Simulation Model of Evacuation Behavior During Post-Earthquake Fires: Incorporating Evacuation-Related Information Acquisition

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Abstract. Most existing evacuation behavior simulation models for large-scale urban fires following major earthquakes rely on extreme idealizations and simplifications. These models often assume that residents begin evacuating immediately after the disaster and follow the shortest possible route. In this study, we develop a more realistic simulation framework by incorporating models for evacuation start timing and route selection, based on questionnaire survey responses. Additionally, we enhance the simulation by integrating key factors that influence evacuation behavior, such as the tendency to follow other evacuees and the means of acquiring disaster-related information. Using this improved model, we analyze evacuation strategies for high-density wooden housing areas during a major earthquake. The results indicate that in regions with a high risk of fire spread, direct evacuation may be more effective than a two-step evacuation process. Furthermore, the presence of early evacuees acting as influencers can significantly impact overall casualty numbers. Therefore, establishing a system for disseminating accurate and timely disaster information is crucial for improving evacuation outcomes.

Keywords: Evacuation behavior · Wide-area evacuation · Multi-agent simulation · Following behavior · Evacuation guidance

1 Introduction

Japan is one of the most earthquake-prone countries, with high risks of building collapse and fire spread, especially in areas with dense, aging wooden housing. Extensive research has focused on understanding physical damage and human casualties through evacuation simulations, which inform urban planning and evacuation strategies.

Zheng et al. (2009) identified seven methodological approaches for crowd evacuation, including cellular automata and agent-based models. Most pedestrian movement models focus on microscopic analysis of individual behavior, with collective phenomena emerging from interactions among evacuees (Bonabeau, 2002). Simulation research, such as that by Aoki et al. (1992), has explored how hearsay information influences evacuation behavior, while Osaragi and Tsuchiya (2018) quantitatively evaluated the impact of such information on wide-area evacuations.

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Studies like those by Vermuyten et al. (2016) and Mabuchi et al. (2008) examined optimization models and effective evacuation methods, including two-step evacuation strategy that will be discussed later Section. Fathianpour et al. (2022) assessed pedestrian evacuation infrastructure resilience, and Esposito et al. (2020) developed a multi-risk agent-based framework for policy applications. Real-world behavior studies, such as those by Makinoshima et al. (2024) and Yabe et al. (2019), leveraged smartphone geolocation data to analyze evacuation patterns during major earthquakes, showing a strong link between seismic intensity and evacuation behavior.

However, many existing models make unrealistic assumptions about evacuation behavior, such as immediate evacuation or shortest-route evacuation, and overlook factors like evacuation start timing and route choice. This study aims to develop a more realistic evacuation behavior model that minimizes these idealizations by constructing sub-models for evacuation start timing and walking route choice, based on questionnaire survey responses. Additionally, we examine the influence of evacuee characteristics, such as following others and information acquisition methods.

Using an enhanced simulation model, we estimate casualties across the region, considering the differentiated behaviors of "influencers" who begin evacuating immediately and influence others. We also explore the effectiveness of evacuation strategies by comparing direct and two-step evacuation strategies.

2 Overview of Simulation Model

Figure 1 shows an overview of the simulation model constructed in this paper. This multi-agent simulation model was constructed by integrating sub-models which will be constructed in the following sections and sub-models of physical damage/trapping inside buildings/streets (Osaragi and Oki, 2017). The sub-models conducted in this paper are highlighted in red color in Fig. 1. In the integrated model, by updating the state of damage inside the target area and the status and behavior of people in the city at fixed time intervals (in this study, 15 s), it is possible to estimate physical damage/human casualties while taking into consideration interactions between physical damage and people in the city.

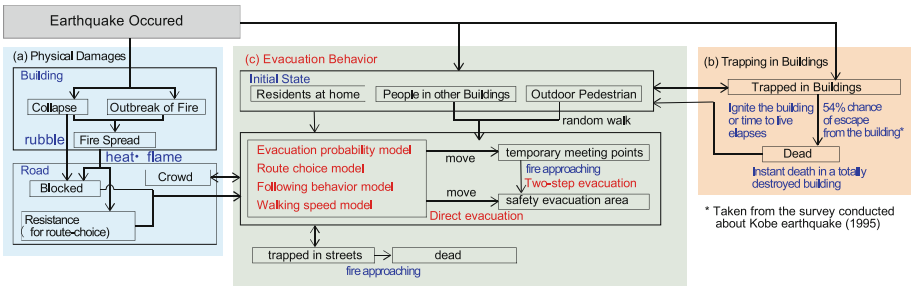


Fig. 1. Structure of the simulation model integrating the sub-models developed in this paper, along with the physical damage and building entrapment sub-models proposed by Osaragi and Oki (2017).

3 Consideration of Evacuation Start Timing

3.1 Evacuation Probability Model

The most crucial aspect of safety in the face of fire is the possibility of safe escape. Kobes et al. (2010) reviewed the available literature on human behavior in a fire building safety and showed that psychonomics appear to have significant influence on occupants' fire response performances, and then the traditional approach to fire safety have to be supplemented by scientific knowledge from this field. Also, Zheng et al. (2009) pointed out the need for taking into consideration the "psychological elements" affecting collective behavior in this context. For considering psychological elements and modeling the evacuation start timing of evacuees, the evacuation urgency of evacuee i, Φ_i, is defined as a variable representing the degree to which the evacuee feels the need to evacuate.

We define two variables: Θ_i, which represents the strength of person i's intention to evacuate, and D_i, which represents the distance of person i from the fire. These variables possess the following four properties:

1. The farther away a person is from the fire, the lower their intention to evacuate:

$$\Delta\Theta_i/\Delta D_i < 0 \tag{1}$$

2. The change in the strength of the intention to evacuate is proportional to the change in distance from the fire, where α_1 is a positive parameter:

$$|\Delta\Theta_i| \propto \alpha_1|\Delta D_i| \tag{2}$$

3. The greater the strength of the intention to evacuate, the larger the change in this strength, with α_2 being a positive parameter:

$$|\Delta\Theta_i| \propto \alpha_2\Theta_i \tag{3}$$

4. As the distance approaches infinity, the strength of intention to evacuate approaches zero:

$$\Theta_i|_{Di=\infty} = 0 \tag{4}$$

Based on properties (1) to (3), we derive the following differential equation, where α is a positive parameter:

$$\Delta\Theta_i = \alpha\ \Delta\ D_i\Theta_i \tag{5}$$

Solving this differential equation with the condition from Eq. (4) yields the following relationship (where α is the distance decay parameter):

$$\Theta_i = \exp[-\alpha D_i] \tag{6}$$

The evacuation urgency of evacuee i, denoted by Φ_i, is then described as a function of three factors: (1) the strength of intention to evacuate, Θ_i, which depends on the distance to the fire, D_i, (2) the percentage of neighboring residents who are evacuating (denoted

by r_i), and (3) whether the individual has received disaster information through various media (Fig. 2(a)). The urgency, Φ_i, is formulated as a polynomial with interaction terms, where λ, $\beta_1 \sim \beta_4$, $\gamma_1 \sim \gamma_4$ are unknown parameters (Fig. 2(a)):

$$\Phi_i = \lambda\Theta_i + \beta_1 r_i + \beta_2\delta_{i2} + \beta_3\delta_{i3} + \beta_4\delta_{i4} + \gamma_1\Theta_i r_i + \gamma_2\Theta_i\delta_{i2} + \gamma_3\Theta_i\delta_{i3} + \gamma_4\Theta_i\delta_{i4} \quad (7)$$

Furthermore, we assume the evacuation probability of person i, denoted by P_i, which satisfies the conditions $P_i|_{\Phi i=\infty} = 1$ and $P_i|_{\Phi i=0} = 0$. The evacuation probability P_i is expressed as follows, with indicating a value between 0 and 1 based on the change in Φ_i.

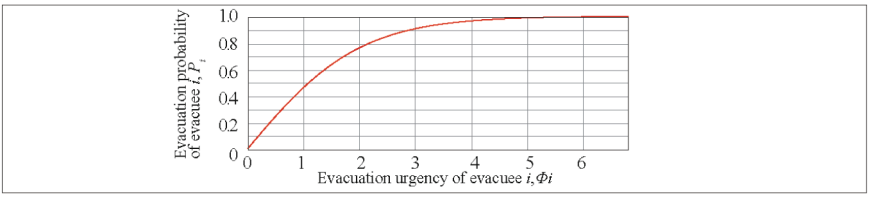
$$P_i = (1 - \exp[-\Phi_i]) \Big/ (1 + \exp[-\Phi_i]), \Phi_i \geq 0 \quad (8)$$

The relationship between P_i and Φ_i is shown in Fig. 2(b). The unknown parameters in Eq. (7) can be estimated using observed values of P_i via the following regression model derived from Eq. (8):

$$(1 - P_i) \Big/ (1 + P_i) = \Phi_i = \lambda\Theta_i + \beta_1 r_i + \beta_2\delta_{i2} + \beta_3\delta_{i3} + \beta_4\delta_{i4} + \gamma_1\Theta_i r_i + \gamma_2\Theta_i\delta_{i2} + \gamma_3\Theta_i\delta_{i3} + \gamma_4\Theta_i\delta_{i4} \quad (9)$$

Visual information	D_i : Distance between person i and fire building r_i : Percentage of person i's neighbors who have begun evacuation
Evacuation Information	$\delta_{i2} \sim \delta_{i4}$: Dummy variable indicating whether resident i receives evacuation information from the following media δ_{i2} : Evacuation advisory information on the Disaster Prevention Administrative Radio δ_{i3} : Information from TV and radio δ_{i4} : Information from web sites and SNS

(a) Explanatory variables used in mathematical descriprions



(b) Relationship between the evacuation probability of person i, P_i, and the evacuation urgency of evacuee i, Φ_i

Fig. 2. Relationship between the evacuation probability of individual i and the evacuation urgency of evacuee i, Φ_i.

3.2 Questionnaire Survey

To estimate each model parameter, a web-based questionnaire survey about the evacuation start timing and choice of evacuation site in the event of a post-earthquake fire was conducted (Fig. 3(a)). The sampling periods were January and July 2019, with 104 respondents in January and 87 respondents in July. The web-based survey was distributed via mailing lists. In Question I, using an orthogonal array, combinations of the percentage of evacuees among neighboring residents and persons with/without disaster information (eight combinations: Fig. 3(b)) were created. Respondents answered the question of how close the fire would have to come before they started to evacuate under

the circumstances in each combination, i.e., evacuation start timing in terms of distance to the fire (fire proximity). Care was taken to ensure that the respondents could answer intuitively by explaining the envisioned state of damage using photographs and text, with the aim of standardizing respondents' images regarding the state of damage.

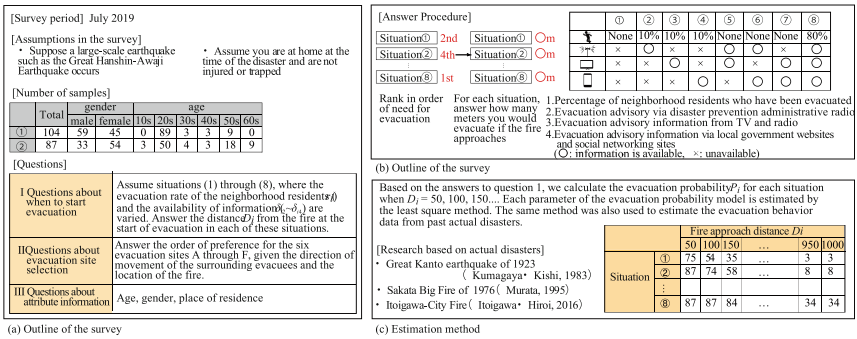


Fig. 3. Web-based questionnaire survey and parameter estimation for evacuation probability models.

3.3 Parameter Estimation and Validation of Evacuation Probability Model

The evacuation probability P_i was calculated based on the answers to Question I, Fig. 3(a), and the parameters of the evacuation probability model were estimated using the least-squares method. Figure 4 shows the fire approach distance D_i and evacuation probability P_i and the estimated results obtained using the model for the eight situations presented in the questionnaire. The descriptive accuracy of the model is shown to be good.

The evacuation probability P_i was calculated using the same method from survey results on evacuation behavior in three actual disasters – the Great Kanto Earthquake (1923), the Sakata Big Fire (1976) (Kumagai and Kishi, 1983), and the Itoigawa City Fire (2016)– and each evacuation probability model was estimated. When the results based on the survey in this study were compared with the results for evacuation behavior during the past disasters, they were found to be generally consistent (Fig. 4).

Figure 5 (left) shows the results of estimating the evacuation probability model in the case of different percentages of evacuees among neighboring residents and with/without disaster information, using the presented models. When the percentage of evacuees among neighboring residents is around 80%, even if a fire is far away, the probability of evacuation starting increases, thus showing that the behavior of other evacuees greatly influences one's own intention to evacuate. Regarding disaster information, when the fire is far away, its influence on the evacuation probability is small, but in circumstances where the fire has come close, it is a factor that increases the evacuation probability.

Next, looking at the results of estimating the model by gender, women (Fig. 5, right) tend to be more sensitive to fire proximity than men (Fig. 5, middle). Hence, women tend to start evacuating even when the fire is far away. Additionally, women tend to be

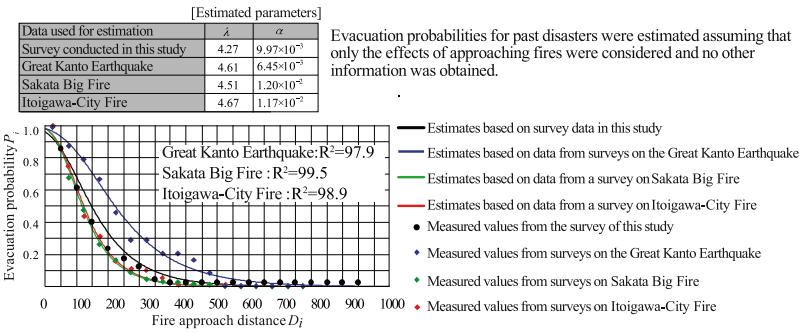


Fig. 4. Comparison of the survey results from this study with observed evacuation behavior during past disasters.

more easily influenced by disaster information than men. Furthermore, the percentage of evacuees among neighboring residents β_1 is smaller for men, but that for interaction with the fire γ_1 is larger for men. This means that, for men, the tendency to follow other people becomes stronger when the fire is close by.

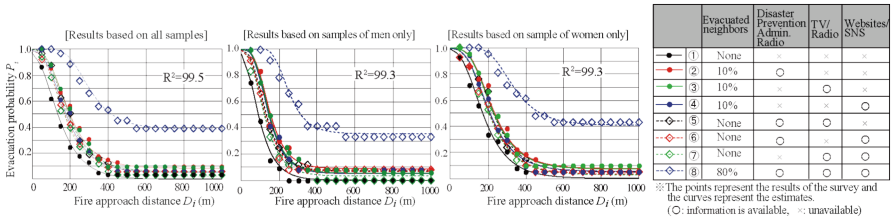


Fig. 5. Estimated evacuation probabilities under varying percentages of evacuating neighbors and the presence or absence of disaster information.

4 Consideration of Evacuation Route and Following Behavior

4.1 Route Choice Model

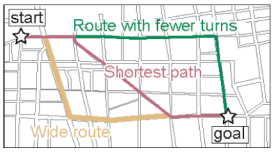
Since the method of choosing an evacuation route was modeled based on analysis results by Osaragi and Tanaka (2018), the route was chosen probabilistically by comprehensively considering the distance to the evacuation site, the number of times the direction changes at intersections (number of turns), and the evacuation road width (Fig. 6). More specifically, the values (influence factors) shown below, which were capable of describing 195 of the total 228 routes obtained from the answers to the questionnaire survey conducted by the existing model (with a concordance rate of 50% or higher) were adopted. The details are described in Osaragi and Tanaka (2018).

Figure 7 shows a graphical representation that combines these influence factors (β, γ) and the distribution of the number of people. Here, since the derived route depends

only on the relative size of the influence factors, α is fixed at 1. The circle sizes in Fig. 7 represents the number of respondents for the route derived from the combination of influence factors (β, γ), and the respondents can generally be classified into three types: a distance-oriented type in which the respondents are concentrated (β, γ are small), a turn-oriented type (β is large), and a width-oriented type (γ is large). The respective influence factors for these combinations are as follows:

(1) Distance-oriented type (β, γ) = (0.1, 0.0) (88 people).
(2) Turn-oriented type (β, γ) = (0.3, 0.0) (48 people).
(3) Width-oriented type (β, γ) = (0.1, 0.1) (48 people).

In the simulation model in this paper, evacuees were considered to choose an evacuation route probabilistically from among the routes calculated by combinations of these three influence factors. From the ratio of the number of respondents for the distance-oriented, turn-oriented, and width-oriented types, the choice probabilities were: distance-oriented type 46%, turn-oriented type 27%, and width-oriented type 27% (Fig. 6).



route j's Total Cost C_j

$C_j = \alpha \times D_j + \beta \times T_j + \gamma \times W_j$

D_j: Distance Cost (route j's walking distance)
T_j: Turn Cost (number of turns)
W_j: Width Cost (the inverse of the road width)
($\alpha \sim \gamma$: unknown parameter)

① Distance oriented type (α=1, β=0.1, γ=0)	46%
② Turn oriented type (α=1, β=0.3, γ=0)	27%
③ Width oriented type (α=1, β=0.1, γ=0.1)	27%

(1) Calculate 3 routes using a combination of parameters in the table on the right, with reference to the results of Osaragi and Tanaka (2018)
(2) Choose a route from these 3 routes by the probabilities shown in the table

Fig. 6. Route choice model incorporating distance to the evacuation site, number of turns at intersections, and evacuation road width, based on Osaragi and Tanaka (2018).

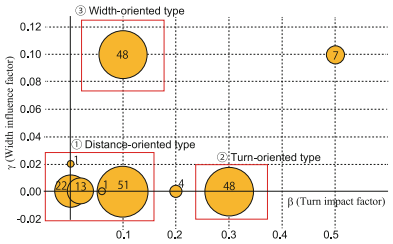


Fig. 7. Graphical representation combining two influence factors (β and γ) with the distribution of the number of individuals by route selection type, based on Osaragi and Tanaka (2018).

Evacuees were assumed to have no information about road blockage points at the starting evacuation time and were expected to remember each time they encountered a blockage point during an evacuation. Additionally, evacuees were modeled on the assumption that they use the information on blockage points remembered up to that point in time to search again for an evacuation route.

4.2 Following Behavior Model

Van den Berg et al. (2018) quantified the impact of others' evacuation behavior on an individual's decision to evacuate through an experiment using a serious game, involving approximately 400 participants. The results indicated that observing others evacuating increases the likelihood of individuals deciding to evacuate themselves. Evacuee following behavior was modeled with reference to Osaragi and Tsuchiya (2018) (Fig. 8). Here, evacuees were considered to decide whether or not to follow other people at each intersection. More specifically, first, the direction of travel of Evacuee A was determined probabilistically based on the number of other evacuees in each direction of travel at the intersection (Fig. 8(1)). Then, evacuee following behavior was modeled by replacing the destination and evacuation route of Evacuee A with the destination and evacuation route of Evacuee B, randomly selected from among the other evacuees traveling in the same direction (Fig. 8(2)). However, if the selected Evacuee B was less familiar with the local area than Evacuee A, Evacuee A was assumed to keep to the destination and evacuation route instead of following Evacuee B.

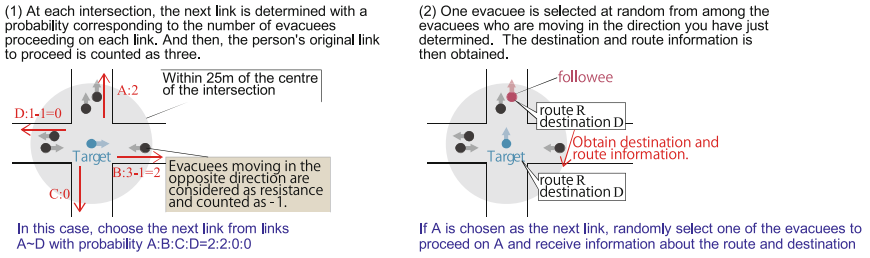
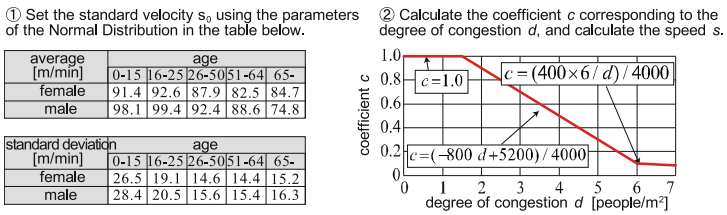


Fig. 8. Following behavior model considering the influence of word-of-mouth communication on large-scale evacuation after a severe earthquake, based on Osaragi and Tsuchiya (2018).

4.3 Walking Speed Model

Bosina and Weidmann (2017) described the most important factors influencing walking speed based on existing literature and estimates their impact. Different conditions average walking speeds were calculated and the significance of the walking speed differences was determined. Several experimental studies have examined the density-speed correlation in earthquake evacuation (Bosina and Weidmann, 2017). However, due to variations in walking speed across sex and age groups, we used the standard walking speed proposed by Willis et al. (2004) in this study. Walking speed during evacuation was, therefore, modeled as determined by gender/age of evacuees and the congestion degree (pedestrian density in persons/m^2) in the surrounding areas, and pedestrian density was updated at fixed time intervals (Fig. 9). Walking speed decreases when pedestrian density reaches 1.4 persons/m^2 or more. In situations where the density exceeds 6 persons/m^2, walking speed decreases abruptly.



average [m/min]	age				
	0-15	16-25	26-50	51-64	65-
female	91.4	92.6	87.9	82.5	84.7
male	98.1	99.4	92.4	88.6	74.8

standard deviation [m/min]	age				
	0-15	16-25	26-50	51-64	65-
female	26.5	19.1	14.6	14.4	15.2
male	28.4	20.5	15.6	15.4	16.3

Fig. 9. Variation in walking speed by sex, age group, and pedestrian density in surrounding areas.

5 Setting and Scenario for Simulation Analysis

5.1 The Initial State of Evacuees and Evacuation Behavior

In this paper, people at home, people in buildings other than their home, and outdoor pedestrians in the analysis target area are considered evacuee agents. Considering that the evacuation behavior pattern for each evacuee will differ depending on their level of familiarity with the local area and where they are when the disaster occurs, three types of evacuation behavior were established (Fig. 10). Both people in buildings other than their home and outdoor pedestrians were assumed to be unfamiliar with the local area and to repeatedly move towards a randomly set destination until they arrive at a point within 50 m of the evacuation site.

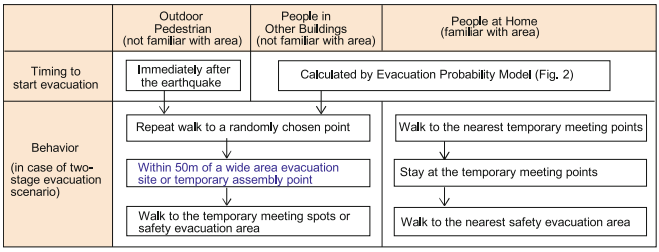


Fig. 10. Three types of evacuation behavior patterns for each evacuee, categorized by their level of familiarity with the local area and their location at the time of the disaster.

5.2 Analysis Target Areas and Simulation Conditions

Figure 11 shows the simulation conditions used in this study, which focused on various parts of Tokyo. More specifically, Senju in Adachi-ku (Kita-Senju), Machiya in Arakawa-ku (Machiya), and Taishido in Setagaya-ku (Taishido), all of which are designated as "high fire risk zones", were selected as the areas for analysis.

According to the Seventh Community Earthquake Risk Assessment Study for the Tokyo Metropolitan Area (Bureau of Urban Development, Tokyo Metropolitan Government, 2022), the Kita-Senju and Machiya areas have been judged to have the highest fire risk (Rank 5), while the Taishido area is considered to have a slightly lower risk (Rank 3).

Simulation Conditions

Japanese intensity scale of earthquake	6 large (PGA = 6.16)
Season / wind speed / wind direction	winter / north wind / 8 [m/s]
Earthquake occurence time	6:00 p.m. on weekdays (Simulation up to 24 hours after the earthquake)

Target Area

	Area 1	Area 2	Area 3
Area name	Kita-Senju	Machiya	Taishido
All analyzed people	9655 (100%)	8376 (100%)	11218 (100%)
People at home	6990 (72.4%)	5332 (63.6%)	6502 (72.4%)
People in other buildings	2409 (25.0%)	2724 (32.5%)	3946 (25.0%)
Outdoor pedestrians	256 (2.3%)	320 (3.8%)	770 (2.3%)
Number of buildings	4307	4360	3638

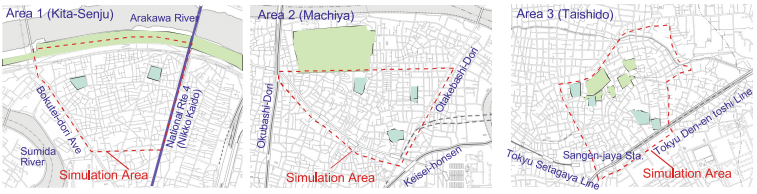
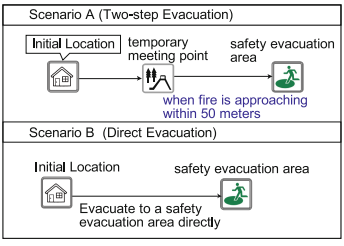


Fig. 11. Target areas and simulation conditions used in this study, focusing on different regions of Tokyo.

5.3 Evacuation Method Scenarios

A two-step evacuation is sometimes recommended in the event of a post-earthquake fire. The two-step evacuation system is implemented by the Tokyo Metropolitan Government and other local authorities. During the short-term evacuation phase, there are two types of shelters: temporary meeting points and evacuation areas. Temporary meeting points consist of school grounds or neighborhood parks that provide sufficient space to ensure the safety of the people gathered. Evacuation areas, which are designed to protect evacuees from the spread of fire, total 221 in the Tokyo Metropolitan area. These areas are typically large, open spaces, such as city parks, university campuses, and other open areas. The service range of an evacuation area is typically less than 3 km, and each evacuee is required to have at least 1 m^2 of space within the area.

In two-step evacuation, people evacuate to their nearest temporary meeting point immediately after the disaster occurs, and after assessing the state of damage, then evacuate to a wide-area evacuation site (evacuation area) when the timing is judged to be appropriate. The two-step evacuation method is recommended by many local authorities from the perspective of mitigating congestion and controlling chaos near wide-area evacuation sites.



	Two-step evacuation rules	Distance to fire for 2nd-evacuation
Scenario A	always two-step evacuation	50 m
Scenario A- I	always two-step evacuation	100 m
Scenario A- II	conditional two-step evacuation ※	50 m
Scenario A- III	conditional two-step evacuation ※	100 m

※ Evacuate directly if there is no safe (more than 100m away from the fire) temporary meeting point closer than the wide area evacuation site.

Fig. 12. Evacuation scenarios based on direct evacuation and two-step evacuation methods.

In this paper, the method in which evacuees evacuate directly to a wide-area evacuation site immediately after the disaster occurs is referred to as "direct evacuation," and two simulations, one assuming two-step evacuation (Scenario A) and another assuming direct evacuation (Scenario B), were performed. Differences in how the evacuation route is chosen and the number of casualties were analyzed. More specifically, the four scenarios in Fig. 12 (A, A-I–III) were created and compared. In Scenario A, two-step evacuation is always performed, and the second evacuation to a wide-area evacuation site is performed when the fire approaches to 50 m from the temporary meeting point (the re-evacuation distance is 50 m). In Scenario A-I, the re-evacuation distance is assumed to be 100 m. Scenario A-II is a two-step evacuation scenario with a degree of freedom, in which the evacuation changes to a direct evacuation if there is no safe temporary meeting point further than 100 m from a point where the fire is spreading. Scenario A-III is a combination of Scenario A-I and Scenario A-II, in which the re-evacuation distance is taken as 100 m, and it is possible to switch to a direct evacuation. A value of 50 m/h is commonly used as the average speed of fire spread in densely built-up wooden residential areas and is often applied in simulation analyses (Osaragi and Oki, 2017).

5.4 Influencer Behavior Scenarios

In this section, we examine the influence that the behavior of some evacuees has on the magnitude of damage in the entire region due to influencing the behavior of other evacuees. During a disaster, it is difficult to provide all evacuees with information about physical damage (collapsed buildings, road blockages, fire spread, etc.) and information that encourages appropriate evacuation behavior in real time. Therefore, by assuming cases in which some evacuees who can have an influence (influencers) possess accurate information and perform rational evacuation behavior, the possibility of the behavior of those influencers affecting residents overall and leading to a smooth evacuation was examined. More specifically, 1% of people at home were randomly selected as influencers, and by varying their evacuation behavior patterns (evacuation start timing and method of choosing an evacuation route), changes in the evacuation start timing and route choice of other evacuees, and as a result, the number of casualties, could be considered. For illustrative purposes, we assumed 1% of people, representing a very small portion of the population. This value is used purely as an example and does not carry any specific significance.

Table 1 shows a comparison of the scenarios. First, in Scenario C, the evacuation start timing of influencers is set to immediately after the disaster occurs. By comparing Scenario C and Scenario A, the question of how much the immediate evacuation behavior of some evacuees affects the extent of human casualties is analyzed. In Scenarios D, E, and F, the method by which influencers choose an evacuation route differs. Scenario D assumes a case in which rational route information is provided to influencers in real time. In this scenario, the influencers are considered to be all-knowing and all-powerful, which means they know about all road blockage points and evacuate via the shortest route. In Scenario E, influencers first move to a wide main road that is unlikely to be blocked and then continue to evacuate using main roads wherever possible. Scenario F assumes a case in which influencers are able to determine the congestion situation of evacuation routes in real time and then choose the route with the shortest travel time

(rather than travel distance) after determining the congestion on all road links in the target area.

Table 1. Evacuation scenarios.

	Timing of evacuation start	Evacuation route
Scenario A	No influential person	No influential person
Scenario C	Immediate evacuation	Same as other evacuees (route selection model (Fig. 8))
Scenario D	Same as other evacuees (evacuation probability model (Fig. 2))	All-knowing and all-powerful
Scenario E		Main roads
Scenario F		Congestion avoidance

[All-knowing and all-powerful evacuation] Obtaining the information on the blockage status of all road links in the target area, and select the shortest route to the evacuation site
[Main road evacuation] After moving to the main road (Fig. 19(a)), evacuate along the wide road to the evacuation site
[Congestion avoidance evacuation] Obtaining the information on the congestion of all road links in the target area, and select the temporal shortest route to the evacuation site

6 Results of Analysis

6.1 Comparison of Evacuee Route Choice

Next, the evacuation routes of evacuees in each area were examined. The simulation was performed 100 times for both two-step and direct evacuation, and the numbers of people passing through each road link were tallied. Figure 13 shows an example for the Kita-Senju area. Basically, it appears that wide road links are chosen and that the evacuation route choices were generally consistent for both the two-step and direct evacuation methods. However, in the Kita-Senju area, in the case of two-step evacuation, the numbers of people passing through road links near the temporary meeting points were extremely high, and there was potential for chaos. This means that, based on the assumption that many evacuees will concentrate at temporary meeting points, these points must be accessible by roads of sufficient width.

6.2 Comparison of Two-Step and Direct Evacuations

Simulations were conducted for all scenarios in each area, and the estimated numbers of casualties were compared between two-step evacuations (Scenarios A, A-I–III) and direct evacuations (Scenario B). Figure 14 presents the results. In the Kita-Senju area, some cases show a significant increase in casualties in Scenario A compared to direct evacuation (Scenario B). To better understand this, Fig. 15 illustrates the change

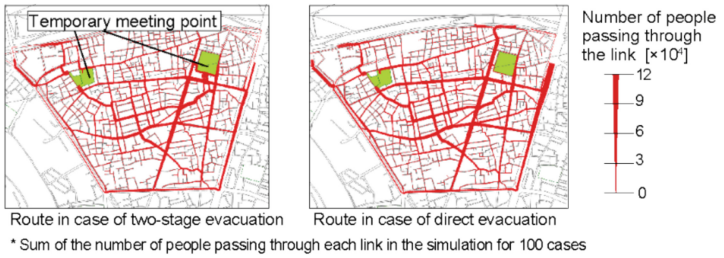


Fig. 13. Comparison of direct and two-step evacuation: the number of people passing through each road link in the Kita-Senju area.

in casualties over the first 24 h following the disaster. This figure displays the average and maximum casualties for 100 simulated cases of physical damage at each time point. While average casualty numbers show no substantial differences across scenarios, the maximum values exhibit a sharp increase. In the Kita-Senju area, large casualties arise around six hours after the disaster in Scenario A, and about seven hours after the disaster in the Machiya area. Notably, the timing of re-evacuation—affected by the re-evacuation distance (50 m in Scenario A, 100 m in Scenario A-I)—has a considerable impact. This highlights the risk that delayed re-evacuation could result in significant damage, despite two-step evacuation being designed to enhance safety. In contrast, Scenarios A-I and A-II, which modify parts of Scenario A, reduce the emergence of large casualties. Scenario A-III, which includes a 100 m re-evacuation distance and shifts to direct evacuation, shows the greatest reduction in casualties, suggesting the importance of timely re-evacuation and the flexibility to switch to direct evacuation based on real-time information about fire spread and origin.

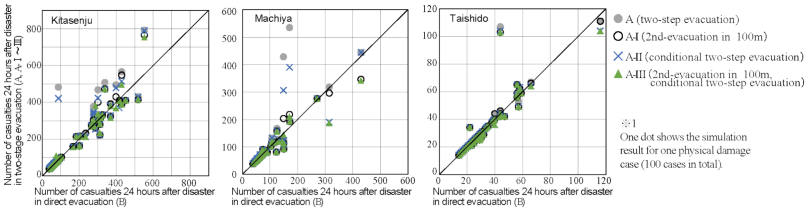


Fig. 14. Number of casualties in direct evacuation and two-stage evacuation.

However, 24 h after the disaster, direct evacuation (Scenario B) results in fewer casualties compared to two-step evacuation scenarios (A, A-I–III). The spatial distribution of casualties for two-step evacuation in the Kita-Senju area (Fig. 16) shows a concentration of casualties around the temporary meeting point in the northwest. Visualizing individual evacuee behavior revealed that evacuees who attempted to re-evacuate from the meeting point to a wide-area evacuation site were hindered by fire-related road blockages, leading to casualties. This suggests that in high-risk fire areas, a direct evacuation strategy from the outset may be more effective than a two-step approach.

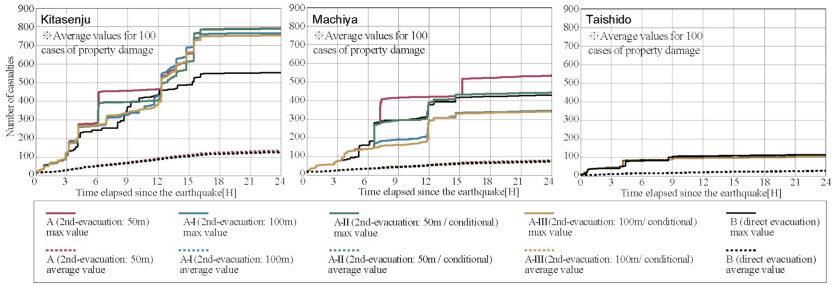


Fig. 15. Temporal change in the number of casualties during direct evacuation and two-stage evacuation.

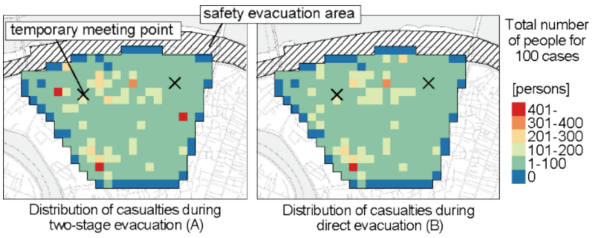


Fig. 16. Spatial distribution of casualties in direct evacuation and two-stage evacuation.

While the focus here is on casualties from the evacuation process, it is important to note that building vulnerability—affecting fire risk after earthquakes—also plays a significant role, especially in areas with a high risk of fire spread. Similar results were observed in the Machiya area (Fig. 15, center), but in the Taishido area (Fig. 15, right), no significant differences were found between two-step and direct evacuation scenarios. This is likely due to the lower risk of fire spread in the Taishido area compared to the Kita-Senju and Machiya areas, making the evacuation scenario less impactful on the danger level.

6.3 Influencer Effect on Evacuation Start Timing

Next, the Kita-Senju area, where the degree of damage was most serious, is analyzed. Figure 17 shows the overall results of analyzing the ripple effect on evacuees when influencers evacuate immediately after the disaster occurs (Scenario C). Looking at the number of evacuation starters in the period up to one hour after the disaster occurs, it is evident that the evacuation start timing of approximately 1,000 evacuees (approximately 10% of the total) is brought forward because they follow influencers who evacuate immediately (Fig. 17(a)). Also, in physical damage cases with a high number of human casualties, bringing the evacuation start timing forward reduces the possibility of evacuees becoming caught in the fire, and the number of casualties decreases by approximately 100 people (Fig. 17(b), (c)). This shows that in areas like Kita-Senju, where damage due to fire spread is serious, the earliest possible evacuation behavior is vital to disaster mitigation.

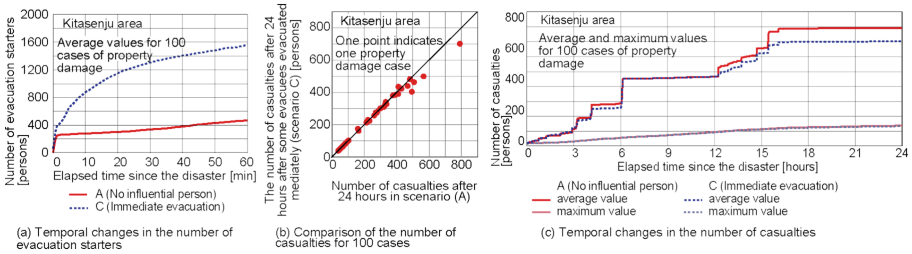


Fig. 17. The impact of the evacuation-start time of leading evacuees.

6.4 Influencer Route Choice Effects

Figure 18 shows the results of analyzing the differences in human casualties in the case of all-knowing and all-powerful influencers (Scenario D), using main roads (Scenario E), and congestion avoidance (Scenario F) by influencers. In physical damage cases with a high number of human casualties, the number of casualties decreases in all the scenarios. For example, for main-road evacuation (Scenario E), it is found that the number of evacuees choosing main roads increases because they follow influencers (Fig. 18(a), (b)). In other words, influencers indirectly guide evacuees to safer evacuation routes, and as a result, the evacuees move along safe routes without encountering road blockages caused by collapsing buildings or spreading fires, and the number of human casualties therefore decreases.

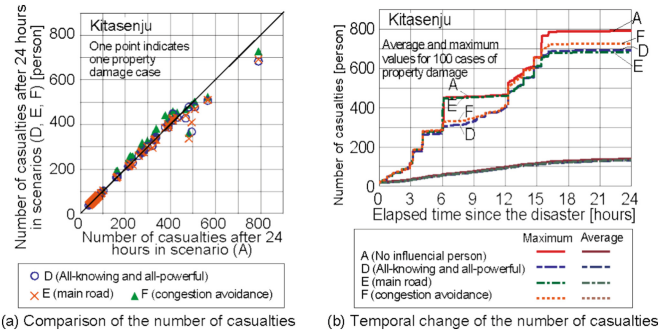


Fig. 18. Analysis of differences in human casualties under three scenarios: all-knowing and all-powerful influencers (Scenario D), use of main roads (Scenario E), and congestion avoidance by influencers (Scenario F).

Next, the routes taken by evacuees in Scenario A and Scenario E were compared in order to analyze how the routes of other evacuees changed because they followed the influencers. In Fig. 19(b), which shows the evacuation routes of influencers in Scenario E, it can be seen that the number of people passing along the main roads shown in Fig. 19(a) is high. Next, comparing the chosen routes of all evacuees when there are no influencers (Fig. 19(c)) and the chosen routes of all evacuees when the influencers guide

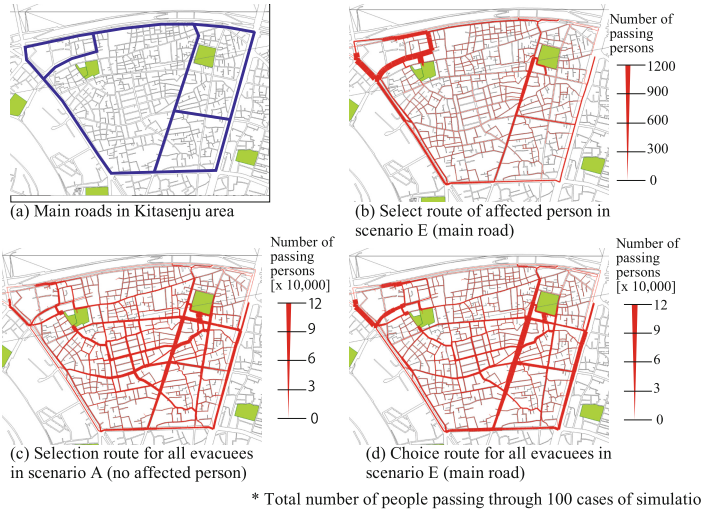


Fig. 19. Impacts of influencers' route selection on the route choices of other evacuees.

main-road evacuation (Fig. 19(d)), it can be seen that the number of people passing along the main roads increases because many evacuees follow the influencers.

Taken together, the above results show that if some evacuees (influencers) can be provided with correct information about road blockage conditions, etc., in real time, it may be possible to reduce the number of human casualties.

7 Summary and Conclusions

In this study, we first constructed an evacuation probability model that determines the evacuation start timing while taking into account the influence of approaching fires and the evacuation behavior of neighboring residents. We also constructed a route choice model that describes route selection behavior, taking into account the route choice characteristics of evacuees and difficulties imposed by spreading fires. Furthermore, by modeling the following behavior among evacuees, we investigated the influence that evacuees have on each other. Then, by integrating this evacuation behavior model with previously constructed physical damage models that consider collapsing buildings, road blockages, spreading fires, persons trapped inside buildings, etc., we were able to create a multi-agent-based evacuation behavior simulation model.

Next, we organized the given conditions of the simulation analysis and the analysis target areas in metropolitan Tokyo (Kita-Senju, Machiya, Taishido) and performed a comparative analysis of each scenario using the simulation. Specifically, we performed simulations of two-step and direct evacuation scenarios and showed that in areas with a high risk of fire spread, large numbers of casualties may occur in the two-step scenarios. The results also showed the possibility of suppressing the number of casualties in a two-step evacuation by bringing forward the re-evacuation timing (second evacuation to a wide-area evacuation site) and changing to direct evacuation depending on the circumstances by determining physical damage states.

Additionally, targeting the Kita-Senju area, we created scenarios for the evacuation behavior of some evacuees (influencers) and showed that differences in influencer evacuation behavior affect not only the behavior of other evacuees but also the number of casualties throughout the region. Specifically, we showed that when 1% of people at home, who were selected as influencers, evacuate immediately after the disaster occurs, the evacuation start timing of other evacuees is brought forward due to following behavior, and human casualties can be reduced. We also showed that influencers could reduce human casualties in the case of all-knowing and all-powerful influencers, main road usage, and congestion avoidance. In other words, we demonstrated that providing accurate real-time information about the situation regarding road blockages and congestion to some evacuees, and the presence of some evacuees who vacate the area by prioritizing the use of routes that are unlikely to become blocked, may have a ripple effect leading to a substantial reduction in the number of human casualties. However, it is important to note that this also indicates that influencers with incorrect damage information and those who take irrational evacuation actions may act dangerously and increase the number of human casualties.

Below is a summary of our future work. First, regarding the following behavior model, there is little past research or data providing concrete evidence on a mechanism explaining the circumstances in which evacuees follow other people. However, it is known that following behavior, particularly in extreme situations, has been observed. We aim to incorporate this behavior, which varies depending on individual characteristics. Accordingly, we intend to work on validating the models and model parameters employed in this study. Additionally, since it is anticipated that people will evacuate in groups (such as cohabiting family members) when post-earthquake fires approach, we would like to investigate an evacuation behavior model that assumes evacuees depart the area in groups. Additionally, 1% of people at home were selected as influencers in this paper, but the relationship between the percentage of influencers and the degree of influence on other evacuees requires further analysis, the results of which can be expected to provide insights on how many influencers will need to be provided with correct disaster information in the event of a post-earthquake fire. Furthermore, there is a need to develop information systems capable of providing accurate, real-time updates on road blockages and congestion to evacuees.

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