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Large-scale optimization strategies for risk-informed decision support in infrastructure systems: an application to transportation networks exposed to seismic hazards

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Abstract: Efficient strategies to avoid and/or minimize the interruption of services provided by physical infrastructure networks are essential for society's normal functioning. Assessing their risk to natural hazards and being able to evaluate adequate prevention and recovery decisions is a paramount, but complex task. We discuss a recently introduced decision support model that uses stochastic programming to efficiently integrate risk assessment and optimization for complex infrastructure networks. The model seeks to balance the importance of retrofit decisions in a transportation network with respect repair actions throughout a set of damage scenarios. The model is subject to parameters that define how preferable prevention actions are, compared to corrective actions. Furthermore, the model considers performance measures (travel time) for pre-specified portions of the network and allows to demand certain compliance from each after disastrous situations. We study the impact of these parameters on the resulting retrofit/repair policies and discuss the benefit of the model for the analysis of large-scale systems, and the adjustments necessary to cope with real-world infrastructure networks. An example is presented for the case of the San Francisco Bay Area transportation network, for which a comprehensive probabilistic analysis of seismic hazards and a traffic model are available from previous work. Different risk management policies are provided for varying degrees of risk aversion (given by different retrofit/repair cost ratios), whose computation takes advantage of the computational efficiency of the stochastic programming approach.

1 Introduction

Improving the resilience of infrastructure systems is a paramount engineering challenge, as they constitute the backbone of urban societies. In addition to the cost of corrective actions associated to the damage of large infrastructure systems, efforts in prevention are vital due to the impacts associated to loss of life, property, and business interruption.
Infrastructure networks are comprised of large numbers of components and complex interactions that often make performance computations expensive at urban or regional scales. Similarly, probabilistic analyses of network performance under natural hazards imply evaluating a large number of potential disaster scenarios. Furthermore, to determine an optimal set of actions that improves network resilience (e.g., retrofitting bridges), it is necessary to evaluate all combinations of actions and their effect on network performance for all potential scenarios.

Because of the described sources of complexity, heuristic optimization approaches are most commonly adopted when evaluating risk management actions. Although heuristic approaches often allow to deal with larger systems than exact optimization techniques, the latter provide guarantees of optimality that are particularly valuable when considering uncertainty.

The problem of determining retrofit and/or repair actions to improve the expected performance of a network exposed to seismic hazards is addressed in [2] through a combination of sophisticated seismic risk assessment techniques and exact optimization. While the work in [2] describes the mathematical detail of a stochastic programming procedure that integrates risk assessment and exact optimization, this paper presents the type of analysis that can be derived from such approach by evaluating the impact of risk aversion on the optimal retrofit policy.

A segment of the San Francisco Bay area transportation network is presented as an example, considering the travel time along key origin-destination pairs as the performance metric of interest. The network is exposed to significant seismic activity resulting from the San Andreas and Hayward faults, for which a set of hazard consistent scenarios have been previously created. Information about users' origin-destination patterns and preferences are available as a result of previous studies along with the Department of Transportation of California.

The analysis, thus, focuses on an element of the model for which information is not readily available: the costs and impact of retrofit and repair actions. The approach in [2] is used to repeatedly solve the risk management problem for several valuations of preemptive actions relative to corrective actions.

Section 2 provides an overview of related work. Section 3 describes the methodology in [2] to address risk management problems in complex infrastructure networks. Section 4 presents the analysis of variations in risk aversion for retrofit decisions on the San Francisco Bay area transportation network. Section 5 discusses limitations and potential extensions of the work in [2] to cope with larger and more realistic assumptions for actual infrastructure systems. Section 6 provides conclusions and ideas for future work.

2 Related work

Related efforts in addressing decision problems within risk assessment and management of complex infrastructure networks include research by: Ouyang et al. [10] regarding a framework to analyze infrastructure resilience; Lim et al. [5] regarding efficient reliability assessment for complex infrastructure networks; Hu et al. [4] regarding optimal management of large-scale transportation networks; and Nogal et al. [9] regarding the study of transportation network resilience under extreme events.

From an optimization perspective, Frangopol and Bocchini [1] propose the use of resilience as an optimization criterion for bridge rehabilitation, considering the maximization of the transportation network resilience as well as the minimization of the total rehabilitation cost, relying on bi-objective genetic algorithms for the construction of an efficient frontier (i.e., a set of solutions not outperformed by others). Regarding decisions to improve the resilience of infrastructure systems, Xu et al. [11] address the scheduling of response actions for power infrastructure under seismic hazards by means of genetic algorithms. Miller-Hooks et al. [8] deal with resilience in freight transportation networks, accounting for the impact of pre-disaster decisions on recovery related decisions with the objective of maximizing the flow throughout the network; their approach relies on stochastic programming but is not integrated with probabilistic risk assessment for realistic complex networks.

3 Stochastic programming for infrastructure risk management

3.1 Problem description

The risk management problem considered in this paper addresses the decision of whether to retrofit a set of bridges in a transportation network, or repair them only after the occurrence of a specific earthquake scenario. Figure 1 shows a step-by-step account of the methodology used in [2]. Ground Motion Prediction Equations (GMPE) are used to create a set of earthquake scenarios, following the work in [6]. The fragility of the bridges under consideration is used to generate realizations of damage on bridges as a function of the site's ground motion intensity [7]. Then, versions of the network for each earthquake scenario are put into graphs (associated with the occurrence rate of each scenario) [2], with which travel times are computed through a traffic simulation. The problem is stated as minimizing the costs of retrofit actions and the expected costs of repair actions in order to preserve pre-specified travel times between selected origin-destination pairs, throughout the set of graphs representing the realizations of networks obtained for earthquake scenarios.

The stated problem involves traffic simulations for each earthquake scenario. In the proposed optimization approach, each of these simulations is captured as a realization of the graph that represents the network with an associated probability of occurrence, thus, having a discrete distribution of graphs. Retrofit actions have an effect on all graphs (since the retrofit element would be strengthened preemptively for all possible realizations), whereas repair actions affect components only on the graph associated to the realization for which the repair action is planned.

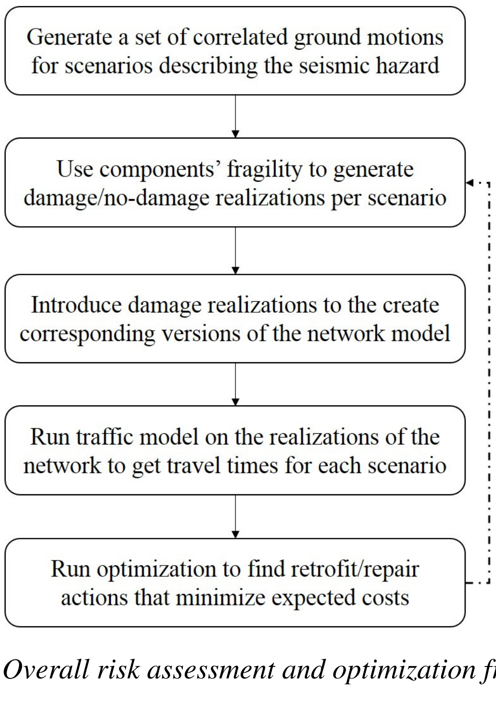

Figure 1: Overall risk assessment and optimization framework

3.2 Mathematical formulation

The term *stochastic programming* refers to the inclusion of uncertainty into the parameters that define an optimization problem. Often, the optimization problem is solved by evaluating variables throughout discrete potential future scenarios. The problem described in the previous sub-section requires: the set of variables x_a, which determine whether arc $a \in \mathscr{A}$ is retrofitted; the set of variables $y_{\xi,a}$, which determine whether arc $a \in \mathscr{A}$ is repaired in earthquake scenario $\xi \in \Xi$; an objective function (Equation 1) to incorporates the retrofit and expected repair costs;

and a set of constraints (Equation 2) relating travel times for arcs under normal operation, $t_{0,a}$, and those observed in the traffic model for earthquake scenarios; $t_{\xi,a}$ (travel times take the value of their corresponding scenario unless either of the actions are taken). The optimization problem is then formulated as a Mixed Integer Program as follows:

$$\min\left(\sum_a c_{retrofit} x_a + E_\xi\left[\sum_a c_{repair} y_{\xi,a}\right]\right) \tag{1}$$

Subject to:

$$\sum_{a\in\mathbf{p}} t_{0,a}\left[x_a + y_{\xi,a}\right] + t_{\xi,a}\left[1-\left(x_a + y_{\xi,a}\right)\right] \leq t^*_{\mathbf{p}}(1+\varepsilon);\forall\mathbf{p}\in\mathscr{P},\forall\xi\in\Xi \tag{2}$$

$$x_a \in \{0,1\}\,\forall a\in\mathscr{A} \tag{3}$$

$$x_{\xi,a} \in \{0,1\}\,\forall a\in\mathscr{A},\forall\xi\in\Xi \tag{4}$$

Equation 2 encapsulates one constraint for each origin-destination pair ($\mathbf{p}\in\mathscr{P}$) of interest; the travel time obtained for an origin-destination pair ($\mathbf{p}\in\mathscr{P}$) as a result of retrofit/repair decisions is enforced to be within a tolerance (ε) of a target travel time $\mathbf{p}^*$.

Since the size of the problem may grow quickly with the number of scenarios, decomposition approaches are used to separate the original problem into a master problem and a set of independent problems per scenario, which is the approach followed in [2]. The articulation of the master problem and sub-problems is achieved through constraints that enforce some master variables to be turned on (i.e. enforce some retrofit actions) in the next iteration if they have the potential to improve the overall objective function.

4 Analysis of preemptive and corrective decisions

A portion of the San Francisco Bay area transportation network is used as an example to test how different parameters affect the outcome of the proposed optimization problem, particularly those that capture the risk aversion of the decision makers. In this sense, we explore variations in risk management actions for different relative costs of repair actions with respect to retrofit actions. The latter captures the loss aversion by more strongly valuing repair actions to indirectly include loss of life, business interruption and increased logistic costs.

Retrofit costs were fixed to unit values while repair costs were iteratively modified starting from a large value for which no repair action should be pursued by the optimizer: this value was set to $1/r_{min}$, where r_{min} is the smallest occurrence rate for a scenario (such that even for the most unlikely scenario, retrofit actions would be preferable to repair actions).

Then, different values were identified for the specific case of the San Francisco network which would lead to different risk management policies, for instance: in order to observe retrofit actions only (i.e., never accept the risk of leaving a bridge to be repaired afterwards) the repair costs (and consequences) should be 7143 times larger than repair costs, which may not be necessarily realistic; the value for which repair actions are preferable (and no retrofit actions are observed) is when repair actions are only 43 times more expensive than retrofit actions. Figure 2 (upper part) summarizes the relationships in between those extremes in terms of the value of both parts of the objective function; the cost of retrofit actions equals the expected cost of repair actions at about the $1/100$ ratio. Figure 2 (lower part) shows the same progression for the number of elements intervened (with either retrofit or repair actions) in each case; the dotted lines compare the average and expected number of components repaired through scenarios, with the latter being much smaller, given the low probabilities associated to each scenario.

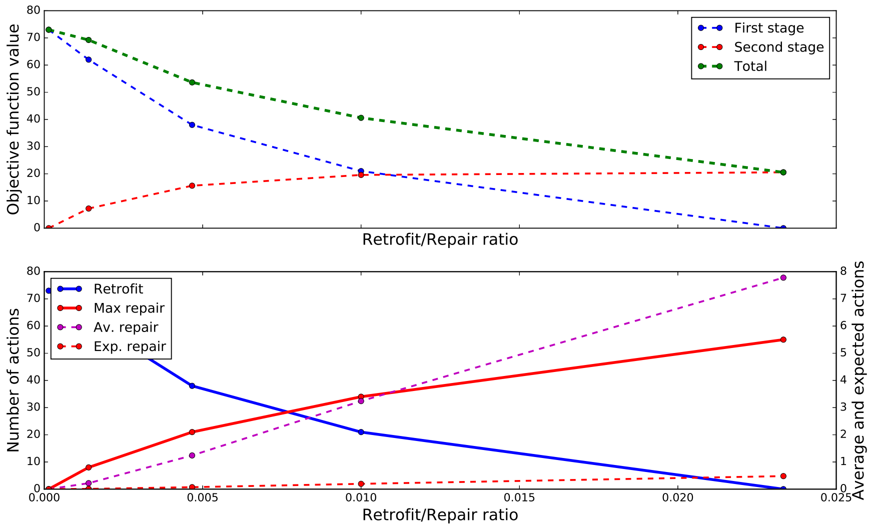

Figure 2: Evolution of retrofit/repair actions with retrofit/repair ratio

Figure 3 shows an example of a retrofit repair policy for the area of San Francisco and Oakland (in the Bay area transportation network) for one of the explored ratios, in which retrofit actions (red dots in left-hand side) are dominant with respect to repair actions (red dots in right-hand side). Although the bridges left to be repaired after an earthquake seem geographically important, the scenarios in which they are repaired have a very low occurrence rate, which explains the fact that those are not retrofitted before the earthquake.

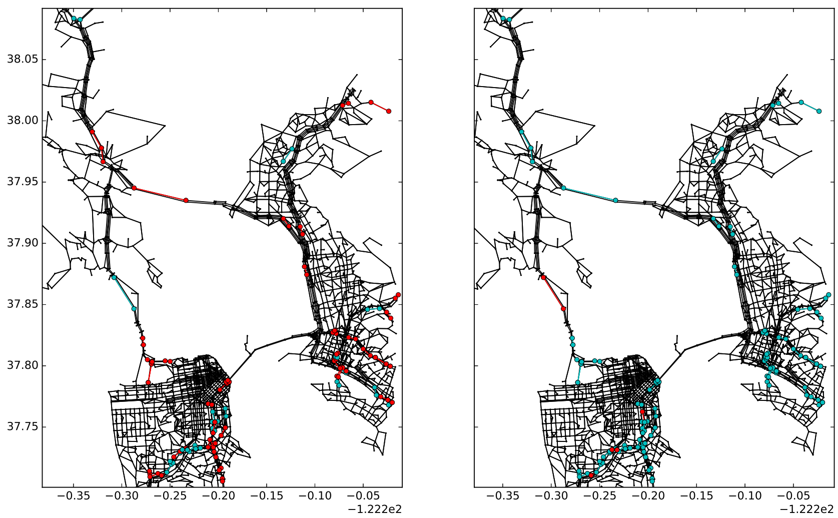

Figure 3: Instance of retrofit (left-hand side) and repair (right-hand side) actions for a portion of the San Francisco Bay area transportation network: on both sides, red dot represent performed actions, while cyan dots denote bridges for which the action was not taken.

5 Limitations and potential extensions for realistic cases

The analysis of decisions on complex infrastructure networks in the context of risk management poses important computacional challenges resulting from: the large number of elements in real-world networks makes analysis prohibitive due to the exponential growth of operations in network optimization problems; the treatment of uncertainty demands evaluating numerous scenarios describing a hazard of interest; the multiplicity of decision alternatives over time and the relationships among them implies the analysis of the combined effect of different combinations of decisions on a model which is already complicated by the previous two factors.

An important limitation in the proposed approach is that the effect of decisions is assumed to combine linearly, which is not necessarily the case in traffic problems, since the (un)availability of bridges may affect not only the roads directly associated to them but also others because of network effects. In this sense, applying actions on two bridges may lead to a different result than that of accounting for the separate effect of the actions on the bridges independently. The adequate approach to account for network effects is to run the traffic model for each combination of decisions. This is, running the traffic model for all possibilities with one retrofit, all possible combinations of two retrofit actions and so on. Such procedure would be expensive, not only because of the large number of combinations that a large network would imply, but also because each run of the traffic model can be expensive itself.

In order to capture the network effects, the current approach requires a way to obtain feedback from the traffic model, so that travel times can be updated to account for the combined effect of several concurrent actions (retrofit or repair). Although conceptually simple, this would require evaluating too many combinations of decisions. The literature of operations research offers further decomposition approaches, such as column generation strategies [3], in which variables are introduced one at a time without having to explore the whole set of combinations.

Ongoing research is devoted to capturing such aspects of transportation networks. Although this would not easily capture the full extent of nonlinearities in a dynamic traffic model, it has the potential to capture the combined effect of relevant combinations of decisions (i.e., evaluate the combined effect of actions on a few neighboring bridges).

6 Conclusions

Stochastic programming provides a powerful tool to deal with risk management problems involving large sets of scenarios, specially when using decomposition approaches (when scenarios are independent) to avoid dealing with impractically large problems. Being able to efficiently assess the effect of retrofit and repair actions in a transportation network throughout a comprehensive set of earthquake scenarios enable analysts to perform more comprehensive evaluations, namely: not being limited by the uncertainties related to the hazard of interest, it was possible to examine the impact of an unknown cost structure of the problem (i.e., retrofit/ repair costs) on the obtained risk management policies by successively running the proposed optimization problem. The proposed approach relies on mixed integer programming, which operates on the assumption of linearity, thus, not capturing network effects that may affect the decisions. Ongoing research is devoted to accounting for combinations of decisions through further decomposition approaches.

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