# Optimizing Seismic Retrofit of Bridges: Integrating Efficient Graph Neural Network Surrogates and Transportation Equity


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## ABSTRACT

Natural hazards can substantially damage bridge networks. Therefore to protect these lifelines, a bridge maintenance and retrofit strategy is imperative. To prepare for earthquakes in particular, conventional methods for seismic risk analysis needs to calculate network response which is a computationally intensive process. This prevents the optimal bridge maintenance for seismic events from being widely done for large networks. Also, it is critical to integrate measures of equity in these optimal asset management solutions to ensure equitable post-disaster access to mobility across all income levels. In this study, we propose a graph neural network (GNN) surrogate model for rapid estimation of transportation performance and a bridge maintenance optimization framework that considers network connectivity and equity measures. The proposed multi-objective optimization, via genetic algorithm with graph neural network surrogates, identifies the optimal bridge retrofit strategies constrained by a retrofit budget. The efficacy and accuracy of the proposed algorithm are demonstrated using a road network in the California Bay Area as a case study. Also, it will be shown that integrating income disparities in the region into the optimization framework can lead to improved transportation equity measures.



## CCS CONCEPTS

• **Applied computing → Transportation**.

## KEYWORDS

infrastructure, equity, bridge retrofit, graph neural network

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## 1 INTRODUCTION

The transportation system, as one of the sixteen critical infrastructure systems [1], plays a significant role in integrating other lifelines and facilitating recovery after natural hazards [2]. Bridges, as fundamental components of transportation systems, are widely regarded as the most vulnerable elements; they are exposed to aging, flood, and seismic damage. Retrofitting bridges can be an expensive and time-consuming endeavor, making it imperative to optimize the retrofit strategy for a network with multiple bridges before seismic events. Various bridge seismic retrofit prioritization approaches have been proposed in the literature. They can be categorized into heuristic and optimization-based approaches [2, 7]. The heuristic approaches utilize bridge importance measurements obtained from bridge characteristics [13] to select the bridges to be retrofitted. Although a heuristic approach is straightforward and easy to implement, it requires substantial computational resources and neglects retrofit budget constraints and bridge retrofit effects.

Optimization-based approaches, on the other hand, aim to optimize customized objective functions, thereby yielding optimal retrofit plans. The objective function for transportation networks can be divided into two broad categories: connectivity-based and traffic-based metrics. The connectivity-based approach optimizes the post-earthquake transportation system completeness [14]. However, the connectivity-based metric ignores the traffic flow performance after natural hazards, leading to the consideration of traffic-based metrics using origin-destination (OD) demand. These traffic-based methods provide information about post-disaster link flow-capacity ratio, and total system travel time [17]. Additionally, when considering multi-objective optimization, genetic algorithms (GAs) are widely used as the metaheuristic search algorithm for bridge retrofit optimization to determine optimal retrofit plans [7].

These aforementioned approaches are not suitable for large-scale bridge networks due to the high computational cost [5]. As a solution, neural network (NN) surrogates are proposed to approximate the network response that is expensive to compute in the objective functions. For example, a surrogate model using conventional fully-connected networks (FCNs) has been developed to take fixed-size inputs such as link failure probabilities and node connectivity characteristics to make predictions [17]. These kinds of surrogates have limited applicability. In particular, FCNs cannot be used when the graph topology changes since the input dimension changes. To allow for the flexibility for various graph topologies, we propose a graph neural network (GNN) based surrogate model and apply it to predict transportation network performance. GNNs aggregate node features and edge features by recursively passing neural messages along the edges [20]. Compared to feed-forward neural networks, GNNs are capable of effectively capturing the local and global structure of graphs [12], making them well-suited for applications such as node-level and link-level prediction in transportation systems.

Another important aspect of bridge network maintenance optimization is to take social equity into the decision making process.



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Typically, the performance of transportation systems is evaluated based primarily on traffic speeds and delays, which favors high-income communities with vehicles over low-income communities [3]. Recently, discrepancies in access to resources among different income classes have received growing attention. An equitable transportation system needs to satisfy different stakeholders for their unique needs [11]. Transportation equity can be categorized into horizontal equity, and vertical equity [11]. Horizontal equity is referred to the equal distribution of resources among equal members of the population. For instance, all residents should have the same level of access to hospitals after an earthquake. Vertical equity is more concerned with the distribution of resources among different people. For instance, residents with more severe injuries and lower incomes should receive higher attention from medical resources. The absence of social equity after natural hazards could affect transportation systems [3]. Despite its importance, the consideration of social equity in transportation decision-making under seismic damage is often underrepresented in the literature.

In this paper, we propose a computationally efficient optimization methodology for equitable maintenance management of a regional bridge network subject to seismic hazards. The major contributions of this work are as follows: (1) the proposed framework optimizes multiple objectives considering both equity-based connectivity improvement and traffic congestion cost; (2) a graph neural network surrogate model is proposed to replace the computationally intensive network response evaluation; (3) a GA-GNN algorithm is proposed for solving the optimization, which combines the GNN surrogates with genetic algorithm to find the optimal bridge retrofit strategy. Via numerical experiments, we show that the proposed framework can effectively accelerate the decision-making process using a case study of highway bridge networks in the California Bay Area. We will also demonstrate when social equity metrics and income disparities are integrated, it will improve transportation performance and support low-income communities.

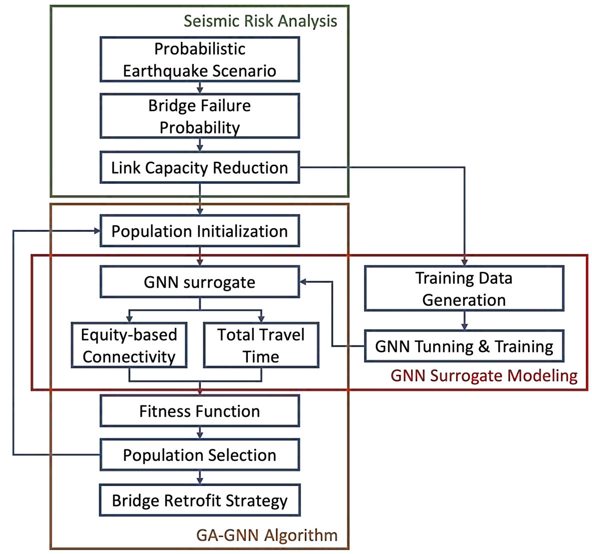



**Figure 1: Methodology Framework.**

## 2 METHODOLOGY

The proposed bridge retrofit framework is threefold, as shown in Figure 1. The first step is to conduct the regional seismic risk analysis, where the seismic damage of bridges and road capacities are calculated. The second step is to train the GNN surrogate to calculate transportation network performance. Two separated surrogates for objective function are trained; one for the equity-based connectivity measure and the other one for the calculation of the total system travel time. The last step is to find the optimal bridge retrofit strategy using the GA-GNN algorithm.

### 2.1 Seismic Risk Analysis

The first step of seismic risk analysis is to generate probabilistic earthquake scenarios, which are calculated by the ground motion prediction equations (GMPEs). GMPEs predict the characteristics of ground motion, including peak ground acceleration (PGA), spectral acceleration, and its associated uncertainty at each bridge site. This study adopts the Graizer-Kalkan GMPE (GK15) and PGA in logarithmic scale is represented as follows:

$$\ln(\mathrm{PGA}) = \ln(G_1)+\ln(G_2)+\ln(G_3)+\ln(G_4)+\ln(G_5)+\sigma_{\ln(\mathrm{PGA})}, \quad (1)$$

where $G_1$ is the scaling function for magnitude and faulting, $G_2$ models the ground-motion distance attenuation, $G_3$ adjusts the distance attenuation rate, $G_4$ models the site amplification factor, $G_5$ is a basin scaling function, and $\sigma_{\ln(\mathrm{PGA})}$ represents variability in the ground motion. The failure probability of bridge $i \in \mathcal{I}$ under intensity measure $im \in \mathcal{M}$ is computed using the fragility function from HAZUS-HM [10] as follows:

$$P(DS_i \geq ds_h | IM_i = im) = \Phi((\ln(y/\alpha_i \theta_{i,h}))/(\beta_{i,h})), \quad (2)$$

where $DS_i$ and $IM_i$ denote the damage state and intensity measure of bridge $i$. $ds_h \in \{1, \ldots, 5\}$ represents the damage state including none, slight, moderate, extensive, and complete damage. $\Phi$ represents the standard normal distribution CDF. $\theta_{i,h}$ and $\beta_{i,h}$ denote the median and the dispersion of $\ln IM$. $\alpha_i$ is the improvement factor that indicates retrofitting action, $\alpha = 1.25$ if retrofit and $\alpha = 1$ if no action [2]. In this work, we assume the capacity of bridges is reduced when the damage state is aggravated, as commonly considered in the literature [21]. The link capacity will be reduced to 75%, 50%, and 25% of the original capacity if the most damaged bridge on that link is subject to slight, moderate, and extensive damage, respectively. And the bridge will stop functioning and be considered disconnected when beyond the extensive damage.

### 2.2 Equity-Based Connectivity Improvement

A multi-objective optimization is proposed for bridge retrofit optimization. The objective functions measure cost and connectivity benefits, which are explained in the following sections. In this section, we present the equity-based connectivity measure. In particular, if path $l$ between source node $s$ and the target node $t$ contains $m_{s,t}$ bridges, the survival probability of the path $l$ can be given by:

$$p_{s,t,l} = \prod_{j=1}^{m_{s,t}} (1 - p_{s,t,l,j}), \quad (3)$$

where $p_{s,t,l,j}$ is the probability of $j^{\text{th}}$ bridge exceeding extensive damage according to Equation 2. The node-to-node connectivity probability can then be calculated using Monte Carlo Simulation (MCS) [12]. The node-to-node connectivity between $s$ and $t$ for realization $m$, $p^m_{s,t}$ will be 0 if all paths between $s$ and $t$ are disconnected, and otherwise $p^m_{s,t}$ is equal to 1. The connectivity probability is calculated with $N_{mc}$ realizations:

$$P_{s,t} = \frac{1}{N_{mc}} \sum_{m=1}^{N_{mc}} p^m_{s,t}. \tag{4}$$

The consequences of seismic events on regional connectivity can result in a disruption of access to critical locations, such as hospitals and airports. Thus, it is significant to include the impact of transport externalities on low-income communities and establish a more comprehensive vision of transportation equity. The transportation equity after seismic damages can be analyzed from two perspectives. On the one hand, all the locations should have some level of connectivity to critical locations. This is aligned with horizontal equity and can be measured by the Gini Index $GI$ [4]. In this paper, we use $f_h$, improvement of the Gini Index after a retrofit action under seismic damages to evaluate the effect of retrofit, as

$$f_h = \mathbb{E}\left[\frac{|GI - GI^o|}{GI^o}|im\right] = \sum_{m=1}^{N_{eq}} \alpha(im_m)\frac{\left|GI_m - GI^o_m\right|}{GI^o_m}, \tag{5}$$

where $N_{eq}$ is the number of earthquake scenarios, $GI_m$ and $GI_{m,o}$ denotes the Gini Index under the case with and without retrofit subject to seismic scenario $m$. $\alpha(im_m)$ represents the earthquake occurrence probability. On the other hand, the seismic impact on mobility and access of low-income communities is arguably more severe. Thus, there should be more emphasis on maintaining connectivity between low-income communities and critical locations. In this paper, we use weighted node-to-node connectivity $f_v$ to evaluate the connectivity improvement of vertical equity:

$$\begin{aligned} f_v &= \mathbb{E}\left[\sum_{j\in\mathcal{N}}\sum_{t\in\mathcal{T}} \beta_j \frac{\left|p_{j,t} - p^o_{j,t}\right|}{p^o_{j,t}}|im\right] \\ &= \sum_{m=1}^{N_{eq}}\sum_{j\in\mathcal{N}}\sum_{t\in\mathcal{T}} \alpha(im_m)\frac{\beta_j}{|\mathcal{N}|\times|\mathcal{T}|}\frac{\left|p^m_{j,t} - p^{m,o}_{j,t}\right|}{p^{m,o}_{j,t}}, \end{aligned} \tag{6}$$

where $p^{m,o}_{j,t}$ and $p^m_{j,t}$ denote the connectivity probability between node $j \in \mathcal{N}$ and target node $t \in \mathcal{T}$ before and after bridge retrofits under earthquake scenario $m$. $\beta_j$ characterizes the income factor for node $j$. Higher $\beta_j$ indicates more emphasis should be given to the lower-income class of community $j$.

## 2.3 Cost of Road Network Performance

The total cost function consists of direct costs $C_d$, associated with the retrofit process, and indirect costs $C_{id}$ associated with the traffic delays due to the traffic capacity reduction. The direct retrofit cost is given by

$$C_d = \sum_{i\in\mathcal{I}} \mu_i \times RUC \times A_i \times \xi, \tag{7}$$

where $\mu_i$ is a binary indicator of whether the bridge is repaired. $RUC$ is the replacement unit cost as 292 \$/ft$^2$ according to Federal Highway Administration [9], $A_i$ is the bridge area and $\xi$ is the mean retrofit cost ratio as 25% [2]. The indirect cost refers to the economic loss due to increased system travel time compared with the non-seismic scenario. The total system travel time $TSTT$ is calculated using static traffic assignment (STA) which is an equilibrium state, where no traveler can reduce their travel time by changing their route unilaterally. The link travel time $t_e$ on specific link $e \in \mathcal{E}$ is calculated based on the Bureau of Public Roads (BPR) function as a function of flow-capacity ratio $\delta_e = f_e/c_e$:

$$t_e = t_e(f_e/c_e) = t_{e,0}(1 + 0.15(f_e/c_e)^4), \tag{8}$$

where $t_{e,0}$, $f_e$ and $c_e$ are the free flow travel time, actual flow and the capacity of link $e$, respectively. In each iteration, the $f_e$ and $t_e$ are updated based on the current flow and shortest path between the origin and destination. The total system travel time $TSTT$ under static user equilibrium is calculated by:

$$TSTT = \sum_{e\in\mathcal{E}} \int_0^{f_e} t_e(w)\mathrm{d}w = \sum_{e\in\mathcal{E}} f_e t_e(\delta_e). \tag{9}$$

The indirect cost could be calculated as a function of the unit value of time $\gamma$ and $\Delta TSTT$:

$$C_{id} = T \times \gamma \times \Delta TSTT, \tag{10}$$

where $T$ is the time period measuring damage persists in the transportation network, which is chosen as 125 days. The unit value of time $\gamma$ can be estimated by calculating hourly median household income in California Bay Area, which is 48 \$ per hour [2].

## 2.4 Bridge Retrofit Problem under Budget Constraint

Given the selected earthquake scenarios $\mathcal{M}$ for transportation system $G$, the optimal retrofit strategy $\mu^*$ can be identified with the following optimization problem:

$$\max_{\mu} \quad f_h(\mu; G; \mathcal{M}) + f_v(\mu; G; \mathcal{M}) \tag{11}$$

$$\min_{\mu} \quad C_d(\mu; G) + C_{id}(\mu; G; \mathcal{M}) \tag{12}$$

$$\text{s.t.} \quad \mu_i = \begin{cases} 0 & \text{if not repair} \\ 1 & \text{otherwise} \end{cases} \quad i \in \mathcal{I} \tag{13}$$

$$\sum_{i\in\mathcal{I}} \mu_i \times RUC \times A_i \times \xi_i \leq B \tag{14}$$

Via Equation 11, we seek to maximize the equity-enhanced connectivity improvement, which is calculated using the Equation 5 and 6 from Section 2.2 with Monte Carlo Simulation. Via Equation 12, we aim to minimize the overall cost including the retrofit cost and the traffic delay cost using STA from Section 2.3. The constraint 14 imposes the budget restriction on the retrofit projects. As will be shown in the numerical example, the two objectives are competing, and there is no single best solution for this problem. Instead, a Pareto near-optimal set of solutions will be identified. In particular, to solve this optimization problem, we use a Non-dominated sorting genetic algorithm II for optimization [6]. However, the MCS and

STA in the objective function evaluation are computationally expensive [12, 17]. In this paper, we use two independent GNN surrogates that replace the most computationally expensive steps in the objective evaluation: the calculation of node-to-node connectivity and static traffic assignment.

## 2.5 Neural Network Surrogate for Traffic Performance Evaluation

Neural networks have been successfully used to approximate non-linear relationships [12, 14]. As a basic form for neural networks, the fully connected network (FCN) at layer $k$ is introduced. In this layer, FCN maps a $p$-dimensional input vector $h^k \in \mathbb{R}^p$ into $q$-dimensional the output $h^{k+1} \in \mathbb{R}^q$:

$$h^{k+1} = \sigma(h^k W_k + b_k), \tag{15}$$

where $W_k \in \mathbb{R}^{p \times q}$ and $b_k \in \mathbb{R}^{1 \times q}$ denote the weight and bias term, respectively. The function $\sigma(\cdot)$ is a nonlinear activation function. By stacking multiple layers, the capacity of neural networks can be readily increased. The neural network has shown promising accomplishments in computer vision, and natural language processing [18]. However, FCN cannot handle non-Euclidean data like graph data containing different topologies and relationships, which is more suitable for GNN. Compared with FCN, the GNN has an additional step to aggregate the node feature and edge feature along the edges of the input graph before being updated by FCN, which is called neural message passing. Mathematically speaking, the graph can be represented with $G = (V, E, X_v, X_e)$ where $V$ and $E$ denote node set and edge set. $X_v \in \mathbb{R}^{|V| \times F_v}$ and $X_e \in \mathbb{R}^{|E| \times F_e}$ represent the features corresponding to node $v \in V$ and edge $e \in E$, respectively. $|V|$ and $|E|$ denote the number of nodes and edges in the graph, $|F_v|$ and $|F_e|$ denote the dimension of features for each node and edge, respectively. In the aggregation stage of message passing, we aggregate the node features and edge features from neighbors, at layer $k = 0, \ldots, K-1$, where $K$ is the maximum aggregation step:

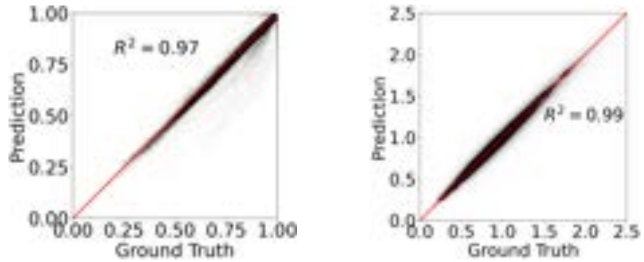
$$\begin{aligned} x_{\mathcal{N}(v)}^{k+1} &= f\left(\{x_u^k, \forall u \in \mathcal{N}(v)\}\right) && \forall v \in V, \\ x_{\mathcal{E}(v)}^{k+1} &= f\left(\{x_e^k, \forall e \in \mathcal{E}(v)\}\right) && \forall v \in V. \end{aligned} \tag{16}$$

where $f$ is the aggregation function, here chosen to be the mean aggregator function. Then in the update stage, the node feature at $k^{\text{th}}$ layer will be updated through the FCN by concatenating original features with aggregated features:

$$x_v^{k+1} = \sigma\left(g\left(\phi\left(x_v^k, x_{\mathcal{N}(v)}^{k+1}, x_{\mathcal{E}(v)}^{k+1}\right); W\right)\right), \ \forall v \in V. \tag{17}$$

where $\phi$ is a concatenate function. $g(x; W)$ represents a FCN with parameter $W$. By repeatedly using Equations 16 and 17, the node and edge features of multiple-hop neighbors of the central node are aggregated into the features of that central node.

For the traffic performance evaluation, two independent neural networks are trained to predict the node-to-node connectivity $P_t \in \mathbb{R}^{|V| \times 1}$ to target node $t$ and total system travel time $TSTT$ used in objective function 11 and 12, respectively. The node and edge features should characterize the graph information from both global and local perspectives. For the connectivity surrogate, the features for node $s$ include the out-degree $\deg(s)$, the largest failure probability of links connected to the node $\max(\{p(e), \forall e \in \mathcal{E}(s)\})$, and the number of hops on the shortest path to the target node $\mathrm{h}(s, t)$. For the traffic assignment surrogate, the features of node $v$ are the OD demand $OD_v$ from $v$ and the normalized geocoordinates of node $v$. The features for edge $e$ are chosen to be free flow travel time and the capacity after seismic damage. The output of the traffic assignment surrogate is the edge-level flow-capacity ratios $\delta_a \in \mathbb{R}^{|E| \times 1}$. Then the $TSTT$ will be calculated by flow-capacity ratios by Equation 9.




**(a) Node-to-Node Connectivity** **(b) Flow-Capacity Ratio**

**Figure 2: Comparison between GNN and Simulation.**

## 3 NUMERICAL CASE STUDY

The performance of the proposed algorithm is evaluated using a case study of highway bridge networks in the California Bay Area. Figure 3 shows the transportation network under study (obtained from OpenStreetMap [15]). This study area connects critical locations like airports and hospitals with a large population base. The transportation network consisting of 152 bridges is represented by a directed graph $G(V, E)$ with 39 nodes and 128 edges. Bridge information is collected from the National Bridge Inventory [8]. In this case study, it is assumed that bridges are the only components subjected to seismic damage. Furthermore, in order to incorporate the equity-based metric, which takes into account multiple income classes, the median household income data is collected from the United States Census Bureau [19]. The low-income community is defined as households with a median household income less than 50% of the area median income [16].

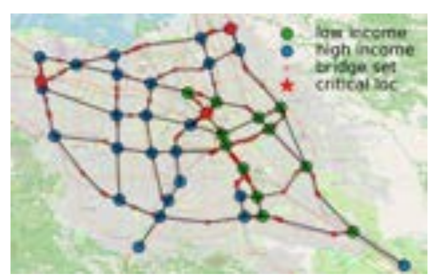
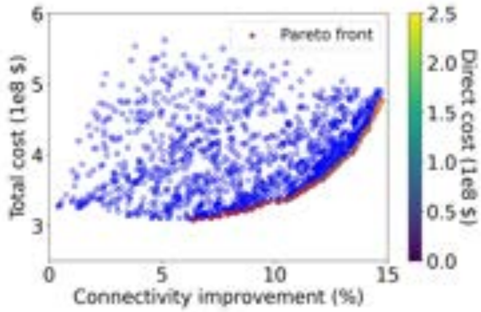


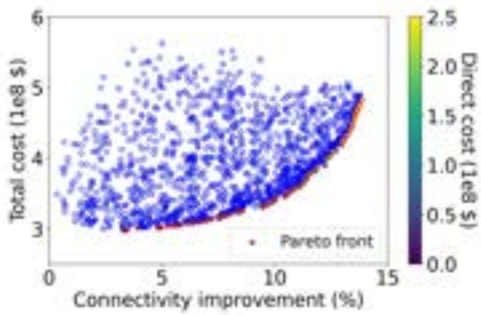

**Figure 3: Map Illustration of Road Network.**

A representative $M_w$ 6.9 earthquake with varying magnitudes is used in this case study. The earthquake magnitude $M_i$ is sampled from:

$$M_i = M_u - \lambda_i, \tag{18}$$




**(a) Considering Income Difference ($\beta_j$ = 5.0)**




**(b) Ignoring Income Difference ($\beta_j$ = 1.0)**

**Figure 4: Candidate solutions and Pareto Solutions of All Generations by GA-GNN Algorithm.**

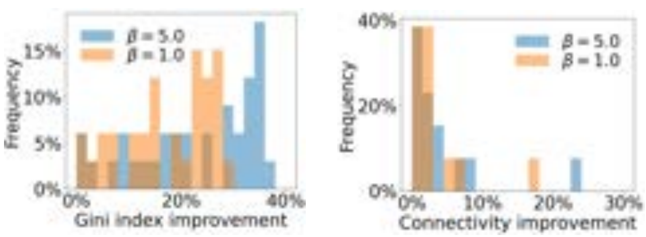



**Figure 5: Performance Comparisons of Different Strategies Between Considering Community Income Inequality ($\beta$ = 5.0) and Ignoring Community Income Inequality ($\beta$ = 1.0).**

where $M_u$ is the maximum earthquake magnitude and set to be 8.0 in this study, and $\lambda_i$ is a truncated exponential distribution random variable with the shape parameter of 1.5. The link failure probability and capacity are calculated according to the bridge fragility function. For the connectivity evaluation, three nodes are selected containing critical facilities, including airports and hospitals.

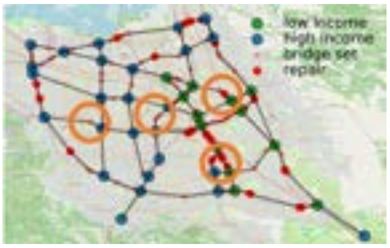
For GNN surrogate training, the training data is generated by randomly sampling the seismic magnitudes and performing MCS and STA. For each realization, the link damage state and link capacity are sampled from the link failure probability calculated based on the discussion in Section 2. The OD demand of each realization is generalized from the base OD demand, where 185,649 trips are assigned to the road network between the 1428 OD pairs throughout the region. The OD demand $D_m^{o,d}$ from $o$ to $t$ of $m^{\text{th}}$ realization is calculated from the base OD demand:

$$D_m^{o,d} = \tilde{D}^{o,d} \times \omega_m^{o,d}, \tag{19}$$

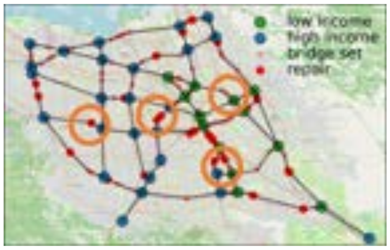
where $\tilde{D}^{o,d}$ is the OD demand between OD pair $(o, d)$ in the base case, $\omega_m^{o,d} \sim U(0.5, 1.5)$ is the random variable following uniform distribution over the interval $[0.5, 1.5]$. The randomness adding to OD demands and link capacities enables the generalization ability of the GNN surrogate to different seismic scenarios. The base OD demand is used during the optimization process. A total of 10,000 realizations are generated for each surrogate model, where 80% of the dataset is used for training. In the training process, the number of epochs and the learning rate are 200 and 0.001, respectively. Figure 2 compares values from the GNN surrogate prediction and the traffic simulation on test sets. For connectivity prediction, the mean absolute error (MAE) and the coefficient of determination $R^2$ between GNN and the MCS are 0.026 and 0.972, respectively. For flow-capacity ratio prediction, the MAE and $R^2$ between prediction and the STA is 0.033 and 0.991, respectively. And mean relative error and $R^2$ of the $TSTT$ calculated based on flow-capacity ratio prediction is 3.3% and 0.973. In terms of computational time, The GNN surrogate can perform analysis approximately 45 times faster than the original simulation model. The pretrained surrogate model could be used for evaluation of objective function 11 and 12.

In the genetic algorithm setup, the number of generations is chosen as 50, and the population per generation is 100. The total budget for retrofitting bridges is set to be 250, 000, 000 \$. Two different retrofit strategies are considered in case studies: retrofit considering the income difference ($\beta_j = 5.0$) in Equation 6 and retrofit ignoring the income difference ($\beta_j = 1.0$). All the sampling points with the Pareto frontier of the two strategies are shown in Figure 4. The color of the Pareto frontier indicates the direct cost of bridge retrofit. For both strategies, when the direct cost increases, the connectivity improvement increases as well. Even though the total cost increases, the indirect cost decreases when more bridges are repaired, indicating the traffic capacity are restored and improved.

To conduct more detailed comparisons between the two strategies, the optimal strategies with a total cost of 450, 000, 000 \$ are selected. The locations of retrofitted bridges are shown in Figure 6 with the red dot. The difference between the two strategies is shown with orange circles. It is shown that when income inequality is considered ($\beta = 5.0$), the retrofitted bridges will be concentrated within the low-community region. However, if the community incomes are homogeneous, the optimal retrofit strategies will be different and will not support the low-income community, as shown in Figure 5. Figure 5 shows the Gini index improvement for the whole region and the connectivity improvement for the low-income community, which could represent horizontal equity and vertical equity. The Gini Index improvement is 26.4% when considering income differences while 17.5% when neglecting income differences. The maximum connectivity improvements are 25% and 18% when $\beta_j = 5.0$ and 1.0, respectively. It indicates that the network gains more connectivity improvement when considering income differences. The regional transportation system also gains benefits from reducing the connectivity imbalance under seismic damage.




**(a) Considering Income Difference**




**(b) Ignoring Income Difference**

**Figure 6: Locations of Retrofitted Bridges and Location Comparison of Difference Strategies.**

## 4 DISCUSSION AND CONCLUSION

This study proposes GNN surrogate models for rapid estimation of transportation performance evaluation. Two distinct GNN surrogates are trained to predict the node-to-node connectivity probability and the flow-capacity ratio under seismic disruptions. Compared to conventional methods for evaluating traffic performance, the GNN surrogate models require only 1/45 of the computational time and achieve highly accurate ($R^2 = 0.97$) predictions compared to results obtained from Monte Carlo Simulation and exact static traffic assignment. The proposed GA-GNN algorithm integrates GNN surrogates and genetic algorithm solvers in a multi-objective optimization framework that determines the optimal bridge retrofit strategies with retrofit budget constraints. The distinguishing features of the proposed multi-objective optimization include (1) incorporation of both connectivity-based and traffic-based metrics, (2) integration of transportation equity by modeling different income classes with varying income-based emphasis.

A case study is performed using the road network in California to demonstrate the efficacy and accuracy of the GA-GNN algorithm. The results indicate that a strategy considering income disparities among communities can result in different optimal repair strategies resulting in more equitable transportation solutions. Specifically, we showed how areas with a higher concentration of low-income communities can receive more attention depending on the weights that stakeholders choose. Transportation performance improvement by optimal strategies indicates that considering multiple income classes not only improves connectivity probability to critical locations for low-income communities but also improves the regional community's Gini Index. These results demonstrate the benefits of considering equity-based metrics in transportation planning. Even though the focus of this study was on bridges, as the only components subject to seismic damage, the proposed framework can be easily extended to incorporate damages to other network components, such as tunnels and road segments. Besides, more generalized cases should be considered for the GNN surrogate training, including varying earthquake scenarios and network topologies.

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