Estimation of Day-long Population Dynamics of Workers Using Nation-wide Statistical Data and its Application to the Keihanshin Metropolitan Area, Japan

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Abstract

Extent of fatality due to natural disaster depends largely on spatial distribution of population at the moment the disaster occurs. In this study, a computational model for estimating day-long spatio-temporal distribution of workers was developed by using a number of nation-wide statistical data such as "Population Census", "Survey on Time Use and Leisure Activities", and “Economic Census”. The model estimates behavior of individual workers by considering their attributes including gender, occupation, place of work and residence, and whether he/she works at home or not. As a case study, the proposed model was applied to the Keihanshin (Kyoto-Osaka-Kobe) Metropolitan Area, one of the largest metropolitan areas in Japan. Estimated instantaneous number of workers unable to return home becomes the maximum of about 1.4 million between 10:00 and 16:00, around which the utmost disorder in association with traffic disruption is expected if an earthquake strikes.

1. Introduction

Appearance of disaster considerably changes due to the time of its occurrence. Kobe Earthquake (1995) occurred at 5:46 in the early morning of 17th January. Although the area of severe seismic shaking was relatively small, the most severe shaking hit the center of Kobe city, one of the largest cities in Japan. As a consequence, number of fully-collapsed houses in the affected area sums up to 104,906 and that of burnt buildings sums up to 7,534 (FDMA, 2006). Because most of people in the affected area experienced the shaking when they were asleep, majority of fatalities, which is reported to be 6,437, were caused mostly by the collapse or burn of their own houses.

On the other hand, Tohoku Earthquake (2011) occurred at 14:46 in the afternoon of 11th March. The estimated moment magnitude of this earthquake was 9.0, the largest among the recorded history of Japan. Wide range area of eastern Japan experienced severe seismic shaking and tsunami arrival subsequent to it. It is reported that the number of fully-collapsed houses sums up to 129,391, and that of fatalities including missing persons sums up to 20,960 (FDMA, 2012). Contrary to Kobe Earthquake, most of physical and human losses were caused by the tsunamis arrived at the Pacific coast. And because most of people were out for their work or school when the earthquake occurred, family members were forced to evacuate from the tsunamis and take a shelter for several following days separately. To make the matter worse, prompt provision of relief activities was hampered by the fragmentation of transportation and communication networks due to the seismic shaking and tsunamis.

Appearance of the above disasters might have been much different if the time of their occurrence were the other way round, i.e., if Tohoku Earthquake were to occur at 5:46 and the tsunamis were to arrive when people were asleep, number of fatalities must have been no less than the actual. This is attributed to the population distribution at the moment the earthquake occurs. In other words, the impact of disaster is substantially affected by the extent of human exposure to the hazard.

The importance of human exposure evaluation on planning disaster mitigation strategy is widely shared. Nojima et al. proposed an index PEX (population exposure to seismic intensity) and conducted a retrospective assessment in the five major earthquake events in Japan (Nojima et al., 2004). Dilley et al., on an attempt of identifying key hotspots where the risk of natural disaster is particularly high, assessed the risk of disaster-related mortality by combining hazard exposure with historical vulnerability for gridded population for six major hazards: earthquakes, volcanoes, landslides, floods, drought, and cyclones (Dilley et al., 2005). Peduzzi et al. proposed an index DRI (disaster risk index) for monitoring the evolution of global risk to natural hazards, in which human vulnerability was measured by crossing exposure with selected socio-economic parameters (Peduzzi et al., 2009). Aubrecht et al. provided an overview on available multi-level geospatial information and modeling approaches from global to local scales that could serve as inventory for people involved in disaster-related areas (Aubrecht et al., 2012).

One of the possible approaches for the human exposure evaluation is to use the population census data. The Center for International Earth Science Information Network (CIESIN) provided the Gridded Population of the World (GPW) v.3 representing the residence-based population distribution across the globe. The Global Rural-Urban Mapping Project (GRUMP) v.1 was built on GPW increasing its spatial resolution by combining census data with satellite data (Balk et al., 2010). While the spatial resolution of population distribution is of critical importance for disaster impact assessment, enhancing temporal resolution of population distribution poses another great challenge. Dobson et al. developed the LandScan Global model and database which represents an "ambient" population distribution over a 24 hour period by integrating diurnal movements and collective travel habits into a single measure (Dobson et al., 2000). Bhaduri et al. extended the LandScan Global model and developed the LandScan USA model which allows the creation of population distribution data at a spatial resolution of 3 arc seconds (~90m). The model contains both a night-time residential as well as a baseline day-time population that incorporates movement of workers and students (Bhaduri et al., 2007). Freire, by combining census data and mobility statistics with physiographic data, developed a model to allocate day-time and night-time population distribution in Portugal (Freire, 2010). Unlike the above mentioned census-based models, Osaragi developed a model for estimating the travel behavior of individuals calibrated with questionnaire- and person-trip surveys, and delineate the overall population distribution by integrating the output travel behavior of individuals (Osaragi, 2012).

From the viewpoint of disaster mitigation planning, several requirements could be imposed on the output of exposure estimation, e.g., (1) spatial and temporal resolution of the output should be fine enough to accurately capture the appearance of disaster; (2) the output should contain not only distribution of population, but also its attribute such as gender or age for the better estimation of human loss from hazard; and (3) the model should be scalable and should be applicable to a wide-range area because affected area of disasters generally crosses over administrative boundaries. To add, (4) it is preferable that the model is extensible, i.e., the model is not designed for a specific area, but is applicable to an arbitrary area. To date, it has not been that straightforward to satisfy all of the requirements, but they are only partly fulfilled by the existing models. The advantage of the census-based data is its availability that base data of equal quality are available all over the country. On the other hand, because the census data can only provide population distribution at two time-points a day, enhancement of temporal resolution has been a common challenge for the models of this type. The advantage of the person-trip survey data is its thoroughness which contributes to the modeling of detailed travel behavior of individuals. On the other hand, because person-trip surveys are conducted only at large cities and their surrounding areas in Japan, the models of this type is not applicable to an arbitrary area.

In this paper, a new model for estimating the day-long population dynamics of people is presented. The new model is a census-based model, but has a feature of trip-based models at the same time. It simulates travel behavior of individuals by using multiple nation-wide statistical data to enhance its temporal resolution. However, the model is still under development, and currently, it is only applicable to estimating travel behavior of workers on weekdays. In this paper, the model is further applied to the Keihanshin (Kyoto-Osaka-Kobe) Metropolitan Area as a case study, in which the disorder due to a seismic-induced disruption of transportation is studied.

2. Outline of the population dynamics model

The estimation model is developed by using "Population Census" data which provides static population distribution at two time-points at relatively high spatial resolution (MIC, 2007a). Uniqueness of this model is that it simulates the day-long travel behavior of individual workers by interpolating the population distribution of the two time-points spatially and temporally. This is implemented using additional statistical data, "Economic Census" (MIC, 2007b) and "Survey on Time Use and Leisure Activities" (MIC, 2007c) in an integrated manner. Fig.1 shows the schematic of the model. Although behavior of workers is complex in general, we assumed that all the workers behave routinely in a day, i.e., they take routine actions in an order of

1) leave home for work (t_1)
2) arrive at work place (t_2)
3) leave work place for home (t_3)
4) arrive at home (t_4)

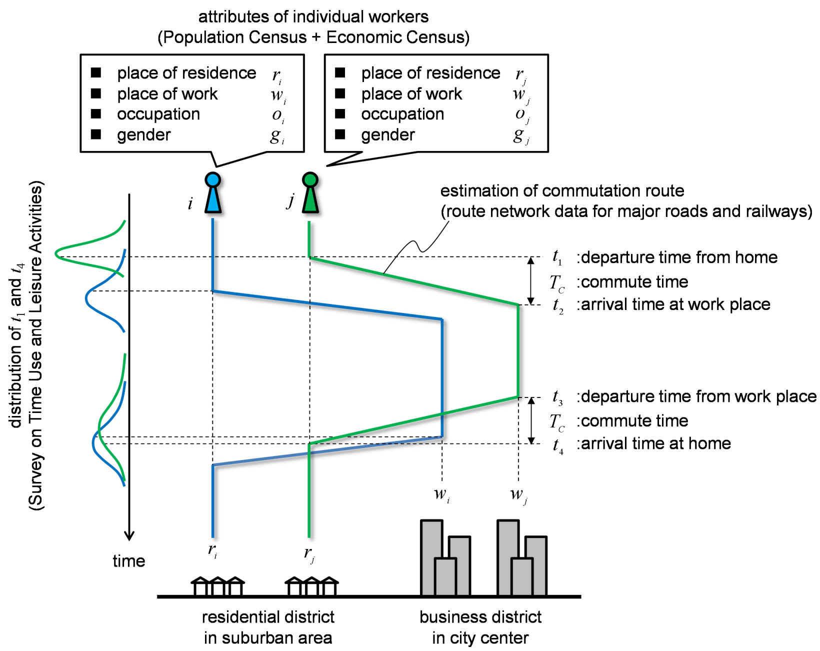

Fig.1. Schematic of the population dynamics model. Spatio-temporal distribution of population is estimated by simulating travel behavior of individual workers.

Note that signs in the parentheses are the times for the respective action. Location of a worker at an arbitrary time can be traced by determining the times of actions t_1, t_2, t_3, and t_4, and commutation route; a worker is at home during the period t_4 - t_1, on the commutation route during the period t_1 - t_2 and t_3 - t_4, and at work place during the period t_2 - t_3. However, assuming that the commutation times to and from work are the same, t_2 and t_3 can be expressed as,

$$t_2 = t_1 + T_C \quad \text{and} \quad t_3 = t_4 - T_C$$

where T_C is the commutation time. Thus, the four parameters necessary to determine the time of the routine action can be reduced to three, i.e., t_1, t_4, and T_C.

The times of the routine action t_1 and t_4, commutation time T_C, and commutation route are determined probabilistically by considering attributes of individual workers, which are,

- place of residence (r)

- place of work (w)
- occupation (o)
- gender (g)

Note these are the minimum required attributes for travel behavior estimation. Additional attributes such as "age", which is generally in high correlation with the extent of human loss, may be considered in the future analysis. These attributes of individual workers are extracted from "Population Census"-based cross tables aggregated for every component municipalities within the target area. However, because the cross tables are available only at the level of municipalities, extracted place of residence r and place of work w of individual workers are further processed to enhance their resolution by the Monte Carlo sampling method using additional data of "Population Census" and "Economic Census".

3. Times of the routine action t_1 and t_4

Times of routine action t_1 and t_4 for individual worker are determined from the distribution functions of departure time from home $f_1(t)$ and distribution of arrival time at home $f_4(t)$, which are both derived from "Survey on Time Use and Leisure Activities". These distributions are obtained for every combination of occupation o and gender g, which are considered influential on t_1 and t_4.

However, a drawback of this approach is that the times of actions t_1 and t_4 are obtained from independent distribution functions $f_1(t)$ and $f_4(t)$. Thus, time spent at work place T_W and time spent at home T_H derived from times of routine action t_1, t_2, t_3, and t_4 can be inconsistent with the generally expected time durations. In order to accommodate such an inconsistency, additional constraints are set in obtaining the times of routine action t_1 and t_4,

$$t_3 - t_2 = t_4 - t_1 - 2T_C > T_W \quad \text{and} \quad 24 - (t_4 - t_1) > T_H \quad \text{(hr)}$$

where T_W is obtained from the distribution function $f_W(T)$ derived from "Population Census", and T_H is sum of the mean hours of sleep T_S and mean hours for personal care T_{PC} which are both derived from "Survey on Time Use and Leisure Activities".

4. Commutation route and time T_C

One of the features of commutation in Japan is that railway is the major means of transportation and the proportion of its use increases with increase in commutation distance. Fig.2 shows one of the results of the 4th person trip survey of the Keihanshin Metropolitan Area which is carried out in 2000 (MLIT, 2000). It shows the change in proportion of the means of transportation for commutation with regard to direct distance between home and work place. On simulating travel behavior of individual workers, primary means of transportation is probabilistically determined by using this relationship. However, note that a worker may use multiple means

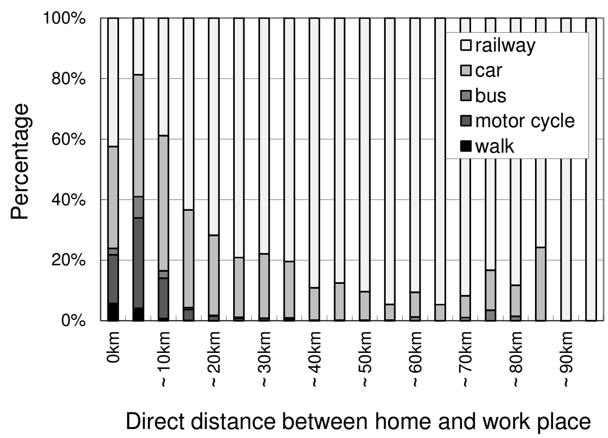

Fig. 2. Means of transportation for commutation in the Keihanshin Metropolitan Area with regard to direct distance between home and work place (MLIT, 2000).

of transportation, and the primary means of transportation is the one which covers the longest travel distance. In case a worker uses multiple means of transportation, secondary means of transportation is selected in association with the primary means of transportation.

For workers using railway as the primary means of transportation, commutation route is selected by seeking the shortest route between stations nearest to one's home and work place along the railway network. Effect of fare or number of connections on one's selection of commutation route is neglected in the present model. Commutation time T_C for the selected commutation route is calculated by assuming a uniform train velocity of 40km/hr (MLIT, 2008) for simplicity. To add, a uniform time for connection of 200s is assumed also for simplicity (MLIT, 2008), regardless of connection distance.

Secondary means of transportation for railway-using workers covers transportation between one's home or work place and the nearest stations. Secondary means of transportation is probabilistically determined by using the usage proportion derived from the results of the 4th person trip survey of the Keihanshin Metropolitan Area (MLIT, 2000) similar to Fig.4. However, unlike the way calculating commutation time T_C for railway transportation, T_C for the secondary means of transportation is calculated by dividing direct distance between one's home or work place and the nearest stations by the travel speed of selected means of transportation, i.e., 66.7m/min for walk, 183m/min for bicycle, and 276m/min for the other including car, bur and motor cycles.

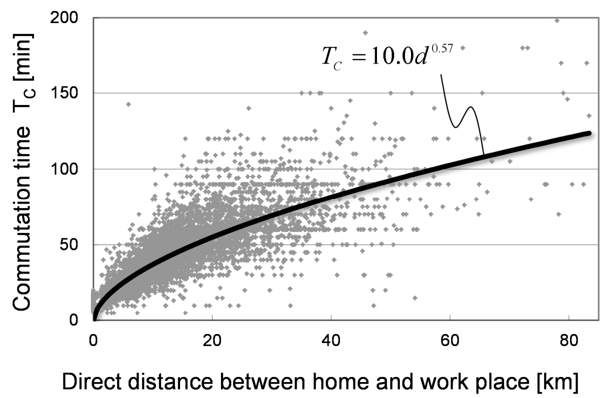

Fig.3. Commutation time T_C by using road transportation such as car, bus and motor cycle in the Keihanshin Metropolitan Area (MLIT, 2000).

For workers not using railway as the primary means of transportation, major means of transportation are car, bus and motor cycles which can generally termed as road transportation. A straightforward way to calculate commutation route and time T_c by road transportation is to analyze one's travel behavior along the road network similar to that of railway network described above. However, because road network data is substantially larger than railway network data in general, computational load for analyzing travel behavior of individual workers along road network for wide-range area inevitably becomes high. Thus, in the present model, commutation route for one's using road transportation is neglected, and only T_C is calculated by using a curve obtained by approximating the results of the 4th person trip survey of the Keihanshin Metropolitan Area (MLIT, 2000) as shown in Fig.3. The approximate curve is given as,

$$T_c = 10.0d^{0.57}$$

where d is the direct distance between home and work place.

5. Day-long population dynamics of workers in the Keihanshin Metropolitan Area

According to the definition of “Population Census” (MIC, 2007a), metropolitan area is the wide area ranging beyond administrative boundary of municipalities, which comprises central municipality and the surrounding

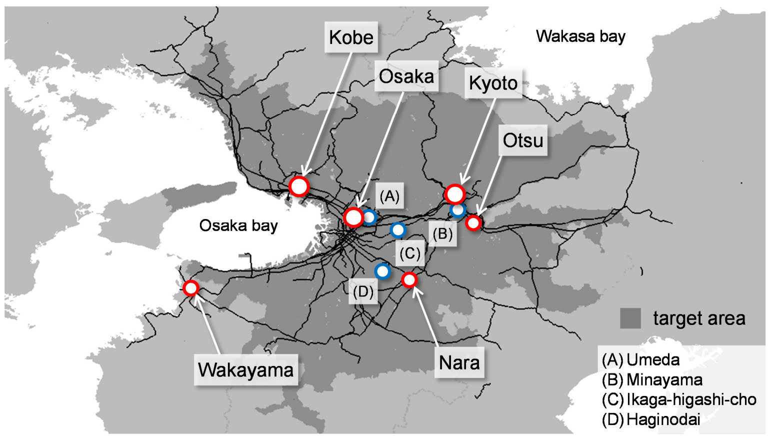

Fig. 4. Target area of case study, the Keihanshin Metropolitan Area, and the route network of major railways.

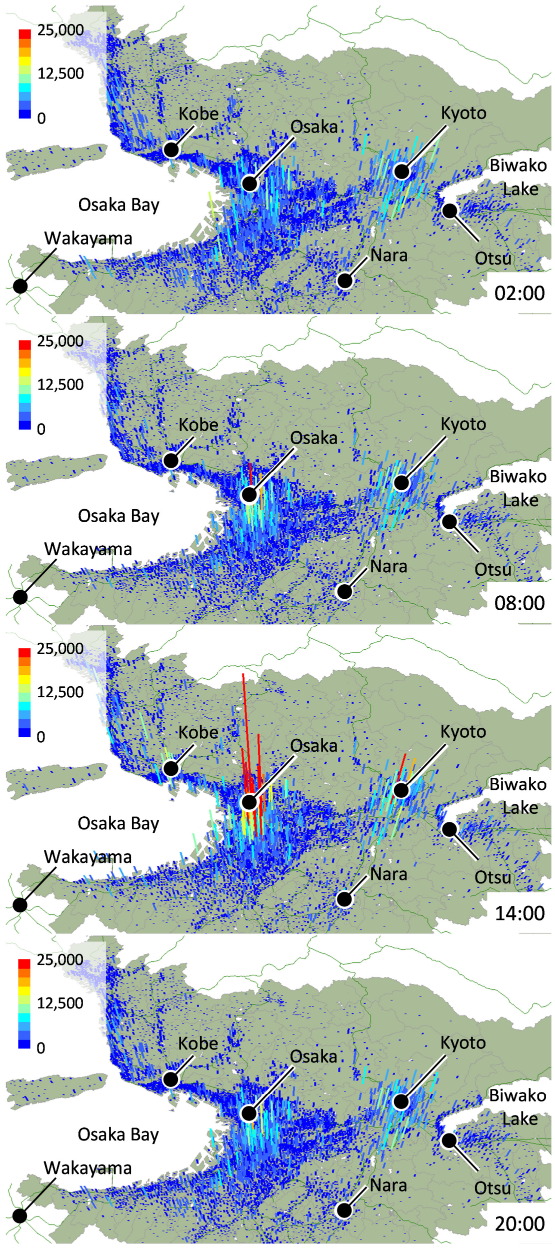

Fig. 5. Estimated spatial distribution of workers in the Keihanshin Metropolitan Area in a weekday.

municipalities linked with the central municipality socially and economically. As for the surrounding municipality, number of workers commuting to the central municipality needs to exceed 1.5% of all the population of the surrounding municipality and the area needs to adjoin to those of the other surrounding municipalities. The Keihanshin Metropolitan Area comprises 151 municipalities with the central municipalities of Kyoto, Osaka and Kobe as shown in Fig.4. This is one of the largest metropolitan areas in Japan with 18.8 million of people living in an area of about 11,600km^2. Among the overall population, target population of the present model is 8.5 million which is equivalent to 45.4% of the overall population.

Estimated distributions of workers at 2:00, 8:00, 14:00, 20:00 in a weekday are aligned in Fig.5. The model depicts a day-long movement of workers between suburban area and city centers; people dispersedly distributed in suburban area at night gathers to city centers such as Kobe, Osaka, and Kyoto in daytime, and return home after finishing their work.

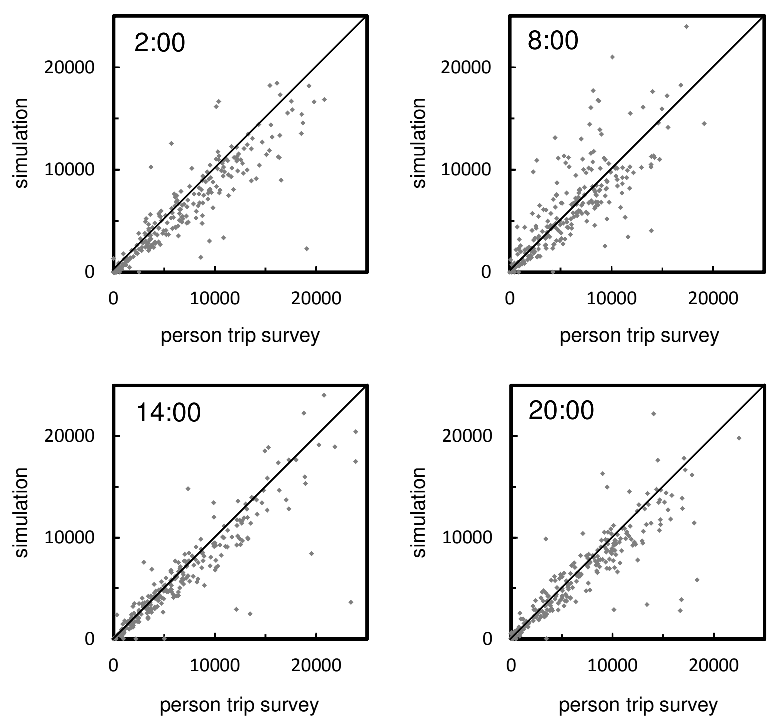

Fig. 6. Estimated and observed number of workers at each unit areas at four time point in a weekday.

In order to validate the present model, estimated number of workers at component unit areas is compared with that of the 4th person trip survey of the Keihanshin Metropolitan Area (MLIT, 2000). Note, however, that of moving workers is excluded from the number because the present model does not explicitly trace commutation route for those using cars, buses and motor cycles as the primary means of transportation. The comparison result at four time points of 2:00, 8:00, 14:00, and 20:00 of a weekday is shown in Fig.6. Although there are certain discrepancies, plots gather around the 45^{o} line on which the estimation result is identical to the person trip survey result. Such scatter of the plots may be attributed to the out-of-routine actions; in reality, one may leave the work place during the working hours for meeting with a client, or one may have a lunch with colleagues at a restaurant somewhat distant from the work place.

6. Anticipated disorder in the Keihanshin metropolitan area due to seismic-induced disruption of transportation

Overall travel behavior of workers in the Keihanshin Metropolitan Area is shown in Fig.7, in which estimated populations are illustrated in two ways: on the left hand side, state of individuals is displayed in three ways, i.e., at home, commuting, or at work place; on the right hand side, location of individuals in terms of distance from home, and estimated number of workers unable to return home is displayed. Note that the number of workers unable to return home is estimated by a simple model shown in Fig.8, which discerns the possibility of returning home on foot as a function of one’s location from home (TMGO, 2006).

Transition of macroscopic travel behavior of workers in the Keihanshin Metropolitan Area is delineated by integrating estimated travel behavior of individuals. Among the target 8.5 million workers, 7.2 million were those who actually commute to a place outside of their home. Instantaneous number of commuting workers, which are traveling mostly from home to work place, starts to increase from around 6:00, and becomes the maximum of 0.8 million at around 8:00. Overall number of workers at work place becomes almost stable at around 6.8 million between 10:00 and 16:00, around which the instantaneous number of workers unable to return home becomes the maximum of 1.4 million. However, note that because workers commuting via road network are not included due to the incompleteness of the present version of the model, the number and the peak hours may be corrected in the future analysis. Number of commuting workers, which are traveling mostly from work place to home at this time, starts to increase again at around 16:00, and becomes the maximum at around 17:45. However, because commuting hours is more dispersed in the evening than in the morning, the instantaneous number of workers is about 0.4 million at the most.

Estimated travel behavior of workers at four selected locations of distinct features in the Keihanshin Metropolitan Area is shown in Fig.9. Note that specific locations of the selected locations are indicated in Fig.4.

(A) Umeda, Kita ward, Osaka

Umeda area is one of the major city centers in the Keihanshin Metropolitan Area where a number of important railway stations and high-rise buildings are located. Although the number of workers gathering Umeda

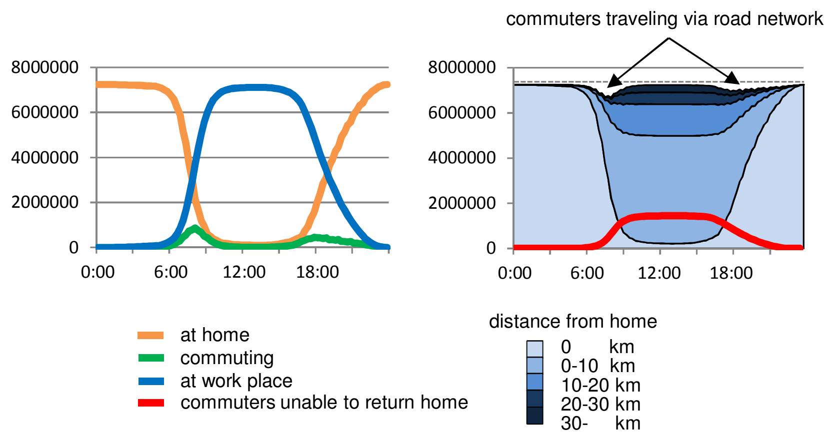

Fig. 7. Overall travel behavior of workers in the Keihanshin Metropolitan Area estimated by the present model.

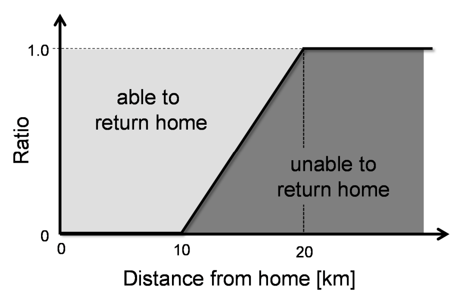

Fig. 8. A simple model for determining workers unable to return home at the occurrence time of an earthquake.

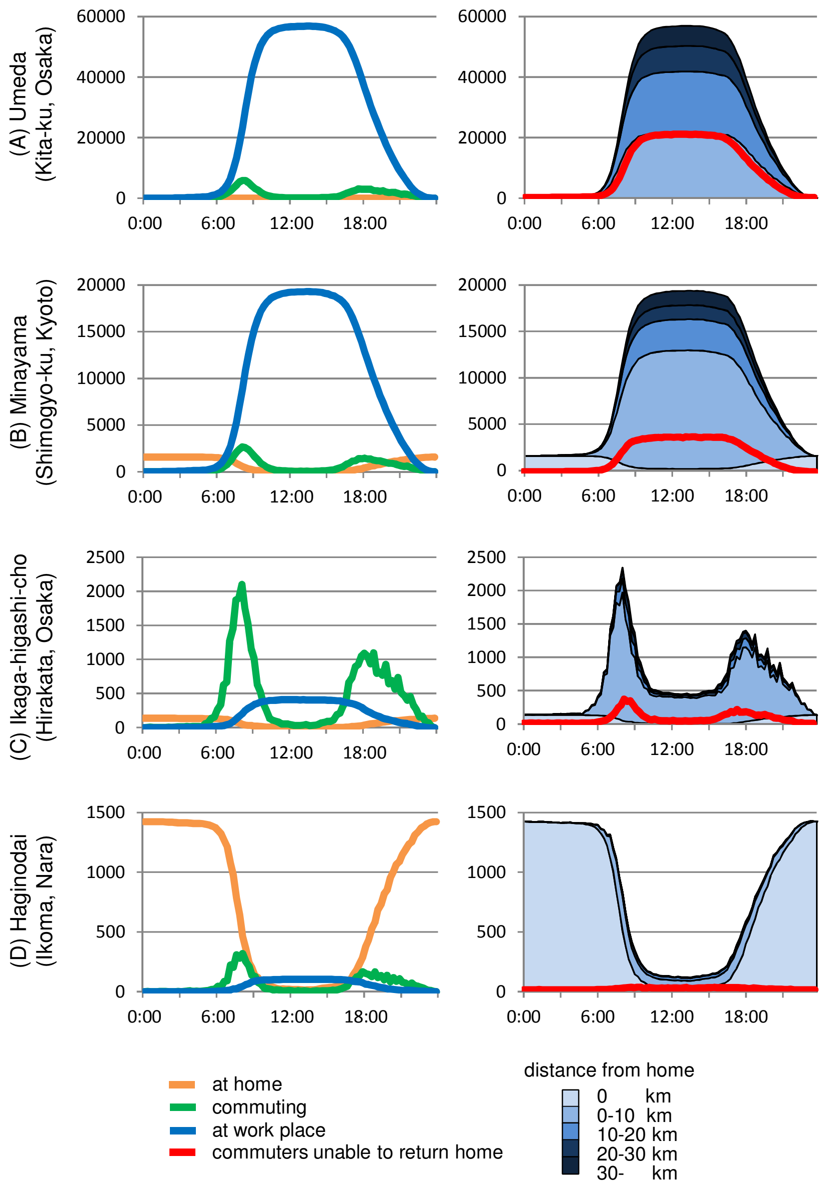

Fig. 9. Travel behavior of workers at four locations in the Keihanshin Metropolitan Area estimated by the present model.

area is about 56,000, only few workers reside in this area. Proportion of workers commuting from areas outside of the 20km-diameter circle is as high as 30%. As a consequence, expected number of workers unable to return home becomes as many as 20,000 at the maximum.

(B) Minayama, Shimogyo ward, Kyoto

Minayama area is another major city centers in the Keihanshin Metropolitan Area. Similar to Umeda area, several important railway stations, including Kyoto station, are also located in this area. As a consequence, estimated transition of population and its breakdowns are similar to those of Umeda area though respective numbers are comparatively small. Estimated number of workers unable to return home becomes about 3,500 during the peak hours. However, in contrast with Umeda area, number of population does not become near zero in Minayama area, but about 2,000 people reside even in the night-time.

(C) Ikaga-higashi-cho, Hirakata, Osaka

Ikaga-higashi-cho area is located at almost equivalent distance from Osaka and Kyoto. Because one of the important railways passes through Ikaga-higashi-cho area, there are two peak hours of workers' population at around 8:00 and 18:00, which are by those transiting the railway station in this area. About 100 workers, who reside in Ikaga-higashi-cho area, commute to the areas outside every day. About 500 workers staying in this area in the day-time are mostly from the neighboring areas within the 10km-diameter circle.

(D) Haginodai, Ikoma, Nara

Haginodai area is a residential area where only few workers stay in the day-time. The population decreases in the day-time and increases in the night-time, which is contrastive with those of city centers such as Umeda area or Minayama area. Although there is a railway station within Haginodai area, number of transiting workers is not as many as Ikaga-higashi-cho area. Number of workers staying in this area in the day-time is about 100, who are mostly from the neighboring areas within the 10km-diameter circle.

7. Conclusions

A day-long population dynamics model for workers is proposed in this paper using several nation-wide statistic data such as such as "Population Census", "Survey on Time Use and Leisure Activities", and “Economic Census” in an integrated manner. The model is applied to simulate travel behavior of 8.5 million workers in the Keihanshin Metropolitan Area, one of the major metropolitan areas in Japan, and number of workers unable to return home due to a seismic-induced traffic disruption is estimated. Development of the model is still ongoing. Points of future refinement includes: (1) estimation of commutation route for those using cars, buses, and motor cycles in addition to those using railways; (2) estimation of travel behavior of non-workers including infants, students, housewives, or elderly people; and (3) estimation of population dynamics in non-weekdays.

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