Seismic resilience assessment of urban communities using Bayesian network

Chulyoung Kang
Postdoctoral Researcher, Structural and Seismic Safety Research Division, Korea Atomic Energy Research Institute, Daejeon, Republic of Korea

Taeyong Kim
Assistant Professor, Dept. of Civil Systems Engineering, Ajou University, Suwon, Republic of Korea

ABSTRACT: The importance of the disaster resilience of urban communities becomes substantial as people and capital are integrated and affect each other both directly and indirectly. This study presents three main contributions to quantify the seismic resilience performance of an urban community and support the decision-making process. First, a Bayesian network (BN)-based regional seismic resilience assessment framework is developed to estimate the seismic losses of an urban community considering the structural deterioration efficiently and effectively. Second, a resilience assessment framework is developed, which estimates the reliability and recoverability indices of every district in the urban community. A concept of resilience limit-state is introduced with a graphical representation tool. Third, a retrofit strategy is proposed from the disaster resilience perspective, which facilitates finding the optimal scheme considering the multidimensional aspects of the urban community. An urban community consisting of 10 districts mimicking the downtown Vancouver area is introduced as a numerical example to demonstrate the efficiency and applicability of the findings.

1. INTRODUCTION

The growing rate of urbanization and the increase in population density may make urban communities more vulnerable to seismic hazards. Since an urban community is comprised of interrelated structural systems having different characteristics, a seismic vulnerability assessment needs to be carried out at the community-level to reduce the disaster risk and improve the risk management level of public safety. Moreover, to reduce the short- and long-term impacts of the disaster on multidimensional aspects of an urban community, a concept of resilience needs to be introduced.

Many research efforts have been made to assess the disaster resilience of a community in an engineering field (Bruneau et al., 2003; Chang et al., 2004; Despotaki et al., 2018; Sutley et al., 2019). Such studies employed a large number of datasets including hazard scenarios, building inventory, and recovery data, but consideration of social and economic impacts is limited. On the other hand, various methods have been developed to assess community-scale disaster resilience in the field of social science (Cutter et al., 2010; Cutter et al., 2014). The social science aspects of disaster resilience are comprehensively addressed by using parameters from the census dataset, yet a relatively simple approach has been used to assess the structural vulnerabilities. Choi and Song (2022) developed a community disaster resilience clustering method to consider both the physical vulnerability of building portfolios and socioeconomic recoverability from the census data, but such a method cannot facilitate the probabilistic inference of the resilience performance of an urban community. Moreover, few methodologies have been proposed to use the analysis outcomes and identified patterns from the assessment in the decision-making to improve the community resilience performance.

To address the research needs, this study first develops a Bayesian network (BN)-based regional seismic resilience assessment framework to estimate the regional economic losses. BN is a type of probabilistic graphical model to represent probability distributions of random variables using nodes and directed edges. In establishing the BN model, a ground motion prediction equation by Boore and Atkinson (2008) is adopted to represent the seismic hazard, while a coefficient method by ASCE 41-17 (2017) is employed to describe the impact of the hazard on a set of structural systems in the districts. Note that an urban community consists of multiple districts, and we analyze the resilience performance in a district level. Furthermore, a new random variable termed structural status factor is introduced in the BN model to consider the change of structural characteristics due to deterioration in the assessment.

The BN model describing the damage and losses of spatially distributed buildings given seismic hazards is integrated with the socioeconomic recoverability index estimated by the census data of the target community following a framework developed by Choi and Song (2022). Such a way of obtaining the recoverability index is termed the baseline resilience indicator for the community (BRIC) model which is favorable, especially when no recovery regression model or recovery model is available in the community (Cutter et al., 2010; Cutter et al., 2014). We mark the reliability (β) and recoverability (γ) indices of each district in a form of a scatter plot. The plot termed a β-γ diagram helps gain a comprehensive insight to support the decision-making process in terms of community resilience.

Next, using the β-γ diagram, we propose an algorithm to optimize the net resilience performance of the urban community. Herein, the net resilience performance is a concept that constitutes both reliability and recoverability aspects. Compared to conventional optimization algorithms which focus solely on reducing the economic losses of urban communities, the proposed algorithm aims at reducing economic losses of districts where the recoverability index is relatively low. The BN model is employed to effectively consider the level of recoverability of each district in the urban community during the optimization.

A numerical example of a hypothetical city having 10 districts is introduced to examine the BN-based regional seismic resilience assessment framework, describe the β - γ diagram, and demonstrate the resilience-based optimization algorithm. A comparison has been made between the developed optimization algorithm and a conventional one in terms of resilience and total economic loss.

This paper mainly consists of five sections. Section 2 describes the BN-based seismic performance assessment, which is followed by the BRIC model-based estimation of the recoverability index. The β - γ diagram and a concept of resilience limit-state are also delineated. Next, Section 3 presents a resilience-based optimization algorithm considering both reliability and recoverability capacities. A numerical example is provided in Section 4 to demonstrate the proposed methods and concepts in Sections 2 and 3. Finally, concluding remarks are presented in Section 5.

2. DISASTER RESILIENCE OF URBAN COMMUNITY: RELIABILITY AND RECOVERABILITY RELATIONSHIP

This section starts by proposing a BN-based framework that can estimate the seismic losses of each district in the urban community. In this regard, a brief description of a BN is provided, which is followed by mathematical formulations that are used to construct the framework. Next, the BRIC model is introduced to facilitate a comparative analysis of the socioeconomic performance of each district in the area. Using the outcomes of BN-based seismic regional loss assessment as a reliability index (β) and those from the BRIC model as a recoverability index (γ), a β-γ point can be estimated for each district in the area. A resilience limit-state is proposed to evaluate the estimated β-γ points in the last part of this section.

2.1. Bayesian network-based regional seismic loss assessment

2.1.1. Bayesian network

Bayesian network (BN) is a probabilistic graphical model formulating a probability distribution using nodes and arcs, which, respectively, represent random variables and their statistical dependence (Koller and Friedman, 2009). Figure 1 presents a typical configuration of a BN. Nodes connected to the tails of the arrows are referred to as *parent* nodes, while those connected to the tail are termed *child* nodes. The nodes can be either parent or child depending on their relationship with other variables.

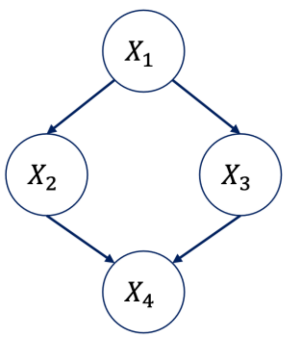

Figure 1: A typical configuration of a BN

Each node in the BN is described by a probability distribution function conditioned on the set of its parent nodes. For instance, the joint probability distribution of X_4 in Figure 1 can be described as

$$P(X_4) = P(X_2|X_1) \cdot P(X_3|X_1) \tag{1}$$

Owing to such a relationship and graphical representation, a BN enables efficient quantification of a causal relationship between random variables and provides systemic probabilistic inference between observed and unobserved variables. Although a BN can deal with both discrete and continuous random variables, this study only handles discrete random variables. Thereby, the probability distribution function in Eq. (1) refers to a probability mass function (PMF), and the relationship between the parent and child nodes is described in terms of a table-based structure, termed conditional probability table (CPT).

2.1.2. Regional seismic loss assessment

A BN-based regional seismic loss assessment consists of two parts. The first part is to obtain the intensity measure (IM) for a given information on seismic hazards. The BN is modeled following a ground motion prediction equation (GMPE). The second part estimates the responses of a set of building for a given IM. Among various nonlinear static procedures, a coefficient method (ASCE 41-17, 2017) is employed in this regard. Details of procedures used in modeling the BN are described as follows.

A GMPE predicts the natural logarithm of the IM y at site i caused by an earthquake event j using the following formula

$$\ln y_{ij} = f\left(M_j, R_{ij}, \theta_i\right) + \sigma_{ij}\varepsilon_{ij} + \tau_j\eta_j \tag{2}$$

where $f\left(M_j, R_{ij}, \theta_i\right)$ is the attenuation law given as a function of magnitude M, epicenter distance R_{ij}, and a set of other explanatory parameters θ_j. ε_{ij} and η_j are respectively the intra- and inter-event residuals, which are modeled as the Gaussian random variables whose mean and standard deviation are zero and one. σ_{ij} and τ_j respectively represent the standard deviation of the intra- and inter-event residuals. This study uses a GMPE by Boore and Atkinson (2008) to model the BN.

The coefficient method (ASCE 41-17, 2017) predicts the peak displacement of a nonlinear oscillator, DS by modifying the peak displacement of a linear oscillator as

$$DS = C_0 C_1 C_2 \frac{S_a(T)}{\omega^2} \mathrm{g} \tag{3}$$

where C_0, C_1, and C_2 are the coefficients to consider different characteristics of nonlinear hysteresis which are empirically obtained, $S_a(T)$ is the spectral acceleration at the first mode period of building, T, ω is the circular natural frequency, and g is the acceleration of gravity.

2.1.3. BN-based regional seismic loss assessment framework

Figure 2 presents the proposed BN-based regional seismic loss assessment, where a white circle represents the random variable while a shaded circle represents the deterministic variable. Using a GMPE by Boore and Atkinson (2008), the first part of the BN is constructed, which is depicted in a red dashed line in Figure 2. As shown in Eq. (2), M, R, and a set of explanatory variables including shear wave velocity V_{S30}, and fault type FT are selected as the nodes of the BN. Note that since the distance between the epicenter and *n*th structure, R_n is automatically determined as the epicenter location L is given, R_n is considered as a deterministic variable. Moreover, the magnitude of inter- and intra-residuals is regarded as deterministic variables because σ and τ are determined once IM is selected according to Boore and Atkinson (2008). Because R_n varies along with each building, a set of IMs is generated as equivalent to the number of buildings in the target district, N. Note that spatial correlation between buildings is considered by ε_{ij}.

Next, a BN network predicting the peak displacement of structures is constructed following Eq. (3) and highlighted by a blue dashed-dot line in Figure 2. To consider the level of deterioration, we introduce a new random variable θ_S called the structural status factor which controls the yield strength of buildings in the community. Depending on the community's seismic resilience performance, a probability distribution function of θ_S could be different. To characterize the deterioration, θ_S ranges from 0 to 1. Details of the impact of θ_S on the seismic loss are covered in Section 4. Although structural deterioration affects both the lateral strength and stiffness of the building, this study assumes that θ_S only controls the yield strength for the sake of simplicity. In other words, θ_S is multiplied to the yield strength to represent the loss of lateral strength due to deterioration. It is, however, noted that this framework can be extended to consider both stiffness/strength degradations together in the loss assessment.

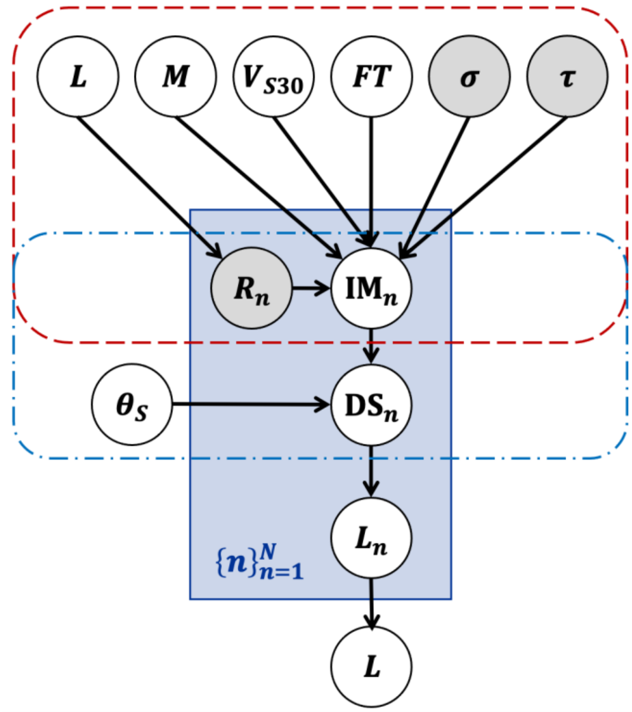

Figure 2: BN-based regional seismic loss assessment framework

Using the predicted peak displacement, the seismic loss can be estimated by following a framework proposed by Goda and Hong (2008). This method introduces a damage factor δ written as

$$\delta_n = \max\left(\min\left(\left(\frac{\mathrm{DS}_n - 1}{\mathrm{DS}_{n,R} - 1}, 1\right)\right), 0\right) \qquad (4)$$

δ which always lies between 0 and 1 is employed to represent three types of monetary losses based on the assumption that the seismic loss initiates as the displacement demand exceeds the yield displacement $\mathrm{DS}_{n,R}$. The seismic loss of an urban area is obtained by summing the three types of monetary losses for every structure as follows

$$L = \sum_{n=1}^{N} \left(L_{BL}(\delta_n) + L_{CO}(\delta_n) + L_{BI}(\delta_n)\right) \qquad (5)$$

where $L_{BL}(\cdot)$, $L_{CO}(\cdot)$ and $L_{BI}(\cdot)$ respectively represent building-related loss, contents-related loss, and business-interruption related loss which are calculated as

$$L_{BL}(\delta) = \delta^{\beta_{BL}} L_{BL}(1)$$
$$L_{CO}(\delta) = \delta^{\beta_{CO}} L_{CO}(1) \qquad (6)$$
$$L_{BI}(\delta) = \delta^{\beta_{BI}} L_{BI}(1)$$

where $L_{BL}(1)$, $L_{CO}(1)$, and $L_{BI}(1)$ represent the three types of losses at the complete damage state, and β_{BL}, β_{CO} and β_{BI} are the parameters of the loss-damage model.

Using the BN, we can estimate the PMF of seismic losses of a district of interest. Among various representative values estimated from the PMF, the following mathematical expression is employed for the reliability index

$$\beta = \frac{L_{Total} - E[L]}{L_{Total}} \qquad (7)$$

where L_{Total} represents the seismic losses at the complete damage state, and $E[\cdot]$ stands for the mathematical expectation. By normalizing through L_{Total}, the index lies between 0 and 1. Because an urban community is comprised of multiple districts, we construct a BN-based frame for each district to properly assess the seismic resilience performance.

2.2. Baseline resilience indicator for the community (BRIC) model

The baseline resilience indicator for the community (BRIC) model characterizes community resilience using six categories such as social, economic, community capital, institutional, infrastructural, and environmental. The six parameters are selected among the census data and transformed into a comparable unit such as percentage or per capita. The recoverability index is then calculated by averaging the six parameters in Cutter et al. (2010). However, Choi and Song (2022) claim to exclude institutional, infrastructural, and environmental features in calculating the recoverability index because the influence of such indices is already considered in calculating the reliability index. Thus, by adopting the framework by Choi and Song (2022), this study estimates the recoverability index by averaging the social, economic, and community parameters obtained from the census data.

2.3. β-γ diagram

The resilience performance of each district can be illustrated as a hollow circle as shown in Figure 3. The x-axis represents the recoverability index from the BRIC model, whereas the y-axis stands for the reliability index estimated from the BN-based regional seismic loss assessment. We termed this scatter plot a β-γ diagram. Moreover, we introduce a resilience limit in terms of β and γ which is presented in a red dashed line in Figure 3. Note that we assume the resilience limit as a function of the l^2-norm of β and γ in this framework, but any mathematical formulations could be used.

As seen in Figure 3, β-γ points located inside the resilience limit-state indicate that the corresponding districts do not satisfy the resilience limit, which needs the retrofit of a set of structural systems and the improvement of the society's recoverability capacity. The graphical illustration facilitates a comprehensive evaluation of the resilience performance of a community and supports resilience-informed decision-making.

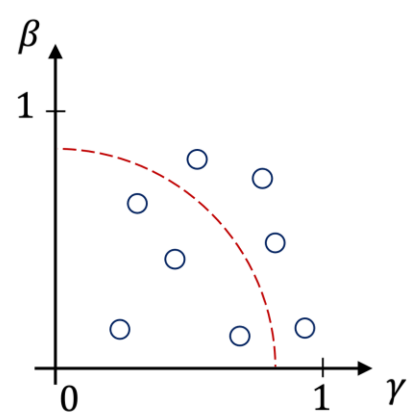

Figure 3: β-γ diagram of the urban community

3. RESILIENCE-BASED OPTIMAL RETROFIT STRATEGY

A retrofit strategy to reduce the seismic losses of a set of buildings under a given budget is first covered. Then, to consider the multidimensional characteristics of community disaster resilience, we propose a resilience-based optimal retrofit approach. Note that the proposed retrofit strategy is carried out in a district level.

3.1. Seismic loss-based optimal retrofit strategy

The retrofit strategy aims to identify the optimal plan to reduce the total seismic losses of every district in the community under a given budget. In this regard, the objective function is defined to maximize the average of the reliability index of all districts, while the constraint is the budget that can improve the lateral resistance of buildings. The retrofit cost is calculated by comparing the PMF of θ_S between existing and retrofitted conditions. Due to high nonlinearity of the problem, a heuristic optimization algorithm such as a genetic algorithm is employed to find the optimal retrofit strategy. This strategy has been conventionally adopted in decision-making process.

3.2. Resilience-based optimal retrofit strategy

We introduce a new objective function to consider multiple criteria in describing the seismic capacity of an urban community. Compared to the conventional strategy, the new approach aims to shift the resilience indices located inside the resilience limit to the outside. However, due to the budget, the aim can be represented by minimizing the distance between the β-γ point of each district and the resilience limit-state, especially those that cannot satisfy the resilience limit-state. Since only β-γ points located inside the resilience limit-states are considered during the optimization, it is expected that the lower the recoverability index is, the greater the number of retrofit efforts has been made. Note that since it is demanding to improve socioeconomic recoverability in the short term, this study invests budgets only on reinforcing the lateral stiffness of buildings to satisfy the resilience limit. Due to the nonlinearity and complexity of the problem, a genetic algorithm is employed to find the optimal allocation for each district in the community.

4. NUMERICAL INVESTIGATION

This section introduces an urban community having 10 districts that mimic a virtual city in Vancouver. In this example, for simplicity, 10 districts are assumed to have the same regional characteristics and building portfolio. The district consists of 200 virtual buildings which are randomly generated and distributed over a 2.5 km × 2.5 km square region with uniform soil conditions as illustrated in Figure 4. To effectively present the change of reliability index along with θ_S, we define different probabilities of the structural status factor, $P(\theta_S = \theta_{S_i})$ for each district as shown in Table 1.

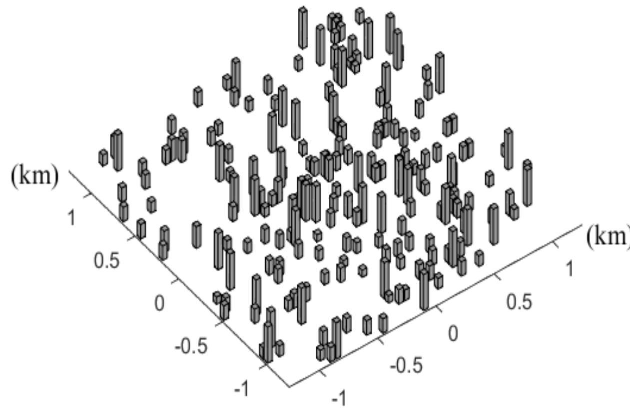

Figure 4: Virtual city in Vancouver area

Table 1: Probabilities of structural status factor θ_S for 10 districts

District No.	$\theta_{S,i}$				
	0.2	**0.4**	**0.6**	**0.8**	**1.0**
1	0	0	0.1	0.3	0.6
2	0.1	0.1	0.1	0.3	0.4
3	0.1	0.3	0.1	0.3	0.2
4	0.2	0.1	0.1	0.1	0.5
5	0.2	0.2	0.2	0.2	0.2
6	0.2	0.4	0.2	0.1	0.1
7	0.3	0.2	0.1	0.3	0.1
8	0.4	0.2	0.2	0.1	0.1
9	0.5	0.1	0.2	0.1	0.1
10	0.6	0.1	0.1	0.1	0.1

In developing the BN-based regional seismic loss assessment for each district, the matrix-based Bayesian network (MBN) developed by Byun and Song (2021) is adopted. The MBN has an advantage of efficient memory storage and flexible inference by utilizing an alternative matrix-based formulation of conditional probabilities, and further details and inference operation algorithms of the MBN can be found in Byun and Song (2021). By adopting the scenarios presented in Byun and Song (2021), the magnitude M is uniformly discretized into five states with 0.5 intervals that [6.0, 6.5), [6.5, 7.0), [7.0, 7.5), [7.5, 8.0), and [8.0, 8.5], which is assumed to follow the truncated exponential distribution (Cosentino et al., 1977)

$$f_M(m) = \frac{\beta \exp[-\beta(m_p - m_0)]}{1 - \exp[-\beta(m_p - m_0)]} \quad (8)$$

where the parameter β, and the minimum and the maximum magnitude m_0 and m_p are considered as 0.76, 6, and 8.5, respectively. On the other hand, the epicenter location L is assumed to follow the uniform distribution over five coordinates (5, 25), (10, 20), (15, 15), (20, 10), and (25, 5) km. For simplicity, V_{S30} and FT are respectively set as 760 m/s and strike-slip fault.

18 different building types idealized as bilinear SDOF systems in Goda and Hong (2008) are considered in this example. The buildings are associated with the HAZUS-Earthquake classifications (2003). Moreover, the three types of monetary seismic losses are also presented in Goda and Hong (2008). 10 BN models are constructed for each set of the structural status factor in Table 1.

Using the developed BN models and Eq. (7), the reliability (β) indices are calculated for 10 districts. As mentioned in Section 2.2, the recoverability (γ) indices are estimated based on the census data. In this study, we assume the recoverability indices using the dataset provided in Choi and Song (2022).

Figure 5 shows the β-γ relationship of the urban community comprised of 10 districts. l^2-norm of β and γ equals 0.95 is assumed to be a resilience limit-state. As can be seen, Districts (5), (7), and (10) satisfy the resilience limit-state, while the other seven districts cannot achieve the goal. In particular, there are two distinct districts in this example: Districts (1) and (10). District (1) has the highest reliability index among all districts but cannot achieve the resilience limit-state, whereas District (10) is the opposite. District (1) represents a newly constructed district but few social infrastructures are provided, while District (10) is the old urban area.

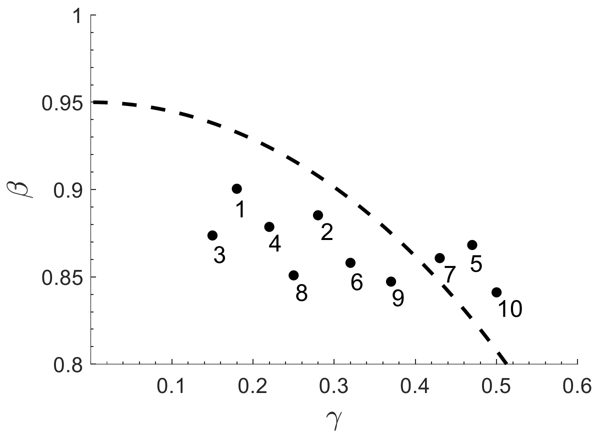

Figure 5: β-γ diagram of virtual city

There are two options to improve the resilience performance of the urban community under a limited retrofit budget. Following the seismic loss-based retrofit strategy, the lateral strength of the buildings in all districts will be reinforced to maximize the reliability indices (maximize the sum of the blue arrows in Figure 6). On the other hand, following the resilience-based retrofit strategy, buildings located in the district having relatively low socioeconomic performance will be reinforced to make the β-γ point close to the resilience limit-state (minimize the sum of the red arrows in Figure 7).

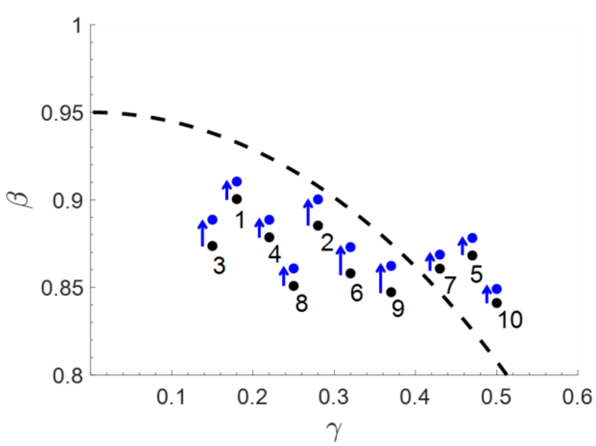

Figure 6: Seismic loss-based optimal retrofit strategy for virtual city

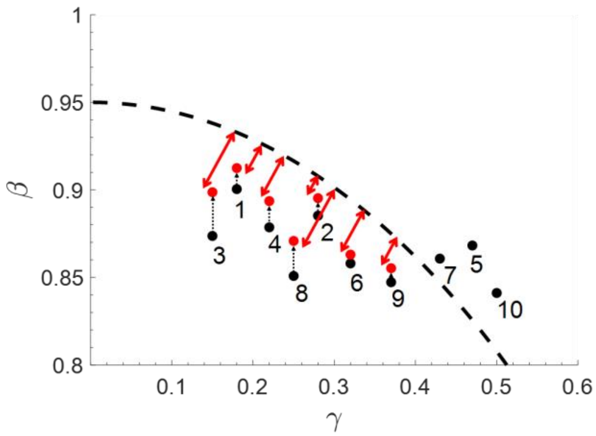

Figure 7: Resilience-based optimal retrofit strategy for virtual city

5. CONCLUSIONS

This study proposed a BN-based regional seismic resilience assessment framework to estimate regional economic losses. The BN model can properly assess the seismic resilience performance of the target district considering the level of deterioration. Using the developed BN model with the BRIC framework, reliability (β) and resilience (γ) indices for community resilience evaluation were introduced. β - γ diagram with a concept of resilience limit-state was proposed to support the resilience-informed decision-making process. To optimize the net resilience performance of the urban community, a resilience-based optimal retrofit strategy was proposed. A numerical example of the virtual urban community to investigate the proposed retrofit strategy.

6. ACKNOWLEDGEMENT

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7. REFERENCES

American Society of Civil Engineers. (2017). Seismic evaluation and retrofit of existing buildings. ASCE/SEI 41-17.

Boore, D. M., Atkinson, G. M. (2008). Ground-motion prediction equations for the average horizontal component of PGA, PGV, and 5%-damped PSA at spectral periods between 0.01 s and 10.0 s. Earthquake spectra, 24, 1, 99-138.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. Earthquake spectra, 19, 4, 733-752.

Byun, J. E., Song, J. (2021). Generalized matrix-based Bayesian network for multi-state systems. Reliability Engineering & System Safety, 211, 107468.

Chang, S. E., Shinozuka, M. (2004). Measuring improvements in the disaster resilience of communities. Earthquake spectra, 20, 3, 739-755.

Choi, E., Song, J. (2022). Clustering-based disaster resilience assessment of South Korea communities building portfolios using open GIS and census data. International Journal of Disaster Risk Reduction, 71, 102817.

Cutter, S., Burton, C. Emrich, C. (2010). Disaster Resilience Indicators for Benchmarking Baseline Conditions. Journal of Homeland Security and Emergency Management, 7, 1.

Cutter, S. L., Ash, K. D., Emrich, C. T. (2014). The geographies of community disaster resilience. Global environmental change, 29, 65-77.

Despotaki, V., Sousa, L., Burton, C. G. (2018). Using resilience indicators in the prediction of earthquake recovery. Earthquake Spectra, 34, 1, 265-282.

Goda, K., Hong, H. P. (2008). Spatial correlation of peak ground motions and response spectra. Bulletin of the Seismological Society of America, 98, 1, 354-365.

Federal Emergency Management Agency (FEMA) and the National Institute of Building Sciences (NIBS) (2003). HAZUS-Earthquake: technical manual. Washington, DC: FEMA and NIBS.

Koller, D., Friedman, N. (2009). Probabilistic graphical models: principles and techniques. MIT press.

Sutley, E., Hamideh, S., Dillard, M., Gu, D., Seong, K., van de Lindt, J. (2019). Integrative modeling of housing recovery as a physical, economic, and social process.