PACIFIC EARTHQUAKE ENGINEERING
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Use of Corridors for Decision Making in Transportation Networks in Seismic Regions

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ABSTRACT

This report presents the results of the study that proposes a retrofitting strategy to manage seismic risk via identification of what constitutes ”Corridors” in transportation networks. We define a Corridor as a set of bridges that work together to ensure connectivity and traffic flow between areas of a region. We propose using a Markov clustering algorithm to detect Corridors, whereby it selects sets of bridges that correspond to highway and main road segments that are effective in reducing disruption when jointly retrofitted. We then use a two-stage stochastic optimization to identify corridors that can be retrofitted to efficiently reduce seismic risk. This two-stage stochastic optimization couples retrofitting actions over bridges in a Corridor with repair actions to damaged bridges after an earthquake. We observe that this Corridors-supported optimization approach yields better relative performance than retrofitting approaches that consider bridges as individual entities or rank them using PageRank. We also propose techniques for selecting parameters in the corridor selection step that perform well in the retrofit optimization.

This content is currently under review for publication in an archival journal. It is being submitted here also as a technical project report, per the requirements of the PEER Transportation Systems Research Program.

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1 Introduction

Transportation networks are a fundamental part of cities, allowing the flow of goods and people for the proper functioning of communities. However, the bridges and roads of these systems may experience damage during an earthquake, causing disruption for users. In this study, we present the concept of ”Corridors” as a tool to support seismic management of bridges in transportation networks. We define a Corridor as a set of bridges that works as a unit to ensure connectivity or steady traffic flow between different zones of a region. A Corridor can intuitively be a section of the transportation network, such as a highway, an avenue, or one of the main roads. Corridors support decision-making by grouping bridges that, if retrofitted jointly, effectively reduce the risk that services will be disrupted after an earthquake. Given a set of Corridors, we use a stochastic optimization to select retrofitted bridges by limited consequences over a set of potential future seismic scenarios.

Given the importance of transportation networks to functionality of cities, retrofitting bridges is one way communities can prepare for disruptive events. Resilience, as defined by Bruneau et al. (2003), is the ability of a system to reduce the impacts of a shock, absorb a shock if it occurs, and recover quickly afterward. Resilience can be improved by reducing the probability of failures, reducing the consequences of failures, and reducing the recovery time. This study increases the resilience of transportation networks by proposing retrofitting actions to reduce the probability of damage to the bridges and reduce consequences in terms of network performance.

Identifying actions to enhance the resilience of transportation networks poses many challenges. First, these systems are complex, and the impact of one element, such as a bridge, on the system is highly nonlinear and computationally expensive to model. Second, the real optimization problem is combinatorial: considering that real transportation systems have thousands of bridges, it is computationally unfeasible to exhaustively evaluate the immense number of permutations of bridges that could be retrofitted. Finally, the previous complexities scale further, given that the proposed actions have to be evaluated for several probabilistic seismic scenarios.

To support decision-making for transportation networks, we use a proxy optimization, which is a limited optimization focused on specific aspects of the problem, such as ensuring the capacity of the transportation network (Chang et al., 2012), the resilience of the system (Frangopol and Bocchini, 2011), or travel time (Lu et al., 2018). The optimization will not necessarily predict the exact set of bridges that may minimize the impacts of potential earthquakes. Considering this limitation, we evaluate the Corridors-Supported Optimization through a relative comparison with other strategies, such as not using Corridors or using ranking algorithms to select which bridges to retrofit.

The main contribution of this study is to propose an optimization framework that incorporates Corridors to support decision-making problems in complex systems, while at the same time managing computational costs. Moreover, from a logistical point of view, the implementation of retrofitting actions over whole sections of the network minimizes traffic disruption and optimizes construction resources (Hajdin and Lindenmann, 2007).

The rest of the paper is structured as follows: Chapter 2 discusses prior studies that quantify resilience in transportation networks, develop optimization frameworks to manage these systems, and use clustering techniques in complex infrastructure systems. Chapter 3 describes how Corridors are used in a two-step stochastic optimization. Chapter 4 presents an example implementation for the San Francisco Bay Area. Chapter 5 explores the characteristics of effective Corridors. Finally, Chapter 6 presents the conclusions of this study.

2 Related Work

A key aspect of evaluating the effectiveness of retrofitting actions over transportation networks involves quantifying the changes observed in the system's seismic risk due to these actions. In this regard, several authors have explored efficient ways in which seismic risk in distributed systems can be assessed. Many of these approaches use the general approach of Monte-Carlo-simulating seismic scenarios, simulating realizations of bridge damage using fragility functions, and computing consequences for each simulation, (e.g., Bommer et al., 2002). Chang et al. (2000) proposed a framework to extend risk analysis for distributed systems while accounting for spatial correlation and network performance indicators. Kiremidjian et al. (2007) explored the effects of an earthquake on the transportation network of the San Francisco Bay Area, considering disruption generated by ground motion and liquefaction. Han and Davidson (2012) developed a methodology to efficiently compute the seismic risk of spatially distributed infrastructure by selecting earthquake scenarios and combining sampling importance and optimization techniques. Building upon this model, Miller and Baker (2015) developed an optimization that—besides minimizing the error with respect to seismic hazard—incorporates fitting network performance into the objective function to select seismic scenarios. Using subsets of scenarios allows for the evaluation of several retrofitting frameworks while keeping the problem computationally feasible.

Given a seismic risk assessment framework, we can then evaluate various retrofitting frameworks. A common retrofitting strategy is to rank individual bridges and select top-ranked bridges subject to a budget constraint. Early ranking models were developed by Maroney (1990) for the California Department of Transportation (Caltrans) and by the Federal Highway Administration (Applied Technology Council, 1984). Currently, Caltrans prioritizes bridges according to their seismic guidelines (Caltrans, 2019) that classify bridges as "ordinary," "recovery," or "important," which is based on their role in the transportation system, though these types are not objectively defined. Other ranking techniques take advantage of the graph structure of transportation networks and use topological centrality measures to propose bridges for retrofitting. Rokneddin et al. (2013) explored different centrality measures, out of which a modified PageRank (Page et al., 1999), yielded the best results. In general, ranking strategies have the limitation that they cannot capture the inherent interdependencies of bridges within a transportation network.

Stochastic optimization techniques have been shown to improve the performance of transportation systems while capturing some of their complexities, such as modeling traffic and dealing with optimally allocating resources. Fan et al. (2010) proposed using stochastic programming to decide what pre-disaster actions most improve the performance of the network after an earthquake, incorporating the effect of spatial correlation of ground motions and using bridge fragility functions to quantify damage states of the network. However, their approach relies on a flow-based mathematical formulation to estimate traffic impacts, which does not scale well with network size, and it is not able to capture traffic congestion. Fan et al. mention that retrofitting sets of bridges could enhance the transportation system's performance, aligning with the Corridors proposal in this paper. Peeta et al. (2010) and Du and Peeta (2014) also implement stochastic optimization to relate pre-event actions with the consequences for multiple seismic scenarios, but they assume that the probability of damage of a bridge is known rather than letting it vary depending upon the seismic scenario. Gomez and Baker (2019) used a two-step stochastic optimization to couple actions made before and after a disruptive earthquake by using a decomposition algorithm to decrease computational costs and allow scaling to large problems; however, they approximated the impact of bridge damage by summing impacts of individual bridges rather than quantifying network effects due to traffic rerouting.

Hajdin and Lindenmann (2007) shows that through the use of Corridors, construction resources can be allocated more efficiently compared to retrofitting just individual sections of the network. Given a Corridor, the study by Hajdin and Lindenmann (2007) minimizes the impacts on road users while fulfilling budget and spatial constraints of construction intervention. This optimization would not be possible if bridges in the network were considered independent elements. Hajdin and Lindenmann (2007) also mention that while the use of Corridors is becoming more popular, their detection is a matter of further research.

Clustering techniques have previously been used in transportation systems to identify network structure and generate simplified versions of real-life settings. Özdamar and Demir (2012) used hierarchical clustering to change the resolution of a transportation network while maintaining consistency in properties such as demand. Lim et al. (2015) used spectral clustering to develop a surrogate of the original network to compute zones of greater importance connected by super links.

The proposal described in the following chapters aims to build on this prior work in network risk assessment and optimization, and to deploy clustering to support actions taken over sets of components in the network.

3 Methodology

The optimization question of interest herein is how to invest resources to retrofit bridges. The solution to this problem is combinatorial, consisting of evaluating all possible groups of bridges, computing the network's performance for each group, and then selecting the least expensive group that satisfies the performance constraints. This combinatorial number can be considerable. For instance, if we were to retrofit ten bridges for a network of 1000 bridges, the number of combinations is of the order of 10^{23}; such an exhaustive search is unfeasible.

We propose using a Corridors-Supported Optimization, a proxy optimization that selects possible candidates of bridges that can be retrofitted. We define a Corridor as a segment of the network that works together to ensure connectivity and traffic flow between different areas of a region. We detect a Corridor using the Markov Clustering algorithm, a method that uses Random Walks to aggregate nodes according to patterns in paths performed over the graph.

Given a set of Corridors, we performed a Corridor-Supported Optimization, which is a two-step stochastic optimization, defining the set of potential bridges to be repaired based on damage realizations obtained for hazard consistent seismic scenarios. To evaluate the adequacy of a given retrofitting strategy, we assessed the seismic performance of the network in terms of a loss exceedance curve of increase of cumulative time for all users, defined here as a loss curve for transportation systems. Because the true optimum of the problem is unknown, we evaluated the approach by comparing our results to those obtained using alternate methods.

Figure 3.1 summarizes the methodology, with numbers indicating key steps:

1. We first defined a transportation network by collecting information regarding traffic demand, roads, and bridges of the system.
2. In parallel, we obtained hazard consistent seismic scenarios.
3. Using these seismic scenarios with fragility data obtained for the bridges, we obtained realizations of damaged networks.
4. Using the network information, we identified sets of Corridors, using a Markov Clustering Algorithm.
5. We then performed the optimization proposed herein, which produces a set of retrofitting actions to perform.

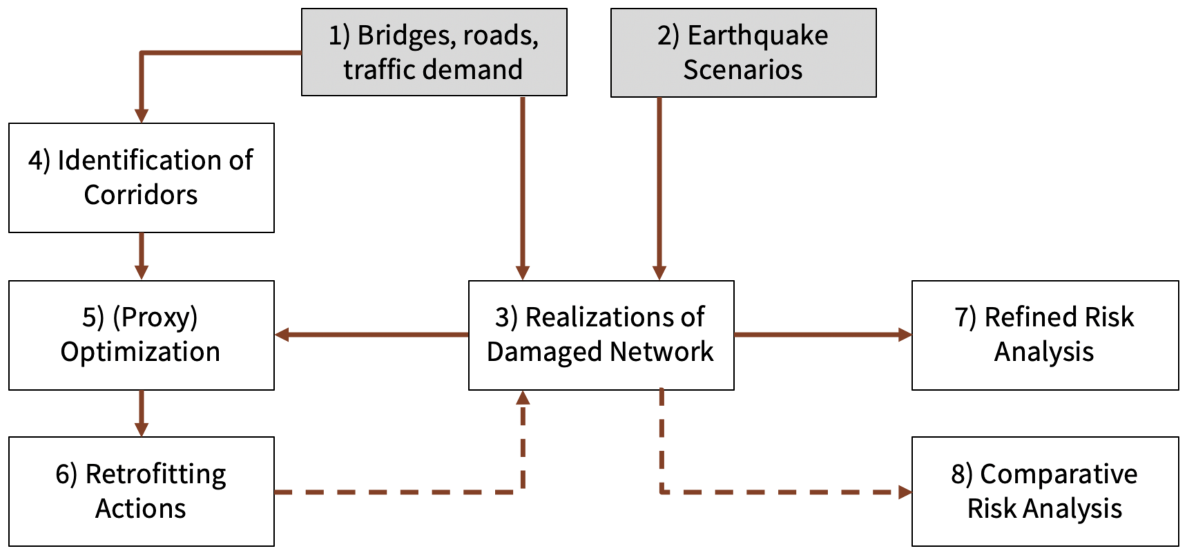

Figure 3.1: Diagram of the flow of information and computations in the presented study.

6. We 'performed' these retrofits by modifying the fragilities of the bridges in the network model, and used these new fragilities to generate new damage realizations (with less frequent damage to the retrofit bridges).

7. With the original network, we perform a full risk analysis considering the original network using a transportation model while avoiding simplifications used in the step 5 optimization.

8. Similarly, we perform a risk analysis for the retrofitted network, and compare the results to those from step 7 in order to evaluate the effectiveness of the actions.

The following sections will present additional detail on this process, and steps 4, 5, and 7 in particular.

3.1 CORRIDOR DETECTION

We consider a Corridor as a section of the network that works together to ensure connectivity and traffic flow between areas of a region. To identify Corridors (Step 4 of Figure 3.1), we explored algorithms such as Spectral Clustering (Ng et al., 2002), Louvain Modularity (Blondel et al., 2008), K-Means (Wagstaff et al., 2001) and Markov Clustering Algorithm (Van Dongen, 2000). We evaluated the suitability of each algorithm by conducting an assessment of several simplified graphs; in particular, we paid attention to how the clustering techniques captured groups of bridges that aligned with travelers' main paths and rerouting options. We then utilized the various methods to identify clusters in the case-study network described below, and utilized the full evaluation method of Figure 3.1. The Markov Clustering Algorithm (MCL) produced the most intuitive Corridors in the simplified graphs and performed best in the case-study evaluation. Based on this, we adopted MCL as the recommended Corridor detection algorithm.

The MCL is an unsupervised classification method based on random walks performed over the nodes of a graph representing the transportation network. It identifies clusters by localizing zones of the graph where random walks tend to be confined—that is, it is unlikely that a random walk within a cluster will move to another cluster. Significant locations, which can be either intersections between roads or auxiliary nodes to account for the shape of a road, define the nodes of the graph. The roads that connect the network define the edges of the graph.

The MCL computes clusters by performing two operations over the adjacency matrix that characterizes the transportation network: inflation and expansion. The adjacency matrix A_{ij} is a representation of the transportation network in which the term ij of the matrix consists of scalar values (weights) that represent how strongly node i of the graph is connected to node j. For the transportation network, the adjacency matrix weight is the capacity (in terms of vehicles per hour) of the road connecting nodes i and j. This means that A_{ij} is the value of the capacity of the connecting road. The inflation operation raises each column of the adjacency matrix A_{ij} to a non-negative power r, and then the column is re-normalized. This inflation operation Γ_r is defined as:

$$(\Gamma_r A)_{ij} = \frac{(A_{ij})^r}{\sum_{k=1}^{K}(A_{kj})^r} \tag{3.1}$$

where r is an inflation parameter, and k is a parameter used to normalize each column by adding over its K elements after inflation. This inflation operation has the effect of strengthening stable clusters and weakening weak ones.

The expansion operation of the algorithm is defined by:

$$A'_{ij} = A^e_{ij} \tag{3.2}$$

This expression is the adjacency matrix A_{ij} raised to a power given by the expansion parameter e. The expansion operation allows different regions of the graph to connect, thus increasing the size of clusters. Once the inflation and expansion operations are repeated several times, the result will converge to a matrix in which only some rows will be non-zero. Each of these non-zero rows will be a cluster, and the non-zero columns will be the nodes that belong to that cluster. The index of the row that forms a cluster will be the centroid node for the cluster. The value that is not zero in the resultant matrix will be the probability that the node belongs to the specific cluster. Most of the time, this value is one. In this study, we define each of the detected clusters as a "Corridor." Hence, these clusters will be called Corridors in the following sections and chapters.

Figure 3.2 illustrates how this algorithm obtains Corridors for a simple network that connects locations A and B. The capacity of the edges is indicated on them. Bridges of the network are indicated with B_i with i an index of the bridge. Corridors are shown in different colors and types of lines. We obtain two clusters, one containing bridges B_A, B_B, and B_C, and the other containing B_D and B_E. The algorithm can detect segments of the network with intuitively strong relations,

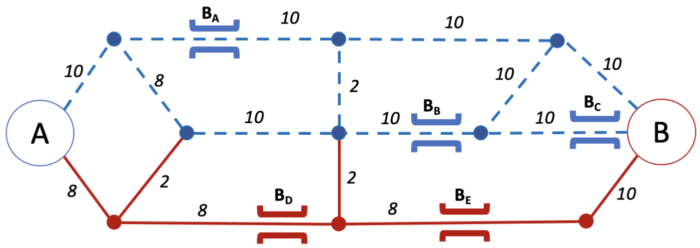

Figure 3.2: Example of Corridor identification in simplified network. Numbers next to edges indicate their capacities. The MCL parameters are $e = 6$, $r = 6$. Two clusters are shown, one in red solid red lines and the other one in dashed blue lines. Bridges B_A, B_B, and B_C belong to the blue cluster, and bridges B_D and B_E belong to the red cluster.

or Corridors. In this case, MCL detects two main paths between A and B. The size of the clusters depends on the inflation and expansion parameters e and r. Selection of these parameter values will be discussed later in Chapter 5.

The MCL groups all nodes in Corridors. In transportation networks, bridges are associated with edges (i.e., roads), not nodes (i.e., intersections). We define Corridors by groups of bridges for which their nodes fall within the same Corridor. Bridges in edges with nodes in different Corridors are assigned to the Corridor with more bridges because that showed better performance in our analyses. If the Corridors are the same size, we randomly assign the bridge to one of the Corridors. In Figure 3.2, the bridges were assigned considering the Corridor to which the nodes of their edges were assigned. Note that the red edge that is adjacent to node B was assigned randomly to be red since node B belonged to the blue Corridors, and the other ending node was red. The analysis of edges without bridges does not matter to the optimization in this paper since no action is taken on them.

3.2 CORRIDORS-SUPPORTED OPTIMIZATION

With the corridors now defined, next we performed an optimization to identify retrofitting actions (Step 5 of Figure 3.1). We proposed minimizing the cost of actions under a time constraint and a physical constraint that bridges in a Corridor all receive the same retrofit decision. We termed the optimization that uses Corridors to support the seismic enhancement of bridges as a "Corridors-Supported Optimization."

The Corridors-Supported Optimization is a two-step stochastic optimization: it couples the decision of retrofitting bridges before a disruptive event with repairing damaged bridges after an earthquake. This optimization minimizes the cost of these actions while enforcing a network performance constraint.

Mathematically, we formulated Corridors-Supported Optimization as:

$$\min \left(\sum_{c \in C} c_{\text{retrofit}} x_c + E_{\xi} \left[c_{\text{repair}} y_{\xi,b} + \omega_{\xi} \right] \right) \tag{3.3}$$

Subject to:

$$\sum_{b \in p} t_{0,b}[x_b + y_{\xi,b}] + t_{\xi,b}[1 - (x_b + y_{\xi,b}))] \leq t_p^*(1+\varepsilon), \quad \forall p \in P, \forall \xi \in \Xi \tag{3.4}$$

$$x_b = x_c, \quad \forall b \in c \tag{3.5}$$

where:
c_{retrofit} = Cost of retrofitting a bridge
c_{repair} = Cost of repairing a bridge
ξ = A seismic scenario
c = A specific Corridor
b = A specific bridge
x_c = Binary indicator for retrofitting bridges in Corridor c
x_b = Binary indicator for retrofitting bridge b
$y_{\xi,b}$ = Binary indicator for repairing bridge b in scenario ξ
ω_{ξ} = Consequences of scenario ξ
$t_{0,b}$ = Travel time for bridge b with no damage
$t_{\xi,b}$ = Travel time for bridge b under scenario ξ
t_p^* = Travel time on path p with no damaged bridges
ε = Acceptable increase of travel time of sets of origins and destinations.
P = Set of paths between selected origins and destinations.
Ξ = Set of seismic scenarios.

The objective function aims to minimize the cost of improvement actions and transportation disruption. The cost of improvement actions is the sum of the cost of the retrofitting actions that are certain, c_{retrofit}, plus the expected cost of repairing actions, c_{repair}. Considering that occurrence of bridge damage is dependent on scenario ξ, the cost of repair actions is computed as the expected value of repair costs over different seismic scenarios ξ (denoted in Equation 3.3 by $E_{\xi}[\,]$. This expectation makes the problem a two-step stochastic optimization.

We define two constraints, one related to network performance and another that incorporates Corridors. Regarding network performance, Equation 3.4 restricts the increase in travel time between a set of origins and destinations t_p^*. Paths connecting origins and destinations used in the optimization are named in this study as "Optimization Paths," and are described in the equations by the set P. When considering the Corridors' role, Equation 3.5 enforces that the same retrofitting action should be performed over all bridges b within a Corridor c.

As input for the optimization, we defined seismic scenarios Ξ that are consistent with the hazard of the region of study; see Step 2 of Figure 3.1. Creating seismic scenarios involves obtaining realizations of earthquake ruptures in the region of interest for different earthquake sources in the area. Based on these ruptures, we used ground-motion models (GMMs) to estimate the distribution of intensity measures (IMs) at the location of the bridges in the transportation network, and sampled IM values from that distribution. For each seismic scenario ξ, we sampled realizations of damage using the fragility function of each bridge and the sampled IM values; see Step 3 of Figure 3.1. Using these realizations of damage, we can now compute travel times between the origins and destinations of interest, and for each bridge along the paths that connect them ($t_{\xi,b}$).

To compute travel times for each damage realization for each bridge b, we computed an undamaged travel time and a damaged travel time. In the case where a bridge b in edge a experiences damage, we defined its travel time $t_{\xi,b}$ as the undamaged travel time of that edge ($t_{0,b}$) plus the increase of the travel time in the specific path under analysis, considering that the bridge is damaged but all other bridges within that path are not. This increase in time is caused by rerouting effects. To compute these travel times, we need the travel demand in the region and a traffic model.

For computational efficiency, the paths between the origins and destinations are assumed to be unchanged when bridges are damaged. This simplification causes a significant decrease in computation times since it allows pre-computing travel times for all of the edges of the set of paths $t_{\xi,b}$ for each scenario ξ without requiring an update for each iteration of the optimization. The real solution would be to recompute the paths each time bridge damage causes disruption. Note: this would be computationally expensive, and, more importantly, it would change the set of optimization variables at each scenario, which is problematic for the optimization.

As a summary, the following information is required to perform the Corridors-Supported Optimization:

1. Set the origins and destinations for the region under analysis.
2. The traffic demand for each origin and destination.
3. Define optimization paths (P), which are the shortest paths connecting each origin to each destination.
4. Determine a set of seismic scenarios and their respective rates of occurrence Ξ.

The final output of the Corridors-Supported Optimization is a set of Corridors to be retrofitted.

Implicit in the optimization is that once a retrofitting action is taken, the bridge becomes invulnerable and will not experience damage. Therefore, the travel time over that bridge is the undamaged travel time. Also, as a consequence of this invulnerability, retrofitting and repair actions do not happen simultaneously for each bridge. These assumptions are limited to the formulation of the optimization and are not included in the performance assessment described in Section 3.3. Since the results are ultimately evaluated using the procedure outlined in Section 3.3, the optimization formulation's assumptions do not limit the scope of the proposal.

The above model formulation builds off of the proposal by Gomez and Baker (2019), with a few additions and refinements. The main difference between that study and the study presented herein is that we changed the constraints to enforce that every bridge within the Corridor gets the same action, instead of considering individual bridges. Also we implemented a different travel time definition from the one defined by Gomez and Baker (2019), who defined the penalty for damage as an infinite time increase in the edge. That penalty forced a retrofitting action for all bridges that experienced damage in at least one scenario in order to meet the travel time constraint. For this study, we defined the travel time of a damaged bridge as the undamaged travel time over the bridge, plus the increase in travel time if only that single bridge is damaged. Below we will consider an alternate optimization approach that does not consider Corridors (like Gomez and Baker, 2019), but with our updated definition of travel time for damaged bridges instead of theirs. We will refer to this alternate approach as "No-Corridors optimization."

Another difference with the model proposed by Gomez and Baker Gomez and Baker (2019) is that their model includes a constraint that limits the number of retrofitting actions; ours does not. Gomez and Baker needed that constraint since their damage travel time forced a maximum number of bridges to be retrofitted. This constraint was active. In most of the cases we analyzed, the time constraint was not active. In terms of our proposed methodology, the number of retrofitting actions is the result of the combination of time performance constraints, selected scenarios, and the cost ratio between retrofitting and repairing actions. As a benefit of our modification, management actions enforce a network performance. As a disadvantage, the desired number of retrofits is not an input for the model, but it comes as an indirect effect of the travel time constraint and the selected corridors.

3.3 PERFORMANCE EVALUATION

To assess the effectiveness of retrofitting actions, we evaluated the improvement in network performance compared to its current state (Steps 7 and 8 of Figure 3.1). We defined network performance as the annual rate of increase of travel time, considering a set of hazard consistent potential future seismic scenarios. The process of evaluating network performance comprised three steps: simulating seismic scenarios, simulating bridge damage, and performing traffic demand assignment on the damaged network to compute travel times.

The first step in assessing the system's performance was to generate seismic scenarios that are consistent with the seismic hazard of the region. These scenarios are the same as those used for the optimization in Equation 3.3.

The second step was to develop realizations of damage for each bridge based on the IMs of the previous step and the fragility function for each bridge. For each scenario, we simulated one realization of damage. The results of this step are n versions of the transportation network that has lost connectivity along some roads due to bridge damage. It is also possible to simulate multiple damage maps per ground-motion map. To measure the impact of a retrofitting strategy, we also evaluated the network performance once the retrofitting actions have taken place. We do this by modifying the fragility functions of the bridges to make them less likely to experience damage for a given level of shaking. By repeating the travel time analyses using damage realizations from the new fragility functions, now we can measure the decreased risk in the system without needing any of the simplifying assumptions used in the initial optimization. The bridge fragility functions (with and without retrofit) are defined as follows:

$$P(DS_i \geq ds_k|Y_i = y) = \Phi\left(\frac{\ln(y/(\alpha\lambda_{k,i}))}{\beta_{k,i}}\right) \tag{3.6}$$

where:
$DS_i =$ Damage state of component i
$ds_k =$ Damage state k
$Y_i =$ Ground motion intensity measure value at the location of component i
$P(DS_i \geq ds_k|Y_i = y) =$ Probability of component i's damage state being ds_k or greater, given $Y_i = y$
$\Phi() =$ Standard normal cumulative distribution function
$\alpha =$ Factor that indicates retrofitting action: $\alpha = 1$ for no retrofit and $\alpha > 1$ for retrofit
$\lambda_{k,i} =$ median of Y_i causing damage state k
$\beta_{k,i} =$ Standard deviation of $ln(Y_i)$ causing damage state k.

The final step was to compute travel time for the users of the system. Once we have a damaged version of the transportation system, we performed a traffic assignment, which determined the number of vehicles circulating in an hour for each road of the network and the time that it took them to travel over that road. Using this model's output, we computed the increase in total travel time for all users of the network (tt), which is a global indicator of the impact of bridge damage.

Using the results of the previous three steps, we can define a loss exceedance curve for the transportation network, associating annual rates of occurrence of seismic scenarios w_j with a percent increase in aggregated travel time of users for each scenario and damage map. The annual rate of exceedance of a given travel time increase is computed as:

$$\lambda_{\Delta t \geq \Delta t'} = \sum_{k=1}^{n} w_k \mathbf{I}(\Delta t_k \geq \Delta t') \tag{3.7}$$

where:
$\Delta t_k =$ Increase in travel time between an undamaged network and that from damage map k, expressed as a percent increase with respect to the undamaged condition
$\Delta t' =$ Some level of increase in travel time
$\lambda_{\Delta t \geq \Delta t'} =$ Annual rate of exceedance of $\Delta t'$
$w_k =$ Annual rate of occurrence of damage map k (based on the occurrence rate of the associated seismic scenario)
$n =$ Number of damage maps considered
$\mathbf{I}(\,) =$ an indicator function equal to 1 if the argument is true and 0 otherwise.

The increase in travel time Δt for damage map k, with respect to the undamaged condition UD, is defined as:

$$\Delta t_k = \frac{tt_k - tt_{UD}}{tt_{UD}} \times 100 \tag{3.8}$$

where tt_k is the cumulative travel time for all users in scenario k, and tt_{UD} is the cumulative travel time for all users in undamaged condition of the network

Another indicator of network performance is the expected annual increase in travel time:

$$E[\Delta t] = \sum_{k=1}^{n} w_k \, \Delta t_k \tag{3.9}$$

This aggregated measure allows us to compare the effects of different retrofitting strategies.

4 Application to the Transportation Network of the San Francisco Bay Area

To illustrate the Corridors-Supported Optimization, we applied the methodology to the San Francisco Bay Area's transportation network. Following the steps described above, we demonstrate the results from the analysis.

The graph representing the Bay Area consists of 11,921 nodes, connected by 32,588 edges, and includes 1743 bridges. The information on the fragility curves of the bridges was provided by Caltrans. Instead of looking at the effect of specific retrofitting actions such as installing isolators or jacketing bridge columns, we modeled the general effect of conducting a retrofitting action. We use $\alpha = 1.2$ in Equation 3.6 for all bridges if they are retrofitted, which was based on representative values for bridge retrofits from Padgett and DesRoches (2008). This reasonable but generic α value serves to illustrate the methodology of interest here without requiring detailed discussion of specific bridges and retrofit options.

To model traffic, we considered data from the Metropolitan Transportation Commission (MTC) (Erhardt et al., 2012), which shows that 11 million trips are traveled daily by car that are grouped in 34 districts. Figure 4.1 shows a map of the network.

4.1 CORRIDOR DETECTION

To illustrate results using different sets of Corridors, we considered clustering with two sets of parameters. "Set A" uses r = 3 and e = 4, while "Set B" uses e = 6 and r = 2. Set A represents a set of Corridors that is close to optimal (as will be seen below), and Set B is an example of inefficient Corridors. Figures 4.2 and 4.3 show the results of clustering for a subset of the network near the city of San Jose (omitting Corridors with fewer than 4 bridges, for clarity). Both figures show nodes in each cluster with a different color. Although all nodes are assigned to a Corridor, we will focus on three examples on each figure to exemplify what a Corridor is. In Figure 4.2, Set A, note that the clustering identifies major highways in the region, which can be seen in the figure as multiple links running in parallel for long distances, representing the multiple lanes of these roads. The Corridors in Set B are generally bigger than in Set A. Although we show the clustering results only for a subset of the network, similar patterns are seen throughout the study area.

To illustrate how parameters of the MCL affect clustering results, Figure 4.4 shows the av-

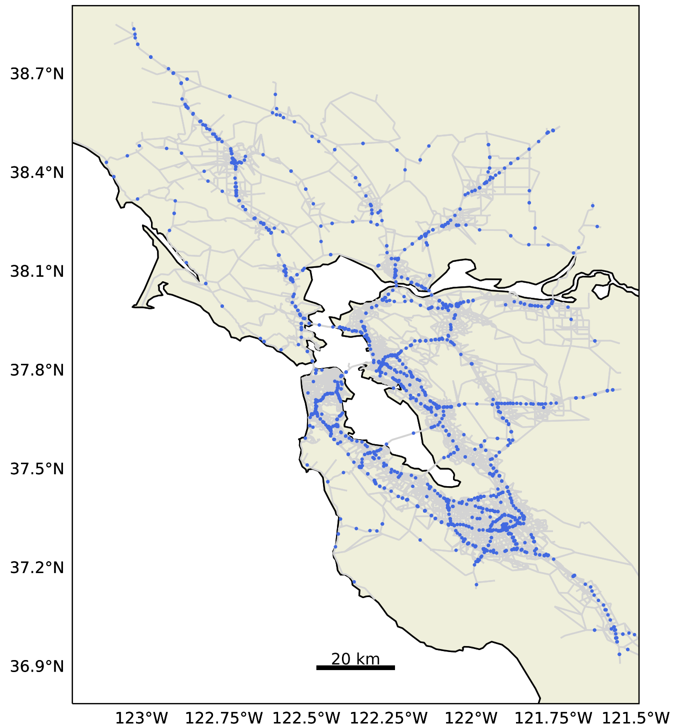

Figure 4.1: Road network model utilized in this study. Grey lines represent roads and blue dots represent bridges.

erage number of bridges per Corridor as a function of e and r. Bigger values of r tend to create smaller Corridors, and bigger values of e tend to generate bigger Corridors. Note that this plot only shows a correlation with Corridor size, but it does not comment on the improvement of network performance due to the clustering process's parameters. The relationship between optimization performance and parameters e and r is discussed in Chapter 5. Note also that Figure 4.4 shows only the average number of bridges on each Corridor. There is significant variability on the specific number of bridges on each Corridor. We did not observe any trend between e, r, and the coefficient of variation of the number of bridges in the Corridors.

4.2 CORRIDORS-SUPPORTED OPTIMIZATION

Given the previous sets of Corridors, we performed a Corridors-Supported Optimization. A crucial part of the optimization is the selection of origin and destination pairs to define optimization paths. For this model, traffic was assigned over 35 supernodes that characterize the superdistricts defined by the MTC. If we were to select only the shortest paths between these origins and destinations as the paths for optimization, only 256 of the 1743 bridges in the model would lie on the paths; the other bridges would not play a role in the optimization calculation. In order to generate paths

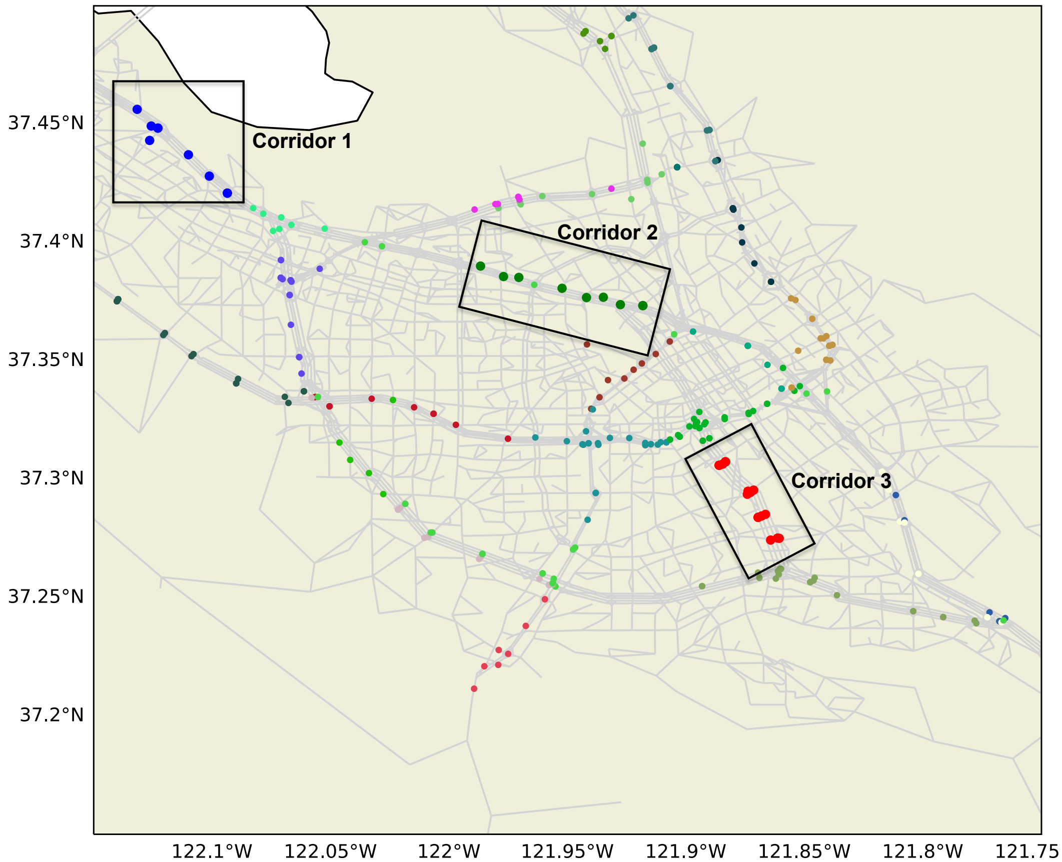

Figure 4.2: Zoomed in map of the southern area of the road network, with Corridors "Set A" (e = 3, r = 4) indicated by dots of a given color. Three example corridors are also noted with boxes.

for optimization that incorporate all of the bridges in the system, we used paths between the 35 supernodes, plus paths between each bridge. This selection gave us 3459 paths, which included all bridges. To improve computational performance, we pruned paths that were within other ones. Finally, we used 678 paths that were distributed throughout the region and incorporated all bridges in the system.

One of the inputs required to perform the optimization is the selection of seismic scenarios Ξ. We used a catalog generated by the OpenSHA Event Set Calculator (Field et al., 2003). As inputs for the OpenSHA model, we selected the UCERF2 seismic-model source model (Field et al., 2009), the Boore and Atkinson (2008) GMM, and the Wald and Allen (2007) topographic model to estimate soil conditions at each site (needed for ground-motion prediction). The catalog includes the mean and standard deviation of IM values for each event for all bridge sites. The IM used in the fragility functions of the bridges is the 5% damped pseudo-absolute spectral acceleration at a period of $T = 1s$. For computational efficiency, we used the optimal scenario selection of Miller and Baker (2015). These calculations produced $n = 1992$ seismic scenarios.

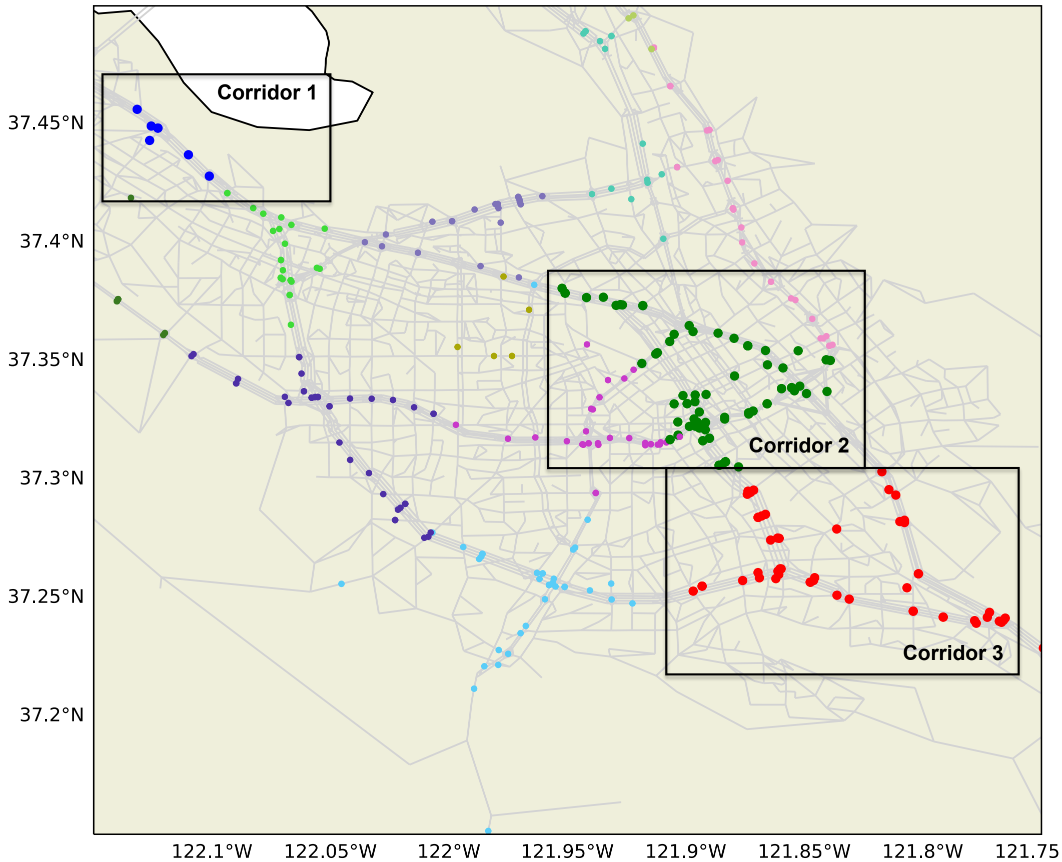

Figure 4.3: Zoomed in map of the southern area of the road network, with Corridors "Set B" (e = 6, r = 2) indicated by dots of a given color. Three example corridors are also noted with boxes.

We considered that the cost of retrofitting bridges was proportional to their area, measured as the length of a bridge times its number of lanes, and that the cost of repairing bridges was the retrofitting cost multiplied by $15,000$. this is a value close to the inverse of the minimum rate of occurrence of the seismic scenarios considered (6.98×10^{-5}). We did this normalization to reflect the disruption costs of dealing with damage and performing rapid repairs, with the preference for retrofitting bridges pre-event rather than repairing them post-event. Taking this into account, for the results shown, we used the same budget. As parameters of the constraint presented in Equation 3.4, ϵ for Corridors Set A was 0.47 and $\epsilon = 0.51$ for Corridors Set B. Note that a different ϵ is required when comparing the performances of retrofitting sets; therefore, it is necessary to have the same cost, which comes not as a constraint but as a result of the objective function of the optimization. The results shown here for the different approaches correspond to retrofitting 258 bridges. Figure 4.5 shows the proposed sets of retrofitted bridges using the Set A and Set B corridors, as well as the No-Corridors Optimization.

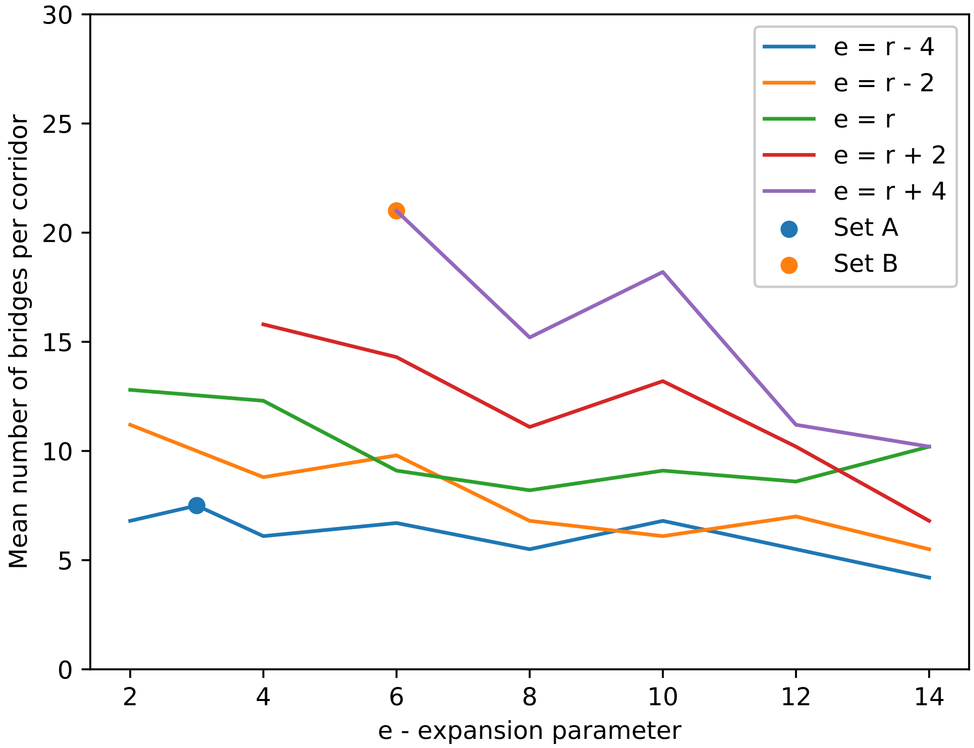

Figure 4.4: Average number of bridges in Corridors as a function of the inflation and expansion parameters.

For the results shown herein, the indirect consequences of a seismic event due to damage to the transportation network, ω, are not directly considered in the optimization, although they are indirectly included in the high repair cost. However, the proposed framework is flexible, and if these consequences are expressed in terms of monetary value, this approach can include them.

4.3 PERFORMANCE EVALUATION

The first step required to assess performance is to compute ground-motion maps. For this study we used the same 1992 seismic scenarios that we considered for the Corridors-Supported Optimization. As the second step to evaluate network performance, we obtained realizations of damage for each bridge based on the simulated IMs of the previous step and the fragility functions for each bridge. For this study, we considered only extensive damage, and we used the fragility functions provided by Caltrans (2019).

For the final step to evaluate network performance, we computed travel time for the users of the system. Using a damaged state of the transportation network, we performed an iterative traffic assignment (Beckmann et al., 1955) that determines the number of vehicles circulating in an hour

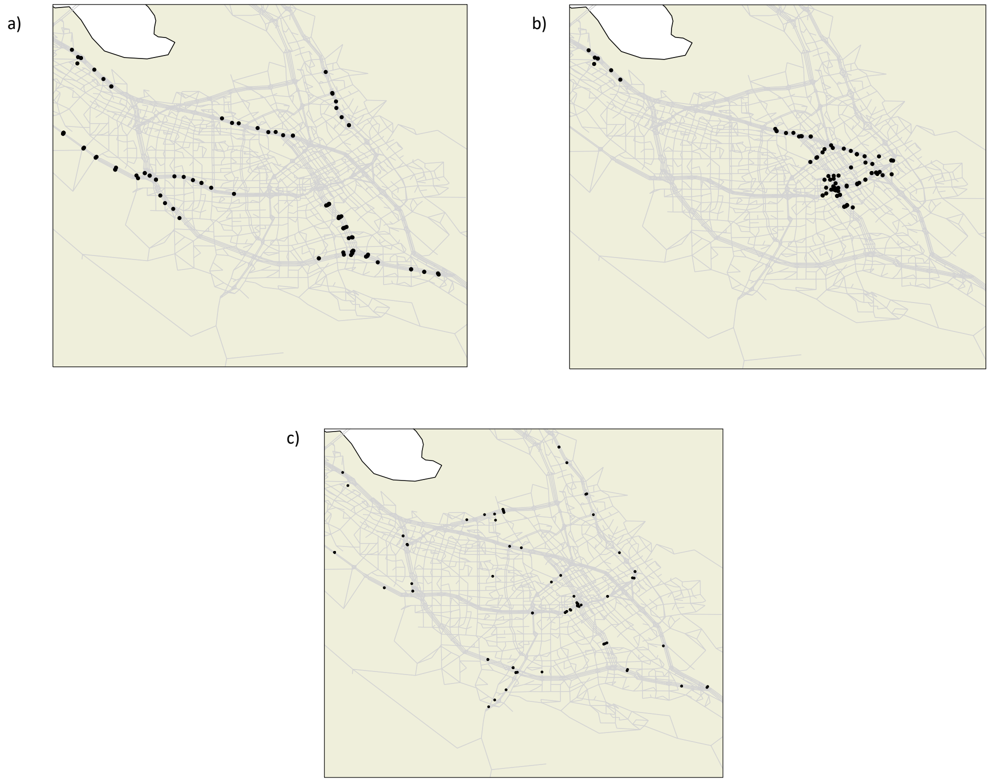

Figure 4.5: Retrofitted bridges for each method. Intervened bridges shown in black: (a) results for Set A: (b) results for Set B; and (c) results for No-Corridors Optimization.

for each link of the network and the time it takes them to go over that road. This assignment algorithm models all users as trying to minimize their travel time. Given its iterative nature, it accounts for congestion updates to the road segments. This algorithm was applied to the San Francisco Bay Area using used the traffic demand provided by the MTC (Erhardt et al., 2012). Using the output of this model, we aggregated the travel time of all users of the network.

Using the previous steps, and Equation 3.7, we evaluated the network performance for different retrofitting policies under the same budget. These policies include No-Corridors Optimization, Set A, Set B, and a ranking system that uses PageRank to classify the importance of the bridges. Using PageRank, the index to rank a bridge is defined by the average of the PageRank indices of the nodes that comprise an edge where a bridge is. We included this centrality measure to show the difference between approaches that use a ranking and the ones that use stochastic optimization. The loss curves associated with each retrofitting protocol are shown in Figure 4.6.

Figure 4.6 shows that Corridors-Supported Optimization yields the best results for the given

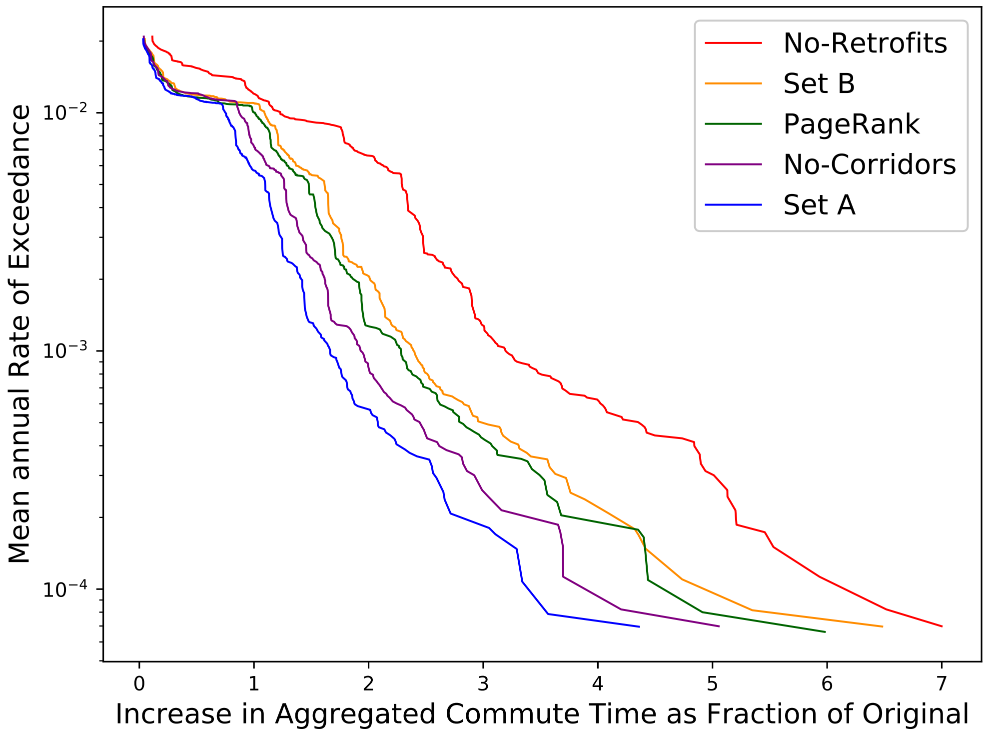

Figure 4.6: Comparison of different retrofitting approaches in terms of the mean annual rate of exceedance of the increase in cumulative travel time expressed a fraction of the undamaged condition. The No-Retrofits case shows performance of the original network, and the other cases show performance when 258 bridges (15% of total) are identified using various strategies and retrofitted.

retrofit budget, as it produces the lowest rates of exceeding various levels of travel time. Additionally, there is a substantial variation in the effectiveness of using Corridors depending on how these Corridors were defined: for this case, Set A has much better performance than Set B. Chapter 5 will further explore how to select the set of Corridors with the best performance.

By using Corridors-Supported Optimization, bridges are grouped indirectly according to the continuity of users' flow over the network, which is strongly correlated to their location. As a result, bridges retrofitted using the Corridor-Supported Optimization align with an intuitive decision of retrofitting: consider an avenue or a segment of a highway, instead of distributed and unrelated bridges. Figures 4.5(a) and 4.5(b) show the results of the Corridor-Supported Optimization, with retrofits that align with major highways in the region. Figure 4.5(c) shows bridges retrofitted using No-Corridors Optimization: although there are some bridges along highways, they are scattered throughout the region. Given that the objective of this framework is to serve as an input to decision-makers, the intuitive pattern of Corridor retrofits is appealing; it also better matches the current approach developed by Caltrans.

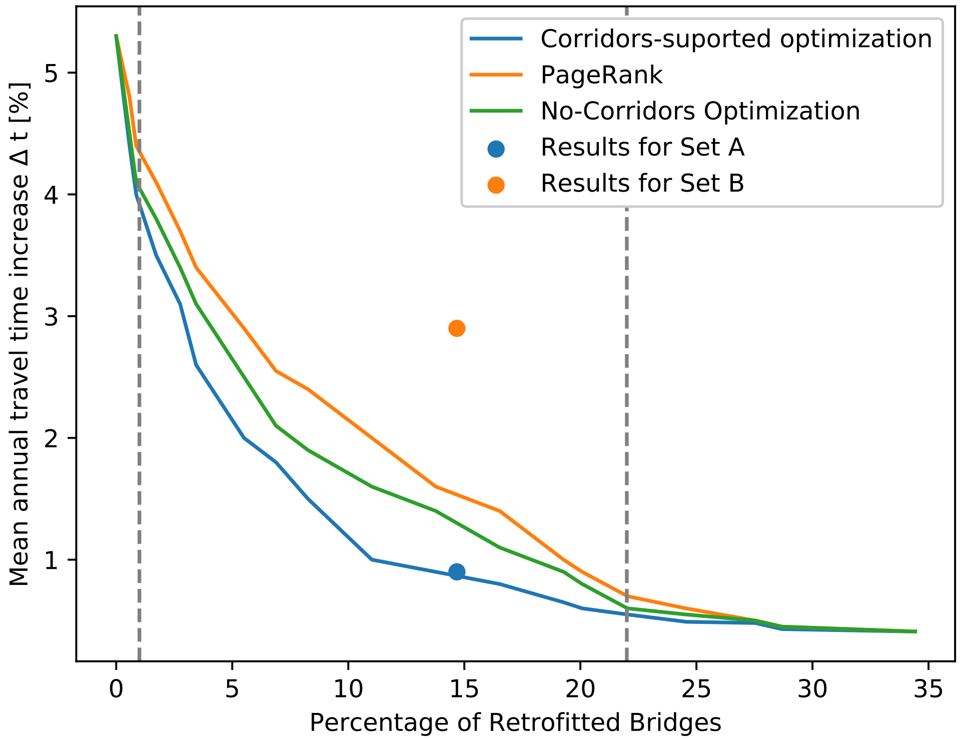

Figure 4.7: Comparison of expected increase in travel time as a function of the percentage of the total number of bridges. The Corridors-Supported Optimization result is for the best clustering parameters at the given retrofit budget. Vertical dashed lines indicate the range in which the use of Corridors yields significantly better performance than the No-Corridor approach.

It may appear as counter-intuitive that adding constraints in the optimization of Equations 3.3-3.5 produces better network performance. The improvement in performance is because this optimization is not the real solution of the management problem. The Corridor consideration accounts for the relations between bridges and rerouting options in a way that the simplified treatment of travel time in the optimization does not.

4.4 PERFORMANCE FOR VARYING LEVELS OF RETROFITS

The previous section showed performance given a specific retrofit budget. In this section, we compare the performance of the Corridor-Supported Optimization with other approaches. For this comparison, we present a set of Corridors for each retrofitting budget that showed the smallest expected annual increase in travel time, as defined in Equation 3.9.

Figure 4.7 shows that the use of Corridors yields smaller annual expected increase in cumulative travel time than the other methods. We distinguish three ranges in terms of the relative performance of using or not using Corridors in the optimization. When the number of bridges to retrofit is less than 3%, there are few total retrofits. As they are often optimally placed in isolated locations, considering Corridors with multiple bridges is not conceptually relevant. For between 3% and 22% retrofits, Corridors-Supported Optimization performs much better than the other approaches. Finally, for more than 22% retrofitted bridges, the difference between the Corridor approach and the No-Corridors Optimization decreases. This is because once a significant number of bridges have been retrofitted, the marginal benefit of an additional retrofit is negligible.

4.5 IMPACT OF PRE-SCREENING HIGH PERFORMING BRIDGES

One limitation of the Corridors-Supported Optimization is that all bridges in a cluster are retrofitted, meaning that some high-performing bridges (with low probability of damage) may be forced to be retrofitted. To address this problem, we evaluated the effect of screening high-performing bridges and excluding them from consideration before performing the optimization. We ranked the bridges according to their annual probability of damage over the full suite of ground-motion maps and damage realizations used above, and pre-screened $x\%$ of them by removing them from consideration for retrofit during the clustering and Corridors-Supported Optimization process.

Figure 4.8 compares the expected annual travel time increase for different percentages of pre-screened bridges. Although the pre-screened cases show better performance (i.e., a lower expected annual travel time increase for a given percentage of retrofitted bridges), the results are similar for all three cases. By removing the best-performing bridges from consideration while leaving many bridges to be considered during the optimization step, pre-screening 10% of the bridges generally produces the best performance for this network. The pre-screening of bridges was not observed to affect any of the trends observed earlier in this section.

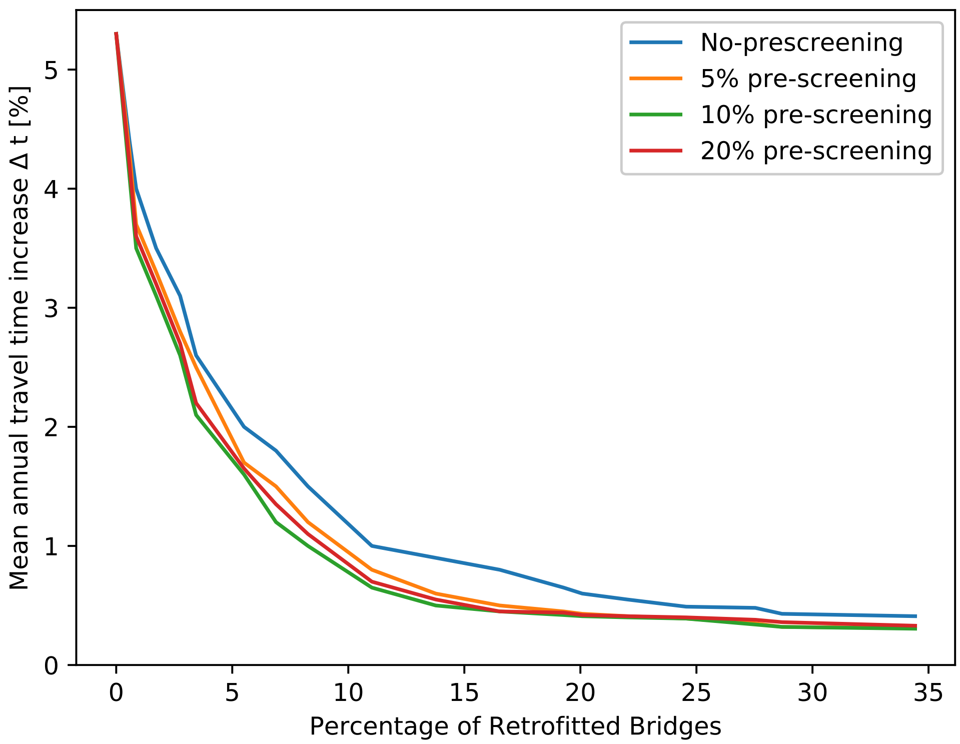

Figure 4.8: Mean annual cumulative increase in travel time for different numbers of pre-screened and retrofitted bridges.

5 Corridors Selection

The performance of the Corridor-Supported Optimization depends upon the initially specified Corridors. Hence, this approach requires effective selection of Corridors. To support this selection, we further examine the impact of various clustering parameters and Corridors characteristics.

First, the seismic assessment of the transportation network is based on the assignment of traffic for origin–destination (OD) pairs, which can be different from those that define the optimization paths. We detected a correlation between retrofitted bridges within the Corridors that were also within the shortest paths of the demand OD pairs. Figure 5.1 shows how the mean annual increase of travel time calculated using Equation 3.9 changes as a function of the number of retrofitted bridges that are outside of the shortest paths but within retrofitted Corridors. To create Figure 5.1, we computed different sets of Corridors by using Equations 3.1–3.2 with different combinations of e and r. Given a number of retrofitted bridges for each set of Corridors, we determined the number of bridges that were within the shortest paths that connect the points of traffic demand and also within the retrofitted Corridors. The star with the corresponding color shows the respective results obtained by using the No-Corridors Optimization. The number of bridges retrofitted outside of the shortest paths in the No-Corridors case is computed in the same way as the Corridor approach; all bridges are considered in Corridors for the purpose of this plot. To illustrate a bridge outside of the shortest path, the black arrows in Figure 5.2 show the shortest path between A and B. As discussed in Figure 3.2, bridges B_A, B_B, and B_C belong to the blue Corridor. If we were to retrofit that Corridor, then bridge B_A would be in the shortest path between nodes A and B, but bridges B_B and B_C would be outside of that path.

Figure 5.1 shows that there is an initial decrease in the impacts to the network, which we believe is due to the retrofitting of rerouting options that the No-Corridors strategy is unable to capture. Note: as the number of bridges outside the shortest paths between OD pairs further increases, the disruption impacts increase, as the retrofitted bridges do not contribute significantly to network performance. This trend of initial drop and later increase is present for a wide range of retrofit budgets. This suggests that Corridors that align with the shortest paths between origins and destinations in the undamaged network tend to produce better performance. This can be achieved by modifying e and r in the clustering step of analysis.

Second, the Corridor selection performance relates to the average number of bridges on retrofitted Corridors. Figure 5.3 shows the expected annual increase of travel time as a function of the average Corridor size. We computed the expected annual increase in travel time after 258

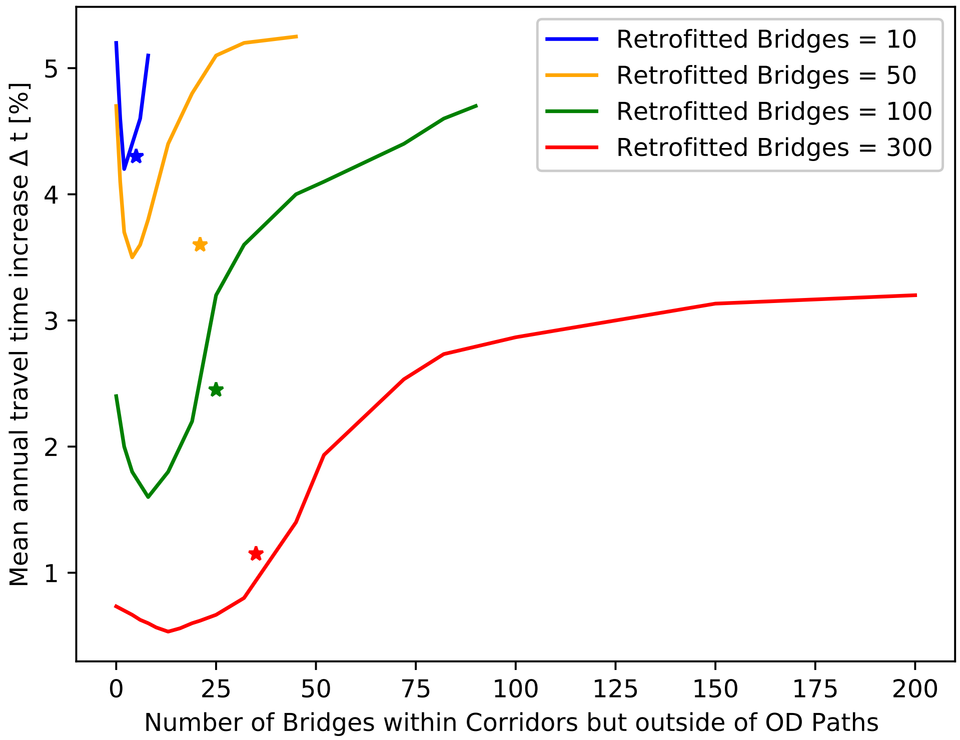

Figure 5.1: Mean annual increase of travel time as a function of the number of bridges outside of OD paths. The star of each color shows the result for the No-Corridors approach.

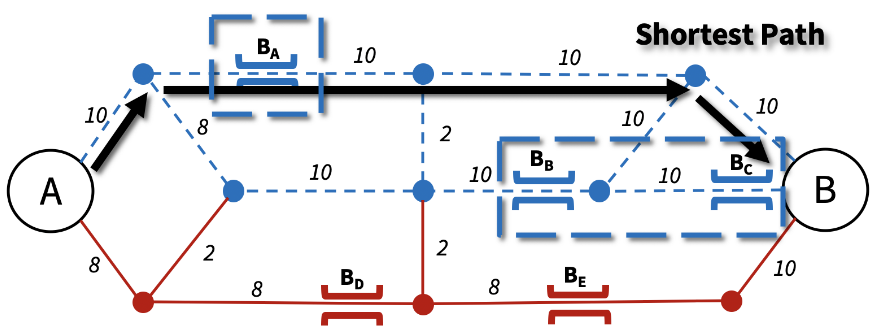

Figure 5.2: Diagram illustrating the meaning of a bridge outside of a shortest OD pair. Bridge B_A is in the shortest path between nodes A and B; bridges B_B and B_C are in the same Corridor but outside of that path.

bridges were retrofitted, using different sets of Corridors that were obtained from varying the e and r values in the clustering. For each set of Corridors, we took the average number of bridges on the Corridors that were retrofitted. As the average Corridor size grows, we observe an initial drop of the mean increase in travel time, followed by an increase. Bigger Corridors tend to force retrofitting bridges that do not have a significant role in the network; hence, they tend to become inefficient. However, small Corridors incorporate bridges that are part of rerouting once bridges from the main paths connecting origin and destination are damaged. Based on Figure 5.3, we recommend increasing the size of Corridors when a decrease on the network performance is observed. We observed this trend for retrofit budgets ranging from 50 to 400 bridges (3% to 22% of the network). When retrofitting less than 50 bridges, the number of retrofitted Corridors is too small to compute the curve of Figure 5.3.

The mean Corridor size does not account for the cluster size variability. To control for variability, the results shown in Figure 5.3 are based on Corridor sets that have coefficients of variation smaller than one. We achieved this by perturbing the clustering parameters to produce clusters with this characteristic. This avoids the need to consider extreme sets of Corridors with hundreds of bridges or only individual bridges. This step is practically useful but does not significantly affect the results presented here.

Finally, we explored how MCL parameter values relate to the performance of the network. Figure 5.4 shows the expected annual increase of travel time for different combinations of e and r when we retrofit 258 bridges. Smaller values of e and smaller values of r (which produce bigger Corridors) tend to perform worse. This is consistent with Figure 5.3.

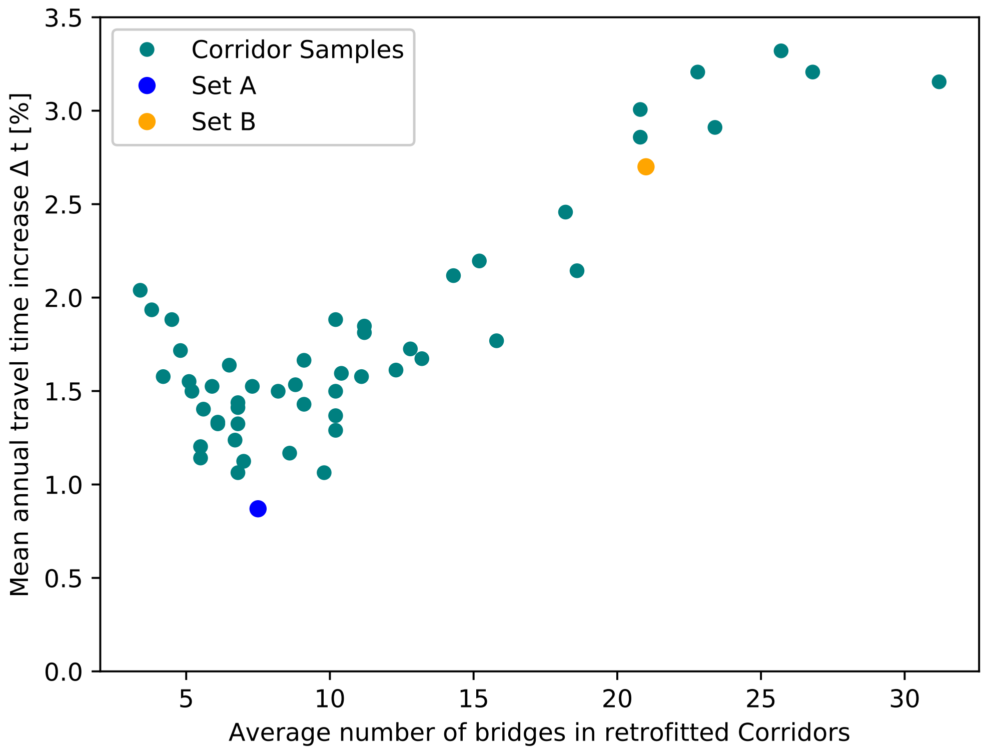

Figure 5.3: Mean annual increase of travel time Δt as a function of the average number of bridges in retrofitted Corridors. Corridor Set A and Set B are labeled in the Figure.

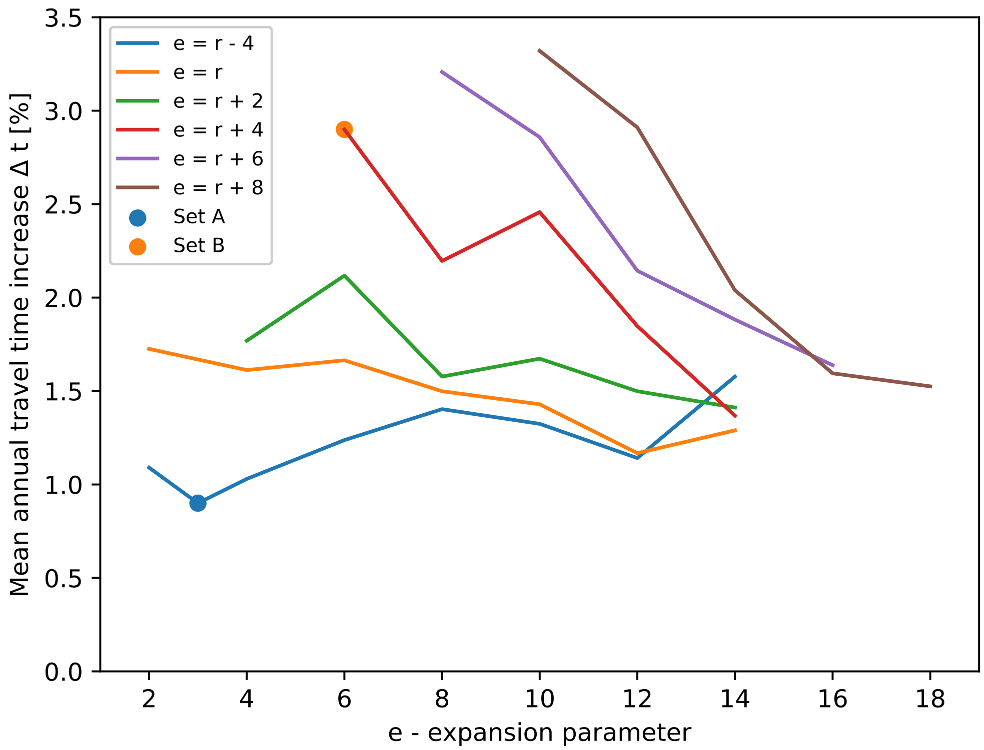

Figure 5.4: Mean annual increase of travel time Δt as a function of the MCL inflation and expansion parameters e and r. All results were obtained for a retrofit budget of 258 bridges.

6 Conclusions

Proposed within is a strategy to identify bridges in a transportation network that could be retrofitted in order to efficiently reduce seismic risk. Corridors-Supported Optimization, a combination of a network clustering process and a two-stage optimization, minimizes the expected annual increase in cumulative travel time in transportation networks, showing better results than other existing approaches.

We verified that the Markov Clustering Algorithm could detect Corridors in transportation networks: sets of bridges that work together as a unit. The results of the clustering process are consistent with the main roads and highways of the example model.

We compared results from this approach with results based on a centrality based ranking prioritization and with a No-Corridors Optimization. The Corridor approach yields retrofits that produce reduced travel time exceedance due to earthquake-induced bridge damage. Travel time exceedance was measured via a loss exceedance curve as well as an expected annual increase. We explored different retrofitting budgets and observed that the Corridors-Supported Optimization performs best in most cases. The performance difference is greatest when considering an intermediate number of bridges for retrofit.

In this report, we propose guidelines to select a suitable set of Corridors. We explored three trends to select Corridors based on network performance: bridges outside of main paths between origin–destination pairs, the size of retrofitted Corridors, and the parameters of the Markov Clustering Algorithm. We observed that Corridors show better performance when they capture bridges within main paths, which have higher flow in normal network conditions. Regarding the size of retrofitted Corridors, we observe that medium-sized Corridors were able to capture rerouting effects without introducing inefficiencies by retrofitting too many bridges of small importance.

The use of decomposition techniques for stochastic optimization (Gomez and Baker, 2019) allows the formulation to remain computationally inexpensive despite the complexity of transportation systems subject to seismic hazard. The computational feasibility of the method does not require neglecting processes critical to an informed retrofitting decision. The process incorporates complex processes such as traffic rerouting, iterative traffic assignment, uncertain future seismic events with spatially varying shaking intensity, and stochastic bridge damage.

A limitation of this work is that we cannot *a priori* ensure a set of Corridors that minimizes network disruption out of all sets of Corridors. However, it is feasible to re-run the process multiple times with alternate Corridors as part of the search process. Even with this search process, the approach is much faster than an exhaustive search of the solution space. With reasonable Corridor choices, this approach outperformed other approaches.

In terms of public policy, Corridor retrofits are appealing since the bridges are close together or belong to the same road or highway. This is a classical approach when performing other construction activities (e.g., Hajdin and Lindenmann, 2007). The above considerations indicate that Corridors are a promising tool to support decision making in transportation networks subject to seismic hazard.

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