APPLICATION OF CELL PHONE STATISTICS FOR ESTIMATING STRANDED PEOPLE BEHAVIOR AFTER SEVERE EARTHQUAKE IN TOKYO

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ABSTRACT:

In this paper, we present a walking home simulation as anticipated after a large earthquake, and analyze people's behaviors, walking and stopping, including the crowding of facilities by those unable to walk all the way home. For creating the necessary data for this simulation, we construct a method to estimate the spatiotemporal distribution of people with detailed individual information such as sex-age classification, and home location, by assembling population distribution data (Mobile Spatial Statistics and Person Trip survey data). The walking home simulation results verified significant variations in the crowding of facilities for stranded people due to differences in the day of the week and the time of the earthquake. Locations in Tokyo with insufficient numbers of facilities for stranded people were identified and some spatiotemporal characteristics of crowding, such as changes in crowding with time elapsed since the earthquake, were described.

1. INTRODUCTION

The issue of how stranded people are to return home in the aftermath of a disaster has become the object of ever-growing concern among the public since the Great East Japan Earthquake of March 11, 2011, as it has been discussed extensively in the mass media and elsewhere. Previous attempts by the national and the Tokyo governments at estimating the number of post-disaster stranded people have assessed an individual as "stranded" based on the distance to his/her home from his/her location at the time the disaster strikes. This is a simple method that is easy to assess, but decisions by workers, shoppers, etc., visiting Tokyo or people who happen to be traveling through Tokyo at the time of the disaster ("stranded people") as to whether to return home are complicated by a great number of factors. These include the age and sex of the person, whether he/she lives alone and or with others, available information about the safety of their family members, and his/her reason for being in Tokyo. With such factors in mind, Osaragi (2012) conceived a stochastic model for estimating the degree of a person's desire/intention to return home that varies significantly depending on his or her attributes and the situation at the time of the disaster. He then constructed a multi-agent simulation model that incorporated this stochastic model.
Reflecting on the lessons of the Great East Japan Earthquake, the Tokyo Metropolitan Government enacted the Metropolitan Tokyo Ordinance on Measures Concerning Stranded Persons (Tokyo Metropolitan Government, 2012), which is hereafter referred to as the Tokyo Metropolitan Government Ordinance (TMGO), on April 1, 2013. This ordnance instructs employers and schools to make efforts to keep their employees, students, or young children in place, rather than allowing them to attempt to travel homeward in a chaotic fashion. Subsequently, Osaragi et al. (2019) carried out a wide survey of people who had directly experienced the Great East Japan Earthquake and who currently commute to work or school in metropolitan Tokyo in order to assess the effects of the TMGO. The survey questions centered on how the respondents' views had changed after the earthquake on the subject of going home after a disaster. Osaragi then attempted analysis by simulating the situation after the TMGO was enacted to estimate the extent of crowding in shelters for support of stranded people (temporary shelters, support stations, large railroad stations, and others) (Osaragi and Nakasone, 2017).
Although person-trip (PT) survey data (Tokyo Metropolitan Area Transportation Planning Council, 2021) from moving and static people in Tokyo have been the basis of all similar research previously, these data are collected approximately every 10 years, which means they quickly become outdated and cannot be considered to adequately represent the spatiotemporal distributions of moving and static people in Tokyo, which vary dramatically from year to year, due to changes in transportation modes and lifestyles.
Separately, it has become possible in recent years to use location information from mobile phones to create spatiotemporal population statistical data for Tokyo occupants. However, although this type of raw data (which includes owner age and sex) could be extremely useful, the phone owners' other personal attributes and related information must be anonymized in order to protect their privacy. As a result, it is not possible to carry out multi-agent simulation models, simulation-based analyses, or home return intention models based solely on mobile phone data, because all of these models require other information, such as how many people, if any, the individual lives with, and his/her reason for being in Tokyo.
In recent years, attempts have been made to analyze the movements of urban population using location data taken from GPS attached to mobile phones (Ashbrook et al., 2003; Gonzalez et al., 2008; Sevtsuk et al., 2010; Calabrese et al., 2011). In relation to natural disasters, there are studies conducted using mobile phone location data that consider unusual human movements during large earthquakes (Lu et al., 2012; Song et al., 2013; Yabe et al, 2016). However, many of these studies have analyzed only the movement of people after a disaster, while very few have examined essential facilities that will be in short supply after a disaster. The novelty of this research lies in the attempts to provide information for such facilities to reduce the confusion immediately after a disaster.

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The objective of this research is to examine a method of creating an enhanced population statistical dataset in which several available population statistical datasets are integrated, thus making it possible to exploit the advantages of each dataset and compensate for their individual inadequacies. Also, is to examine the dynamic circumstances of stranded people, those walking home, and crowding in shelters opened to support stranded people by applying the enhanced dataset in a simulation of people walking home.

2. CONSTRUCTION OF DATA FOR SIMULATION OF PEOPLE WHO TRAVEL ON FOOT

2.1 Overview of Simulation of People Traveling on Foot and Input Data

Due to the limitation of available pages, this section only outlines the models that explore the actions of people who travel on foot after a large earthquake, which is made up of the following two components, as shown in Fig. 1. The details are described in Osaragi (2012).

2.1.1 Model of fractions of population classified by intended actions: This decision-making model explores how an individual selects his/her destination when moving on foot after the occurrence of a severe earthquake. Specifically, it models the decision-making process regarding the choices of heading for or staying home, going to one's workplace or school, or heading for some other place (a train station or temporary shelter), based on his or her immediate situation.

2.1.2 Foot travel model: This decision-making model examines whether to change destinations in the midst of walking to a presumed relatively distant location, due to physiological factors. It simulates actions during foot travel such as stopping at support stations (for toilet breaks), detouring to large railroad stations (for information, toilet breaks), or stopping on the street (giving up on trying to get home). It also includes a model for selecting between a railroad station and a temporary shelter, both of which are numerous in Tokyo. When the Great East Japan Earthquake (2011) occurred, mobile phones were out of service. As a result, a great number of people rushed to railway stations to seek information on the disaster and to confirm the possibility of returning home by train. Based on this experience, large railway stations are expected to play a role of temporary shelters. Generally, large public facilities are designated as temporary shelters for stranded people to escape the cold and rain for their safety. Examples include city halls, public high schools, and public theaters. However, underground car parks are not included in the temporary shelters because they are dangerous due to cars (gasoline) at an earthquake and difficult to withstand the cold.

The above models simulate the behaviors of stranded people in Tokyo while accounting for details of their attributes, which we define as aspects that affect their decision-making. The following attributes were included for reference: age; sex; occupation; living with other people; the presence of family 12 years of age or younger; and information availability regarding family members' safety. In addition, an individual's post-disaster behavior was predicted based on his/her location at the time of the disaster (in or outside a building; if outside, the distance from that location to one's home, workplace, or school), the time of the disaster, and other factors (the above-mentioned attributes of stranded people).

Here, facilities designated by local authorities in the Tokyo area for accommodating stranded people ("temporary shelters"), facilities designated by a total of nine prefectural and city governments for supporting those walking home ("support stations"), and large railroad stations are collectively called "facilities for assisting stranded people".

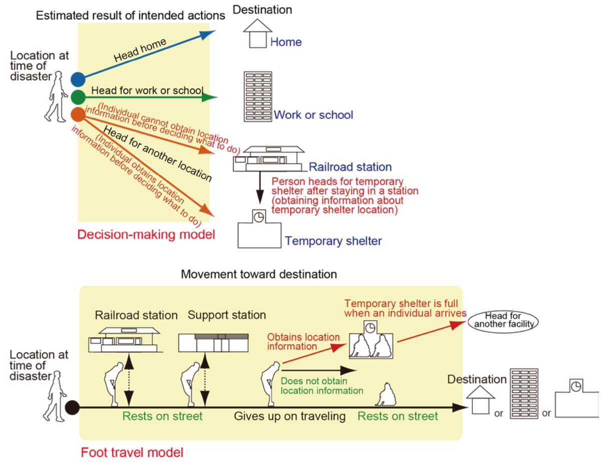

Figure 1. Overview of the simulation model for people traveling on foot.

2.2 Distinctive Features and Limitations of Mobile Phone Statistics

In recent years, population statistical information based on mobile phone location data has been marketed under the name of Mobile Spatial Statistics (MSS). These statistics show the spatiotemporal distribution of Tokyo occupants and have been used in a wide number of fields. These statistics are gathered from a wide variety of samples (the sheer number of mobile phone users) and have been validated for accuracy (Seike, et al., 2011). The greatest benefit of MSS is that they provide accurate numbers for people at any given time and any given location.

However, in order to maintain users' privacy, no details of individual users' attributes aside from sex, age, and other very basic information are provided. Hence, MSS alone cannot provide sufficient information for the two simulations mentioned above as those models require detailed data about individual attributes (residence location, occupation, live with family or not, have young children or not, etc.).

2.3 Estimating Numbers of Occupying Building Types Classified by Residence Location, Sex, and Age

In order for the reader to have a better understanding of the arguments below, we will provide an outline of the method of constructing the dataset employed here (Fig. 2).

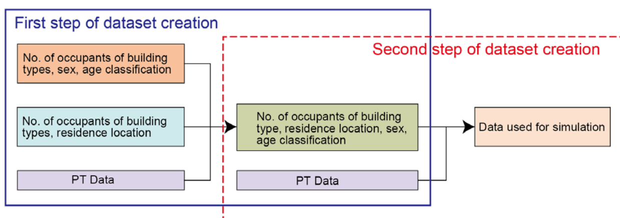

Figure 2. Flow chart for construction of simulation data.

(1) First, the people were grouped as follows (occupying building type × sex-age classification) and (occupying building type × residence location). These were combined to obtain the subsets (occupying building type × sex-age classification ×

residence location). Here, "building type" means "building of a certain use classification".
(2) Next, the occupants' family structure and other information that cannot be obtained from the MSS were supplemented with the PT Data using (building type × sex-age classification × residence location) as the key. The data for use in the simulation were then compiled by converting the estimated numbers of occupants of each grid cell unit into the agents that will appear in the simulation.
Next, we present a detailed explanation of the calculation process (Fig. 3).

MSS Data (Number of occupants)

Sector i Time t Bldg. use type j	Sex-age class u	Sum
Residence h	Y^t_{ijhu} unknown values	Y^t_{ijh}
Sum	Y^t_{iju}	Y^t_{ij}

PT Data (Probability of distribution)

Sector i Time t Bldg. use type j	Sex-age class u	Sum
Residence h	P^t_{ijhu}	P^t_{ijh}
Sum	P^t_{iju}	1

A convergence calculation was performed using the maximum entropy method to estimate the number of occupants

Figure 3. Estimation of populations based on building type, individuals' residence locations, and sex-age classification.

(1) First, the number of occupants of buildings of type j at time t in grid cell i with residences in location h, Y^t_{ijh}, and the number of people of sex-age classification u at the same i and t, Y^t_{iju}, are calculated from MSS and the building point data using the procedure developed in Osaragi and Kudo (2021).
(2) Next, in view of these constraints (the marginal distribution of the matrix in Fig. 3), the occupant fraction of buildings of type j with residential location h × sex-age classification u in cell i at time t, P^t_{ijhu}, is interpreted as the probability of occurrence.
(3) The maximum likelihood method is then used to estimate the number of occupants of buildings of type j × those of sex-age classification u in cell i with residences in location h at time t, Y^t_{ijhu}.
The following is a mathematical description of the above method using. The number of people having residential location h and the number in sex-age classification u are respectively given as follows:

$$Y^t_{ijh} = \sum_u Y^t_{ijhu} \tag{1}$$

$$Y^t_{iju} = \sum_h Y^t_{ijhu} \tag{2}$$

where Y^t_{ijhu} is with residential population at location h of sex-age classification u at time t in buildings of type j in cell i.
Using Eqs. (1) and (2) as constraints, the number of people with residential location h and sex-age classification u, Y^t_{ijhu}, can be obtained by maximizing the statistical quantity Q^t_{ij} below, using the occupant fraction P^t_{ijhu} as the occurrence probability

$$Q^t_{ij} = \prod_h \frac{Y^t_{ijh}!}{\prod_u Y^t_{ijhu}!} \times \prod_h \prod_u \left(P^t_{ijhu}\right)^{Y^t_{ijhu}} \tag{3}$$

where P^t_{ijhu} represents the occupants of buildings of type j with residential location h × sex-age classification u in cell i at time t, as obtained from the PT Data. Maximizing the logarithm of Q^t_{ij} is equivalent to maximizing Q^t_{ij} itself, so the logarithms of both sides of the above expression are taken, yielding the following for consideration:

$$\ln Q^t_{ij} = \sum_h \ln Y^t_{ijh}! - \sum_h \sum_u \ln Y^t_{ijhu}! + \sum_h \sum_u \left(Y^t_{ijhu} \ln P^t_{ijhu}\right) \tag{4}$$

Next, using Stirling's equation ($\ln N! = N \ln N - N$), we can rewrite Eq. (4) as follows:

$$\begin{aligned} \ln Q^t_{ij} &= \sum_h \left(Y^t_{ijh} \ln Y^t_{ijh} - Y^t_{ijh}\right) - \sum_h \sum_u \left(Y^t_{ijh} u \ln Y^t_{ijhu} - Y^t_{ijhu}\right) \\ &\quad + \sum_h \sum_u \left(Y^t_{ijhu} \ln P^t_{ijhu}\right) \\ &= \sum_h \left(Y^t_{ijh} \ln Y^t_{ijh}\right) + \sum_h \sum_u \left(Y^t_{ijhu} \ln \frac{P^t_{ijhu}}{Y^t_{ijhu}}\right) \end{aligned} \tag{5}$$

The problem of maximizing $\ln Q^t_{ij}$ under the constraints of Eqs. (1) and (2) can be formulated using Lagrange's method of undetermined multipliers:

$$L^t_{ij} = \ln Q^t_{ij} + \lambda^t_{ijh}\left(Y^t_{ijh} - \sum_u Y^t_{ijhu}\right) + \gamma^t_{iju}\left(Y^t_{iju} - \sum_h Y^t_{ijhu}\right) \tag{6}$$

The parameters λ^t_{ijh} and γ^t_{iju} that yield the maximum L^t_{ij} can be found by differentiating Y^t_{ijhu} with respect to L^t_{ij} and solving for zero:

$$\frac{\partial L^t_{ij}}{\partial Y^t_{ijhu}} = \left(\ln \frac{P^t_{ijhu}}{Y^t_{ijhu}} - 1\right) + (-\lambda^t_{ijh}) + (-\gamma^t_{iju}) = 0 \tag{7}$$

Then Y^t_{ijhu} can be expressed by the following equation:

$$Y^t_{ijhu} = P^t_{ijhu} \times \exp\left[-\lambda^t_{ijh} - \gamma^t_{iju} - 1\right] \tag{8}$$

Next, terms are added to both sides of Eq. (8), and then Eqs. (9) and (10) are obtained to separate h and u.

$$A^t_{ijh} = \frac{Y^t_{ijh}}{\sum_u P^t_{ijhu} B_u}, \quad B^t_{iju} = \frac{Y^t_{iju}}{\sum_u P^t_{ijhu} A_h} \tag{9}$$

where

$$A^t_{ijh} = \exp\left[-\lambda^t_{ijh} - \frac{1}{2}\right], \quad B^t_{iju} = \exp\left[-\gamma^t_{iju} - \frac{1}{2}\right] \tag{10}$$

The variables A^t_{ijh} and B^t_{iju} are mutually dependent quantities. The initial values were chosen arbitrarily and iterated in order to eventually converge on the real values for A^t_{ijh} and B^t_{iju}. The values for parameters λ^t_{ijh} and γ^t_{iju}, which provided convergence, are now substituted into Eq. (8) in order to calculate Y^t_{ijhu}.

2.4 Data calculation for simulation entries

People whose attributes match the occupants in building with type j, with residential location h × sex-age classification u, at time t in cell i are selected from the PT Data, and the attribute details necessary for use in the home return on foot simulation are added. Attribute information not included in the MSS is now selected for insertion, with reference to the other established attributes, in order to create a set of consistent attributes. This process is necessary because if the various attribute types are estimated under the assumption that they are completely independent, contradictions can arise among attribute details. For example, "No family" and "One child five years of age or under" would be contradictory. To avoid such conflicts, attributes were grouped into the sets shown in Table 1, which were constructed to preclude attribute contradictions within each set. Specifically, the attributes were estimated using the following:

$${}_{D_k}Y^t_{ijn} = \frac{{}_{D_k}P^t_{ijn}}{\sum_{D_k} {}_{D_k}P^t_{ijn}} \times Y^t_{ijn} \tag{11}$$

where ${}_{Dk}Y^t_{ijn}$ is the number of occupants with attributes D_k of basic attribute combination n in buildings of type j at time t in cell i in data employed in simulations; Y^t_{ijn} is the number of occupants in buildings of type j at time t in cell i in data employed in simulations; ${}_{Dk}P^t_{ijn}$ is occupant fraction with

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attributes D_k of basic attribute combination n in buildings of type j at time t in cell i in data employed in simulations; n is basic attribute combination (set combining people with sex-age classification u having residence location h); D_k is Work set (k = 1), Family set (k = 2), Action set (k = 3).

Set name	Incorporated information about attributes
Work set	Occupation, profession, work location
Family set	Family/no family, children/no children 5 years of age or under
Action set	During/not during the commute, destination, current situation

Table 1. Breakdown of attributes in sets employed in simulations.

3. VALIDATION OF MODEL AND SIMULATION RESULTS

3.1 Concept of The Return Home on Foot Simulation and Data Employed

This study assumes that the public transportation system is completely paralyzed after an earthquake directly strikes the Tokyo region. Since the potential issues addressed in this study would become extremely complicated if the effects of physical damage (roof collapses, building fires, street blockages, etc.) were considered and discussion of what other effects will occur would impede observations, physical damage factors were neglected in this study. Instead, it was assumed that the physical situation would be the same as after the Great East Japan Earthquake of March 11, 2011, in which people were able to walk along the streets safely in Tokyo.

An earthquake was assumed to have struck on a weekday (Tuesday, October 20, 2015) or a weekend day (Sunday, October 18, 2015) at 0900, 1400, or 1800. The simulation covered the period of 720 minutes (12 hours) immediately after the earthquake. Table 2 shows the assumptions taken in this simulation. The PT Data for the weekend day were constructed with the aid of the relevant research (Osaragi, 2016).

Date and time of the earthquake	Weekday: Oct. 20, 2015 (Tues.); Weekend: Oct. 18, 2015 (Sun.); 0900, 1400, 1800 (Simulation runs for 12 hours after the occurrence.)
Damage sustained	No fires or roadway closures due to earthquake; stranded people able to walk all roadways in safety.
Means of transportation	All public transportation is stopped; only walking is assumed.
Roadways employed in the simulation	Roadways in Tokyo, Kanagawa, Saitama Pref., Chiba Pref., south part of Ibaragi Pref. (Private and public expressways assumed closed.)

Table 2. Simulation assumptions.

Stochastic decision-making models (Osaragi, et al., 2019) were made for the following quantities: intended actions of an individual on foot, time at which an individual begins to act, the maximum distance an individual has the strength to walk, the time between toilet visits, and rest time. The specific action taken by each individual was determined using uniform random numbers.

Since many simulations employ Monte Carlo methods in order to minimize the influence from bias in random numbers, it is desirable to evaluate the above method using means and dispersion. However, since that would impose an excessive computation load on the simulation, we decided to run each of the simulations 100 times and use the mean values found.

The people on foot simulation model constructed in Osaragi and Nakasone (2017) was employed here, and the paths stranded people took from their locations at the time of the earthquake were predicted using information about their locations at the time of the earthquake, the locations of their homes, and their reasons for being where they were when the earthquake struck. We determined which building each occupant is staying at the earthquake as follows; first the use of the building is determined based on the occupant's occupation and purpose of stay. Next, which building each occupant is staying was determined according to the size of the total floor area of the buildings with the same building use.

Any individual who was outside the buildings was assigned to a random starting point at one of the nearest intersections in the region. The Building Point Data (published 2015) and the Japan Digital Road Map (DRM) Database (ver. 3.0) were used to estimate the individual's home location, location during the earthquake, and the route he/she would take to get home. For predicting homeward routes and during the simulation, the roadways in the DRM Database were classified into three types: those unusable by pedestrians, main roadways, and small roadways.

Since this paper focuses on people traveling on foot, expressways and roads for exclusive use by automobiles were eliminated as possible paths home. Private expressways were also eliminated from consideration, as little information was available about them. Additionally, since it was assumed that those who had particularly long walks home would prefer to walk along the highways, Dijkstra's Algorithm was employed to predict the shortest route.

3.2 Validation of foot travel simulation

Insufficient observational data have been collected after severe earthquakes necessary to validate simulations such as this. More specifically, since most facilities for assisting stranded people were designated as such after the Great East Japan Earthquake, no observational data exist yet, so no comparative investigations have been made of facility crowding under actual conditions. Therefore, we attempted to validate this simulation from the viewpoint of people's behavior while walking home by referring to survey information collected from the actual conditions observed by people as they walked home on March 11, 2011.

Some of the respondents to the survey (2,026 samples) caught trains home, once service had been restored, so only the responses of those whose feet were their only means of transportation home (619 samples) were extracted for consideration here. From the information in the answers about respondents' locations at the time of the earthquake and their residences, the latitudes and longitudes of those locations were found using the address matching service of the Center for Spatial Information Science at The University of Tokyo. The roadway network distance between each location pair was estimated by multiplying the straight-line distance between them by 1.16; this was used as the distance to the individual's home (Tamura, et al., 2001).

The respondents providing these data included some who gave incomplete information about their home locations, but all respondents provided the names of their home cities, wards,

villages, etc. Therefore, typical areas were selected for the individuals providing vague information about home locations.
The results from the 1400 weekday simulation, which closely matched the timing of the actual earthquake (14:46 on Friday, March 11, 2011) were compared with the survey results. Let us begin with the fraction of people who set out for home and actually walked there within 12 hours of the earthquake, which is shown in Fig. 4 based on the distances walked. Note that since few respondents reported walking further than 24 km, those individuals are excluded here. The fractions of people walking all the way home are well approximated by the following equations:

$$\textit{Fraction who walked home}\left[\textit{survey}\right]\,(\%) = \frac{\textit{Number of respondents reporting walking home within 12 hours}}{\textit{Total number of respondents}} \times 100 \tag{12}$$

$$\textit{Fraction who walked home}\left[\textit{simulation}\right]\,(\%) = \frac{\textit{Number of people walking home within simulation time}}{\textit{Total number of respondents}} \times 100 \tag{13}$$

The reader can see in Fig. 4 that there was little difference in the fraction of respondents who walked all the way home between the survey results and the simulation prediction for distances 6 km and less. However, for distances of 8 km and more, the simulation predicted fewer people walking all the way home than the survey respondents reported. This simulation assumes full preparations as provided in the TMGO, i.e., provision of information about family members' safety, and facilities at workplaces and educational institutions for accommodating workers and students.
However, it is possible that this simulation underestimates how many workers and students would actually have decided to return home, given that the preparations under the TMGO did not exist at the time of the Great East Japan Earthquake. It is also notable that the disaster occurred on a Friday, when people are typically more motivated to go home, which might also explain the discrepancy between the simulation and the survey results.

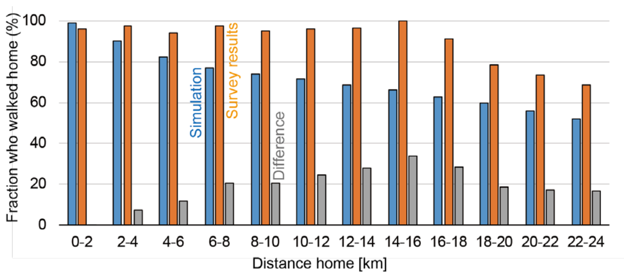

Figure 4. Fraction of respondents who walked all the way home.

Next, Fig. 5 provides the fractions among the stranded population who returned home on foot in terms of their arrival time after the earthquake. In this figure, a similar discrepancy is found between the survey and simulation, in which fewer people were assumed to head for home by taking advantage of the facilities made available under the TMGO.
Figure 6 compares the fraction of the stranded people for different ranges of distance. Distributions were calculated for the ranges 0–10, 10–20, and 20–30 km. It shows that when the distance is in the 0–10 km range, a high simulation-predicted fraction of people who return home would take little time. However, when the distance was in the 20–30 km range, the simulation predicted another high fraction of people who would have to walk for a much longer time. A possible reason for this difference may well be a difference in behavior between groups of people who face differing distances in their walk home. Nevertheless, the predicted distributions of the fractions of people who opt to walk home, with respect to the time required for such a journey, showed an overall resemblance to the reported distributions.

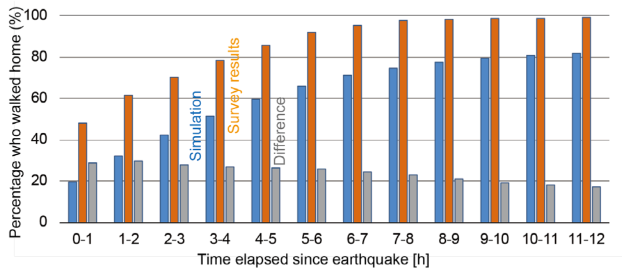

Figure 5. Fraction of respondents who walked all the way home.

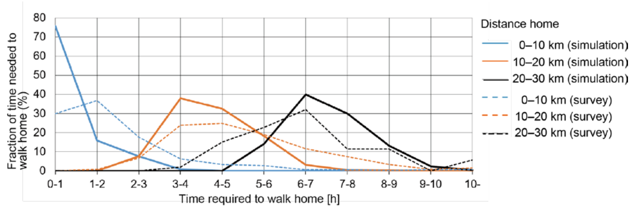

Figure 6. Fraction of time required to go home for different travel distances.

The mean lengths of time required for walking home are graphed with respect to the distance in Fig. 7. Here, it can be seen that the simulated times resemble the times reported in the survey, thus suggesting that the simulation is fairly accurate for estimating walking speed.

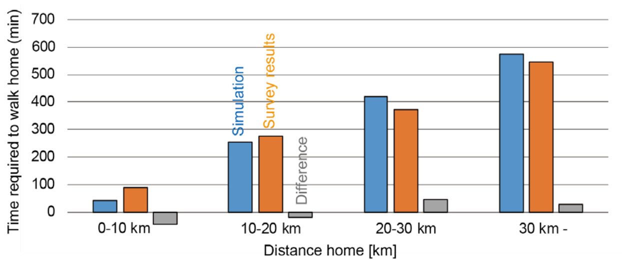

Figure 7. Mean time required to get home versus distance.

Thus, considering the distance to their homes and the time needed to walk there, these findings verified that the simulated actions of people returning home on foot did not differ significantly from the actions of real people.

3.3 Spatiotemporal Distribution of People Walking Home

Next, we make some observations about the results of the above calculations for the model of fractions of population classified by intended actions. Figure 8 shows the predicted numbers of people intending to walk to different destinations. In these figures, "Other institutions" refers to "the railroad station nearest his/her location at the time of the earthquake" or "temporary shelter". Alternatively, for cases of those on their way to work or school, it refers to "workplace" or "school".
Considering the number of people intending to walk home for different distances to their homes on weekdays and weekends,

we can see more people would choose to walk to the more distant homes on weekdays than on weekends. This is probably because many people travel to distant locations to work or attend educational institutions on weekdays. A comparison of the numbers based on their destinations after the earthquake shows that a higher fraction would head for home or to “other institutions” on weekends than on weekdays. This is probably because most people leave home on weekends on personal business and have no place to stay temporarily, so many such stranded people would deem it best simply to head back home.

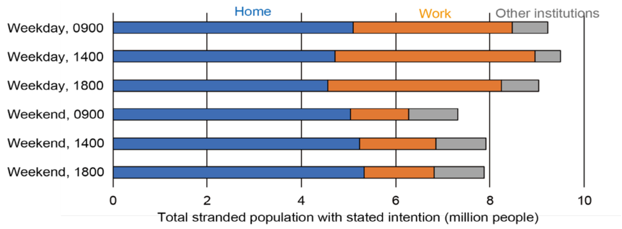

Figure 8. Combined numbers of people by intended destination.

3.4 Temporary Shelter Crowding

Figure 9 shows the hourly mean extent of crowding in temporary shelters. The “extent of crowding” is defined according to the following equation:

$$Extent\ of\ crowding = \frac{Number\ of\ stranded\ people\ in\ temporary\ shelter\ [people]}{Shelter\ capacity\ [people]} \quad (14)$$

Temporary shelter crowding is most severe after earthquakes at 1400, when central Tokyo has its highest population, on both weekdays and weekends. However, the extent of crowding is worse on weekends because most of the people in central Tokyo on days off are there on personal business. Hence, after a disaster strikes, many will go to railroad stations or temporary shelters rather than home or their place of work or school.

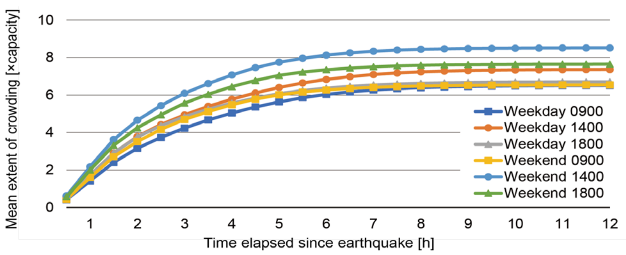

Figure 9. Mean values for crowding at shelters.

Figure 10 provides aggregate calculations of the mean crowding in locations on concentric circles about Tokyo Station, at 2 km increments of radial distance. This shows that crowding will be extremely severe in the city center, but will tend to decrease with distance from the center. However, it will still tend to reach increased levels in the bands 6 to 14 km from Tokyo Station. This is blamed on two factors: that many stranded people will walk to these areas and then give up on reaching home, and the low density of shelters in these areas.

The spatial distribution of crowding at temporary shelters 12 hours after the earthquake is shown in Fig. 11. Here, it can be seen that crowding will be higher on weekends than on weekdays in these shelters, which are distant from central Tokyo. It is also clear that the capacity of these shelters to accommodate the anticipated number of stranded people is wholly inadequate.

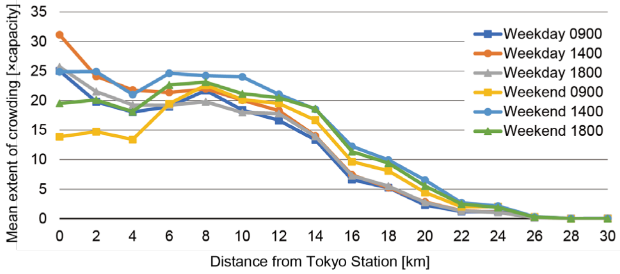

Figure 10. Crowding at shelters in concentric regions at given radii from Tokyo Station.

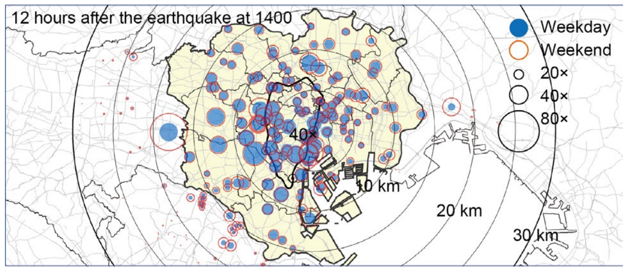

Figure 11. Spatial distribution of shelters with high crowding.

3.5 Crowding in Support Stations

Figures 12 and 13 show how the toilet crowding and the numbers of people resting in support stations, respectively, are predicted to vary with the passing of time. The toilet crowding can be defined as follows:

$$Crowding\ at\ toilets = \frac{Number\ of\ people\ using\ or\ waiting\ to\ use\ toilets\ [people]}{Number\ of\ toilets\ [commodes]} \quad (15)$$

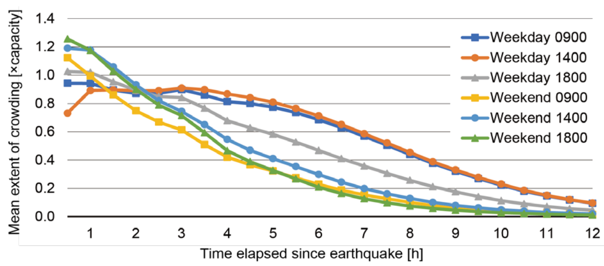

Figure 12. Mean values for toilet crowding.

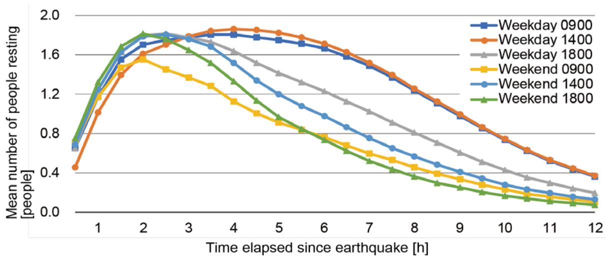

Figure 13. Mean number of people resting in support stations.

When an earthquake occurs on a weekend, people have no particular place they can seek refuge in, so many take immediate action. That is why toilets become more crowded and the number of people resting reaches a peak more quickly than on a weekday. Conversely, people at work or school on weekdays are more dispersed when they begin to act, which delays the peak. The crowding then diminishes but tends to do so at a modest pace and over a long period.

Figure 14 shows the spatial distribution of people resting 6 hours after the earthquake. The locations where these people were the most numerous on a weekend than on a weekday were widely scattered and rather distant from central Tokyo.

The above results show the need for resources to cope with people who begin walking home soon after an earthquake on a weekend and to provide long-term support to people stranded after an earthquake on a weekday.

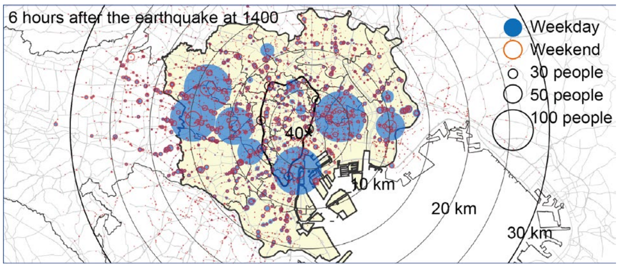

Figure 14. Spatial distribution of the number of people resting.

3.6 Extent of crowding in railroad stations

Figure 15 shows the estimated mean number of stranded people in railroad stations as a function of time after the earthquake, Fig. 16 shows the spatial distribution of people. These numbers exceed the mean ridership of trains at the busy hours of 0900 and 1400 on both weekdays and weekends. Additionally, the spatial distribution of people resting 30 minutes after an earthquake occurring at 1800 shows quite high numbers around the largest stations on the Yamanote Line, particularly Ikebukuro, Shinjuku, and Shibuya. The reader can also see high concentrations at the large stations of other railroad lines (Chuo Line, Keihin-Tohoku Line, Saikyo Line, Joban Line, and Sobu Line) connecting to those stations (Fig. 16).

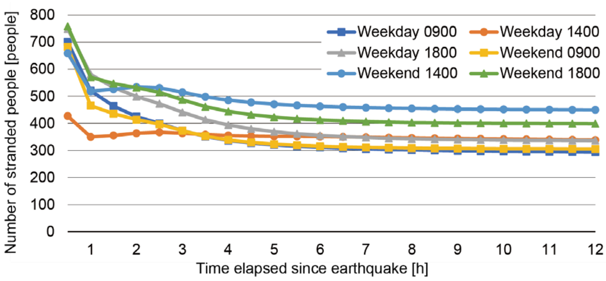

Figure 15. Number of people resting in and around railroad stations.

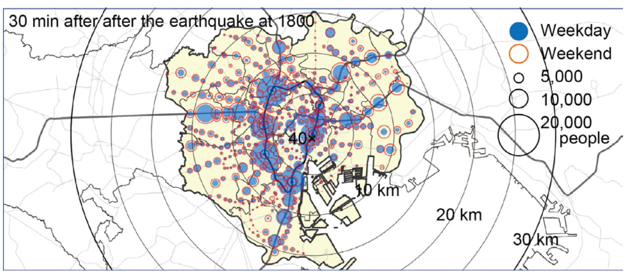

Figure 16. Spatial distribution of people resting at railroad stations.

3.7 People Who Have Given up on Walking Home and Remain on The Streets

Figure 17 presents the hourly growth in the number of people remaining on the streets. A large number of people on the streets of Tokyo on weekdays will be pedestrians, especially after earthquakes occurring at 0900 or 1400. Examination of these hourly results for people on the street by distance from Tokyo Station indicates that more people gave up on walking home as the distance from Tokyo Station increased, and the maximum numbers were at the radii 8 through 12 km (Fig. 18).

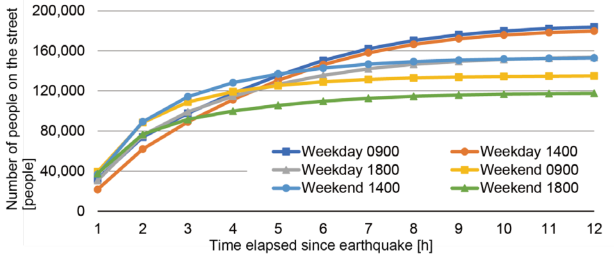

Figure 17. Number of stranded people on the street.

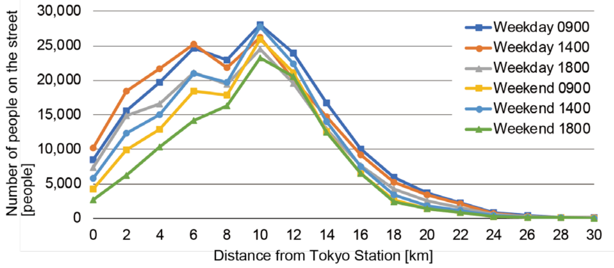

Figure 18. Number of people on the street versus radial distance from Tokyo Station.

4. SUMMARY AND CONCLUSIONS

This paper presented an estimate of the number of occupants of buildings in Tokyo classified by building type and clock times on a geographical grid cell. The necessary information was gleaned from population distribution data in MSS and from building floor areas extracted from building use information in building point data, which contain detailed information about the attributes of structures. Next, the uses of the buildings occupied by people, classified by the grid cell, and the time information were employed as keys, along with detailed attribute information provided by PT data, to estimate how many people of each sex and age classification were in buildings of each type, in each grid cell, at any given time, and also to classify those people by their home locations.

Next, the constructed data described above were employed to create simulations of people walking home after the occurrence of a large earthquake. The specific process for this was as follows.

(1) The population was classified by clock time, grid cell, type of building occupied, sex, and age.

(2) The population was classified by residence location.

(3) The distribution density of people classified by time, grid cell, building type, sex, age classification, and residence location inferred from the PT Data were used to estimate the population subdivided by residence location, sex, and age classification, using the maximum likelihood method.

Finally, family structure and other attributes furnished by the PT Data were added, using the combination of clock time, grid cell, building type, residence location, sex, and age

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classification as keys, to create a dataset for simulating walking home from within Tokyo.

The data assembled by the above procedure were employed in a walking home simulation, and people's behaviors, walking and stopping, as anticipated after a large earthquake, including the crowding of facilities by those unable to walk all the way home, were analyzed. The simulation results verified significant variations in the crowding of facilities for stranded people due to differences in the day of the week and the time of the earthquake. Locations in Tokyo with insufficient numbers of facilities for stranded people were identified and some spatiotemporal characteristics of crowding, such as changes in crowding with time elapsed since the earthquake, were described.

The method developed for this paper can enable researchers to construct a quasi-real-time detailed dataset describing the attributes of stranded people in Tokyo at any given time on any day of the week. This dataset can be applied in simulations of people walking home and enables visualization of the crowding that will vary widely with the day of the week and the time of the earthquake.

In our future studies, we will use the procedure proposed here to examine strategies for reducing crowding and confusion after an earthquake occurs and will attempt to validate the effectiveness of such countermeasures.

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