

Use of Corridors to Select Bridges to Retrofit in Road Networks in Seismic Regions

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Abstract

This study proposes the use of bridge clusters, defined as Corridors, to support optimal bridge retrofitting strategies for seismic risk management of road networks. A Corridor is defined as a set of bridges that works jointly to ensure connectivity and traffic flow between different areas of a region. To detect Corridors, a Markov Clustering Algorithm is proposed. Using the San Francisco Bay Area road network as a testbed, this clustering technique selects sets of bridges that correspond to main traffic arteries such as highways and high-capacity road segments. After Corridors have been detected, a two-stage stochastic optimization is implemented to detect which bridges should be retrofitted to ensure an acceptable performance under uncertain conditions. The proposed optimization couples retrofitting actions over bridges in a Corridor with the repair actions to individual damaged bridges after an earthquake. The Corridors-Supported Optimization is shown to decrease road network disruption more than other approaches based on ranking bridges according to their traffic capacity or their location in the network.

1 Introduction

Transportation networks are fundamental lifelines for cities, allowing the flow of people and goods indispensable for the proper functioning of communities. However, these systems comprise bridges and roads that may experience damage during an earthquake, disrupting users. In this study, we present the use of Corridors as a tool to propose optimal bridge retrofitting strategies for seismic risk management of road networks. We define a Corridor as a set of bridges that works as a unit to deliver a transportation service. A Corridor can intuitively be observed as a section of the road network, such as a highway, an avenue, or a main traffic artery. The proposed Corridor approach supports decision-making by grouping bridges that, if retrofitted jointly, effectively reduce the risk of losing connectivity or affecting traffic flow throughout the system. To select bridges to retrofit, given a set of Corridors, we use a stochastic optimization that minimizes costs subject to an acceptable network performance.

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 recovery time. This study increases community resilience by proposing an optimal bridge retrofitting strategy that reduces the probability of failure of the system, minimizing the consequences of road network disruption.

Identifying retrofitting strategies 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 non-linear and computationally expensive to model. Second, the choice of bridges to retrofit is combinatorial. Real transportation systems have thousands of bridges, making it impossible to evaluate the immense number of permutations of bridges that could be retrofitted. Finally, the previous complexities scale further if we consider that the proposed actions must be evaluated for several probabilistic seismic scenarios. Accounting for these challenges, this study proposes a bridge retrofitting strategy that accounts for the computational and network complexities of road networks. Currently, there is no tractable approach for identifying strategies that optimally reduce risk under uncertain future seismic events scenarios.

The main contribution of this study is to propose an optimization framework that incorporates Corridors to support decision-making problems in complex systems while simultaneously managing computational costs. Moreover, from the logistical point of view, implementing 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: Section 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. Section 3 describes how Corridors are used in a two-step stochastic optimization. Section 4 presents an example implementation for the San Francisco Bay Area. Section 5 explores the characteristics of effective Corridors. Finally, Section 6 presents the conclusions of this study.

2 Related Work

Given the importance of road networks for communities, decision-makers face the challenge of optimally maintaining and operating these systems in the face of uncertain natural hazards such as earthquakes (Sánchez-Silva et al., 2016). In this context, seismically retrofitting bridges has proven to be effective at decreasing the probability of failure due to ground shaking of these critical infrastructure (Buckle et al., 2006; Shinozuka et al., 2003); therefore, decision-makers have explored methods to optimally select bridges to retrofit as a way to improve the resilience of complex infrastructure by enhancing their preparedness (Ouyang et al., 2012). A key aspect of evaluating the effectiveness of retrofitting bridges over transportation networks is quantifying the changes observed in the system’s seismic risk due to these actions over several seismic scenarios, as implemented by Mayet and Madanat (2002). Several authors have explored efficient ways to assess seismic risk in distributed systems (Faturechi and Miller-Hooks, 2015). Many of these approaches use Monte Carlo methods to simulate seismic scenarios, resulting in bridge damage and network consequences (Bommer et al., 2002). Chang et al. (2000) proposed a framework to extend risk analysis for distributed systems accounting for spatial correlation and network performance indicators. Decò and Frangopol (2011) introduced a methodology to incorporate different hazards that affect road networks. 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 combining sampling importance and optimization techniques. Building upon this model, Miller and Baker (2015) developed an optimization that, besides minimizing seismic hazard error, incorporates network performance into the objective function to select seismic scenarios. Using subsets of scenarios allows the evaluation of several retrofitting policies while limiting computational cost.

Given a seismic risk assessment framework, we can proceed to evaluate retrofitting policies. 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 (Council, 1984). Currently, Caltrans prioritizes bridges according to their seismic guidelines (Caltrans, 2019), which classify bridges as “ordinary,” “recovery,” or “important,” 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 Frangopol and Bocchini (2012).

Stochastic optimization techniques have proved to improve the performance of transportation systems while capturing some of their complexities, such as modeling traffic assignment and dealing with optimally allocating resources. In that regard, Fan et al. (2010) proposes stochastic programming to decide what

pre-disaster actions most improve the network’s performance 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 can not capture traffic congestion. Fan et al. (2010) 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. However, they assume that the probability of damage to 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. They use a decomposition algorithm to decrease computational costs and allow scaling to large problems. However, they approximate the impact of bridge damage by summing the impacts of individual bridges rather than quantifying network effects due to traffic rerouting.

Given the computational costs of modeling complex road networks, proxy optimizations (simplified optimizations focused on specific aspects of the problem) are generally preferred to exhaustive optimization. This approach of focusing on an individual network performance metric has been proposed by Chang et al. (2012) who targeted the capacity of the transportation network, Frangopol and Bocchini (2011) who maximized the resilience of the system, and Lu et al. (2018) who focused on travel time.

Regarding the use of Corridors, Hajdin and Lindenmann (2007) show that through their use, 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) use hierarchical clustering to change the resolution of a transportation network while keeping consistency in properties such as its demand. Lim et al. (2015) use spectral clustering to develop a surrogate of the original network, computing zones of greater importance connected by super links.

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

3 Methodology

3.1 Overview

The optimization problem addressed here is to allocate resources to retrofit bridges so network disruption is minimized for uncertain seismic scenarios. Considering this problem, we formulate the optimization as minimizing the cost of retrofit actions, subject to an allowable increase in travel time between different origins and destinations of interest.

The real-closed solution to this problem is combinatorial, consisting of evaluating all possible groups of bridges, computing the network’s performance for each group, and selecting the least expensive group that satisfies the performance constraint. This combinatorial number can be considerable; for instance, retrofitting ten bridges in a network of 1000 bridges leads to approximately 10^{23} possible combinations, making an exhaustive search impossible.

To overcome the computational challenges of the exhaustive search solution, we propose a Corridors-Supported Optimization, a proxy optimization that selects candidate sets of bridges. We define a Corridor as a network segment that works together to deliver a transportation service. We detect a Corridor using

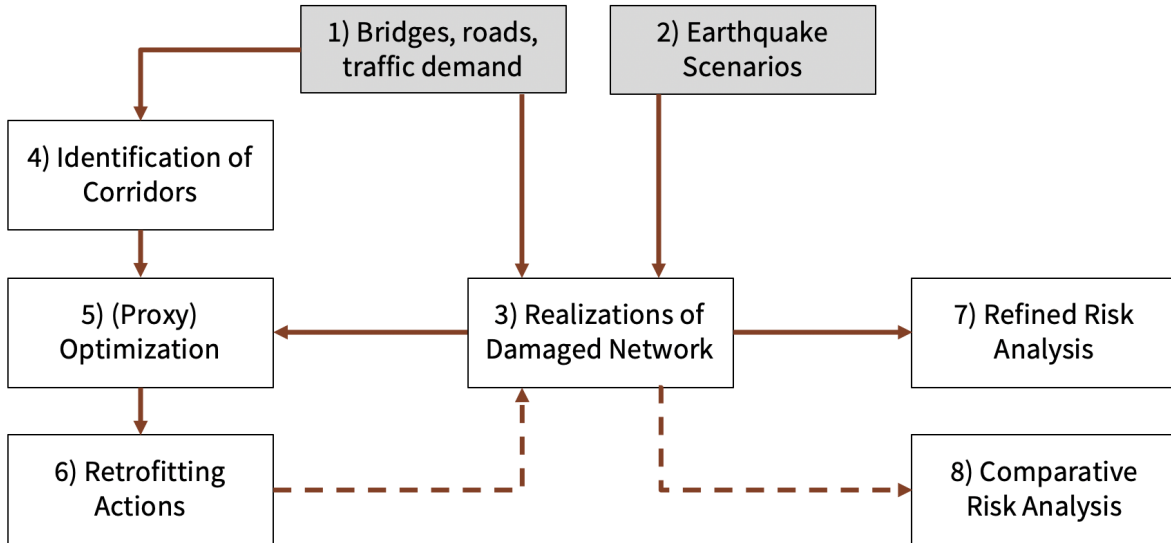


Figure 1: Diagram of the flow of information and computations in the presented study.

the Markov Clustering algorithm, which uses Random Walks to aggregate nodes according to patterns in paths performed over the graph.

Given a set of Corridors, we perform a Corridors-Supported Optimization, a two-step stochastic optimization that utilizes damage realizations for hazard-consistent seismic scenarios. To evaluate the adequacy of a given retrofitting strategy, we assess 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. The true optimum of the problem is unknown, so we evaluate the approach by comparing our results to those obtained using alternate methods.

Figure 1 summarizes the methodology, with numbers indicating key steps. 1) We first define a transportation network by collecting information on traffic demand, roads, and bridges. 2) In parallel, we obtain hazard-consistent seismic scenarios. 3) Using these seismic scenarios and fragility data for the bridges, we obtain realizations of damaged networks. 4) Using the network information, we identify sets of Corridors using a Markov Clustering Algorithm. 5) We then perform the optimization proposed in this study, which produces 6) a set of retrofitting actions. We ‘perform’ these retrofits by modifying the fragility functions of the bridges in the network model and use these new fragility functions to generate new damage realizations (with less frequent damage to the retrofit bridges). 7) With the original network, we perform a full risk analysis, using a transportation model and avoiding simplifications used in step 5, “optimization.” 8) We similarly perform a risk analysis for the retrofitted network and compare the results to those from step 7 to evaluate the actions’ effectiveness. The following subsections will present additional detail on this process, and steps 4, 5, and 7 in particular.

3.2 Corridor Detection

We consider a Corridor as a network section that works together to deliver a transportation service. To identify Corridors (Step 4 of Figure 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 each algorithm’s suitability by assessing 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 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.

MCL is an unsupervised classification method based on random walks performed over the nodes of a graph representing the transportation network. MCL 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 graph nodes. The roads that connect the network define the edges of the graph.

The MCL algorithm 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 definition 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:

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

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:

$$A'_{ij} = A_{ij}^e \quad (2)$$

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, 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. This study defines each detected cluster as a “Corridor.” Hence, these clusters will be called Corridors in the following sections.

Figure 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 network segments with intuitively strong relations 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 Section 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 as groups of bridges whose 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,

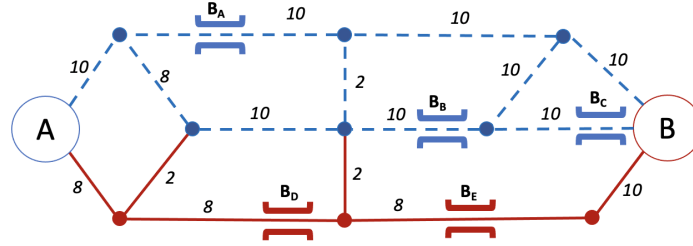


Figure 2: Example of Corridor identification in simplified network. Numbers next to edges indicate their capacities. The MCL parameters are $e = 6$, $r = 6$. Two clusters are shown, one in red solid lines and the other one in blue dashed lines. Bridges B_A , B_B and B_C belong to the blue cluster, and bridges B_D and B_E belong to the red cluster.

we randomly assign the bridge to one of the Corridors. In Figure 2, bridges were assigned considering the Corridor to which the nodes of their edges were assigned. Note that the red edge 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 has been taken on them.

3.3 Corridors-Supported Optimization

With the corridors defined, we next perform an optimization to identify retrofitting actions (Step 5 of Figure 1). We propose minimizing the cost of actions under time and physical constraints so that bridges in a Corridor receive the same retrofit decision. We define 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, coupling the decision of retrofitting bridges before a disruptive event as a first step, with repairing damaged bridges after an earthquake, as a second step. This optimization minimizes the cost of these actions while enforcing a network performance constraint defined as a maximum acceptable time increase for sets of origins and destinations of interest.

Mathematically, we formulate Corridors-Supported Optimization as:

$$\min \left(\sum_{c \in C} c_{\text{retrofit}} x_c + E_{\xi} [c_{\text{repair}} y_{\xi, b} + \omega_{\xi}] \right) \quad (3)$$

Subject to:

$$\sum_{b \in p} t_{0, b} [x_b + y_{\xi, b}] + t_{\xi, b} [1 - (x_b + y_{\xi, b})] \leq t_p^* (1 + \varepsilon), \quad \forall p \in P, \forall \xi \in \Xi \quad (4)$$

$$x_b = x_c, \quad \forall b \in c \quad (5)$$

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 c_{retrofit} , which are certain, and 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 by $E_{\xi}[\cdot]$). This expectation makes the problem a two-step stochastic optimization.

We define two constraints, one related to network performance and the other incorporating Corridors. Regarding network performance, Equation 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 "Optimization Paths," and are described in the equations by the set P . To consider the Corridors' role, Equation 5 enforces that the same retrofitting action should be performed over all bridges b within a Corridor c . The complete formulation of a Corridors optimization relies on the implementation of the two constraints simultaneously. The first constraint ensures acceptable traffic performance; the second constraint, groups actions on bridges to consider Corridors.

As input for the optimization, we define seismic scenarios Ξ that are consistent with the hazard of the region of study (Step 2 of Figure 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 use Ground Motion Models to estimate the distribution of intensity measures at the bridges' locations in the transportation network and sample intensity measure values from that distribution. For each seismic scenario ξ , we sample damage realizations using each bridge's fragility functions and the sampled intensity measure values (Step 3 of Figure 1). Using these realizations of damage, we can 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 on each path p , we compute an undamaged travel time and a damaged travel time. In case a bridge b in an edge a experiences damage, we define its damaged travel time $t_{\xi,b}$ as the undamaged travel time of that edge ($t_{0,b}$) plus the increase of the travel time between the origin and destination that define the path p , considering that the bridge is damaged, but all other bridges in the network are intact. This increase in time is caused by rerouting effects due to the impossibility of using the damaged bridge.

For computational efficiency during the optimization, 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. However, this is computationally expensive, and more importantly, it would change the set of optimization variables in each scenario, which is problematic for the optimization. It is important to note that during the performance evaluation of the retrofitted bridges, the assumption of fixed paths between origin and destinations is not considered, allowing for rerouting on each seismic scenario.

In summary, the following information is required to perform the Corridors-Supported Optimization. 1) Set of Origins and Destinations for the region under analysis. 2) Traffic Demand for each Origin and Destination. 3) Optimization Paths (P) are the shortest paths connecting each origin to each destination. 4) Set

of seismic scenarios and their respective occurrence rates Ξ . The final output of the Corridors-Supported Optimization is a set of Corridors to be retrofitted.

The optimization implies 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 optimization formulation and are not included in the performance assessment described in Section 3.4. Since the results are evaluated using the Section 3.4 procedure, the optimization formulation’s assumptions do not limit the proposal’s scope.

The above model formulation builds off the proposal by Gomez and Baker (2019), with a few additions and refinements. The main difference with that study is that we change the constraints to enforce that every bridge a the Corridor gets the same action instead of considering individual bridges. We also refined the travel time definition. Gomez and Baker (2019) defined the penalty for damage as an infinite time increase in the edge, which forced a retrofitting action for all bridges that experienced damage in at least one scenario 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.”

Our model also omits the Gomez and Baker (2019) constraint that limits the number of retrofitting actions. Gomez and Baker needed that constraint since their damage travel time forced a maximum number of bridges to be retrofitted. In most cases, we analyzed that the constraint was active, and the time constraint was not active. In our methodology, the number of retrofitting actions results from 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 achieve the target network performance. However, the retrofits are not a model input but must be achieved by varying the travel time constraint.

3.4 Performance Evaluation

To assess the effectiveness of retrofitting actions, we evaluate the improvement in network performance compared to its current state (Steps 7 and 8 of Figure 1). We define network performance as the expected annual travel time increase, considering a set of hazard-consistent potential future seismic scenarios. Evaluating network performance comprises three steps: simulate seismic scenarios, simulate bridge damage, and perform traffic demand assignment on the damaged network to compute travel times.

The first step in assessing the system’s performance is 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.

The second step is to develop realizations of damage for each bridge based on the intensity measures of the previous step and the fragility function for each bridge. For each scenario, we simulate 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 evaluate the network performance once the retrofitting actions have taken place. We do this by modifying the bridges’ fragility functions 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, 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:

$$P(DS_i \geq ds_k | Y_i = y) = \Phi \left(\frac{\ln(y/(\alpha \lambda_{k,i}))}{\beta_{k,i}} \right) \quad (6)$$

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

α = 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 is to compute travel time for the system users. Once we have a damaged version of the transportation system, we perform a traffic assignment, which determines for each road of the network the number of vehicles circulating in an hour and the time that it takes them to travel over that road. Using this output, we compute the increase in total travel time for all network users (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 percent increases in total travel time for each scenario and damage map. The annual rate of exceedance of a given travel time increase is computed as:

$$\lambda_{\Delta t \geq \Delta t'} = \sum_{k=1}^n w_k \mathbf{I}(\Delta t_k \geq \Delta t') \quad (7)$$

Where:

Δt_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:

$$\Delta t_k = \frac{tt_k - tt_{UD}}{tt_{UD}} \times 100 \quad (8)$$

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 the undamaged condition of the network

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

$$E[\Delta t] = \sum_{k=1}^n w_k \Delta t_k \quad (9)$$

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

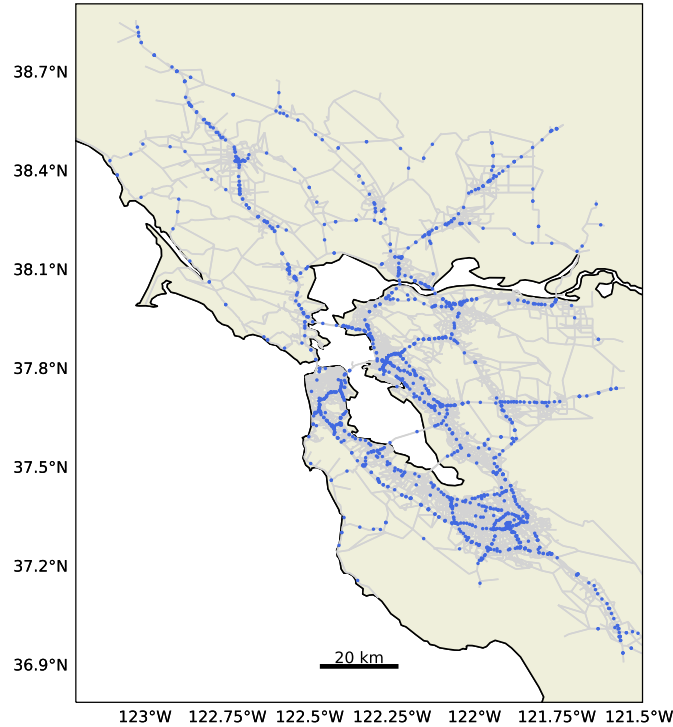


Figure 3: Road network model utilized in this study. Grey lines represent roads and blue dots represent bridges.

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

To illustrate the Corridors-Supported Optimization, we apply the methodology to the San Francisco Bay Area’s transportation network. We show the steps described above and 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 Department of Transportation of California (Caltrans) provided information on the bridges’ fragility curves. Instead of looking at the effect of specific retrofitting actions such as installing isolators or jacketing bridge columns, we model a general effect of conducting a retrofitting action. We use $\alpha = 1.2$ in Equation 6 for all bridges if they are retrofitted, based on representative values for bridge retrofits from Padgett and DesRoches (2008). This reasonable but generic α value illustrates the methodology of interest here without requiring a 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 daily 11 million trips are performed by car grouped in 34 districts. Figure 3 shows a map of the network.

4.1 Corridor Detection

To illustrate results using different sets of Corridors, we consider 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 close to the

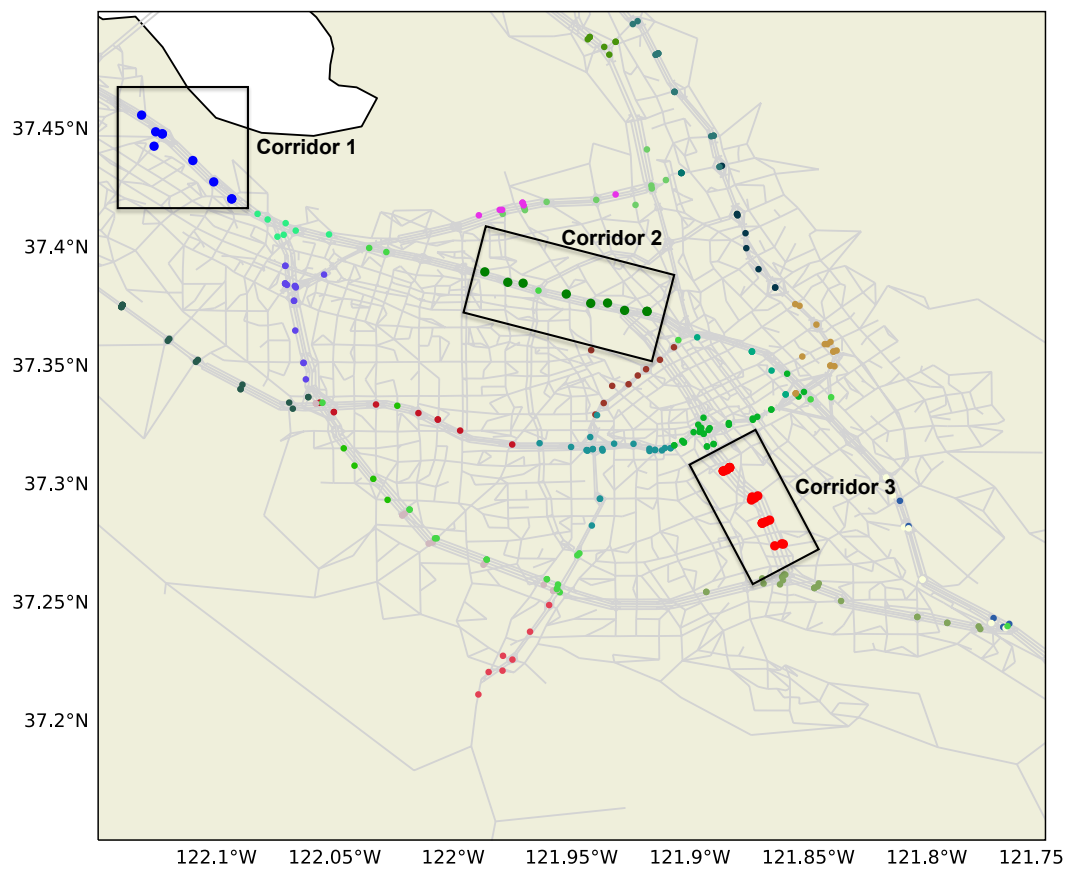


Figure 4: Zoomed in map of the southern area of the road network, with Corridors “Set A” ($e = 3$, $r = 4$) indicated by dots of a given color. Three example corridors are also noted with boxes.

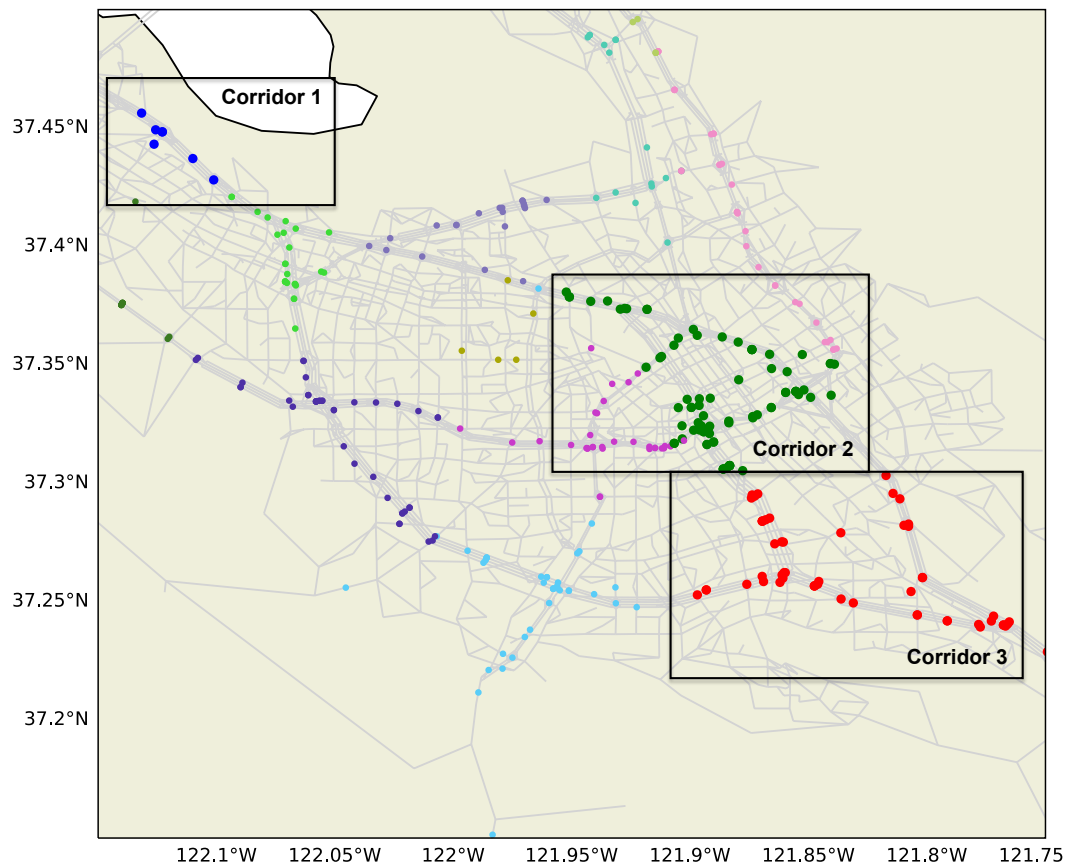


Figure 5: Zoomed in map of the southern area of the road network, with Corridors “Set B” ($e = 6$, $r = 2$) indicated by dots of a given color. Three example corridors are also noted with boxes.

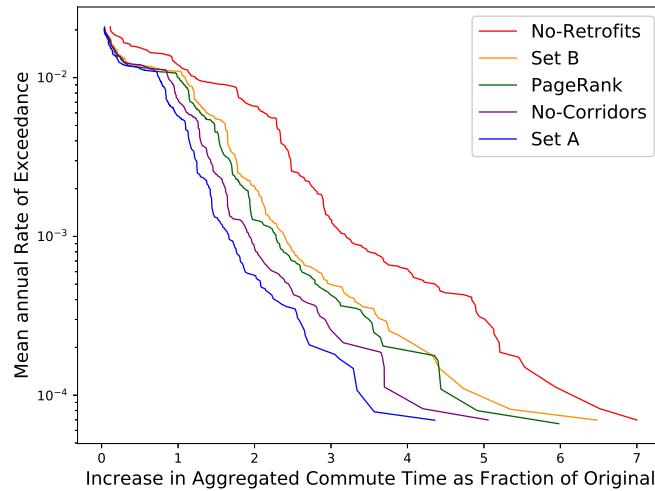


Figure 6: Average number of bridges in Corridors as a function of the inflation and expansion parameters.

optimal (as seen below), and Set B is an example of inefficient Corridors. Figures 4 and 5 show the results of the 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 in each figure to exemplify what a Corridor is. In Figure 4, Set A, we observe 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 exemplify how parameters of the MCL algorithm affect clustering results, Figure 6 shows the average number of bridges per Corridor as a function of e and r . Bigger values of r create smaller Corridors, and bigger values of e generate bigger Corridors. Note that this plot only correlates with Corridor size but does not comment on the network performance improvement due to the clustering process’s parameters. The relationship between optimization performance and parameters e and r is discussed in Section 5. Note also that Figure 6 shows only the average number of bridges on each Corridor. There is significant variability in 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 perform 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 is 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 (and the others would thus not play a role in the optimization calculation). In order to generate paths 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 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) Ground Motion Model, 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 intensity measure values for each event for all bridge sites. The intensity measure used in the bridges’ fragility functions is the 5% damped pseudo absolute spectral acceleration at a period of $T = 1s$. We use the optimal scenario selection of Miller and Baker (2015) for computational efficiency. These calculations produce $n = 1992$ seismic scenarios.

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. We also considered a repair cost equal to 15,000 times the retrofit cost, which 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 costs of disruption and performing rapid repairs and to prefer retrofitting rather than repairing. Taking this into account, we used the same budget for the results shown in this article. As parameters of the constraint presented in Equation 4, ϵ for Corridors Set A was 0.47 and $\epsilon = 0.51$ for Corridors Set B. Note that a different ϵ for each corridor configuration, in order to achieve retrofitting sets with the same cost. The results shown here for the different approaches correspond to retrofitting 258 bridges. Figure 7 shows the proposed sets of retrofitted bridges using the Set A and Set B corridors, as well as the No-Corridors optimization.

For the results shown in this paper, the indirect consequences of a seismic event due to damage to the transportation network, ω , are not directly considered in the optimization, though 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 obtain realizations of damage for each bridge based on the simulated intensity measures of the previous step and the fragility functions for each bridge. For this study, we consider only extensive damage and use the fragility functions provided by Caltrans (2019).

For the final step to evaluate network performance, we compute travel time for the system users. Using a damaged state of the transportation network, we perform an iterative traffic assignment (Beckmann et al., 1956), which determines for each network link the number of vehicles circulating in an hour and the time that it takes them to go over that road. This assignment algorithm models all users as trying to minimize their travel time. Its iterative nature accounts for congestion updates to the road segments. For applying this algorithm to the San Francisco Bay Area, we used the traffic demand provided by the MTC (Erhardt et al., 2012). Using the output of this model, we aggregate the travel time of all network users.

Using the previous steps and Equation 7, we evaluate 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 those that use stochastic optimization. The loss curves associated with each retrofitting protocol are shown in Figure 8.

Figure 8 shows that Corridors-Supported Optimization yields the best results for the given 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, and Set A has much better performance than Set B. Section 5 will further explore how to select the

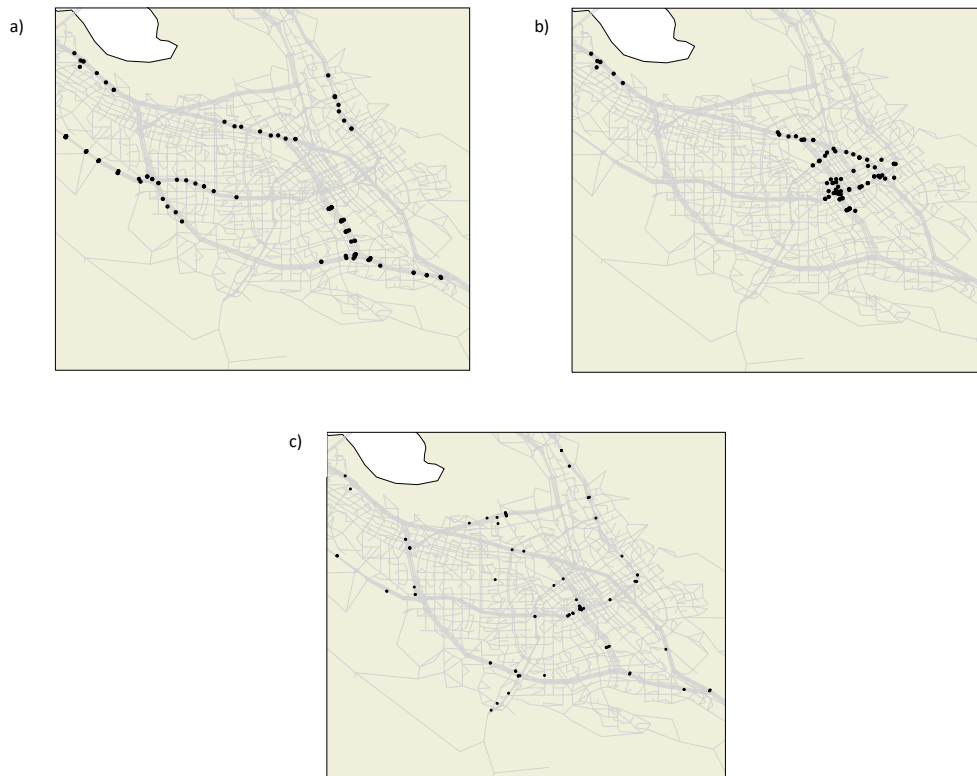


Figure 7: Retrofitted bridges for each method. Intervened bridges shown in black. a) Results for Set A. b) Results for Set B. c) Results for No-Corridors optimization.

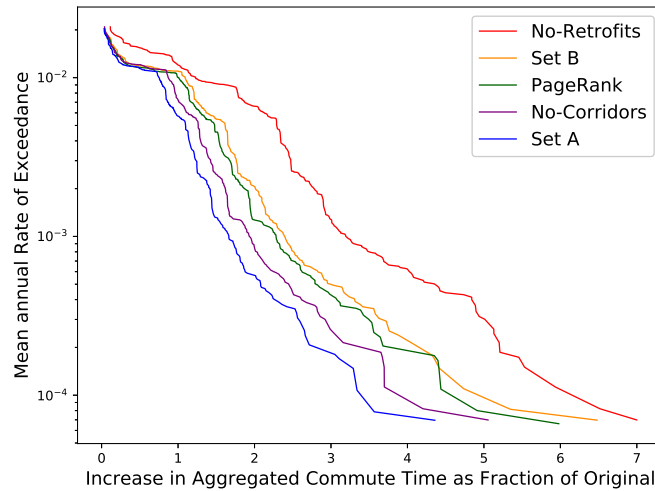


Figure 8: Comparison of different retrofitting approaches in terms of the mean annual rate of exceedance of the increase in cumulative travel time expressed a fraction of the undamaged condition. The No-Retrofits case shows the performance of the original network, and the other cases show performance when 258 bridges (15% of total) are identified using various strategies and retrofitted.

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 strongly correlates to their location. As a result, bridges retrofitted using the Corridor-Supported Optimization align with an intuitive retrofitting strategy: consider an avenue or a highway segment instead of distributed and unrelated bridges. Figures 7a and 7b show the results of the Corridor-Supported Optimization, with retrofits that align with major highways in the region. Figure 7c shows bridges retrofitted using No-Corridors Optimization: although some bridges are 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.

It may be counterintuitive that adding constraints in the optimization of Equations 3-5 produces better network performance. The performance improvement is because this optimization is not the real solution to 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 found a set of Corridors for each retrofitting budget that showed the smallest expected annual increase in travel time, as defined in Equation 9.

Figure 9 shows that the use of Corridors yields a 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, and they are often optimally placed in isolated locations, so considering Corridors with multiple bridges is not conceptually relevant. For between 3% and 22% retrofits, Corridors-Supported Op-

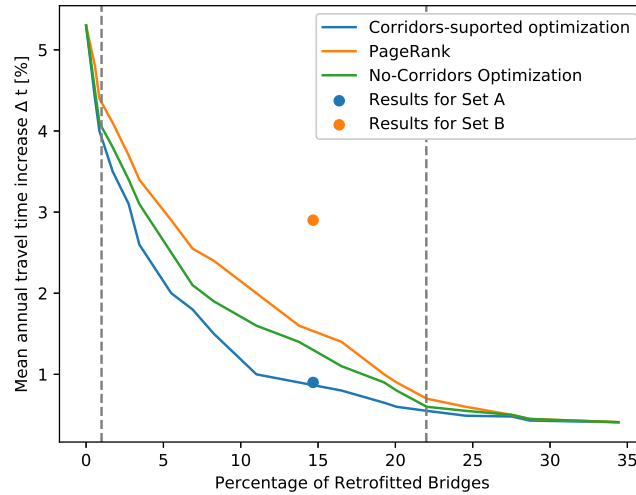


Figure 9: Comparison of the expected increase in travel time as a function of the percentage of the total number of bridges. The Corridors-Supported Optimization result is for the best clustering parameters at the given retrofit budget. Vertical dashed lines indicate the range in which the use of Corridors yields significantly better performance than the No-Corridor approach.

imization 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 decrease 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 a 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 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 $x\%$ by removing them from consideration for retrofit during the clustering and Corridors-Supported Optimization process.

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

5 Corridors Selection

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

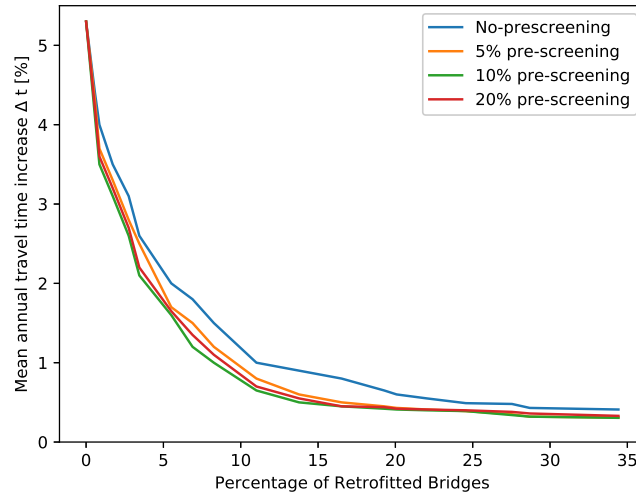


Figure 10: Mean annual cumulative increase in travel time for different numbers of pre-screened and retrofitted bridges.

First, the seismic assessment of the transportation network is based on the traffic assignment for Origin-Destination pairs, which can be different from those that define the optimization paths. We detected a correlation between retrofitted bridges within the Corridors and the shortest paths of the demand OD pairs. Figure 11 shows how the mean annual increase of travel time, calculated using Equation 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 11, we computed different sets of Corridors by using Equations 1-2 with different combinations of e and r . Given several retrofitted bridges, for each set of Corridors, we determined the number of bridges within the shortest paths that connect traffic demand points and within the retrofitted Corridors. The star with the corresponding color shows the individual results obtained using the No-Corridors optimization. The number of bridges retrofitted outside of the shortest paths in the No-Corridors case is computed similarly to the Corridor approach (and all bridges are considered in Corridors for this plot). To illustrate a bridge outside of the shortest path, Figure 12 shows in black arrows the shortest path between A and B. As we discussed in Figure 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 11 shows an initial decrease in the impacts on the network, which we believe is due to the retrofitting of rerouting options that the No-Corridors strategy cannot capture. However, 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 initial drop and later increase trend are present for many retrofit budgets. This trend suggests that Corridors that align with the shortest paths between origins and destinations in the undamaged network produce better performance. This improved performance can be achieved by modifying e and r in the clustering step of the analysis.

Second, the Corridor selection performance relates to the average number of bridges on retrofitted Corridors. Figure 13 shows the expected annual travel time increase as a function of the average Corridor size. We computed the expected annual increase in travel time after 258 bridges were retrofit, 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 retrofitted corridors. As the average Corridor size grows, we observe an initial drop in 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

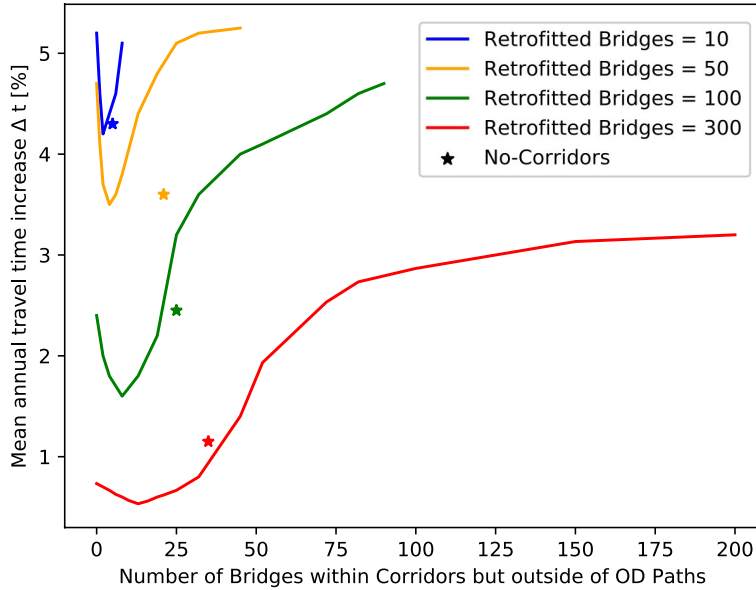


Figure 11: Mean annual increase of travel time as a function of the number of bridges outside of OD paths. The star of each color shows the result for the No-Corridors approach.

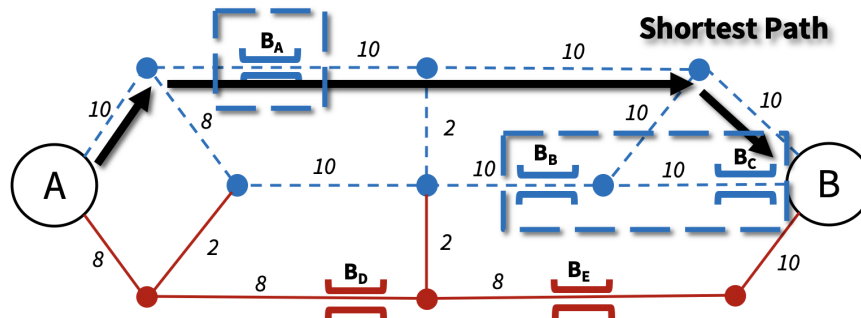


Figure 12: Diagram illustrating the meaning of a bridge outside of a shortest OD pair. Bridge B_A is in the shortest path between nodes A and B; bridges B_B and B_C are in the same Corridor but outside of that path.

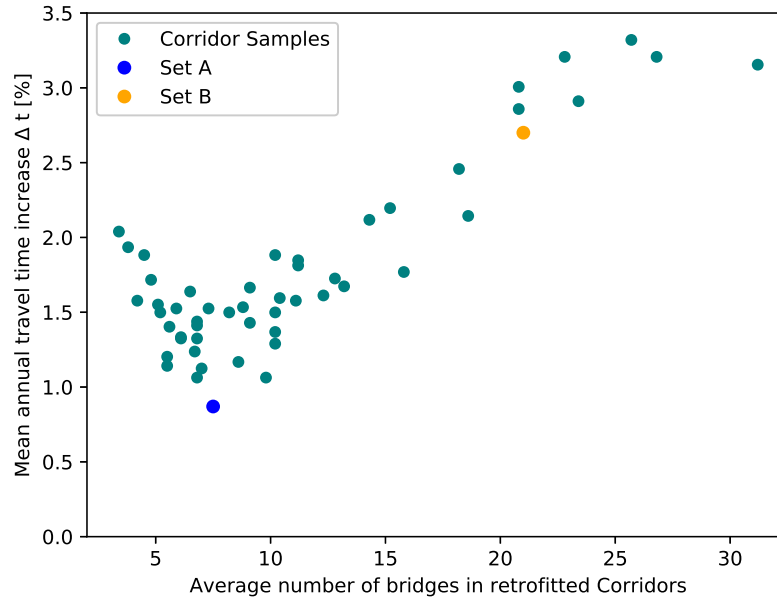


Figure 13: Mean annual increase of travel time Δt as a function of the average number of bridges in retrofitted Corridors. Corridor Set A and Set B are labeled in the Figure.

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 13, we recommend increasing the size of Corridors, and a decrease in 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 retrofit Corridors is too small to compute the curve of Figure 13.

The mean Corridor size does not account for the cluster size variability. To control for variability, the results shown in Figure 13 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 definition of clusters avoids considering extreme sets of Corridors with hundreds of bridges or only individual bridges. This step is useful but does not significantly affect the results presented here.

Finally, we explored how MCL parameter values relate to the network’s performance. Figure 14 shows the expected annual travel time increase 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 13.

6 Conclusions

We propose a strategy to identify bridges in a transportation network that can be retrofitted to reduce seismic risk efficiently. 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.

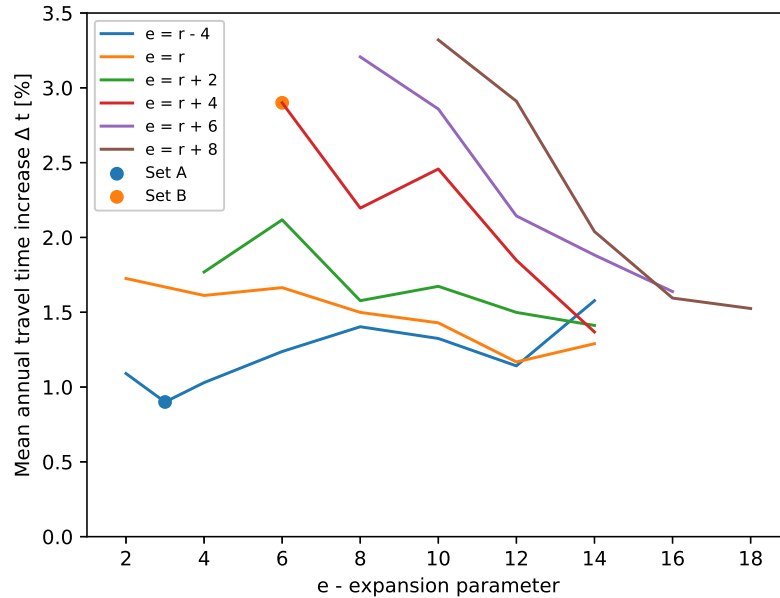


Figure 14: Mean annual increase of travel time Δt as a function of the MCL inflation and expansion parameters e and r . All results were obtained for a retrofit budget of 258 bridges.

We compared this approach with results based on a centrality-based ranking prioritization and a No-Corridors optimization. The Corridor approach yields retrofits that reduce travel time exceedance due to earthquake-induced bridge damage. Travel time exceedance was measured via a loss exceedance curve and 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.

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. Corridors perform better 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 could 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 strategy 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.

7 Acknowledgements

Thanks to Tom Shantz for insights regarding the concept of Corridors in transportation systems and Camilo Gomez for clarifications regarding optimization issues. The State of California supported this work through the Transportation System Research Program of the Pacific Earthquake Engineering Research Center (PEER). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect those of the funding agency.

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