Proceedings of Computational Engineering Conference JSCES
Vol. 28, 2023 May

Seismic Risk Assessment with Fragility Function using the City-scale Numerical Simulation

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This study presents a framework for assessing the seismic risk of buildings using a city-scale numerical simulation combined with sensor observations. In the proposed framework, the Stochastic Green Function is utilized to generate a range of ground motions. A part of Sendai City, Japan, is selected as the target area, and the Integrated Earthquake Simulation (IES) is employed to evaluate the seismic response of buildings. The fragility curve is then used to construct for each building based on the numerical simulation results. Furthermore, sensor data is incorporated using feature perception techniques such as Proper Orthogonal Decomposition (POD) and sparse learning to predict peak ground acceleration across the entire city area. Finally, seismic risk assessment is performed for each building using the corresponding fragility curve. This comprehensive approach provides valuable insights into urban earthquake resilience and helps to inform strategies for mitigating seismic risk.

Key Words : *seismic risk assessment, city-scale numerical simulation, sensor observations, Fragility Function, Proper Orthogonal Decomposition*

1. INTRODUCTION

Developing accurate models to estimate, predict, and control complex phenomena is a challenge in many fields. Although advanced technology allows for massive data collection, like seismic and environmental data, the multi-dimensional nature and varying timescales make real-time processing difficult. This issue hinders quick state estimation for fast, efficient control.

Dimension reduction offers a promising solution to this issue, as many natural science systems exhibit dominant low-dimensional patterns that can effectively explain high-dimensional data. Proper orthogonal decomposition (POD)[2] has emerged as a systematic approach to determine a low-dimensional approximation of high-dimensional data, enabling the exploitation of significant low-dimensional patterns based on efficient reduced-order models. This data-driven sensing approach has led to the development of sparse sensor placement algorithms.

In the context of urban seismic risk assessment, an integrated approach that combines city-scale simulation, sensor observations, and dimension reduction techniques is essential for understanding the potential impacts of earthquakes on city-scale infrastructure. This study presents a city-scale fragility assessment method that addresses the challenges associated with processing large amounts of data, considering uncertainties in building response, and incorporating dimension reduction techniques.

Utilizing the Stochastic Green's function for seismic wave generation and the Integrated Earthquake Simulation (IES)[6] for wide-area city simulations, this method provides valuable seismic motion data, including peak ground acceleration and building response. IES, linked to a Geographic Information System (GIS), incorporates earthquake motion simulation, structural response simulation, and response behavior simulation, contributing vast amounts of data crucial for the data-driven techniques employed in this study.

The proposed method applies POD and sparse learning to process the extracted features and predict overall peak ground acceleration based on local building sensor data. Finally, fragility assessment is conducted using the city-wide predictions, allowing for a comprehensive evaluation of earthquake damage in urban areas.

2. Numerical Simulation

(1) Integrated Earthquake Simulation(IES)

IES[6] is a program that is linked to a Geographic Information System (GIS) and incorporates earthquake motion simulation, structural response simulation, and response behavior simulation **Fig.1**.

Wave propagation simulation: It outputs synthesized earthquake waves based on the fault mechanism. The propagation of waves passing through the crust is calculated, and the amplification of waves near the surface is calculated taking into account the non-linear characteristics of the 3-dimensional topographical effect and the shallow soil layer.

Structural response simulation: It calculates the response for all structures in the targeted area, including residential buildings, concrete infrastructure structures, geological structures, transportation networks, etc. It is necessary to choose an appropriate analysis method depending on the structure of the building.

Response behavior simulation: It is possible to analyze evacuation from building damage, crisis management, and restoration plans.

In this study, wave propagation simulation for the amplification of waves near the surface and the structural response simulation were used. Regarding the structural response simulation, IES provides three modules: Single Degree of Freedom model (SDOF), Multi Degree of Freedom model (MDOF), and One Component Model (OCM). In this study, the analysis was performed using MDOF. Input files for building floors and structures were created using GIS and other tools, and the response of the structure can be output by inputting seismic motions and other factors.

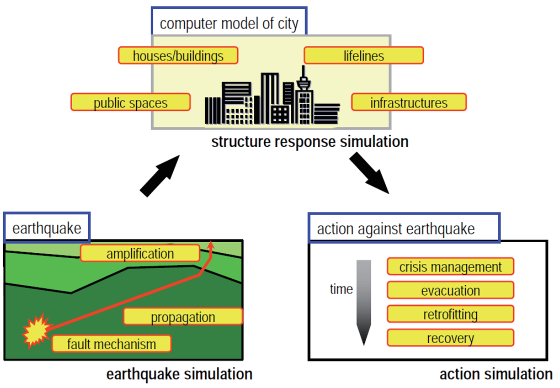

Fig. 1 Flow of IES[6]

(2) Stochastic Green's Function

The Stochastic Green's function method expands on the empirical Green's function method, which was initially introduced by Irikura[7] using a superposition technique. The empirical Green's function method relies on observed records as Green's functions, presuming that the deep and shallow subsurface structures at the observation point are already integrated into the observed records. On the other hand, this method serves as an effective alternative when appropriate observation records cannot be obtained.

In the application of the Stochastic Green's function method by Dan and Sato[4], the fault surface is segmented into small subfaults, and Boore's[1] Stochastic source model is taken into account for each subfault to compute the Green's functions. The deep subsurface structure is treated as a one-dimensional layered structure for ground response analysis. Random phase characteristics are attributed to this Green's function, and waveform synthesis is conducted in accordance with Irikura[7] to derive the seismic waveforms when the entire fault experiences rupture. This study utilizes a program provided by the National Research Institute for Earth Science and Disaster Resilience.

(3) Target Area

In this study, the simulations are performed using the fault parameters of the Nagamachi-Rifu published by the National Research Institute for Earth Science and Disaster Resilience. **Fig.2** displays the locations of the element faults employed in the Stochastic Green's function method, with the first asperity highlighted in red and the second asperity in blue. The second asperity was kept constant, while the position of the asperity was shifted to consider different 30 scenarios.

The Stochastic Green's function method assigns random phase differences to waveforms for each subfault before superimposing the outcomes. As a result, the earthquake waveform shape and the maximum inter-story drift angle of each building may vary based on the utilized random number sequence. To address this variation, analyses were conducted with five different random number sequences for each scenario, producing a total of 150 calculation result sets.

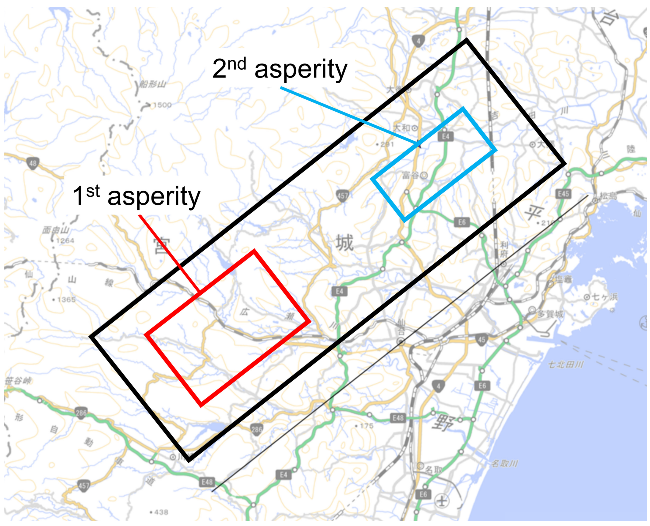

Fig. 2 Asperity of Nagamachi-Rifu fault

3. Fragility, Proper Orthogonal Decomposition, Sparse Learning

(1) Fragility Function

Fragility functions[8] are derived from a structural assessment of the system (in the case of analytical form). In simpler terms, fragility can be defined as the susceptibility of a structure to break or be damaged.

Fragility curve is a general term and may be referred to 2D "fragility curve" or 3D "fragility surface". Basically, there are three ways to get a fragility function, Incremental Dynamic Analysis(IDA), Multi Strip Analysis, Cloud Analysis.

Fragility curve is a continuous function showing the probability of exceedance of a certain limit state(LS) for a specific level of ground motion intensity measure(IM).

$$Fragility = P[LS|IM = im] \tag{1}$$

(2) Cloud Analysis

Cloud analysis[3] uses the linear regression in the logarithmic scale by least squares to establish the relationship between engineering demand parameter (EDP) and IM as follows:

$$\begin{aligned} &E[\ln EDP \mid IM] = \ln \mu_d = \ln a + b \ln IM \\ &\sigma_d = \sqrt{\sum_{j=1}^{N} (\ln EDP_j - \ln \mu_d)^2 / (N-2)} \end{aligned} \tag{2}$$

given IM, $EDP_j = EDP$ obtained from the j-th ground motion, a and b = regression coefficients; and N = number of ground motions. The fragility function is expressed as the damage probability that EDP exceeds the pre-defined value threshold for each limit state (LS) conditional on IM, which can be derived based on the above linear relationship between EDP and IM under the lognormal probability distribution

$$\begin{aligned} &P_f[EDP \geq LS \mid IM, \eta, \beta] \\ &= \Phi\left\{\frac{\ln(\mu_d) - \ln(LS)}{\sigma_d}\right\} = \Phi\left\{\frac{\ln(IM) - \ln(\eta)}{\beta}\right\} \end{aligned} \tag{3}$$

where $\Phi(\cdot)$ = standard normal cumulative distribution function (CDF); η = median of the fragility function, i.e, $ln(\eta) = [ln(LS) - ln(a)]/b$; and β = dispersion of the fragility function, i.e., $\beta = \sigma_d/b$. Note that Eq.3 is a two parameter (η and β) fragility function given IM.

Limit state refers to a specific level of damage or failure that is used to define fragility functions. In this case, the limit states of "moderate" and "severe" were chosen from HAZUS[5] to develop the fragility functions.

(3) Proper Orthogonal Decomposition(POD)

Proper Orthogonal Decomposition(POD)[2] is an analysis technique that can extract modes from numerical analysis results, allowing for mode decomposition based on the theory of principal component analysis. It also enables dimension reduction by extracting only the dominant components from the calculated modes and reconstructing the original data with a small number of modes. Let $\boldsymbol{x}_i$ (n-dimensional) be the simulation result for a certain case i, and define the data $\boldsymbol{X}$ by arranging N cases in a row direction.

$$\boldsymbol{X} = \begin{bmatrix} | & & | \\ \boldsymbol{x}_1 & \cdots & \boldsymbol{x}_N \\ | & & | \end{bmatrix} \tag{4}$$

In this study, since the data dimension is larger than the number of cases ($N << n$), $\boldsymbol{X}$ and $\boldsymbol{X}^T$ are multiplied to reduce the dimension, and the covariance matrix $\boldsymbol{C} = \boldsymbol{X}^T\boldsymbol{X}$ is defined, and eigenvalue decomposition is performed. Let λ_j and v_j be the obtained eigenvalues and eigenvectors, respectively, and let V be a matrix in which the eigenvectors are arranged in column direction. Using these, consider the singular value decomposition [5] of X as follows:

$$\boldsymbol{X} = \boldsymbol{U\Sigma V}^T \tag{5}$$

Here, $\boldsymbol{\Sigma}$ is a matrix in which the square root of the eigenvalues are arranged in diagonal elements, and $\boldsymbol{U}$ is a matrix in which the spatial modes u_j are arranged in column direction. Also, by transforming equation (2), the numerical analysis result x_i of a certain case i can be expressed as a linear combination of coefficients α and spatial modes u_j as follows:

$$\boldsymbol{x}_i = \sum_{j=1}^{N} (\sqrt{\lambda_j} v_{ij}^T) \boldsymbol{u}_j = \sum_{j=1}^{N} z_{ij} \boldsymbol{u}_j \tag{6}$$

Here, the error for each building is defined by the following equation, where $\hat{x}$ is the calculation result by the surrogate model and x is the numerical analysis result by IES.

$$error(\%) = \frac{|\hat{x} - x|}{x} \times 100 \tag{7}$$

From **Fig.3**, it can be seen that the error is generally kept

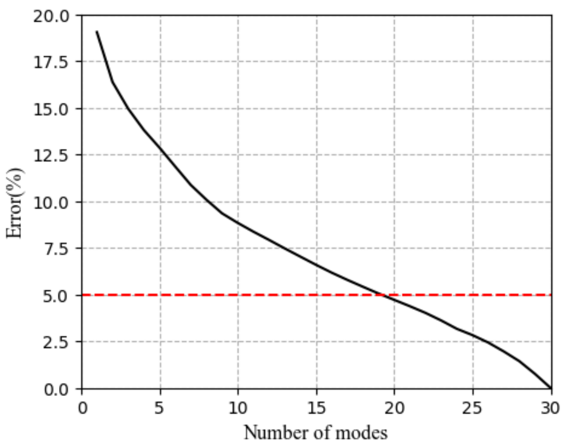

Fig. 3 Error for different number of modes

below 5%. Although there are buildings with errors of 20% or more, this is because the values were originally small, making them susceptible to the effects of reducing the number of modes. Overall, highly accurate results were obtained. Therefore, After dimension reduction, the principal components still retain most of the information in the data.

(4) Sparse Learning[9]

We consider the linear system given by

$$\boldsymbol{y} = \boldsymbol{Hx} = \boldsymbol{HUz} = \boldsymbol{Cz} \tag{8}$$

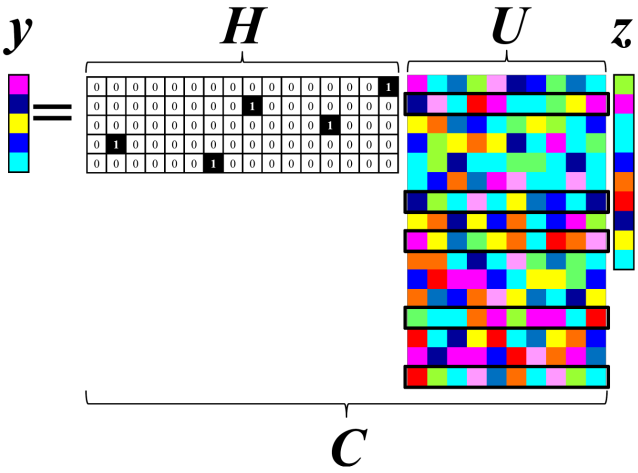

Fig. 4 Graphical image for sensor matrix H[9]

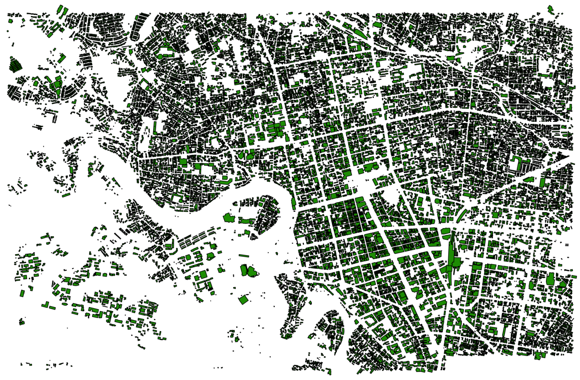

Fig. 5 Part of Aoba-ku, Sendai

where $\boldsymbol{y} \in R^p$, $\boldsymbol{H} \in R^{p\times n}$, $\boldsymbol{U} \in R^{n\times r}$, $z \in R^r$, and $\boldsymbol{C} \in R^{p\times r}$ are the observation vector, the sparse sensor location matrix, and the sensor candidate matrix, the latent state vector, and the measurement matrix ($\boldsymbol{C} = \boldsymbol{HU}$), respectively. Here, the element corresponding to the sensor location is unity and the others are 0 in each row of $\boldsymbol{H}$. In addition, p, n, and r are the number of sensors, the number of spatial dimensions, and the number of latent state variables, respectively. The system above represents the problem of choosing p observations out of n sensor candidates for the estimation of the state variables. The various sensor selections can be expressed by changing H and by selecting row vectors as sensors from the sensor candidate matrix $\boldsymbol{U}$. A graphical image of the foregoing equation is shown in **Fig.4**.

The estimated parameters $\hat{z}$ can be obtained by the pseudo-inverse operation when uniform independent Gaussian noise $N(0, \sigma^2\boldsymbol{I})$ is imposed on the observations as follows:

$$\hat{z} = \begin{cases} \boldsymbol{C}^T\left(\boldsymbol{C}\boldsymbol{C}^T\right)^{-1}\boldsymbol{y} & p \leq r \\ \left(\boldsymbol{C}^T\boldsymbol{C}\right)^{-1}\boldsymbol{C}^T\boldsymbol{y} & p > r \end{cases} \tag{9}$$

Furthermore, sensor selection based on POD is a data-driven approach without the requirement for governing equations. Such data-driven sensing generally needs to determine the optimal sensor locations from a large amount of candidates. Hence, we define a fast greedy optimization method for high performance computing or feedback control:

$$\text{maximize } f_D, \quad f_D = \begin{cases} \det\left(\boldsymbol{C}\boldsymbol{C}^{\boldsymbol{T}}\right) & (p \leq r) \\ \det\left(\boldsymbol{C}^{\boldsymbol{T}}\boldsymbol{C}\right) & (p > r) \end{cases} \tag{10}$$

4. Seismic Risk Assessment

The Seismic Risk Assessment's objective targets a section of Aoba-ku in Sendai City, comprising 30,000 buildings **Fig.5**. Simulated seismic wave data and geographic information from the area are incorporated into the analysis.

With 150 scenarios generated from 30 scenarios each containing 5 random phases, these are divided into test and training sets. One of the 30 scenarios and its 5 corresponding ground motions are extracted. For each building, 145 sets of corresponding peak ground acceleration(PGA) and inter-story drift angles are simulated by IES. Using cloud analysis, with PGA as IM and inter-story drift angle as EDP, fragility functions for all buildings are calculated.

For all 30×5 data sets, the average of each group is taken, yielding $29 + 1$ sets of data, which serve as training and testing sets for POD and sparse learning. Proper Orthogonal Decomposition (POD) and sparse learning are employed for feature extraction. POD acquires the principal bases $\boldsymbol{U}$ of the peak ground acceleration data for the 29 cases, followed by sparse learning application to calculate and obtain new coefficients $\hat{z}$. Genetic algorithms is used for determining the optimal sensor placement.

Once sensor placement points are established, the acceleration map for the entire wide-area region can be inferred in the event of another earthquake, using the peak ground acceleration data collected from the sensors. Reconstruction error through sparse learning decreases with increasing sensor numbers but reaches an even level when the number of sensors hits 20, indicating a saturation point for further sensor additions **Fig.6**.

Assuming earthquake data is obtained through sensors, the acceleration data corresponds to the reserved test case. Balancing accuracy and sensor count, 20 sensors are deployed, and only the acceleration values from buildings with sensors are used as observation data. This approach enables prediction of the peak ground acceleration (PGA) map for the entire city area.

Upon PGA map prediction, a fragility assessment is conducted. By utilizing previously established fragility functions for all buildings and the known intensity measure (IM) – the PGA map – two distinct levels of fragility maps are generated under the current earthquake scenario: moderate, severe.

The two figures **Fig.7 Fig.8** show the fragility under four different limit conditions calculated using the pga map ob-

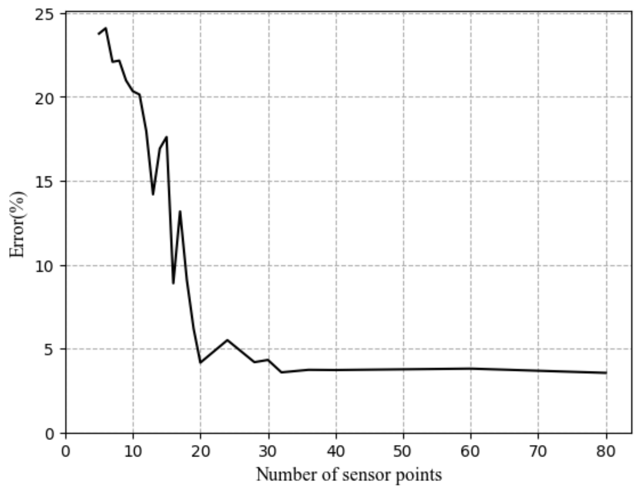

Fig. 6 Error for different number of sensor points

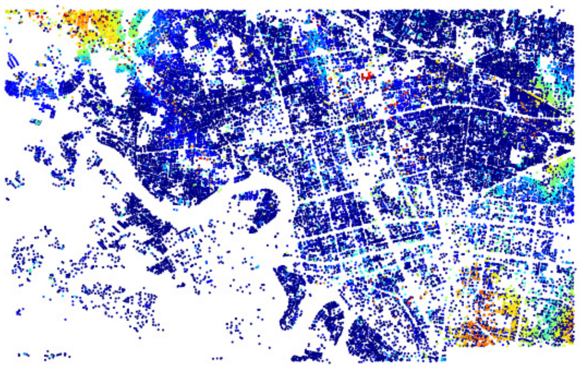

Fig. 7 Probability of damage at the moderate level

Fig. 8 Probability of damage at the severe level

tained from the data measured by sensors during an earthquake.

5. Conclusion

This study presents a method for assessing city-scale earthquake damage by combining simulations, sensor data, and dimension reduction techniques. It involves four steps: generating seismic waves, simulating city-scale effects, perceiving features with POD and sparse learning, and assessing fragility.

The method provides crucial seismic data for the entire city, but further research should consider building uncertainty and increasing sensor numbers. Using POD and sparse learning helps predict peak ground acceleration from local sensor data, although having too few sensors can affect accuracy.

Fragility assessment is done by analyzing city-scale peak ground acceleration predictions. Fragility functions are created using building response, cloud analysis, and HAZUS limit states. To improve reliability, future work should consider a broader range of ground motion. In summary, this method advances efforts to develop accurate models for complex phenomena like seismic risk assessment. By addressing data processing challenges, uncertainty, and incorporating dimension reduction techniques, it can help improve urban resilience against earthquakes.

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