Selection of Stopover Stations by Homeward-bound Railway Users

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Abstract. This study discusses the behavior of railway users who commute to work or school as they choose a station on the way home for eating or shopping. A quantitative grasp of the tendencies in this selection based on personal attributes and time points was obtained by creating models that accounted for the geographical relationships between individuals' residences and their workplaces or schools, and for the environments surrounding stopover stations. It was found that the increased time required for a stopover, or the number of transfers between trains were points of resistance and that the fact that a station on the route home was a transfer station, and the extent of commercial space near that station, affected the attractiveness of that station. The results of a simulation applying the stopover station selection model, indicated that an increase in the commercial establishments near a station and the availability of interconnected railway companies affected the attractiveness of a stopover station.

Keywords: stopover behavior, railway station, Person Trip survey, multinomial logit model.

1 Introduction

1.1 Background and motivation

Railway users tend to engage in increasingly diverse travel patterns as their railway networks expand and the areas near railway stations undergo redevelopment. If we focus on commuters travelling to work or school, who make up the majority of railway users, a decreasing number of these, simply travel in direct paths between their homes and those destinations. Instead, commuters increasingly stop at other destinations on their way home to shop, eat, attend classes, or follow other pursuits. It is essential to obtain a good grasp of this (stopover) behavior, not only to facilitate safer and more comfortable railway operations as well as station facility designs but also to promote discussion on how to rejuvenate the areas around railway stations.

In this study, railway user stopover behavior with respect to objectives such as shopping, eating, and classes, on their way home from work or school were examined, and a model predicting the stopover station for such objectives (stopover station selection model) was constructed. Specifically, we constructed a model that accounted for geographical relations between individual residences and their workplaces or schools, and

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for the environments surrounding stopovers stations. The model was estimated using data from differing time points, and the attractiveness of a given stopover station was quantitatively analyzed as it varied with individual attributes and time points. The model was then applied in a simulation while assuming changes both in the environments surrounding stations and in the railway network, in an attempt to observe the resulting effects on the attractiveness of certain stopover stations.

1.2 Related work

Stopover behavior on the way home, such as shopping, has been studied from various points of view in recent years. For example, Adachi and Yoshikawa (2015) analyzed the spatial composition of locations deemed convenient for after-work stopovers by commuters, while Tanaka (2010) constructed a model for selecting the locations and opening times of services intended to entice the maximum possible stopover passengers and analyzed the convenience of those stations from the viewpoints of time and location. Additionally, Kurita and Homma (2005) described a very interesting analysis in which they expanded what had been a simple model of spatial interaction between two points by constructing a stopover zone to insert between the departure and arrival zones, while Kodama et al. (2006) carried out a survey of commuters working in cities and provided some observations about how their means of commuting and how the characteristics of the stations they used influenced their stopover behavior.

Some studies have also analyzed facility selection behavior using multinomial logit models (Hausman and McFadden, 1984) incorporating stopover behavior. For example, Isono and Kishimoto (2011) modeled library selection behavior, and Tokunaga and Sadahiro (2002) modeled bank automated teller machine selection behavior, in order to identify the optimal scale and disposition of those respective facilities. Additionally, Maekawa and Kurauchi (2011) classified shopper behavior and modeled their location selection patterns.

Thus, many studies have addressed stopovers that were the secondary rather than primary objectives of railway users, which are referred to as “incidental uses” of railway stations. However, few studies have viewed commuters’ deliberate behavior in the selection of stations for stopovers in order to go shopping or to engage in some other activity. In one of those studies, Li et al. (2004) constructed a shopping location selection model that viewed stations in terms of the various alternatives offered. Although that report was quite interesting in its close scrutiny of the influences on selection behavior on individual attributes and customs, and compatibility between items, it did not offer any detailed discussion of stopover stations other than those closest to home or closest to work or school, or any observations about changes in stopover behavior with time.

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2 Construction of Stopover Station Selection Model

2.1 Formulation of model

Figure 1 provides an example of stopover behavior. We consider stopover behavior as that when individual n, who had traveled from station h closest to home (home station) to station i closest to work or school (work/school station) with the objective of commuting, now stops at station j with the objective of shopping, eating, or doing something else on the way home. The means of traveling from station i to station j is disregarded, and the case where station j is identical to station i is included. We assume that individual n acts in such a way as to maximize the utility of the facilities available at the stopover location (select the station where the utility is maximized), and describe commuter behavior selecting stopover station j with the multinomial logit model (Hausman and McFadden, 1984).

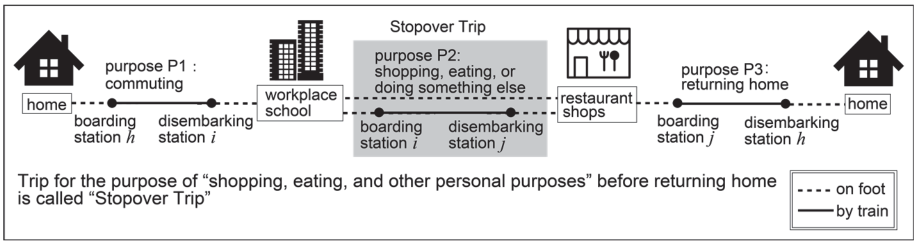

Fig. 1. Example of stopover behavior and trips.

First, the variables necessary for the formulation are defined as follows. Individual n may select stopover station j from the set of alternatives A_n ($j \in A_n$), and the systematic term for the utility obtained by individual n stopping over at station j (the attractiveness of that stopover station) is denoted by V_{jn}. The probability P_{jn} of selecting station j at this time can be expressed as shown in Eq. (1) using the multinomial logit model based on random utility theory (Hausman and McFadden, 1984). Below, this model is referred to as the "stopover station selection model",

$$P_{jn} = \frac{\exp\left[V_{jn}\right]}{\sum_{j' \in A_n} \exp\left[V_{j'n}\right]} \quad (j, j' \in A_n). \tag{1}$$

Next, we consider the following linear model for the utility function V_{jn}:

$$V_{jn} = \sum_k \theta_k X_{jnk} \quad (j \in A_n), \tag{2}$$

where θ_k is an unknown parameter and X_{jnk} is the k-th characteristic variable for alternative j of individual n.

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2.2 Definition of characteristic variable X_{jnk}

Figure 2 provides the definition of the characteristic variable in the stopover station selection model.

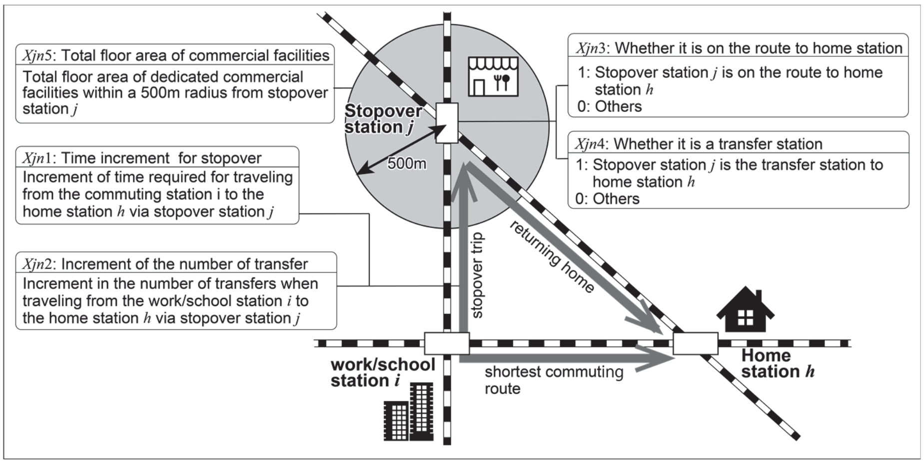

Fig. 2. Definition of the characteristic variables in the stopover station selection model (an example of stopover station which is located not on the shortest commuting route).

First of all, the increase in the travel time home and the increased number of transfers between train lines can be expected to affect the selection of the stopover station. These are expressed using the variables $X_{jn1} - X_{jn4}$. Here, we convert the negative utility accompanying the increased number of transfers between train lines (transfer cost) into increased travel time (Osaragi, 2009). The individual's travel path is assumed to be the path requiring the least travel time, as predicted by Dijkstra's algorithm (Dijkstra, 1959). The travel speed is set for each station section based on the relationship between the average distance between stations and the actual railway speed. We also consider the transfer costs as follows; $C(kx, kx)$ is transfer cost between the same railway company x at station k, $C(kx, ky)$ is transfer cost between different railway companies x and y at station k, $C(kx, ky)$ is transfer cost from station k (railway company x) to station l (railway company y).

$$C(kx,kx) = \alpha R_{kx} + \beta \quad (3)$$

$$C(kx,ky) = \alpha \frac{(R_{kx} + R_{kx})}{2} + \beta + \gamma \quad (4)$$

$$C(kx,ly) = \alpha \frac{(R_{kx} + R_{lx})}{2} + \beta + \delta + T_c \quad (5)$$

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where R_{ky} indicates the number of railway lines connected to station k, and T_c indicates the travel distance divided by 60 m/s. Other constant values are set as follows; α is the transfer time which increases in proportional to the number of railway lines (2 minutes/line), β is the transfer time (5 minutes), γ is the initial resistance for changing to different railway company (7.5 minutes), and δ is the resistance for changing to different station (11.3 minutes). The details of these parameters are described in Osaragi (2009). Stations surrounded by a number of or a rich variety of retail outlets and food services would be the most attractive as stopover stations. Therefore, attractiveness was assumed to be proportional to the total commercial floor space near a given station, and this was used to establish the variable X_{jn5}.

2.3 Determination of the set of alternative stopover stations A_n

We extracted the stopover trips from Person Trip survey data (PT data), which is the key dataset in this research. "Trip" in PT data is illustrated in Fig. 3, as an example. A worker left his home at 8 o'clock, and walked to the train station, and took a train, and arrived at his office at 8:50. In the evening, he left the office at 18:00, and made a stopover trip to station (C) for shopping, which is not located on the daily commuting route, and came back home at 20:20. All the information shown in this figure is contained in the PT data.

The stopover trips were observed by the answers to the questionnaire. More specifically, purpose of trip, destination of trip, time of departure/arrival, means of transportation, etc. are obtained from the answers of respondents. There are insignificant stopovers that are satisfied within the transfer time window, such as purchasing sandwiches/ coffee/ medicines at a drag store. However, these activities are not answered as significant trips by commuters in general. Namely, any activity which was done within a Trip (during movement from origin to destination) are not observable. In other words, the stopover trips in this research are significant trips with specific purposes (excepting for main daily purpose/returning home) that are observed in the questionnaire survey.

Trip of PT data can be divided into unlinked trips as shown in the figure. Using the unlinked trip, we can know the detailed time of departure/arrival, means of transportation, location of station. However, specific purpose is not specified for them.

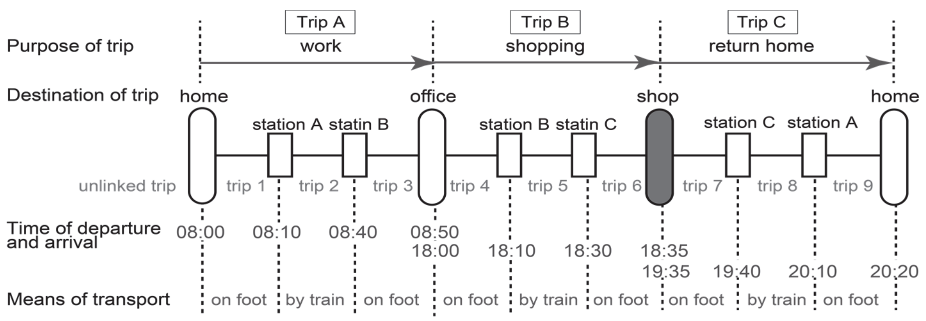

Fig. 3. Example of "Trip" in Person Trip survey data (PT data).

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The set of alternative stopover stations A_n for individual n in the multinomial logit model is defined as follows. A_n is the union of (1) the set of m stations most frequently selected for stopovers S_m (main set of stopover stations [described latter]); (2) the set of stations on the route from work/school station i to home station h; and (3) the set of stations sharing the lines on which work/school station i and home station h are located (Fig. 4). The set of alternative stopover stations A_n for individual n includes the work/school station i (which is not necessarily in the main set of stopover stations S_m). Locations near work or school must also be incorporated in considerations of stopover behavior.) Figure 5 specifically describes the way in which the main set of stopover stations S_m was determined. We extracted the main stopover stations (S_m) as follows. (1) Based on Person Trip survey data (PT data), the number of people who stopover each station, and rank them by each year is calculated, (2) the overall ranking from three years, and regarded the top m stations as the main stopover station is calculated. If there are too many choices (S_m) in the logit model, the estimated parameters of the model become unstable, and if there are too few choices, the explanatory power of the model decreases. Therefore, in order to cover as many stations as possible as long as the estimation accuracy does not decrease, the number of main stopover stations is set to 40 in this research.

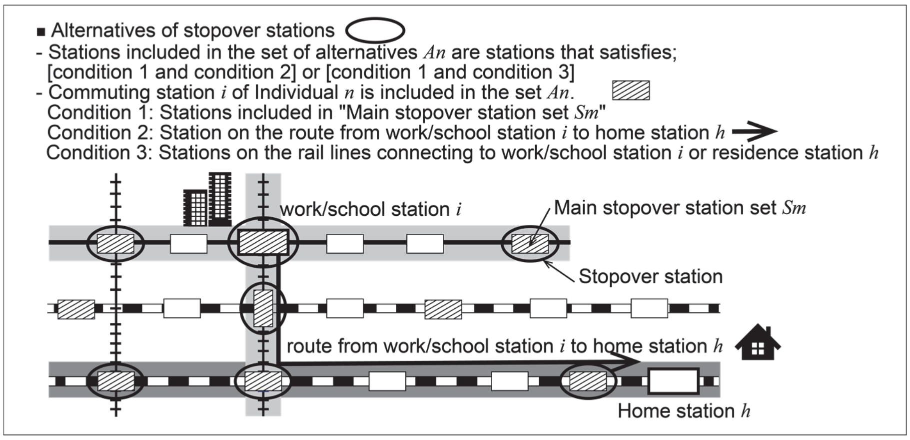

Fig. 4. Setting conditions for choice set of stopover stations (A_n).

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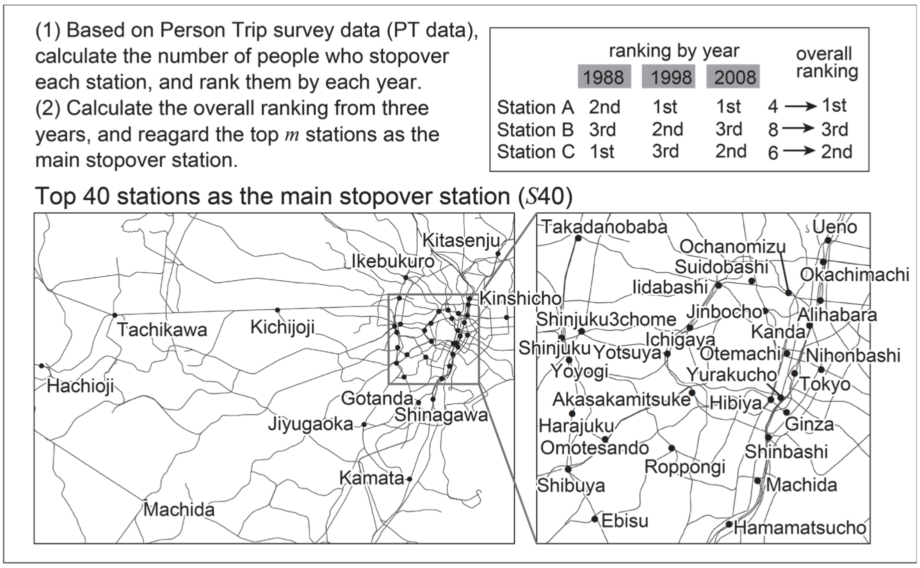

Fig. 5. The way in which the main set of stopover stations S_m was determined.

3 Method for Selection of Target Stations and Population

3.1 Selecting set of target stations

Stopover trip data was extracted from Person Trip survey data (PT data) collected in 1988, 1998 and 2008 in the Tokyo metropolitan area for use in this study. The 40 stations showing the highest frequency as stopover stations at all three time points were extracted to establish the main set of stopover stations S_{40} (S_m, $m = 40$) as target stations. Figure 5 lists the names of the stations in this set. In addition to Shinjuku, Ikebukuro, and Shibuya, which are large stations in central Tokyo, the set includes stations outside the city, such as Tachikawa, Hachioji, and Machida.

3.2 Selecting set of target stations

Figure 6 shows how the railway (including subway here and below) users' trips varied year on year. Examining the findings for daily trip totals for riders who used the railways at least once a day (Fig. 6(a)), the fraction of riders making two trips/day fell year by year, while that of riders making three or more trips/day increased. These were classified by travel objective, and the trips were labeled with alphanumeric codes to generate Fig. 6(b). It can be seen that the travel to work/school and then back home without stopovers (WH) occupied a shrinking fraction year by year, while trips for "Other personal purposes" increased (O). This indicates that users' purposes for their trips were becoming increasingly diverse. Also, in 2008, the fraction reporting travel to work/school, then a stopover on the way home to shop, eat, attend classes, etc. (WSH)

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represented about double the fraction reporting leaving home in order to shop, eat, attend classes, and then returning home (SH).

Therefore, in this study, we focus on “WSH” as a typical pattern for stopover behavior. First, behaviors (1) individuals whose total number of trips per day is 3, and the purpose of movement is “W → S → H”, and (2) individuals whose means of transportation for the 1st and 3rd trips is “railway”, and (3) disembarking and boarding stations are included in the main stopover station S_m in Tokyo, were extracted from the PT data. Then, the individual n of users whose stopover stations were included in the alternative set A_n was selected as the target population (1988, 3,958 samples; 1998, 4,652 samples; 2008, 4,794 samples).

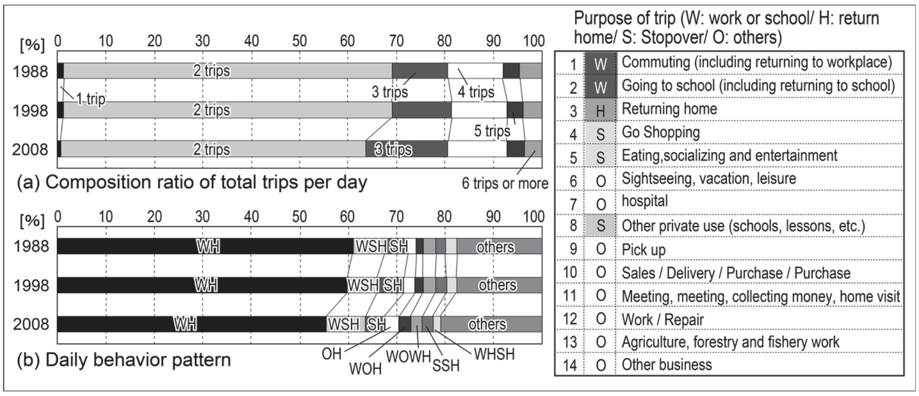

Fig. 6. Changes in behavior of all railway users and extraction conditions of analysis target.

3.3 Overview of target population

Figure 7 presents the target populations extracted under behaviors (1) – (4) in Fig. 6, classified by attributes, at each time point. It can be seen that the fractions represented by women and the elderly increased over the years (Fig. 7(a), (b)). This can mainly be attributed to large changes in the sex makeup and the increasing age of commuting workers over the 20-year interval. Additionally, the stark decrease in the fraction of riders in their twenties as of 2008 is a sign of the dwindling birth rate and aging population of Japan. Examining the means of transportation during the stopover (Fig. 7(c)), the number of commuters walking to locations near work or school fell, while railway riders to the stopover stations increased because commuter mobility had improved. Shopping was the reason for an increasing number of commuter stopovers. There is an increasingly rich variety of retail and eating establishments inside stations themselves, as well as new commercial spaces. Hence, it is possible that these have encouraged the public to eat and shop while returning home from work or school (Fig.7(d)).

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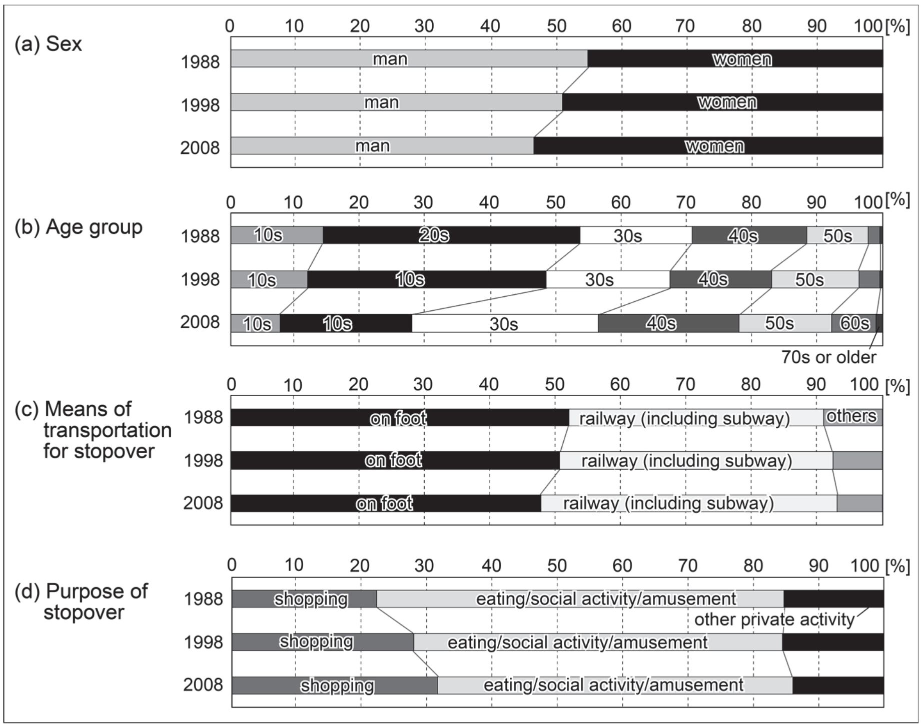

Fig. 7. Changes in the attributes of target populations extracted.

Figure 8 presents histograms of the lengths of time the individuals in the target population spent at their respective stopover stations (the period from ending time of the second trip to starting time of the third trip) and the arrival times at their stopover stations (ending time of the second trip). There were almost no differences between the three surveys (1988–2008) in their stay times when the purpose was shopping. However, while the 8–9 pm arrival period accounted for over half the individuals in 1988, by 2008, the majority of arrival times had shifted later than 9 pm.

Turning our attention to those who stopped for eating, socializing or entertainment, the fraction of stay times under two hours decreased, while that of stay times over three hours increased. The fraction of the population arriving at around 8 pm diminished, while that of people arriving at round 10 pm increased. Thus, the time of stopover behavior shifted later over the years, and the stay time for eating, socializing and entertainment grew longer. Factors in these changes were the lengthening of train and bus operations into the very late evening as late-hour commercial operations began, and then became established practice, and changes in the social environment including the general lengthening of work hours.

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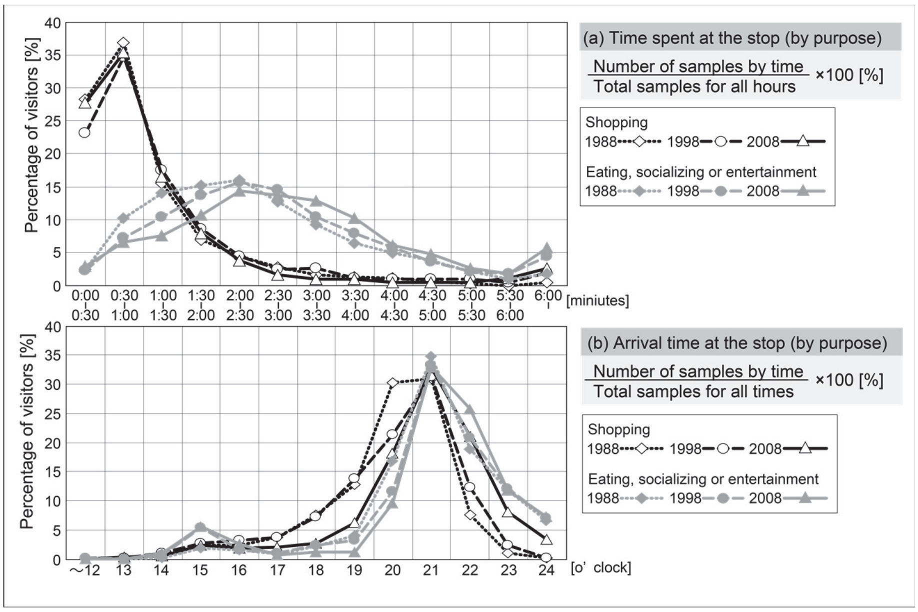

Fig. 8. Lengths of time the individuals in the target population spent at their respective stopover stations.

4 Estimation of stopover station selection model

4.1 Accuracy of estimation of model

Parameter θ_k of the stopover station selection model was estimated by the maximum likelihood method, using the Newton-Raphson algorithm (Ortega and Rheinboldt, 1970). In order to ease identification of strong and weak relationships between the different variables, the data were standardized for each time point and variable (mean = 0, dispersion = 1).

A comparison of the numbers of people estimated by the model to stop over at each time point with the actual numbers reported in the PT data indicates good accuracy of the model (Fig. 9). The reason for the overestimates at Kinshicho Station at all time points was that people who were actually stopping over at Tokyo and Ochanomizu Stations was estimated to got off the trains at Kinshicho Station instead. This was probably because the data had not accounted for the presence of the large number of commercial establishments in the lower floors of what are otherwise massive office buildings standing near Tokyo Station. (In other words, it related to an issue of identification of structure uses).

Accurate estimates of the people stopping over at Ikebukuro Station were obtained for 1988 and 2008, but the estimates were excessive for 1998. Although commercial establishments in the vicinity of Ikebukuro Station were greatly expanded from 1988 through 2008, it is possible that a certain length of time is still required to bear fruit in

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terms of stopover clientele. The likelihood ratios in the models of the three time points rose with the passing of the years, and the relationship between the explanatory variables incorporated in the models and the attractiveness of the stopover stations could be described with increasing clarity.

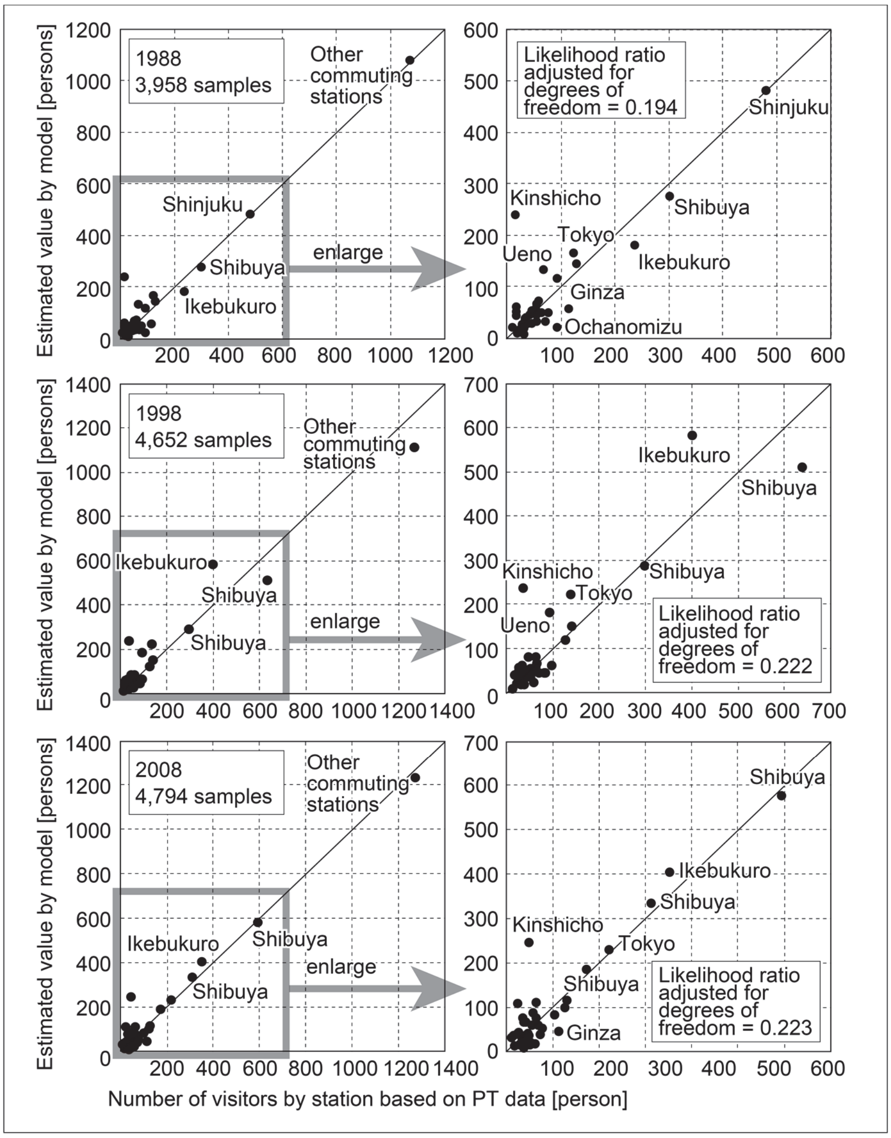

Fig. 9. Estimation accuracy of model (estimated number of stopover samples by station).

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4.2 Interpretation of estimated parameters

Figure 10 shows the estimated parameters for the models. It can be seen that the increased time for stopovers and the number of transfers between train or subway lines acted to lower the attractiveness. This was true at all time points. Conversely, attractiveness was increased when a transfer station was otherwise on the route to work or school or was surrounded by large commercial establishments. Comparing time points, the resistance to the increase in stopover time (X_{jn1}) increased more markedly over the years than the other variables. The appearance of sophisticated navigation services through the Internet in recent years may also have made people more sensitive to the time required to travel through cities. In contrast, over the years, the estimated parameters for X_{jn3} and X_{jn4} have become lower in value than the other variables. As a result, it has become easier to select stations that are not transfer stations or are not on the direct route home.

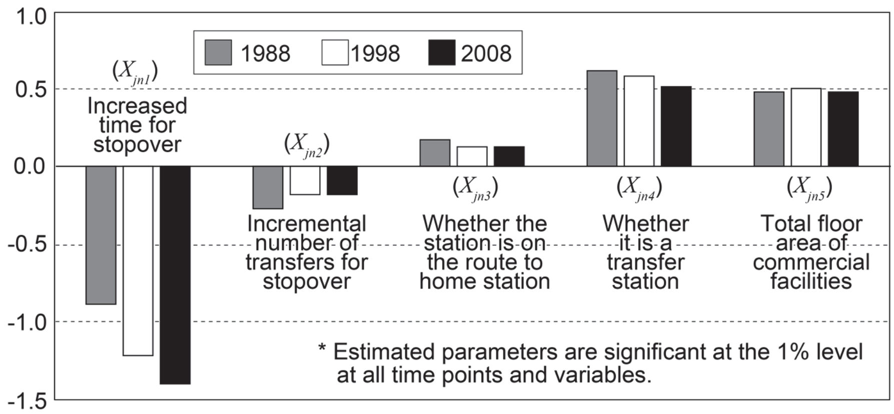

Fig. 10. Estimated parameters for the models.

4.3 Interpretation of estimated parameters

Sex. The target population was classified by sex and models were estimated. Those results are shown in Fig. 11(1). For men, since the parameters for X_{jn1} became increasingly negative with time, this indicated that the resistance due to the increase in time was greater than that due to the number of transfers necessary for a stopover. The parameters for X_{jn4} remained strongly positive for men at all time points, as did those for X_{jn5} for women. In summary, when selecting stopover stations, men tended to look for transfer stations while women tended to look for large floor spaces devoted to commercial activities. However, the difference of estimated parameters for men and women was not tested for significance.

The female employment rate has increased over the last 30 years. In addition, their incomes have been increasing, and in result their mobility within urban spaces has also increased significantly. Given this background, female's shopping has grown

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significantly in the last 30 years. The result shows quite interesting fact from the viewpoint of human geography.

Age. The target populations were classified into age brackets and models were estimated. The results are given in Fig. 11(2). Note that the age brackets varied somewhat from year to year because the number of samples was insufficient to allow completely consistent age brackets. Comparing the likelihood ratios for the age brackets in the estimation models, we note higher likelihoods in the age groups of 25 years and over than in the younger group. This can be attributed to the fact that in the under-25 group, there was a mixture of school and work commuters, and that the behavioral characteristics of those two groups are significantly different from each other.

The higher the age bracket, the more negative the parameter X_{jn1}, and the more positive the parameter X_{jn4}. In other words, the higher the age bracket, the greater the resistance to any lengthened travel times caused by stopovers, while the greater the attractiveness of stopover stations that were also transfer stations. Also, for the younger age brackets, the parameter X_{jn5} was strongly positive at all time points, thus showing the tendency to select stations with high potential for commercial activities.

Objectives of stopover. The target population was classified by their stopover objectives and models were estimated. The results are given in Fig. 11(3). A comparison of the likelihood ratios by stopover objective in the estimation models showed relatively low goodness of fit for the "Other personal purposes" classification. This is because insufficient explanatory variables describing this behavior had been incorporated because the stopover behaviors under "Other personal purposes" are quite diverse (cram schools, other education, etc.). For the "Shopping" objective, however, the goodness of fit was quite high and reliable.

Among passengers whose stopover objective was shopping, variables X_{jn1} and X_{jn5} took high negative and positive signs values, respectively. Thus, this group had a higher resistance to the increase in stopover time than the groups reporting different objectives for their stopovers. This group had a higher tendency to select stations with many commercial establishments in the environs (of note is that X_{jn1} showed increasingly negative values over the years).

The parameters for people reporting eating, socializing or entertainment as their objective grew increasingly positive for X_{jn4}, with a preference for transfer stations. Thus, we can speculate that people who stopped over in order to shop focused on the time required to travel, while those who stopped over to eat, socialize or seek entertainment focused on stations from which passengers could transfer trains or subways, which are convenient locations for meeting up with people arriving from different directions.

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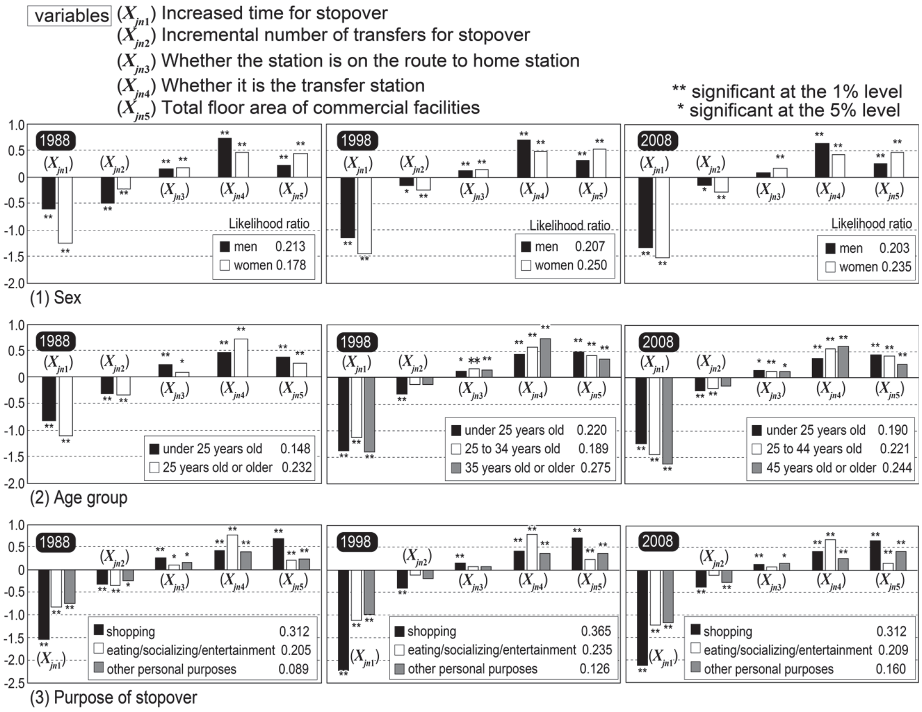

Fig. 11. Model estimated parameters (by attribute).

5 Application of Stopover Station Selection Model

5.1 Viewpoint of analyses

Next, we attempted a simple analysis by simulation, using the estimated stopover station selection model. In this simulation, the surroundings of the stations and their connecting lines were changed virtually and the resulting variations in the numbers of passengers stopping over at the stations were observed. In this way, we observed how the attractiveness of a stopover station varied and the extent of the resulting variation in the number of passengers stopping due to reasons such as changes in the surroundings of a given station or in direct interconnections with other train lines.

5.2 Variation in the attractiveness of a station as a stopover location due to expanded/reduced commercial establishments in its environs

There has been a tendency for commercial establishment growth in the vicinity of railway stations in recent years. One example is the large-scale redevelopment project near Shibuya Station, which is scheduled for completion around 2028. A model of that area was estimated to predict the changes in the attractiveness of stopover stations as the

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commercial establishments were expanded near Shibuya Station (Fig. 12). The percentage change in the population of riders stopping over, assuming that the commercial floor space (X_{jn5}) within 500 m of Shibuya Station, had increased by 100,000 m^2 (values using 2018 as the base), was calculated for each station.

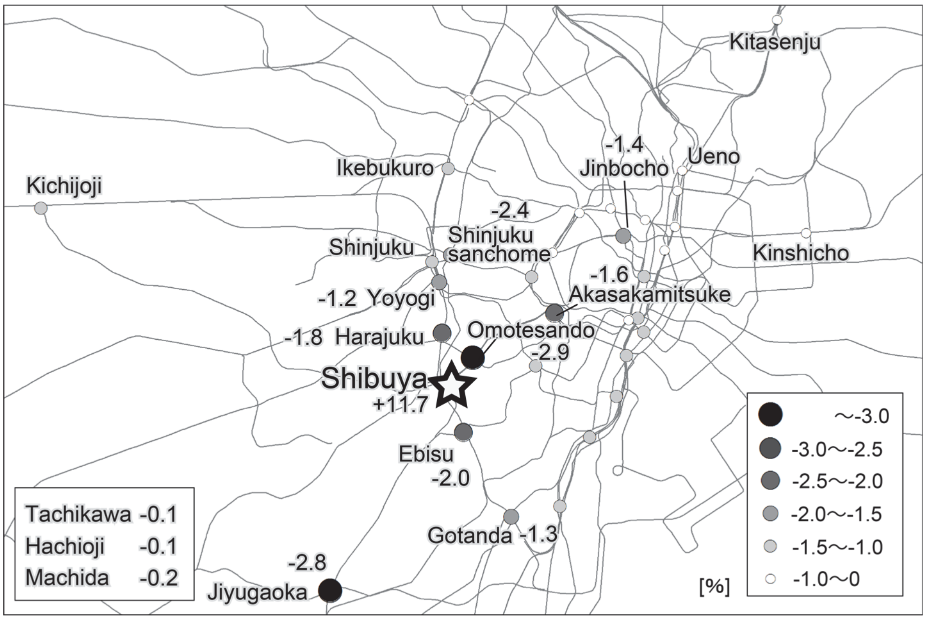

Fig. 12. Attractiveness change due to increase in commercial facilities around Shibuya Station.

It was estimated that stopovers at Shibuya Station would increase by about 12% over the 2018 numbers, while they would fall sharply not only at the immediately neighboring stations of Omotesando, Ebisu, and Harajuku, but also at Jiyugaoka. This shows a reduction in stopover activity at Jiyugaoka for homebound passengers for Yokohama from Shibuya Station. However, there was almost no change at Tachikawa, Machida, or other stations in the suburbs from Shibuya Station, around Tokyo Station, or at stations on the Sobu or Chuo Lines.

5.3 Variation in attractiveness of a station as a stopover location due to availability of interconnected railway companies

We next estimated how the attractiveness of a stopover station varies with the availability of interconnected railway companies. This model attempted to replicate the aftereffects of interconnection of the Tokyu Toyoko Line and the Fukutoshin Line at Shibuya Station and the ending of the interconnection of the Hibiya Line and the Tokyu Toyoko Line at Nakameguro Station (both changes actually occurred in 2013).

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When formulating variables X_{jn1} through X_{jn4} in the model, the transfer cost at the junction of interconnected lines (see Fig. 2) was set to zero to indicate the interconnection virtually, and the difference in stopovers between this situation and that when companies are not interconnected was calculated (Fig. 13). It can be seen that the attractiveness of Shibuya, Shinjuku-sanchome and Ikebukuro Stations, on the Fukutoshin Line, was increased after interconnected operations were inaugurated. However, despite its highest number of stopovers in the Tokyo region, Shinjuku Station, which is near Shibuya and Ikebukuro Stations, saw a slight relative drop in attractiveness, as did Yoyogi and Harajuku Stations, which are also near Shibuya Station. Ginza and Roppongi Stations, which are not close to Shibuya, also saw a fall in stopovers. This is probably due to the obstacles to passenger flows from the Toyoko Line to the Hibiya and Ginza Lines following the inauguration of interconnected operations.

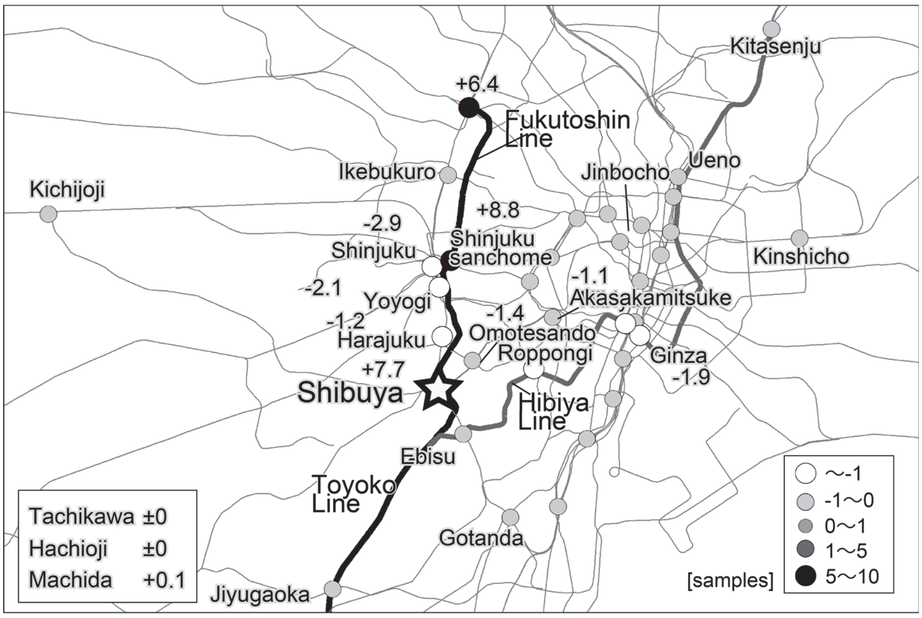

Fig. 13. Attractiveness change by mutual direct operation around Shibuya Station.

6 Summary and Conclusions

The behavior of passengers using trains and subways to commute from work or school was investigated with regard to their selection of stations when stopping over on their way home, using a multinomial logit model. The accuracy of estimates improved in the models constructed from the data for the later years, and this indicated that the explanatory variables employed accurately described the attractiveness of stopover stations. The values of the estimated parameters provided a good grasp of the extent of influence

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of each explanatory variable on the attractiveness of a stopover station, and how those variables changed over the years.

We found that transfer stations on an individual's way home and stations surrounded by many commercial establishments had high attractiveness as stopover stations, regardless of the time point. However, it was also shown that, over the years, resistance grew to the increased time required for stopping over. The railway user samples were also classified by attributes to estimate corresponding models, and quantitative results were obtained for the trends in stopover station selection as they varied with sex, age, and objective of stopover. The following specific findings were obtained:

(1) Men exhibited a preference to stop over at transfer stations rather than stations surrounded by large commercial areas, while women exhibited a preference for stations surrounded by large commercial areas even if they are not transfer stations.
(2) The higher the age bracket, the greater the resistance to the increased time necessary for a stopover. In contrast, the lower the age bracket, the greater the attractiveness of a station with high potential for commercial activities.
(3) Railway users who stopped over in order to shop showed a high resistance to the increased time necessary for a stopover. However, users who stopped over in order to eat, socialize or seek entertainment felt a higher attraction to transfer stations, which are convenient for meeting up. It is possible that this difference is due to the number of other people involved.

Finally, the stopover station selection model was employed to virtually examine cased when the commercial establishments near a station have increased, and when different railway companies have begun interconnected operations, in order to observe changes in the attractiveness of stopover stations and in the number of passengers stopping over. These results showed that large reductions in the number of stopovers occurred at stations neighboring a station around which commercial establishments had increased, or when the attractiveness of stations had increased along a line which interconnected with other lines, thus lowering the attractiveness of other stations on the interconnected line.

From the above results, factors affecting stopover behavior during return railway trips home from work or school were extracted, and a model describing stopover behavior was constructed. It was shown that the stopover station selection model created for this study could be employed to predict the changes in stopover behavior accompanying the redevelopment of areas near stations and in relation to the operation of interconnected railway and subway lines.

This research did not attempt to propose a new analytical method, but to extract people's urban activities from a viewpoint of a novel perspective. In recently, people are moving around urban spaces, shifting to more complex movements than simple round trips. The authors believe that this research is necessary in order to predict and discuss the future of these trends.

This research attempted a new perspective on analysis that has been difficult to achieve due to the limitations of available data. In recent years, although there is a restriction of privacy protection, big data on the personal travel behavior is recently becoming available. Considering the possibility of such new big data, we believe that this research could be an innovative and pioneering study of sufficient value. If the detailed

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data on the travel behavior of individuals similar to PT data can be obtained, it is possible to extract the characteristics of stopover behavior in each country or region, which will lead to deeper insights.

As shown in Fig. 6, there are multiple stopovers, but in this research, we focused on the simple behavior called WSH (Workplace-Stopover-Home) trip, which is the most primitive stopover behavior. We would like to analyze multiple stopover behavior in the future research.

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