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Optimal bridge retrofitting selection for seismic risk management using genetic algorithms and neural network-based surrogate models

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ABSTRACT

This study uses genetic algorithms as part of an optimization framework to directly minimize the expected impacts of road network disruption triggered by seismic events. This minimization is achieved by selecting an optimal set of bridges to retrofit to decrease their probability of being unavailable after an earthquake. We propose a genetic algorithm that outstrips other retrofitting techniques, such as ranking bridges by vulnerability or traffic importance. The proposed framework is demonstrated using the San Francisco Road Network as a testbed. This example shows that bridges selected by genetic algorithms are structurally vulnerable groups of bridges that act as corridors in the network. Additionally, this study evaluates and recommends domain reduction techniques and hyperparameter calibrations that can decrease the computational costs of this approach.

INTRODUCTION

Road networks play a fundamental role in moving individuals and goods. Unfortunately, seismic damage to network elements such as bridges can significantly disrupt their normal functioning. Motivated by their vulnerability and importance, retrofitting bridges has been proposed as an effective way to minimize the impacts of earthquakes on this critical infrastructure (Buckle et al. 2006).

However, evaluating the traffic performance of regional road networks is computationally expensive (Bar-Gera 2010). Multiple researchers have proposed optimization strategies (Liu et al. 2009; Fan et al. 2010; Gomez and Baker 2019) that detect bridges to be retrofitted by solving proxy optimizations that lead to feasible computational times considering a reduced number of bridges and seismic scenarios. Fan et al. (2010) propose a stochastic optimization in which expected costs of repair and traffic flow changes are minimized subject to the number of bridges to be retrofitted. Given the computational challenges associated with estimating road network performance, the study used a reduced number of scenarios, a simplified road network comprising only 13 bridges, and used traffic flow as a performance metric instead of modeling trips in the region using origin and demand information. Gomez and Baker (2019) implemented a stochastic optimization that minimized the cost of retrofitting bridges subject to travel time constraints for fixed sets of origins and destinations. Considering the computational costs involved in evaluating the costs of road network performance, Gomez and Baker (2019) used only 65 bridges, and the metric of network performance was simplified by focusing on specific sets of origins and destinations instead of performing regional analysis. While these previous studies aimed to decrease the expected impacts of road network disruption, they were unable to directly minimize regional changes in road network performance, relying on simplified optimization techniques that act as a proxy of the direct optimization problem and a reduced set of bridges and seismic scenarios.

Motivated by the computational challenges of directly minimizing expected regional impacts of road network disruption, the main contribution of this study is to propose an optimization framework that directly minimizes annualized expected road network disruption in a feasible computational time. Previous studies in the field have either explored simplified models or used proxy optimizations to select bridges to retrofit. To introduce the optimization framework, we use genetic algorithms and a neural network-based surrogate model, and we present recommendations and considerations to implement these techniques in distributed infrastructure by decreasing computational costs and presenting ways of enhancing the interpretability of the results of the optimization process.

RELATED WORK

Evaluating road network retrofitting actions requires quantifying the improvements induced by the selected actions. In that regard, several authors have developed and implemented methodologies to evaluate seismic risk on critical distributed infrastructure (Pitilakis et al. 2014; Franchin and Cavalieri 2015; Argyroudis et al. 2015). In addition, Chang et al. (2000) proposed a probabilistic distributed infrastructure risk assessment approach, by aggregating individual realizations of network performance across several scenarios. This is an extension of the Ebel and Kafka (1999) Monte Carlo approach to perform a seismic risk analysis. A primary challenge of Monte Carlo approach is the computational cost of computing performance for several scenarios. Estimating network performance for complex distributed systems can impede the use of a comprehensive suite of seismic scenarios that represent the seismicity of the region (hazard-consistent scenarios), affecting the reliability of the results of a seismic risk analysis. Motivated by these computational challenges, researchers have developed methodologies to select subsets of seismic scenarios that are equivalent to a hazard-consistent set (Han and Davidson 2012; Miller and Baker 2015). This reduction of seismic scenarios was used by Miller (2014) to quantify seismic risk on road networks efficiently.

Researchers have used several metrics to quantify the seismic risk of road networks. Some examples of these metrics ordered according to increasing complexity in computation, are: network connectivity (Nabian and Meidani 2018), access to emergency service locations (Zanini et al. 2017), traffic capacity (Chang et al. 2012), travel time (Shinozuka et al. 2008), traffic performance (Silva-Lopez et al. 2022), cost (Dong et al. 2014), and system resilience (Bocchini and Frangopol 2012). More complex risk metrics can more directly indicate the contribution of road network disruption to community resilience, but may also require stronger assumptions. For instance, the state of the art of bridge recovery requires further research (Gidaris et al. 2017), and therefore, optimizations that focus on recovery metrics present challenges. Motivated by the previous considerations, this study uses a traffic performance metric as defined by (Silva-Lopez et al. 2022) that aggregates increases in travel time along with the number of trips lost due to road unavailability.

The topic of identifying important bridges for seismic retrofit has been fertile ground for research studies, with ranking bridges being a strategy commonly used by governmental agencies. These ranking methods aim to estimate the contribution of the bridge to changes in the seismic risk of the entire system, based on its characteristics and location in the network. Examples of these approaches include Basoz and Kiremidjian (1995), Zhang and Wang (2016), Bhattacharjee and Baker (2021) and Chang et al. (2012). These approaches provide quick and intuitive retrofitting sets for decision-makers, but the intrinsic network properties of road systems are neglected, and therefore these approaches may lead to suboptimal solutions. In addition to ranking bridges, simplified optimization techniques have been used to detect bridges with high contributions to the network. Gomez and Baker (2019) proposed a two-staged stochastic optimization that simplified network effects by precomputing network performance under seismic scenarios. Najarian and Lim (2020) proposed the selection of components to improve based on resilience-based metrics and a reduced set of scenarios. Dong et al. (2015) introduced a framework to retrofit bridges based on economic, social, and environmental impacts derived from changes in travel patterns.

This study proposes the use of genetic algorithms as a tool to select optimal bridges to retrofit. The concept of genetic algorithms was introduced by Bagley (1967), but De Jong (1975) and Holland (1992) are often considered as seminal studies. More details about the history can be found in Back et al. (1997), but modern conceptions on genetic algorithms originate from Sivanandam and Deepa (2008). Many studies have explored the use of genetic algorithms for problems in civil engineering. One of the first was by Fwa et al. (1996), who explored optimal road maintenance and restoration. Following this work, Morcous and Lounis (2005), implemented genetic algorithms to propose maintenance alternatives for infrastructure facilities. Furuta et al. (2011) proposed a multiobjective genetic algorithms (MOGA) optimization to propose optimal bridge management strategies considering a Life Cycle Cost analysis and impacts of bridge collapse for extreme events. Liu et al. (2021) develop a framework that includes MOGA to propose Resilience Enhancement Solutions for interdependent critical infrastructure. These studies indicate the potential of genetic algorithms to support complex decisions, but none of them could be directly adopted for use in probabilistic risk assessments related to bridge retrofits. In addition, these previous studies have not explicitly proposed techniques to reduce the computational costs involved on the implementation of genetic algorithms in complex distributed systems.

This study proposes using surrogate models to enable a rapid and accurate evaluation of the seismic risk of road networks. Surrogate models have proven effective for reducing computational costs of evaluating the risk of complex distributed infrastructure. Zahura et al. (2020) implemented a random forest model to predict regional flooding estimates, enabling rapid decision-making rapidly. In the realm of risk to road networks, Stern et al. (2017) and Nabian and Meidani (2018) explored neural network-based surrogate models to quantify road network connectivity. Motivated by these previous studies, Silva-Lopez et al. (2022) implemented a deep-learning-based model to estimate increases in travel time and changes in the connectivity of a road network.

METHODS

Methodological Overview

The methodology presented in this article consists of four components: (i) seismic risk assessment of the road network, (ii) implementation of a surrogate model, (iii) optimization using genetic algorithms, and (iv) retrofitting strategy evaluation. This methodology is summarized in Figure 1.

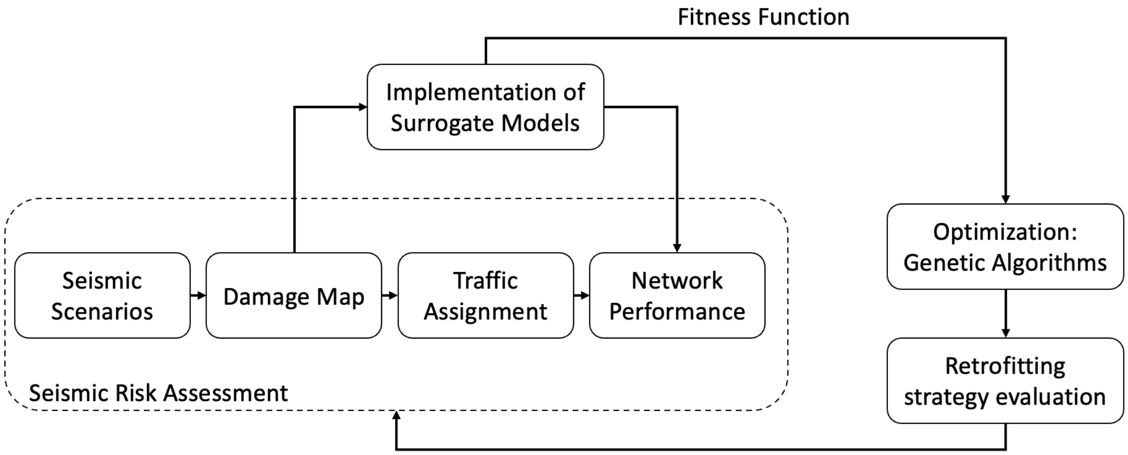

Fig. 1. Diagram of the methodology used in this study.

Seismic risk assessment of road networks

The risk assessment consists of four main steps. First, a suite of seismic scenarios is obtained, consisting of ground shaking intensity measures at critical infrastructure locations such as bridges in road networks. Second, we use fragility functions for each bridge to obtain realizations of damage. Third, we assign trips on the road network using this damaged road network and information on traffic demand. Finally, from the trips, we obtain a global performance metric to quantify the impacts of network disruption due to the seismic scenario.

The suite of seismic scenarios should replicate the natural seismicity of the region to allow the computation of the mean annual loss of complex infrastructure systems. In addition, given the distributed nature of these systems, previous research (Jayaram and Baker 2009) has shown the importance of accounting for spatial correlation to provide more realistic estimates of system performance. Several models can be used to account for this spatial correlation, such as Jayaram and Baker (2009, Heresi and Miranda (2019, Markhvida et al. (2018). Details about the specific model used in the case study for the proposed optimization framework are presented in Section 4.

To obtain damage realizations of the network, it is necessary to have information about the vulnerability of the components in the network that will be subject to improvement. While several components can be considered in a road network, this study focuses on road bridges. To model the vulnerability of these structures, we can use fragility functions that describe the probability of failure of the bridge given a value of intensity measure. A damage map is defined as a network with a damage status for its components.

Estimating network performance requires modeling how commuters travel, considering their origins and destinations. There are several ways in which can be achieved, such as using agent-based models (Balmer et al. 2004), hybrid models, (Burghout et al. 2005), using iterative algorithms (Beckmann et al. 1956) and simplified graph algorithms such as computing the shortest path. Seismic risk assessment of road networks implies assigning traffic for thousands of damage maps and therefore using hybrid, or agent-based approaches are not suitable for this purpose. In addition, to quantify the improvement generated by retrofitting components of a road network, it is necessary to aggregate the changes in travel patterns into a single metric, which is the last step considered in the analysis.

Implementation of surrogate models

Genetic algorithms impose severe computational challenges due to the many evaluations required to achieve convergence. In addition, the risk assessment of complex distributed infrastructure also imposes significant computational challenges. It is thus necessary to increase the computational speed of network performance evaluation without compromising the accuracy of the results. The most expensive analysis step is the estimation of a performance metric from a damaged state of the system, so in this study, we develop a surrogate model that predicts network performance given bridge damage to speed the computation. Similarly, other lifeline systems could use damage indicators of their components as inputs and predict affected users as an output of the neural network.

The surrogate models should be developed only as a replacement for the computationally expensive steps of the risk assessment that have low randomness. For instance, in the seismic risk assessment method, it is not recommended to go directly from the seismic scenario to network performance, as the computational time necessary to obtain damage realizations is low, and the added randomness in the generation of damage maps will impede the accuracy of the surrogate model. In this study, one damage realization is obtained per each seismic scenario to compute the traffic performance metric.

Genetic algorithm optimization

Genetic algorithms are population methods that draw inspiration from biological evolution, in which offspring inherit parents' genes and advantageous genes are more likely to survive to future generations. Resembling natural selection, genetic algorithms are used for optimization by selecting decision points that are combined throughout multiple generations using a fitness function that replicates the objective function of the optimization.

The steps involved in the formulation of a genetic algorithm are (1) Individual and Gene Definition, (2) Population Sampling, (3) Definition of Fitness Function, (4) Parent Selection, (5) Crossover, and (6) Mutation. This process and nomenclature follows Kochenderfer and Wheeler (2019), and is summarized in Figure 2. These six steps are repeated until no improvement in the fitness function is observed in the fittest individuals of the population.

Implementation of this approach for lifeline risk management requires several considerations. The first step, the Individual and Gene definition, should encode the mitigation action explored by decision-makers. For instance, an Individual could be a set of binary variables to indicate whether each component on the lifeline will be retrofitted. Alternatively, an Individual could represent a set of improvement factors for each lifeline component. In this study, we define an Individual as the set of bridges that will be retrofitted through discrete variables representing eligible bridges.

Another implementation consideration is that the Fitness Function introduced in the third step should emulate the goals decision-makers aim to achieve through mitigation actions. The fitness function could represent network performance given a set of retrofitted components, such as the expected annual change in travel time for users or the expected annual number of users disconnected

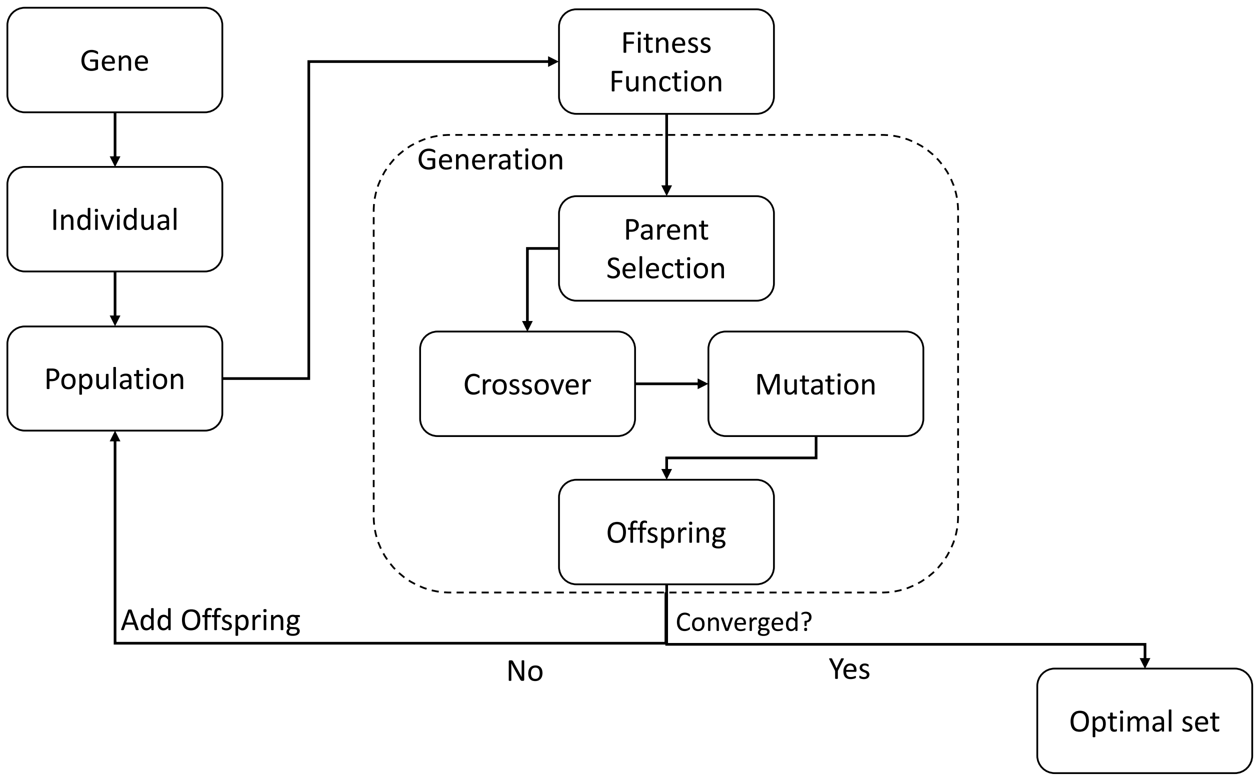

Fig. 2. Diagram of the major steps in the genetic algorithm optimization process.

from service.

Finally, the computational costs of assessing these complex systems and performing genetic algorithms optimization can be managed during model development. This cost reduction can be achieved by (1) evaluating different hyperparameter values for the genetic algorithm crossover, mutation, and parent selection steps, and (2) heuristically reducing the search space of the optimization.

In terms of hyperparameter selection, the mutation rate, mutation protocol, crossover protocol, and probabilities can be calibrated to improve the computational performance of the genetic algorithm while still finding a near-optimal solution. In general, these modifications will guide the genetic algorithm search toward the optimal solution, avoiding non-optimal candidates. Reducing the optimization search space can be implemented on lifeline systems by filtering components that do not contribute significantly to network performance. This selection can be implemented by selecting a heuristic and ranking network components according to this heuristic.

Genetic algorithms are suitable to be implemented in the proposal of mitigation action on distributed infrastructure as they explore a reduced set of solutions to reach the optimum, while avoiding convergence to local optima. On the other side, optimization algorithms such as gradient descent are challenging to utilize with binary variables representing the retrofitting state of the bridges. More complex techniques such as reinforcement learning or Markov decision processes are also challenging for these complex systems as they need to explore a high number of combinations

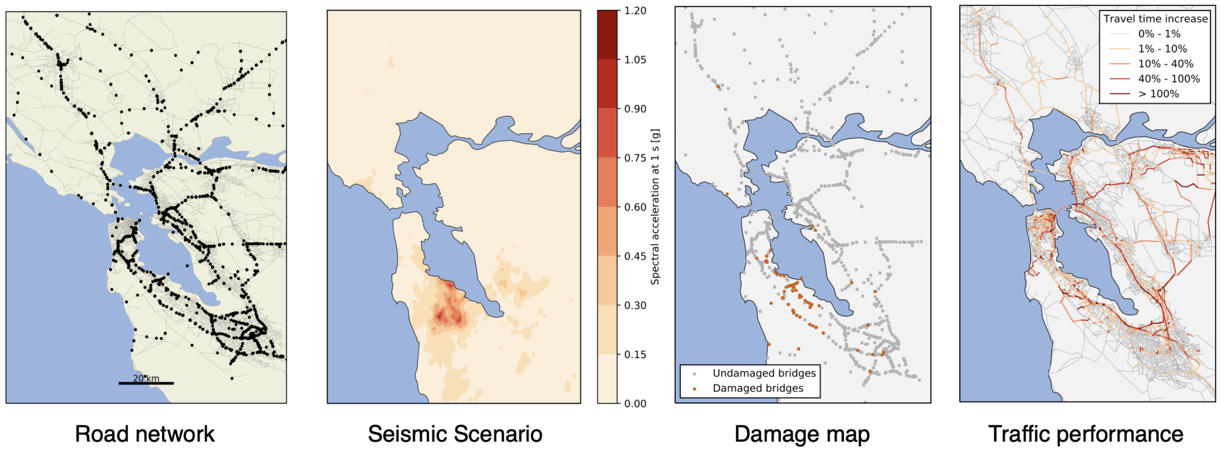

Fig. 3. Map of the case study area, illustrating the major steps of the seismic risk assessment process.

of retrofitted bridges to gather data and propose an optimal solution.

Retrofitting strategy evaluation

The effect of retrofitting bridges is quantified by shifting their fragility functions and quantifying the annual expected performance loss due to future earthquakes. This process is repeated for several numbers of bridges to be retrofitted to analyze the performance of the strategy for different budgetary constrains.

RESULTS FOR THE SAN FRANCISCO BAY AREA ROAD NETWORK

To illustrate the implementation of the optimization framework, we use the road network of the San Francisco Bay Area. Note that the recommendations to reduce computational costs and to enhance interpretability can be used to other regions given that they are based on the theoretical understanding of genetic algorithms as an optimization tool.

San Francisco Road Network Overview

The San Francisco Bay Area road network is used as a testbed to illustrate and evaluate the above methods. The road network is defined by a graph with 32,858 edges and 11,921 nodes, as shown in Figure 3 (Miller 2014). Each edge represents a road segment and contains a number of associated properties, such as free-flow travel time and traffic capacity. The nodes indicate which road segments connect to which others. The model includes 1743 bridges managed by the California Department of Transportation, which are considered susceptible to damage in this study. The study area is home to almost 8 million people, who perform 11 million trips on an average weekday.

Seismic risk assessment

This work follows a seismic risk assessment framework that simulates a set of seismic scenarios, computes ground motion intensity values at locations of bridges; samples damage maps using fragility functions for each bridge, and finally computes road network performance.

We obtained a suite of seismic scenarios for the San Francisco Bay Area using the OpenSHA Event Set Calculator (Field et al. 2003) with the Uniform California Earthquake Rupture Forecast Model 2 (Field et al. 2009). For each seismic scenario, we simulated the values of spectral acceleration (SA) at $T = 1s$ for each bridge location using the Boore and Atkinson (2008) Ground Motion Model and the Jayaram and Baker (2009) spatial correlation model. Information of near-surface shear-wave velocity (V_{s30}) was obtained by the method from Wald and Allen (2007).

Then, we obtained realizations of damage for each bridge for each seismic scenario. We used fragility functions for each bridge from Miller (2014), who complemented the HAZUS (HAZUS 2003) model with information from the California Department of Transportation. Probabilities of damage are computed using fragility functions as shown in Equation 1, and then a binary damage outcome is sampled with the computed probability. This binary model follows the fact that we are modeling conditions of the bridge being operable or not, with severe to complete damage states triggering the closure of the bridge. Bridge retrofit reduces the probability of damage, and is reflected in this model by shifting the fragility function using the parameter α, which is set to 1.17 to 1.32 for retrofits, based on typical performance improvements reported by Padgett and DesRoches (2009). It is important to mention that there are some limitations with the use of these parameters to evaluate the impacts of retrofitting bridges; first, the parameters were not calibrated for California, and second, here, we are using them for SA instead of PGA. While these limitations are significant, the scope of this manuscript focuses on the illustration of the implementation of the optimization framework, and therefore the selection of the above factors is adequate for that purpose. In addition, the proposed methodology is flexible, and it can be replicated with more specific parameters for each study area.

$$P(DS_i \geq ds_j | SA_i = y) = \Phi\left(\frac{\ln\left(y/(\alpha\lambda_{j,i})\right)}{\beta_{j,i}}\right) \tag{1}$$

where,
DS_i = Damage state of bridge i.
ds_j = Damage state j.
SA_i = One-second spectral acceleration value at the location of bridge i.
$P(DS_i \geq ds_j | SA_i = y)$ = Probability of bridge i's damage state being $\geq ds_j$, given $SA_i = y$.
Φ = Standard normal cumulative distribution function.
$\alpha = 1$ for no retrofit and $\alpha = 1.17$ to 1.32 for retrofit.
$\lambda_{j,i}$ = Median of SA_i causing damage state j or greater.
$\beta_{j,i}$ = Standard deviation of $ln(SA_i)$ causing damage state j or greater.

One *damage map*, representing damage realizations for all bridges, is sampled per seismic scenario developed in the previous section. This work followed the work of Werner et al. (2006) to determine the relationship between damage and functionality of bridges. Specifically, a timeframe of one week after the earthquake is considered, and no traffic is allowed on or under bridges in an extensive or complete damage state, while bridges with no, slight, or moderate damage are considered functional (i.e., sufficiently repaired to allow normal traffic). This timeframe was selected following conversations with the Department of Transportation of California, reported in Miller

(2014)

An iterative traffic assignment model is used to model the effect of bridge damage on trip disruption (Chen and Alfa 1991). This traffic model progressively assigns traffic demand between origins and destinations (OD) by computing the shortest path between them and assigning a fraction of the trips to that path. Then, the travel times on each road are updated considering the traffic that is flowing on them according to Equation 2 (Beckmann et al. 1956). This process is repeated until all traffic demand has been assigned.

$$t_a = t_f \left(1 + 0.15 \left(\frac{q_a}{c_f}\right)^4\right) \tag{2}$$

where,
t_a = Travel time on the road segment after flow assignment.
t_f = Free flow travel time on the road segment.
q_a = Current flow on the road segment.
c_f = Capacity of the road segment.

This work computed the network's performance as an aggregated metric obtained from analyzing the assigned trips in the network, using the following metric that combines travel time and lost trips due to loss of connectivity (Silva-Lopez et al. 2022),

$$tp_k = tt_k + \gamma n_{lt_K} \tag{3}$$

where,
tp_k = Traffic performance metric for damage map k (with units of time).
tt_k = Aggregated travel time for users for damage map k.
n_{lt_k} = Number of lost trips due to lack of connectivity for damage map k.
γ = Penalty factor for lost trips. This study considers γ = 4 hours. This value was selected as we assumed the longest possible trip to be performed in a day would be 4 hours, which is explained in (Silva-Lopez et al. 2022).

The percent change in the traffic performance metric Δtp for damage map k is defined as,

$$\Delta tp_k = \frac{tp_k - tp_{UD}}{tp_{UD}} \times 100 \tag{4}$$

where tp_k is from Equation 3 and tp_{UD} is the traffic performance metric in the undamaged condition (which is equivalent to the aggregated travel time for all users, since there are no lost trips in that case).

To evaluate the performance of a retrofitting strategy, it is necessary to aggregate the changes induced by the retrofitting protocol across all scenarios. We compute the expected annual change in traffic performance metric $E[\Delta tp]$ by summing all event-specific impacts, weighted by their annual rates of occurrence:

$$E[\Delta tp] = \sum_{k=1}^{n} w_k \, \Delta tp_k \tag{5}$$

where Δtp_k is the percent increase in traffic performance metric for damage map k from Equation 4, w_k is the annual rate of occurrence of damage map k (based on the occurrence rate of the associated seismic scenario).

Surrogate model implementation

We measured the performance of different retrofitting strategies using the expected annual change in the traffic performance metric $E[\Delta tp]$ (Equation 5). We use a surrogate model to facilitate computation of the many tp_k values for that calculation. For this study, we used a deep neural network surrogate model from Silva-Lopez et al. (2022), which used the same testbed and traffic performance metric as in this study. This neural network takes as input the damage states of bridges and predicts the change in traffic performance with respect to the undamaged condition, as defined in Equation 4. This neural network is presented in Figure 4. This surrogate model reduces computational costs by a factor of 100,000. Note that while training the surrogate model requires computational time, the minimum number of damage realizations needed for an adequate surrogate model was 10,000. This is not a high number as we need 2,000 damage realizations for a single annual loss estimation of the road network. Therefore, the training process is equivalent to five estimations of the mean annual loss. This estimation of mean annual loss needs to be performed hundreds of times in most optimization algorithms, and therefore performing it five times as an initial overhead is neglectable.

Given that extreme events play a significant role in the computation of traffic disruption, we oversample these events when training the model. To oversample these extreme events, we selected different proportions of extreme events on the training data, and selected the proportion that reduced the error on the test data both for extreme and for non-extreme events. An extreme event is defined as an event that can cause considerable damage to the road network and, subsequently, significant disruption to the community. The oversampling of extreme events ensured that the resulting neural network predictions for those events were accurately predicted, and therefore the estimation of risk was also accurate. Further implementation details are presented in Silva-Lopez et al. (2022).

Genetic algorithm optimization

We minimize expected annual traffic performance change $E[\Delta tp]$ in the optimization, subject to a limit in the number n of bridges that can be retrofitted. Mathematically, this can be formulated as

$$\begin{aligned} \min \quad & E[\Delta tp](\mathbf{B_R}) \\ \text{s.t.} \quad & \textstyle\sum_i B_{Ri} \leq n \end{aligned} \tag{6}$$

where $\mathbf{X} = \{B_{R1}, B_{R2}, ..., B_{Rm}$ is a vector representing a set of retrofitted bridges, B_{Ri} is a binary variable equalling 1 if bridge i is retrofitted and 0 otherwise, and $E[\Delta tp](B_R)$ is the expected

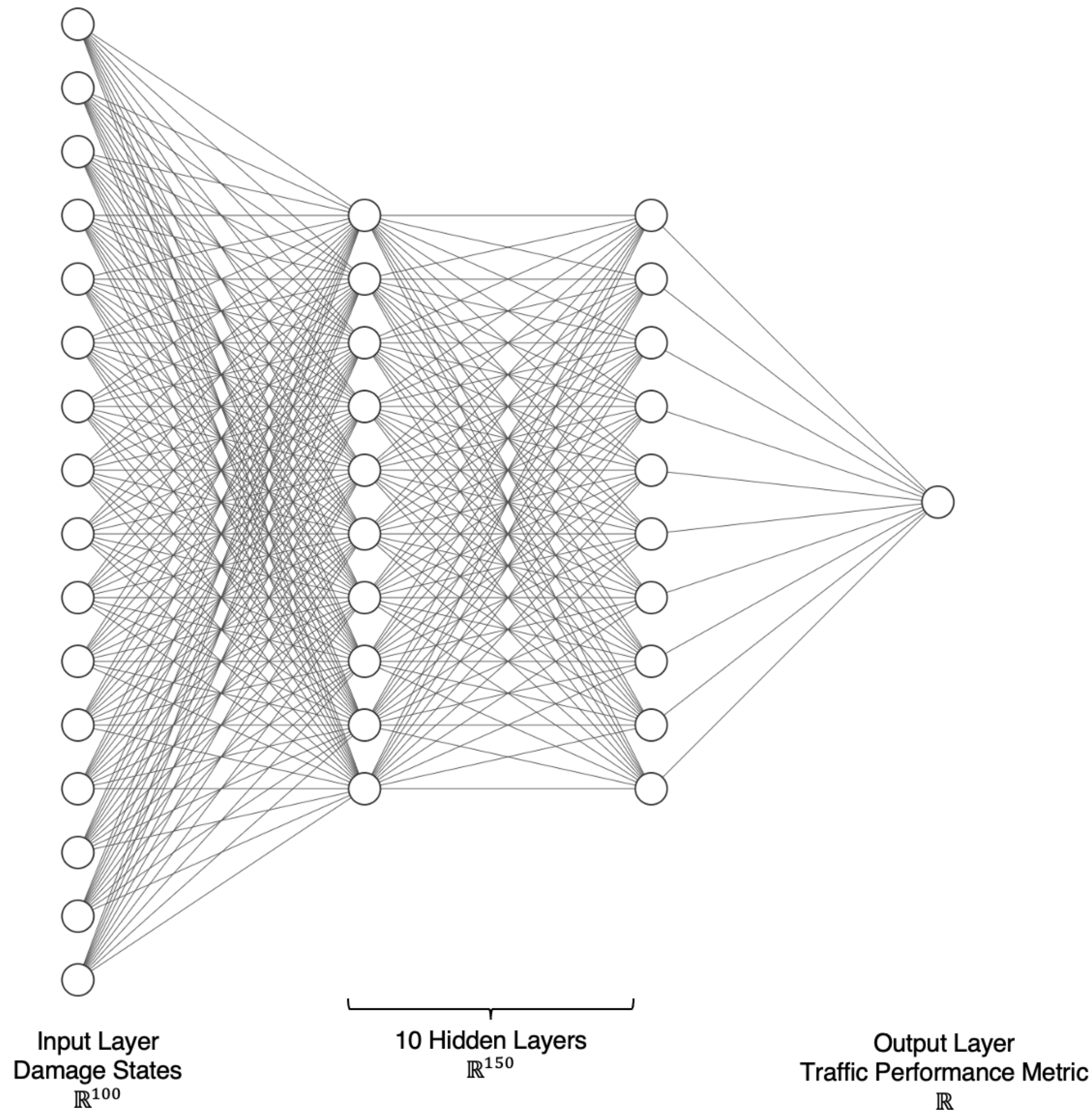

Fig. 4. The structure of the neural network used for this study, which takes as an input a vector of damage states and generates as an output a value of traffic performance metric.

annual change in traffic performance metric given the set of retrofitted bridges B_R.

Following the general formulation of a genetic algorithm in Figure 2, the definition of an individual is a list of n bridges to be retrofitted as n genes. Each gene can be any of the m bridges in the network. This definition is illustrated in Figure 5.

The scope of the proposed optimization is focused on a number of bridges and not budgetary constraints as the authors did not have access to repair or retrofitting costs, and therefore were unable to implement such an optimization without adding additional assumptions into the model. However, to include budgetary constraints the proposed optimization would just need to modify the

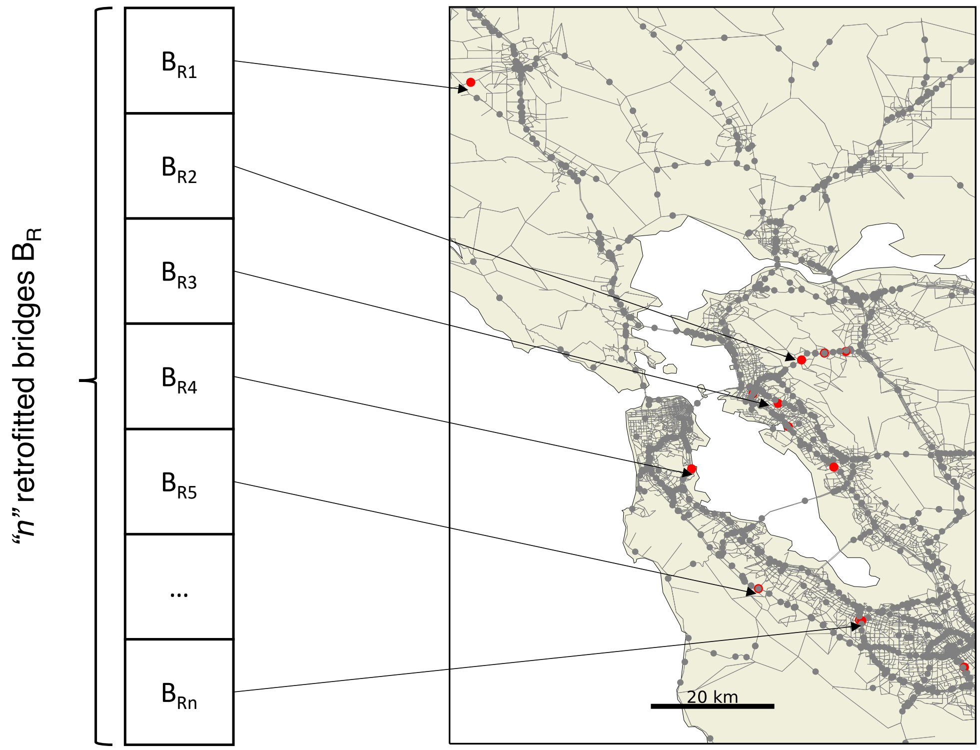

Fig. 5. Individual definition used for this study, where the genes an individual are the bridges selected to be retrofitted. Dots showed in red represent bridges retrofitted as an example.

fitness function to include the cost of repairing the set of bridges as a penalty function that cannot be exceeded. This manner allows the evaluation of the trade-offs of improving a bridge versus the costs associated with enhancing its structural performance.

Next, the sampling of the initial population is performed, where each individual has n different bridges selected randomly (each with equal probability of selection) from the set of all eligible bridges.

The fitness function used in this study is the expected change in traffic performance metric for a fixed suite of scenarios. The fitness function uses the surrogate model to compute impact for each scenario (Equation 3) and then aggregates the traffic performance metric using Equation 5.

Once a set of individuals and their respective fitness function values is available, they are used as parents to generate offspring. This study selects parents by selecting pairs of the fittest individuals. Given the categorical nature of the genes, we use Uniform Crossover to generate offspring. After generating offspring, the individuals genes are mutated. Here we use mutation rates proportional to the importance of the bridges to network performance. This study finds that calibrating hyper-parameters for the Crossover and Mutation steps of the algorithms decreases computational times without compromising the performance of the solution of the algorithm.

Finally, the convergence is established when the expected traffic performance does not improve after several iterations of crossover and mutation. Testing indicated that allowing the algorithm to perform a fixed number of generations after not observing a change in the fittest candidate's performance improved the algorithm's ability to find a better optimum. For the study case this number was 20 generations. This improvement in optimality is due to the randomness induced by mutation and crossover, which expanded the search space and prevented stopping at local optima.

Retrofitting strategy evaluation

The above process produces a set of bridges to be retrofitted. To evaluate the performance of this result, we compare the expected traffic performance of the network with the selected retrofits versus networks with retrofits determined using alternate means.

First we consider a vulnerability metric

$$v_d = \sum_k w_k \mathbb{1}_k \tag{7}$$

where v_r is the annual rate of damage for a given bridge, w_k is the annual rate of the seismic scenario, and $\mathbb{1}_k$ is a binary variable indicating if the bridge was damaged in scenario k. For the *vulnerability* retrofit strategy, the bridges are then sorted in order of damage rate, and the n most frequently damaged bridges. Second, we consider a *traffic importance* strategy, which retrofits the n bridges that carry the most traffic when the network is in its undamaged state. These two simple scoring strategies consider relevant characteristics of the bridges.

Figure 6 compares the results of using the sets proposed by genetic algorithms versus the above two alternative strategies. The genetic algorithms strategy results in much smaller disruption for a given number of retrofitted bridges, as expected since this is the explicit objective function being minimized. We also compared the performance of genetic algorithms with strategies based on several linear and non-linear combinations of traffic importance and vulnerability. No combination was able to surpass the performance of the genetic algorithm, indicating the potential of this direct optimization strategy versus simpler scoring strategies.

The optimal bridges selected by genetic algorithms have an inherent random behavior. To measure this randomness, we repeatedly select the top n using the genetic algorithm by taking the n bridges. Figure 7 shows how frequently some bridges are selected by the genetic algorithm for varying values of n. The figure shows that most of the bridges in the top n are selected in at least 75% of realizations, though an additional few bridges are selected on occasion. This indicates that the algorithm is fairly stable in selecting bridges, though the relative importance of some bridges are quite similar and this can lead to some reordering of selected bridges in final results.

We next interpret the characteristics of selected bridges. Figure 8 shows the study area, with two areas of interested noted. Figure 9 shows shows maps of the two areas of interest, with red markers indicating bridges selected for retrofit by the genetic algorithm. The left panels (a and d) show the results for five retrofitted bridges in total, the middle panels (b and d) show 20 retrofitted bridges, and the right panels (c and f) show 50 retrofitted bridges in total. In addition, the size of the bridge marker indicates its traffic capacity, with a bigger marker pointing to bigger capacities. The type of marker indicates the vulnerability of the bridge, with a circle marker assigned for high

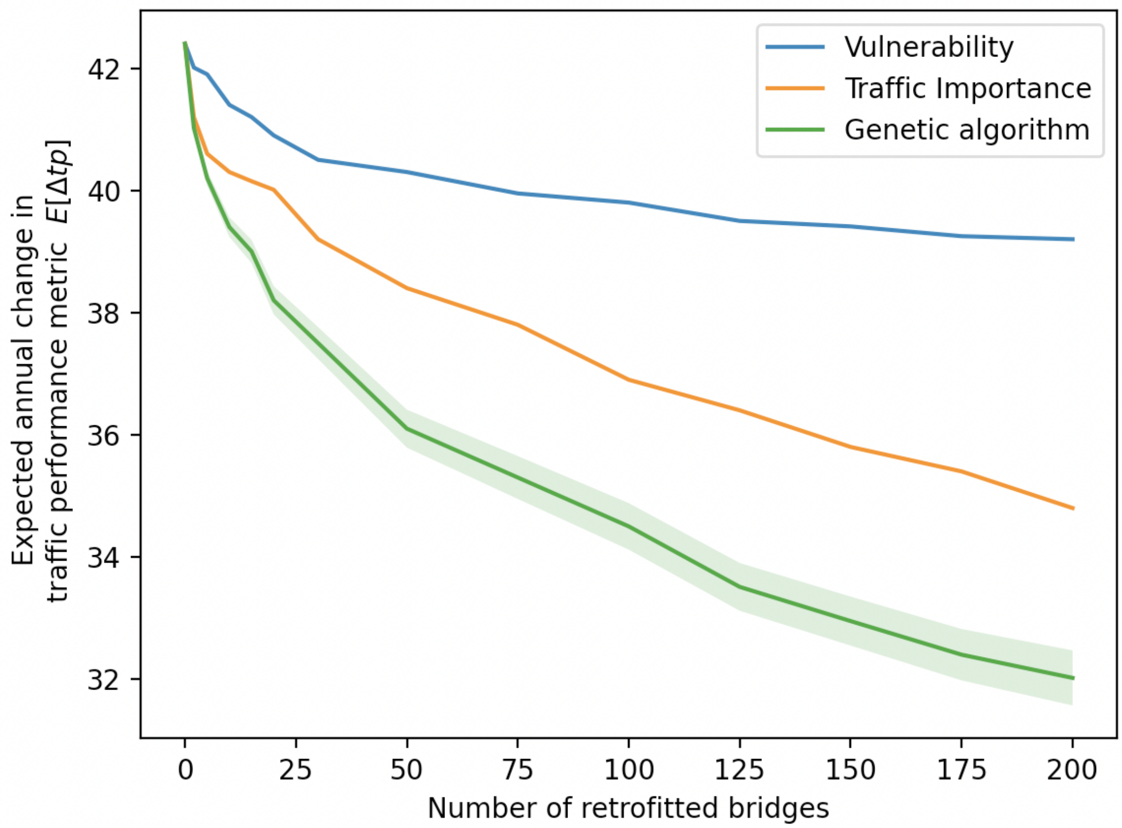

Fig. 6. Comparison of road network disruption given a number of bridge retrofits, for three possible retrofitting strategies: vulnerability, traffic importance, and genetic algorithms. The band over the genetic algorithm line indicates the standard deviation of performance as estimated from several realizations of the algorithm.

vulnerability, a square to medium vulnerability, and a triangle to a low vulnerability. This scale of vulnerability is based on dividing bridges in tertiles obtained using the Equation 7 vulnerability metric. Based on results like Figure 9, we found that the features of bridges selected by the genetic algorithm depend on the total number of bridges targeted to be retrofitted. For a low number of retrofits, the genetic algorithm selects high vulnerability bridges with high traffic capacity that are critical to the network due to the lack of alternatives. For instance, Figure 9 a) and d) show retrofit of bridges that cross the San Francisco Bay and have no alternatives. As the number of bridges to be retrofitted increases, the genetic algorithm additionally selects bridges that are part of a corridor with the previous bridges and are more vulnerable than other nearby bridges. A corridor is defined here as a set of bridges that jointly enable the traffic flow between areas of a region. This trend of vulnerability within corridors is observed in Figure 9 b) and e) as the newly selected retrofitted bridges are shown with circular or square markers. Finally, as more bridges are retrofitted, the genetic algorithm selects other vulnerable bridges that are part of the same corridors, as shown with square markers in panels c) and f).

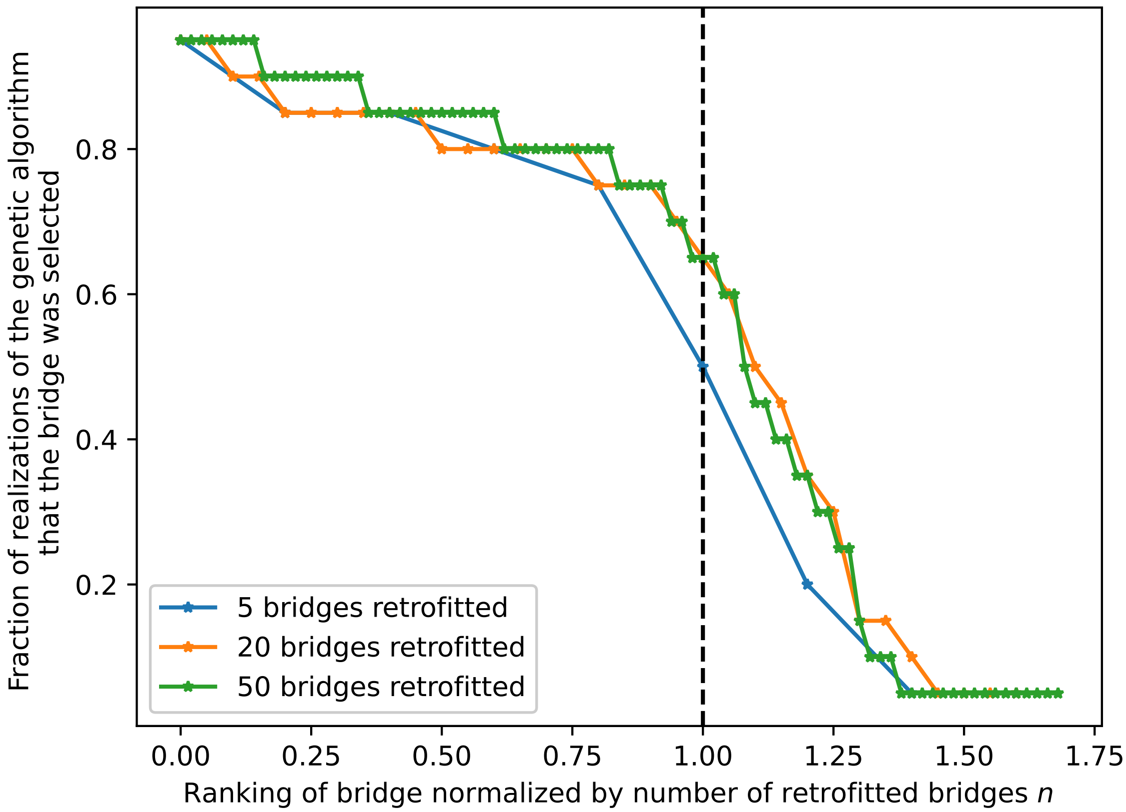

Fig. 7. Figure illustrating identification of top n bridges selected by the genetic algorithm based on the occurrence of a drop in the rate of selection for each bridge. The top n bridges occur when the normalized ranking reaches 1, shown with a vertical dashed line.

Computational cost reduction techniques

Calibration of genetic algorithms hyperparameters

Genetic algorithm optimization can be sped up through calibration of its hyperparameters. This study explores the influence of modifying the Crossover and Mutation steps of the algorithm based on observations that they are critical for computational costs. Crossover affects computational time since it defines how offspring are generated to search for potential solutions. If the offspring generation always to selected the current best genes, the algorithm would quickly converge. Conversely, if the Crossover process was completely random, different individuals would be added to the population at the end of the generation, broadening the search space, increasing computational times but also the likelihood of finding a global optimum. Similarly, the mutation affects computational times as higher mutation rates add randomness to the offspring generation. Therefore, they increase the search space of the genetic algorithm, having similar implications as having a random Crossover process.

This study compares three crossover protocols: (1) Random crossover, (2) Random crossover

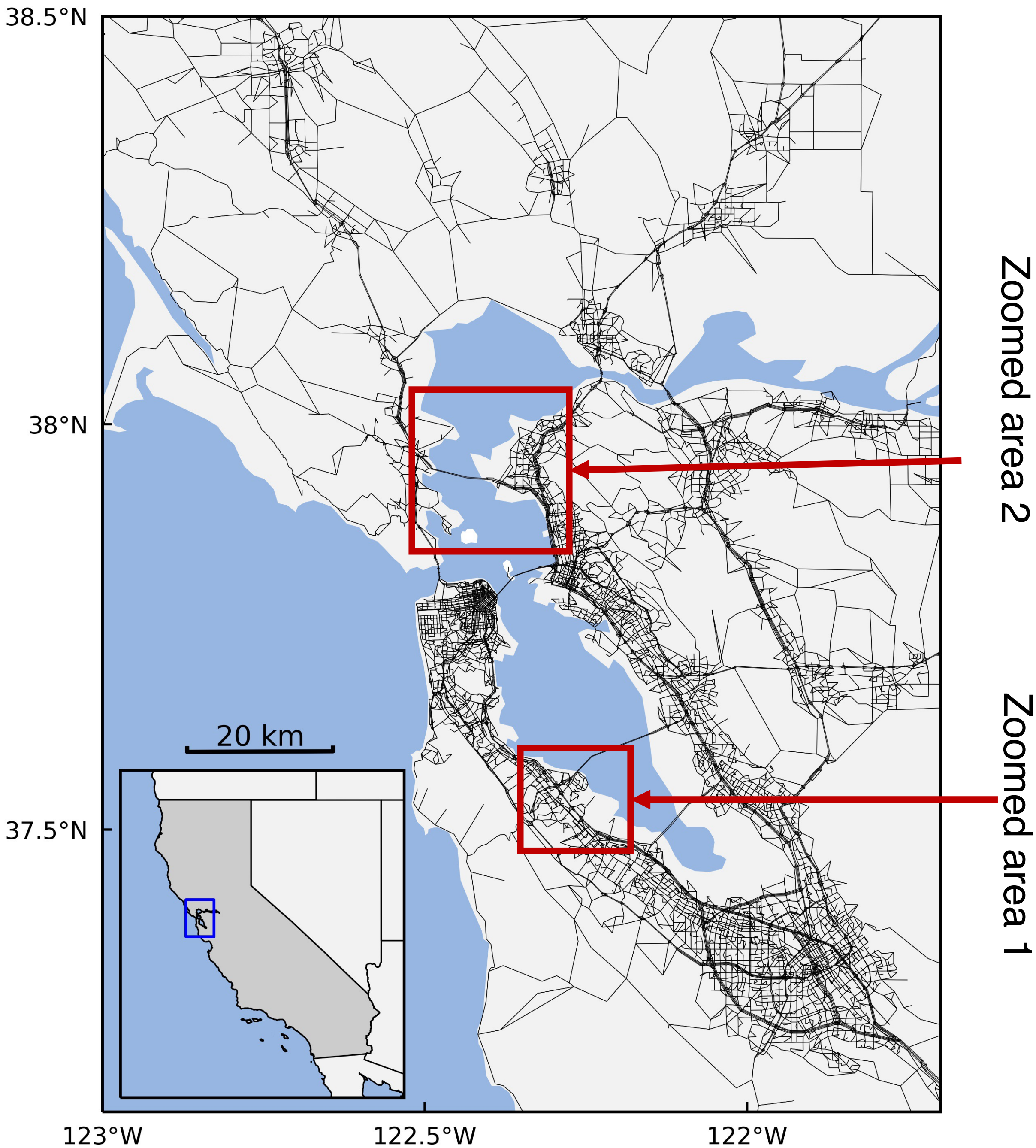

Fig. 8. Zoomed areas to analyze trends of bridges selected by the genetic algorithm.

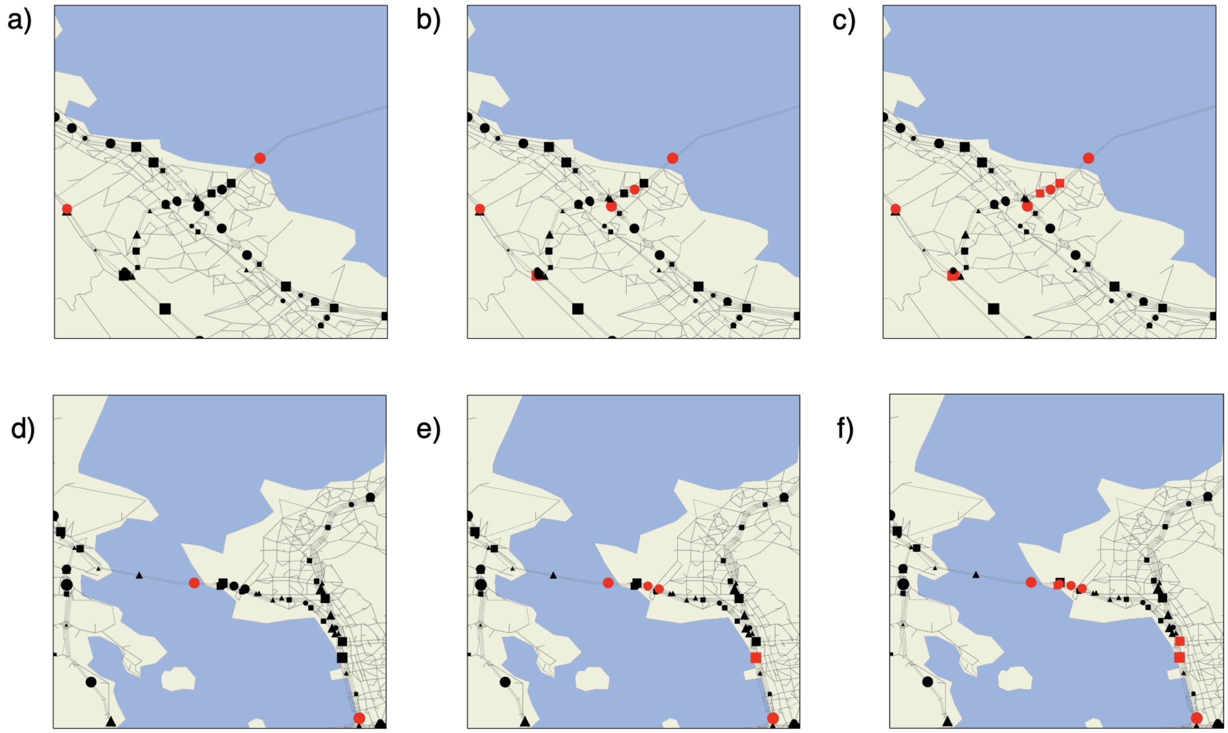

Fig. 9. Observed trends on top bridges. Subfigures in the top correspond to Zoomed Area 1, and subfigures in the bottom to Zoomed Area 2, on Figure 8. Red markers indicate bridges selected by the genetic algorithm. Panels (a and d) show the results for five retrofitted bridges, (b and e) for 20 retrofitted bridges, and (c and f) for 50 retrofitted bridges. A bigger bridge marker indicates a bridge with larger traffic capacity. The type of marker indicates the vulnerability of the bridge, with a circle marker assigned for high vulnerability, a square for medium vulnerability, and a triangle for low vulnerability.

with heuristic probabilities, and (3) Greedy Crossover. Random Crossover selects offspring's genes randomly uniformly from the parents. Random with heuristic probabilities selects randomly but with probabilities proportional to a heuristic, which in this study is the improvement of traffic performance metric generated by the retrofit of the individual bridge. Finally, the Greedy Crossover selects the bridge that induces the biggest reduction in the traffic performance metric for each gene.

We use the following equation to quantify the detriment in optimality caused by the change in hyperparameters

$$\delta tp^* = t\bar{p} - t\hat{p} \tag{8}$$

where,
δtp^* = Detriment in optimal value.
$t\bar{p}$ = Expected annual change in traffic performance induced by the genetic algorithm with specific hyperparameters.
$t\hat{p}$ = Expected annual change in traffic performance induced by the genetic algorithm with Random Crossover or Mutation.

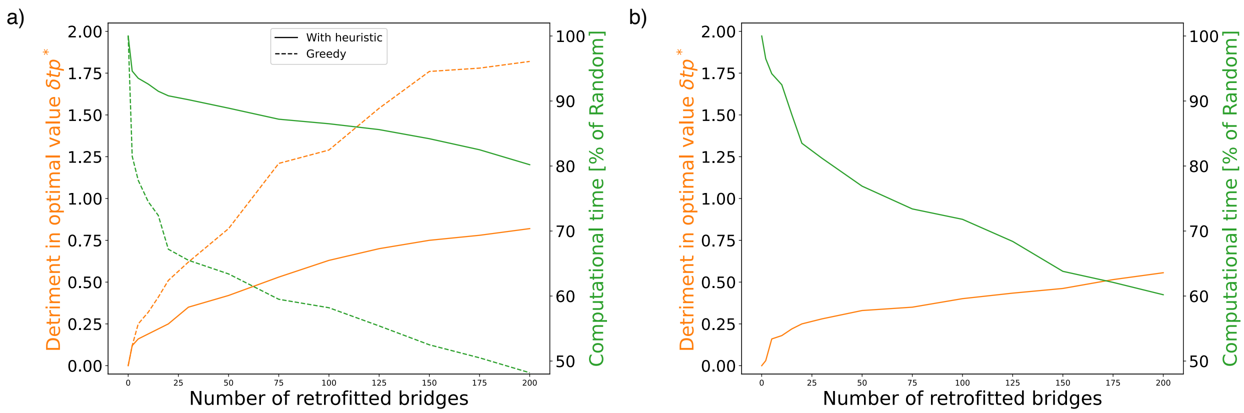

Fig. 10. Changes in computational costs and detriment of optimal values produced by different combinations of protocols for Crossover (a) and Mutation (b).

Figure 10 shows the computational and optimality performance of these three approaches, in which the Crossover that uses Random with heuristic and the one that uses Greedy are compared with respect to the one that uses a random uniform approach, which has the best traffic performance but the highest computational cost. We observe in Figure 10a that while Greedy Crossover significantly decreases computational cost, the detriment on the optimal value is significant, especially since the difference between genetic algorithms and other approaches is around two percent in the case of retrofitting 100 bridges, and therefore any detriment on the genetic algorithm smaller than two percent will still make the genetic algorithms approach better than the other approaches. On the other hand, the heuristic probabilities have much less reduction in optimal traffic performance, while still saving significant computation time. Therefore, considering the savings in computational time, random with heuristic is preferred over the other approaches. As a reference for computational costs, using a fully random selection takes 126 hours in an MacBook Pro (2021) with a M1 Chip of 16 Gb of RAM. The computation of a single realization of traffic performance metric for a single damage realization takes around 30 minutes in the same computer.

Regarding mutation protocols, a 0.2 rate of mutation was selected based on repeated tests to check traffic performance and computational cost. This study further explores the type of mutation that should be performed, which can be either sampling uniformly from the other bridges or sampling proportional to their improvement of network performance, the same heuristic used in the Crossover. Figure 10b shows the performance of random with a heuristic mutation with respect to uniformly random. There is no significant detriment in optimality performance, but there is a significant reduction in computational times introduced using the heuristic. Therefore, this study concludes that using the heuristic is beneficial. While the use of traffic performance metric as a heuristic is specific for this study and testbed, similar heuristics could be used in another context to incorporate network performance to reduce computational costs.

Preselection of bridges

Another way to improve computational performance is to reduce the search space by considering only candidates that have a chance of being in the optimal selection. Some bridges will almost certainly not be part of an optimal retrofitted set since they are rarely damaged or their contribution to network performance is minimal. Their inclusion in the genetic algorithm thus slows the search, with little potential benefit. This study explores the effect of decreasing the number of eligible bridges to retrofit by using two heuristics by searching amongst only candidate bridges with high (1) traffic importance or (2) structural vulnerability.

Figure 11 shows the performance of the genetic algorithm for varying numbers of preselected bridges, concluding that if we select 500 top bridges when trying to retrofit up to 15 bridges, the performance of the genetic algorithm is close to that when considering all bridges. In the same way, considering 1000 candidates to retrofit 200 bridges produces a result close to using all bridges. This strategy reduces computational costs similar to that obtained by including a mutation rate proportional to a heuristic, where bridges with low influence on network performance had a low probability of being selected to be retrofitted by the algorithm. Considering this, using a mutation rate with a heuristic may be preferable to preselecting bridges, as it focuses the search on the likely important bridges without completely preventing the selection of bridges that seem to be less important.

Computational costs evaluation

We next analyze the model with varying numbers of considered bridges and retrofit bridges, to quantify how they drive computational costs. These parameters are important because they define the total number of bridge combinations in the search space. Figure 12a shows that computational costs grow quadratically with the total number of bridges to be retrofitted,

$$n_g = c_0 + c_1 n + c_2 n^2 \tag{9}$$

where n_g is the number of generations and n is the number of bridges retrofitted.

Figure 12b shows that computational costs grow exponentially with the total number of bridges considered in the analysis

$$n_g = c_0 e^{c_1 b_s} \tag{10}$$

where b_s is the number of bridges considered in the analysis.

CONCLUSIONS

This study proposes an optimization framework to directly minimize annual expected seismic loss for road networks in a computationally efficient manner. To achieve this we propose genetic algorithms to identify bridges to be retrofitted to minimize expected road network disruption generated by earthquakes. The use of genetic algorithms is feasible due to incorporating a surrogate model that enables rapid and accurate performance prediction for complex road networks. A case study analysis using the San Francisco Bay Area road network is used to illustrate the approach and explore insights from the results. Results from the proposed approach are compared with other retrofitting strategies, showing that the genetic algorithm finds retrofit strategies more effective than

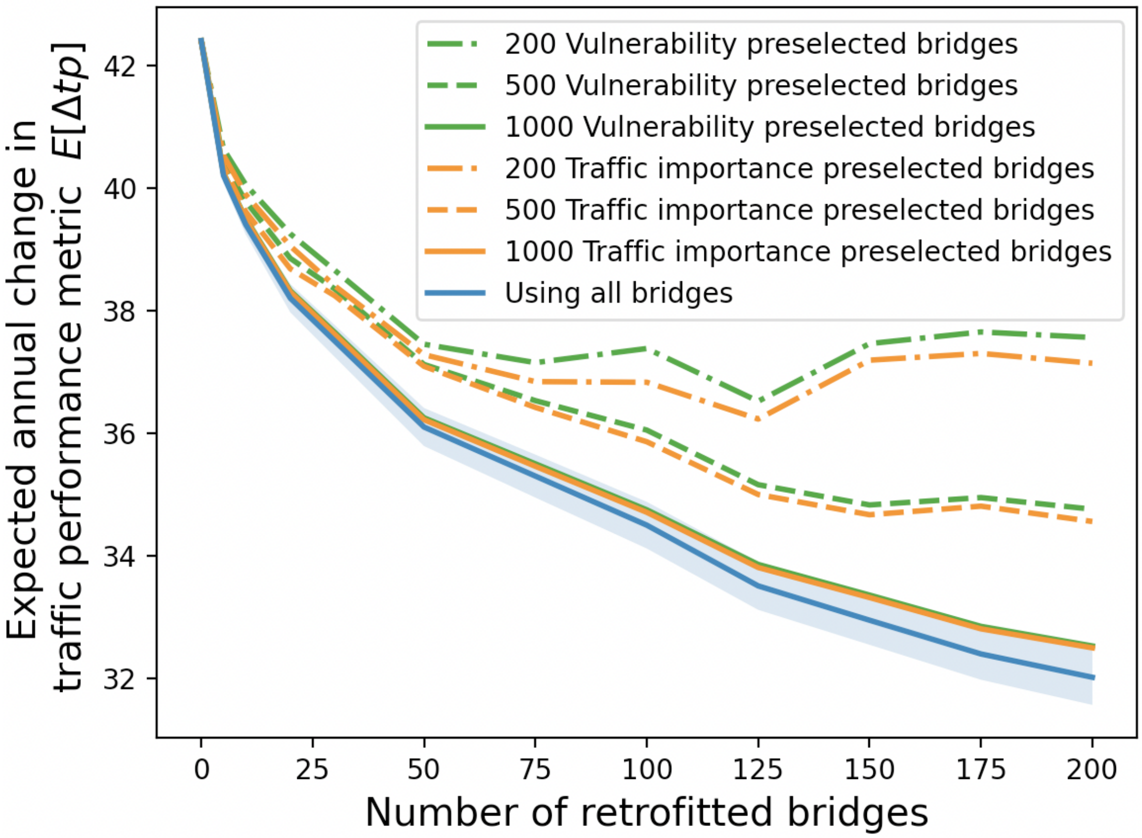

Fig. 11. Detriment in an expected annual change of traffic performance metric associated to different values of preselected bridges.

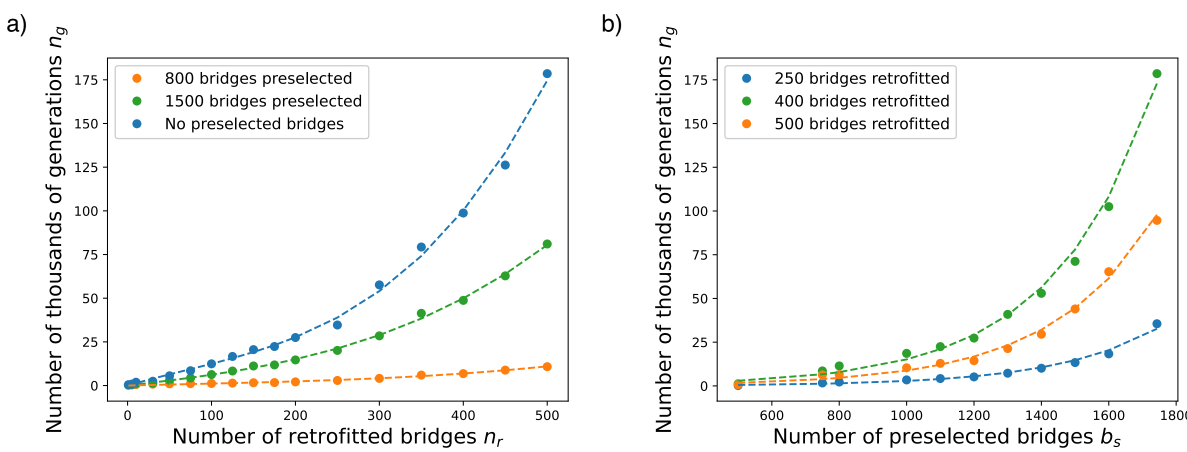

Fig. 12. Computational costs induced by the number of retrofitted (Shown in Figure a) and preselected bridges (Shown in Figure b). Points correspond to data obtained from runs of the genetic algorithm, and lines are fitted versions of Equations 9 and 10.

ranking bridges according to their traffic importance or vulnerability.

A major contribution of this study is to propose a methodology to directly minimize the effects of earthquakes on complex interconnected systems, illustrating the benefits of using a surrogate model to enable rapid and accurate assessment of the systems. This direct approach is preferable to other popular approaches of optimization in complex systems, proxy objective functions are introduced as a replacement to manage computational costs.

In addition to comparing the performance of retrofitting policies in terms of expected traffic performance, this study uses the San Francisco Bay Area road network to explore the interpretability of the results of the optimization. In terms of trends for this region, for a low number of bridges, the algorithm selects bridges that have an important role in the road network. For a mid number of bridges, the genetic algorithm also includes bridges that are part of bridge corridors but are more vulnerable than the rest of the bridges in the corridor. For a higher number of bridges, the genetic algorithm incorporates bridges that are part of bridge corridors but less vulnerable than the previously selected bridges.

This work evaluates two general strategies to manage the computational costs of genetic algorithms; first, it explores modifying hyperparameters of the genetic algorithm. Second, it evaluates the impact of reducing the set of bridges eligible to be retrofitted. In terms of hyperparameters, this study finds that modifying crossover and mutation rates using a heuristic manages to accelerate the search for the optimal without severely impacting the optimal quality. Concerning reducing the set of eligible bridges to be retrofitted, this work observes that while it can significantly improve computational performance, it can also generate a detriment in the performance of the optimal proposed retrofitted set.

This study also explores the factors most affecting the computational costs of the proposed approach. For the implementation presented in this work, computational costs increase quadratically as a function of the number of bridges to be retrofitted and increase exponentially with the number of candidate bridges in the model.

While the practical challenges and proposed solutions for computational costs were calibrated for the San Francisco Bay Area road network, they can be used to infer strategies for other settings. For instance, to identify pipes in a water system to retrofit before an earthquake, the genetic algorithm gene could indicate the pipes selected to retrofit, and the fitness function could be the expected number of users affected by the disruption. In addition, heuristics such as the number of users depending on each pipe can be used in the Mutation and Crossover steps to minimize computational costs.

DATA AVAILABILITY STATEMENT

Some or all data, models, or code generated or used during the study are available from the corresponding author by request, such as the code used for the implementation of genetic algorithms and the surrogate model for the road network.

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