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A surrogate model-based framework for seismic resilience estimation of bridge transportation networks

Sungsik Yoon [1a] and Young-Joo Lee[*2]

[1] *Department of Artificial Intelligence, Hannam University, 70 Hannam-ro, Daedeok-Gu, Daejeon 34430, Republic of Korea*
[2] *Department of Urban and Environmental Engineering, Ulsan National Institute of Science and Technology, 50 UNIST-gil, Eonyang-eup, Ulju-gun, Ulsan 44919, Republic of Korea*

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Abstract. A bridge transportation network supplies products from various source nodes to destination nodes through bridge structures in a target region. However, recent frequent earthquakes have caused damage to bridge structures, resulting in extreme direct damage to the target area as well as indirect damage to other lifeline structures. Therefore, in this study, a surrogate model-based comprehensive framework to estimate the seismic resilience of bridge transportation networks is proposed. For this purpose, total system travel time (TSTT) is introduced for accurate performance indicator of the bridge transportation network, and an artificial neural network (ANN)-based surrogate model is constructed to reduce traffic analysis time for high-dimensional TSTT computation. The proposed framework includes procedures for constructing an ANN-based surrogate model to accelerate network performance computation, as well as conventional procedures such as direct Monte Carlo simulation (MCS) calculation and bridge restoration calculation. To demonstrate the proposed framework, Pohang bridge transportation network is reconstructed based on geographic information system (GIS) data, and an ANN model is constructed with the damage states of the transportation network and TSTT using the representative earthquake epicenter in the target area. For obtaining the seismic resilience curve of the Pohang region, five epicenters are considered, with earthquake magnitudes 6.0 to 8.0, and the direct and indirect damages of the bridge transportation network are evaluated. Thus, it is concluded that the proposed surrogate model-based framework can efficiently evaluate the seismic resilience of a high-dimensional bridge transportation network, and also it can be used for decision-making to minimize damage.

Keywords: artificial neural network; bridge transportation network; seismic resilience; surrogate model; total system travel time

1. Introduction

Recently, frequent natural disasters such as earthquakes have caused the collapse of critical lifeline infrastructures, such as water supply, gas, and bridge networks (Kang *et al.* 2017). Because complex lifeline infrastructures are densely constructed in urban area centers, earthquakes can cause widespread direct damage to the lifeline infrastructure itself, as well as indirect damage to other lifeline infrastructures. In particular, as lifeline infrastructures have a strong impact on the lives of local residents and the economic and industrial activities of the community, severe secondary damage can occur if main infrastructures are damaged by an earthquake. Therefore, various strategies or plans are needed to predict the performance of lifeline facilities and to reduce damage from earthquake disasters.

Bridge transportation networks allow the supply of products to various regions and enable inter-regional travel by connecting source and destination nodes in each region. Bridge structures play an important role in establishing rapid recovery strategies by enabling movement and access to various areas in emergency situations such as man-made hazards and natural disasters (Moomen and Siddiqui 2022). Historical earthquakes in the past, such as the Loma Prieta earthquake (1989), the Northridge earthquake (1994), and the Tohoku earthquake (2011), demonstrated significant reductions in the seismic resilience of bridge transport networks and other lifeline networks due to the deteriorated performance of bridge structures. For this reason, predicting the seismic performance and resilience of deteriorated bridge transportation networks and establishing a recovery strategy are crucial to reduce social disruption.

For this reason, various researchers have conducted research to predict the performance of critical lifeline infrastructures. For example, Yoon *et al.* (2018) introduced a comprehensive framework for seismic risk assessment of water transmission network by employing connectivity-based network analysis. Yoon *et al.* (2020a) proposed flow-based network analyses to evaluate the system- and nodal-serviceability measure of the water transmission network located in a city, South Korea. Nuti *et al.* (2007) and Lee *et al.* (2022) discussed methodologies for maximizing the seismic performance and minimizing the economic damage of an electric power network based on the flow analysis. In addition, Esposito *et al.* (2015) performed a seismic

*Corresponding author, Associate Professor,
E-mail: ylee@unist.ac.kr
[a] Assistant Professor, E-mail: sungsik@hnu.kr

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reliability analysis of a buried gas network in Italy, considering the performance of gas facilities such as metering stations and decompression stations. Dueñas-Osorio *et al*. (2007) quantitatively estimated the interdependency between a water transmission network and an electric power network, and evaluated the seismic performance of each network system according to the interdependency. For bridge transportation networks, Rokneddin *et al*. (2013) assessed the seismic risk of deteriorated highway bridge networks based on Markov Chain Monte Carlo (MCMC) and proposed a bridge retrofit strategy to optimize the performance of transportation networks. Lee *et al*. (2011) adopted matrix-based system reliability (MSR) and evaluated the maximum flow capacity of a bridge transportation network by considering the deterioration of the bridge structures.

In addition, recent research has been conducted to estimate the seismic resilience of critical lifeline infrastructures such as urban water transmission networks (Cimellaro *et al*. 2016, Yoon *et al*. 2021a), seaports (Shafieezadeh and Burden 2014), gas and power networks (Kammouh *et al*. 2018), and hospital networks (Cimellaro *et al*. 2010). For bridge transportation networks, Alipour and Shafei (2016) introduced an optimization algorithm that allocates the traffic volume differently between each origin-destination node considering deteriorated bridge structures. Using the proposed algorithm, they evaluated the seismic resilience curve, direct damage, and indirect damage of a bridge transportation network in California. In addition, Zhang *et al*. (2017) presented a methodology for reducing disaster damage of the bridge transportation network, and assessed a seismic resilience curve according to the recovery priority strategy of individual bridge structures. Moreover, Yoon *et al*. (2020c) introduced neural network-based surrogate model to accelerate system-level seismic risk assessment of bridge transportation network. Based on surrogate model, various epicenter and earthquake magnitudes were considered to evaluate performance of bridge transportation network. Then, Yoon *et al*. (2021b) proposed optimal solution of bridge recovery strategies in bridge transportation network under seismic conditions to evaluate the seismic resilience assessment of bridge transportation network.

However, in previous studies, relatively less accurate performance indicators, such as connectivity-based or maximum flow capacity, were utilized to evaluate the seismic performance of bridge transportation networks, and total system travel time (TSTT) was not introduced to accurately predict network performance. In addition, previous research methodologies have only been applied to low-dimensional networks with simple topology, without demonstration on complex lifeline networks. Moreover, previous studies adopted a naive region-based clustering algorithm to evaluate a seismic resilience curve, direct damage, and indirect damage according to the bridge restoration priority. Therefore, to accurately predict the seismic resilience of bridge transportation networks, a robust performance indicator, TSTT, should be introduced, and the proposed methodology needs to be demonstrated in high-dimensional lifeline networks.

In view of the above, a surrogate model-based comprehensive framework for the seismic resilience estimation of bridge transportation networks is proposed in this study. TSTT is adopted to accurately predict the performance of the road networks, and the excessive computation time cost of TSTT is reduced through an artificial neural network (ANN)-based surrogate model. In addition, the reduced traffic capacity is considered according to the damage state of the bridge structure, and the damage ratio, and required restoration days are examined. To demonstrate the proposed framework, the Pohang bridge transportation network is adopted, and the seismic resilience, direct damage, and indirect damage are compared considering historical earthquake.

2. Flow-based network performance measure

2.1 Ground motion prediction equation

Ground motion refers to a phenomenon in which energy is released as the stress condensed inside the earth is transmitted to the ground surface. The released energy causes various ground motions according to the geotechnical characteristics or propagation path. Because ground motion is transmitted by a physically complex mechanism, researchers have utilized a probability function to express the intensity of ground motion based on conditionally selected variables such as the characteristics of the source, propagation path, and geotechnical characteristics. To represent complex ground motion phenomena with simple mathematical expressions, a ground motion prediction equation (GMPE) is generally adopted to quantitatively predict the intensity of ground motions.

In this study, ground motion intensity is evaluated using the spectral acceleration (SA)-based GMPE proposed by Emolo *et al*. (2015). The GMPE is constructed using ground motion data measured in South Korea at 132 points for 222 historical earthquakes as follows

$$ln(SA_{ij}) = c_1 + c_2M_i + c_3ln\left(\sqrt{{R_{ij}}^2 + h^2}\right) + c_4R_{ij} + c_5s \tag{1}$$

where SA_{ij} denotes the spectral acceleration at specific site j from epicenter i, M_i denotes the earthquake magnitude at epicenter i, R_{ij} denotes the epicentral distance between epicenter i and specific site j, h denotes the focal depth, $c_1 - c_5$ denote the nonlinear regression coefficients, which are respectively assumed to be −5.15, 0.95, −0.92, −0.0003, and 0.208 in this study according to a previous study (Emolo *et al*. 2015), and s denotes the dummy variable which can be −1, 0, or, 1 depending on the station characteristics of the region and is assumed to be −1 in this study.

In addition, inter- and intra-event residual terms are considered for the uncertainty of ground motions that occur differently depending on the characteristics of ground motion itself or the propagation path of seismic waves. Typically, the ground motion uncertainty can be expressed in terms of ρ_{total} as

$$\rho_{total} = \frac{\sigma_{inter}{}^2}{\sigma_{inter}{}^2 + \sigma_{intra}{}^2} + \frac{\sigma_{intra}{}^2}{\sigma_{inter}{}^2 + \sigma_{intra}{}^2}\rho(D_{ij}) \quad (2)$$

where σ_{inter} is the uncertainty of ground motion due to inter-events, σ_{intra} is the uncertainty of ground motion due to intra-events, and $\rho(D_{ij})$ is a spatial correlation equation representing the spatial distribution of ground motion according to the seismic propagation path. In this study, the spatial correlation relation presented by Goda and Hong (2008) is adopted, and it can be expressed by the following equation

$$\rho(D_{ij}) = e^{(-0.509\sqrt{D})} \quad (3)$$

where D_{ij} represents the distance between specific site *j* and epicenter *i*.

2.2 Seismic fragility analysis of bridge structure

In Section 2.2, the failure probability of the bridge structure is calculated based on the intensity of ground motions determined in Section 2.1. The U.S. Federal Emergency Management Agency (FEMA) reports *SA* as the intensity measure that best expresses the seismic fragility curve of bridge structures, and classifies the failure probability of bridge structures into five damage states (No damage, slight damage, moderate damage, extensive damage, complete damage) (FEMA 2003). In particular, to represent the failure probability according to the structural characteristics of a bridge, failure probabilities for a total of 28 types of bridges are presented by adopting the following criteria: seismic design (conventional or seismic), number of spans (single or multiple), structure type (concrete, steel, or others), pier type (single or multiple), abutment and bearing type (monolithic or non-monolithic), and span continuity.

According to FEMA, the lognormal distribution curve has been reported to be the best predictor of the failure probability of bridge structures, and based on empirical data, FEMA provided two parameters (median and standard deviation) that determine the shape of the lognormal distribution curve for 28 bridge classes. Fig. 1 shows the examples of failure probabilities of RC slab bridges and PSC I bridges according to the damage states.

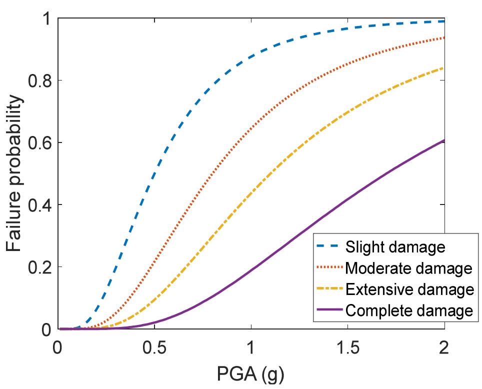
Table 1 Traffic capacity corresponding to damage states

Damage states	Traffic capacity
No damage (DS 1)	100%
Slight damage (DS 2)	75%
Moderate damage (DS 3)	50%
Extensive damage (DS 4)	25%
Complete damage (DS 5)	0%

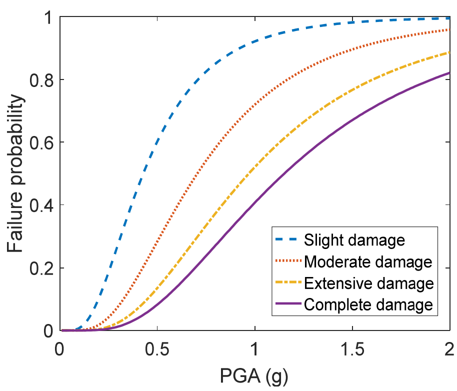
In this study, it is assumed that the vehicle traffic capacity of individual bridges decreases as the structural performance deteriorates to reflect the damage of bridge structures in the network analysis. For this purpose, the reduced traffic capacity is adopted to represent the performance degradation according to the damage states of individual bridge structures in the bridge transportation network. In previous studies, various researchers have tried to predict the reduced traffic volume due to bridge damage (Murachi *et al.* 2003, Mackie and Stojadinovic 2006). In this study, based on previous studies, quarter-based reduced traffic capacity is adopted according to the five damage states of the bridge structure, which reduced the traffic volume by 25% by comparing the no damage state with 100% traffic volume. Table 1 lists the reduced traffic capacity according to the five damage states of the individual bridge structures.

2.3 Restoration of bridge structure

When the damage states of bridge structures are identified, the seismic resilience curve of the bridge transportation network can be evaluated by considering the damage ratio and required restoration days of the individual bridge structures. Numerous studies have been conducted to predict the extent of damage and time required for bridge structure restoration using past earthquake data and numerical analysis models based on field survey data (Porter 2004, Padgett and DesRoches 2007) and mathematical equations (Shinozuka *et al.* 2003, Bocchini and Frangopol 2012). However, the proposed models have limitations in that they do not secure sufficient field survey data and do not reflect the characteristics of various bridges



(a)



(b)

Fig. 1 Failure probability examples of bridge structure (a) RC slab; (b) PSC I

Table 2 Damage ratio range, utilized damage ratio, and required restoration days of damaged bridge structures

Damage states	Damage ratio range	Utilized damage ratio	Restoration days
No damage (DS 1)	0	0	0
Slight damage (DS 2)	0.01~0.03	0.03	0.6
Moderate damage (DS 3)	0.02~0.15	0.15	2.5
Extensive damage (DS 4)	0.1~0.4	0.4	75
Complete damage (DS 5)	0.3~1.0	1.0	230

(bridge material, type, seismic design, etc.). For this reason, this study adopted the bridge restoration function proposed by the Applied Technical Committee (ATC) based on the reported bridge damage and number of days required for restoration after the California earthquake (ATC 1985). The proposed damage ratio and required restorations days for each damage condition are adopted as basic data for the HAZUS-HM program. Table 2 shows the range of the damage ratios, utilized damage ratios, and required restoration days.

2.4 Flow-based network performance indicator

In a bridge transportation network, the network performance is evaluated through the connectivity or flow capacity between various nodes of the target network. Typically, the performance of a bridge transportation network can be evaluated using the following three performance indicators: i) connectivity, ii) maximum flow capacity, and iii) TSTT. Connectivity and maximum flow capacity can be relatively inaccurate because the network analysis is too simplified, whereas a TSTT-based network analysis can provide more accurate network performance results; however, the computational cost of the network analysis is relatively high because it requires sophisticated traffic analysis. Therefore, the determination of an appropriate performance indicator based on the purpose of the network analysis is important.

In this study, TSTT is adopted as a network performance indicator, and a surrogate model is constructed to reduce the computational cost. In addition, the Emme4 software is introduced to identify the optimized traffic volumes at a macro level. Emme4 can build a transportation network model through four procedures (model creation, traffic distribution, transportation mode selection, and network assignment) and enables advanced travel demand modeling to predict and analyze traffic in the target network (Florian 2014). The TSTT of the target network can be calculated as the travel time between all the nodes in a network and can be expressed through the following equation

$$TSTT = \sum_{k=1}^{N} RTV_k RT_k \tag{4}$$

where N is the total number of links in a network, ATV_k is the available traffic volume on the kth link, and RT_k is the time required to pass the kth link, which can be calculated from the results of traffic analysis. When the traffic capacity decreases owing to bridge damage, the RT_k increases and eventually the TSTT of the target network increases.

3. Surrogate model-based seismic resilience estimation

3.1 Conventional Monte Carlo analysis-based direct calculation

Fig. 2 shows the conventional Monte Carlo analysis-based direct calculation method for evaluating the performance of a bridge transportation network. For network analysis, a network map must be constructed first using geographic information system (GIS) information (nodes, links, node connectivity, etc.) of the bridge transportation network. For traffic analysis, the characteristics of the bridges and passing vehicles (lane, type of passing vehicle, and speed limit) must be appropriately implemented. When a network map is constructed, the location of the epicenter and earthquake magnitude are identified, and the ground intensity at the location of the bridge structure is evaluated using the GMPE with spatial correlation.

Once the ground motion of the target network is determined, the failure probabilities of the bridge structures according to the damage states are calculated based on seismic fragility curves. Then, the damage states of bridge structures can be determined through N random samples, each of which contains a number between 0 and 1, and by

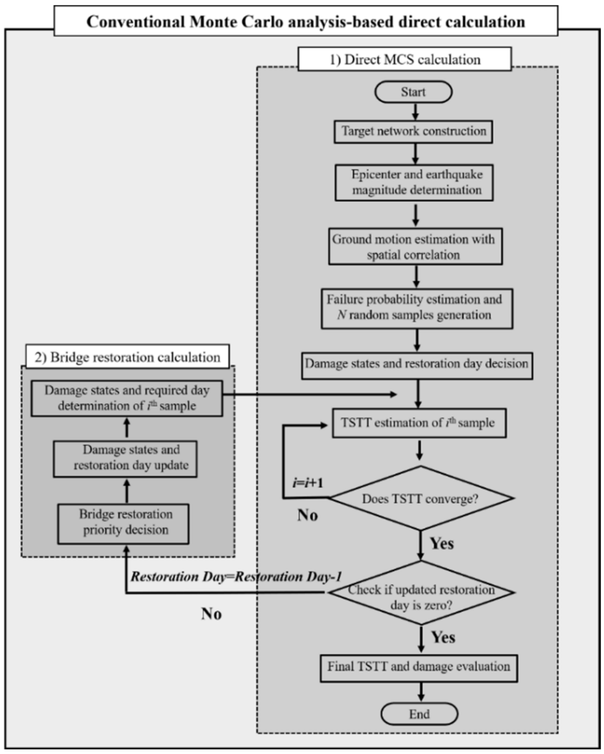


Fig. 2 Flow chart of conventional Monte Carlo analysis-based direct calculation

comparing the random samples with the failure probabilities. When the damage states of the individual bridge structures and the corresponding required restoration days are determined, for each sample, a traffic analysis using Emme4 is performed to calculate the performance of the target network in terms of the TSTT. Based on the calculated TSTT results, the TSTT convergence can be determined. If the TSTT up to the *i*th does not converge, the (*i*+*1*)th sample is added and the corresponding TSTT is computed. This iterative procedure continues until the TSTT converges.

The next procedure is the bridge restoration calculation. Because the required restoration days have already been determined according to the damage states, they are updated according to the restoration priority of the bridge structure. If the corresponding damage state is determined according to the updated required restoration days, the TSTT for the next day can be calculated. When the number of required restoration days updated for all bridge structures becomes 0, restoration of the bridge structure is completed, and the final TSTT, direct damage, and indirect damage are calculated, and the entire algorithm is terminated.

3.2 ANN-based surrogate model construction

ANN is one of the artificial intelligence techniques developed based on the structure of human neurons and derives mathematical relationships between input and output layers through hidden layers and neurons. The technique has been utilized in various fields of civil infrastructure because it is not only fast in computation time but also infers mathematical relationships easily based on simple input and output data. ANN has been utilized in various fields of civil infrastructure such as structural control (Akin and Sahin 2017), structural health monitoring (Asteris *et al*. 2022, Moayedi *et al*. 2022, Almashaqbeh *et al*. 2022), damage detection (Nguyen and Livaoglu 2021, Madenci and Özkılıç 2021, Nguyen *et al*. 2019, Peng-hui *et al*. 2015), and response prediction (Christopher *et al*. 2023, Zha *et al*. 2022, Onat and Gul 2018, Yoon *et al*. 2020b, Shahbazi *et al*. 2014). For this reason, in this study, ANN is adopted to accelerate seismic risk assessment and seismic resilience estimation of the bridge transportation network.

As described in Section 3.1, in the conventional approach based on a Monte Carlo analysis, the TSTT of N samples must be calculated iteratively until the TSTT of all samples converges. In addition, the TSTT of the next day must be calculated when the required restoration days for each sample are updated. In this study, therefore, an ANN-based surrogate model for the seismic resilience estimation of bridge transportation network is proposed to reduce the computational time cost for TSTT evaluation in this study. Using the proposed ANN-based surrogate model, the mean TSTT according to the restoration of individual bridge structures and the converged mean TSTT of the bridge transport network can be calculated.

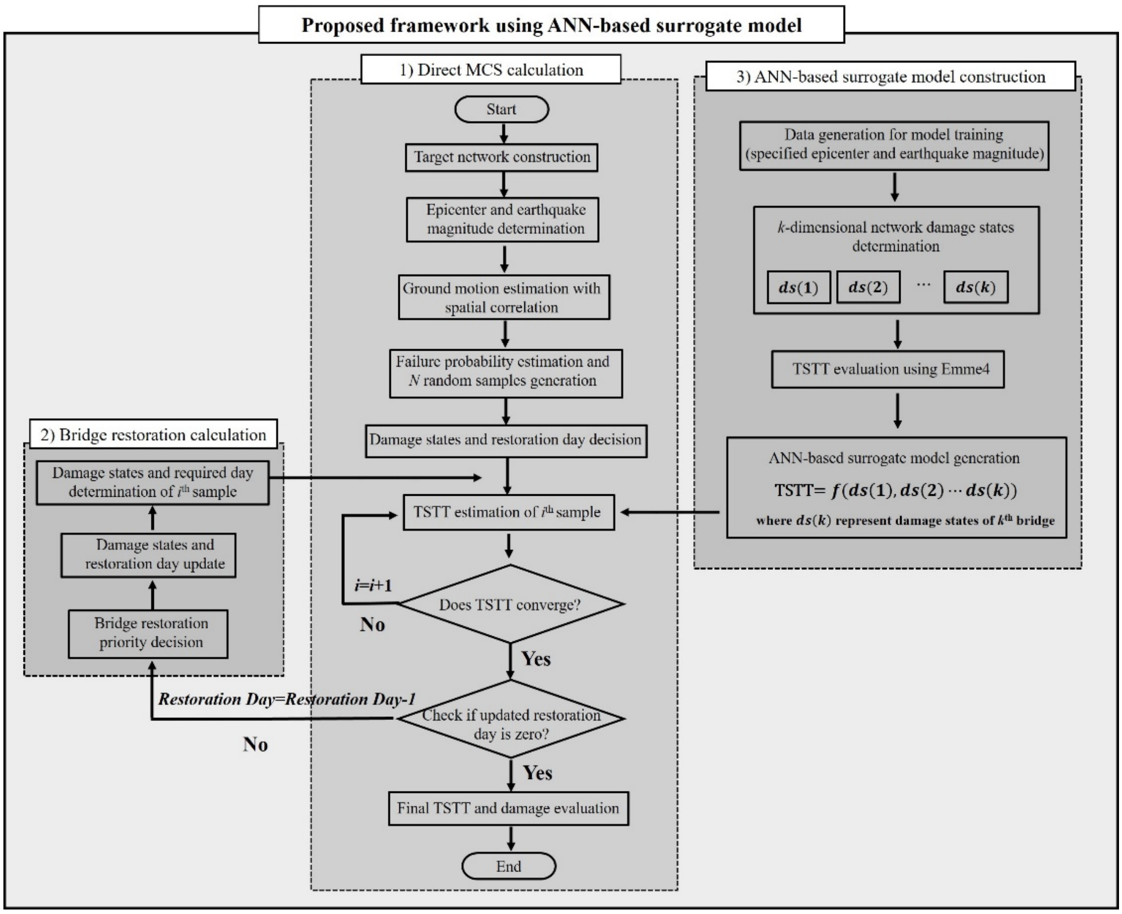


Fig. 3 Flow chart of proposed framework using ANN-based surrogate model

Fig. 3 shows the overall flow chart of the proposed framework using an ANN-based surrogate model to accelerate the performance evaluation of bridge transportation networks. Compared to Fig. 2, 1) the direct Monte Carlo simulation (MCS) calculation part and 2) the bridge restoration calculation part are identical, but 3) ANN-based surrogate model is additionally considered. First, the epicenter and earthquake magnitude must be determined to generate the training data for the surrogate model. From the determined epicenter, the damage states of the k-dimensional bridge are determined, and the corresponding TSTT can be calculated through traffic analysis in Emme4. In this study, a surrogate model is constructed using the damage state of a k-dimensional bridge structure as input data and TSTT as output data. The constructed surrogate model can be utilized to accelerate the TSTT calculation according to the damage states of the bridge for an arbitrary epicenter in the direct MCS calculation.

4. Numerical demonstration

4.1 Target bridge transportation network

To demonstrate the proposed framework, an actual transportation network in Pohang City was introduced. The target area is located in the southeast of South Korea, and in 2017, a magnitude 5.4 earthquake occurred, arousing interest in seismic performance assessment. South Korea has been recognized as a safe region from earthquakes in the past, but owing to the earthquakes that occurred in Gyeongju in 2016 and Pohang in 2017, interest in seismic hazard analysis and seismic resilience analysis has been highlighted.

The Pohang bridge transportation network consists of 1,440 nodes and 3,940 links and includes 48 bridge structures, including highways and national roads. The 48 bridges consist of steel box (13%), Rahmen (17%), RC slab (45%), PSC (19%), and preflex (6%) depending on the superstructure type. The average span length is 102.4 m, the number of spans is 4, the average width is 17.2 m, and the average column height is 5.7 m.

Moreover, the traffic analysis of the bridge transportation network utilized information on the number of lanes, maximum travel speed, and types of passing vehicles of bridge structures in Pohang City. The average daily traffic capacity of bridges was statistically calculated based on the population data of Pohang City, and Fig. 4 shows the traffic volume capacity of each bridge used in this study. Furthermore, to predict the seismic resilience curve of Pohang bridge transportation network, the historical epicenters with a magnitude of 3.0 or greater are considered in the Pohang region. Fig. 5 shows the reconstructed bridge transportation network based on GIS data and the five representative epicenters considered from the historical earthquake data.

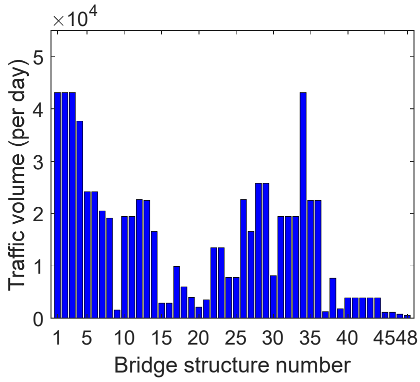


Fig. 4 Traffic volume capacity of each bridge structure

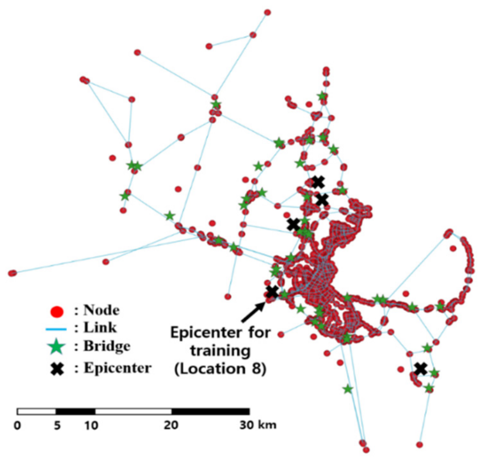


Fig. 5 Reconstructed Pohang bridge transportation network

4.2 ANN-based surrogate model construction

In this section, a surrogate model for predicting the TSTT performance of the Pohang bridge transportation network is described. A total of 100,000 TSTT data from epicenter location 8 and an earthquake magnitude of 7.0 (with a focal depth of 10 km) were utilized to generate training data for various damage states of bridge structures. Table 3 lists the training properties used to construct an ANN-based surrogate model. To prevent overfitting and underfitting of the trained model, 10,000 epochs were considered, and the surrogate model was trained by separating the ratio of training data, test data, and validation data to 0.7:0.15:0.15. Moreover, the accuracy of the training model was improved by setting the number of layers and neurons to 25, learning rate to 0.01, error tolerance to 0.00001, and momentum constant to 0.9. The training model parameters used in this example were determined through trial-and-error procedures, and a mathematical function was constructed to generate one TSTT output from 48 input data of bridge damage states.

Fig. 6 shows the mean square error values of the training, validation, and test data according to epochs for training the surrogate model. In this study, 10,000 epochs were used to avoid overfitting and underfitting, and the minimum error occurred at epoch 9,787. Fig. 7 shows the correlation coefficients for the training, validation, test, and all datasets of the surrogate model. The training results showed that the correlation coefficient was 0.98 for all data. The closer the correlation coefficient is to 1, the smaller is the error between the predicted and observed TSTTs, which

Table 3 Training properties for ANN-based surrogate model

Network type	Feed-forward back propagation
Transfer function	Hyperbolic tangent sigmoid transfer function
Training function	Scaled conjugate gradient backpropagation
Performance function	Mean Squared Error (MSE)
Adaption learning function	Gradient descent with momentum weight and bias learning function
Network dimensions (output)	48 (1)
Number of layers	25
Number of neurons	25

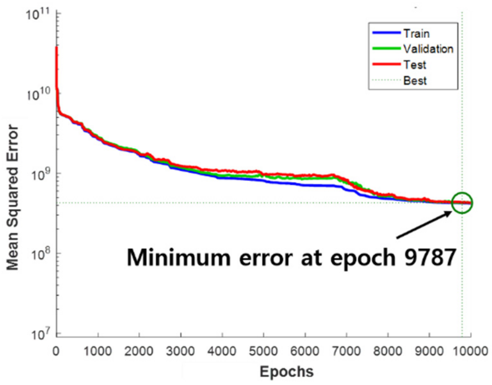


Fig. 6 Mean squared error of trained model

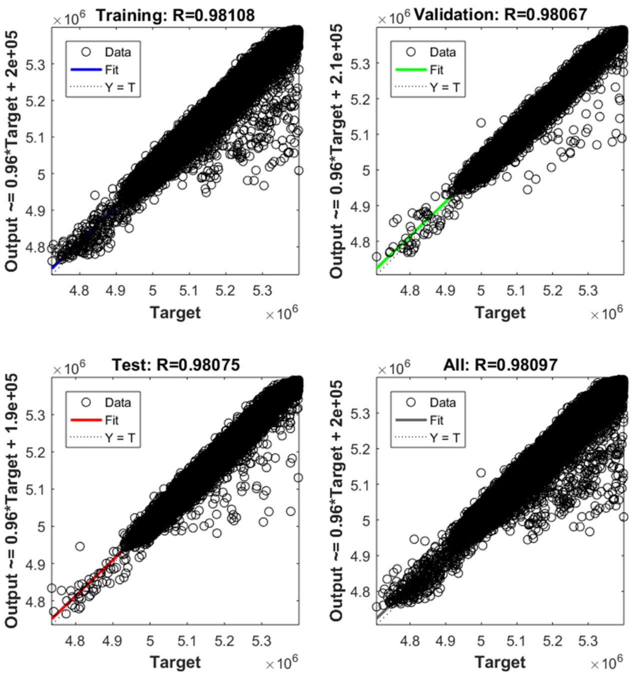


Fig. 7 Correlation coefficients for all datasets

means that the accuracy of the surrogate model was sufficiently high. In addition, it took approximately 2 seconds per each TSTT calculation using Emme4, and the iteration for full convergence required to calculate the TSTT for each scenario was 50 times, approximately 2 minutes. On the other hand, the ANN-based model calculates the

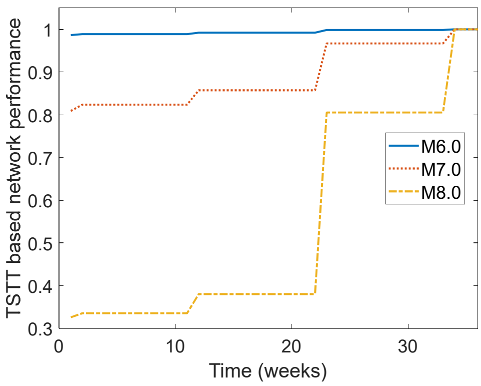


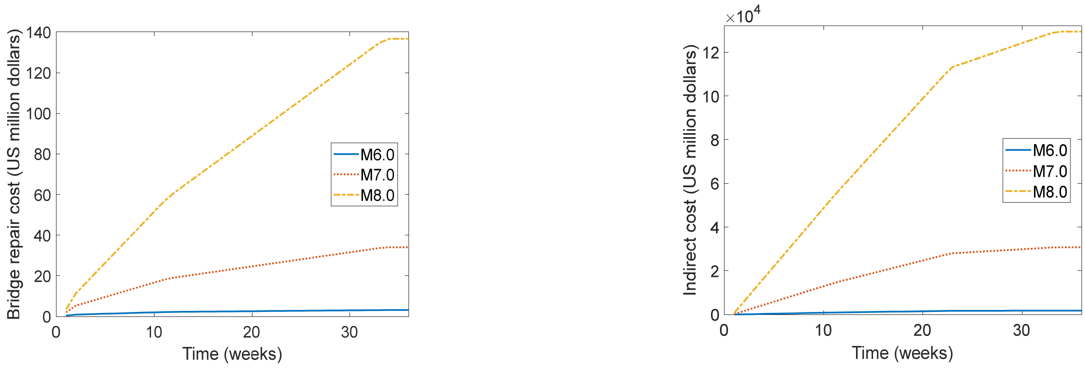
Fig. 8 Seismic resilience curve of Pohang bridge transportation network

TSTT of each scenario within seconds, enabling accelerated computational time cost for seismic risk assessment.

4.3 Seismic resilience curve and damage estimation

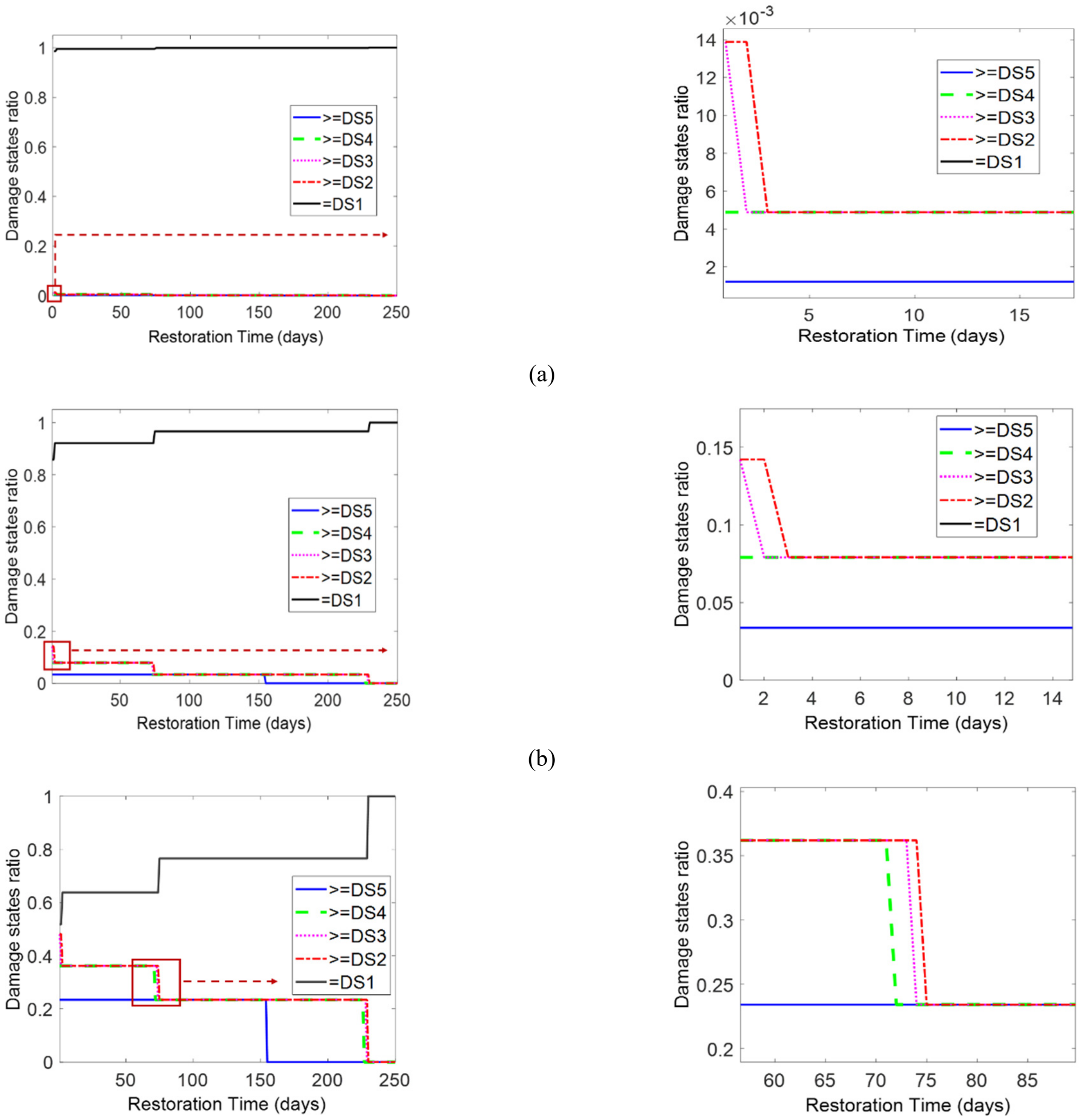
In this section, the seismic resilience curve, direct damage, and indirect damage of the Pohang bridge transportation network are evaluated considering the historical earthquake epicenters shown in Fig. 5. The TSTT performance of the bridge transportation network was calculated using the ANN-based surrogate model described in Section 4.2, and the intact state performance was set to 1 to show relatively degraded TSTT performance.

Fig. 8 shows seismic resilience curves when earthquakes of magnitude 6.0 to 8.0 occurred at the five epicenters. When the earthquake magnitude was 6.0, the damage states of the 48 bridges were almost intact, and the network performance decreased by only approximately 2% immediately after the earthquake. In particular, as shown in Table 2, when slight or moderate damage to a bridge occurred, the required restoration time of the bridge was less than three days, so the network performance was restored rapidly. However, as the earthquake magnitude increased to 7.0 and 8.0, the network performance immediately after the earthquake decreased by 20% and 70%, respectively. In addition, more restoration days were required as the ratio of bridges with extensive and complete damage increased. Moreover, as the bridge traffic capacity increased as individual bridges were restored, at 11 weeks (from extensive damage to no damage), 22 weeks (from



(a) (b)

Fig. 9 Cumulative damage of target network: (a) direct damage; and (b) indirect damage



(a)

(b)

(c)

Fig. 10 Damage state ratio of entire bridges with earthquakes of magnitudes (a) 6.0; (b) 7.0; and (c) 8.0

complete damage to extensive or lower damage), and 32 weeks (from complete damage to no damage), network performance jumped in the resilience curves were examined.

Fig. 9 shows the estimated cumulative direct and indirect damages in the Pohang region according to the seismic resilience curve of the bridge transportation network. For direct damage, the cumulative damage was calculated by considering the damage ratio for each damage state and the construction cost of the individual bridges. On the other hand, indirect damage was calculated by converting the performance degradation of the entire network to economic damage, and indirect damage can be calculated through the following equation

$$ID_i = TD_i \times VOT \times ADT \quad (5)$$

where ID_i is the indirect damage on the *i*th recovery day, TD_i is the time delay of the TSTT on the *i*th recovery day, ADT is the average traffic volume per day (in this study ADT is assumed to be 5000), and VOT is the economic damage caused by travel time delay. VOT represents the drivers' time loss index caused by detouring the travel route owing to bridge construction (Daniels *et al*. 2000). In this example, VOT was set to be 20.63 dollars per hour, which was determined based on research on road traffic volume and time delay in South Korea (Choi *et al*. 2007).

When the earthquake magnitude was 6.0, the bridge damages were minor overall, and the cumulative direct and indirect damages were smaller than 3.6 million dollars and 1.8 billion dollars, respectively. However, as the earthquake magnitude increased to 7.0 and 8.0, it was observed that the costs of direct and indirect damages increased exponentially. In addition, the increasing rate of the economic cost was most severe immediately after the earthquake, and the slopes of the direct and indirect costs gradually decreased as the individual bridges were restored.

Fig. 10 shows the damage state ratio of bridge structures when an earthquake of magnitude 6.0 to 8.0 occurs. With a 6.0 magnitude earthquake, most of the bridges were at the state of no damage (DS1), and the damaged bridges were quickly restored to the intact states as bridge restoration was initiated.

However, when the earthquake magnitude was 7.0, it was observed that approximately 15% of the bridges were damaged, and Fig. 10(b) shows that the damage ratio owing to slight damage (DS 2) was almost zero. In addition, the damage ratio of no damage gradually increased as bridges with slight and moderate damage were restored. As the damage state of the individual bridges were restored, the bridge damage ratio gradually decreased. Finally, the no damage states ratio converged to 1 as the completely damaged bridges were fully restored. Moreover, when the earthquake magnitude was 8.0, the ratio of no damage bridges decreased rapidly by 50% immediately after the earthquake, indicating that the trend of the damage ratio curve was similar to that with a 7.0 magnitude earthquake.

5. Conclusions

In this study, a comprehensive framework for the surrogate model-based seismic resilience estimation of bridge transportation network has been proposed. The proposed methodology consists of three steps: i) direct MCS calculation step, ii) bridge restoration calculation step, which is a conventional direct MCS calculation method, and iii) an ANN-based surrogate model construction step. In the proposed methodology, the TSTT is introduced as a performance indicator to predict the accurate performance of the target network, and a surrogate model is constructed to reduce the computational time cost of the TSTT-based network analysis, which increases the efficiency of an iterative MCS calculation. In addition, the proposed framework includes a methodology for predicting changes in the seismic resilience curve and direct and indirect damages of the bridge transportation network considering the restoration of individual bridge structures.

To demonstrate the proposed framework, the Pohang bridge transportation network, consisting of 1,440 nodes, 3,940 links, and 48 bridges, was introduced as a numerical example. To accelerate the computation of the TSTT, an ANN-based surrogate model is constructed with 100,000 data was constructed by using the damage states of the bridges and the corresponding TSTT as inputs and outputs. In addition, considering the five epicenters of historical earthquakes provided by the Korea Meteorological Association (KMA), the seismic resilience curve, direct damage, and indirect damage of the target network were evaluated according to the earthquake magnitude.

The methodology proposed in this study can be extended to evaluate the seismic resilience of other lifeline networks and can be applied to evaluate interactions and performance changes of interdependent lifeline networks. Thus, it can be concluded that the proposed framework can be useful for efficient disaster policy or optimal decision-making for maintenance and recovery strategies of integrated lifeline networks.

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