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# Integrating Operational and Organizational Aspects in Interdependent Infrastructure Network Recovery

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Managing risk in infrastructure systems implies dealing with interdependent physical networks and their relationships with the natural and societal contexts. Computational tools are often used to support operational decisions aimed at improving resilience, whereas economics-related tools tend to be used to address broader societal and policy issues in infrastructure management. We propose an optimization-based framework for infrastructure resilience analysis that incorporates organizational and socioeconomic aspects into operational problems, allowing to understand relationships between decisions at the policy level (e.g., regulation) and the technical level (e.g., optimal infrastructure restoration). We focus on three issues that arise when integrating such levels. First, optimal restoration strategies driven by financial and operational factors evolve differently compared to those driven by socioeconomic and humanitarian factors. Second, regulatory aspects have a significant impact on recovery dynamics (e.g., effective recovery is most challenging in societies with weak institutions and regulation, where individual interests may compromise societal well-being). And third, the decision space (i.e., available actions) in postdisaster phases is strongly determined by predisaster decisions (e.g., resource allocation). The proposed optimization framework addresses these issues by using: (1) parametric analyses to test the influence of operational and socioeconomic factors on optimization outcomes, (2) regulatory constraints to model and assess the cost and benefit (for a variety of actors) of enforcing specific policy-related conditions for the recovery process, and (3) sensitivity analyses to capture the effect of predisaster decisions on recovery. We illustrate our methodology with an example regarding the recovery of interdependent water, power, and gas networks in Shelby County, TN (USA), with exposure to natural hazards.

**KEY WORDS:** Infrastructure resilience; optimization; sociotechnical systems

## 1. INTRODUCTION

Infrastructure systems are becoming increasingly interdependent, posing new challenges in addressing their vulnerability to natural and human-made hazards. Disruptive events can produce cascading failures throughout multiple infrastructure systems and economic sectors, ultimately impacting the communities that rely on the functionality of these systems. Logistically and financially efficient response and recovery strategies are necessary to mitigate the impacts of disruptions while maximizing

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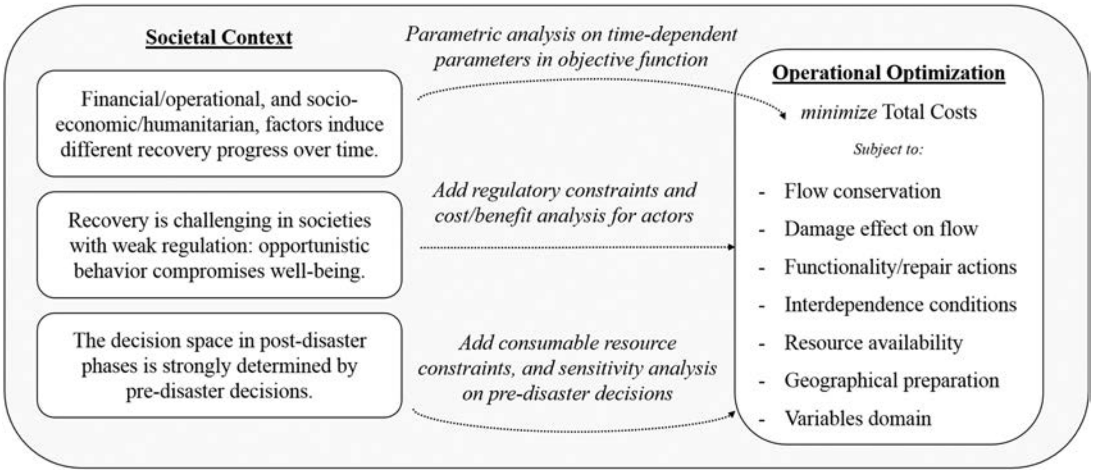


**Fig. 1.** Conceptual framework for the proposed methodology.

benefit at the societal level. The decision processes required in such recovery problems are complex because of the multiple stakeholders involved, whose diverse preferences often lead to competing objectives. In particular, decisions made by infrastructure operators affect communities and are, hence, subject to public policy. Consequently, achieving infrastructure resilience requires solutions that respond to the perspectives of users, public agencies, and infrastructure operators.

Some approaches to infrastructure resilience focus on societal aspects of disaster response and recovery at a macroscopic level, whereas others address detailed operational problems, as discussed in Section 2. Attempting to bridge both views, we adopt mathematical optimization models that support operational decisions and enhance them with capabilities related to the broader societal context, accounting for organizational and policy-related aspects of the entities that use, operate, and regulate infrastructure systems.

Fig. 1 outlines an optimization problem (right-hand block) supporting response and recovery decisions, such as prioritization of component repair activities at different periods with a cost minimization objective, and operational constraints. The left-hand side of Fig. 1 presents societal considerations that, in general, are not treated in mathematical models with the level of operational detail of the problem presented on the right-hand side. The contribution of the proposed framework consists of connecting these operational and societal aspects through innovative variations to mathematical optimization models. First, we define time-dependent cost structures that capture how different combinations of operational and socioeconomic factors may result in different strategies and recovery trajectories; for instance, while financial and operational factors make prompt recovery difficult to achieve, socioeconomic and humanitarian factors make late recovery significantly expensive due to unavailability of essential services, temporary displacements, and business interruption, among others. Second, we propose constraints that model the potential effect of regulatory measures on the recovery processes, along with their associated costs for different actors; this allows to anticipate and avoid behaviors that may jeopardize key recovery actions in weak institutional contexts. Third, we explore scenario-based analyses to assess the influence of predisaster resource allocation on recovery trajectories, as postdisaster strategies are highly limited (or potentiated) by predisaster decisions.

To demonstrate our framework, we adopt the Interdependent Network Design Problem (INDP) (González, Dueñas-Osorio, Sánchez-Silva, & Medaglia, 2016), because of its comprehensive set of constraints, and the time-dependent feature incorporated in González, Chapman, Dueñas-Osorio, Mesbahi, and D'Souza (2017), which is useful for our proposals in Section 4.1. However, note that the proposed methods and analysis could also be used in conjunction with other recovery-oriented mixed integer programming (MIP) models (Cavdaroglu, Hammel, Mitchell, Sharkey, & Wallace, 2011; Lee II, Mitchell, & Wallace, 2007; Nurre, Cavdaroglu, Mitchell, Sharkey, & Wallace, 2012). Our proposal extends the ideas from González et al. (2017) in two main ways. First, our contribution focuses on how operational models can contribute to broader policy analysis of resilience, rather than focusing on specific aspects of an optimization problem. In fact, rather than using optimization to pursue a unique solution to the operational problem, we use it to explore the decision space and analyze the type of recovery strategies that may emerge under different settings of stakeholders' interests and policy alternatives. As a result, our methodology provides the means to evaluate how infrastructure response and recovery processes can be shaped by different stakeholders' perspectives and policy scenarios, without the assumption of an unambiguous, fully defined objective function associated with a centralized decisionmaker. Second, we extend the mathematical formulation with several features, namely: multicriteria objective and time-dependent parameters capturing societal factors; novel constraints to incorporate regulation on recovery trajectories; novel constraints to incorporate the effect of preemptive decisions on recovery, focusing on the time-dependent availability of consumable and nonconsumable resources; additional constraints (i.e., valid inequalities) that improve computational performance.

This article is structured as follows: Section 2 presents related work on addressing organizational, logistical, and socioeconomic aspects in the context of community resilience, and concerning existing approaches to infrastructure network recovery. Section 3 summarizes the key features of the time-dependent INDP ($td$-INDP), as one possible recovery model to demonstrate the proposed methodology. Section 4 discusses the inclusion of multiple actors and interests, as well as regulation and preparedness, within the definition of optimal recovery strategies for interdependent infrastructure systems. Section 5 illustrates the use and capabilities of the proposed framework by presenting a case study on the recovery of the water, power, and gas networks in Shelby County, Tennessee, which is subject to earthquake hazards, due to its proximity to the New Madrid Seismic Zone, and flood risk, given its location near the Mississippi River. Section 6 provides conclusions and ideas for future work.

## 2. BACKGROUND

The treatment of operational problems in infrastructure resilience has been intensive in the areas of optimization and network analyses (Brummitt, D'Souza, & Leicht, 2012; Dueñas-Osorio, Craig, Goodno, & Bostrom, 2007; Medal, Pohl, & Rossetti, 2014), as discussed in Section 2.1. The discussion of broader societal issues regarding human and organizational factors is primarily explored in social sciences (as shown in Section 2.2), with engineering approaches emerging mainly from agent-based and game-theoretical perspectives (Gomez, Sánchez-Silva, & Dueñas-Osorio, 2014; Nikolic & Dijkema, 2006; Osman, 2012; Zhang, Peeta, & Friesz, 2005). Furthermore, survey studies such as Altay and Green (2006) and Galindo and Batta (2013) emphasize the need for approaches to resilience and disaster operations that account for issues related to stakeholders and organizations. A few studies address such issues by addressing challenges in the coordination of humanitarian supply chains (Balcik, Beamon, Krejci, Muramatsu, & Ramirez, 2010). To the best of our knowledge, there is novelty and relevance in proposing a holistic approach that can relate detailed operational decisions with issues such as competing interests from different stakeholders, the effect of regulatory measures, or attitude toward risk.

### 2.1. Interdependent Infrastructure Network Recovery

It is vital to develop appropriate tools and techniques to reduce the vulnerability of critical infrastructure networks and increase their recoverability and overall resilience. However, the rapid growth of infrastructure networks in space and demand, as well as their increasingly interdependent dynamics and operation, increases their vulnerability and their complexity (Havlin, Kenett, Bashan, Gao, & Stanley, 2014). In recent years, there have been diverse works focusing on understanding and modeling interdependent infrastructure systems. Rinaldi, Peerenboom, and Kelly (2001) studied and characterized how multiple infrastructure networks are interconnected and classified infrastructure interdependencies into four main categories: physical, geographical, cyber, and logical. Ouyang (2014) characterized the different approaches that are used to model infrastructure interdependencies into six main categories: empirical, agent based, system dynamics based, economic theory based, network based, and others. In particular, network-based approaches have been extensively studied, since they can relate the damage states of individual components of the systems with its overall performance (by accounting for the flow of commodities through the system of infrastructure networks).

Lee II et al. (2007) proposed a mathematical formulation based on mixed integer programming (MIP) that focused on optimizing the recovery of a system of infrastructure networks, while modeling diverse instances of interdependencies, such as input, mutual, shared, or exclusive dependencies. However, they did not explicitly consider the diverse costs associated with the recovery process. Later, Cavdaroglu, Hammel, Mitchell, Sharkey, and Wallace (2011) presented a mathematical framework that permitted modeling both the recovery process of damaged systems of interdependent networks and the associated job scheduling. However, they did not consider the existence of diverse limited resources or the possible savings associated with recovering multiple colocated components. González et al. (2017) proposed a general mathematical formulation, denominated the $td$-INDP. The $td$-INDP allows determining the minimum-cost recovery strategy for a system of interdependent networks while considering multiple operational constraints such as diverse limited resources, the existence of shared spaces between multiple colocated components, and the existence of multiple types of interdependencies. In particular, the $td$-INDP uses time-indexed cost coefficients, which allow modeling costs or penalizations that change in time while the system's recovery evolves. We adopt the $td$-INDP in this article as a means to test how the interests of different actors, regulatory constraints, and logistical conditions affect "optimal recovery strategies" for interdependent infrastructure networks. However, note that the proposed cost functions and other constraints could be easily adapted and integrated to other mathematical models, such as the one proposed by Cavdaroglu, Hammel, Mitchell, Sharkey, and Wallace (2011).

### 2.2. Organizational Behavior in Resilience Modeling

The role of communities and organizations regarding preparedness for, and recovery from, disasters has been studied for decades (Dynes, 1975). However, prior work in this area has mostly focused on social behavior. Several studies highlight the critical role that social capital plays in disaster management and hazard mitigation (Murphy, 2007). More specifically, the success of mitigation strategies requires shifting the focus toward public participation and community planning (Mileti, 1999; Pearce, 2003). Community engagement is so important that, while government and state agencies establish mitigation policies, their adoption and the implementation of corresponding strategies are dependent on local communities (Godschalk, Kaiser, & Berke, 1998). As a result of communities requesting to be involved in disaster mitigation and recovery decision making (Rubin, 1991), many neighborhood emergency programs are starting to flourish that involve leaders and volunteers contributing to preparedness and recovery of their communities (for example, the Home Emergency Response Organization System [HEROS] in Coquitlam, British Columbia).

Although organizational behavior in disaster relief has been extensively studied from a qualitative perspective, it is still considered to be a gap in infrastructure network recovery modeling (Santos, Herrera, Yu, Pagsuyoin, & Tan, 2014). Organizational strategies are often referred to in great detail in government reports without an assessment of their effectiveness and implication for decision making (Ouyang, 2014). Most models work under the assumption of a single decisionmaker optimizing an objective function. Overlooking the decisionmakers' perspectives and preferences in infrastructure preparedness and recovery across multiple interdependent systems may negatively impact the network performance in the recovery process (Reilly, Samuel, & Guikema, 2015; Sharkey et al., 2015). Several studies use agent-based modeling, and systems dynamics approaches, to address the complexities of decentralized decision processes in infrastructure restoration, modeling infrastructure systems as complex adaptive systems (Ouyang, 2014; Rinaldi et al., 2001). Agent-based modeling involves the definition of agents (infrastructure systems or components, operators, users), their characteristics and values, and the rule according to which they will interact with each other. A simulation-based model is then developed to assess the interactions of agents under different scenarios. Agent-based models have become a popular choice to model infrastructure interdependence (Barton et al., 2000; Barrett et al., 2010; Cardellini, Casalicchio, & Galli, 2007; North, 2001; Rigole, Vanthournout, & Deconinck, 2006). These models, while able to capture interdependencies at multiple scales of infrastructure and human agents, are computationally intensive and highly sensitive to the definition and assumptions of the agents and the simulation model, resulting in a lack of flexibility. On the other hand, system dynamics approaches, which rely on causal influence and information flow through systems, can incorporate utility functions to capture the impact of decisionmakers on infrastructure management strategies (Ouyang, 2014). Applications of these approaches include analysis of power and communications sectors interdependencies in emergencies, considering consumer behavior (Conrad, LeClaire, O'Reilly, & Uzunalioglu, 2006), and modeling the displacement of people after hurricane Katrina (Steinberg, Santella, & Zoli, 2011).

In addition to addressing organizational behavior in modeling interdependent infrastructures, accounting for social impact and public participation in the infrastructure recovery modeling allows for a better understanding of the implication of decisions made at the policy level for local communities. Not only are disasters becoming more frequent and more intense, but they are also expected to result in more severe social and economic impacts as communities rely more on infrastructure systems that are becoming increasingly interconnected through cyber technologies (Robinson, Woodard, & Vanardo, 1998). Also, Quarantelli (1986) argues that shifting communities from being victims to being resources helps avoid organizational problems and improves recovery effectiveness. Therefore, addressing the impact on communities and social systems in infrastructure recovery modeling is critical. The goal of this research is to provide a modeling approach for infrastructure recovery that accounts for both operators' perspective and community impacts.

## 3. OPTIMIZATION OF INTERDEPENDENT INFRASTRUCTURE NETWORK RECOVERY

This section presents a general structure of recovery models proposed in the literature to contextualize typical objective functions and constraints. Without loss of generality, the notation is consistent with the INDP proposed by González et al. (2016) and its time-dependent extension (i.e., the *td*-INDP in González et al., 2017), which is an optimization approach to restore damaged infrastructure networks in which the functionality of nodes may depend on that of nodes in other networks.

The main variables in the model are $\overset{\vartriangle}{w}_{it}$ and $\overset{\vartriangle}{y}_{ijt}$, which are binary decisions on whether to repair node $i$, or arc $(i, j)$, at time $t$, respectively; variables $w_{it}$ and $y_{ijt}$ state whether a node or arc is functional at time $t$, depending on damage states and repair decisions (i.e., a damaged component does not become functional unless it is repaired). Variables $x_{ijlt}$ represent the flow of commodity $l$ through arc $(i, j)$ at time $t$, whereas $\delta^+_{ilt}$ and $\delta^-_{ilt}$, which appear as auxiliary variables in González et al. (2017), are crucial in our analysis, since they represent over- and undersupply (respectively) of commodity $l$ at node $i$ and time $t$. The primary role of $\delta^+_{ilt}$ is to keep track of excess commodity at production nodes whenever flow cannot be delivered due to damage at arcs and/or consumption nodes. For instance, if all arcs were damaged (prohibiting all flows), then $\delta^+_{ilt}$ would absorb excess at production nodes, whereas $\delta^-_{ilt}$ would absorb shortage at consumption nodes, in order to honor the equality in flow balance constraints. An alternative modeling approach (without $\delta^+_{ilt}$) can be achieved by rewriting balance constraints as inequalities.

Expressions $O_1$ through $O_3$ account for terms that participate in a typical objective function, where $f_{ijt}$ and $q_{it}$ denote the cost of repairing arc $(i, j)$ and node $i$ at time $t$, respectively; $c_{ijlt}$ is the unit cost of sending commodity $l$ through arc $(i, j)$ at time $t$, or in a more general sense, it may represent profits instead of costs for providing commodity flow (which guarantees a realistic incentive to satisfy demand for all functional components). Parameters $\mu^+_{ilt}$ and $\mu^-_{ilt}$ represent penalties for over- and undersupplied demand of commodity $l$ at node $i$ and time $t$.

- $(O_1)$ Recovery: $\sum_{t\in\mathcal{T}}(\sum_{(i,j)\in\mathcal{A}'_k} f_{ijt}\overset{\vartriangle}{y}_{ijt} + \sum_{i\in\mathcal{N}'_k} q_{it}\overset{\vartriangle}{w}_{it})$.
- $(O_2)$ Operation: $\sum_{t\in\mathcal{T}}\sum_{l\in\mathcal{L}_k}(\sum_{i\in\mathcal{N}_k}\mu^+_{ilt}\delta^+_{ilt} + \sum_{(i,j)\in\mathcal{A}_k} c_{ijlt}x_{ijlt})$.
- $(O_3)$ Unavailability: $\sum_{t\in\mathcal{T}}\sum_{l\in\mathcal{L}_k}\sum_{i\in\mathcal{N}_k}\mu^-_{ilt}\delta^-_{ilt}$.

A standard optimization model for recovery of interdependent networks would, thus, conform to the following general form:

$$\text{minimize } O_1 + O_2 + O_3, \tag{1}$$

subject to constraints of different types; namely:

- $(C_1)$ Flow conservation: A classical network flow balance condition with additional slack variables $\delta^+_{ilt}$ and $\delta^-_{ilt}$ that allow over- and undersupply (respectively) to model damaged states of the network without infeasibility.
- $(C_2)$ Damage effect on flow dynamics: Flow is not allowed through an arc if any of its end nodes, or the arc itself, are damaged (damaged components are not functional at $t = 0$).

($C_3$) Relationship between functionality and repair actions: A damaged component (node or arc) can only become functional after being repaired (i.e., relating $\Delta w_{it}$ and $\Delta y_{ijt}$ with $w_{it}$ and $y_{ijt}$, respectively).
($C_4$) Interdependence: A node can only be functional if the node(s) upon which it depends are also functional.
($C_5$) Resource availability: Incorporate several types of resources whose scarcity may limit the execution of repair actions.
($C_6$) Variables domain: Repair and functionality variables take binary values ($\overset{\Delta}{w}_{it}$, $\overset{\Delta}{y}_{ijt}$, $w_{it}$, $y_{ijt}$, and $z_{st}$), whereas flow-related variables and their slacks are continuous ($x_{ijlt}$, $\delta^+_{ilt}$, and $\delta^-_{ilt}$).

Although most parameters in the original *td*-INDP formulation include time indices, the potential of their time dependence to model restoration and recovery dynamics is not explored in González et al. (2017), where parameters have constant values over time. In Section 4, we exploit this feature to incorporate postdisaster dynamics from the perspective of infrastructure operators and users.

The mathematical formulation in González et al. (2017) relies on the assumption that, in any of the networks, repair actions are instantaneous, which may not necessarily be the case. Incorporating repair times of more than one period (in at least one network) would require adjustments (e.g., using the smallest time unit, and including precedence and continuity constraints, typical of scheduling problems). However, such adjustments are not necessary for the analysis proposed in this work. The Appendix provides an instance of a detailed mathematical formulation of the problem described in this section, based on González et al. (2017) and updated with the methodology proposed in Section 4.

## 4. SOCIETAL-LAYERED INTERDEPENDENT INFRASTRUCTURE NETWORK RECOVERY

The proposed methodology incorporates organizational and socioeconomic factors into mathematical optimization models that address operational problems for the restoration of interdependent infrastructure networks, thus enriching decision processes for systems' resilience. Section 4.1 explores how tradeoffs between operational and socioeconomic interests give rise to a variety of "optimal recovery strategies"; we implement this by running the optimization model for a set of objective functions that weight time-dependent costs differently. Section 4.2 focuses on cases in which operational interests may compromise societal well-being, and on the impact of possible regulations to overcome such situations; we implement this by running the optimization model subject to constraints that model regulatory policies and assessing their impact on the objective function(s). Section 4.3 explores how predisaster resource allocation may affect recovery trajectories; we implement this by running the optimization model for different levels and types of available resources.

### 4.1. The Impact of Operational and Socioeconomic Factors on Recovery Strategies

Prompt recovery often demands a plentiful allocation of resources in predisaster stages, as well as a capacity to operate under crisis circumstances (involving training, extra investments, etc.). Late recovery, on the other hand, leads to costs related to lack of access to basic services, temporary displacements, and business interruption. Although both types of costs are relevant to all actors (operators, users, policymakers), societal factors (e.g., cultural and institutional norms, attitude toward risk) can drive recovery strategies and prioritization in different directions. Accordingly, we classify the terms in the objective function presented in Equation (1) into different categories, namely: $O_1$ and $O_2$ refer to operational costs (i.e., node/arc restoration and flow transmission), whereas $O_3$ can be related to the socioeconomic consequence of service unavailability. The prioritization of these objectives may be different for different actors, as well as across socioeconomic contexts. Specifically, weak institutions and regulations may induce poor restoration and recovery processes as a result of individual financial interests in conflict with societal well-being (Ambraseys & Bilham, 2011; Reid, 2013; Saharan, 2015).

We propose a multicriteria objective function that allows us to model strategies that follow both operational and socioeconomic optimality. In the following sections, we introduce time-dependent parameters to capture specific postdisaster dynamics. First, $f_{ijt}$ and $q_{it}$ (cost of repairing arcs and nodes, respectively) might evolve differently over time for different operators depending on their level of organizational and logistical preparedness. Second, $\mu^-_{ilt}$ (penalty on undersupply) can also evolve in a way that responds to users' tolerance to the lack of service of a specific commodity, depending on the type of user (e.g., residential and industrial) and socioeconomic conditions as well. Equation (2) presents an updated objective function, in which $\alpha \in [0, 1]$ represents how operational and socioeconomic factors are weighted (i.e., larger values of $\alpha$ favor operational interests, and vice versa).

$$\text{minimize } \alpha * [O_1 + O_2] + (1 - \alpha) * [O_3] \quad (2)$$

### 4.1.1. *Decreasing Crisis Cost for Operations*

Equation (3) defines $\Gamma(t)$ as a function that captures a crisis-induced cost increase $\Delta$ in the immediate aftermath of a disaster, decreasing back to normality at a rate $\lambda$ over time:

$$\Gamma(t) = 1 + \Delta e^{-\lambda t}. \quad (3)$$

Parameter $\lambda$ can be interpreted as the operator's organizational adaptation capacity (i.e., how fast the operator can bounce back to normal operation), which is central to infrastructure resilience. Stronger capacity can be expected from organizations with adequate predisaster resource allocation, personnel training, and expedited administrative and financial procedures.

We use $\Gamma$ to incorporate abnormal organizational and logistical effects of the postdisaster stage into the costs of repairing nodes and arcs. The expressions $f_{it} = f_{i*}\Gamma(t)$ and $q_{ijt} = q_{ij*}\Gamma(t)$ assign the described time-dependent feature to the static costs $f_{i*}$ and $q_{ij*}$.

### 4.1.2. *Increasing Penalty on Service Unavailability*

We introduce a parameter $\mu^-_{ilt}$ (Equation (4)) that captures negative effects due to unsupplied demand of commodity $l$ at node $i$ at time $t$ (e.g., users' dissatisfaction, business interruption, temporary displacement). The dynamics of $\mu^-_{ilt}$ has several characteristics: an initial value of zero, accounting for users' tolerance to unavailability in the immediate aftermath of a disaster, and a threshold time period $\tau_{li}$, representing the point at which lack of commodity $l$ becomes critical for node $i$ (i.e., when buffers such as batteries or collected water become insufficient). And a rate $\kappa$ at which the dissatisfaction reaches a steady-state value given by the function's numerator. Parameter $M^-$ is a rescaling factor based on an upper bound for reconstruction investment (Equation (5)) to make $\mu_{ilt}$ comparable with operational costs (i.e., to balance the terms in the ob-

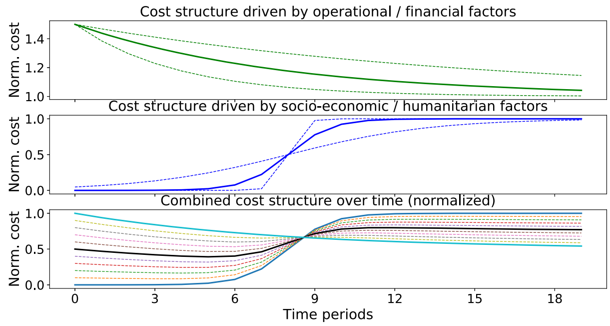


**Fig. 2.** Evolution of costs (normalized) over time, driven by: operational/financial factors (above), socioeconomic/humanitarian factors (center), and possible aggregation depending on stakeholders' preferences (below).

jective function). Parameter $\eta_i$, on the other hand, seeks to capture the relative socioeconomic importance of nodes in the area of interest to determine adequate priority levels for nodes. Although several indices could fit this purpose, we compute $\eta_i$ as the Social Vulnerability Index (SoVI) for the correspondent geographical location. The SoVI is built from information collected at the census-tract level (data obtained from the Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry/Geospatial Research, Analysis, and Services Program), and has been previously used in infrastructure restoration problems (Barker, Karakoc, & Almoghathawi, 2018). The index accounts for 15 social factors grouped under four components: (i) socioeconomic, (ii) housing composition and disability, (iii) minority status and language, and (iv) housing and transportation:

$$\mu^-_{ilt} = \frac{(1 + \eta_i) M^-}{1 + e^{\kappa(t - \tau_{li})}}, \quad (4)$$

$$M^- = \left[ \sum_{k \in K} \sum_{t \in T} \left[ \sum_{i \in N'_k} q_{it} + \sum_{(i,j) \in A'_k} f_{ijt} \right] \right]. \quad (5)$$

Fig. 2 illustrates the cost structures enabled by the introduced time-dependent functions. From an operational/financial point of view, disaster-induced disruptions discourage early restoration actions, which appear costly in the upper section of Fig. 2. From a socioeconomic/humanitarian point of view, failure to restore services that respond to basic human needs (as well as the overall functioning of society) rapidly results in negative consequences, as seen in the middle section of Fig. 2. The cultural and regulatory context of different societies may reflect different combinations of these interests (lower section of Fig. 2), and these, in turn, produce different recovery processes. The role of optimization in the proposed methodology, unlike in previous works, is not to provide a prescriptive restoration solution, but to model and understand how rational actors may respond to different socioeconomic settings (e.g., how may restoration unfold in societies where operators lack adaptation capacity, or institutions cannot enforce efficiency or transparency).

The functions in Fig. 2 are a conceptual representation of time-dependent postdisaster processes. Parameters are not conceived as inherent characteristics of actors, but as a means to capture general temporal patterns. For example, parameter $\lambda$ is not directly mapped to any one characteristic of an organization's adaptation capacity; instead, it models the normalization effect between crisis costs and routine costs. Similarly, $\tau_{li}$ and $\kappa$ do not correspond to specific users' variables, but model the transition from a phase of tolerable interruption to a phase of scarcity and other major consequences (e.g., sanitation problems, perished goods, lost revenue). Therefore, although the functions are sensitive to these parameters, the general patterns of these time-dependent phenomena remain valid. For instance, the transition to costly consequences might occur on day five rather than day three, and be more (or less) smooth, but the rationale and pattern of the phenomenon remains valid, capturing the fact that decision processes respond to a society's (undeclared) way of balancing the investment necessary to react early and the need to avoid negative consequences. Furthermore, specific values of $\lambda$, $\tau_{li}$, and $\kappa$ may represent situations in which crisis-induced costs normalize well before consequences become critical; these cases do not invalidate our modeling but represent minor disruptions in which little or no conflict arises between operational and societal interests. Similarly, minor disruptions imply smaller cost increases $\Delta$ and consequences $\mu^{-}_{ilt}$; as a result, time-dependent parameters become plainer and lead the model to more evident unique solutions, which follows the logic of a situation close to normal operation.

### 4.2. The Effect of Regulation on Recovery Strategies and Outcomes for Actors

Section 4.1 illustrated how societal settings might give rise to a variety of recovery processes, and highlighted how a lack of regulation and institutional strength might hinder adequate recovery. We enhance the $td$-INDP formulation by adding constraints that model potential regulatory policies that demand different levels of demand satisfaction after specific periods in the aftermath of a disaster.

Let us consider regulatory constraints that enforce satisfying at least $\epsilon_e$% of the demand by period $\theta_e$, for conditions $e \in \mathcal{E}$ (e.g., satisfying 50%, 90%, and 97% of the demand by periods 5, 10, and 15, respectively). It is possible to quantify the percentage of unsupplied demand at a given period (by summing unsupplied demand $\delta^{-}_{ilt}$ for a commodity $l$ at node $i$ and time $t$). Equation (6) computes unsatisfied demand as the ratio between cumulative unsatisfied demand $\delta^{-}_{ilt}$, and the cumulative demand $b_{ilt}$, both until period $\theta_e$. This regulatory constraint enforces that such ratio is no more than $(1-\epsilon_e)$ for a set of pairs: $\epsilon_e, \theta_e$:

$$\frac{\sum_{t=1}^{\theta_e}\left(\sum_{i\in N}\sum_{l\in L}\delta^{-}_{ilt}\right)}{\sum_{t=1}^{\theta_e}\left(\sum_{i\in N}\sum_{l\in L}b_{ilt}\right)} \leq (1-\epsilon_e), \quad \forall e \in \mathcal{E}. \quad (6)$$

By incorporating such constraints, it is possible to assess how a specific policy may affect different parts of the objective function (i.e., $O_1$ through $O_3$) and, in turn, different stakeholders. For instance, a policy demanding unrealistic early demand satisfaction may improve service availability ($O_3$, more closely associated with users) at the expense of disproportionate restoration costs ($O_1$, more closely associated with operators), and vice versa. Optimization, thus, allows an exploration of the decision space that can help decisionmakers in dismissing policies that produce undesirable outcomes for any stakeholders. Finally, aside from modeling regulatory policies, these constraints can be used to design restoration processes that pursue a desired recovery trajectory, and to determine necessary actions and resources to achieve it (thus, being able to evaluate whether its benefits justify its costs).

### 4.3. The Impact of Preemptive Decisions on Recovery

Recovery processes are not only affected by the decisions made in the recovery stage itself, but they are also highly impacted (either limited or potentiated) by predisaster decisions. Although several predisaster decisions are important (retrofitting components, communicating risk, and training personnel), we focus on the availability of resources (financial, material, and human) that directly impact recovery capabilities. We classify resources as consumable or nonconsumable. For instance, human resources and equipment are nonconsumable since they can be reused at each period; financial resources and materials, on the other hand, are consumed as used. Nonconsumable resources (e.g., teams), encapsulated in set $R$, limit the number of restoration actions that can be executed per period, whereas consumable resources (e.g., budget), in set $R'$, limit the overall actions through the time horizon.

The original $td$-INDP includes resource constraints that are adequate for nonconsumable resources (Equation (7)), where $h_{ijrt}$ and $p_{irt}$ denote the amount of resource $r \in R$ necessary to restore nodes or links at time $t$, respectively, and $v_{rt}$ is the amount of available nonconsumable resource $r \in R$ at time $t \in T$:

$$\sum_{i \in N'} p_{irt} \overset{\Delta}{w}_{it} + \sum_{(i,j) \in A'} h_{ijrt} \overset{\Delta}{y}_{ijt} \leq v_{rt}, \quad \forall r \in R, t \in T. \tag{7}$$

For consumable resources, we update the $td$-INDP with resource constraints that follow an inventory structure that models how resources are acquired, stored, and consumed throughout the time horizon. Variables $I_{rt}$ represent the inventory for resource $r$ at time period $t$, $\tilde{I}_{r,0}$ is a parameter for the initial amount of resource $r$, and $\rho_{rt}$ represents potential replenishment of resource $r$ at time $t$ (e.g., from federal and international funds), which may enable further repair actions. Equations (8)–(10) describe the introduced set of constraints:

$$I_{r0} = \tilde{I}_{r,0}, \quad \forall r \in R', \tag{8}$$

$$I_{rt} = I_{r,t-1} + \rho_{rt} - \sum_{i \in N'} p_{irt} \overset{\Delta}{w}_{it} - \sum_{(i,j) \in A'} h_{ijrt} \overset{\Delta}{y}_{ijt}, \quad \forall r \in R', t \in T, \tag{9}$$

$$I_{rt} \geq 0, \quad \forall r \in R', t \in T. \tag{10}$$

The modeling capabilities provided by these constraints enable analyses of the impact of predisaster resource availability on recovery efficiency, allowing decisionmakers to evaluate compromises between preemptive investments and the corresponding decrease in total losses. In Section 5, we explore a scenario-based analysis to evaluate different predisaster policies. A two-stage stochastic optimization version of such analysis, resembling the work in Gomez and Baker (2019), is part of ongoing research. The recovery optimization problem is computationally demanding, and the extensive development to embed it in a two-stage approach exceeds the scope of this article.

The Appendix details the incorporation of these and other minor novel features into the $td$-INDP and related models.

## 5. ILLUSTRATIVE EXAMPLE

We illustrate the proposed methodology with an example that addresses the recovery of the water, gas, and power networks in Shelby County, Tennessee, under exposure to seismic hazards due to the New Madrid seismic zone (NMSZ). The water, gas, and power networks are represented as graphs with 49, 16, and 60 nodes, and 142, 34, and 152 arcs, respectively, plus a set of 45 physical interdependence links across networks. This modeling produces optimization problems on the order of 30,000 variables and 30,000 constraints for each scenario (with variations due to differing numbers of damaged components across scenarios). These graphs represent real infrastructure networks that are currently operated by the Memphis light, gas, and water company, which serves more than 400,000 customers in the City of Memphis and Shelby County. Our case study is limited to this unique operator, although future work aims at including multiple actors. It is worth noting that the choice of this case study is due to the availability of network data, and there is no relationship between the company and the hypothetical behaviors and strategies described in the article. Fig. 3, originally presented in González et al. (2017), illustrates the topology of the networks. Each node has an associated socioeconomic vulnerability index, which depends on users' geographical location and commodity type, as discussed in Section 4.1.

A set of 2,000 recovery experiments was solved, accounting for 20 objective function weights ($\alpha$), equally spaced in the $[0, 1]$ range. Each of these objective functions is run for 100 realizations of damage based on the NMSZ hazard, considering earthquake magnitudes 6, 7, 8, and 9. Realistic information on the Shelby County network recovery problem was retrieved from previous studies (González et al., 2016; Hernandez-Fajardo & Dueñas-Osorio, 2011; Song & Ok, 2010), where data, as well as their gathering and processing procedures, are detailed. A time horizon of 20 days is proposed, considering a range of three weeks to recover the three networks.

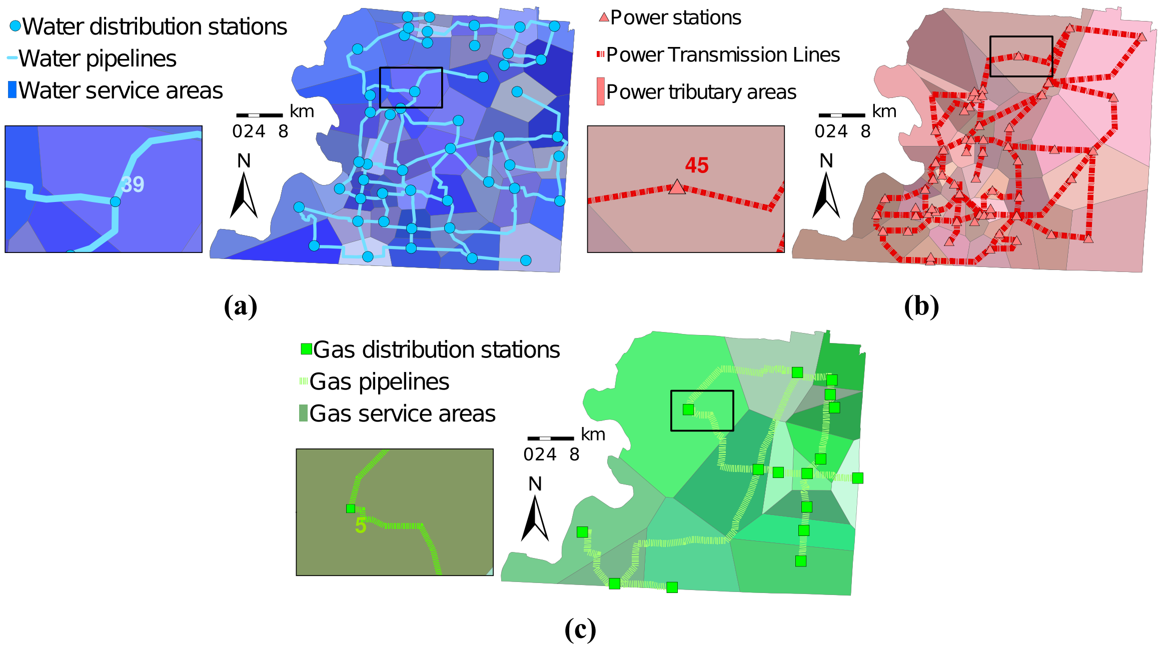


**Fig. 3.** Spatial representation of (a) water, (b) power, and (c) gas networks for Shelby County.

The implementations were coded in Python, using Gurobi on a personal computer with an Intel Core i7@2.5GHz processor and a RAM of 8GB. Solving one instance of our problem for 100 damage scenarios takes an average of 4 minutes; running for 20 objective function weights, four regulation policies, and six resource scenarios may take a few hours (instances with major damage, scarce resources, or stringent policies are generally slower).

### 5.1. Restoration Strategies for Different Societal Settings

Fig. 4 shows illustrative cases of network restoration over time for different weights ($\alpha$) of the objective function. The number of repair actions per period is shown, as well as the progress of percentual demand satisfaction. Vertical dashed bars indicate, from left to right, the period at which demand satisfaction reaches 50%, 90%, and 97% (noted $\theta_{50}$, $\theta_{90}$, and $\theta_{97}$).

The patterns in Fig. 4 evidence how the optimization produces less effective restoration processes (longer times to achieve demand satisfaction) as the focus deviates from societal consequences toward operational/financial interests. This pattern is of special concern in cases in which weak institutions and regulation may lead to moral hazard (i.e., someone having an incentive to make potentially irresponsible decisions when consequences are likely to be suffered by others), particularly when those in charge of implementing recovery actions have interests misaligned with societal goals.

### 5.2. Modeling and Evaluation of Regulatory Policies

For illustrative purposes, we consider a moderate policy A ($\mathcal{E}_A$) and a strong policy B ($\mathcal{E}_B$). The moderate policy (A) demands achieving 50%, 90%, and 99% of demand satisfaction by periods 5, 12, 18, respectively; thus, $\epsilon_e = 0.5, 0.9, 0.97$ and $\theta_e = 5, 12, 18$. The strong policy (B) is characterized by $\epsilon_e = 0.5, 0.9, 0.97$ and $\theta_e = 2, 4, 7$. The two policies are tested under intermediate and operationally oriented objective functions (i.e., $\alpha = 0.4$ and $0.9$). Since $\alpha = 0.4$ is already biased toward socioeconomic outcomes, the effects of "civic-minded" regulation are not so notorious. We focus on the more interesting $\alpha = 0.9$, in which both policies are able to obtain societal benefit from a hypothetical operationally driven actor (with different outcomes in terms of cost–benefit).

Fig. 5 illustrates the effects of the strong and moderate policies on operational and socioeconomic objectives. The moderate policy (A) can improve benefit from a socioeconomic perspective (i.e.,

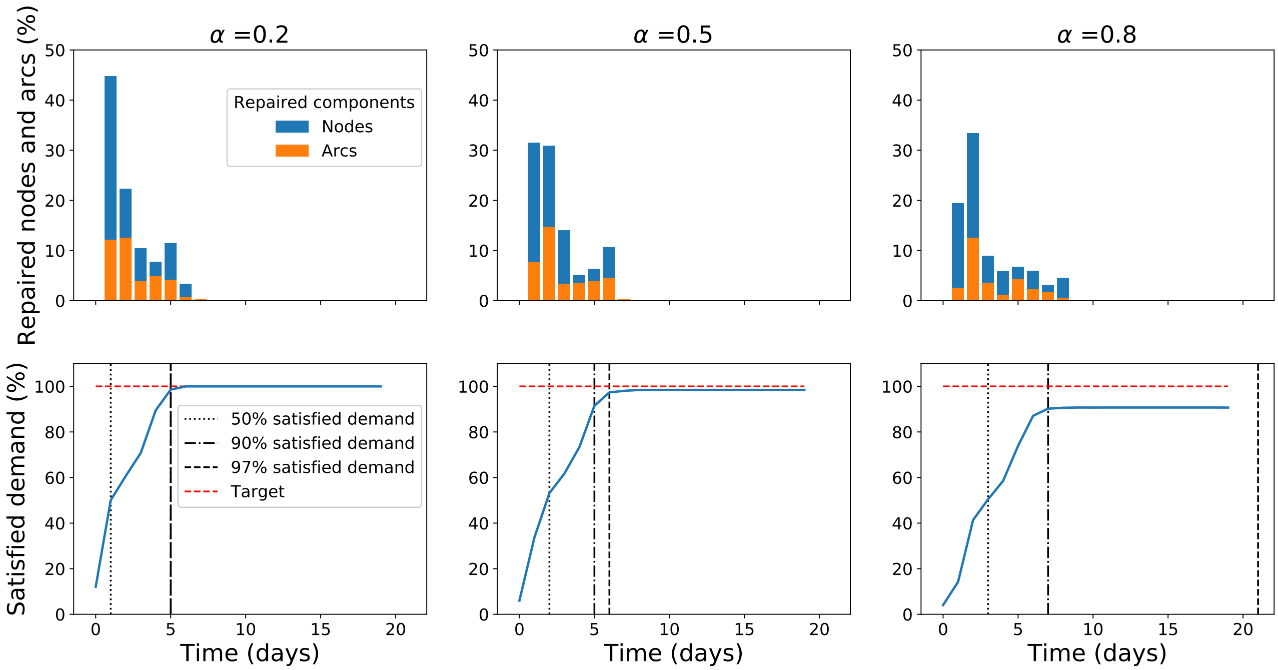


**Fig. 4.** Instances of optimal recovery strategies for different weights for actors in the objective function: from left to right, 20%, 50%, and 80% assigned to the operator. Executed repair actions per period (upper section) and satisfied demand over time (lower section).

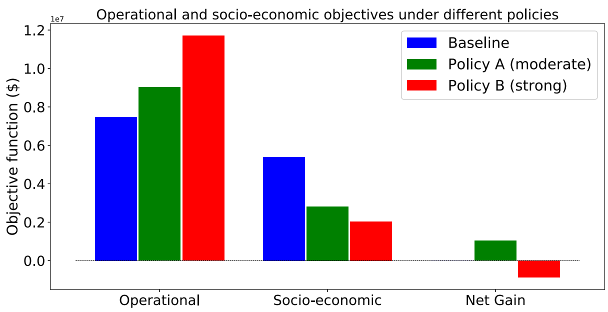


**Fig. 5.** Analysis of moderate and strong regulation policies (A and B) for network restoration. Impact on operational (left) and socioeconomic (middle) outcomes, as well as net gain in terms of benefit–cost (right).

diminishes aggregate unsatisfied demand over time), and while such benefit implies a cost, the balance is convenient (i.e., the net gain is positive). The strong policy (B), on the other hand, can further improve societal benefit, but this extra benefit takes a disproportionate toll on operational costs, thus producing a negative net gain, and making the policy unattractive.

Beyond this illustration, the inclusion of regulatory aspects within comprehensive quantitative techniques adds value to resilience engineering by coupling high-level strategic and policy-making decisions with operational and tactical decisions. Also, policymakers can anticipate how different actors may respond to potential regulatory conditions (i.e., what would their optimal reaction be under assumptions of rationality and perfect information).

### 5.3. Evaluating the Impact of Preemptive Decisions

Decisions on adequate preemptive investments to minimize expected consequences are a central problem in risk and resilience engineering. We address the impact of predisaster resource allocation on network recovery by subjecting our updated version of the $td$-INDP to different scenarios of resource availability. Without loss of generality, we assume that resources are quantified in such a way that one unit is necessary for one recovery action, and perform sensitivity analysis on the possibility of having one through six resources available (e.g., recovery crews) from the predisaster stage. Fig. 6(a) shows how recovery trajectories are affected by resource availability, where the slowest and fastest recovering instances correspond to one and six resources, respectively. Moreover, Fig. 6(b) presents marginal costs and savings associated with each additional unit of resource. For instance, when passing from one to

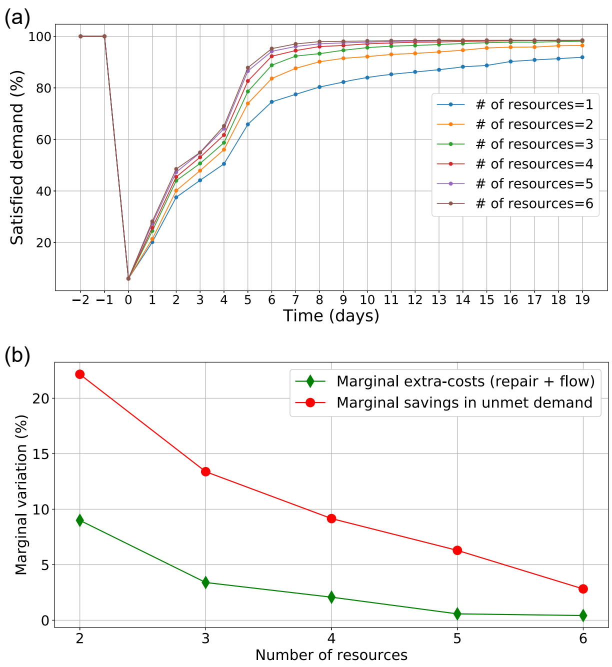


**Fig. 6.** Optimal recovery trajectories depending on available resources from predisaster stage (upper part). Marginal costs (green) and savings (red) associated with each additional unit of resource (lower part).

two resource units, unmet demand can be reduced by over 20%, with an increase of under 10% in extra costs (more repair actions and flow transmission are possible with more resources). The marginal savings consistently outweigh the cost increase when augmenting the number of resources, but the benefit is more drastic when fewer resources were initially available. For example, passing from five to six resources appears less attractive than passing from three to four, as the obtained benefit is lower. Depending on the absolute costs and savings associated with these increases in resources, it is possible to quantify the maximum price that should be paid for every extra unit of resource (i.e., the idea of shadow price, or dual variable, which is not generally available in integer problems).

Because the proposed methodology integrates a broad set of aspects of infrastructure network recovery, we rely on several assumptions to build parameters that reflect logistical, organizational, and socioeconomic features of the problem. In general, our analysis addresses questions related to macroscopic dynamics and behaviors (rather than specific numeric results); thus, the significance of our contribution holds despite numerical variations that may appear in solutions due to potential changes in parameter values.

## 6. CONCLUSIONS

We propose an optimization-based framework to analyze how recovery processes in interdependent infrastructure networks respond to societal factors such as stakeholders' interests, institutional and regulatory contexts, and relationships between pre- and postdisaster decisions (e.g., resource allocation). Without loss of generality, we test our framework on the *td*-INDP and enhance its mathematical formulation to relate its operational decisions (on repairing components) to broader aspects of disaster recovery. We incorporate time-dependent parameters that capture specific postdisaster dynamics and evaluate tradeoffs between operational and societal factors that drive recovery processes in different directions. We, thus, model how a society's undeclared preferences may produce restoration strategies that favor expensive early actions over the (more) costly consequences of late recovery, and vice versa. We enhance the *td*-INDP with constraints that model regulatory (or self-imposed) recovery policies, allowing analysts to determine their suitability in terms of the costs and benefits for different actors. Furthermore, we evaluate the effect of resource availability (predisaster) on the trajectory of recovery.

Improving resilience implies significant expenses that may discourage decisionmakers' initiatives to protect infrastructure and communities. Our contribution focuses on assuring a recovery process that safeguards the needs of vulnerable communities through the incorporation of socioeconomic vulnerability metrics and the development of models that help understand and regulate potential conflicts of interest that compromise adequate recovery in societies with weak institutional contexts. The proposed methodology can help evaluate the quantifiable benefits of infrastructure protection investments to justify and communicate the costs and benefits of such efforts. As a result, our methodology can help policymakers by providing informed evaluations of how potential policies would affect the needs of infrastructure operators and users, as well as proposing standards, best practices, and regulation regarding preparedness decisions. For instance, our methodology can offer support to specify guidelines for regulation and predisaster resource allocation, which highly impact recovery trajectories, as observed in our numerical results.

Ongoing research is devoted to mathematically coupling the recovery process with preemptive stages including decisions on retrofitting and resource allocation, as well as to improve the quantification of, and relax assumptions about, organizational and socioeconomic factors.

## ACKNOWLEDGMENTS

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## APPENDIX A: SOCIETAL-LAYERED *td*-INDP (MATHEMATICAL MODEL)

This appendix provides one possible mathematical implementation of the framework described in Sections 3 and 4. The notation and main structure of this model follow the $td$-INDP devised by González et al. (2017). Section A.1 summarizes the model's notation, whereas Section A.3 presents the full mathematical formulation. The mathematical formulation relates directly to the modeling approach described in Section 3, and includes the updates devised in Section 4 in order to enhance the approach proposed in González et al. (2017) with a societal-layered analysis.

### A.1. Model Notation

Table AI presents the sets required in our mathematical formulation, whereas Tables AII and AIII describe utilized parameters; Table AII refers specifically to parameters associated with the societal-layered version of the INDP, whose novelty and relevance is discussed in Section A.3. Table AIV presents decision variables, the first one of which is new to our formulation. It is worth noting that the formulation in González et al. (2017) considers an additional index $k \in \mathcal{K}$ accounting for the network $k$ to which nodes $i$ or arcs $(i, j)$ belong; by assigning unique IDs to all components, we were able to omit such index (and reduce the space of variables) in our current contribution. The following notation, however, includes such index.

**Table AI.** Sets

| | |
|---|---|
| $\mathcal{E}$ | Set of regulatory policies |
| $\mathcal{N}$ | Nodes before a destructive event |
| $\mathcal{A}$ | Arcs before a destructive event |
| $\mathcal{T}$ | Periods for the recovery process (time horizon) |
| $\mathcal{S}$ | Geographical spaces (which contain the infrastructure networks) |
| $\mathcal{L}$ | Commodities flowing in the system |
| $\mathcal{R}$ | Limited resources to be used in the reconstruction process |
| $\mathcal{R}^c$ | Consumable resources to be used in the reconstruction process |
| $\mathcal{K}$ | Infrastructure networks |
| $\mathcal{N}_k^*$ | Nodes in network $k \in \mathcal{K}$ that require fully satisfied demand to be functional |
| $\mathcal{N}_k$ | Nodes in network $k \in \mathcal{K}$ before a destructive event |
| $\mathcal{N}_k'$ | Destroyed nodes in network $k \in \mathcal{K}$ after the event |
| $\mathcal{A}_k$ | Arcs in network $k \in \mathcal{K}$ before a destructive event |
| $\mathcal{A}_k'$ | Destroyed arcs in network $k \in \mathcal{K}$ after the event |
| $\mathcal{L}_k$ | Commodities that flow through network $k \in \mathcal{K}$ |

**Table AII.** Parameters Incorporated for the Societal-layered INDP

| | |
|---|---|
| $\mu_{iklt}^-$ | Costs of unsatisfied demand of commodity $l$ in node $i$ in network $k$ at time $t$ |
| $f_{ijkt}$ | Cost of recovering arc $(i, j)$ in network $k$ at time $t$ |
| $q_{ikt}$ | Cost of recovering node $i$ in network $k$ at time $t$ |
| $\eta_i$ | Measure of socioeconomic vulnerability for node $i$ |
| $\alpha$ | Weight of the objective functions (operator vs. users) |
| $\rho_{rt}$ | Rate of replenishment of consumable resource $r$ at time $t$ |
| $\epsilon_e$ | Desired performance specified by policy $e$ |
| $\theta_e$ | Time period at which policy $e$ enforces certain performance compliance |
| $\kappa$ | Rate at which the penalty for unsupplied commodity increases |
| $\tau_{li}$ | Users' tolerance to unsupplied commodity $l$ in days |
| $\lambda$ | Organizational adaptation capacity in the aftermath of a disaster |

### A.2. Additional Updates on the Original INDP

The $td$-INDP, part of the model dynamics, depends on its unique objective function, thus producing inconsistencies when focusing on isolated terms. For instance, when dismissing the cost of sending flow through arcs, spurious flows may appear. Similarly, when dismissing repairing costs, components might be unnecessarily repaired more than once. The following constraints prevent such

**Table AIII.** Original *td*-INDP Parameters

| | |
|---|---|
| $v_{rt}$ | Availability of resource $r$ at time $t$ |
| $h_{ijkrt}$ | Usage of resource $r$ related to recovering arc $(i, j)$ in network $k$ at time $t$ |
| $p_{ikrt}$ | Usage of resource $r$ related to recovering node $i$ in network $k$ at time $t$ |
| $M^{+}_{iklt}$ | Costs of excess of supply of commodity $l$ in node $i$ in network $k$ at time $t$ |
| $\phi ijkst$ | Indicates if repairing arc $(i, j)$ in network $k$ at time $t$ requires preparing space $s$ |
| $\beta_{ikst}$ | Indicates if repairing node $i$ in network $k$ at time $t$ requires preparing space $s$ |
| $\gamma_{ijk\tilde{k}t}$ | Indicates if at time $t$ node $i$ in network $k$ depends on node $j$ in network $\tilde{k} \in \mathcal{K}$ |
| $g_{st}$ | Cost of preparing geographical space $s$ at time $t$ |
| $f_{ijkt}$ | Cost of recovering arc $(i, j)$ in network $k$ at time $t$ |
| $q_{ikt}$ | Cost of recovering node $i$ in network $k$ at time $t$ |
| $c_{ijklt}$ | Commodity $l$ unitary flow cost through arc $(i, j)$ in network $k$ at time $t$ |
| $u_{ijkt}$ | Total flow capacity of arc $(i, j)$ in network $k$ at time $t$ |
| $b_{iklt}$ | Demand/supply of commodity $l$ in node $i$ in network $k$ at time $t$ |

**Table AIV.** Decision Variables

| | |
|---|---|
| $I_{rt}$ | Inventory of consumable resource $r$ at time $t$ |
| $\delta^{+}_{iklt}$ | Excess of supply of commodity $l$ in node $i$ in network $k$ at time $t$ |
| $\delta^{-}_{iklt}$ | Unmet demand of commodity $l$ in node $i$ in network $k$ at time $t$ |
| $x_{ijklt}$ | Flow of commodity $l$ through arc $(i, j)$ in network $k$ at time $t$ |
| $w_{ikt}$ | Binary variable that indicates if node $i$ in network $k$ is functional at time $t$ |
| $y_{ijkt}$ | Binary variable that indicates if arc $(i, j)$ in network $k$ is functional at time $t$ |
| $\overset{\Delta}{w}_{ikt}$ | Binary variable that indicates if node $i$ in network $k$ should be recovered at time $t$ |
| $\overset{\Delta}{y}_{ijkt}$ | Binary variable that indicates if arc $(i, j)$ in network $k$ should be recovered at time $t$ |
| $\overset{\Delta}{z}_{st}$ | Binary variable that indicates if space $s$ has to be prepared at time $t$ |

behavior and contribute to a tighter solution space, which favors computational efficiency:

$$\sum_{t \in T} \overset{\Delta}{w}_{it} \leq 1, \quad \forall i \in N', \tag{A1}$$

$$\sum_{t \in T} \overset{\Delta}{y}_{ijt} \leq 1, \quad \forall (i, j) \in A'. \tag{A2}$$

Note that using strict equalities in these constraints enforces repairing all damaged components, which is not currently desired since satisfying unmet demand does not necessarily require so. Finally, the formulation in González et al. (2017) considers an additional index denoting the network to which a node or arc belongs; by assigning unique IDs to all components, we are able to omit such index and reduce the space of variables.

### A.3. Mathematical Model

The mathematical formulation presented in this section follows the structure of the *td*-INDP from González et al. (2017), and incorporates the following updates in order to provide a substantial societal-layered analysis:

- The objective function is transformed to a multicriteria function in order to capture the effect of including the interests of multiple stakeholders (particularly, infrastructure operators and users). The updated objective function is shown in Equation (A3). The inclusion (or modification) of parameters $\mu^{-}_{iklt}$, $f_{ijkt}$, $q_{ikt}$, $\eta$, and $\alpha$ was key in modeling the time-dependent preferences of multiple stakeholders; specifically, $\lambda$ is a key parameter that captures the organizational adaptation capacity of operators after disasters, whereas $\tau_{li}$ and $\kappa$ help modeling users' response to lack of service for specific commodities. The incorporation of the constraints in Section A.2 was necessary to avoid unrealistic solutions when transforming the *td*-INDP to multiple objectives. These constraints also improve computational efficiency.
- A fundamental update lies in the inclusion of regulatory constraints that model the effect of different policies that demand certain performance compliance levels from operators. These are captured in Equation (A4). The inclusion of set $\mathcal{E}$, and parameters $\theta_e$ and $\epsilon_e$, allowed us to model regulatory policies and their impact on infrastructure recovery.
- A relevant update consists in the distinction between consumable and nonconsumable resources, with the former not being accounted for in the original INDP formulation. Equations (A17), (A18), and (A22) provide an inventory structure that models consumable resources that add a realistic dynamics to recovery problems, in which time-dependent availability of resources is exploited. The inclusion of variable $I_{rt}$ and parameters $\rho_{rt}$, $H$, and $\tilde{I}$ allowed for a comprehensive modeling of resource availability and usage.

Minimize

$$\sum_{k\in\mathcal{K}}\Bigg(\alpha\Bigg[\sum_{t\in\mathcal{T}|t>0}\sum_{s\in\mathcal{S}}g_{st}\Delta z_{st} + \sum_{t\in\mathcal{T}}\Bigg(\sum_{(i,j)\in\mathcal{A}'_k}f_{ijkt}\overset{\Delta}{y}_{ijt}+\sum_{i\in\mathcal{N}'_k}q_{ikt}\overset{\Delta}{w}_{it}\Bigg) + \sum_{t\in\mathcal{T}}\sum_{l\in\mathcal{L}_k}\Bigg(\sum_{i\in\mathcal{N}_k}\mu^{+}_{iklt}\delta^{+}_{iklt}+\sum_{(i,j)\in\mathcal{A}_k}c_{ijklt}x_{ijklt}\Bigg)\Bigg] + (1-\alpha)\Bigg[\sum_{t\in\mathcal{T}}\sum_{l\in\mathcal{L}_k}\Bigg(\sum_{i\in\mathcal{N}_k}\mu^{-}_{iklt}\delta^{-}_{iklt}\Bigg)\Bigg]\Bigg) \quad \text{(A3)}$$

subject to:

$(C_0)$ *Regulatory constraints*:

$$\frac{\sum_{t=1}^{\theta_e}\left(\sum_{i\in N}\sum_{l\in L}\sum_{k\in K}\delta^{-}_{iklt}\right)}{\sum_{t=1}^{\theta_e}\left(\sum_{i\in N}\sum_{l\in L}\sum_{k\in K}b_{iklt}\right)} \le (1-\epsilon_e), \quad \forall e\in\mathcal{E}. \quad \text{(A4)}$$

$(C_1)$ *Flow conservation*:

$$\sum_{j:(i,j)\in\mathcal{A}_k}x_{ijklt}-\sum_{j:(j,i)\in\mathcal{A}_k}x_{jiklt}=b_{iklt}-\delta^{+}_{iklt}+\delta^{-}_{iklt}, \quad \forall k\in\mathcal{K},\forall i\in\mathcal{N}_k,\forall l\in\mathcal{L}_k,\forall t\in\mathcal{T}. \quad \text{(A5)}$$

$(C_2)$ *Damage effect on flow dynamics*:

$$\sum_{l\in\mathcal{L}_k}x_{ijklt}\le u_{ijkt}w_{ikt}, \quad \forall k\in\mathcal{K},\forall(i,j)\in\mathcal{A}_k, \quad \forall t\in\mathcal{T}, \quad \text{(A6)}$$

$$\sum_{l\in\mathcal{L}_k}x_{ijklt}\le u_{ijkt}w_{jkt}, \quad \forall k\in\mathcal{K},\forall(i,j)\in\mathcal{A}_k, \quad \forall t\in\mathcal{T}, \quad \text{(A7)}$$

$$\sum_{l\in\mathcal{L}_k}x_{ijklt}\le u_{ijkt}y_{ijkt}, \quad \forall k\in\mathcal{K}, \quad \forall(i,j)\in\mathcal{A}'_k, \quad \forall t\in\mathcal{T}, \quad \text{(A8)}$$

$$w_{ik0}=0, \quad \forall k\in\mathcal{K}, \quad \forall i\in\mathcal{N}'_k, \quad \text{(A9)}$$

$$y_{ijk0}=0, \quad \forall k\in\mathcal{K}, \quad \forall(i,j)\in\mathcal{A}'_k. \quad \text{(A10)}$$

$(C_3)$ *Relationship between functionality and repair actions*:

$$w_{it}\le\sum_{\tilde{t}=1}^{t}\overset{\Delta}{w}_{i\tilde{t}}, \quad \forall k\in\mathcal{K},\forall i\in\mathcal{N}'_k, \quad \forall t\in\mathcal{T}\mid t>0, \quad \text{(A11)}$$

$$y_{ijt}\le\sum_{\tilde{t}=1}^{t}\overset{\Delta}{y}_{ij\tilde{t}}, \quad \forall k\in\mathcal{K},\forall(i,j)\in\mathcal{A}'_k, \quad \forall t\in\mathcal{T}\mid t>0, \quad \text{(A12)}$$

$$\sum_{t\in T}\overset{\Delta}{w}_{it}\le 1, \quad \forall i\in N', \quad \text{(A13)}$$

$$\sum_{t\in T}\overset{\Delta}{y}_{ijt}\le 1, \quad \forall(i,j)\in A'. \quad \text{(A14)}$$

$(C_4)$ *Interdependence*:

$$\sum_{i\in\mathcal{N}_k}w_{ikt}\gamma_{ijk\tilde{k}t}\ge w_{j\tilde{k}t}, \quad \forall k,\tilde{k}\in\mathcal{K},\forall j\in\mathcal{N}_{\tilde{k}},, \quad \forall t\in\mathcal{T}. \quad \text{(A15)}$$

$(C_5)$ *Resource availability*:

$$\sum_{k\in\mathcal{K}}\Bigg(\sum_{(i,j)\in\mathcal{A}'_k}h_{ijkrt}\overset{\Delta}{y}_{ijt}+\sum_{i\in\mathcal{N}'_k}p_{ikrt}\overset{\Delta}{w}_{it}\Bigg)\le v_{rt}, \quad \forall r\in\mathcal{R},\forall t\in\mathcal{T}\mid t>0, \quad \text{(A16)}$$

$$I_{r0}=\tilde{I}_{r,0}, \quad \forall r\in R', \quad \text{(A17)}$$

$$I_{rt}=I_{r,t-1}+\rho_{rt}-\sum_{i\in N'}h_r\overset{\Delta}{w}_{it}-\sum_{(i,j)\in A'}p_r\overset{\Delta}{y}_{ijt}, \quad \forall r\in R',t\in T \quad \text{(A18)}$$

$(C_6)$ *Geographical preparation*:

$$\Delta w_{ikt}\phi_{ikst}\le\Delta z_{st}, \quad \forall k\in\mathcal{K},\forall i\in\mathcal{N}'_k,\forall s\in\mathcal{S}, \quad \forall t\in\mathcal{T}\mid t>0, \quad \text{(A19)}$$

$$\Delta y_{ijkt}\beta_{ijkst}\le\Delta z_{st}, \quad \forall k\in\mathcal{K},\forall(i,j)\in\mathcal{A}'_k, \quad \forall s\in\mathcal{S},\forall t\in\mathcal{T}\mid t>0, \quad \text{(A20)}$$

$$w_{ikt}|b_{iklt}|\le|b_{iklt}|-\delta^{-}_{iklt}, \quad \forall k\in\mathcal{K},\forall i\in\mathcal{N}^{*}_k, \quad \forall l\in\mathcal{L}_k,\forall t\in\mathcal{T}, \quad \text{(A21)}$$

$(C_7)$ *Variables domain*:

$$I_{rt} \geq 0, \quad \forall r \in R', t \in T \tag{A22}$$

$$\delta^{+}_{iklt} \geq 0, \quad \forall k \in \mathcal{K}, \forall i \in \mathcal{N}_k, \forall l \in \mathcal{L}_k, \quad \forall t \in \mathcal{T}, \tag{A23}$$

$$\delta^{-}_{iklt} \geq 0, \quad \forall k \in \mathcal{K}, \forall i \in \mathcal{N}_k, \forall l \in \mathcal{L}_k, \quad \forall t \in \mathcal{T}, \tag{A24}$$

$$x_{ijklt} \geq 0, \quad \forall k \in \mathcal{K}, \forall (i, j) \in \mathcal{A}_k, \forall l \in \mathcal{L}_k, \quad \forall t \in \mathcal{T}, \tag{A25}$$

$$w_{ikt} \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \forall i \in \mathcal{N}_k, \quad \forall t \in \mathcal{T}, \tag{A26}$$

$$y_{ijkt} \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \forall (i, j) \in \mathcal{A}'_k, \quad \forall t \in \mathcal{T}, \tag{A27}$$

$$\Delta w_{ikt} \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \forall i \in \mathcal{N}'_k, \quad \forall t \in \mathcal{T} \mid t > 0, \tag{A28}$$

$$\Delta y_{ijkt} \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \forall (i, j) \in \mathcal{A}'_k, \quad \forall t \in \mathcal{T} \mid t > 0, \tag{A29}$$

$$\Delta z_{st} \in \{0, 1\}, \quad \forall s \in \mathcal{S}, \forall t \in \mathcal{T} \mid t > 0. \tag{A30}$$

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