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Facility Location for Recovering Systems of Interdependent Networks

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***Abstract*—Modern communities heavily depend on critical infrastructure networks, such as power, water, gas, telecommunications, and transportation. These infrastructure networks are often dependent upon each other for operation. The interdependence of infrastructure networks makes them more vulnerable to disruptive events, such as malevolent attacks, natural disasters, and random failures. Since daily life requires the effective operation of these networks, it is important that they are able to withstand or recover quickly from a disruption. To return the networks to some desired level of performance, work crews must be scheduled to restore certain disrupted components (nodes or links). The proposed model is a multiobjective mixed-integer programming formulation that integrates 1) the order of link and node recovery, 2) the scheduling of recovery tasks to work crews, and 3) the location of facilities (or resources), where each work crew should originate from to effectively facilitate the recovery process. This study demonstrates the use of the model through an illustrative example of two interdependent infrastructure networks that exhibit behaviors of electric power and water networks. Considering four disruption scenarios, the example illustrates how recovery may change by varying the number of facilities established for work crews in each network.**

***Index Terms*—Facility location, interdependent infrastructure systems, multiobjective optimization, resilience, restoration.**

I. Introduction

FOR a number of years, the United States, as well as many countries around the globe, have been interested in effectively preparing for and responding to disruptive events including malevolent attacks, natural disasters, and other failures [1]. In particular, this means maintaining "secure, functioning, and resilient critical infrastructure" [2]. Critical infrastructure networks are "systems and assets, whether physical or virtual" that underpin society and whose roles are so vital that their incapacity or destruction "would have a debilitating impact on security, national economic security, national public health or safety, or any combination of those matters" [3]. Common examples of critical infrastructure networks are water, electricity, gas, communications, and transportation.

As many functions of society have become more dependent on critical infrastructure, it is increasingly important to not only protect current infrastructure networks, but also to be able to rebuild portions of a network that have been disrupted. Infrastructure resilience, specifically, "depends upon its ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event" [4]. The Department of Homeland Security has focused largely on resilience in terms of preparing for, withstanding, and recovering from deliberate attacks that may affect multiple critical infrastructures networks.

Not only do critical infrastructure networks influence society, but also affect the operation and resilience of other critical infrastructure networks [5]. Interdependence is defined as "a bidirectional relationship between two infrastructures through which the state of each infrastructure influences or is correlated to the state of the other" [6]. The interconnectedness of critical infrastructures is becoming increasingly prevalent and complex, and interdependencies of infrastructure networks may cause them to be more vulnerable to a disruptive event. If a disruption compromises the operability of a certain network, the functionality of any dependent network may also be affected. Decision makers must take this into consideration when recovering after an extreme event affecting multiple critical infrastructure systems. An increase in interdependence also increases the complexity of planning for recovery.

The goal of this study is to help decision-makers plan for recovery after a disruptive event; it addresses the recovery of systems of interdependent infrastructure networks by solving a facilities location model to determine where work crews or other resources should be stationed following a disruption and scheduling those work crews to repair disrupted components (nodes or links) to attain a desired level of resilience. The resilience of the interdependent networks is determined in this study based on the vulnerability and recoverability of the networks.

The remainder of this paper is organized as follows. Section II provides brief definitions and notation, an overview of network resilience, and disruption scenarios. The proposed resilience-driven multiobjective optimization model for the recovery of interdependent infrastructure networks is presented in Section III. In Section IV, an illustrative example is presented with generated interdependent power-water networks considering different disruptions scenarios. Finally, concluding remarks are provided in Section V.

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II. Methodological Background

This section reviews some literature critical to developing the methodology addressed in the remainder of this paper.

A. Interdependent Network Restoration

There has been a significant amount of research in the area of critical infrastructure restoration (e.g., Nurre *et al*. [7] for single infrastructure networks, González *et al.* [8] for interdependent networks). This study focuses primarily on the restoration of systems of interdependent critical infrastructure networks. Lee *et al.* [9] recognize the complexities involved in the interdependence of critical infrastructure networks. The authors also define multiple types of interdependence including mutual dependence. Mutual dependence may be described by a scenario where all networks in a set of critical infrastructure networks require the output of another network to be operational. This study primarily proposes a model to restore disrupted components in a set of interdependent infrastructure networks by minimizing the cost associated with unmet demand. The model, however, does not consider the cost associated with the restoration process and it is not time dependent. As a result, there is no fixed restoration time associated with disrupted components. Moreover, the model does not associate work crews with the restoration process and, therefore, cannot schedule specific work crews to restore the disrupted components.

Gong *et al.* [10], on the other hand, proposes a multiobjective optimization model to schedule emergency work crews for restoration of interdependent networks. This model assumes that all restoration tasks have a defined due time and is, thus, a time-dependent model. The objectives are to minimize the cost, time to restoration, and delay in restoration time. The main purpose of this study is to consider when each task should be completed and create a schedule for restoration. The model also assigns available work crews to each restoration task. Although this study does not actually restore the disrupted components, the scheduling of work crews and associating time with restoration tasks are important contributions.

Cavdaroglu *et al.* [11] combine the work of Lee *et al.* [9] and Gong *et al.* [10] by specifically accounting for the interdependencies that exist between critical infrastructure networks. An important consideration is that the operability of one network is dependent on the functionality of certain components in another; furthermore, any change to one network may affect another, whether positive or negative. This study specifically uses a network flow model to determine which disrupted components should be restored, create a schedule for restoration, and assign restoration to tasks to available work crews. The objective is to minimize the total cost including flow cost, restoration cost, and cost of unmet demand.

Almoghathawi *et al.* [12] propose a recovery model for interdependent infrastructure much like Cavdaroglu *et al*. However, instead of a single-objective mixed-integer programming (MIP) model, Almoghathawi *et al.* propose a multiobjective model where the objectives are to minimize the total cost related to of the restoration process (i.e., fixed restoration costs, flow cost, and cost of unmet demand), while maximizing the combined resilience of the interdependent infrastructure network system. The authors recognize that the resilience of one network is dependent on another due to the interdependencies between them; these interdependencies are considered bidirectional, meaning the output of each network is dependent on the output of another. In this study, four disruption scenarios are modeled: two malevolent attack scenarios, a random failure scenario, and a spatial disruption scenario. For each scenario, disrupted components must be scheduled to be restored. Restoration processes are time dependent and require a work crew for completion. Thus, the model also model accounts for the availability of work crews during each time period and schedules them to restoration processes.

B. Facility Location

Part of the proposed model is to determine where work crews in each network should dispatch from. As a result, the following literature discusses facilities location models in the context of emergency response.

Batta and Mannur [13] propose a model for emergency response related to the service coverage of a given set of demand points. The objective of the model is to maximize the coverage provided by M facilites, where M is a parameter. The value of M may also be defined by the number of work crews available to service a given network. An important finding of this study is that positioning more than one work crew at any given facility does not improve the objective of maximizing service coverage for a given set of demand points.

Jia *et al.* [14] address the problem of facilities location for emergency response to large-scale problems. Specifically, the authors propose a facility location that may be used in the event of a terrorist attack or natural disaster; events that most first responders are not regularly accustomed to. An important contribution from this study is that the quality of service from a facility is dependent on its proximity to a demand point. Thus, the closer a facility is to a demand location, the better that facility may be.

Afacan and McLay [15] propose a model for emergency response specific to the context of critical infrastructure recovery. This study discusses the interdependence of critical infrastructures and emergency responders. Following a disruptive event, portions of critical infrastructure networks become unusable, which makes the job of first responders much more difficult. The model, thus, accounts for work crews restoring disrupted network components and solves a P-median facilities location model for the dispatch of those work crews. In addition to dispatching work crews, the model also schedules network recovery by assigning work crews to restoration tasks over a finite-time horizon. Multiple case studies are examined in the work to fully assess the usability of the model. Interdependence is considered in this study, but in the context of work crews and first responders rather than the interdependence of infrastructure.

Although there has been significant work done in the areas of interdependent infrastructure restoration and facilities location models for emergency response, there is a gap in literature to combine to the two topics. This study develops a model to

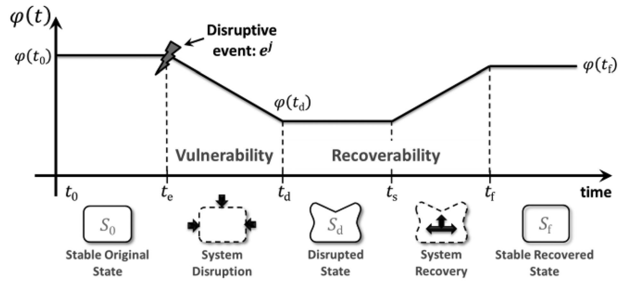

Fig. 1. Network performance $\varphi(t)$ as a function of time (adapted from [22]).

determine where work crews should be stationed in an emergency such that a set of critical infrastructure networks are able to return to full resilience.

C. Network Resilience

The literature has quantified resilience in a variety of ways [16], including the resilience of interdependent systems [17], [18] and systems of systems [19]. Fourteen top-level different approaches or techniques offered in the literature to help achieving the resiliency of engineered systems such as infrastructure networks [20]: absorption, physical redundancy, functional redundancy, layered defense, human in the loop, reduce complexity, reorganization, repairability, localized capacity, loose coupling, drift correction, neutral state, internode interaction, and reduce hidden interactions. These approaches are categorized into four groups according to the attribute of resilience that they help decision makers to attain [21]: 1) capacity, 2) flexibility, 3) tolerance, and 4) cohesion. This study considers the reorganization and reparability approaches which fall under the flexibility attribute of resilience (i.e., the ability of the system of interdependent infrastructure networks to adapt to a disruptive event).

In this study, resilience is considered to be a function of the performance of a system of networks before, during, and after a disruptive event. The framework of network resilience is adapted from Henry and Ramirez-Marquez [22] and shown in Fig. 1. This framework focuses on two phases of system performance: vulnerability and recoverability. Vulnerability is considered the susceptibility of system components to a disruptive event [23]. Initially, the system exists at some stable performance level. At the time of a disruption, though, the system becomes vulnerable to failures, leading to a loss in system performance. At this point, the system exists at a disrupted state until it can be recovered. The recoverability of a system is defined by how quickly it can be restored to some desired level of resilience after a disruption [24]. As the system is recovered, its performance is improved until it reaches a desired state of recovery. These phases of system performance are depicted in Fig. 1.

System performance as a function of time $\varphi(t)$ may be used to mathematically represent resilience. In this study, network resilience Я may be described as the ratio of time-dependent recovery to loss (i.e., $\text{Я}(t) = \frac{\text{Recovery}(t)}{\text{Loss}}$) [22]. This relationship is defined more explicitly in (1). Hence, this relationship considers the two phases of system performance described earlier: vulnerability and recoverability, as shown in Fig. 1. $\varphi(t|e^j)$ is the system performance at time t following disruptive event e^j, $\varphi(t_d|e^j)$ is the system performance immediately following a disruption, and $\varphi(t_0)$ is the system performance prior to a disruption. $\text{Я}(t|e^j)$ may range between 0 and 1, where 1 means the system is fully resilient

$$\text{Я}_{\varphi}\ \left(t|e^j\right) = \frac{\varphi\left(t|e^j\right) - \varphi\left(t_d|e^j\right)}{\varphi\left(t_o\right) - \varphi\left(t_d|e^j\right)}\ , t \in \left(t_s, t_f\right). \quad (1)$$

D. Disruption Scenario

Interdependent infrastructure networks are susceptible to several different types of disruptions. These disruptions may be divided into three distinct groups: malevolent attacks, random failures, and spatial failures [25]. Malevolent attacks are intentional disruptions caused as an act of terrorism against specific infrastructure components. These attacks can be separated into two groups: capacity-based attacks and degree-based attacks. In a capacity-based attack, network components with higher capacity are targeted. A link's capacity is defined as a network parameter u_{ij}^k and indicates the maximum flow across each link. The capacity of a node is defined by the minimum of the sum of incoming and outgoing links associated with that node ($u_i^k = \min(\sum_{(j,i)\epsilon L^k} u_{ji}^k, \sum_{(i,l)\epsilon L^k} u_{il}^k)$). In a degree-based attack, network components with the greatest connectivity to other network components (i.e., highest degree) are targeted. The degree of a node is defined by the number of bidirectional links that are connected to it; the degree of a link is the average of the degree of the two nodes it connects (i.e., $\text{degree}_{ij} = \frac{1}{2}\ (\text{degree}_i + \text{degree}_j)$). A random disruption may include any man-made failure or a failure due to the age of a network component, among others. In this study, all network components are considered to have an equal probability of failure for random disruptions. Finally, all natural disasters such as hurricanes, earthquakes, or any other failure related to the physical location of network components are captured by the spatial disruption scenario [12].

III. Proposed Optimization Model

This section provides the proposed model that integrates 1) the resilience-driven optimization model for interdependent infrastructure network recovery by Almoghathawi *et al.* [12] with 2) the facility location problem. The model is formulated as a MIP model. It is a multiobjective optimization model with competing objectives.

A. Notation

This model contains a set of networks $K = \{1, \ldots, \kappa\}$ and a set of time periods $T = \{1, \ldots, \tau\}$. In each network $k \in K$, there is a set of nodes N^k and a set of links between nodes L^k. Each network $k \in K$ has a set of source nodes $N_s^k \subseteq N^k$ and a set of demand nodes $N_d^k \subseteq N^k$. There is a set of disrupted nodes $N'^k \subseteq N^k$ and disrupted links $L'^k \subseteq L^k$ for each network $k \in K$ following a disruption.

Supply for each node $i \in N_s^k$ in network $k \in K$ is denoted by b_i^k. Supply b_i^k is considered to be the maximum flow from node $i \in N_s^k$ to all demand nodes in network $k \in K$ and is considered to be independent of time. Unmet demand for network $k \in K$ during time $t \in T$ in node $i \in N_d^k$ is represented as slack s_{it}^k. Slack may be described as the extent to which demand is not being met, and as such it is, in part, used to represent resilience. Each network $k \in K$ has a weight μ^k such that $\sum_{k \in K} \mu^k = 1$. The total slack at all demand nodes in network $k \in K$ prior to a disruption and immediately following a disruption are represented by S_0^k and S_d^k, respectively.

In this study, fn_i^k and fl_{ij}^k are the fixed restoration costs for node $i \in N'^k$ and link $(i,j) \in L'^k$ for network $k \in K$, respectively. The decision variable z_i^k is a binary variable that equals 1 if node $i \in N'^k$ in network $k \in K$ is chosen for restoration and 0 otherwise. Similarly, y_{ij}^k is a binary decision variable that equals 1 if link $(i,j) \in L'^k$ in network $k \epsilon K$ is chosen for restoration and 0 otherwise. There are also per-unit costs associated with flow and unmet demand. Let c_{ij}^k be the cost of each unit of flow on link $(i,j) \in L^k$ in network $k \in K$, and let p_i^k be the cost of unmet demand at node $i \in N_d^k$ in network $k \in K$. Flow across link $(i,j) \in L^k$ in network $k \in K$ in period $t \in T$ is represented by the continuous decision variable x_{ijt}^k. As before, unmet demand is equated to slack and represented by s_{it}^k for node $i \in N_d^k$ in network $k \in K$ in period $t \in T$.

Each network $k \in K$ has a set of work crews R^k dedicated to restoring its disrupted components. Each work crew $r \in R^k$ in network $k \in K$ must dispatch from an assigned location. Work crews are assigned to origin locations such that the fixed cost of establishment and the distance travelled is minimized. There is a set of candidate sites M, where work crews must be assigned (we distinguish between *sites* as candidates and *facilities* as the sites chosen among the candidates). Before a work crew can be assigned to a facility, the facility must be established in a candidate location. Binary decision variable v_m equals 1 if candidate site $m \in M$ is established and is 0 otherwise. There is a fixed cost associated with establishing a resource facility; this cost is represented by cs_m for site $m \in M$. Furthermore, if work crew $r \in R^k$ in network $k \in K$ is stationed at site $m \in M$, the binary decision variable w_m^{kr} equals 1 and is 0 otherwise. Of course, each candidate site is positioned some distance from all disrupted components in network $k \in K$. For nodes, this distance is the Euclidean distance from candidate site $m \in M$ to node $i \in N'^k$ in network $k \in K$ and is represented by ns_{im}^k. For links, the Euclidean distance from candidate site $m \in M$ to the midpoint of link $(i,j) \in L'^k$ in network $k \in K$ is represented by ls_{ijm}^k. There is also a cost associated with the distance a work crew must travel from each candidate site to a disrupted element. This cost is captured by ds_m for site $m \in M$.

Each disrupted element has a fixed restoration time that must be elapsed before an element may be considered operational. The restoration times for node $i \in N'^k$ and link $(i,j) \in L'^k$ are denoted by dn_i^k and dl_{ij}^k, respectively. Once a disrupted element has been selected for restoration and has completed its restoration time, it becomes operational. Two binary decision variables β_{it}^k and α_{ijt}^k indicate the status of node $i \in N^k$ and link $(i,j) \in L'^k$, respectively. β_{it}^k equals 1 if node $i \in N^k$ in network $k \in K$ is operational during time $t \in T$ and is 0 otherwise. Similarly, α_{ijt}^k equals 1 if link $(i,j) \in L'^k$ in network $k \in K$ is operational during time $t \in T$ and is 0 otherwise. There are two decision variables associated with scheduling work crews to restore disrupted components γ_{it}^{kr} and δ_{ijt}^{kr}. γ_{it}^{kr} equals 1 if work crew $r \in R^k$ in network $k \in K$ is selected to restore node $i \in N'^k$ during time $t \in T$ and 0 otherwise. In the same way, if work crew $r \in R^k$ in network $k \in K$ is chosen to restore link $(i,j) \in L'^k$ during time $t \in T$, δ_{ijt}^{kr} equals 1 and is 0 otherwise. Finally, each network contains nodes that are dependent on specific nodes from another network being operational. In this study, Ψ is used to represent interdependence such that $((i,k),\ (\bar{i},\ \bar{k})) \in \Psi$ indicates that node $\bar{i} \in N^{\bar{k}}$ in network $\bar{k} \in K$ requires node $i \in N^k$ in network $k \in K$ to be operational.

1) Review of Set Notation

K	Set of interdependent infrastructure networks, K
T	Set of time periods, $T = \{1, \ldots, \tau\}$
N^k	Set of nodes in network $k \in K$
N_s^k	Set of source nodes, $N_s^k \subseteq N^k$ in network $k \in K$
N_d^k	Set of demand nodes, $N_d^k \subseteq N^k$ in network $k \in K$
N'^k	Set of disrupted nodes, $N'^k \subseteq N^k$ in network $k \in K$
L^k	Set of links in network k
L'^k	Set of disrupted links, $L'^k \subseteq L^k$ in network $k \in K$
R^k	Set of work crews in network $k \in K$ dispatched from an assigned location
M	Set of candidate sites for location of resources
Ψ	Set of interdependent nodes such that node $\bar{i} \in N^{\bar{k}}$ in network $\bar{k} \in K$ requires node $i \in N^k$ in network $k \in K$ to be operational

2) Review of Parameter Notation

b_i^k	Supply for node $i \in N_s^k$ in network $k \in K$
μ^k	Importance weight given to network $k \in K$
S_0^k	Total slack at all demand nodes in network $k \in K$ prior to a disruption
S_d^k	Total slack at all demand nodes in network $k \in K$ just after a disruption
fn_i^k	Fixed restoration cost for node $i \in N'^k$ in network $k \in K$
fl_{ij}^k	Fixed restoration costs for link $(i,j) \in L'^k$ in network $k \in K$
c_{ij}^k	Cost of each unit of flow on link $(i,j) \in L^k$ in network $k \in K$
p_i^k	Cost of unmet demand at node $i \in N_d^k$ in network $k \in K$
cs_m	Cost associated with establishing a resource facility at site $m \in M$
ns_{im}^k	Euclidean distance from candidate site $m \in M$ to node $i \in N'^k$ in network $k \in K$
ls_{ijm}^k	Euclidean distance from candidate site $m \in M$ to the midpoint of link $(i,j) \in L'^k$ in network $k \in K$
ds_m	Cost associated with the distance a work crew must travel from each candidate site $m \in M$ to a disrupted element
dn_i^k	Restoration time for node $i \in N'^k$ in network $k \in K$
dl_{ij}^k	Restoration time for link $(i,j) \in L'^k$ in network $k \in K$

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3) Review of Variable Notation

s^k_{it}	Continuous decision variable representing unmet demand for node $i \in N^k_d$ in network $k \in K$ at time $t \in T$
S^k_t	Continuous decision variable representing unmet demand in network $k \in K$ at time $t \in T$
z^k_i	Binary variable that equals 1 if node $i \in N'^k$ in network $k \in K$ is chosen for restoration and 0 otherwise
y^k_{ij}	Binary decision variable that equals 1 if link $(i, j) \in L'^k$ in network $k \,\epsilon\, K$ is chosen for restoration and 0 otherwise
x^k_{ijt}	Continuous decision variable representing flow across link $(i, j) \in L^k$ in network $k \in K$ in period $t \in T$
v_m	Binary decision variable that equals 1 if candidate site $m \in M$ is established and is 0 otherwise
w^{kr}_m	Binary decision variable that equals 1 if work crew $r \in R^k$ in network $k \in K$ is stationed at site $m \in M$ and 0 otherwise
β^k_{it}	Binary decision variable that equals 1 if node $i \in N^k$ in network $k \in K$ is operational during time $t \in T$ and 0 otherwise
α^k_{ijt}	Binary decision variable that equals 1 if link $(i, j) \in L'^k$ in network $k \in K$ is operational during time $t \in T$ and 0 otherwise
γ^{kr}_{it}	Binary decision variable that equals 1 if work crew $r \in R^k$ in network $k \in K$ is selected to restore node $i \in N'^k$ during time $t \in T$ and 0 otherwise
δ^{kr}_{ijt}	Binary decision variable that equals 1 if work crew $r \in R^k$ in network $k \in K$ is selected to restore link $(i, j) \in L'^k$ during time $t \in T$ and 0 otherwise

B. Multiple Objective Functions

The first objective of the proposed model is to maximize the resilience of the set of interdependent infrastructure networks K. Resilience can be described as the loss of maximum flow in a network. Equation (2) quantifies resilience as the proportion of slack in the time periods following a disruption to the total slack at all demand nodes in the set of interdependent networks immediately following a disruption. Hence, S^k_t represents the recovery of network $k \in K$ at time $t \in T$, while its total loss is represented by $(S^k_d - S^k_0)$

$$\sum_{k\in K} \mu^k \left[\frac{\sum_{t=1}^{\tau} S^k_t}{S^k_d - S^k_0}\right]. \tag{2}$$

In addition to maximizing the resilience in the set of interdependent networks, a competing objective is to minimize the total cost of restoration. Total cost of restoration is a function of fixed restoration costs, flow cost, the cost of unmet demand, the cost of establishing a facility, and the cost associated with the travel distance from candidate sites, as captured by (3). The aim of including the flow cost in the objective is to compare [8]: 1) the actual (current) flow cost, with 2) the minimum flow cost related to the optimal configuration of the interdependent networks prior to the disruption (i.e., fully operational systems of interdependent networks). Accordingly, it indicates how much of the required demand at the demand nodes in the system of interdependent networks have been supplied from the supply nodes [8]. That is, 1) if the ratio of the actual flow cost to the minimum flow cost prior to the disruption is less than 1, it indicates that the demand is not satisfied at some demand nodes in the system of interdependent networks (i.e., the maximum flow from all supply nodes to all demand nodes in the system has not yet been achieved), and 2) if the ratio of the actual flow cost to the minimum flow cost prior to the disruption is greater than 1, it means that though the flow cost is now higher than the minimum flow cost prior to the disruption, it is less than the restoration cost of some of the components in of the system interdependent networks that might not need to be restored. The travel distance is multiplied by 2 considering that a work crew dispatches from a candidate site to which they return after each restoration activity

$$\begin{aligned}\sum_{k\in K}\Bigg(&\sum_{i\in N'^k} fn^k_i z^k_i + \sum_{(i,j)\in L'^k} fl^k_{ij} y^k_{ij}\\ &+\sum_{t\in T}\Bigg[\sum_{(i,j)\in L^k} c^k_{ij} x^k_{ijt} + \sum_{i\in N^k_d} p^k_i s^k_{it}\Bigg]\Bigg)\\ &+\sum_{m\in M}\Bigg[cs_m v_m + \sum_{t\in T}\sum_{r\in R^k} 2\Bigg[\sum_{i\in N'^k} ns^k_{im} ds_m w^{kr}_m \gamma^{kr}_{it}\\ &+\sum_{(i,j)\in L'^k} ls^k_{ijm} ds_m w^{kr}_m \delta^{kr}_{ijt}\Bigg]\Bigg].\end{aligned} \tag{3}$$

C. Constraints

The first set of constraints, (4) through (10), is dedicated to the network flow. Specifically, (4) specify that each source node $i \in N^k_s$ in network $k \in K$ for each time $t \in T$ cannot output more than its supply b^k_i. Flow must be conserved into and out of node $i \in N^k \backslash \{N^k_s,\ N^k_d\}$, as governed by (5). The combination of flow into all demand nodes $i \in N^k_d$ and the amount of unmet demand at those nodes (i.e., slack) must equal the demand in network $k \in K$ during time $t \in T$, as described in constraints (6). Each link $(i, j) \in L^k$ in network $k \in K$ has a capacity that is described by u^k_{ij}. As such, the flow across each link x^k_{ij} for all $(i, j) \in L^k$ in network $k \in K$ cannot exceed that link's capacity. This is dictated by (7) through (10)

$$\sum_{(i,j)\in L^k} x^k_{ijt} \le b^k_i,\ \ \forall i \in N^k_s,\ k \in K,\ t \in T \tag{4}$$

$$\sum_{(i,j)\in L^k} x^k_{ijt} - \sum_{(j,i)\in L^k} x^k_{jit} = 0,\ \forall i \in N^k \backslash \left\{N^k_s,\ N^k_d\right\},\ k \in K,\ t \in T \tag{5}$$

$$\sum_{(j,i)\in L^k} x^k_{jit} + s^k_{it} = b^k_i,\ \forall\, i \in N^k_d, k \in K,\ t \in T \tag{6}$$

$$x^k_{ijt} - u^k_{ij} \le 0,\quad \forall\,(i, j) \in L^k,\ k \in K,\ t \in T \tag{7}$$

$$x^k_{ijt} - u^k_{ij}\beta^k_{it} \le 0,\quad \forall\,(i, j) \in L^k,\ i \in N^k,\ k \in K,\ t \in T \tag{8}$$

$$x_{ijt}^k - u_{ij}^k \beta_{jt}^k \leq 0, \quad \forall (i,j) \in L^k,\ j \in N^k,\ k \in K,\ t \in T \tag{9}$$

$$x_{ijt}^k - u_{ij}^k \alpha_{ijt}^k \leq 0, \quad \forall (i,j) \in L'^k,\ k \in K,\ t \in T. \tag{10}$$

The interdependence among the infrastructure networks is described by (11) such that node $\bar{i} \in N^{\bar{k}}$ in network $\bar{k} \in K$ may not be operational unless its interdependent node $i \in N^k$ in network $k \in K$ is also operational

$$\beta_{\bar{i}t}^{\bar{k}} - \beta_{it}^k \leq 0, \quad \forall \left((i,k), (\bar{i},\bar{k})\right) \in \Psi,\ t \in T. \tag{11}$$

The scheduling of work crews to restore disrupted components is determined by (12) through (18). Constraints (12) and (13) state that a work crew must be assigned to repair all components that have been selected for restoration. Constraint (14) ensures that work crew $r \in R^k$ for network $k \in K$ can only restore one disrupted element during time $t \in T$. A disrupted element cannot be operational unless a work crew has been assigned to it; thus, (15) and (16) are included. Constraints (17) and (18) are introduced so that a disrupted element cannot be considered operational until it has completed its restoration time

$$y_{ij}^k = \sum_{r \in R^k} \sum_{t \in T} \delta_{ijt}^{kr}, \quad \forall (i,j) \in L'^k,\ k \in K \tag{12}$$

$$z_i^k = \sum_{r \in R} \sum_{t \in T} \gamma_{it}^{kr}, \quad \forall i \in N'^k,\ k \in K \tag{13}$$

$$\sum_{(i,j) \in L'^k} \sum_{l=t}^{\min\left\{\tau, t+dl_{ij}^k - 1\right\}} \delta_{ijl}^{kr} + \sum_{(i,j) \in N'^k} \sum_{l=t}^{\min\left\{\tau, t+dn_i^k - 1\right\}} \gamma_{il}^{kr} \leq 1,$$
$$\forall\, k \in K,\ r \in R^k,\ t \in T \tag{14}$$

$$\alpha_{ijt}^k \leq \sum_{r \in R^k} \sum_{l=1}^{t} \delta_{ijl}^{kr}, \quad \forall (i,j) \in L'^k,\ k \in K,\ t \in T \tag{15}$$

$$\beta_{it}^k \leq \sum_{r \in R^k} \sum_{l=1}^{t} \gamma_{il}^{kr}, \quad \forall i \in N'^k,\ k \in K,\ t \in T \tag{16}$$

$$\sum_{r \in R^k} \sum_{t=1}^{dl_{ij}^k - 1} \delta_{ijt}^{kr} = 0, \quad \forall (i,j) \in L'^k,\ k \in K \tag{17}$$

$$\sum_{r \in R^k} \sum_{t=1}^{dn_i^k - 1} \gamma_{it}^{kr} = 0, \quad \forall i \in N'^k,\ k \in K. \tag{18}$$

The facility location decisions are made by (19) through (21). Constraint (19) states that candidate site $m \in M$ may be assigned to at most one work crew $r \in R^k$ in network $k \in K$. This also implies that there may not be work crews from different networks assigned the same site. It is also important to consider the fact that a work crew cannot be assigned to a site that is not established; thus, (20) are in place so that work crew $r \in R^k$ for network $k \in K$ may not be assigned to site $m \in M$ unless it has been selected to be established. It should be noted that a work crew may not change locations. Therefore, each work crew $r \in R^k$ in network $k \in K$ may only be assigned to one selected site, as described by (21)

$$\sum_{k \in K} \sum_{r \in R^k} w_{mr}^k \leq 1, \quad \forall\, m \in M \tag{19}$$

$$v_m \geq w_{mr}^k, \quad \forall\, m \in M,\ r \in R^k,\ k \in K \tag{20}$$

$$\sum_{m \in M} w_{mr}^k = 1, \quad \forall\, r \in R^k,\ k \in K. \tag{21}$$

The nature of all decision variables (i.e., whether they are continuous or binary) is described by

$$S_t^k = \sum_{i \in N_d^k} s_{i(t-1)}^k - \sum_{i \in N_d^k} s_{it}^k, \quad \forall k \in K,\ t \in T \tag{22}$$

$$\sum_{i \in N_d^k} s_{i0}^k = S_d^k, \quad \forall k \in K \tag{23}$$

$$s_{it}^k \geq 0, \quad \forall i \in N^k,\ k \in K,\ t \in T \tag{24}$$

$$x_{ijt}^k \geq 0, \quad \forall (i,j) \in L^k,\ k \in K,\ t \in T \tag{25}$$

$$y_{ij}^k \in \{0,1\}, \quad \forall (i,j) \in L'^k,\ k \in K \tag{26}$$

$$z_i^k \in \{0,1\}, \quad \forall i \in N'^k,\ k \in K \tag{27}$$

$$\alpha_{ijt}^k \in \{0,1\}, \quad \forall (i,j) \in L'^k,\ k \in K,\ t \in T \tag{28}$$

$$\beta_{it}^k \in \{0,1\}, \quad \forall i \in N^k, k \in K,\ t \in T \tag{29}$$

$$\delta_{ijt}^{kr} \in \{0,1\}, \quad \forall (i,j) \in L'^k,\ k \in K,\ t \in T,\ r \in R^k \tag{30}$$

$$\gamma_{it}^{kr} \in \{0,1\}, \quad \forall i \in N'^k,\ k \in K,\ t \in T,\ r \in R^k \tag{31}$$

$$v_m \in \{0,1\}, \quad \forall\, m \in M \tag{32}$$

$$w_{mr}^k \in \{0,1\}, \quad \forall\, m \in M,\ r \in R^k,\ k \in K. \tag{33}$$

Accordingly, the proposed multiobjective optimization model can be summarized as

$$\begin{aligned} &\max\,(2) \\ &\min\,(3) \\ &\text{Subject to:} \\ &(4) - (33). \end{aligned}$$

D. Nonlinearity in the Model

The proposed multiobjective optimization model is a mixed-integer nonlinear program due to products of binary variables in two terms in the cost objective (3) (i.e., $w_m^{kr} \gamma_{it}^{kr}$ and $w_m^{kr} \delta_{ijt}^{kr}$). However, we would like to linearize the objective function so that we can simplify the model and continue using a linear solver. Hence, both nonlinearities can be linearized [26] by introducing two binary variables G_{imt}^{kr} and H_{ijmt}^{kr} that satisfy

$$G_{imt}^{kr} \leq \gamma_{it}^{kr}, \quad \forall\, i \in N'^k,\ t \in T,\ m \in M,\ r \in R^k,\ k \in K \tag{34}$$

$$H_{ijmt}^{kr} \leq \delta_{ijt}^{kr}, \quad \forall\, i\,(i,j) \in L'^k,$$
$$t \in T,\ m \in M,\ r \in R^k,\ k \in K \tag{35}$$

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

$$G_{imt}^{kr}, H_{ijmt}^{kr} \leq w_m^{kr}, \quad \forall\, i \in N'^k, (i,j) \in L'^k,$$
$$t \in T,\ m \in M,\ r \in R^k,\ k \in K \qquad (36)$$

$$G_{imt}^{kr} \geq \gamma_{it}^{kr} + w_m^{kr} - 1, \quad \forall\, i \in N'^k,$$
$$t \in T,\ m \in M,\ r \in R^k,\ k \in K \qquad (37)$$

$$H_{ijmt}^{kr} \geq \delta_{ijt}^{kr} + w_m^{kr} - 1, \quad \forall\ (i,j) \in L'^k,$$
$$t \in T,\ m \in M,\ r \in R^k,\ k \in K. \qquad (38)$$

IV. Illustrative Example

The proposed facility location model for interdependent infrastructure network recovery is illustrated with some network examples in this section.

A. Data

Real data related to existing infrastructure networks are often difficult to find to protect against the risk of malevolent attacks. As such, to test the proposed model, a network with randomly generated components is used. This set of simulated interdependent infrastructure networks is created in R using the method originally described by Casey [27]. The network itself is generated by first establishing the random networks then creating interdependencies between them. Once the network is in place, the candidate sites for work crews are added to the graph. Note that only network flow properties are considered for the networks and no nonlinear phenomena are considered (e.g., power flow models in electric power networks [28] or cascading effects [29]).

First, the independent networks must be established. The coordinates of the nodes in each network are random and uniformly distributed between 0 and 1. Source nodes are the first to be added for each network. At this point, they are considered independent of each other, so there are no links established between them. As each node is added to the network, it is connected to the nearest existing node from the same network in the graph. Each link is considered undirected (i.e., there may be flow in either direction). "Nearness" is determined by smallest Euclidean distance.

Next, the interdependencies between networks must be established. As described by Almoghathawi *et al.* [12], the two interdependent infrastructure networks present in this study simulate water and power networks. Power generators and substations act as supply and demand nodes, respectively, in the power network; power lines act as the links between them. In the water network, supply nodes represent water pumps and demand nodes represent storage tanks. The links between them represent pipelines. The water network depends on the power network to pump and distribute water; the power network depends on the water network for cooling and to reduce emissions. Accordingly, interdependence links are established between the two networks considering the nearness, defined as the smallest Euclidean distance, between the nodes from both networks (see Fig. 2).

Finally, candidate sites must be incorporated into the graph. In this study, candidate sites are placed on the graph in a 5×5 grid resulting in a total of 25 candidate sites. The candidate locations are equally spaced in the vertical and horizontal directions, as shown in Fig. 2. Note that candidate sites set in a grid makes for a more interesting illustration, though it is more likely that a (perhaps smaller) discrete set of candidate sites would realistically be available.

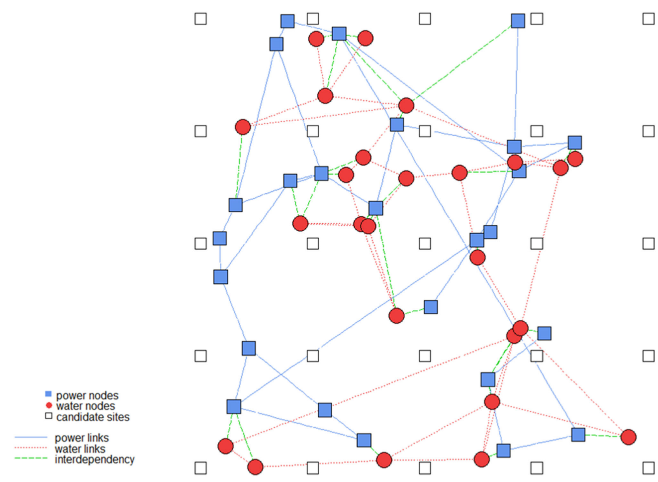


Fig. 2. Interdependent network graph with 25 candidate sites.

B. Example

For each disruption scenario, there is a certain number of components removed to simulate a disruption. For random, capacity-based and degree-based disruptions, 21% of components are disrupted (five nodes and seven links from each network). For spatial disruption scenarios, however, the disrupted components are confined to a specific area. As a result, demand in other nodes may still be met through other channels. To combat this phenomenon, the special disruption scenario requires a greater number of components to be disrupted for the same loss in network flow efficiency as the other disruption scenarios. For this scenario, 27% of network components are disrupted (four nodes and six links from the power network; eight nodes and 13 links from the water network). The experiment is performed using LINGO 16.0.

1) Pareto-Optimal Solutions: The proposed optimization model has multiple competing objectives which could be difficult to solve since many tradeoff solutions between the multiple objectives must be identified for consideration in the restoration of interdependent infrastructure networks. Consequently, we use the ε-constraint method to generate Pareto-optimal solutions for our restoration model [30]. Hence, the problem is solved for varying values of ε to assess how the total cost of restoration changes for different levels of resilience and create the Pareto frontier of nondominated solutions for each disruption scenario. Pareto-optimal solutions are only available when the cost of restoration fn_i^k is greater than the cost of unmet demand p_i^k for node $i\,\epsilon\, N'^k$. Because both objectives are focused on minimizing the unmet demand if $fn_i^k < p_i^k$ given there is enough time to restore essential disrupted components, resilience will always reach 1. Therefore, to create the Pareto frontier, unmet

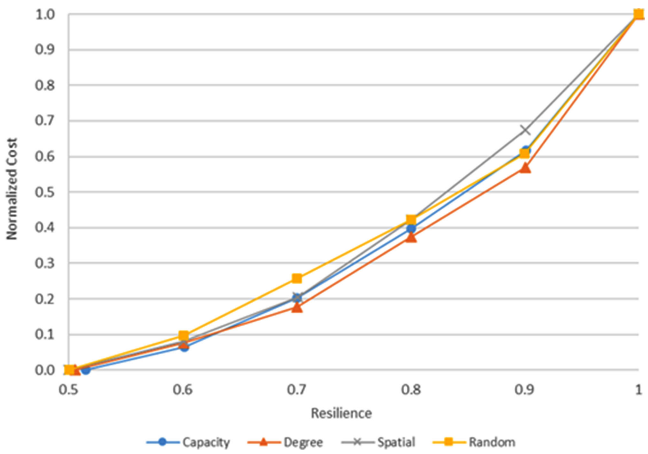


Fig. 3. Pareto-optimal frontier for competing objectives of cost versus resilience.

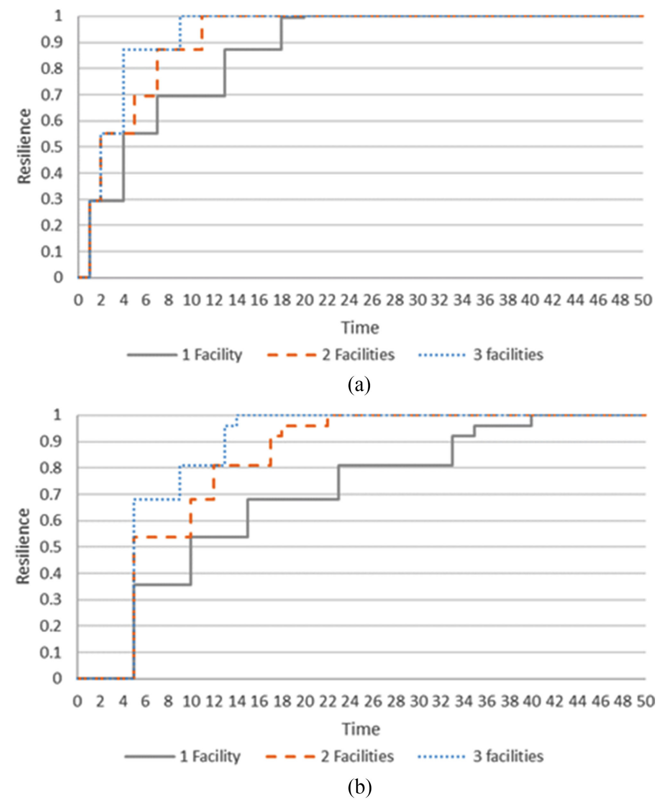


Fig. 4. Resilience versus time for a capacity-based disruption for (a) power network and (b) water network considering a different number of established facilities.

demand is underpenalized. Fig. 3 shows the set of Pareto optimal solutions for the capacity-based, degree-based, random, and spatial disruption scenarios with $\varepsilon = [0.5, 1]$ considering the availability of three work crews for each infrastructure network.

Naturally, the lowest cost is observed when resilience $= 0.5$ and the highest cost occurs for resilience $= 1$ for all disruption scenarios. The capacity-based disruption scenario results in the highest total restoration cost, while the spatial disruption scenario has the lowest total restoration cost, regardless of level of resilience.

2) Assessment of Varying the Number of Facilities Chosen: For the remainder of the experiment, without loss of generality, the parameters are set as follows: $\mu^k = 1/|K|$, $T = 50$, fn_i^k, fl_{ij}^k, u_{ij}^k, $cs_m \sim U(20, 50)$, c_{ij}^k, $ds_m \sim U(1, 10)$, $p_i^k = 60$, and dn_i^k, $dl_{ij}^k \sim U(1, 5)$. Figs. 4 through 7 show the resilience across the available time periods for restoration given the selection of 1, 2, and 3 sites for work crews in each network.

As shown in Figs. 4–7, increasing the number of facilities and, in turn, increasing the number of work crews in each network, reduces the time to full resilience. It should also be noted that because of the interdependencies between the two networks, one network may reach full resilience before the other. The model inherently prioritizes the recovery of interdependent nodes, but one network may take longer to reach full resilience.

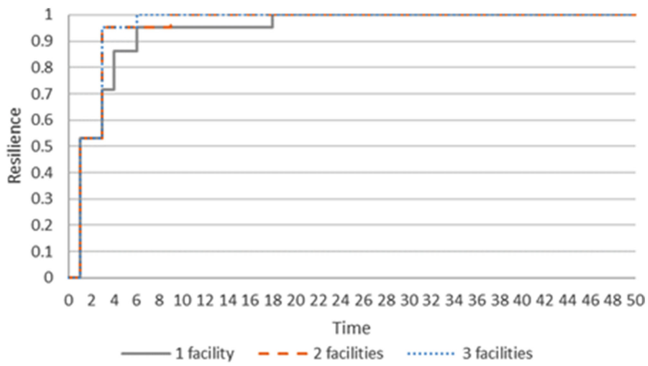
There is a tradeoff that occurs when increasing the number of facilities. As the number of established facilities increases, additional fixed facilities costs are incurred. However, there may exist some benefits to increasing the number of facilities. By establishing additional facilities, the distance each work crew must travel to repair a disrupted element and the number of time periods with unmet demand are decreased. As such, determining the number of facilities to establish is dependent upon the cost parameters associated with these decision variables. In the case of this experiment, increasing the number of established facilities decreases the total cost of restoration because the fixed cost of establishing a facility is small compared to the cost of unmet demand.

3) Stationing Multiple Work Crews at the Same Facility: The proposed model assumes that only one infrastructure network may use an established facility as shown in (19). That is, only one work crew from any one of the interdependent infrastructure networks can utilize this established facility. However, it may be more economical to 1) allow work crews from different infrastructure networks to be stationed at the same facility (i.e., colocating resources from different networks) or 2) allow more than one work crew from the same infrastructure network to utilize the same facility. Accordingly, (19) could be replaced by 1) (39) to allow for at most one work crew from each of the interdependent infrastructure networks to be stationed at this established facility, or 2) (40) to allow for more than one work crew from the same infrastructure network or different crews to be stationed at the same established facility, where θ is the maximum number of work crews to be stationed in one facility

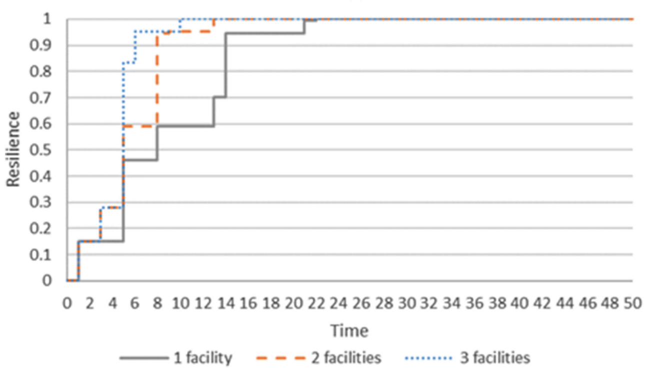
$$\sum_{r \in R^k} w_m^{kr} \leq 1, \quad \forall\, m \in M,\ k \in K \tag{39}$$

$$\sum_{k \in K} \sum_{r \in R^k} w_m^{kr} \leq \theta, \quad \forall\, m \in M. \tag{40}$$

Regarding the cost of establishing the facilities considering the possibility of assigning multiple work crews to them, two assumptions could be addressed. First, the cost of establishing a facility is fixed regardless of the work crews assignment. In this case, the cost objective function will remain the same without any changes in the cost terms. Second, the cost of establishing a facility depends on the number of work crews that will be stationed in this facility. Consequently, the cost objective function should be modified to accommodate

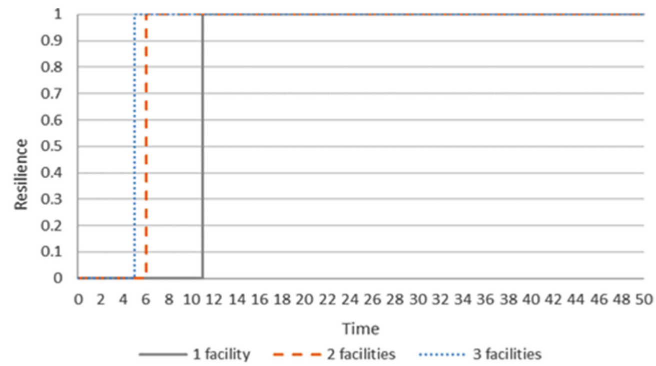


(a)

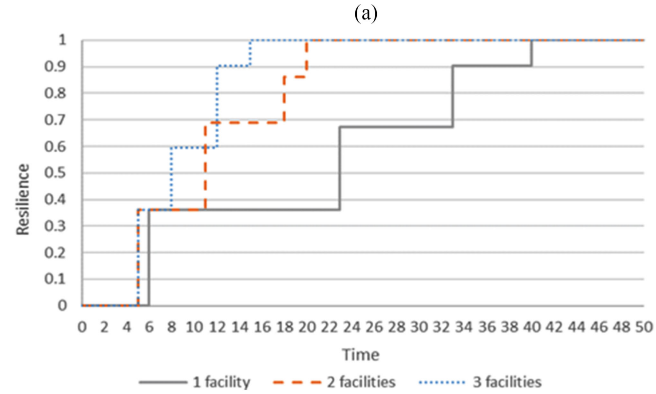


(b)

Fig. 5. Resilience versus time for a degree-based disruption for (a) power network and (b) water network considering a different number of established facilities.



(a)



(b)

Fig. 6. Resilience versus time for a spatial disruption for (a) power network and (b) water network considering a different number of established facilities.

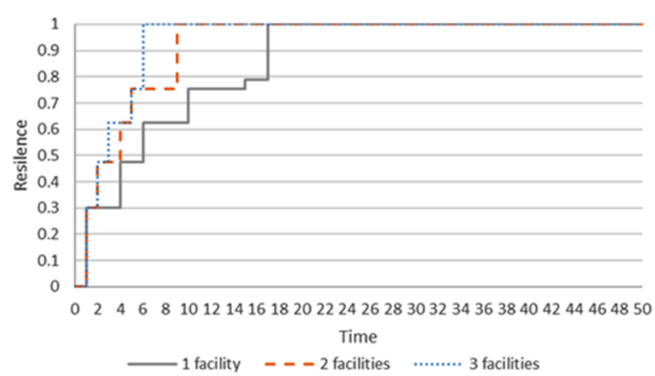
such costs. Hence, $\sum_{m\in M} cs_m v_m$ would be replaced by $\sum_{k\in K}\sum_{m\in M} cs_m v_m w_m^{kr}$. As a result, the proposed optimization model will be a mixed-integer nonlinear program due to products of the binary variables $v_m w_m^{kr}$ which can be replaced by equivalent linear expressions as discussed earlier in Section III-D. Thus, a new binary variable, O_m^{kr}, is introduced that satisfy

$$O_m^{kr} \le v_m,\ \ \forall\, m \in M,\ r \in R^k,\ k \in K \tag{41}$$

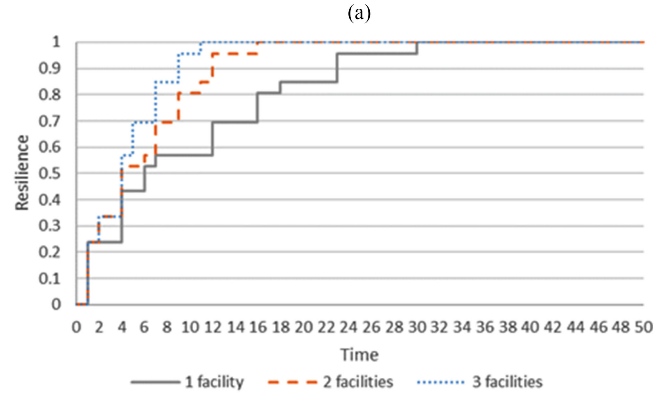
$$O_m^{kr} \le w_m^{kr},\ \ \forall\, m \in M,\ r \in R^k,\ k \in K \tag{42}$$

$$O_m^{kr} \ge v_m + w_m^{kr} - 1,\ \ \forall\, m \in M,\ r \in R^k,\ k \in K. \tag{43}$$

Different scenarios can be addressed with the different consideration of work crew assignments to chosen facilities along with different cost assumptions for establishing a facility. Table I summarizes the different scenarios with the cost assumption for each. To compare among these scenarios, we study a random disruption to the interdependent networks as shown in Fig. 8, where the yellow nodes and thick links are the disrupted networks components, considering the availability of three work crews for each network, 20 time periods, and a maximum of three work crews stationed in a facility $\theta = 3$. Moreover, we consider two different assumptions for the cost of establishing a facility: 1) "fixed," which means that the cost of establishing a facility is fixed regardless of the number of work crews stationed at



(a)



(b)

Fig. 7. Resilience versus time for a random disruption for (a) power network and (b) water network considering a different number of established facilities.

TABLE I
DIFFERENT COST ASSUMPTION SCENARIOS FOR ESTABLISHING FACILITIES

Scenario	Description	Cost assumption for establishing a facility	No. of facilities established	Normalized cost
S1	At most one work crew from any network can be stationed in a chosen facility	Fixed	6	1.00000E+00
S2	At most one work crew from each network can be stationed in a chosen facility	Fixed	3	9.99461E-01
S3		Depends on number of work crews	3	9.99942E-01
S4	Multiple work crews from the same network or different networks can be stationed in a chosen facility	Fixed	2	9.99292E-01
S5		Depends on number of work crews	2	9.99919E-01

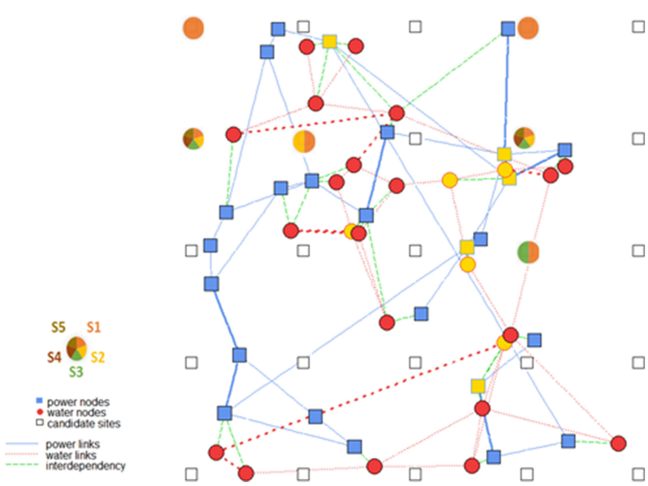


Fig. 8. Location of established facilities with the selected sites highlighted according to the cost scenario, where yellow nodes and thick line represent disrupted components.

that facility, and 2) “depends on number of work crews,” which means that the cost of establishing a facility increases as the number of work crews stationed at that facility increases (i.e., the cost of establishing a facility is multiplied by the number of work crews stationed at that facility).

The number of facilities selected by each of the five different scenarios is provided in Table I and depicted graphically in Fig. 8. In addition, the restoration cost [i.e., objective (3)] for each scenario is shown in Table I, normalized by a reference value (i.e., the restoration cost of the original scenario, S1) using the parameters in Section IV-B2 but with $T = 20$ as considering the availability of three work crews require less time to restore a fully resilient set of interdependent networks. As shown in Table I, allowing multiple work crews to be stationed at the same facility will result in a lower restoration cost when the cost of establishing a facility is fixed regardless of the number of work crews stationed at that facility. This result is illustrated shown in scenarios S2 and S4 when compared with the original scenario S1. Furthermore, stationing more than one work crew at the same facility will lead to a lower restoration cost even if the cost of establishing a facility is multiplied by the number of work crews stationed at that facility, as shown in scenarios S3 and S5 when compared with scenario S1. In general, determining the number of facilities to station the work crews depends on several factors: 1) the location of disrupted network components and candidate sites, 2) the available work crews, and 3) the cost of allowing multiple work crews to be stationed at the same facility compared to the travel cost.

V. CONCLUDING REMARKS

Modern society heavily depends on critical infrastructure networks, such as electricity, water, transportation, and telecommunications, for everyday activities. Just as we are dependent on these networks, these networks also depend on each other for operation. There exist several complex relationships between each of these critical infrastructures that make them highly vulnerable in the event of a malevolent attack, natural disaster, or random failure. As such, it has become increasingly important to not only protect these networks, but also create a plan for restoring them.

This study proposes a model that can be used following a disruptive event to restore interdependent infrastructure networks to some desired level of resilience while minimizing the total cost of restoration. The model not only schedules work crews to restore disrupted components, but also determines where work crews should originate from, given a set of candidate locations. The proposed optimization model considers the physical interdependence between the infrastructure networks as well as the geographical interdependence when allowing work crews from different infrastructure networks to be stationed at the same established facilities. The proposed optimization model focuses on maximizing the measure of resilience of the interdependent infrastructure networks to retain their performance level prior to the disruption. Hence, disrupted networks components might not be all restored, especially if they do not influence the resilience of the system of interdependent infrastructure networks.

A. Future Work

This study represents a first step in formulating a model to address the location of facilities and other resources to aid in the recovery of interdependent infrastructures, and several subsequent enhancements will be made.

Moreover, this study provides a general restoration model that could be applied to any set of physically interdependent networks. However, network-specific models could also be developed.

To improve the solution of this model from a computational point of view, it may be important to introduce a clustering of network nodes. In doing so, candidate sites could be located at the center of these clusters to minimize the distance a work crew would need to travel to restore disrupted components. It is important to note that although candidate sites may exist at the center of these clusters, it may not be optimal to position a work crew in those locations.

An increase in interdependence also increases the complexity of planning for recovery, particularly as there is a social element to these cyber-physical infrastructure systems. As such, in future applications of this study, it will be important to consider recovery as it relates to community resilience and the spatial distribution of vulnerability populations. Finally, the proposed formulation considers only a lone disruption. Future work will produce a formulation that provides a means to locate recovery resources that is robust to a host of disruptions with varying likelihoods.

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