

Optimal Restoration of Community Structures for Enhancing Interdependent Infrastructure Network Resilience

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Abstract

Community structures exist in different infrastructure networks such as water, gas, and power networks, among others, where each network is split into multiple sets of components. Such sets are sparsely connected but have densely connected components within each one of them. Such community structures are formed in infrastructure networks based on physical connections within each network or their spatial characteristics, among others. However, infrastructure networks depend on one another for their proper functionality. Though the interdependencies across infrastructure networks can improve their efficiency, they make them highly vulnerable to any disruption. In this work, we address the interdependent network restoration problem from community structures restoration perspective. That is, how to restore community structures in a set of infrastructure networks that are physically interdependent following a disruption. Accordingly, we propose an optimization model using mixed-integer programming aiming to enhance the resilience of the system of interdependent infrastructure networks. The model provides a set of restoration tasks for each infrastructure network, according to their influence on the performance of their respected networks, and allocates and schedules the selected restoration tasks to the available work crews. The proposed model is demonstrated with a system of interdependent infrastructure networks considering different disruption scenarios.

Keywords

Interdependent networks, community structures, resilience, restoration, and optimization.

1. Introduction

Modern societies rely on the continuous operation of different infrastructure networks such as transportation, water, gas, telecommunication, and power networks among others since they provide them with the essential services to support their economy. Such infrastructure networks can be affected by different types of disruptions including, random failures, targeted attacks, or natural disasters, which could significantly affect their performance differently and could adversely impact economic productivity. Moreover, infrastructure networks are not working apart from each other, but rather they depend on each other in multiple different ways for them to be properly functioning. Hence, they exhibit interdependency (Rinaldi et al. 2001). In general, interdependencies across critical infrastructure networks can improve their operational efficiency since they lead to greater centralization of control, hence they have a major role in the continuous and reliable operation of infrastructure networks (Rinaldi et al. 2001). However, the proliferation of different interdependencies among multiple networks may potentially make them highly vulnerable to disruption. Consequently, if the operability of an infrastructure network is affected by the occurrence of a disruptive event, this could lead to cascading inoperability in some or all dependent infrastructure networks due to their interdependencies; hence, a much more significant impact on society and its economy (Little 2002). Therefore, it is crucial for decision makers to account for interdependencies between infrastructure networks when preparing the plans for their recoverability to obtain a realistic analysis of their performance. In addition, performing restoration activities for each infrastructure network independently could lead to improper utilization of available resources, wasted time, and may even cause further disruptions when improperly scheduled (Baidya and Sun 2017). Therefore, restoring such interdependent infrastructure networks after a disruption is becoming a more difficult job for decision makers since the increase in infrastructure networks interdependencies magnifies the complexity of the planning for their post-disruption recovery and operation. This work addresses such a problem but from a resilience perspective.

The ability of a network to survive after a disruption, adapt to it, and recover from it to a targeted level of performance is referred to as resilience (Barker et al. 2017), which can be quantified by several different approaches that are offered in the literature (Hosseini et al. 2016). In this project, we will consider the paradigm, depicted in Figure 1, provided by Henry and Ramirez-Marquez (2012) that considers a performance function by which the resilience of the network is measured.

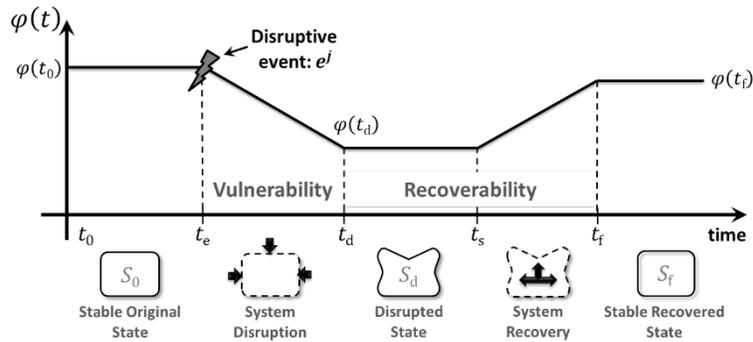


Figure 1: A depiction of a performance function of a network through different transition states over time.

According to Henry and Ramirez-Marquez (2012), network resilience, denoted by \mathfrak{R} , is defined as proportion of the recovered performance of a network out of the maximum loss in the network performance following a disruption, e^j , where J is the set of all possible disruptive events. Hence, the mathematical representation of network resilience is expressed by Eq. (1), where $\varphi(t|e^j) - \varphi(t_d|e^j)$ represent the recovered network performance at time t , and $\varphi(t_0) - \varphi(t_d|e^j)$ represent the loss (degradation) of the network performance up to time t_d , $t_d < t$.

$$\mathfrak{R}_\varphi(t|e^j) = \frac{\varphi(t|e^j) - \varphi(t_d|e^j)}{\varphi(t_0) - \varphi(t_d|e^j)}, t \in (t_s, t_f) \quad (1)$$

According to Eq. (1), $\mathfrak{R}_\varphi(t|e^j) \in [0,1]$ where $\mathfrak{R}_\varphi(t|e^j) = 1$ indicates that the network has reached the maximum level of resilience. In this work, we study the restoration problem of a set interdependent infrastructure network with the objective of enhancing their resilience.

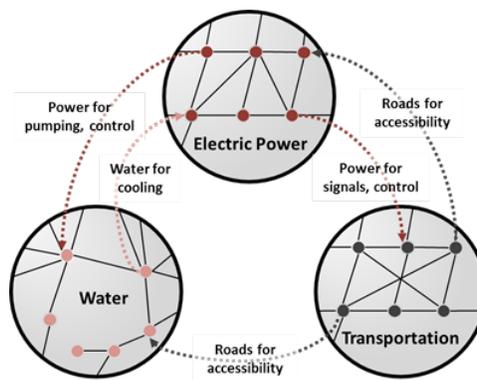


Figure 2: An example of interdependences among different infrastructure networks.

There exist several different types of interdependencies among multiple networks which can be classified into four different types (Rinaldi et al. 2001): (i) physical interdependency, if a network requires a physical output from another network to be functioning, (ii) cyber interdependency, if a network depends on some transmitted information from another network, (iii) geographical interdependency, if a network is affected by a local disruption that affects another one, and (iv) logical interdependency, all interdependencies other than (i), (ii) and (iii). Figure 2

shows an example of the interdependencies between different infrastructure networks. In this work, we consider a set of multiple infrastructure networks that are physically interdependent.

Though this project will address the interdependent network restoration problem (INRP), we will be specifically focusing on restoring of community structures that exist in a set of infrastructure networks which are physically interdependent. Community structures exist in different infrastructure networks such as water, gas, and power networks among others, where each network is split into multiple sets of components. Such sets are sparsely connected but have densely connected components within each one of them (Porter et al. 2009). An example of three community structures with different characteristics within a network is illustrated in Figure 3, which could be the result of geographical constraints or other topological requirements of the network. Such community structures are formed in infrastructure networks based on physical connections within each network or their spatial characteristics, among others. Several approaches are provided in the literature to identify community structures in networks (Fortunato 2010). In this work, we consider the Fast Modularity algorithm proposed by Clauset et al. (2004) to identify community structures in a set of infrastructure networks that are physically interdependent.

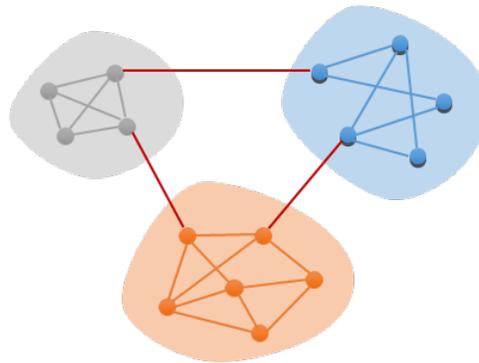


Figure 3: An example of three community structures within a network.

2. Literature Review

Studying critical infrastructure networks under disruption has attracted many researchers in the past fifteen years. Hence, several papers have studied the vulnerability of infrastructure networks and accordingly provide importance measures that help in identifying critical component that could influence the performance of their network (e.g., LaRocca et al. 2015, Nicholson et al. 2016). Other papers have addressed the recoverability of infrastructure networks following a disruption; hence they provide optimization models and approaches to restore disrupted components in such networks (e.g., Fang et al. 2016, Iloglu and Albert 2018).

Several papers in the literature have studied the INRP following the occurrence of a disruption from multiple different perspectives. Accordingly, difference questions are answered: (i) which disrupted component should be selected for restoration in order to retain the prior disruption network performance (e.g., Lee et al. 2007), (ii) what sequence should be followed for the restoration activities (e.g., Gong, et al. 2009), (iii) which work crew should be assigned for each restoration activity (e.g., Duque et al. 2016), or (iv) an integrated approach to answer any two combinations of (i), (ii), and (iii) or to answer all of them (e.g., Cavdaroglu et al. 2013, González et al. 2016, Almoghathawi et al. 2019). In this project, we will also address the INRP but with the focus on post-disruption restoration of community structures within a set of infrastructure networks that are physically interdependent with the aim of enhancing their resilience which has not been addressed explicitly in the literature.

Few recent papers in the literature have addressed the analysis of community structures resilience in a network (e.g., Ramirez-Marquez et al. 2018, Rocco et al. 2018). Ramirez-Marquez et al. (2018) study the community structures resilience in a network considering the network partition similarity as a function to measure the performance and resilience of the network. They provide a methodology that quantifies the community structures ability to: (i) survive following a disruptive event, and (ii) return back to their initial formation after restoration, which helps in choosing a restoration sequence for the disrupted components in a network. Rocco et al. (2018) propose a methodology to assess community structures resilience in a network after considering the effect of disruptive events to communities or the total network. The approach helps in evaluating the vulnerability and recoverability of the

network and suggesting different network restoration sequences accordingly for the disrupted components in a network. Though both approaches by Ramirez-Marquez et al. (2018) and Rocco et al. (2018) have not considered the availability of work crews during the restoration process, they consider a single network only (i.e., not a system of interdependent networks).

In this work, we address the INRP from community structures restoration perspective. Hence, we focus on post-disruption restoration of community structures that exist in a set of infrastructure networks that are physically interdependent with the goal of enhancing their resilience. Accordingly, we develop an optimization model to solve the problem using mixed-integer programming (MIP) considering the time and infrastructure-specific resources that are available for the restoration process. The model provides a set of restoration tasks for each infrastructure network, according to their influence on the performance of their respected networks, and allocates and schedules the selected restoration tasks to the available work crews.

3. Restoration Model

There are some assumptions considered by the proposed model: (i) network components, nodes or links, might be partially or completely disrupted, (ii) each disrupted component can be restored with different restoration rates, and (iii) each disrupted component, node or link, cannot be operational until it is completely restored. The model aims to enhance the resilience of a set of interdependent networks considering multiple sets of constraints: network flow, restoration, interdependence, logical link between network flow and restoration, and nature of decision variables.

3.1 Notation

We are given a set of available time periods $T = \{1, \dots, \tau\}$, a set of infrastructure networks, K , and a set of Interdependent nodes, Ψ . For network $k \in K$, there is a set of community structures, C^k , and a set of resources, R^k . For community structure $c \in C^k$ in network $k \in K$, there are sets of nodes, N^{ck} , links, L^{ck} , supply nodes, $N_s^{ck} \subseteq N^{ck}$, demand nodes, $N_d^{ck} \subseteq N^{ck}$, disrupted nodes, $N'^{ck} \subseteq N^{ck}$, and disrupted links, $L'^{ck} \subseteq L^{ck}$. The weight of community structure $c \in C^k$ in network $k \in K$ and the weight of network performance at time $t \in T$ are represented by ω^{ck} and μ_t , respectively. The original maximum flow, prior to disruption (i.e., at time t_e), is denoted by $MF_{t_e}^{ck}$.

Let s_{it}^{ck} and d_{it}^{ck} be the supply capacity and demand at node $i \in N_s^{ck}$ and node $i \in N_d^{ck}$, respectively at time period $t \in T$. The capacity of link $(i, j) \in L^{ck}$ is denoted by o_{ij}^{ck} . The initial post-disruption status of disrupted components is represented by y_{i0}^{ck} and z_{ij0}^{ck} for node $i \in N'^{ck}$ and link $(i, j) \in L'^{ck}$, respectively. The restoration rate of node $i \in N'^{ck}$ and link $(i, j) \in L'^{ck}$ for work crew $r \in R^k$ at time period $t \in T$ is denoted by γ_{it}^{ckr} and δ_{ijt}^{ckr} , respectively. The maximum number of work crews that can work at the same time on node $i \in N'^{ck}$, link $(i, j) \in L'^{ck}$, and community structure $c \in C^k$ is θ_{it}^{ck} , ρ_{ijt}^{ck} , and π_t^{ck} , respectively.

The amounts of supply at node $i \in N_s^{ck}$, unmet demand (i.e., slack) at node $i \in N_d^{ck}$, and flow through link $(i, j) \in L^{ck}$ at time period $t \in T$ are represented by the decision variables u_{it}^{ck} , q_{it}^{ck} , and x_{ijt}^{ck} , respectively. Disrupted components, nodes and links, might be restored but not functional due to interdependencies or some other operational constraints. Hence, the status and functionality of node $i \in N^{ck}$ at time period $t \in T$ is represented by decision variables y_{it}^{ck} and α_{it}^{ck} , respectively. Similarly, the status and functionality of link $(i, j) \in L^{ck}$ at time period $t \in T$ is represented by decision variables z_{ijt}^{ck} and β_{ijt}^{ck} , respectively. The binary decision variable v_{it}^{ckr} equals 1 work crew $r \in R^k$ is working on node $i \in N'^{ck}$ at time period $t \in T$; and 0 otherwise. Likewise, the binary decision variable w_{ijt}^{ckr} equals 1 work crew $r \in R^k$ is working on node $(i, j) \in L'^{ck}$ at time period $t \in T$; and 0 otherwise.

3.2 Mathematical Model

$$\max \sum_{k \in K} \sum_{c \in C^k} \omega^{ck} \sum_{t=1}^{\tau} \mu_t \mathcal{R}_q(t|e^j) \quad (2)$$

$$\mathfrak{H}_q(t|e^j) = \left(\frac{MF_{t_e}^{ck} - \sum_{i \in N_d^{ck}} q_{it_d}^{ck}}{MF_{t_e}^{ck}} \right) + \left(\frac{\sum_{i \in N_d^{ck}} q_{it_d}^{ck}}{MF_{t_e}^{ck}} \right) \left[\frac{\sum_{i \in N_d^{ck}} q_{it_d}^{ck} - \sum_{i \in N_d^{ck}} q_{it}^{ck}}{\sum_{i \in N_d^{ck}} q_{it_d}^{ck} - \sum_{i \in N_d^{ck}} q_{it_e}^{ck}} \right] \quad (3)$$

$$\sum_{c \in C^k} \sum_{(i,j) \in L^{ck}} x_{ijt}^{ck} - \sum_{c \in C^k} \sum_{(j,i) \in L^{ck}} x_{jit}^{ck} \leq u_{it}^{ck}, \quad \forall i \in N_s^{ck}, c \in C^k, k \in K, t \in T \quad (4)$$

$$\sum_{c \in C^k} \sum_{(i,j) \in L^{ck}} x_{ijt}^{ck} - \sum_{c \in C^k} \sum_{(j,i) \in L^{ck}} x_{jit}^{ck} = 0, \quad \forall i \in N^{ck} \setminus \{N_s^{ck}, N_d^{ck}\}, c \in C^k, k \in K, t \in T \quad (5)$$

$$\sum_{c \in C^k} \sum_{(j,i) \in L^{ck}} x_{jit}^{ck} - \sum_{c \in C^k} \sum_{(i,j) \in L^{ck}} x_{ijt}^{ck} + q_{it}^{ck} = d_{it}^{ck}, \quad \forall i \in N_d^{ck}, c \in C^k, k \in K, t \in T \quad (6)$$

$$q_{it}^{ck} - d_{it}^{ck} \leq 0, \quad \forall i \in N_d^{ck}, c \in C^k, k \in K, t \in T \quad (7)$$

$$x_{ijt}^{ck} - o_{ij}^{ck} \leq 0, \quad \forall (i,j) \in L^{ck}, c \in C^k, k \in K, t \in T \quad (8)$$

$$\sum_{c \in C^k} \sum_{i \in N^{ck}} v_{it}^{ckr} + \sum_{c \in C^k} \sum_{(i,j) \in L^{ck}} w_{ijt}^{ckr} \leq 1, \quad \forall k \in K, r \in R^k, t \in T \quad (9)$$

$$\sum_{r \in R^k} v_{it}^{ckr} \leq \theta_{it}^{ck}, \quad \forall i \in N^{ck}, c \in C^k, k \in K, t \in T \quad (10)$$

$$\sum_{r \in R^k} w_{ijt}^{ckr} \leq \rho_{ijt}^{ck}, \quad \forall (i,j) \in L^{ck}, c \in C^k, k \in K, t \in T \quad (11)$$

$$\sum_{i \in N^{ck}} \sum_{r \in R^k} v_{it}^{ckr} + \sum_{(i,j) \in L^{ck}} \sum_{r \in R^k} w_{ijt}^{ckr} \leq \pi_t^{ck}, \quad \forall c \in C^k, k \in K, t \in T \quad (12)$$

$$y_{it}^{ck} \leq y_{i0}^{ck} + \sum_{r \in R^k} \sum_{l=1}^t \gamma_{il}^{ck} v_{il}^{ckr}, \quad \forall i \in N^{ck}, c \in C^k, k \in K, t \in T \quad (13)$$

$$z_{ijt}^{ck} \leq z_{ij0}^{ck} + \sum_{r \in R^k} \sum_{l=1}^t \delta_{ijl}^{ck} w_{ijl}^{ckr}, \quad \forall (i,j) \in L^{ck}, c \in C^k, k \in K, t \in T \quad (14)$$

$$\alpha_{it}^{ck} \leq y_{it}^{ck}, \quad \forall i \in N^{ck}, c \in C^k, k \in K, t \in T \quad (15)$$

$$\beta_{ijt}^{ck} \leq z_{ijt}^{ck}, \quad \forall (i,j) \in L^{ck}, c \in C^k, k \in K, t \in T \quad (16)$$

$$\alpha_{it}^{\bar{c}\bar{k}} - \alpha_{it}^{ck} \leq 0, \quad \forall ((i, c, k), (\bar{i}, \bar{c}, \bar{k})) \in \Psi, t \in T \quad (17)$$

$$u_{it}^{ck} - s_{it}^{ck} \alpha_{it}^{ck} \leq 0, \quad \forall i \in N_s^{ck}, c \in C^k, k \in K, t \in T \quad (18)$$

$$x_{ijt}^{ck} - o_{ij}^{ck} \alpha_{it}^{ck} \leq 0, \quad \forall (i,j) \in L^{ck}, i \in N^{ck}, c \in C^k, k \in K, t \in T \quad (19)$$

$$x_{ijt}^{ck} - o_{ij}^{ck} \alpha_{jt}^{ck} \leq 0, \quad \forall (i,j) \in L^{ck}, j \in N^{ck}, c \in C^k, k \in K, t \in T \quad (20)$$

$$x_{ijt}^{ck} - o_{ij}^{ck} \beta_{ijt}^{ck} \leq 0, \quad \forall (i,j) \in L^{ck}, c \in C^k, k \in K, t \in T \quad (21)$$

$$u_{it}^{ck} \geq 0, \quad \forall i \in N_s^{ck}, c \in C^k, k \in K, t \in T \quad (22)$$

$$q_{it}^{ck} \geq 0, \quad \forall i \in N_d^{ck}, c \in C^k, k \in K, t \in T \quad (23)$$

$$x_{ijt}^{ck} \geq 0, \quad \forall (i,j) \in L^{ck}, c \in C^k, k \in K, t \in T \quad (24)$$

$$y_{it}^{ck}, z_{ijt}^{ck} \in [0,1], \quad \forall i \in N^k, (i,j) \in L^{ck}, c \in C^k, k \in K, t \in T \quad (25)$$

$$\alpha_{it}^{ck} \in \{0,1\}, \quad \forall i \in N^{ck}, c \in C^k, k \in K, t \in T \quad (26)$$

$$v_{it}^{ckr} \in \{0,1\}, \quad \forall i \in N^{ck}, c \in C^k, k \in K, t \in T, r \in R^k \quad (27)$$

$$\beta_{ijt}^{ck}, w_{ijt}^{ckr} \in \{0,1\}, \quad \forall (i,j) \in L^{ck}, c \in C^k, k \in K, t \in T, r \in R^k \quad (28)$$

Objective (2) maximizes the resilience of the set of interdependent networks over the restoration time horizon, where $\mathfrak{R}_q(t|e^j)$ is the resilience of the system of interdependent networks at time period $t \in T$ given the occurrence of disruptive event e^j . The value of $\mathfrak{R}_q(t|e^j)$ is determined by function (3). Constraints (4-8) represent the network flow constraints for network $k \in K$. The flow conservation in community structure $c \in C^k$ is represented by constraints (4-6). The capacity constraints of supply node $i \in N_s^{ck}$ and link $(i,j) \in L^{ck}$ is represented in constraints (7) and (8), respectively. The restoration decisions are represented by constraints (9-16). Work crew $r \in R^k$ can work on the restoration of a single disrupted component, i.e., node or link, in network $k \in K$ at time period $t \in T$, as shown in constraints (9). Constraints (10-12) ensure that the number of work crews working simultaneously on the same disrupted node, disrupted link, or community structure, respectively cannot exceed the maximum allowed limit for each one of them. The recovery status of disrupted components, i.e., node $i \in N^{ck}$ and link $(i,j) \in L^{ck}$, is determined by constraints (13) and (14), respectively. A disrupted component, i.e., node $i \in N^{ck}$ or link $(i,j) \in L^{ck}$, is not operational at time period $t \in T$ unless it is completely restored, as shown in constraints (15) and (16), respectively. The physical interdependence among different community structures in different networks is captured by constraints (17) which ensure that for node $\bar{i} \in N^{\bar{c}k}$ in community structure $\bar{c} \in C^k$ in network $\bar{k} \in K$ to be operational, node $i \in N^{ck}$ in community structure $c \in C^k$ in network $k \in K$ must be operational. Constraints (18-21) represent the logical link between network flow and restoration decisions. The flow through link $(i,j) \in L^{ck}$ is determined by the capacity of the link as well as the operational status of the nodes at both ends of the link, i.e., constraints (19) and (20), and the operational status of the link itself, i.e., constraint (21). Finally, the nature of decision variables is represented by constraints (22-28).

4. Illustrative Example

We illustrate our proposed model through a system of interdependent power and water networks in Shelby County, TN, USA. There are 256 network components in the system: 109 nodes and 147 links (González et al. 2016). The power network consists of 60 nodes and 76 links, while the water network consists of 49 nodes and 71 links, as shown in Figure 4.

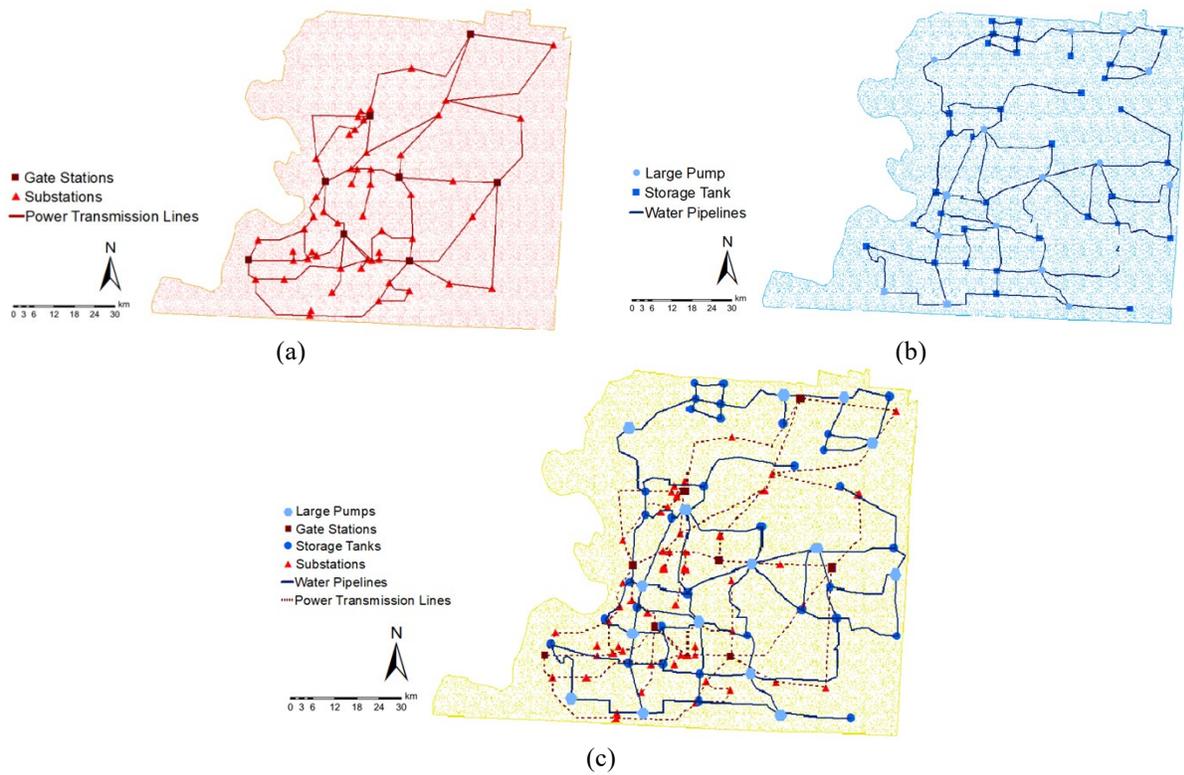


Figure 4: Graphical representations of the, (a) power, (b) water, and (c) interdependent water and power networks in Shelby County, TN, USA (adapted from González et al. [2016]).

Figure 5 shows the community structures in the system of interdependent power and water networks in Shelby County, TN, USA, which are identified using the Fast Modularity algorithm. Accordingly, there are seven community structures in the power network and five community structures in water network, see Figure 5. Furthermore, community structures in both power and water network are with different sizes (i.e., they have different number of network components, nodes and links), as shown in Figure 5.

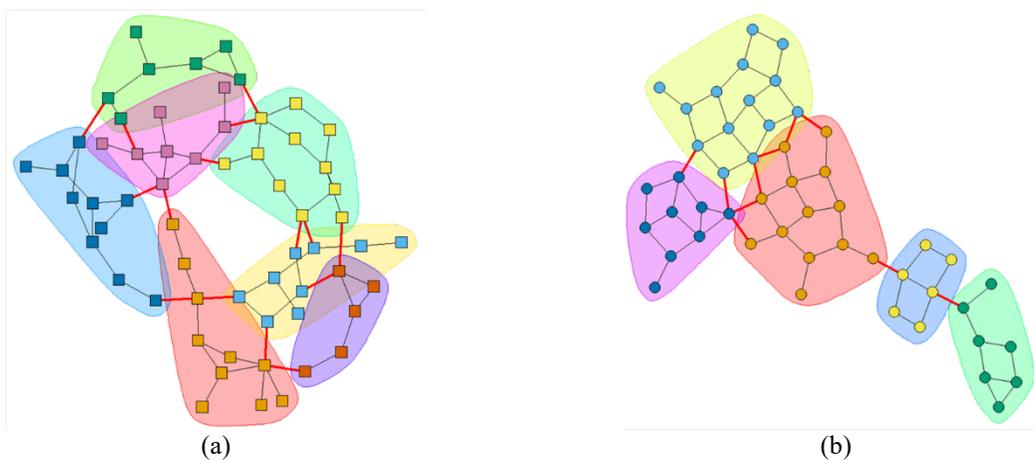


Figure 5: Community structures in the interdependent (a) power, and (b) water networks in Shelby County, TN, USA

The supply and demand in each community structure in the interdependent power and water networks in Shelby County, TN, USA are shown in Figure 6. As can be observed from Figure 6, the supply of some community structures in both power and water networks is more than their demand (e.g., community structures 2, 3, and 5 in the power network, community structures 1, 4, and 5 in the water network). Consequently, such community structures might be less affected than others by a disruption. On the other hand, the demand of some community structures is more than their supply (e.g., community structures 4, 6, and 7 in the power network, community structures 2 and 3 in the water network). Accordingly, such community structures might be more affected by a disruption than others.

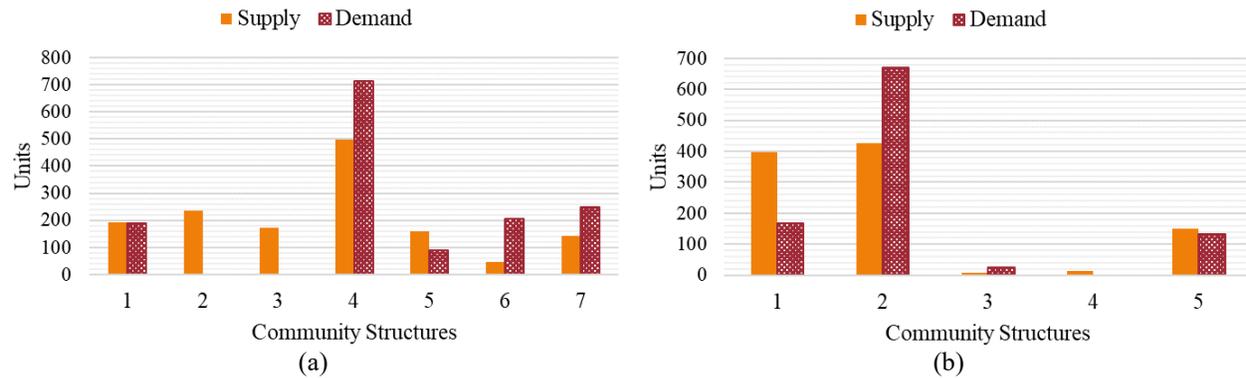


Figure 6: Supply and demand in each community structure in the interdependent (a) power, and (b) water networks in Shelby County, TN, USA

We explore four different magnitudes for hypothetical earthquake scenarios in Shelby County, TN, USA, which are adopted from González et al. (2016). Hence, different failure probabilities of each component, node or link, in the system with each hypothetical earthquake scenario are considered. Average disruption size (and number of disrupted components) are: 13 (5.1%), 31 (12.1%), 58 (22.7%), and 90 (31.2%) for hypothetical earthquake scenarios $M_w = 6$, $M_w = 7$, $M_w = 8$, and $M_w = 9$, respectively. Figure 7 shown the unmet demand in each community structure in both power and water networks following the occurrence of different hypothetical earthquake scenarios with different magnitudes, $M_w \in \{6,7,8,9\}$.

As shown in Figure 7, though community structures in both power and water networks are with different sizes, some of them were not affected by any of the hypothetical earthquake scenarios with different magnitudes, $M_w \in \{6,7,8,9\}$, such as community structures 2 and 3 in the power network and community structure 4 in the water network. This could be due to their location (i.e., they might be far from the location where the disruptive event occurs) or the network components in such community structures might not be influential. On the other hand, other community structures were affected differently following different hypothetical earthquake scenarios due to their different sizes or the importance of their network components such as community structure 6 in the power network and community structures 1 and 2 in the water network, as presented in Figure 7.

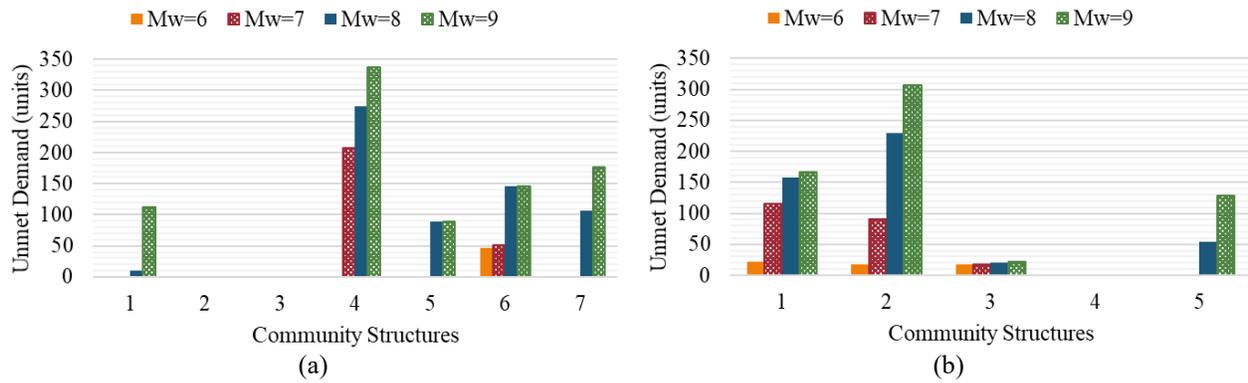


Figure 7: Unmet demand following the occurrence of hypothetical earthquake scenarios with different magnitudes, $M_w \in \{6,7,8,9\}$, in each community structure in the interdependent (a) power, and (b) water networks in Shelby County, TN, USA.

The trajectory of resilience enhancement for the system interdependent networks in Shelby County, TN, USA, obtained by the proposed model is depicted in Figure 8 considering hypothetical earthquake scenarios with different magnitudes, $M_w \in \{6,7,8,9\}$, and the availability of six work crews for each infrastructure network during the restoration process. Naturally, as the magnitude of the hypothetical earthquake increases, the time to reach to a fully resilient system of interdependent network increases. However, it might not be the case when dealing with networks individually. Moreover, we consider in this work equal weight of community structures, ω^{ck} , as well as equal weight of network performance at time $t \in T$, μ_t . Hence, having one of these two weights or both of them different (i.e., not equal), might lead to different trajectories of resilience enhancement for the system interdependent networks.

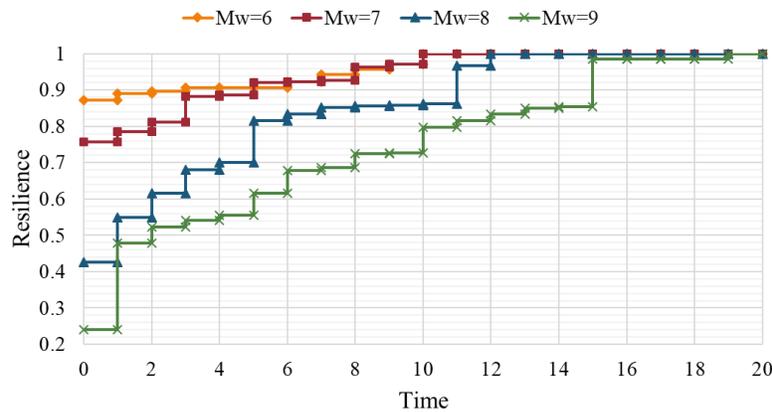


Figure 8: Trajectory of resilience of the system of interdependent networks in Shelby County, TN, USA considering hypothetical earthquake scenarios with different magnitudes, $M_w \in \{6,7,8,9\}$.

Furthermore, in Figure 8, we consider the maximum number of work crews who can work simultaneously at time period $t \in T$ on the same disrupted node, θ_{it}^{ck} , disrupted link, ρ_{ijt}^{ck} , or in the same community structure, π_t^{ck} , to be one, one, and three, respectively. However, changing such numbers by either allowing for more or less work crews could change the trajectory of the resilience of the system of interdependent networks. Hence, Figure 9 shows the trajectory of the resilience of the system of interdependent networks considering a hypothetical earthquake scenario with magnitude 8, i.e., $M_w = 8$, with four different restoration strategies exploring different limits for the maximum number of work crews who can work simultaneously at time period $t \in T$ on the same disrupted node, disrupted link, or in the same community structure, i.e., $(\theta_{it}^{ck}, \rho_{ijt}^{ck}, \pi_t^{ck})$. Accordingly, $M_w = 8(3,3,6)$ in Figure 8 indicates that the maximum number of work crews who can work simultaneously at time period $t \in T$ on the same

disrupted node, same disrupted link, and same community structure, are three, three, and six, respectively and so on. Consequently, allowing for more work crews could lead to a less time to reach a fully resilient system; however, it might not be the case for all disruption scenarios.

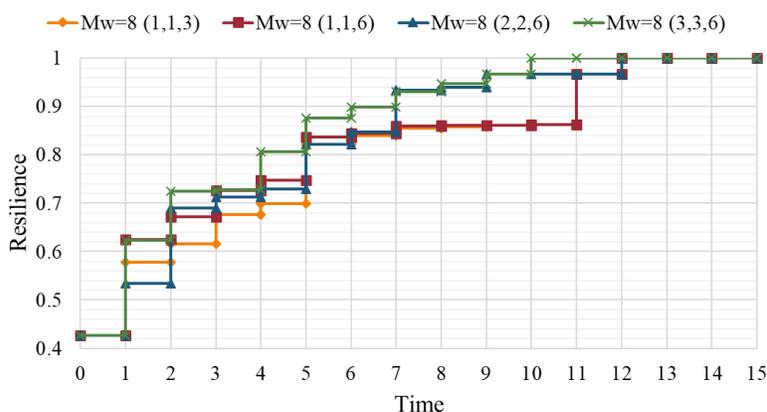


Figure 9: Trajectory of resilience of the system of interdependent networks in Shelby County, TN, USA considering different restoration strategies.

5. Conclusion

In this work, we study the INRP from community structures restoration perspective. Accordingly, we propose a restoration model using MIP to restore community structures in a set of infrastructure networks that are physically interdependent following a disruption. The objective of the model is to enhance the resilience of the system of interdependent networks considering the availability of time and infrastructure-specific resources. The model provides a set of restoration tasks for each infrastructure network, according to their influence on the performance of their respected networks, and allocates and schedules the selected restoration tasks to the available work crews.

Multiple factors could affect the trajectory of resilience enhancement for the system of interdependent networks: (i) the disruption size (i.e., number of disrupted network components), (ii) nature of the interdependencies among networks, (iii) recovery durations of disrupted components, and (iv) availability of work crews for each network. In addition, available time and budget could also limit the restoration process.

The proposed model could be extended to consider: (i) other interdependencies among infrastructure networks (e.g., geographical interdependency), (ii) location of work crews, (iii) accessibility of the roads, (iv) parameters uncertainty, and (v) cascading disruptions. Finally, community structures could be identified using different algorithms based on different perspectives, i.e., other than Fast Modularity algorithm.

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Biography

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