one thousand observations of G2 per day in our data.

5.2. Estimated out-of-station waiting

Because the TTY-N station has a low boarding demand in off-peak hours, there is no out-of-station waiting at off-peak hours (based on reality). Therefore, we regard the walking time as a constant and determine it by the median value of all d_{transfer} during 12:00–4:00 p.m. Next, we can calculate the observed waiting time, as shown in the black points in Fig. 7. We can see the noise is very high for the observed waiting time.

Next, we fit a GP with student-*t* likelihood for each day. A GP at the scale of this study can be solved by a personal computer with Intel Core i7-8700 Processor in around 1 min. Sparse GP (e.g., Titsias, 2009; Gardner et al., 2018) can be used when the number of observations

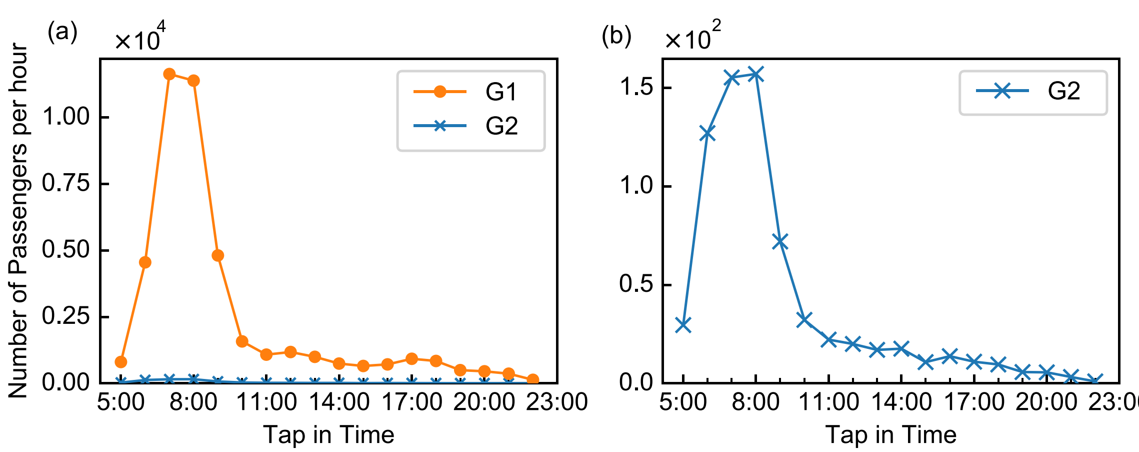

Fig. 6. The number of boarding passengers per hour at the TTY-N station (Monday, August 3rd, 2015).

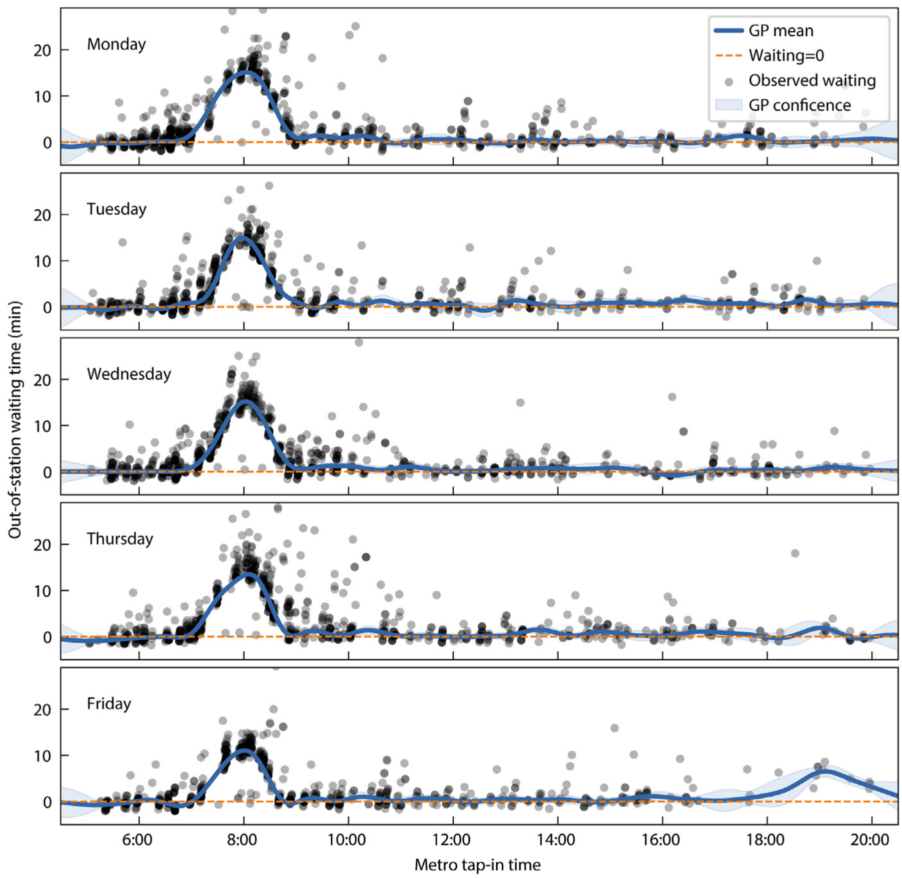

Fig. 7. The observed waiting time, the GP posterior mean, and the 95% confidence interval of the GP posterior mean.

becomes too big. Fig. 7 shows the posterior mean and confidence interval of the estimated out-of-station waiting time. We can see the GP with a Student-*t* likelihood is robust to the noise, and the estimated waiting time makes intuitive sense. Despite the presence of outliers, the estimated waiting time in general wiggles around zero from 5:00 to 7:00 a.m. and after 9:00 a.m., which is consistent with the real-life situation. We also see the confidence interval is larger in the period with fewer observations. The estimated waiting time on Friday night is unusually high (also with larger confidence intervals), this could be caused by too few G2 passengers during that period. We expect the estimated waiting time for morning peaks to be more reliable because of the larger number of observations and narrower confidence intervals. All five weekdays have significant out-of-station waiting from around 7:00 to 9:00 a.m. The maximum waiting time is around 15 min for Monday to Thursday, and the waiting time on Friday is relatively shorter. The quantitative results for the waiting time are shown in the Table 1.

5.3. *Queueing analysis*

This section analyzes the out-of-station waiting by queueing diagrams. We first set negative values in the estimated waiting time to zero. Following the illustration in Fig. 5, we next establish queueing diagrams for the five weekdays, as shown in Fig. 8.

The upper half of Fig. 8 shows the cumulative arrival curve and departure curve at the TTY-N metro station. Note that the “departure” means entering the metro gantry rather than boarding a train. The arrival/service rate at time t is estimated by the average arrival/service rate in [$t-5$ min, $t+5$ min], as shown in the lower half of Fig. 8. For all five days, we can see the arrival rates are larger than the service rates from around 7:00 to 7:50 a.m., and queues are therefore formed. The maximum arrival rate is often more than 300 people/min, while the maximum service rate is only around 200 people/min. The queue lengths start to decrease after around 7:50 a.m. and the queue dissipates at around 9:00 a.m.

Table 1
Quantifying the out-of-station queueing from 7:00 to 9:00 a.m.

	Monday	Tuesday	Wednesday	Thursday	Friday	Average
Total number of passengers	22 740	23 193	22 964	23 241	22 524	22 932
Maximum waiting time (min)	15.1	15.0	15.3	13.5	11.1	14.0
Total waiting time (h)	3665	2984	3240	3006	2194	3018
Average waiting time (min)	9.7	7.7	8.5	7.8	5.8	7.9
Maximum queue length (people)	3191	3188	3251	2893	2310	2967
Maximum arrival rate (people/min)	295	384	319	302	280	316
Maximum service rate (people/min)	212	220	219	220	215	217
The time with the longest queue	7:48	7:43	7:44	7:52	7:49	7:47

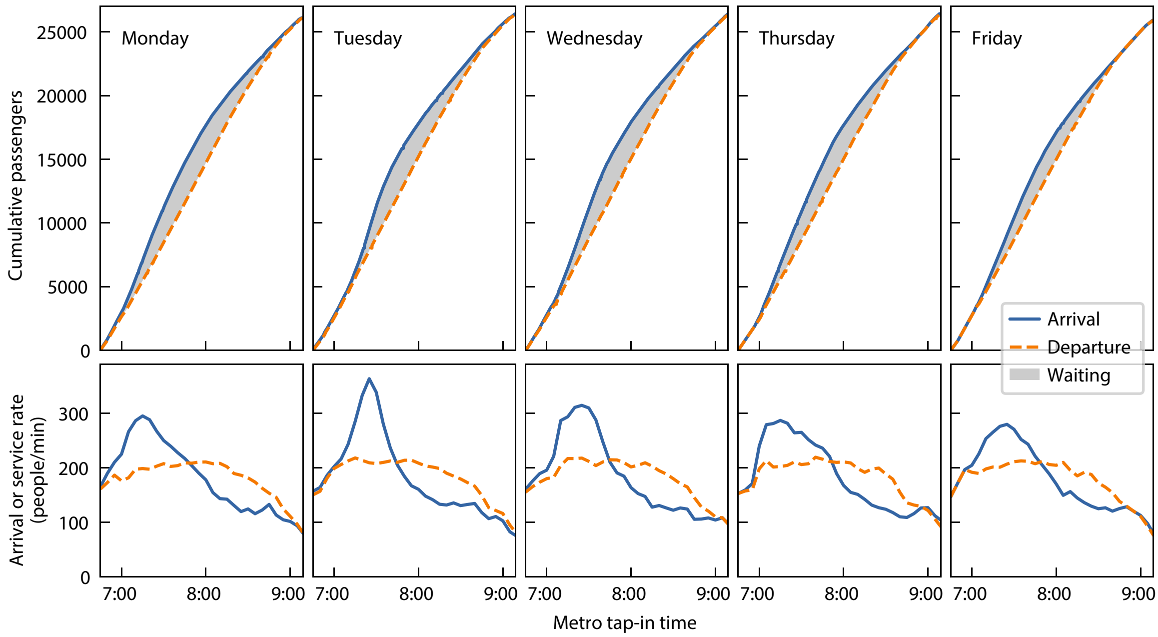

Fig. 8. The queueing process in the morning peak.

Table 1 summarizes major indices for the out-of-station queueing. We can see the out-of-station waiting greatly impact passengers' travel. The maximum arrival rate is 50% larger than the maximum service rate. When the queue has a maximum length, over three thousand passengers are waiting in the queue, and it takes around 15 min for a passenger to enter the station. On average, every passenger waits 8 min outside the station in the morning peak. Considering the number of passengers, the total out-of-station waiting time exceeds three thousand hours per day at the TTY-N station; the queueing is a big waste of time and efficiency.

5.4. Validation by a simulation

Because the real out-of-station waiting time is unknown, we design a numerical simulation to assess the accuracy of the proposed method. The simulation reproduces a queueing process in the morning from 6:00 to 9:00. The parameters in the simulation are simplified from the smart card data. We set the service rate at the metro entrance to be 200 people/min and the bus headway to be 5 min. We divide the simulation into four periods, 6:00–7:00, 7:00–7:40, 7:40–7:50, 7:50–9:00, and use different passenger arrival rate for these periods. The arrival of G1 passengers follows Poisson distributions with means of 100, 300, 180, and 120 people/min for the four periods, respectively. We set the number of G2 passengers per bus to be 10, 15, 10, and 8 people for the four periods, respectively. The bus tap-out time of a passenger is uniformly distributed in the 1-min period after the arrival of a bus. Finally, we use two sources of noise to imitate the complex noise structure in the observed waiting time: (1) We assume the walking time d_{walk} from the bus station to the metro station follows a normal distribution, i.e., $d_{\text{walk}} \sim \mathcal{N}(\mu = 3, \sigma^2 = 0.5^2)$. (2) We assume 20% of the G2 passengers have intermediate activities in their bus-to-metro transfer and the activity duration d_{transfer} follows a shifted exponential distribution, i.e., $(d_{\text{transfer}} - 1) \sim \text{Exp}(\lambda = \frac{1}{3})$, where λ is the rate parameter. We use the shifted exponential distribution for the activity duration because we find it produces a similar noise pattern as the real-world data.

Using the above configuration, we can simulate a queueing process and calculate the "real" waiting time and the observed waiting time in the simulation. Next, we apply the GP regression with student-t likelihood to estimate the out-of-station waiting time and compare it with the real waiting time. The estimation results are shown in Fig. 9, where we also use a moving average (MA) of the nearest 30 data points for comparison. We can see the estimation of the GP regression is pretty close to the real waiting time. In fact, the maximum difference between the GP estimation and real waiting time is around 1 min (54 s). In contrast, the estimation of the MA is affected by the noise and shows a significant bias. We also calculate the root-mean-square errors (RMSE) between the real and the estimated waiting time; it shows that the RMSE of GP regression (0.258) is much smaller than that of the MA (0.802). Note that we did not use the student-t distribution in the simulation for the noise of the observed waiting time, but the GP regression with student-t likelihood still shows excellent robustness to the noise, indicating our model has a certain extent of generality for different types of noise. Although the simulation cannot completely reproduce the real-world queueing process (e.g., the arrival and service rate is time-varying and the noise is more complex), the results of the simulation give a reference for the accuracy of the GP regression.

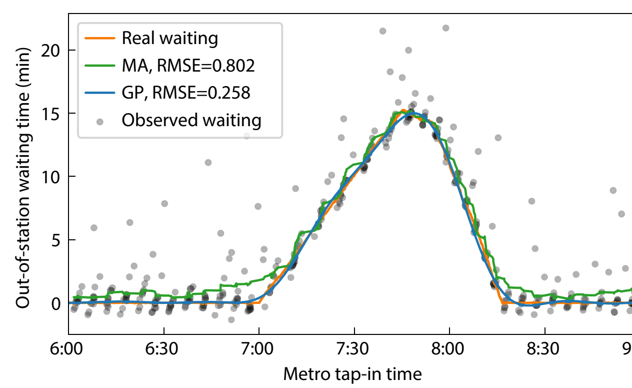

Fig. 9. The out-of-station waiting time estimation of GP and MA in the simulation.

6. Potential solutions for out-of-station queueing

Queueing outside of metro stations has a substantial negative impact on passenger travel experience. In this section, we discuss existing and potential solutions to this problem. The fundamental reason for the out-of-station waiting is the mismatch between demand and supply. The commuting demand is rooted in the urban structure and can hardly be changed. Many traffic congestion problems should be avoided in the initial urban planning stage. However, we can still manage the demand from a temporal aspect (Halvorsen et al., 2019). For example, providing reduced-rate fares to off-peak trips can flatten the peak-hour demand (e.g., shift peak-hour trips to pre-peak and after-peak hours). The temporally differentiated fare scheme has been studied in much research (Yang and Tang, 2018; Lu et al., 2020; Li et al., 2018; Ma and Koutsopoulos, 2019; Adnan et al., 2020). A few real-world practices show that properly designed off-peak discounts can help reduce metro crowding (Halvorsen et al., 2016; Greene-Roesel et al., 2018). More generally, systematic public travel demand management (PTDM, Ma et al., 2021) could be designed to influence passengers' mobility behavior. Based on the queueing analysis of Section 5.3, a potential solution is to design a fare scheme for the TTY-N metro station to reduce the boarding demand from 7:00 to 8:00 a.m. Overall, using a temporally differentiated fare scheme is a potential solution, although the effect is hard to evaluate in advance.

Beijing metro has made a lot of efforts from the supply side. In fact, the minimum headway of most metro lines of Beijing has been reduced to less than 2 min to increase network capacity. Moreover, the original TTY-N metro station has been integrated into Tiantongyuan North Transportation Hub since October 13, 2019. The TTY-N Transportation Hub integrates metro line 5, coaches, buses, and a P+R (Park and Ride) parking lot. There is a large-scale waiting lobby in the hub, and passengers no longer need to queue in the open air, which is helpful under bad weather conditions. New transportation facilities are also under construction or planning. For example, the Beijing metro line 13A, which is expected to complete in 2023 (National Development and Reform Comission, 2019), can significantly relieve the commuting pressure of the Tiantongyuan area.

Reducing perceived waiting time can also improve the level of service. For example, providing shelters (Fan et al., 2016) and improving the thermal environment (Zhang et al., 2021) can significantly reduce the perceived waiting time. Besides, it has been shown that providing real-time information can reduce the anxiety for uncertainty and the perceived waiting time (Watkins et al., 2011; Brakewood et al., 2014). Therefore, providing real-time queueing information has the potential to improve transit services (Brakewood et al., 2015).

Finally, using other transportation modes to share the metro's demand is also a solution. Normally, the bicycle is not an ideal substitution for the metro considering its short travel distance. However, there are always special cases. In 2019, a 6.5 km elevated bicycle-only path was built in Beijing to share the extremely high commuting demand between Huilongguan and Shangdi, where Huilongguan is another high-density residential area suffering from out-of-station queueing. It is reported that cycling between Huilongguan and Shangdi takes around 30 min, while it could take more than 40 min to commute by metro in the rush hour (China Daily, 2021).

7. Concluding remarks

This paper proposes a data-driven method to estimate the waiting time outside of an oversaturated metro station due to flow control measures. To the best of our knowledge, this paper presents the first quantitative study to measure passengers' out-of-station waiting time. By combining smart card data from the metro and bus system, we use transfer passengers as a proxy to quantify the queueing time outside of a metro station. A probabilistic approach by Gaussian Process regression is developed to infer the out-of-station waiting time for all passengers. Besides, we propose to analyze the queueing process by a queueing diagram. In the TTY-N metro station case study, results show our method is robust to the noise in data and provides a reliable estimation for out-of-station waiting time. We find that out-of-station waiting can be a big burden—more than 15 min waiting time—for passengers in oversaturated metro stations. Our results could help transit agencies better understand service performance. Considering out-of-station waiting is a recurring issue in megaticies like Beijing and Shenzhen, the accurate estimation of out-of-station waiting should be used to evaluate user utility and social cost, which could be further used to support decision-making, such as designing better flow-control strategies.

A limitation of this work is the lack of validation by a field survey. Because we can only access the smart card data of 2015, but the boarding demand at the TTY-N station has drastically changed since the completion of the TTY-N Transportation Hub and the outbreak of COVID-19. Nevertheless, the GP regression produces reasonable confidence intervals (validated in the off-peak hours), and we believe that our estimation should be a solid reference. The numerical simulation in Section 5.4 also verifies the accuracy of the GP regression. Although only a small sample of data is available for this study, authorities that have access to data can use our method for large-scale and long-term monitoring.

There are several directions for future research. First, the performance of metro systems can be re-evaluated by taking the out-of-station waiting into account. Our case study shows that passengers at Tiantongyuan North suffer while downstream passengers benefit from the flow-control measures. A critical research question is to balance the trade-off and design optimized flow-control strategies based on passenger flow assignment when demand exceeds network capacity. Second, because waiting in an open air is more vulnerable to extreme weather, it is important to quantify the disutility of out-of-station waiting time (Tirachini et al., 2016; Zhang et al., 2021). Furthermore, how the waiting time affects mode choice is also worthy of investigation (Sun and Xu, 2012). Finally, an interesting and important research direction is to develop time- and station-dependent transit fare schemes to flatten peak hour demand and thus reduce the mismatch between demand and supply (Yang and Tang, 2018; Lu et al., 2020; Li et al., 2018; Adnan et al., 2020).

Replication description

The smart card data used in this research were provided by Beijing Transportation Information Center. The code of this research can be found at https://github.com/chengzhanhong/out-of-station-waiting.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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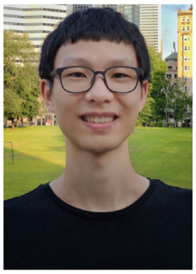

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