Coupled pre- and post-disaster decisions in the context of infrastructure resilience

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Abstract

Pre- and post-disaster decisions made by infrastructure operators are often coupled and have significant impact on the extent of disruptions and the ability to recover. Specifically, the downtime following a disruption in infrastructure networks can be diminished (at a cost) depending on how resources are previously allocated and located. A further challenge is devising measures of the societal impact of such decisions and strategies to steer adequate risk management decisions. A stochastic programming approach is proposed to couple decisions regarding pre-disaster resource allocation and post-disaster routing of crews for early damage assessment while capturing the effects of disaster scenarios on the decision problem. Societal consequences and constraints can be captured within stochastic programming and analyzed through a game theoretical approach.

1 Introduction

Among key problems in infrastructure operation, resilience has gained particular attention in the research literature [1–3] and in practice [4, 5] under the challenges imposed by increasing urban concentration, sustainable development, lifeline interdependencies, and multiple evolving hazards. This paper deals with two problems within infrastructure resilience: how decisions on disaster preparedness affect decisions on disaster response (affecting long-term recovery, in turn); and how the societal effects of these decisions can be captured and used to steer better decision making.

This research is motivated by the challenges of the San Francisco Bay Area in terms of disaster preparedness under seismic hazards. For instance, the coordination and planning for the several governance bodies and agencies at the region level who are involved in risk management tasks [5], so as to enable decentralized yet coordinated recovery. Furthermore, beyond engineering challenges, sustainability and resilience in the region demand diminishing the already pervasive inequalities related to income disparity, gentrification, and access to transit, which might dramatically worsen after a disastrous event [6]. In addition to providing a compelling context for societal decision-making, these issues match challenges for operational research in disaster management, as highlighted in [7].

Figure 1 illustrates the framework in which these issues are treated, namely: there is a first moment in which a set of decisions are made to prepare for a disruptive event with uncertainty about its location, time, and magnitude; and a second moment where a set of decisions are made to respond to the disruptive event with at least partial knowledge of the scenario. The treatment of

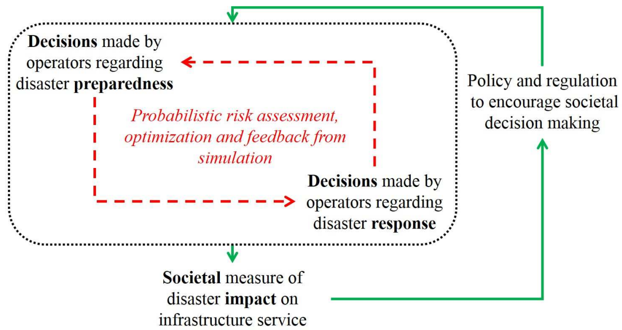

Figure 1: Overall conceptual basis of the paper

these two problems under a probabilistic risk analysis framework is common practice in engineering. The coupling of both decision problems and the consideration of societal measures of their impact are at the core of this research, accounting for how users' preferences are compromised during disruption and analyzing how a "fair" portion of societal dis-utility could be transferred to the operators (e.g., through fines, bad reputation, bans) under reasonable liability conditions.

Section 2 introduces the problem of coupled pre- and post-disaster decisions along with key features of stochastic programming that make it a compelling framework to pursue risk analysis involving coupled decisions, uncertainty, and societal consequences. Section 4 develops a mathematical model for the specific problem of allocating headquarters for disaster response throughout a transportation network, coupled with the routing of crews from such headquarters to other points in the network where damage assessment and immediate response actions are necessary, considering several disaster scenarios. Section 3 elaborates on the type of measures that may be used within the proposed approach to better account for societal decision making. Section 5 presents an illustrative example to showcase the features of the proposed approach while Section 6 presents the conclusions and ongoing research.

2 Coupled decisions on disaster preparedness and response

Several types of decisions are made with regards to disaster preparedness within infrastructure systems: at a technical level, consider physical maintenance and updating (e.g. retrofitting, expansion, redundancy); at a logistical level, consider the strategic allocation and location of key physical and human resources such as qualified personnel for reconnaissance tasks and damage assessment, as well as machinery for debris removal, etc.; and at a governmental level, consider the adopted standards, training programs, regulation, and agencies' roles in long-term planning, which affect disaster and risk management in general.

At the post-disaster stage, decisions can be better classified in terms of the different phases of recovery: during response, tasks related to reconnaissance and damage assessment are paramount and happen to depend heavily on logistics given the criticality of time; during the early recovery and reconstruction phases, the focus is on restoration of different levels of service which often rely on intensive physical repairs and replacements; finally, long-term recovery towards resilience (e.g., build back better) depends on combined efforts of all kinds but has a particular connection to a governance structure with the capacity to coordinate and expedite actions that are coherent with long-term planning goals.

Further elaboration of relationships between pre- and post-disaster decisions requires analyzing specific instances as will be the case of allocation and routing of inspection crews in Section 4. However, the common aspect of these different relationships is the commitment to one decision at a moment of uncertainty, which might leverage or limit future decisions, such that the consequences for the system are a result of the coupled decision process and the mediating uncertain event. Such situation, precisely, has been formally defined in what is known as stochastic programming.

Stochastic programming [8, 9] incorporates scenario evaluation into an exact programming procedure, allowing for a subset of decision variables to be tied to the scenario outcome while others remain fixed. The latter, as opposed to iterating the processes of simulation and optimization, provides the benefits of exact optimization (e.g., availability of economic interpretations and a *gap of optimality* due to duality properties [10]) for the pre- and post-disaster decisions, and the scenario evaluation, altogether, at the cost of limited computational scalability.

The left-hand side of Table 1 shows the standard form of a stochastic program: variables x represent to preparedness decisions with cost c_p; variables y_ξ represent response decisions under scenario ξ with cost c_r; and $Q(x, y_\xi)$ represents a consequence as a function of both sets of decisions. Because of the so-called L-shaped structure of the problem (i.e., that only one of the two set of constraints relates x and y_{xi}), it can be decomposed as shown on the right-hand side of Table 1: one problem can be formulated for the preparedness decisions alone, whose solution can be passed as a constant when solving an independent problem for response (under all scenarios); the consequence of that particular combination of solutions, $Q(x^*, y^*_\xi)$, can be stored in ϕ, which is used in iteratively added constraints that pull auxiliary variable θ towards a closer approximation of the consequences in the first problem (through linear functions f and g), thus, coupling the whole decision process.

Table 1: Structure and decomposition of a standard stochastic program

Coupled Problem	.	**Preparedness Problem**	**New Constraint**
$\min cx + dy_\xi + Q(x, y_\xi)$	.	$\min c_p x + \theta$	$\leftarrow f(x, \theta) \geq g(\phi))$
$\mathrm{A}_1 x + \mathbf{0} y_\xi \leq b_1$	.	$\mathrm{A}_1 x \leq b_1$	**Response Problem**
$\mathrm{A}_2 x + B_2 y_\xi \leq b_2$	.	**Solution**	$\min dy_\xi$
	.	$(x^*, \theta^*) \rightarrow$	$\mathrm{A}_2 x^* + B_2 y_\xi \leq b_2$
	.		**Consequence Term**
	.		$\phi = Q(x^*, y^*_\xi)$

3 Societal and organizational considerations

In practice, decisions about risk management are made and implemented by a set of actors corresponding to private and/or public entities with active roles in managing risks. Each of these actors has different available actions, access to information, risk profiles, and purposes, in general, that cause their decisions to deviate from what is considered optimal from a technical perspective alone. The following paragraphs discuss the importance of: (a) identifying and accounting for those dependencies and interactions among actors that might compromise the outcomes of these decisions; and (b) evaluating such outcomes in terms of the benefit they represent to society.

Regarding interactions among actors, suppose that the preparedness and response decisions introduced above are in charge of a set of operators (referred to here as agents) under the supervision of a governmental entity representing the public interest (referred to here as the principal). The latter, known as the agency problem, is executed through contractual agreements and often occurs when the principal lacks practical capacity to provide certain demanded services. Such regulatory framework drives the behavior of the agents and, in turn, the decisions that will ultimately affect the performance of the system. In this senses, it is of paramount importance to understand the relationships among relevant actors and furthermore, to generate agreements that reconcile agents' rational motivation to operate efficiently, with the principal's purpose of pursuing societal interests. Game theoretical approaches allow to model and analyze interactions between agents making rational decisions as stated above, relying on computational support tools to efficiently explore the combinations of decisions and their consequences. In this paper, the game situation is defined by how an agent's risk management strategy (i.e., its preparedness and response decisions) performs in terms of its own costs of operation and of a societal measure expected by the principal.

With regards to measures for the societal impact of agent's risk management strategies, the so-called mode-destination accessibility measure was previously applied to the case of the San Francisco Bay Area transportation network [11], which uses actual user preferences about preferred trips and transportation modes to evaluate how their aggregated utility function is affected by a catalog of seismic scenarios. The latter is useful for the game formulation since it allows to connect the two parts of the problem, namely: an agent's preparedness or response decision that might make certain trips unavailable, and its impact on users' satisfaction. In agreement with the definition of a *consequence term* in Section 2, a function can be tailored to transfer a fair portion of societal disutility back to the agents within the proposed stochastic programming approach:

$$Q(x, y_\xi) = \Gamma_\xi U(x, y_\xi)$$

where $U()$ is the aggregated utility derived from certain preparedness and response decisions; and Γ_ξ is the weighting factor that determines the portion to be transferred, which depends on the disaster scenario ξ because operators cannot be equally liable for all disastrous events, as occurs in cases of catastrophic damage.

4 Coupled allocation and routing of disaster response crews

Consider the case of pre-location of resources and personnel for immediate disaster response in the context of infrastructure networks. It is argued that response effectiveness under a disruptive event can be diminished (possibly at an extra cost) depending on how resources are allocated and located. Restoration times are, thus, expected to be reduced by locating resources in a strategical way that responds to the spatial features of the network and the hazard under consideration.

Regarding preparedness decisions, a *Capacitated Facility Location Problem* (CFLP) [12] from the operational research literature is implemented to determine locations of "disaster response centers" and the nodes in the transportation network that will be served by them. The CFLP aims at minimizing the cost of installing a set of "response centers" of different capacities (first term in resource allocation objective in Table 2), and the cost of reaching specific sites that require inspection for damage assessment (second term in allocation objective in Table 2). The model states that all nodes must be attended (first constraint below the objective in Table 2) and that their demand must be satisfied without exceeding resource capacity (second constraint for the same problem).

Regarding response decisions, a *Vehicle Routing Problem* (VRP) [13] is implemented to define routes for inspection. The VRP seeks to minimize the cost (which usually represents distance or time) of visiting a series of nodes with a demand; in this paper, "vehicles" denote a crew of technicians and their available resources. Variable $y_{ij}(\xi)$ denotes that, in a specific route, node j is immediately preceded by node i. Constraints 1 and 2 enforce the degree for the depot (labeled as node 1 by convention) and the rest of the nodes, respectively. The depot has an in-going link and an out-going link for each of m vehicles; "customer nodes" are restricted to a degree equal to 2 (in-going and out-going link) since a larger degree would lead to bifurcations rather than routes.

A stochastic programming approach similar to that followed in [3] is implemented to couple preparedness decisions (the CFLP), response decisions (the VRP), and a set of hazard scenarios (scenarios from a probabilistic risk assessment for the San Francisco Bay Area transportation network [11]), leading to the formulation in Table 2.

Table 2: Resource allocation and crew routing as a stochastic integer program

Optimal Resource Allocation	**New Constraint**
$\min c_{ih}x_{ih}^{(n)} + c_{ij}x_{ij}^{(a)} + \theta$	$\leftarrow f(x,\theta) \geq g(\phi); \text{If}\theta^* \leq \phi$
$\sum x_{ij}^{(a)} = 1$	**Optimal Crew Routing**
$\sum x_{ih}^{(n)} k_h \geq \sum x_{ij}^{(a)} \rho_j$	z=min $c_{ij}(\xi) y_{ij}(\xi)$
Solution	$\sum y_{1j}(\xi) = 2m$
$(x^*, \theta^*) \rightarrow$	$\sum y_{ik}(\xi) + \sum y_{kj}(\xi) = 2$
	Consequence Term
	$\phi = \mathbf{\Gamma}_\xi \mathbf{U} \left\{ p_\xi \sum_\xi max_{crews} \left[z^* \right] \right\}$

It is important to highlight that the *Optimal Crew Routing* problem in Table 2 is to be solved for as many head quarters as assigned by the *Resource Allocation Problem* under each of the considered disaster scenarios. The outcomes of such collection of optimization problems is aggregated back into a single consequence term, ϕ, by taking the completion time of the slowest crew (i.e., the maximum objective value z^* for all crews) for each disaster scenario, and then taking the expectation throughout the scenarios ξ, e.g., using the annual rates of exceedence for each seismic scenario. The utility function U and penalty term Γ_ξ are as described in Section 3 and complement the consequence term by bringing key information about the broader organizational and societal context of the infrastructure risk management problem.

5 Illustrative example

The network shown in Figure 2 was used for methodological verifications in which distances before and after a disastrous event can be adjusted arbitrarily to test whether the optimization responds accordingly. To provide a sense of the complexity of the problem, this network with 36 nodes, 372 links, 2 types of resources (i.e., headquarters with larger or smaller capacity), and 4 disaster scenarios, produces an optimization problem with 1560 variables.

Figure 3 shows the solutions provided by the stochastic program when applied to the designed network. Each set of axes shows assigned headquarters as shaded circles, along with the correspond-

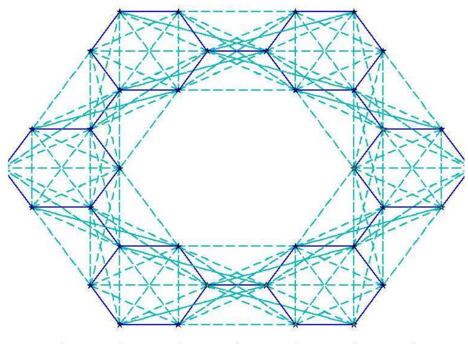

Figure 2: Synthetic network for methodological verifications with adjustable distances before and after a disastrous event.

ing nodes to-be-served (as empty circles), and colored routes to be followed by crews. The lower middle sub-problem makes it apparent that there are resources of larger size available, and that there are several outlined routes (in different colors) for different scenarios, which are superposed and not appreciable for several other sub-problems.

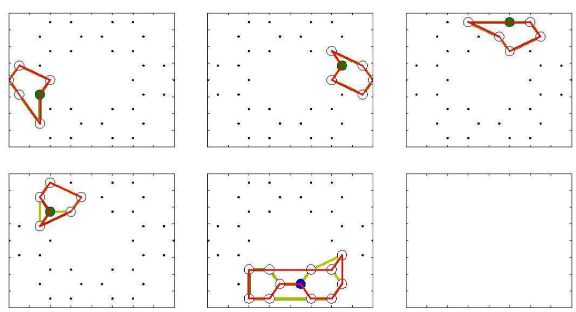

Figure 3: Optimal resource allocation and routing diagrams: shaded circles denote allocated resources; routes of different color denote how crews visit network locations for different disaster scenarios.

Figure 4 shows the evolution of the optimization process: the upper axes show the progress of the overall objective function (for the coupled decisions) towards convergence; the middle axes show investments in resource allocation vs iterations with stars denoting each of the two terms of such objective function; and the lower axes show the time to completion for all crews (dots) for all scenarios (colors) vs iterations.

Although these results respond to a hypothetical network, we want to highlight how the proposed approach reflects the coupled decision process under uncertainty, allowing to evidence interesting patterns. For instance, not every configuration representing higher investments in resource allocation leads to improved completion times, which may seem trivial from an engineering perspective but does challenge the logic sometimes applied by policy-makers, which focus more on the investment itself rather than the effectiveness of strategies it can fund. Furthermore, some network configurations (i.e., intermediate solutions in the iteration process) show a low dispersion of the dots of all colors, which has the following two interpretations: first, the fact that dots of different colors (i.e. crews under different scenarios) fall into similar completion times can be attributed to a robust resource allocation policy for which similar (and acceptable) performance can be expected for the different disaster scenarios considered; and second, the fact that dots of the same color (i.e., different crews for one disaster scenario) fall into similar completion times can be attributed to an equitable resource allocation policy in the sense that there is no significant preferential treatment for certain portions of the network, which is a challenge in many realistic situations in which socio-economically vulnerable population has disadvantageous access to infrastructure and means for recovery (e.g., the San Francisco Bay Area [6]).

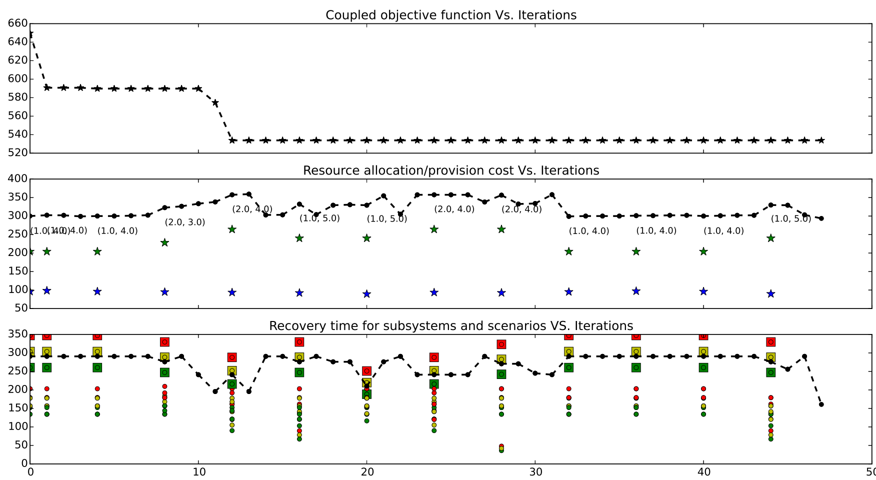

Figure 4: Evolution of the optimization process: aggregate objective function for the coupled decisions (upper axes); investments on resource allocation with stars denoting each of the two terms of such objective function (middle axes); performance -completion time- of the combined allocation and routing strategy for different headquarters shown as dots with different color for different scenarios (lower axes).

6 Conclusions

This paper proposed stochastic programming as a framework for dealing with coupled decisions and uncertainty regarding disaster preparedness and assessment, particularly, considering the problem of allocation of headquarters for disaster response and the routing of inspection crews under seismic scenarios. The main advantage of the proposed approach is that it captures the consequences of decisions made under uncertainty on future related decisions, within an exact approach, and with flexible possibilities to include functions that are not necessarily linear into consequence evaluation since it is done off -although during- the optimization process. This feature was exploited to incorporate measures that account for the societal impact of analyzed decisions (e.g., compromised users' preferences) and even include contractual features of the interactions between the operators making decisions about infrastructure risk management and an entity that represents the public interest. Like most exact methods, the proposed approach has limited scalability, but because of its decomposition features, it has potential for parallel computation, combined use of heuristics, or systems-of-systems approaches [14, 15] to solve smaller sub-systems and keep track of accuracy loss; the possibly large number of scenarios to consider may also be overcome using variance reduction techniques [16] to reduce sample sizes while maintaining probabilistic properties. The refinement of the whole framework along with the latter improvements is being carried out aiming to tackle the San Francisco Bay Area transportation network, which is challenging in terms of network size and gathering information related to the societal aspects of the problem.

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