ABM-Based Emergency Evacuation Simulation considering Dynamic Dependency in Infrastructures

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Nuclear or radiological accidents can cause significant consequences to people and the environment and may lead to a massive evacuation. Emergency preparedness and response plans are inevitable to mitigate and minimize the consequences. Generally, evacuation planning is based on various assumptions to simplify situations, and the effect of infrastructure systems is not considered explicitly. The infrastructures’ availabilities are highly uncertain and difficult to be quantified due to their dynamic dependency, on each other. In this study, we propose a method to optimize the scenarios of emergency response and evacuation using an agent-based model. Within the simulation platform, the dynamic dependency in infrastructures is modelled by constructing loading-dependent state transition probability. Moreover, we demonstrate how to find major elements in evacuation using importance measures.

Keywords: Emergency Evacuation, Dynamic dependency, Agent-based model.

1. Introduction

Nuclear or radiological accident can cause significant consequences to people and the environment and leads to a massive evacuation. Emergency preparedness and response plans are inevitable to mitigate and minimize the consequences. Generally, evacuation planning is based on various assumptions to simplify situations, and the effect of infrastructure systems such as power systems, telecommunication, transportation, manpower, and so on is not considered explicitly. In the event of a major disaster, the infrastructures’ availabilities are highly uncertain and have temporal and spatial dependencies, that is dynamic dependency, on each other. It is also called as cascading effect or domino effect. Various approaches have been implemented to model the dependency of infrastructures such as the network model (Krings and Oman (2003), Ciaradonna et al. (2011), Rehak et al. (2018)), Leontief input-output model (Leontief (1986), Oliva et al. (2011), Haines and Jiing (2001)), multi-agent system (Baig (2012)), and Bayesian network (Schaberreiter et al. (2013), Di and Liberati (2012)). Leontief input-output model is widely used in various areas due to its simplicity, and the dynamic Bayesian network model can consider the temporal dependency (Khakzad (2015)). Furthermore, there are some studies to handle the spatial dependency by loading-dependent failure model (Dobson et al. (2005)). In this study, we propose a simulation method to optimize the strategy (or scenario) of emergency response and evacuation. In the previous work, the authors suggested an objective function to quantify the effectiveness and efficiency of emergency response and evacuation in terms of resilience and identified input variables of the objective function as hazards, evacuees, and infrastructure elements (Kim et al. (2020)). The variables interact with each other under temporal and spatial dependencies, and they can be modelled by an agent-based model (ABM) platform. ABM is a method that can simulate complex phenomena with massive autonomous decision-making agents (Wilensky and Rand (2015)). Within the ABM platform, the variables are defined as the agent classes distributed in space. Each agent’s behaviour is modelled by the first principles or empirical rules and simulated simultaneously while interacting with each other. For instance, the spread of hazard elements and the availability of infrastructure are simulated while affecting the path and speed of evacuees and determine the time of evacuation as a result. Here, the dynamic dependency between the infrastructures is modelled by constructing loading-dependent state transition probability.

In this paper, we present a method for simulating emergency response and evacuation in terms of resilience using ABM with a simple case study. Through the case study, we demonstrate how the hazard and infrastructure elements affect evacuation. Furthermore, as one approach of optimizations, we identify major infrastructure elements for emergency response and evacuation introducing the concept of risk achievement worth (RAW) and risk reduction worth (RRW) concept. We note that there are many detailed methods for modelling hazard spread, infrastructures, and evacuation, but as this study is in a conceptualization phase, we used the simplified models and assumptions for better
understanding and focussed on demonstrating the procedure of constructing an emergency response and evacuation simulation model.

2. Methods

2.1. Problem definition
In this section, we conceptualize and abstract the problem and define the target and input variable of the problem. In the previous study, the authors defined the target variable that is a quantitative measure using resilience concept (Kim et al. (2020)). We defined resilience for emergency response and evacuation as:

\[ RES(t) = \Pr(T \leq t | REC \geq REC^*) \] (1)

It means that resilience, RES(t) is the ‘probability that the degree of recovery, REC goes back to its original level or required level REC* within a required time t’. For predicting the defined target variable, involved input variables need to be identified. For the REC in Eq. (1), here, we assumed that it is determined by the stress of evacuees as:

\[ REC(t) = REC_0 - \sum_{i=1}^{n_{\text{evacuees}}} S_i(t) \] (2)

where \( REC_0 \) is an initial value of \( REC \), \( S_i(t) \) is the stress of \( i \)-th evacuee at time \( t \), and \( n_{\text{evacuees}} \) is total number of evacuees. When an emergency situation occurs, the stress of evacuees would increase, and therefore the degree of recovery decreases. As emergency response and evacuation proceed the stress would decrease and the degree of recovery would go back to its original level. The stress is simply assumed to decrease as the evacuee gets closer to a shelter. That is, the stress is a function of distance to the shelter as:

\[ S_i(t) = S_{i,0} * \frac{\|r_{\text{shelter}} - r_i(t)\|}{\|r_{\text{shelter}} - r_{i,0}\|} \] (3)

where \( S_{i,0} \) is an initial stress of \( i \)-th evacuee, \( r_{\text{shelter}} \) is a position of the shelter, \( r_i(t) \) is a position of \( i \)-th evacuee at time \( t \), and \( r_{i,0} \) is an initial position of \( i \)-th evacuee. The position of evacuee can be calculated by its velocity \( v \) as:

\[ r_i(t) = r_{i,0} + \int_0^t v_i(t) dt \] (4)

Here, it can be regarded that the velocity of evacuees is affected by the hazard and infrastructure elements. So, it is reasonable that there is a deterministic or probabilistic relationship between evacuee, hazard, and infrastructure elements as:

\[ R_{\text{evacuee}}(t) = f(t | R_{\text{hazard}}(t), R_{\text{infra}}(t)) \] (5)

where \( f(\cdot) \) is a deterministic function or probabilistic distribution, and \( R^i \) is a state vector of each element, for instance, for the evacuee, it could be position, velocity, and stress, for the hazard, it could be a severity or concentration of hazardous material, and for the infrastructure, it could be reliability or load. Fig. 1 is a schematic diagram conceptualizing the problem above. It represents the evacuation of a single evacuee in one-dimensional space. There are one shelter, one arbitrary hazardous element, and one arbitrary infrastructure system. The infrastructure system consists of five identical subsystems. The severity of the hazardous element varies with space and observed at five discretized points where the infrastructure system is located.

Meanwhile, the improved strategy of emergency response and evacuation can be found by optimization as:

\[ \max_R REC(T_r) = \min_R \sum_{i=1}^{n_{\text{evacuees}}} S_i(T_r) \] (6)

where \( T_r \) is a required time to evacuate, \( R \) is a combination of the state vector of hazard, evacuee, and infrastructure elements. Eq. (6) means that finding \( R \) that maximizes \( REC \) at the required time \( T_r \) or minimizes the sum of all evacuees’ stress at the required time \( T_r \).

2.2. Agent-based model
For the simulation of emergency response and evacuation, the behaviour of hazard, evacuee, and infrastructure elements should be simulated simultaneously and interaction between them does as well. Within an ABM platform, hazard, evacuee, and infrastructure elements are defined as different agent classes. Their behaviour is modelled by a rule, and the agent behaves interacting with other agents.

2.3. Dynamic dependency in infrastructures
In this study, we constructed a loading-dependent state transition probability to simulate the dynamic dependency in infrastructures. It is assumed that the infrastructure has two states that are normal and fail. A simple state transition matrix can be constructed using failure rate \( \lambda \) and repair rate \( \mu \) as Table 1. The transition probabilities change over time.

<table>
<thead>
<tr>
<th>State transition matrix</th>
<th>Normal</th>
<th>Fail</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>( e^{-\lambda t} )</td>
<td>( 1 - e^{-\lambda t} )</td>
</tr>
<tr>
<td>Fail</td>
<td>( 1 - e^{-\mu t} )</td>
<td>( e^{-\mu t} )</td>
</tr>
</tbody>
</table>

Considering the load of the infrastructure agent, the spatial dependency can be modelled. And by assuming that the failure and repair rate are dependent on the load, temporal dependency in the infrastructure agent arises. As Fig. 1, infrastructure agents are distributed in space and assuming...
that each infrastructure agent takes a certain load, a load of the infrastructure agent can be defined as:

\[
L_i(t) = \begin{cases} 
L_i(t - \Delta t) + A_i & \text{Normal} \\
0 & \text{Fail} 
\end{cases} 
\]

(8)

\[A_i = \frac{1}{\sum \left(\frac{1}{d_i}\right)} * L_{\text{Fail}}\]

where \(L_i\) is a load of \(i\)-th infrastructure agent, \(A_i\) is an additional load, \(d_i\) is the distance between \(i\)-th infrastructure agent and failed infrastructure agent, and \(L_{\text{Fail}}\) is a load that is taken by the failed infrastructure agent. If an infrastructure agent fails, then its load is distributed to other infrastructure agents according to the distance. For instance, if a traffic jam occurs on one road, the congestion is spread to surrounding roads. If one infrastructure agent fails, the load on the other infrastructure agent increases, which increases the failure rate. As a result, failure of one infrastructure agent induces successive failure (i.e., cascading effect).

2.4. Optimization

The final purpose of this study is to find a better strategy for emergency response and evacuation. As mentioned before, it can be achieved by finding the optimal combination of agent variables. In this study, as one approach of optimizations, we used RRW and RAW importance measures to find major infrastructure agents. RRW and RAW are used in reliability engineering to identify components that are critical to system reliability (Modarres (2016)). The definition of RRW and RAW is as:

\[
RRW = \frac{F_S[q(x)]}{F_S[Q(t)|Q(t) = x]} \quad (9)
\]

\[
RAW = \frac{F_S[q(x)]}{F_S[q(0)]} \quad (10)
\]

where \(F_S[q(x)]\) is unreliability (or risk) of the system (base unreliability), \(F_S[Q(t)|Q(t) = x]\) is the unreliability of the system when the unreliability of component \(i\) is \(x\). RRW is a measure of change in unreliability when the unavailability of a component is set to 0 (i.e., never fails). RAW is similar to RRW, but it is for the unavailability of a component is set to 1 (i.e., always fails). In this study, we use the measures by substituting the unreliability with the stress of evacuees at the required evacuation time and substituting \(Q_i(t)\) with state of \(i\)-th infrastructure agent. That is, RRW in this study is a measure of change in stress of the evacuee when the \(i\)-th infrastructure agent never fails.

3. Case study

As a case study, simple emergency response and evacuation as Fig. 1 is simulated. We used the ‘Netlogo’ ABM tool to develop a simulation model. Fig. 2 shows the developed simulation model. We simulated that one evacuee evacuates to a shelter in one-dimensional space. Therefore, the available evacuation path is only one. We assumed certain infrastructure system is distributed with constant intervals and arranged 5 infrastructure agents. Simulation conditions are presented in Table 1.

![Fig. 2. Developed emergency response and evacuation simulation model using ‘Netlogo’ ABM tool.](image)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of space</td>
<td>10 km</td>
</tr>
<tr>
<td>Initial speed of evacuees</td>
<td>60 km/h</td>
</tr>
<tr>
<td>Required evacuation time</td>
<td>10 min (600 s)</td>
</tr>
<tr>
<td>Simulation time step</td>
<td>10 s</td>
</tr>
<tr>
<td>Number of evacuee agent</td>
<td>1</td>
</tr>
<tr>
<td>Initial stress</td>
<td>100</td>
</tr>
<tr>
<td>Number of infrastructure agent</td>
<td>5</td>
</tr>
<tr>
<td>Initial failure rate</td>
<td>0.001</td>
</tr>
<tr>
<td>Initial repair rate</td>
<td>0.001</td>
</tr>
<tr>
<td>Number of iterations</td>
<td>1,000</td>
</tr>
</tbody>
</table>

Besides, the speed of an evacuee is determined by the state of the nearest infrastructure agent. If the state is normal the speed is randomly sampled from \(N(60,5)\), otherwise, it is sampled from \(N(30,5)\). The simulation result with the conditions is shown in Fig. 3 and 4. Fig. 3 shows the stress of an evacuee over time. The stress of evacuee decreases as evacuation proceeds. Fig. 4 shows the distribution of the stress at the required evacuation time. In this case, the mean stress at the required time is 37.435. To see the effect of failure rate, we implemented simulations while varying the failure rate. The result is shown in Table 3 and Fig. 5. Table 3 represents the mean and standard deviation of the stress at the required time according to the initial failure rate. Fig. 5 shows the plot of the mean stress according to the failure rate. It is shown that after some degree of failure rate the growth rate of the stress is rapidly decreased. It is because the state of almost all infrastructure agents stays in fail if the failure rate is larger than some extent. Moreover, more failed infrastructure accelerates the cascading effect.
To pinpoint a major infrastructure agent from the viewpoint of evacuation optimization, we computed RRWs and RAWs. Table 4 represents the result of stress with the fixed state of the target infrastructure agent with RRWs and RAWs. It was found that the stress could be minimized if the second infrastructure agent stays normal. On the other hand, if the first infrastructure agent fails at all times, the stress is maximized. As a result, the second and first infrastructure agents turned out as the most important for the evacuation in terms of RRW and RAW, respectively. It is because an evacuee cannot move far within the required time so that it is affected by infrastructure agents located at the front. Therefore, in this case, decreasing the failure rate of the first and second agents is the most effective way of improving the evacuation effect.

### Table 4. The RRW and RAW values of each infrastructure

<table>
<thead>
<tr>
<th>State of infra</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal mean</td>
<td>28.205</td>
<td>24.777</td>
<td>24.809</td>
<td>27.424</td>
<td>32.139</td>
</tr>
<tr>
<td>Fail mean</td>
<td>45.111</td>
<td>39.507</td>
<td>39.493</td>
<td>39.500</td>
<td>39.201</td>
</tr>
<tr>
<td>Fail std</td>
<td>2.124</td>
<td>3.601</td>
<td>3.469</td>
<td>3.558</td>
<td>3.627</td>
</tr>
<tr>
<td>RRW</td>
<td>1.327</td>
<td>1.510</td>
<td>1.508</td>
<td>1.365</td>
<td>1.164</td>
</tr>
<tr>
<td>RAW</td>
<td>1.205</td>
<td>1.055</td>
<td>1.054</td>
<td>1.055</td>
<td>1.047</td>
</tr>
</tbody>
</table>

### 4. Conclusions

A variety of factors are involved in emergency response and evacuation and the factors interact with each other under dynamic dependency. Such dependency should be explained when assessing the effectiveness and efficiency of the emergency response and evacuation. In this study, we presented a method of simulating the evacuation using the target variable we have defined. From the target variable, we identified required input variables and models. We modelled dynamic dependency in infrastructure by constructing loading-dependent state transition probability. Furthermore, we demonstrated the simulation model with a
simple case study. From the case study, we presented how the failure rate (i.e., independent and dependent behaviour) of the infrastructure affects the evacuation. Lastly, we identified the major infrastructure agents by observing RRW and RAW. In the further study, we are planning to improve the models and include more factors to make the simulation more realistic. For instance, we will increase the number of evacuees, extend the problem space to two-dimensional so that the evacuation paths can be diversified, including various infrastructure systems and their dependency models.

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References


