Transportation Research Part A 77 (2015) 292–304

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Does crowding affect the path choice of metro passengers?

Kyung Min Kim [1], Sung-Pil Hong *, Suk-Joon Ko, Dowon Kim [2]

Dept. of Industrial Eng., Seoul National University, San 56-1 Shilim-dong, Kwanahk Gu, Seoul 151-742, Republic of Korea

ARTICLE INFO

Article history:
Received 29 April 2014
Received in revised form 17 October 2014
Accepted 28 April 2015

Keywords:
Crowding
Path choice
Logit model
Case study

ABSTRACT

This paper investigates crowding effect on the path choice of metro passengers. We show people reroute not only to avoid the delay from crowding but also to evade crowding itself. More specifically, a logit model fits best when it uses the transit delay from crowding as well as the passenger load of a connection in addition to the conventional explanatory variables. Also, we demonstrate that crowding decreases the overall welfare of metro passengers. The model is tested on the real path choice data acquired by the recent algorithm by Hong et al. (2015) known to detect the real path choice from Smart Card data in more than 90% of the cases.

1. Introduction

This paper addresses the following question. Does the crowding of a connection affect the path choice of a metro passenger, and if so, in what manner and to what degree? It is not difficult to conjecture that crowding might affect the path choice of metro passengers by delaying their transit. We assert not only crowding delay but also crowding itself are equilibrated in the path choice of metro passengers. Therefore, the conventional variables alone cannot assess the welfare of metro passengers.

The exclusive right-of-way of metro restricts a crowding delay mainly to the dwell of a train or the transfer movement of a passenger. Accordingly, we refine transit time of a passenger into the proper components on each of which crowding delay is analyzed separately to the level of passenger traffic.

As a result, we found that the dwell time delay affects the path choice of passengers. The effect of transfer delay, on the other hand, was insignificant. There are two reasons for this. First, in total, the transfer delay is smaller than the dwell time delay accumulating at every stop. Second, passengers tend not to perceive the delay in a transit movement so significantly as in a dwelling train.

Does crowding, then, affect the path choice only via a delayed transit? In Seoul where passengers are allowed up to 200% of the design capacity of a vehicle in peak hours, there has been a folklore that many people travel further along a roundabout path, to avoid crowded sections, such as the notorious Shindorim–Gangnam sections. (By a *section* we mean the physical intervals between two adjacent stations.) Although the longer connections are not preferable in any other respect either, the passengers along them are more than can be explained by a perception error.

It suggests passengers perceive another type of disutility from crowding than delay: e.g. seat unavailability, displeasure of crush with people, being unable to read or use a smart phone, or a worry of a sexual harassment, etc. We will collectively

* Corresponding author. Tel.: +82 2 880 1477.
E-mail address: sphong@snu.ac.kr (S.-P. Hong).
[1] Current address: Policy-Technology Convergence Research Division, Korea Railroad Research Institute, Republic of Korea.
[2] Current address: Engineering Innovation Center, BISTel Inc., Republic of Korea.

http://dx.doi.org/10.1016/j.tra.2015.04.023
0965-8564/

address them as *crowding stress* and use the passenger load, i.e. the number of passengers per vehicle as its explanatory variable.

We verified that, in peak hours, the dwell time delay combined with the passenger load provides the best combination of explanatory variables if added to the conventional set of variables, such as the in-vehicle time and the transfer time of a connection. (In Seoul, the fare is fixed for the same *O–D* regardless of the actual connection of a passenger, and a monetary term, therefore, was excluded from explanatory variables.) Ours is, to the best of the authors' knowledge, the first to examine crowding effect in delay and stress.

Previous works mostly relied on a survey of passengers asked to valuate the crowding with a finite and discrete set of grades. Then the grade is input as the explanatory variable for crowding, whose effect is tested on stated path choice of passengers. The proposed model uses, instead, the specific delay and passenger load of a connection, and furthermore, verify their effect on the real path choice.

Such an approach necessitates the data on the number of passengers along each and every sequence of trains connecting an *O–D* pair at each time of a day. A difficulty was, as also noted in Ceapa et al. (2012) and Jang (2010), the real path choice of a passenger is hidden; the actual transfer station(s) chosen by passengers are not readily determined when there are multiple connections of similar costs. The pervading Smart Card automated fare collection system, or *Smart Card* could not easily resolve the problem, as initially expected, since, typically, it maintains no more than the tap-in and tap-out time and station of a passenger but not his/her transfer station.

Recently, Hong et al. (2015) developed an algorithm that detects an exact path choice for more than 90% of the passengers from Smart Card data. The algorithm relies on the disjoint time intervals that identify each passenger to his/her boarding, alighting, or connecting train.

Such unprecedented real path choice of an absolute majority of passengers provides, among others, a precise and complete logical-level metro passenger traffic in Seoul metropolitan area where the Smart Card is the only pay method. Our model was tested on the data.

Note, however, that we could not study the inter-modal effects of crowding. Even though buses have been integrated in the Smart Card system, the exact tap-out time/location of a passenger is not always available in the data; the algorithm (Hong et al., 2015) does not apply in the case.

This paper is organized as follows. The section continues with a summary of previous logit models that consider crowding effect. In Section 2, for the sake of completeness, we discuss the recent path detecting method by Hong et al. (2015). In Section 3, we propose two measures of crowding delay. We provide an improved regression of delay of a connection on the level of passenger traffic. In Section 4, we identify crowding stress as an essential factor of path choice and propose its measure. Section 5 discusses explanatory variables and parameter estimation, and evaluates the performance of the model. Finally, concluding remarks and some ongoing research are provided in Section 6.

Although unheralded usage has already appeared, we use *path* and *physical connection* interchangeably in this paper. By a *logical connection*, we mean the sequence of trains on a physical connection that a passenger can take for her/his *O–D* trip.

1.1. Previous transit assignment models considering crowding effect

Li and Hensher (2011) analyzed the data on the willingness to pay to avoid crowding of passengers surveyed in the previous studies from UK, USA, Australia and Israel, to conclude that crowding increases the cost of a connection.

Previous studies on crowding effect are commonly based on a multinomial logit model. Crowding is measured in a finite and discrete set of grades from surveyed passengers and its effect is tested on stated path choice of passengers.

Lam et al. (1991), for instance, represented the crowding of a connection with a binary variable, meaning 'crowded' or 'not crowded' according to the statement of surveyed passengers and check its effect on the stated path choice of the passengers. Douglas and Karpouzis (2006) surveyed Sydney rail users who were asked to choose from two connections, one, shorter but crowding and the other, longer but less crowding. A binary logit model was developed on the basis of the passengers' choice. The criteria of crowding, in the survey questionnaire, are crowded seat, standing, and crush standing time. Whelan and Crockett (2009), on the other hand, used the time spent sitting and standing, the occupancy rate, i.e., the ratio of load to capacity, and the number of passenger per square meter as the criteria. They computed, from the logit model, the time multiplier of crowding, i.e. the marginal rate of substitute of crowding to transit time, to the trip purposes of passengers, which was 11% higher in business passengers than in non-business passengers. Wardman and Whelan (2011) performed a meta-analysis of time multiplier of crowding by pooling the surveyed data from 17 rail-crowding related studies from UK. They noted that the marginal value of time increases with the level of crowding. Kato et al. (2010) enhanced the accuracy of a logit- and probit-based stochastic user equilibrium model by including, as an explanatory variable, the crowding graded by passenger on the basis of squared occupancy rate.

As pointed by Lathia and Capra (2011) there can be a significant gap between the real and surveyed travel behavior of metro passengers. However, the literature is scant on the studies based on a revealed path choice and, preferably, a direct crowding measure, e.g. delay or passenger load.

Raveau et al. (2011) is perhaps the only model that used a revealed path choice of sample passengers. It graded the crowding of a connection according to the occupancy rate.

We also note the dependence of marginal value of time to the level of crowding was insignificant in our data. Our model use, therefore, a linear function of explanatory variables. Table 1 summarizes the previous studies in comparison to ours.

Table 1
Studies on crowding effects on path choice of metro passengers.

	Location	Num. samples	Path choice	Crowding measure	Criteria
Lam et al. (1991)	Hong Kong	80	Stated	Grades from passengers	Average pedestrian area occupancy, occupancy rate
Douglas and Karpouzis (2006)	Sydney	583	Stated	Grades from passengers	Crowded seat, standing, and crush standing times
Whelan and Crockett (2009)	UK	2314	Stated	Grades from passengers	Sitting and standing time, occupancy rate
Wardman and Whelan (2011)	UK	–	Stated	Grades from passengers	Occupancy rate
Kato et al. (2010)	Tokyo	3707	Stated	Grades from passengers	Squared occupancy rate
Raveau et al. (2011)	Santiago	28,961	Revealed	Grades	Occupancy rate
Ours	Seoul	428,184	Revealed	Dwell & transfer delay, passenger load	–

2. Detecting real path choice from Smart Card data

The path choice detecting algorithm proposed by Hong et al. (2015) examines the gate times from Smart Card data to derive the reference points and time intervals identifying passengers boarding, transferring, and alighting from trains at each station. Such time intervals are the consequences of the boarding and alighting behavior of passengers.

Fig. 1 compares the behaviors of passengers in their boarding and alighting by plotting the entry and exit times of Shillim–Gangnam passengers on Line 2, between 8 and 9 AM on November 21, 2011.

It is typical that passengers alighting from a train rush to the gates and accomplish their exit as soon as possible. The platform-to-gate time of each passenger is, thus, the maximum speed of a passenger and hence has the characteristic known as an extreme value (Einmahl and Smeets, 2011).

In fact, according to Ko et al. (2015) the platform-to-gate time of an alighting passenger is best fitted by an extreme value distribution, called the *Fréchet distribution*. This produces a sequence of non-overlapping time intervals of passenger groups alighting from trains arriving at a station in most cases. Overlapping alighting groups were found only in 1.2% of the cases, in which case, the algorithm, by the rule, fails. The smallest headway, e.g. from the busiest Line 2 was 3.5 min in peak hours (07:00–10:00), which still seems large enough in comparison to the platform-to-gate time 1.9 and 1.0, the mean and standard deviation.

Similar to the alighting case, we can compute a sequence of time intervals for boarding trains. In boarding, although devoid of such a set of disjointed time intervals in Fig. 1, the first-come-first-served queue discipline is well observed and hence the arrival order of passengers at a gate is well maintained. It transpired that, in the case of Seoul metropolitan area, the entry time at a gate of a passenger falls either in a unique time interval or in the intersection of, at most, two consecutive time intervals.

The alighting and boarding behaviors of metro passengers, if combined, manifest the clusters passengers to their trains as in Fig. 2.

However, that the boarding or alighting time intervals may be far from evident from a simple plotting of the entry or exit times of passengers at a gate. In- and out-bound passengers of trains from single or multiple lines may merge at their entry or exit at a gate. Thus we need a method that disaggregates passengers' gate times from their boarding or alighting from trains.

In this sense, the second ingredient of the algorithm, known as the *reference passengers*, is essential. By a reference passenger, we means a passenger whose *O–D* trip presents a unique physical connection that is significantly and uniformly better in all aspects than any other path.

Such an *O–D* trip is determined by comparing its paths. If a path has k or more sections than any other path less in transfers, it is removed. If repetition of the procedure leaves exactly a single path, the *O–D* passengers are added to the reference passengers with their unique path. From a case analysis, we set $k = 10$, which is equivalent to about 25 min in in-vehicle time.

In the case of Seoul metropolitan area, Hong et al. (2015) found that at least 47% of the daily passengers are reference passengers. This provides a sufficient set of entry and exit gate times to construct reliable alighting/boarding time intervals.

By looking up the connecting trains of the reference passengers we can verify if a transfer has actually been made between the trains intersecting at a transfer station. We will refer to such a passenger as a *transfer reference passenger*.

The path detecting algorithm combines the boarding/alighting time intervals with the transfer reference passengers to check, for each tentative logical connection for the *O–D* trip of a passenger, if it is consistent with the entry and exit times of a passenger:

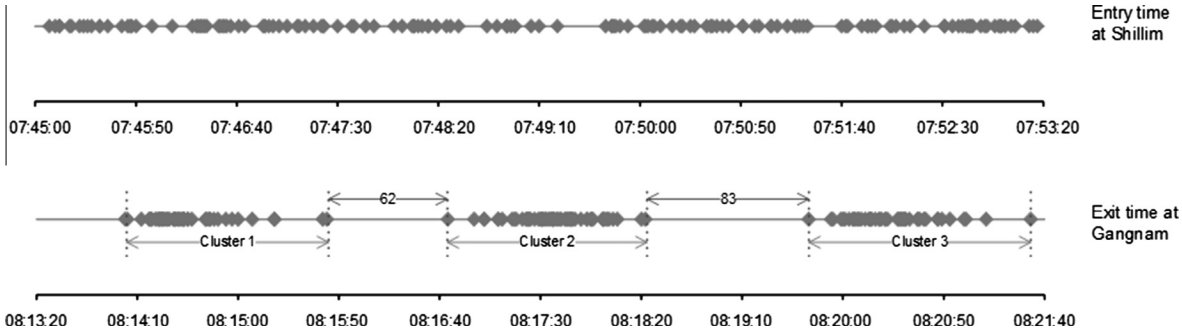

Fig. 1. Entry and exit time plotting of the Shillim–Gangnam passengers.

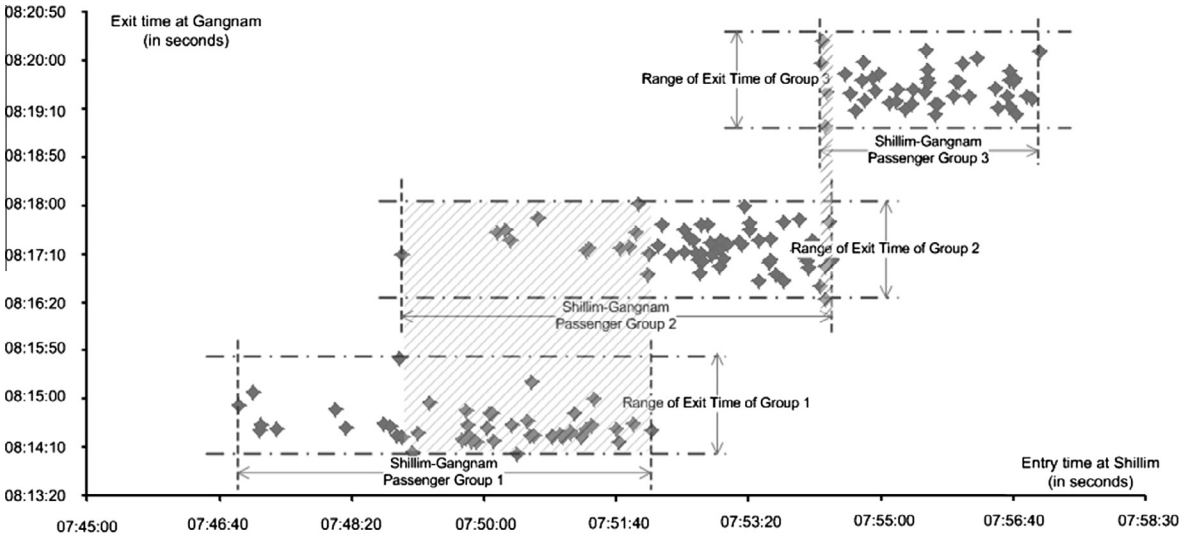

Fig. 2. Entry-exit map of Shillim–Gangnam passengers.

1. Suppose a tentative logical connection involves no transfer. We then call the connection consistent with the gate times of a passenger if the entry and exit times fall in the boarding and alighting time intervals, respectively, of the two trains of the logical connection.
2. When the connection requires transfer(s), we additionally check if there are transfer reference passengers for the connecting trains of each transfer. If that is the case, we call the logical connection consistent with the entry and exit times of a passenger.

The algorithm returns a physical connection only if it is a unique path along which exits a logical connection consistent with the gate times of the passenger. Note that a true path is necessarily among such physical connections. Thus if there is a unique such physical connection, it should be a true path of the passenger. The algorithm has been reported to successfully return a unique path for the 92% of passengers.

3. Crowding delay

In this section, we discuss how to measure dwell and transfer delay in the level of passenger traffic.

3.1. Dwell time delay

We refine the dwell time of a train into *the minimum dwell time*, denoted by δ_{MIN}, the time to observe safety headway, and the rest to embark/disembark passengers, or to ventilate a vehicle, etc. We also fix the following terms.

- Inter-gate time (in seconds): the time from entry at a gate at origin to exit at a gate at destination (available from Smart Card data).

- In-vehicle time (in seconds) = In-vehicle-movement time + Minimum dwell time, δ_{MIN}.

Note that, by definition, the delay in dwelling from crowding is not included in in-vehicle time.

In Seoul, the dwell time per station has been uniformly scheduled to 30 s. A significant gap between the scheduled and actual dwell times is observed on November 21, 2011 as in Table 2 (which suggests a better operation is attainable by scheduling dwell time to passenger traffic).

There have been studies that quantify dwell time as a function of passenger traffic (Yang et al., 2012; Puong, 2000; Jong and Chang, 2011; Lin and Wilson, 1991), or models the passenger interaction while getting on and off a train with cellular automata (Qi et al., 2008). Puong (2000), for instance, regressed the dwell time with linear terms in on-platform passenger traffic and a nonlinear term in the number of in-vehicle passengers.

Relying on the passenger flow obtained by the path-choice detecting algorithm, we could build an intensive set of passenger traffic data, the 19,627 dwell times of the 515 daily trains at the 43 stations on Line 2 on November 21, 2011. Fig. 3 shows a two-dimensional plotting of the dwell times versus n, the total number of alighting and boarding passengers of a train.

Each black dot represents the least dwell time, denoted by $\text{LDT}(n)$, observed for each n. Thus $\text{LDT}(n)$ is a reasonable estimate of the least time necessary for embarking and disembarking n passengers to or from a train, adjusting the headway, and ventilation, etc. Although the variance gets larger as n grows, the figure shows $\text{LDT}(n)$ is, as expected, an increasing function. Also the least observed value of a dwell time is 23, which is also a good estimate of the minimum dwell time δ_{MIN}. $\Delta(n) := \text{LDT}(n) - \delta_{\text{MIN}}$ then represents the dwell-time delay of a train to embark or disembark n passengers on platform at each stop. $\text{LDT}(n)$ fitted best to the exponential function,

$$\text{LDT}(n) = 24.708e^{0.0012n}.$$

For our model, however, we adopt a more elaborated measure: following Puong (2000), LDT is regressed on the number of alighting (n_A), boarding (n_B), and on-board (n_O) passengers of a train. We obtained, as a result, the exponential function in (1) as the best fit.

$$\begin{array}{lllll} \ln \text{LDT}(n_A, n_B, n_O) = & 3.1840+ & 0.0055 * n_A+ & 0.0076 * n_B+ & 0.00026 * n_O \quad (\overline{R}^2 = 0.71) \\ & (494.62) & (17.89) & (29.47) & (36.42) \end{array} \tag{1}$$

We also tested the Puong's model (Puong, 2000) to the same data set to obtain $\overline{R}^2 = 0.55$ compared to $\overline{R}^2 = 0.71$ from our model.

Relying on (1), at each station, we get the dwell-time delay of a train DDT $=\text{LDT}(n_A, n_B, n_O) - \delta_{\text{MIN}}$. The dwell-time delay a connection is defined as

$$\overline{\text{DDT}} := \text{Mean of DDT over the stations of a connection} \tag{2}$$

3.2. Transfer delay

Transfer is a well-known factor of metro connection cost (see, e.g. Yang and Shon, 2000; Kim, 2004; Guo and Wilson, 2011; Hibino et al., 2005; Shin et al., 2007). According to Hong et al. (2015), more than 40% of the connections of daily metro passengers involve a transfer.

In Fig. 4, each dot indicates a pair of connecting trains at the Daerim station of Line 2. The horizontal axis represents the time of a day, and vertical axis the number of connecting passengers, 396, 297 and 1897, that are, respectively, the mean, variance and maximum.

We now quantify the delay in transfer as a function of connecting passenger traffic. By the *transfer time*, we mean the sum of

- the minimum transfer movement time denoted by θ_{MIN}, the time between two platforms of a passenger when the traffic is minimum, and
- the waiting time, namely, a half of headway.

Again, by definition, the delay from crowding is excluded from a transfer time.

Similarly, the smallest transfer time observed for each n, the number of connecting passengers is denoted by $\text{LTT}(n)$. At Daerim station, for instance, $\text{LTT}(n)$ was fitted best to

$$\text{LTT}(n) = 111e^{0.0008n}.$$

Based on the smallest observed transfer time, 144, the transfer delay at Daerim station is estimated as $TDT(n) := 111e^{0.0008n} - 144$. A transfer delay of a connection is, accordingly, defined as

$$\overline{\text{TDT}} = \text{Mean of TDT over the transfer stations of a connection} \tag{3}$$

Table 2
Dwell time on Line 2.

	Num. trains	Num. dwell times	Average	Minimum	Maximum	Standard dev.
Peak hours	270	8007	43.7	24	242	17.9
Non-peak hours	245	11,620	39.5	23	249	14.4

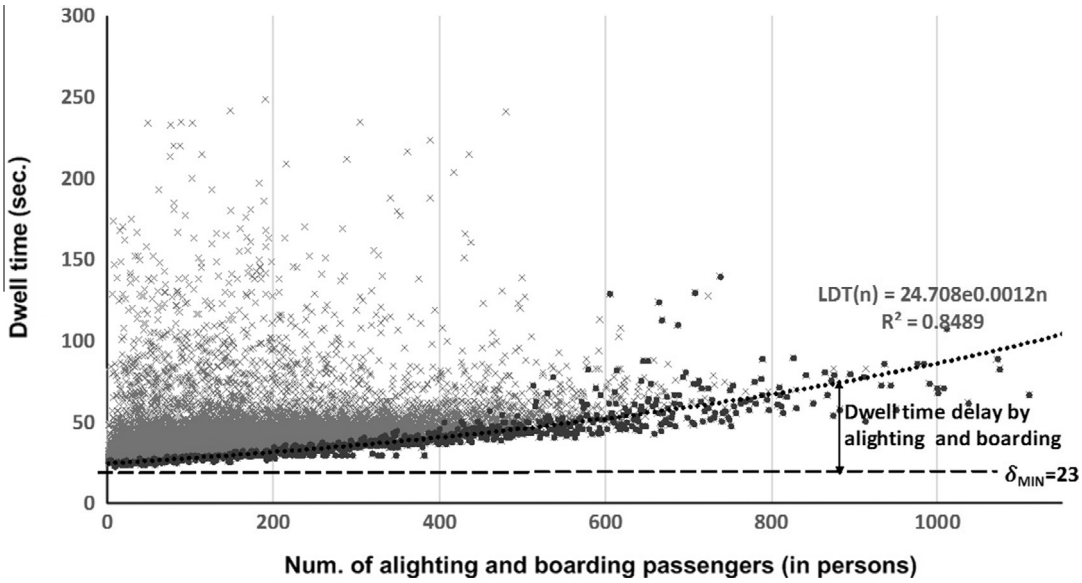

Fig. 3. Number of alighting and boarding passengers versus dwell time on Line 2.

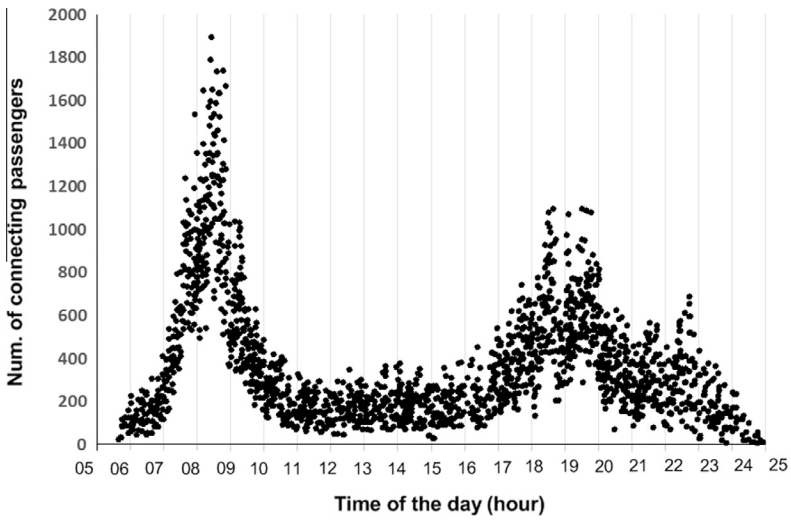

Fig. 4. Number of passengers of a pair of connecting trains at Daerim station.

4. Measure of crowding

The Shindorim–Gangnam interval on Line 2 is notorious for the worst crowding. From the passenger flow, we computed the passenger load of a train, i.e. the number of in-vehicle passengers a section, by subtracting the cumulative number of alighting passengers from the cumulative number of boarding passengers at each station as in Fig. 5.

The mean and maximum passenger load from 245 trains off peak were 838 and 2487, and 1365 and 4428 from 270 trains at peak on Shindorim–Gangnam interval. Hence peak occupancy rates are 85% and 276%, on average and at maximum, of 1600, the design capacity of a vehicle.

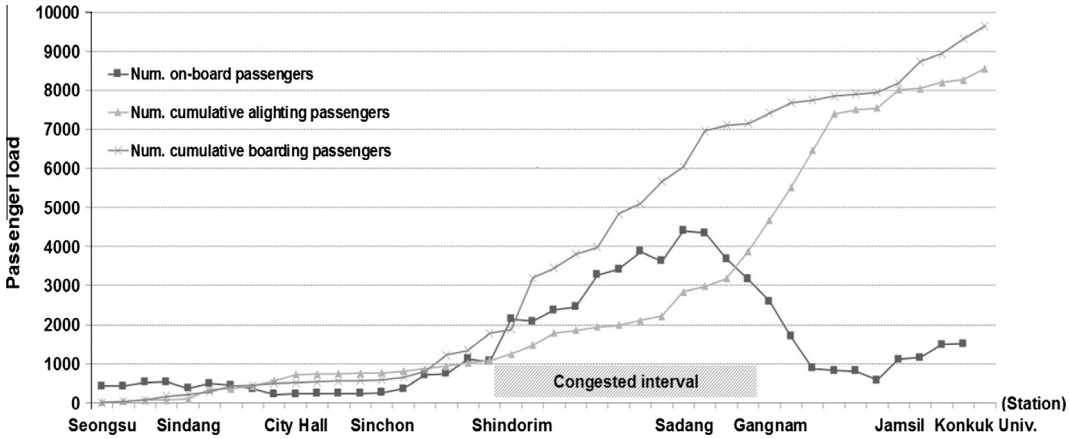

Fig. 5. Passenger load a train on Line 2 in peak hours, November 21, 2011.

Fig. 6 shows in-vehicle and crowding at a station in the interval in peak hours.

Fig. 7 illustrates two physical connections, I and II, including the Shindorim–Gangnam interval.

They are only alternative connections from Gwangmyung station, Line 7 to Jamshil station, Line 2; Path I consists of 25 sections, and a single transfer to Line 2 at Konkuk University station while Path II 21 sections, and a transfer to Line 2 at Daerim station. From Table 3, Path II is preferable in any respect except for passenger load.

In such a case, a logit model based on conventional variables, the in-vehicle and transfer time, would assigns an absolute majority, 85.8%, to Path II. However, only 61.8%, 197 out of 319, of the peak-time Gwangmyung–Jamshil trips actually chose Path II.

As the transit time includes the dwell time delay from crowding, the only explanation is that significant portion from 38.2% of passengers preferred the longer connection, Path I, to avoid crowding itself along Path II including Shindorim–Gangnam interval on Line 2. Over Path II, the average passenger load a train is 1640 while over Path I, 1113.

The path choice of Gwangmyung–Jamshil passengers in non-peak hours is also presented in Table 4.

Although somewhat smaller, there is still a gap between predicted and actual choice of Path I, 9.7% and 28.9%. Over Path I, the average passenger load a train is 512 while 480 seats are available per train. Thus, most passengers can sit in Path I while nearly an half of passengers cannot in Path II. Again crowding explains the gap.

We extended the analysis to the passengers from the 5 consecutive origins, Cheonwang, Gwangmyung, Cheolsan, Gasan Digital Complex, and Namguro on Line 7, collectively, (boxed in Fig. 7), to each of the 3 destinations, Gangbyeon, Seongnae and Jamshil on Line 2. The solid line in Fig. 8 indicates, for each destination, the ratio of passengers along Path I versus the transit time gain of Path I over II. The latter gets bigger along, Gangbyeon (•), Seongnae (◆) and Jamshil (■) in the order.

Accordingly the ratio of passengers gets smaller from 0.82 to 0.34. However, they are uniformly larger, by 0.22 on average, than the logit-based prediction indicated with dotted line. Thus the crowding stress effect is, as expected, commonly observed at the destinations. Furthermore, considering the passenger load reduction (provided in parentheses) not varying significantly over the destinations, there is an approximately linear trade-off between the path-choice and transit time.

5. The model and the experimental results

We adopted a multinomial logit model whose parameters are estimated to have maximum likelihood.

5.1. The data set

The model is tested on the passenger trips of Seoul metropolitan area metro network, which, as of November 2011, operates 5000 trains on 15 lines connecting 412 stations and transports about 7 million passengers a day. The Smart Card system, introduced in 2004, has become a unique payment method as of 2009.

The data was built by applying the path detecting algorithm Hong et al. (2015) to the Smart Card data from the two whole five-weekday sets, November 20–25, 2011 and March 19–23, 2012. There was no change in physical network topology between two weeks. According to Hong et al. (2015), the path choice of metro passengers is actually the same across the weekdays of a week.

For parameter estimation, we chose from the November data, the *O–D* pairs with more than one alternative physical connections and with 100 or more passengers both in peak hours (07:00–10:00 AM and 18:00–21:00 PM) and the remaining 12 non-peak hours.

Fig. 6. In-vehicle and on-platform crowding, Shindorim–Gangnam interval, Line 2.

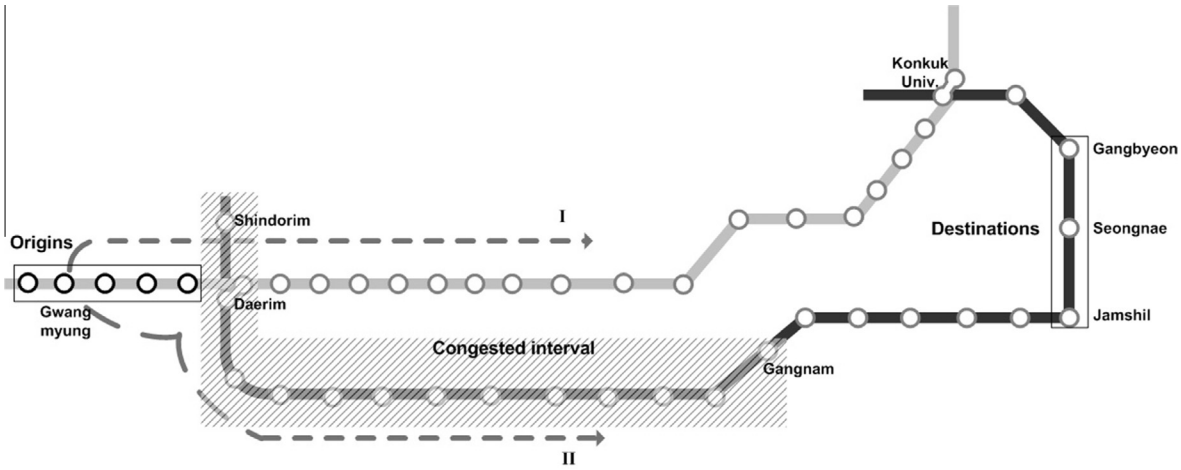

Fig. 7. Alternative physical connections from Gwangmyung to Jamshil.

Table 3
Alternative paths of Gwangmyung–Jamshil pair in peak hours.

Paths	Real path choice	Logit-based path choice (%)	Num. sections	Transit time	Passenger load
I	122(38.2%)	14.2	25	3387	1113
II	197(61.8%)	85.8	21	3056	1640

Table 4
Alternative paths of Gwangmyung–Jamshil pair in non-peak hours.

Paths	Real path choice	Logit-based path choice (%)	Num. sections	Transit time	Passenger load
I	58(28.9%)	9.7	25	3373	512
II	143(71.1%)	90.3	21	2905	863

The data set, Set 1 in Table 5, amounts to 1312 *O–D* pairs, and 222,091 and 216,093 passengers in peak and non-peak hours, respectively.

We constructed 3 additional data sets for model evaluation. Set 2, consists of 3000 *O–D* pairs randomly chosen from the November data to have more than one alternative physical connections (but with no restriction on passenger traffic). Sets 3 and 4 were built from the March data, similarly with the method used for Set 1 and 2, respectively.

5.2. The explanatory variables

We performed a preliminary experiment to find that, other than a crowding-related variable, the in-vehicle time and the transfer time defined in Section 3 were the best set of explanatory variables. (As mentioned, the fare, fixed for the same *O–D*, was excluded, *a priori*).

$\overline{\text{DDT}}$ from (2) and $\overline{\text{TDT}}$ from (3) were used as the dwell-time and transfer delay, respectively, of a connection.

Besides the passenger load defined in Section 4, we also tested an alternative measure of crowding on the hypothesis that passengers chose a path based on the passenger load difference among the alternative paths rather than continuously

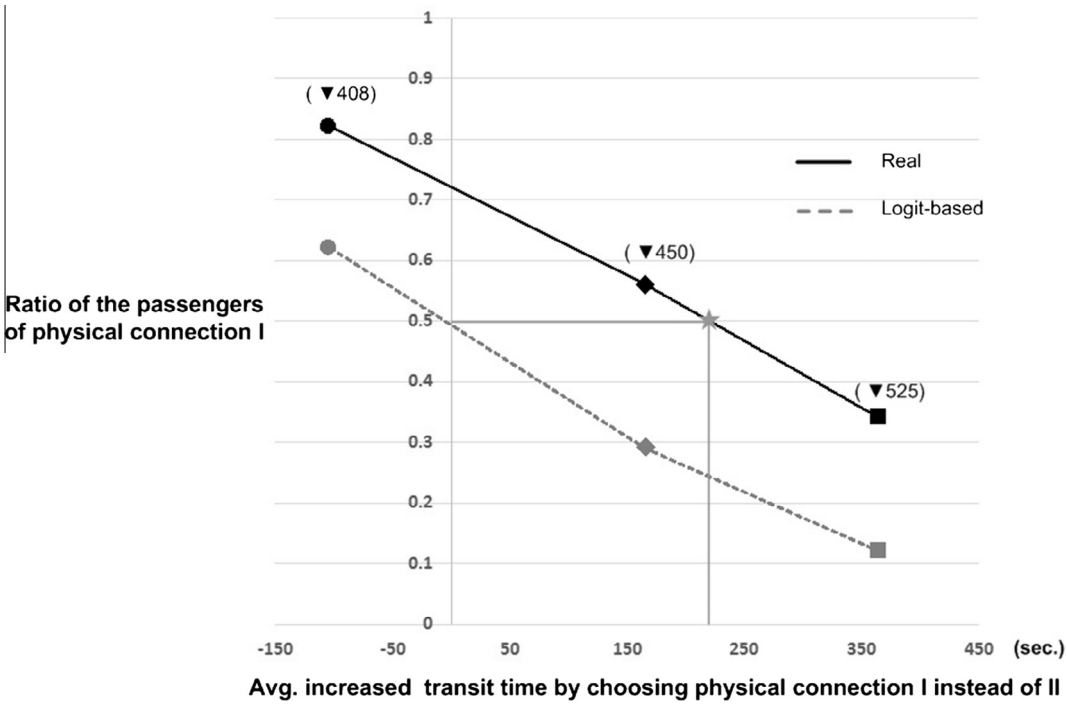

Fig. 8. Ratio of passengers versus transit time gain in peak hours.

Table 5
Data sets for parameter estimation and model evaluation.

	Dates	Peak/non-peak	Num. trips	Num. *O–D* pairs	Num. physical connections	Num. logical connections
Estimation						
Set 1	November 21–25, 2011	Peak	222,091	1312	4226	150,113
		Non-peak	216,093	1312	4227	172,096
Evaluation						
Set 2	November 21–25, 2011	Peak	269,141	3000	11,319	237,260
		Non-peak	259,710	3000	11,294	253,664
Set 3	March 19–23, 2012	Peak	202,267	1263	3766	140,436
		Non-peak	193,442	1263	3740	158,968
Set 4	March 19–23, 2012	Peak	275,848	3000	11,320	240,227
		Non-peak	259,805	3000	11,226	253,755

measuring the passenger load individually. We assign 1 to a path if the passenger load exceeds the minimum of an alternative path by a predetermined value, $\gamma > 0$; and 0, otherwise. The binary value will be referred to as the *relative crowding* of a path.

Table 6 summarizes the mean and variance of the measures other than relative crowding. The in-transit times are similar in peak and non-peak hours. Transfer time is, however, longer in non-peak hours due to larger headway. The crowding related variables, dwell time delay, transfer delay, and passenger load have larger mean and variance in peak hours.

Table 7 presents the correlation coefficients among the explanatory variables. A strong correlation, 0.49, was observed between the passenger load and the relative crowding ($\gamma = 400$) since the latter is defined as the difference in the former of paths. The dwell time delay and passenger load have a correlation of 0.37 since they have a common factor, the number of on-board passengers, n_O. Similarly, the dwell time delay is also strongly correlated with relative crowding. The correlation, 0.26, between the dwell time delay and the in-vehicle time is from that the longer a path is, the higher the probability is that crowding sections are included in the path.

5.3. The parameter estimation

In addition the conventional explanatory variables, in-vehicle time and transfer time, we tested each possible combination of the four crowding related explanatory variables.

Table 6
The explanatory variables and their statistics.

	Peak		Non-peak	
	Mean	Standard dev.	Mean	Standard dev.
In-vehicle time (s)	1456.5	597.3	1417.9	615.3
Transfer time (s)	281.2	189.4	459.9	316.1
Dwell time delay (s/section)	7.9	2.5	3.4	1.7
Transfer delay (s)	79.0	122.7	38.3	81.7
Passenger load (persons/section)	1093.4	517.6	699.9	346.9
Num. sections	14.3	5.0	13.9	5.2

Table 7
Pearson correlation coefficients among explanatory variables.

	In-vehicle time	Transfer time	Dwell time delay	Transfer delay	Passenger load	Relative crowding
In-vehicle time	1.0	−0.018*	0.260*	−0.010*	−0.008*	0.108*
Transfer time	–	1.0	−0.055*	0.136*	0.122*	0.177*
Dwell time delay	–	–	1.0	0.044*	**0.374***	**0.341***
Transfer delay	–	–	–	1.0	0.145*	0.090*
Passenger load	–	–	–	–	1.0	**0.491***
Relative crowding	–	–	–	–	–	1.0

Bold values emphasize the coefficients over 0.3.
* Significance level of 1%.

Unlike the dwell time delay, the transfer delay could not improve the predictability of model. There are two reasons for this. First, in total, the transfer delay is smaller than the dwell time delay accruing at every stop. Second, passengers tend not to perceive the delay in a transit movement so significantly as the delay experiencing in a dwelling train. This is consistent with the report (Douglas and Karpouzis, 2005) that passengers perceive crowding cost 1.5 times higher on platform than in accessway.

In any case, the passenger load explained the path choice better than the relative crowding by adjusting γ in the range of 100–500.

We also tested the nonlinear disutility function obtained by Box–Cox transform (Mandel et al., 1994) of crowding related variables. The improvement of log-likelihood was, however, marginal, namely 0.12% consistently with (Wardman and Whelan, 2011; Whelan and Crockett, 2009). Thus we used a linear cost function of explanatory variables.

In sum, we excluded transfer delay and relative crowding, which results in the three possible models besides the base model. Table 8 summarizes parameter estimation and the pseudo *t*-values in peak hours.

Every model attained the significance level of 1% in the parameter estimation. From the last column of the table, each crowding-related variable, improves log-likelihood of the base model by more than 20. This rejects the null hypothesis that the base model and any other model are equivalent ($2 \times 20 = 40 > \chi^2 = 9.2$) with 99% confidence with 2 degrees of freedom. In Model 3, the cost weights of dwell time delay and passenger load, reduced from −0.2716 in Model 1 to −0.1521, and from −0.0025 in Model 2 to −0.0017, respectively. This is due to the strong correlation between two crowding variables from Table 7. The statistical significance of the model is, nevertheless, maintained since, compared to any other model, log-likelihood is improved by at least 3.

The same set of results are presented for non-peak hours in Table 9. Models 1 and 2 also attained the significance level of 1% in their estimation compare to base model. Unlike in the peak hours, including both of crowding variables in Model 3 did not significantly improves the log-likelihood, let alone, the significance of dwell time delay deteriorates to 10% from 1% in Model 1.

Model 2 is the best in predictability. The moderate dwell time delay in non-peak hours has no significant effect on a path choice. However, even off peak, the passenger load still matters since it influences e.g. seat availability as was also observed in Table 4.

The marginal rate of substitution for each explanatory variable in terms of their equivalence in the in-vehicle time is indicated in Table 10. In peak hours, a unit transfer time was perceived by the passengers as 1.48–1.91 times a unit in-vehicle move time.

From Model 3, a unit dwell-time delay (per section) was equivalent to 27.0 s of in-transit time with 95% confidence interval $[4.49, 50.30]$. The average number of sections are 14.3 (Table 6) and, hence, a unit dwell-time delay is perceived as much as 1.8 (=27.0/14.3) second increase in the in-vehicle time. Also a unit increase in the passenger load, namely 1 person/section is equivalent to 0.30 s of in-vehicle time with 95% confidence interval $[0.14, 0.45]$.

We repeated the same analysis, but, this time, on hourly refined data; we sorted peak hour trips, for instance, to their departure hour, 07:00–08:00, 08:00–09:00, 18:00–19:00, or 19:00–20:00. We conducted Wilcoxon signed-rank test on the cost coefficients of each variable across the 4 time bands to find they are statistically the same. The two time bands, peak and non-peak, therefore, reasonably describes the continuous path choice of metro passengers.

Table 8
Estimated parameters and their pseudo *t*-values in peak hours.

Variables	In-vehicle time	Transfer time	Dwell time delay	Passenger load	Log-likelihood
Base model	−0.0053**	−0.0086**	–	–	−257.7
	(−11.537)	(−17.167)			
Model 1	−0.0050**	−0.0095**	−0.2716**	–	−233.5**
	(−10.474)	(−16.424)	(−6.255)		
Model 2	−0.0060**	−0.0089**	–	−0.0025**	−230.4**
	(−11.762)	(−16.298)		(−6.314)	
Model 3	**−0.0056****	**−0.0094****	**−0.1521****	**−0.0017****	**−227.0****
	(−10.677)	(−15.500)	(−2.654)	(−3.504)	

Bold values emphasize the coefficients over 0.3.
** Significance level of 1%.

Table 9
The estimated parameters and their pseudo *t*-values for each model in non-peak hours.

Variables	In-vehicle time	Transfer time	Dwell time delay	Passenger load	Log-likelihood
Base model	−0.0037**	−0.0046**	–	–	−348.6
	(−10.530)	(−16.276)			
Model 1	−0.0036**	−0.0050**	−0.2109**	–	−338.3**
	(−9.760)	(−16.087)	(−4.407)		
Model 2	**−0.0041****	**−0.0047****	–	**−0.0020****	**−336.0****
	(−10.754)	(−16.226)		(−4.656)	
Model 3	−0.0039**	−0.0049**	−0.0820*	−0.0015**	−335.4†
	(−9.682)	(−15.419)	(−1.104)	(−2.346)	

Bold values emphasize the coefficients over 0.3.
† Insiginificant.
* Significance level of 10%.
** Significance level of 1%.

Table 10
Marginal rates of substitution for each factor in in-vehicle time in peak hours.

	Base model	Model 1	Model 2	Model 3
In-vehicle time	1.0	1.0	1.0	1.0
Transfer time	1.6	1.91	1.48	1.67
Dwell time delay	–	54.51	–	27.04
Passenger load	–	–	0.41	0.30

5.4. Performance evaluation of the model and welfare analysis

As in Table 11, the crowding-related explanatory variables improve model accuracy considerably: the mean-square error was reduced by 11.7–12.8% at peak and 11.8–12.3% off peak in November, 2011. This is much the same in March, 2012.

This means the welfare of metro passengers cannot be properly quantified without considering crowding. More specifically, the total disutility of the 222,091 passengers in peak hours increases by 39% in the cost function estimated from Model 3 than in the cost function from the base model.

Also from a theoretical point of view, Model 3 explains a Wardrop equilibrium better. Consider an imaginary station on the solid line corresponding to the ratio 0.5 in Fig. 8 whose cost factors are linearly interpolated from those of the 'adjacent' stations, Seongnae and Jamshil in each direction. Since Path I and II are chosen with a equal chance, their costs should be the same. They are 16.3 and 15.1 in the base model while 20.4 and 20.3 in Model 3. The gap reduces from 7.1% to 0.4% by considering crowding related variables.

We now quantify the change in overall welfare due to rerouting from crowding in peak hours. To do so, we computed stochastic user equilibria, one by using the best cost function not considering crowding, namely the cost function from the base model and the other by the cost function from Model 3. Their disutility is then evaluated in the cost function from Model 3. It is 7% larger in the latter than in the former. This implies the welfare increase from the peak crowding reduction is smaller than the welfare decrease from the extended utilization of metro network.

Thus crowding decreases, overall, the welfare of metro passengers seeking selfish routing. As a path choice incentive to recover welfare, an adaptive pricing seems hard to implement; the metro fare is associated with other 'public fares' rigidly a pricing-policy agenda of government in Korea. We suggest, instead, to operate express trains covering congested sections.

Table 11
Mean-square errors of the base model and Model 4 on four data sets.

	Peak time			Non-peak time		
	Base model	Model 3	Improvement (%)	Base model	Model 2	Improvement (%)
Set 1	716.52	632.39	11.7	804.08	708.81	11.8
Set 2	305.79	266.69	12.8	304.70	267.33	12.3
Set 3	765.69	663.12	13.4	858.05	746.14	13.0
Set 4	315.40	276.92	12.2	306.46	274.50	10.4

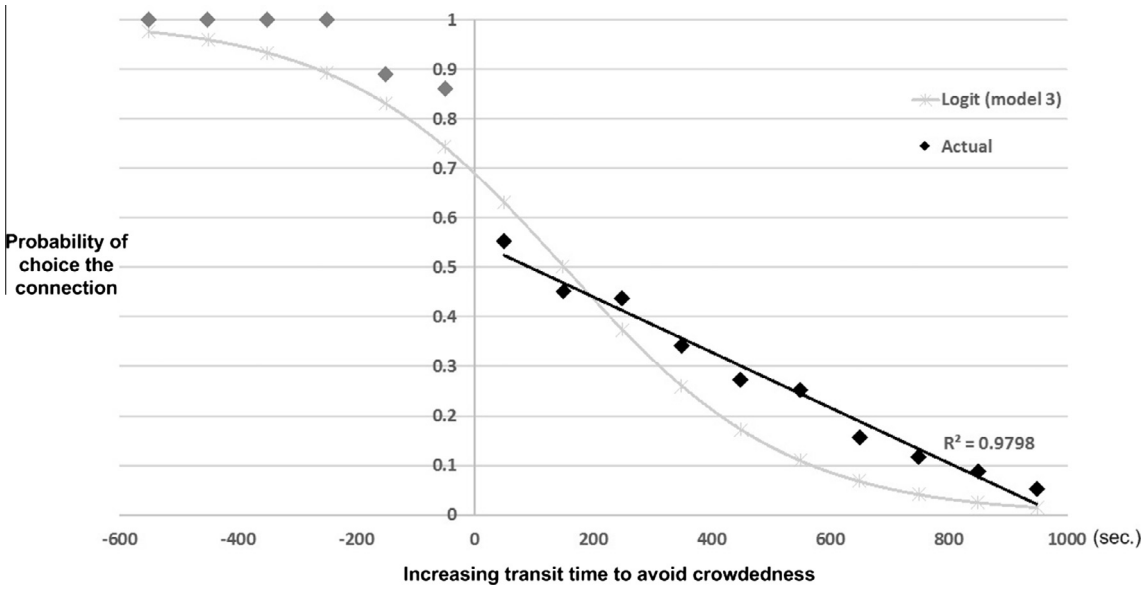

Fig. 9. Probability of choosing a 500-less-passenger-load connection at the expense of increase in transit time in peak hours.

6. Conclusion and discussion

We have shown the welfare of metro passengers is captured more properly by considering crowding effects on their path choice. More specifically,

1. we showed metro passengers equilibrate not only the delay from crowding but also crowding itself in their path choice. In doing so, we proposed a logit-based transit assignment model which includes the dwell-time delay and the passenger load in the explanatory variables.
2. The model was tested on an intensive set of real path choice obtained by a precise path-detecting method (Hong et al., 2015) to two five-weekday Smart Card data sets of Seoul metropolitan area, one from November, 2011 and the other from March, 2012.
3. Finally, we demonstrated that crowding decreases the overall welfare of metro passengers and suggested an operation of express trains covering congested connections to recover the welfare.

Fig. 9 plots the probability that a passenger chooses an alternative path 500-less in passenger load versus the increase in transit time.

We can observe, the probability decreases linearly in the transit time gain in contrast to the nonlinear sigmod curve from a logit-based estimation. The trade-off between passenger load and transit time is thus more diverse than can be described by a distribution unimodal around its mode.

From the graph, if the alternative path is also preferable in transit time considerably, namely, 200 s or more, then, with a very few exception (perhaps, due to a perception error) passengers chose it as expected.

These suggest a more realistic transit assignment requires a model that captures both preference diversity and rationality, in the path choice of metro passengers.

Acknowledgments

We are grateful for the helpful comments of the reviewer that improved the paper significantly. This research was supported in part by the BK21 Plus Program (Center for Sustainable and Innovative Industrial Systems) funded by the Ministry of Education, Korea, and by Basic Science Research Program (2014R1A2A1A11049663) through the National Research Foundation of Korea (NRF).

References

Ceapa, I., Smith, C., Capra, L., 2012. Avoiding the crowds: understanding tube station congestion patterns from trip data. In: Proceedings of the ACM SIGKDD International Workshop on Urban Computing, pp. 134–141.
Douglas, N., Karpouzis, G., 2005. Estimating the passenger cost of station crowding. In: The 28th Australasian Transport Research Forum.
Douglas, N., Karpouzis, G., 2006. Estimating the passenger cost of train overcrowding. In: The 29th Australasian Transport Research Forum.
Einmahl, J.H.J., Smeets, S.G.W.R., 2011. Ultimate 100m world records through extreme-value theory. Stat. Neerl. 65 (1), 32–42.
Guo, Z., Wilson, N., 2011. Assessing the cost of transfer inconvenience in public transport systems: a case study of the London underground. Transport. Res. Part A 45, 91–104.
Hibino, N., Uchiyama, H., Yamashita, Y., 2005. A study on evaluation of level of railway services in Tokyo metropolitan area based on railway network assignment analysis. J. Eastern Asia Soc. Transport. Stud. 6, 342–355.
Hong, S.-P., Min, Y.-H., Park, M.-J., Kim, K.M., Oh, S.M., 2015. Precise estimation of connections of metro passengers from *Smart Card* data. Transportation (April 01) (published online).
Jang, W., 2010. Travel time and transfer analysis using transit smart card data. Transport. Res. Rec.: J. Transport. Res. Board 2144, 42–149.
Jong, J.-C., Chang, E.-F., 2011. Investigation and estimation of train dwell time for timetable planning. In: Proceedings of 9th World Congress on Railway Research.
Kato, H., Kaneko, Y., Inoue, M., 2010. Comparative analysis of transit assignment: evidence from urban railway system in the Tokyo metropolitan area. Transportation 37, 775–799.
Kim, K.J., 2004. Estimating Transfer Penalties Considering Transfer Movement: A Case of Subway in Seoul. MS Thesis, Seoul National Universiy, Seoul (in Korean).
Ko, S.-J., Kim, K.M., Hong, S.-P, 2015. Estimation of Transfer Times and Alighting Times of the Metro Passengers in Seoul Metropolitan Area. Working Paper.
Lam, W.H.K., Cheung, C.-Y., Lam, C.F., 1991. A study of crowding effects at the Hong Kong light rail transit stations. Transport. Res. Part A 33, 401–415.
Lathia, N., Capra, L., 2011. How smart is your smart card measuring travel behaviours perceptions and incentives. In: 13th ACM International Conference on Ubiquitous Computing, pp. 17–21.
Li, Z., Hensher, D., 2011. Crowding and public transport: a review of willingness to pay evidence and its relevance in project appraisal. Transp. Policy 18, 880–887.
Lin, T.M., Wilson, N.H.M., 1991. Dwell time relationships for light rail systems. Transport. Res. Rec., 1361
Mandel, B., Gaudry, M., Rothengatter, W., 1994. Linear or nonlinear utility functions in logit models? The impact on german high-speed rail demand forecasts. Transport. Res. Part B 28 (2).
Puong, A., 2000. Dwell Time Model and Analysis for the MBTA Red Line. Master's Thesis, Massachusetts Institute of Technology.
Qi, Z., Baoming, H., Dewei, L., 2008. Modeling and simulation of passenger alighting and boarding movement in Beijing metro stations. Transport. Res. Part C 16, 635–649.
Raveau, S., Muñoz, J.C., de Grange, L., 2011. A topological route choice model for metro. Transport. Res. Part A 45, 138–147.
Shin, S.G., Cho, Y., Lee, C., 2007. Integrated Transit Service Evaluation Methodologies using Transportation Card Data. Technical Report 2007-R-09, Seoul Development Institute (in Korean).
Wardman, M., Whelan, G., 2011. Twenty years of rail crowding valuation studies: evidence and lessons from british experience. Transp. Rev. 31 (3), 379–398.
Whelan, G., Crockett, J., 2009. An investigation of the willingness to pay to reduce rail overcrowding. In: Proceedings of the First International Conference on Choice Modelling.
Yang, C.H., Shon, E.-Y., 2000. Estimation of transfer related values of Seoul subway users using stated preference and revealed preference analyses. J. Korean Soc. Transport. 18 (4), 19–30 (in Korean).
Yang, D., Li, F., Duan, Z., 2012. Dwell time estimation models for bus rapid transit stations. J. Mod. Transport. 20 (3), 168–177.