Recovery Optimization of Interdependent Infrastructure: A Multi-Scale Approach

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ABSTRACT: Rapid post-disaster recovery of infrastructure is necessary for prompt societal recovery. Regional resilience analysis can promote mitigation and recovery strategies that reduce the spatial extent and duration of infrastructure disruptions. Three significant challenges in regional resilience analysis are 1) modeling the physical recovery of infrastructure; 2) modeling the associated service recovery; and 3) developing a computationally manageable approach for the recovery modeling and optimization. This paper presents a novel multi-scale approach for the post-disaster recovery modeling and optimization of interdependent infrastructure. The multi-scale approach facilitates the recovery modeling and enables developing recovery strategies that are feasible to implement and easy to communicate. To enhance regional resilience, the paper integrates the recovery modeling into a multi-objective optimization problem. The optimization problem aims to schedule the required recovery activities such that disrupted services are restored as fast as possible, while minimizing the incurred cost. In the optimization problem, resilience metrics are introduced to monitor and quantify service recovery. The optimization problem is subject to recovery scheduling and network flow constraints, where each is formulated as a nested optimization. The multi-scale approach to the recovery optimization highlights the role of infrastructure at multiple scales to achieve selected recovery objective(s). As an illustration, the proposed approach is used to optimize the post-disaster recovery of interdependent infrastructure in a virtual community testbed.

1. INTRODUCTION

The prosperity of modern societies and public well-being increasingly depend on interdependent infrastructure to enable the continuous flow of essential resources and services such as water and power to communities (Corotis 2009; Ellingwood et al. 2016; Gardoni et al. 2016). Infrastructure loss of functionality in the aftermath of hazards can disrupt regular residential, commercial, and industrial activities, hinder emergency responses, and adversely impact the societal recovery (Guikema and Gardoni 2009; Lee et al. 2011). Regional resilience analysis aims to predict the ability of structures, infrastructure and communities to absorb disturbances from external stressors and return to normalcy (Sharma et al. 2018a,b; Gardoni and Murphy 2018). Regional resilience of the built-environment is shaped by intrinsic characteristics of infrastructure as well as external factors such as infrastructure interdependencies, the mitigation and recovery strategies, and the availability of resources to implement the mitigation and post-disaster recovery strategies. Regional resilience analysis broadly consists of 1) modeling the post-disaster physical recovery of structures and infrastructure, 2) modeling the dynamics of interdependent structures and infrastructure and the respective functionality recovery as the physical recovery progresses, and 3) predicting the implication on resilience objectives. Integrating the regional resilience analysis with an optimization formulation allows us to unveil the bottlenecks of regional recovery and guide the development of effective mitigation and recovery strategies.

In recent years, there has been a growing interest in regional resilience analysis and post-disaster recovery optimization. For example, minimum-cost recovery strategies have been developed, using a monetary metric to aggregate diverse consequences of disrupted services throughout the recovery (Lee II et al. 2007; Cavdaroglu et al. 2013; González et al. 2016). The primary focus of current approaches has been the formulation of the optimization problem to accurately capture the interdependencies of infrastructure throughout the recovery. However, the current approaches do not properly model the physical recovery and the associated dynamics of infrastructure. Modeling the dynamics of infrastructure entails network flow analyses that capture both the physical connectivity and service flow stability. Service areas that are physically connected may still be non-functional if specific flow constraints are violated (e.g., voltage stability in electric power infrastructure.) Furthermore, the formulation of the optimization problem does not capture the physical and logical constraints to implement the regional recovery of infrastructure that are often spread over a large area. Physical and logical constraints include recovery activities precedence, workforce and material availability, and work continuity. These limitations affect, to different degrees, the development of the recovery strategy to enhance regional resilience.

This paper develops a novel mathematical formulation for the regional resilience optimization that captures the physical and logical constraints in the implementation of regional recovery strategies. The proposed formulation consists of 1) a multi-scale approach to model the physical recovery of infrastructure; 2) a mathematical model of infrastructure to translate the physical recovery into the recovery of disrupted services; and 3) a multi-objective optimization formulation to enhance regional resilience. The optimization problem aims to schedule the recovery activities for the repair or replacement of damaged infrastructure components (e.g., bridges) such that the disrupted services are restored as fast as possible, while minimizing the incurred cost. We use resilience metrics to monitor and quantify the recovery of disrupted services; thus, we avoid concerns about the appropriateness of monetizing social losses associated with the lack of access to essential resources and services (Ackerman and Heizerling 2002; Tabandeh et al. 2018). In the proposed formulation, we also use a multi-scale approach (Sharma et al. 2018b) to overcome the issue of dimensionality in the regional recovery optimization that often involves scheduling a large number of recovery activities. The proposed multi-scale approach defines several recovery zones that partition the footprint of infrastructure and develop separate schedules for the hierarchy of inter- and intra-zones physical recovery. The multi-scale approach also enables developing a recovery schedule that is feasible to implement and easy to communicate (Sharma et al. 2018b). Furthermore, recognizing the complex, multi-disciplinary nature of the service recovery modeling, we decouple the dynamic analysis of interdependent networks (i.e., mathematical models of infrastructure) such that each network can be modeled in a rigorous and consistent manner (Sharma and Gardoni 2018). We then develop interface functions (Sharma and Gardoni 2018) to capture the effects of interdependencies on the dynamic analysis of individual networks.

2. RECOVERY MODELING OF INTERDEPENDENT INFRASTRUCTURE

2.1. Physical recovery modeling

The physical recovery modeling consists of scheduling the recovery activities required for the repair or replacement of damaged infrastructure components, and modeling the respective effects on the structural characteristics. The physical recovery modeling often entails scheduling a large number of activities for the repair or replacement of components that are spread over a large area. The multi-scale approach provides a natural way to overcome the inherent complexity of the problem and develop a realistic recovery strategy.

Here, we discuss the physical recovery modeling with two levels of hierarchy, named as *Zonal* and *Local* recovery scales. At zonal scale, we define a set of recovery zones that partition the footprint of infrastructure. The damaged components in each zone recover with the same zonal priority. The recovery zones can be defined based on, for example, functional logic, geographic proximity, land use, and community neighborhood. At local scale, we identify the required recovery activities in each zone, assign the identified activities to available crews, and develop a detailed schedule for the crews to perform the set of assigned activities.

We use information from the recovery progression to model the effects on structural characteristics. Specifically, we model the effects on the vector of state variables, including material properties, member dimensions, and boundary conditions for each component. Following Sharma et al. (2018b), we write the vector of state variables for each component as

$$\mathbf{x}(\tau) = \sum_{i=1}^{\infty} \mathbf{x}(\tau_{r,i-1}) \mathbf{1}_{\{\tau \in [\tau_{r,i-1}, \tau_{r,i})\}} + \sum_{i,j=1}^{\infty} \Delta\mathbf{x}(\tau_{s,j}) \mathbf{1}_{\{\tau \in (\tau_{r,i-1}, \tau_{r,i}), \tau_{s,j} \in (\tau_{r,i-1}, \tau)\}}, \quad (1)$$

where $\mathbf{x}(\tau)$ is the vector of state variables at time τ, since the beginning of the recovery; $\mathbf{x}(\tau_{r,i})$ is the vector of state variables after repairing or replacing a damaged member (e.g., a bridge column) at time $\tau_{r,i}$; $\mathbf{1}_{\{\cdot\}}$ is an indicator function; $\Delta\mathbf{x}(\tau_{s,j})$ is the state change due to the occurrence of a disrupting shock during the recovery at time $\tau_{s,j} \in (\tau_{r,i-1}, \tau_{r,i})$. To explicitly show the effects of multi-scale modeling, we can write $\tau_{r,i}$ as $\tau_{r,i} = \xi_{r,z} + \xi_{r,l} + \xi_{r,i}$, where $\xi_{r,z}$ is the starting time of the zonal recovery; $\xi_{r,l}$ is the starting time of the local recovery on the specific component, measured with respect to $\xi_{r,z}$; and $\xi_{r,i}$ is the repair or replacement time of member i of the specific component, measured with respect to $\xi_{r,l}$. We then use the estimates of $\mathbf{x}(\tau)$ for the dynamic analysis of infrastructure and service recovery modeling, discussed next.

2.2. Service recovery modeling

We model each infrastructure as a collection of networks, where each network is a mathematical representation of a performance measure (Sharma and Gardoni 2018). For example, we can model the electric power infrastructure with two networks, where the structural network models the structural state and the flow network models the functionality state of the infrastructure.

Let $\mathcal{G} = \{G^{[k]} = (V^{[k]}, E^{[k]}) : k = 1, \dots, K\}$ be the collection of all networks required to model interdependent infrastructure. Each network k is a graph $G^{[k]}$, composed of a set of vertices, $V^{[k]}$, and a set of edges, $E^{[k]} \subset (V^{[k]} \times V^{[k]})$. The vertices are nodal components (e.g., water tanks) and the edges are line components (e.g., water pipelines). Each network is characterized by a unique set of capacity, demand, and supply measures. To model the recovery of capacity and demand measures, we use the estimates of $\mathbf{x}(\tau)$ for each component in the respective capacity and demand models. For example, Gardoni et al. (2002, 2003) developed general probabilistic capacity and demand models for structural network components. To quantify the ability of a given network $G^{[k]}$ to serve the imposed demand, we define the supply measure as $\mathbf{S}^{[k]}(\tau) = \mathbf{S}^{[k]}\left[\mathbf{x}^{[k]}(\tau), \mathbf{C}^{[k]}(\tau), \mathbf{D}^{[k]}(\tau), \mathbf{\Theta}_S^{[k]}\right]$, where $\mathbf{x}^{[k]}(\tau)$ is the vector of control state variables (e.g., voltage in power flow network or pressure in water flow network); $\mathbf{C}^{[k]}(\tau)$ is the vector of capacity estimates for the components of $G^{[k]}$; $\mathbf{D}^{[k]}(\tau)$ is the respective vector of demand estimates; and $\mathbf{\Theta}_S^{[k]}$ is the vector of model parameters. To capture different aspects of the service recovery, we can define derived performance measures as functions of $(\mathbf{C}^{[k]}, \mathbf{D}^{[k]}, \mathbf{S}^{[k]})$. For example, to capture the fraction of demand served by a network, Sharma et al. (2018b) defined a derived performance measure as $\mathbf{Q}^{[k]}(\tau) = [\mathbf{S}^{[k]}(\tau) \oslash \mathbf{D}^{[k]}(\tau)] \odot \mathbf{1}_{\{\mathbf{D}^{[k]}(\tau) \succ 0\}}$, where $\oslash$ and $\odot$ are elementwise division and multiplication operators; and $\mathbf{1}_{\{\mathbf{D}^{[k]}(\tau)\succ 0\}}$ is to ensure that $\mathbf{Q}^{[k]}(\tau)$ is defined only for components that place a demand on $G^{[k]}$.

To account for the effects of networks interdependencies, we introduce interface functions that modify the capacity and demand estimates as (Sharma and Gardoni 2018)

$$\begin{cases}\mathbf{C}'^{[k]}(\tau)=\mathbf{C}^{[k]}(\tau)\odot\boldsymbol{\mathcal{M}}_C^{[k]}(\tau)\\ \mathbf{D}'^{[k]}(\tau)=\mathbf{D}^{[k]}(\tau)\odot\boldsymbol{\mathcal{M}}_D^{[k]}(\tau)\end{cases}, \quad (2)$$

where $\mathbf{C}'^{[k]}(\tau)$ is the vector of modified capacity estimates at time τ; $\boldsymbol{\mathcal{M}}_C^{[k]}(\cdot)$ is the vector of interface functions for the capacity measures; $\mathbf{D}'^{[k]}(\tau)$ is the modified demand estimates at time τ; and $\boldsymbol{\mathcal{M}}_D^{[k]}$ is the vector of interface functions for the demand measures.

Using $\mathbf{C}'^{[k]}(\tau)$ and $\mathbf{D}'^{[k]}(\tau)$ in the model for the respective supply measure, we can obtain the modified supply estimates $\mathbf{S}'^{[k]}(\tau)$. Likewise, we can obtain the modified derived performance measure $\mathbf{Q}'^{[k]}(\tau)$. Accordingly, we define an aggregate performance measure $Q'^{[agg]}(\tau)=Q'^{[agg]}(\{\mathbf{Q}'^{[k]}(\tau): k=1,\dots,K\})$ to quantify the overall regional recovery (Sharma et al. 2018).

3. REGIONAL RECOVERY OPTIMIZATION

The optimization problem aims to schedule the sequence of recovery zones for each damaged network (i.e., decision variables) such that the disrupted services are restored as fast as possible, while minimizing the incurred cost.

Let $G_{\mathcal{D}}^{[k]}=\left(V_{\mathcal{D}}^{[k]},E_{\mathcal{D}}^{[k]}\right)$ denote the damaged network k, where $V_{\mathcal{D}}^{[k]}\subseteq V^{[k]}$ is the set of damaged nodal components and $E_{\mathcal{D}}^{[k]}\subseteq E^{[k]}$ is the set of damaged line components. We use $\mathcal{G}_{\mathcal{D}}$ to denote the collection of all damaged networks. Furthermore, let $\mathbf{z}^{[k]}=[z_{\sigma(1)},\dots,z_{\sigma(n_k)}]$ be the tuple of the recovery zones for $G_{\mathcal{D}}^{[k]}$, where $[\sigma(1),\dots,\sigma(n_k)]$ is a permutation of $(1,\dots,n_k)$. Tuple $\mathbf{z}^{[k]}$ defines a partition $\mathcal{P}_{\mathbf{z}^{[k]}}(\cdot)$ on $G_{\mathcal{D}}^{[k]}$ such that $\mathcal{P}_{\mathbf{z}^{[k]}(i)}\left(V_{\mathcal{D}}^{[k]}\right)\cap\mathcal{P}_{\mathbf{z}^{[k]}(j)}\left(V_{\mathcal{D}}^{[k]}\right)=\emptyset$, for all $i\neq j$, and $\bigcup_{i=1}^{n_k}\mathcal{P}_{\mathbf{z}^{[k]}(i)}\left(V_{\mathcal{D}}^{[k]}\right)=V_{\mathcal{D}}^{[k]}$, and the same conditions hold for $E_{\mathcal{D}}^{[k]}$, where $\mathcal{P}_{\mathbf{z}^{[k]}(i)}\left(V_{\mathcal{D}}^{[k]}\right)$ is the subset of $V_{\mathcal{D}}^{[k]}$ that are located in zone $\mathbf{z}^{[k]}(i)$. We can then write the optimization problem as

$$\text{minimize }\{\rho[Q'^{[agg]}(\tau,\mathcal{Z})],c_r(\mathcal{G}_{\mathcal{D}},\mathcal{Z})\} \quad (3)$$

where $\rho=\int_0^{T_R}\tau dQ'^{[agg]}(\tau,\mathcal{Z})\Big/\int_0^{T_R}dQ'^{[agg]}(\tau,\mathcal{Z})$ is a resilience metric (Sharma et al. 2018a), in which T_R is the total recovery duration; $\mathcal{Z}=\{\mathbf{z}^{[1]},\dots,\mathbf{z}^{[K]}\}$ is the collection of the recovery zones for all networks; and $c_r(\cdot)$ is the incurred cost that consists of material cost and schedule-dependent crew cost. Mathematically, we can write $c_r(\cdot)$ as

$$\begin{aligned}c_r(\mathcal{G}_{\mathcal{D}},\mathcal{Z})=&\\ \sum_{\mathbf{z}\in\mathcal{Z}}\sum_{i=1}^{|\mathbf{z}|}&\Big(\sum_{v\in\mathcal{P}_{\mathbf{z}(i)}(V_{\mathcal{D}})}\sum_{a\in A_v}c_{m,a}q_a+\\ &\sum_{e\in\mathcal{P}_{\mathbf{z}(i)}(E_{\mathcal{D}})}\sum_{a\in A_e}c_{m,a}q_a\Big)+\\ \sum_{\mathbf{z}\in\mathcal{Z}}\sum_{\kappa\in K_{\mathbf{z}}}&c_{c,\kappa}q_\kappa\Delta\tau_\kappa(\mathbf{z}),\end{aligned} \quad (4)$$

where the first term is the material cost and the second term is the crew cost, in which A_v is the set of recovery activities required for the repair or replacement of nodal component v in zone $\mathbf{z}(i)$; $c_{m,a}$ is the per unit cost of material for activity $a\in A_v$; and q_a is the respective material quantity; A_e is the set of recovery activities required for the repair or replacement of line component e in zone $\mathbf{z}(i)$; $K_{\mathbf{z}}$ is the set of different crew types for the recovery of networks with zonal schedule $\mathbf{z}$; $c_{c,\kappa}$ is the cost of workforce and equipment per unit time for a single crew of type κ; q_κ is the number of crews of type κ; and $\Delta\tau_\kappa(\mathbf{z})$ is the respective working duration for crew type κ, under zonal schedule $\mathbf{z}$. The optimization problem in Eq. (3) is subject to physical and service recovery constraints, each entails a nested optimization, discussed next.

3.1. Physical recovery optimization

To develop the recovery schedule for each zone, we formulate an optimization problem that minimizes the total recovery duration of the zone, while complying with physical and logical constraints to implement the recovery schedule. Mathematically, we can write the physical recovery optimization for each zone z as

$$\text{minimize } \max\{\tau_{r,a}: a \in A_z\}$$

subject to

$$\xi_{r,\sigma(a)} - \Delta\xi_{r,\sigma(a)} \geq \xi_{r,\sigma(a-1)} + \Delta\xi_{lag,\sigma(a-1)}, \quad \text{for all } a \in A_l$$

$$\xi_{r,\sigma(l')} + \xi_{r,\sigma(a)} - \Delta\xi_{r,\sigma(a)} \geq \xi_{r,\sigma(l)} + \xi_{r,\sigma(a)} + \Delta\xi_{lag,\sigma(l)}, \quad \text{for all } a \in \{A_{\sigma(l)} \cap A_{\sigma(l')}\} \quad (5)$$

where $A_z = \{\forall a \in A_l: l \in \{\mathcal{P}_z(V_\mathcal{D}) \cup \mathcal{P}_z(E_\mathcal{D})\}\}$ is the set of all recovery activities in zone z and A_l is the set of recovery activities for component l; $\sigma(a)$ is the priority of activity a; $\xi_{r,\sigma(a)} - \Delta\xi_{r,\sigma(a)}$ is the starting time of activity $\sigma(a)$ for a given component, in which $\Delta\xi_{r,\sigma(a)}$ is the respective recovery duration; $\Delta\xi_{lag,\sigma(a-1)}$ is the time lag between activity $\sigma(a-1)$ and its successor $\sigma(a)$ for the given component; $\sigma(l)$ is the priority of component l; $\Delta\xi_{lag,\sigma(l)}$ is the time lag between same activities in two different components, with priorities $\sigma(l') > \sigma(l)$. The first constraint in Eq. (5) is logical and ensures that the recovery activity $\sigma(a)$ for a given component can start only after completing its predecessor activity $\sigma(a-1)$ for the same component. This logical constraint is a finish-to-start type; other types of logical constraints are discussed, for example, in El-Rayes and Modelhi (2001). The second constraint in Eq. (5) captures the crew availability and ensures that activity $\sigma(a)$ for component $\sigma(l')$ starts only after the same activity for component $\sigma(l)$ ($< \sigma(l')$) is completed. The allocated workforce and material constraints are inherited from the global optimization in Eq. (3).

3.2. Service recovery optimization

The objective of the service recovery optimization is to minimize a measure of discrepancy (i.e., a loss function) between the demand and supply measures. Mathematically, we can write the service recovery optimization for each $G_k \in \mathcal{G}$ as

$$\text{minimize} \quad \ell^{[k]}[\mathbf{D}'^{[k]}(\tau), \mathbf{S}'^{[k]}(\tau), \mathbf{w}^{[k]}]$$

subject to

$$\mathbf{S}'^{[k]}(\tau) \preccurlyeq \mathbf{C}'^{[k]}(\tau)$$

$$S'^{[k]}_v(\tau) = \sum_{e=(u,v):u\in V^{[k]}} S'^{[k]}_e(\tau) - \sum_{e=(v,u):u\in V^{[k]}} S'^{[k]}_e(\tau), \text{for all } v \in V^{[k]} \quad (6)$$

where $\ell^{[k]}[\cdot]$ is the loss function, in which $\mathbf{w}^{[k]}$ is a weight vector to capture the importance of different components; the first constraint ensures that the supply estimates do not exceed the respective capacity; the second constraint ensures the flow balance, in which $S'^{[k]}_v(\tau)$ is the modified supply estimate at node $v \in V$ and $S'^{[k]}_e(\tau)$ is the modified in-flow to node v for $e = (u, v)$, and out-flow from node v for $e = (v, u)$. In addition to these generic constraints, there are network-specific constraints, which also need to be satisfied, such as continuity equations for water flow network (Todini and Pilati 1987) and power balance equations for power flow network (Glover et al. 2012).

4. NUMERICAL EXAMPLE

We illustrate the proposed formulation for the recovery optimization of interdependent electric power and potable water infrastructure in a virtual community testbed, known as Centerville (Ellingwood et al. 2016). In this example, we consider a scenario earthquake with magnitude 6.5, located approximately 25 km southwest of Centerville. The spatial variation of the hazard intensity is provided by Guidotti et al (2016). We model the electric power infrastructure following the description in Unnikrishnan and van de Lindt (2016). The potable water infrastructure model is from Guidotti et al (2016).

4.1. Multi-scale recovery modeling

To model the recovery of the infrastructure, we first estimate the damage to the vulnerable components and then develop a detailed schedule for the recovery of damaged components. The seismic vulnerability of the power and water infrastructure components, and details of the recovery scheduling are available in Sharma et al. (2018b). The recovery zones and resources for the power and water infrastructure are described next.

We define 10 recovery zones for the electric power infrastructure, consisting of 2 main zones, 1 transmission zone, 6 distribution zones, and 1 industrial zone. We define two different recovery projects as 1) critical repairs, required to recover non-functional substations, and 2) non-critical repairs, required to recover the functional but damaged substations. Critical and non-critical repairs are performed sequentially. We assume two recovery teams, each consists of 1 diagnostic and commissioning crew, and 2 repair crews. Both recovery teams have 20 working hours per day after an 8-hour delay in the beginning. The assumed numbers are typical for the emergency repairs of electric power infrastructure (Sharma et al. 2018b).

We define 8 recovery zones for the potable water infrastructure, consisting of 2 main zones, 4 residential-commercial zones, 1 industrial zone, and 1 open-area zone. The water infrastructure recovery consists of 1) facility repairs, required to recover non-functional pumps and tanks, 2) pipeline repairs, required to recover the pipeline breaks and leaks. We assume 16 working hours per day for the crews and consider a 12-hour delay for preparations. The shorter working hours with respect to that of the power infrastructure is due to the hazardous working conditions in underground construction. Also, the longer preparation time follows from slower diagnostics and the vulnerability of underground pipelines to the seismic event. We assume two recovery teams for pipeline repairs, each consists of 6 earthwork crews, 5 shoring crews, 7 repair crews, and 1 testing crew. Facility repairs progress in parallel, assuming enough resources.

4.2. Recovery optimization

Decision variables for the recovery optimization are the priorities of the recovery zones in $\mathcal{Z} = \{\mathbf{z}^{[1]}, \mathbf{z}^{[2]}, \mathbf{z}^{[3]}, \mathbf{z}^{[4]}\}$, where $\mathbf{z}^{[1]} = \mathbf{z}^{[2]} = [z_{\sigma(1)}, \dots, z_{\sigma(10)}]$ is the tuple of the recovery zones for the two networks of the electric power infrastructure, and $\mathbf{z}^{[3]} = \mathbf{z}^{[4]} = [z_{\sigma(1)}, \dots, z_{\sigma(8)}]$ is the tuple of the recovery zones for the two networks of the potable water infrastructure.

In this example, we use the genetic algorithm (GA) (Goldberg 1989) to solve the recovery optimization (while other algorithms could also be used.) The basic operations of GA begin with generating a (random) initial population $\{\mathcal{Z}_i : 1, \dots, n_{pop}\}$, where each $\mathcal{Z}_i$ is a realization of the zonal sequence for the networks. The algorithm then advances in generations based upon ranking and selection rules. Specifically, individuals are selected from the current population according to their fitness. We define the fitness of each $\mathcal{Z}_i$ proportional to $\rho_Q[Q'^{[agg]}(\tau, \mathcal{Z}_i)]$. In this example, we consider the resilience metric as the sole recovery objective, but GA can handle multi-objective optimizations (Mathakari et al. 2007). New population is generated by modifying the selected individuals, using the crossover and mutation operators. The process is repeated until the pre-assigned number of iterations is achieved, or a convergence criterion is met.

For the physical recovery optimization, we developed minimum-duration recovery schedules for each zone, while complying with the assumed resources and crews. For the service recovery optimization of the power flow network, we performed a linear optimal dispatch, followed by a nonlinear Newton-Raphson power flow (Brown 2018). For the service recovery optimization of the water flow network, we performed a pressure-driven demand analysis (Klise et al. 2017).

Figure 1 shows the recovery of services in terms of $Q'^{[agg]}_{cell}(\tau) = Q'^{[epn]}_{cell}(\tau) Q'^{[pwn]}_{cell}(\tau)$, where $cell$ is a region served by a unique pair of nodes in the electric power and potable water networks. The results are according to the optimized recovery and the current practice (Sharma et al. 2018b). The optimized recovery results in $\rho[Q'^{[agg]}(\tau, \mathcal{Z}_{opt})] =$ 116.34 hours, compared to $\rho[Q'^{[agg]}(\tau, \mathcal{Z}_{curr})] =$ 129.34 hours for the current practice (i.e., 10% improvement.)

Since the power infrastructure recovers fairly quickly, $\tau \approx 32$ hours, $Q'^{[agg]}$ is controlled by the potable water infrastructure. The significance of the optimized recovery becomes clearer when we note that for Centerville, with a population of about 50,000 people, the 14-hour improvement in

$\rho[Q'^{[agg]}(\tau, \mathcal{Z}_{opt})]$ implies 350,000 people-hours more access to the essential services.

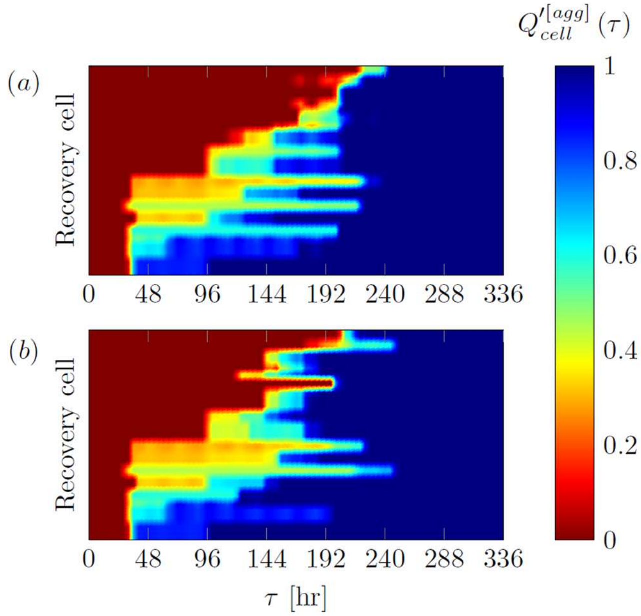

Figure 1: Predicted aggregate performance measure based on (a) current practice and (b) optimized recovery

5. CONCLUSIONS

This paper developed a novel formulation for the post-disaster recovery modeling and optimization of interdependent infrastructure. The recovery formulation consists of 1) a multi-scale approach to model the physical recovery, and 2) a mathematical approach to translate the physical recovery to the recovery of disrupted services. To enhance the regional resilience, the recovery formulation is integrated into a multi-objective optimization that aims to restore disrupted services as fast as possible, while minimizing the incurred cost. The proposed multi-scale approach to the optimization problem provides several significant advantages, including 1) enables overcoming the curse of dimensionality in the regional recovery optimization that often involves scheduling a large number of recovery activities, 2) contributes to developing a recovery strategy that is feasible to implement and easy to communicate, and 3) highlights the importance of infrastructure components at different scales to achieve desired recovery objective(s). The formulation also captures the adaptability of recovery teams and infrastructure operations to deal with dynamic changes in infrastructure capacities and demands. The results from a realistic example underscore the significance of the recovery optimization to enhance regional resilience. The results also indicate that different infrastructure have different recovery horizons and, thus, control the regional recovery at different time scales.

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