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Decentralized Resource Allocation for Interdependent Infrastructure Networks Restoration: A Cooperative Game Approach

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Abstract

Interdependent critical infrastructures are governed by several sectors working together to maintain social, economic, and environmental well-being. Although many models focus on a centralized view for networks for the restoration planning of these networks, rarely is there only one decision-maker for the infrastructure networks. In the decentralized decision-making paradigm, individual decision-makers need to decide how to prioritize areas of the network and eventually improve the aggregated infrastructure systems resilience. There is a dearth of quantitative studies analyzing resource allocation decisions considering both decentralized and cooperative aspects. This paper aims to propose a coalitional game theory approach to address decentralized resource allocation for interdependent water distribution and road networks. In particular, combining coalitional game theory with weighted graphs creates an order of repair for each node in the coalitions. Subsequently, the decision-makers can pass the information on to the master problem, reducing the complexity of the resource allocation problem for the interdependent networks. The proposed approach is applied to water distribution and transportation networks in the City of Tampa, FL. We compare the decentralized solutions to centralized solutions in different scenarios to demonstrate the feasibility of our approach for the city-scale networks. The results indicated the superiority of the proposed framework in terms of computational time and solution quality.

Keywords: Game theory, Fairness, Interdependent infrastructures, Graph weighting, Coalitions, Network optimization

1. Introduction

The Department of Homeland Security has identified sixteen critical infrastructure sectors necessary for the functionality of the city, one of which focuses on one essential element (DHS, 2003). The disrupted components of these infrastructures must be repaired promptly after a disruptive event such as a natural

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disaster to restore the city normalcy and maintain social and economic well-being (Aslani et al., 2021; Huang et al., 2019). The restoration activities use resources such as work crews, money, and supplies for this purpose. The administrators need to decide resource allocation strategies to minimize the total time for the restoration of the infrastructures. Traditional resource allocation models assume the centralization approach, in which all geographical areas and infrastructures share one decision-maker, one set of resources, and one aggregated goal (Sharkey et al., 2015). However, infrastructures are highly interdependent on one another, such as the geospatial interdependency of the water and transportation infrastructures (see Mohebbi et al. (2020b)). Pipelines are commonly placed underneath roads, meaning that if a pipe breaks, the col-located road in the transportation network must be damaged to repair the water failure. This leads to competing interests between the transportation infrastructure and the water infrastructure, along with separate goals for different physical locations. Hence, it is imperative to understand the collective behavior of decision-makers for managing infrastructure systems.

The complexity of centralized approaches and the need for decentralized solutions have led to considerable efforts in the decision science literature to find low complexity and distributed algorithms (Arnold and Schwalbe, 2002; Mohebbi and Li, 2015). In the decentralized decision-making paradigm, individual decision-makers are responsible for prioritizing disrupted areas of the networks to improve the aggregated infrastructure system resilience. There are several studies in the literature advocating cooperative management strategies to enhance the resilience of infrastructure systems facing disruptive events (see Whittington et al. (2005); Hophmayer-Tokich and Kliot (2008); Bel et al. (2013)). Nonetheless, there is a lack of studies focusing on quantitative modeling the co-existence of cooperation and decentralization for interconnected infrastructure network restoration. Therefore, in this paper, we propose a decentralized resource allocation framework for restoring interdependent infrastructure networks based on cooperative game theory.

In the framework of cooperative game theory, interdependent infrastructure systems can be modeled as a set of coalitions sharing their resources to restore network components and meet the global performance. A coalition is a group of fully cooperative connected actors/network components (i.e. nodes or arcs). In the interface of game theory and networks such as routing (Das and Tripathi, 2018), network partitioning (Avrachenkov et al., 2017), biological networks (Moretti et al., 2010), and Chinese postman (Borm et al., 2001) problems, it is common to define nodes or arcs as the set of players. As coalitions are mutually disjoint, no one node/arc is present in two coalitions. The individual resources now belong to the coalition, and the allocation are decided based on cooperative game solutions.

We consider the nodes of various infrastructures as actors in this study. We identified important nodes (key nodes) for each infrastructure to form coalitions reflecting essential aspects of the network. Due to interdependencies among infrastructures, the coalitions can have nodes from multiple networks. Figure 1 demonstrates a sample coalition for interdependent water and transportation networks, where the key node is a water valve. This coalition is comprised of two directly connected water nodes to the valve and the co-located transportation node. For the transportation network, the important/key nodes are based on the priority of the geographic area as determined by land use (e.g. residential, institutional, hospitals, etc.) and average daily traffic volume (e.g. see Vidrikova et al. (2011); Papakonstantinou et al. (2020)). Key nodes in the water distribution network, on the other hand, are based on physical and hydraulic characteristics of the pipeline network (e.g. reservoirs, valves, tanks, and pump stations).

It should be noted that coalitions are determined based on: (a) geospatial interdependencies between and within infrastructure networks, and (b) the importance of key nodes to the networks. Hence, a coalition of nodes appear to be clustered in the same geographical area. Water and transportation infrastructures are two separate sectors with different procedures. Hence, key nodes are determined by the decision-maker of each infrastructure network independently. In face of disruptive events, decision-makers then need to prioritize and allocate resources (work crews, money, etc.) to restore disrupted network components.

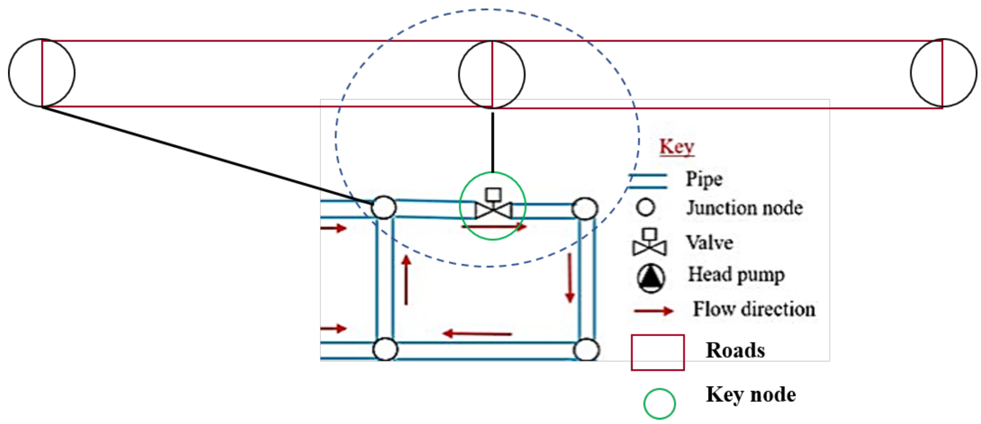

Fig. 1. Sample Coalition for co-located water and transportation networks

After forming the coalitions, the individual contribution of each node to the interdependent networks can be calculated based on cooperative game solutions. Concepts of the core and the Shapley value are the primary tools for determining the fairness criteria for cooperative games. The core and Shapley value are the main solution concepts in cooperative games that are equivalent to the Nash Equilibrium in non-cooperative games (Myerson, 1991). Since the core can be empty or quite large, the selection of a suitable core allocation can be challenging. As a result, the search for a unique payoff vector known as the Shapley value is a common approach in cooperative games. We use Shapley value to calculate the individual contribution of every node to the entire network of infrastructures.

Shapley values can be calculated based on the number of key nodes in the coalition and their interaction with non-key nodes. This calculation method does not consider the characteristics of the nodes, though. An important feature of each node in the water or transportation infrastructures is the maximum capacity of flow (Gonzalez-Aranguena et al., 2014). For instance, the daily amount of pumping water for a pump station varies, and the importance of this element to the surrounding area is related to the amount of flow the pump services. Likewise, a transportation intersection can be defined by its daily traffic, and its importance to the surrounding area is dependent on the amount of flow in the node. We followed a weighting scheme for each node in a coalition to capture this important characteristic in our model. The goal of this procedure is to identify the nodes with more flow, which are more critical to the network. The coalition then can allocate resources in an order based on the Shapley values.

The complexity of the optimization of resource allocation reduces by incorporating coalitions to the problem. In the new setting, by grouping nodes together into cooperative coalitions, each coalition allocates its resources to the nodes in a decentralized manner. The restoration plan from each coalition is then passed on to the master problem, which allocates resources to the whole interdependent networks.

As a result, the contributing nodes in the master problem are reduced, which subsequently influence the computational complexity.

The remainder of this paper is organized as follows: In Section 2, the literature on two main streams of interdependent infrastructure modeling, including game theory and optimization techniques, is reviewed. Section 3 explains the methodology and the proposed decentralized resource allocation framework. Section 4 provides the performance evaluations of the proposed framework applied to water distribution and transportation networks in the City of Tampa. Finally, Section 5 includes concluding remarks, limitations, and future research directions.

2. Literature Review

Optimization and game theory methods are the two key components of the proposed framework in this paper. Each modeling approach has been applied to the restoration problem of interdependent critical infrastructures in the literature, with different assumptions and applications.

2.1. Optimization in Interdependent Infrastructures

A rich stream of the literature for resource allocation optimization problems in interdependent infrastructure networks relies on assumptions of centralized decision-making (Zhang et al., 2018; Kong et al., 2019; Rong et al., 2018; Sharkey et al., 2015; Cavdaroglu et al., 2013). For instance, Cavdaroglu et al. (2013) proposed mathematical models and efficient optimization algorithms that integrate the restoration and planning decisions for interdependent systems. The proposed solution method is heuristic and centralized as all decisions are made from one source. This assumption presumes that in the entire network, there is only one decision-maker, who is responsible for allocating resources to the disrupted systems and there is also complete information of all resources and flow for making the decisions (Rong et al., 2018). Sharkey et al. (2015) extended the centralized optimization in Cavdaroglu et al. (2013) by partitioning the objective function among multiple players to demonstrate the value of information sharing. In small-scale disruptions, this decision maker can be the infrastructure managers; in large-scale disruptions, this person can be the local government (Zhang et al., 2018). The decision-maker must have a holistic understanding of the entire network under their jurisdiction, including resources, disruptions, interdependencies, and repair times for each node. The centralized decision-making assumption is impractical in larger-scale networks, considering the complex interactions among infrastructures and different types of interdependencies (physical, informational, and so on).

In such centralized optimization models, most models seek to maximize the resilience of the network. One approach to maximize resilience is to simply make the resilience metric the focus of the optimization model (Zhang et al., 2018). More complex models can be conceptualized and capture different aspects of the problem, such as developing a two-stage optimization model that first restores the minimum level of service before minimizing the losses in the network (Kong et al., 2019). Although this setting is more realistic, the associated complexity increases the amount of required information for the decision-maker to plan.

Some studies in the literature have addressed the decentralized network optimization problem for infrastructures (e.g., see He et al. (2017); Talebiyan and Duenas-Osorio (2020)). Nonetheless, the resulting models are mainly applicable to small or county-level networks, due to the assumption that all actors are individually making decisions (Talebiyan and Duenas-Osorio, 2020). Smith et al. (2020) investigated non-cooperative decision making when information is incomplete and two decision-makers cannot negotiate. They analyzed the convergence properties, and applied the proposed ad hoc solution to the Shelby County dataset to demonstrate the extent of the tradeoff between optimality and computational efficiency. Reilly et al. (2014) studied strategic investment decisions by two operators of privately owned infrastructure systems when they do not communicate with one another and select resources in the narrow interests of their own system. It was shown that their decision can lead to underinvestment and underperformance in infrastructure systems, and underinvestment is likely to be stronger when there are greater interdependencies. Therefore, the interdependent nature of the infrastructures must be considered to capture the true complexity of the network accurately. The decentralized optimization models in the literature do not always incorporate the interdependent nature of the infrastructures to their problems (He et al., 2017). This leaves a gap for models that include both decentralization and are computationally tractable for large-scale networks. To tackle this issue, we propose a decentralized optimization model for city-scale interdependent infrastructure networks. The framework provides information regarding restoration planning for decision-makers in a reasonable time, making the model more broadly applicable.

2.2. Cooperative Game Theory in Interdependent Infrastructures

Cooperative game theory has been applied to many fields, such as economics, government policy, genetics, and healthcare systems (Mohebbi and Li, 2015; Choi et al., 2020; Moretti et al., 2010; Mohebbi et al., 2020a). The main feature of such games is that decision-makers seek to optimize a common goal such that decisions/actions do not degrade their individual purpose and performance. In order to optimize a common goal in networks, particularly one related to restoration, the characteristics of components and nodes must be understood. One key feature of a node can be the importance of the node in relation to the interdependent network, referred to as the Shapley value of the node. Shapley values are central to many cooperative games in a variety of scenarios (Borm et al., 2001), which provide a unique solution and allow the decision-makers to make informed choices.

Decentralization of the network allows for the different sectors to cooperate while retaining their independent decision-making power and resources, in addition to reducing the computational complexity of the resource allocation problem (Ellinas et al., 2015). A graph dividing approach must be implemented to decentralize the network. One viable procedure is the division based on the node location. This method uses identified important nodes by the decision-maker, known as key nodes, to create coalitions (Moretti et al., 2010). Thus, as the coalitions are restored, the repairs will be focused on these key nodes. Mathematically, there are a large number of ways to identify the important nodes and coalitions in interdependent networks.

However, by considering the physical characteristics of nodes, their geographical and land use classification, a smaller set of key nodes can be identified. In the water infrastructure, these key nodes are identified as nodes with different characteristics, such as reservoirs, pumps, valves, and tanks. The other nodes in a water network are demand nodes or pipeline junctions, neither of which control the flow throughout the system. In the transportation infrastructure, the identification of key nodes such as bridges, highway intersections, and other important intersections are based on land use classifications and average daily traffic volume.

Finally, to accurately capture the characteristics of the network components, a weighting scheme must be applied to highlight the more vital parts of the network to the city. There are multiple ways to assign weights to a network, one of which is based on the cost of transportation (Allen and Arkolakis, 2019). However, this technique is only beneficial when plotting routes through an infrastructure. A more efficient way is focusing on the flows between the links in the infrastructure, which assigns weights based on existing flow (Gonzalez-Aranguena et al., 2014).

Our proposed model combines both the key-node based coalition formation and the flow-based weighting of a graph, creating a unique configuration that addresses both the relative importance of a node to significant areas in the interdependent infrastructures and the importance of the node characteristics. This approach is vastly different from previous methods developed in the literature, due to the dual approach of weighted graphs and game theory. Weighted coalitions are first formed based on direct and interdependency links and do not change. Afterwards, the master problem of optimizing resource allocation must be addressed.

3. Analytical Modeling

The proposed decentralized resource allocation framework utilizes cooperative game theory and network optimization techniques. We first present the formulation and solution for the cooperative game and then provide the optimization model for interdependent infrastructure networks.

3.1. Game Formulation

3.1.1. Unanimity Game

The basic cooperative game can be defined as $< N, v >$, where N is the set of players and v is the characteristic function. In this paper, N is the set of all non-key nodes and the characteristic function is a measure of the connectedness of the non-key nodes to the key nodes. Given a subset $E \subseteq N$, the characteristic function $v(E) \in \mathbb{R}$ and $v(\emptyset) = 0$. A group of nodes C can form a coalition if $C \subseteq N$.

For a unanimity game, the coalitions are represented by $u_E(C) = 1$ if $E \subseteq C$ and $u_E = 0$ if $E \nsubseteq C$, where $\emptyset \neq E \subseteq N$. Cooperative games can be written as a linear combination of unanimity games in a unique way. The coefficients of the characteristic function are $\lambda_E(v)$ for all subsets $E \in 2^N \setminus \emptyset$. Thus, the unanimity game characteristic function v is

$$\sum_{E \subseteq N, E \neq \emptyset} \lambda_E(v) u_e \tag{1}$$

We use Shapley value to solve the game. This solution can be described in several ways, and we use the following formula (Shapley, 1953):

$$\phi_i(v) = \sum_{E \subseteq N: i \in E} \frac{(|E|-1)!(|N|-|E|)!}{|N|!}[v(E) - v(E \setminus \{i\})], \quad \forall i \tag{2}$$

In our model, the Shapley value is based on the number of key nodes that are exclusively connected to the coalition (see Moretti et al. (2010)). The specific coefficients of the characteristic function must reflect this definition. To find this characteristic function, the links between key nodes and nodes must be identified as $L_E \subseteq \{\{i,k\}|i \in E, k \in K\}$ where K is the set of all key nodes. A single key node that is directly connected to a subset E can be calculated through the following Equation:

$$M_E = \begin{cases} 1, & \text{if } \{i,k\} \in L_E \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

This function needs to be summed over all of the key nodes, represented as $\lambda_E(v) = \sum_{k \in K} M_E$. The characteristic function v remains the same as Equation 1. Hence, coalitional structures can be determined by the vectors formed by the same function as M_E,

$$C_k(i) = \begin{cases} 1, & if \{i,k\} \in L_E, \forall k \in K, \forall i \in E \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

It should be noted that for each city-scale infrastructure network, key nodes are distributed and independent, i.e. they do not directly interact. This is due to the fact that the field validated network models are created by following skeletonization procedures, i.e. merging original nodes/links by applying the combination of attributes to the newly merged nodes/links (see Santana (2015); Abdel-Mottaleb et al. (2019)). Hence, to simplify the presentation of the game and weighted graphs, we consider one key node per coalition. However, this assumption is not fundamental and key nodes in one network can be linked to those of other infrastructure networks via interdependency links if they are geographically co-located. If a group of k key nodes directly interact, it will be sufficient to merge them into an individual key node whose importance equals k times the importance of a single key node. To this end, the network optimization model needs to be elaborated by adding an index to decision variables that would ensure the important coalitions are prioritized first.

3.1.2. Restricted Weighted Graphs

Having identified coalitional structures for the interdependent networks, we need to calculate the Shapley value vector for each coalition. In addition to nodes characteristics, the flow on specific links of infrastructure networks is important in calculating the Shapley value. This is because such links might contribute more to a key node than others.

In order to allow for weighting different non-key nodes in the individual coalition, the overall network must be restricted to a graph that contains coalition C. The new set of restricted players R is simply $R \subseteq N, R \neq \emptyset$, where $C \subseteq R$. The connections in the entire graph, $I_N = \{\{i,j\}i, j \in N, i \neq j\}$, is restricted to I_R or the set of connections that include only those connections in R. Thus, a restricted graph is presented as $< R, I_R >$. From this restricted graph, a subgraph that contains strictly the connected components of coalition C. The set of links $\eta \subseteq I_R$ where C is connected in η and the set of players $D(\eta) = \{i \in N$ such that $\exists j \in N$ where $\{i, j\} \in \eta\}$ form the new connection subgraph. Finally, the weighted graph $< N, I_w >$ is comprised of the set of players N and the weighted links $I_w = \{I, \{w_A\}_{A \in I}\}$.

However, the weighted graph must be transformed before it can be used to calculate the Shapley values of the coalition. We used the set of proportional contribution that each coalition C contributes after the graph has been weighted to measure contribution, $\alpha(I_w)$. For each coalition, the proportional contribution is equal to $\{\alpha_C^R(\{w_A\}_{A \in I}) \in [0, 1]\}$. The exact value of α_C^R depends on the type of weight that best fits the current situation for the overall network. In our model, flow between nodes is used to weight the graph, as the flow of commodities are important measures to capture in infrastructure modeling.

In other words, w_A is the flow on arc A and must be within $[0, \infty]$. For instance, water flow in each link/pipe can be obtained by simulating the water distribution network using EPANET Tools software. For the transportation network, average annual daily traffic or network measures can be used to simulate traffic flow in each link/road. Thus, $(\alpha)_C^R$ can be calculated as below (see Gonzalez-Aranguena et al. (2014)):

$$(\alpha)_C^R = \max_{i=1 \dots t(R)} \left\{ \frac{1}{1 + \max\limits_{L \in \eta_i^{C,R}} w_A} \right\} \text{ for } |C| \geq 2 \text{ and } = 1 \text{ if } |C| = 1 \tag{5}$$

Gonzalez-Aranguena et al. (2014) demonstrated that the α-weighted restricted graph is decomposable on unanimity games. Hence, the modified characteristic function for the restricted weighted graph is:

$$v^{I_w, \alpha}(R) = \sum_{\emptyset \neq C \subseteq R} \lambda_C(v) \alpha_C^R(\{w_A\}) \tag{6}$$

This characteristic function measures the level of maximum flow that can pass between each group of connected nodes, or route to the key node, in the coalition.

According to Equation 6, the computation of the Shapley value for the corresponding game is straightforward as below.

$$\phi_i = \sum_{i \in C \subseteq N} \frac{\lambda_C(v)}{|C|}, \forall i \tag{7}$$

Simply put, this is the value that each node contributes, measured by the amount of flow that goes through the node and accounting the number of routes to the key node that the node is a part of, resulting in a vector for each coalition. It should be noted that this value will not add to one similar to other unanimity games, due to the restricted nature of the graph. Each coalition can find the Shapley value vector for itself and determine the allocation of resources and order of repair for disrupted nodes based on this value. A node is not operational until all links connected to the node have been fully recovered. If multiple links with equal flows (importance) are connected to the node and lead to the same met demand, the links to be repaired are randomly chosen. Another approach is to consider the flow cost, i.e., unitary cost of carrying flow through links, as the second criterion to choose from multiple flows with the same met demand. In this study, we only considered met demands as our objective function. The allocation of resources to nodes will be fair, due to the fairness property and axioms of Shapley values. These axioms are intrinsic to the Shapley value and ensure the fairness of the result. The efficiency axiom represents the group rationality, the symmetry axiom ensures that if two players have equal contributions, they will have equal payoffs, the dummy axiom awards no payoff to players with no contribution to the coalition, and the additivity axiom forces the combined Shapley value for two coalitions to be the same regardless of the order that they are added.

3.1.3. Proposed Algorithm

In summary, the general flow of the problem starts with the formation of the coalitions. The coalitions are formed around the identified key nodes by the decision-makers using the direct links in the physical network and the interdependency links. If a non-key node is between two non-interdependent key nodes, it belongs to the coalition with most flow. The characteristic function can be calculated using weighted links for each coalition. Afterward, the Shapley value vector can be calculated and used to create a unique order of restoration for each coalition. The coalitions can then send the repair orders to the network-wide optimization problem (i.e., master problem). The procedure is outlined in Algorithm 1.

Algorithm 1 Proposed algorithm for fair allocation of resources within coalitions

```
Procedure: Coalitional Game
for all coalitions do
    Calculate the flow equation for each link;
    Compute the characteristic function ;
    Use the unanimity game formulation to calculate the Shapley value vector for the coalition;
    Formulate an order of repair for disrupted nodes based on the Shapley value vector;
    Send order of repair to 'Master Problem' Procedure;
end for
```

3.2. Optimization Model

After identifying the coalitions and calculating the Shapley value vectors, the results can be used to optimize the resource allocation in a decentralized manner. The optimization of the resource allocation is best described as two decomposed problems: one sub-problem for coalitions and one master problem that accounts for the entire network.

3.2.1. Restoration of Coalitions

Within each coalition, the Shapley value vector can be utilized to finalize the order of restoration and resource allocation decisions. The order of repair is strictly based on the Shapley value: the damaged node with the largest Shapley value will be repaired first, then the second-largest damaged node, and so forth. However, if the key node itself is damaged, the key node automatically is the first to receive repair resources. If the coalition has resources available to use, such as local funds, the available resources will be applied in that order.

Although the calculated Shapley values are for nodes, disruptions most often occur in the arcs of the network. To model disruption at the node level, we assumed that a node is failed when a connected arc is disrupted. When a node receives resources from the coalition, all arcs connected to the node are restored during the time frame. If the coalition does not have enough resources or has no available resources, the order of repair will be sent to the master problem, the network-wide optimization model. Once the resource is assigned to the coalition, the nodes will be restored, still following the predetermined order of repair. If there are not enough resources to repair all nodes, the sub-problem will send the level of disrupted flow remaining back to the master problem. This cycle repeats until the coalition is fully restored. The proposed sub-problem for restoring coalitions is outlined in Algorithm 2.

Algorithm 2 Proposed algorithm for restoring coalitions

Sub-problem: Coalition Repair
for each coalition C_k **do**
    Order list of disrupted nodes by decreasing Shapley value;
    Send order to 'Master Problem';
    Receive resources if needed from network;
    if received resource is equal to cost of repairs **then**
        Repair all nodes;
    end if
    Repair list in order;
    Send total remaining disrupted flow to 'Master Problem';
end for

3.2.2. Interdependent Networks Optimization

The master problem receives the order of repair from the coalitions and integrates it into the overall optimization model. The following network optimization problem is formulated which is mainly based off the work presented by Sharkey et al. (2015).

3.2.3. Sets and Parameters

- M: Set of all infrastructures
- N^m: Set of all nodes in infrastructure m
- S^m: Set of all supply nodes in infrastructure m
- T^m: Set of all transshipment nodes in infrastructure m
- $\bar{E}^m$: Set of all arcs that can be installed in the network in infrastructure m
- E^m: Set of all initially available arcs in infrastructure m
- C: The set of all coalitions, with 0 being the centralized coalition set
- A: The set of all arcs that connect to key nodes and are therefore a part of a coalition

Set of constraints for the Master problem

$$\sum_{(i,j)\in E^m\cup\bar{E}^m} x_{ijt}^m - \sum_{(i,j)\in E^m\cup\bar{E}^m} x_{jit}^m = s_i^m, t=1,...,T, \forall i\in S^m, \forall m\in M \tag{8}$$

$$\sum_{(i,j)\in E^m\cup\bar{E}^m} x_{ijt}^m - \sum_{(i,j)\in E^m\cup\bar{E}^m} x_{jit}^m = 0, t=1,...,T, \forall i\in T^m, \forall m\in M \tag{9}$$

$$\begin{aligned}\sum_{(i,j)\in E^m\cup\bar{E}^m} x_{ijt}^m - \sum_{(i,j)\in E^m\cup\bar{E}^m} x_{jit}^m = -v_{it}^m - \sum_{((i,m),(a,b),n)\in NTP} v_{nabt}^{mi},\\ t=1,...,T, \forall i\in D^m, \forall m\in M\end{aligned} \tag{10}$$

$$0\leq v_{it}^m \leq d_i^m, t=1,...,T, \forall i\in D^m, \forall m\in M \tag{11}$$

$$0\leq \sum_{(i,j)\in E^m\cup\bar{E}^m} x_{ijt}^m \leq u_i^m, t=1,...,T, \forall i\in T^m, \forall m\in M \tag{12}$$

$$0\leq x_{ijt}^m \leq u_{ij}^m, t=1,...,T, \forall m\in M, \forall (i,j)\in E^m \tag{13}$$

$$0\leq x_{ijt}^m \leq u_{ij}^m \beta_{i,j,0,o,t}^m, t=1,...,T, \forall m\in M, \forall (i,j)\in \bar{E}^m \tag{14}$$

$$\sum_{(i,j)\in\bar{E}^m} \sum_{s=t}^{min\{T,t+p_{ij}^m-1\}} \alpha_{kij0s}^m \leq 1, t=1,...,T, \forall m\in M, \forall c\in C, k=1,...,K^m \tag{15}$$

$$\beta_{i,j,0,o,t}^m - \beta_{i,j,0,o,(t-1)}^m = \sum_{k=1}^{K^m} \alpha_{kij0t}^m, t=2,...,T, \forall m\in M, \forall (i,j)\in\bar{E}^m \tag{16}$$

$$0\leq d_i^m - v_{it}^m \leq (1-y_{n,j,t}^{m,i})(d_i^m), t=1,...,T, \forall (i,j)\in F(m,n), j\in N^n, i\in D^m \tag{17}$$

$$\sum_{(j,h)\in\bar{E}^m\cup\bar{E}^m} x_{jht}^n \leq s_j^n y_{n,j,t}^{m,i}, t=1,...,T, \forall (i,j)\in F(m,n), j\in S^n, i\in D^m \tag{18}$$

$$\sum_{(j,h)\in\bar{E}^m\cup\bar{E}^m} x_{jht}^n \leq d_j^n y_{n,j,t}^{m,i}, t=1,...,T, \forall (i,j)\in F(m,n), j\in D^n, i\in D^m \tag{19}$$

- Q: Set of all nodes not in a coalition in the network
- D^m: Set of all demand nodes in infrastructure m
- s_i^m: The amount of supply available at node $i\in S^m$ in infrastructure m
- d_i^m: The amount of demand at node $i\in D^m$ in infrastructure m.
- w_i^m: The weight associated with meeting one unit of demand at node $i\in D^m$ in infrastructure m.
- u_i^m: The capacity of node i in infrastructure m.
- u_{ij}^m: The capacity of arc (i,j) in infrastructure m.
- $F(m,n)\subseteq D^m\times N^m$: The set of all parent/child node pairs in parent infrastructure m and child

infrastructure n.

3.2.4. Decision Variables

From these sets, the decision variables can be created. The first three decision variables are solely for the master problem, including remaining nodes that are not in coalitions. However, the other two variables gain additional indices to represent the coalitional nodes as well. For α, the decision variable that determines when the arc is repaired, an additional binary index was added to represent if either of the two nodes in the arc are in a coalition. For β, the decision variable that displays that an arc is restored, two additional indices were added. The first is the same binary index as in α, while the second represents the repair order determined by the Shapley value.

- x_{ijt}^{m}: The amount of flow on arc of node $(i, j) \subseteq E^m \cup \bar{E}^m$ in infrastructure m at time t.
- v_{it}^{m}: The amount of demand met at node $i \subseteq D^m$ in infrastructure m at time t.
- $y_{n,j,t}^{m,i}$: A binary variable for $(i, j) \subseteq F(m, n)$ representing whether sufficient demand is met at node i in infrastructure m so that node j in infrastructure n is operational at time t.
- $\alpha_{k,i,j,c,t}^{m}$: The binary variable which is equal to 1 if arc $(i, j) \in E^m$ in infrastructure m is completed by work crew k at time t where c is equal to 0 if the node i and j are not in a coalition and the number of the coalition otherwise.
- $\beta_{i,j,c,o,t}^{m}$: The binary variable which is equal to 1 if arc $(i, j) \in E^m$ in infrastructure m is available at time t where c is equal to 0 if the node i and j are not in a coalition and the coalition number otherwise and o is the order number from the game theory solution.

3.2.5. Objective Function

The objective function is to maximize the met demand.

$$Max\ Z = \sum_{t=1}^{T} \sum_{m \in M} \sum_{i \in D^m} v_{it}^{m} \tag{20}$$

The decomposed set of constraints for the Sub-problem

$$\beta_{i,j,c,o,t}^{m} \geq \beta_{k,l,c,o+1,t}^{m}, \forall (i, j), (k, l) \in A_c, \forall c \in C \tag{21}$$

$$\sum_{(i,j) \in \bar{E}^m, \notin Q} \sum_{s=t}^{min\{T, t+p_{ij}^{m}-1\}} \alpha_{kijcs}^{m} \leq 1, t = 1, ..., T, \forall m \in M, \forall c \in C, k = 1, ..., K^m \tag{22}$$

$$\beta_{i,j,c,o,t}^{m} - \beta_{i,j,c,o,(t-1)}^{m} = \sum_{k=1}^{K^m} \alpha_{kijct}^{m}, t = 2, ..., T, \forall m \in M, \forall (i, j) \in \bar{E}^m \notin Q, \forall c \in C \tag{23}$$

$$0 \leq x_{ijt}^{m} \leq u_{ij}^{m} \beta_{i,j,c,o,t}^{m}, t = 1, ..., T, \forall m \in M, \forall (i, j) \in \bar{E}^m \notin Q, \forall c \in C \tag{24}$$

3.2.6. Constraints

The constraints can be added to the model as follows. Constraints 9, 10, and 11 are defined to ensure that the flow in and out of supply nodes, transshipment nodes, and demand nodes match the needed outflow. Constraint 11 does have an extra value that can be utilized to ensure that the model follows the proper interdependency rules. Constraints 12 and 13 address demand and capacity limits for the nodes and the arcs. Constraint 14 addresses the initially available node capacity due to the arcs that are undamaged by the disruption. Constraint 15 links the β value to the flow. If the β value is not 1, then the arc is not available and so no flow should exist. Constraints 16 and 17 correspond with α. The first ensures that each arc is only started to be fixed by one work crew in one time period over the entire time period. The second ties α to β, so that the arc is available after it is restored. Constraints 18, 19, and 20 ensure that the binary node operation variable y is linked to the demand, transshipment, and supply nodes.

The constraints in the sub-problem were added to handle the coalitions. For all constraints in the master problem, the coalitional index c for decision variables α and β is always equal to zero, ensuring that only those arcs that are not in a coalition are handled by the master problem. Prior to the master problem, the sub-problem handles all the arcs whose coalitional index c for decision variables α and β correspond with a coalition. In other words, the constraints in the master model were only applied to those decision variables with a coalitional binary variable of 0, indicating the arcs are not connected to a node in the coalition. As a result, the decision variables β in the master problem are related to the disrupted components outside the coalitions, and the β decision variables in the sub-problem are associated with the failed parts in coalitions. However, all constraints with α or β were replicated to connect the demand with β. Constraint 21 is the only constraint that directly applies only to the coalitional nodes to make sure that disrupted components in the coalitions are restored based on the order of repair. More precisely, it ensures that the higher-order nodes from any coalition get repaired before the lower order nodes. For example, all first ranked damaged nodes across all coalitions must be fixed before any second-ranked nodes.

After the model is run and the results are received, the master problem can send out the order of repair for the non-coalitional damaged nodes, and work crews will begin to restore the network. The proposed procedure is summarized in Algorithm 3.

Algorithm 3 Proposed algorithm for the optimization of the entire network

```
Procedure: Master Problem
Receive order of repairs for coalitions from the sub-problem;
Run optimization model for all nodes;
Send resources to nodes based on results;
if there is not enough resources to repair all disrupted nodes then
    Receive disrupted flow from coalitions;
    Add penalty for unrepaired remaining flow;
end if
```

4. Validation and Performance Evaluation

This study used data from a simplified version of the water distribution and road infrastructure networks in the City of Tampa, Florida. Existing tanks, pump stations, and reservoirs from the data were used as key nodes for the water network. Valves were simulated by finding water nodes where at least four pipelines intersected. For the transportation network, we first calculate the betweenness centrality measure to simulate traffic flow. Then, all nodes that exceeded a certain threshold of flow were considered as important intersections (nodes). This assumption is based on previous work on traffic flow (Kazerani and Winter, 2009). In this paper, we focused only on geographical co-location to determine interdependencies for the water and transportation networks. The overlaid networks are illustrated in Figure 2, with the brown being the water infrastructure and the green being the transportation network.

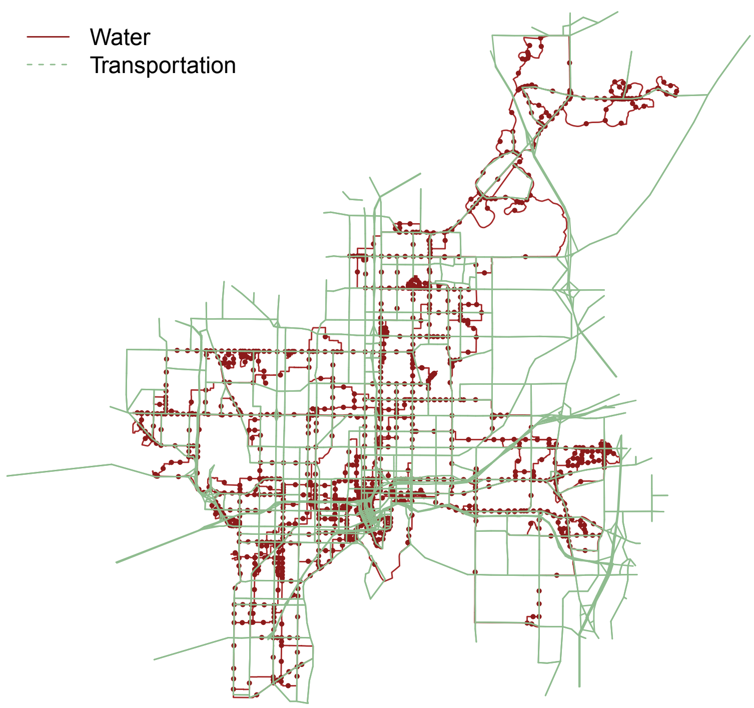

Fig. 2. Interdependent water-transportation networks

In the simplified networks, there are 4312 nodes in both the transportation and water networks. There are 48 key nodes in the water network and 45 key nodes in the transportation network, based on a predefined betweenness threshold of greater than 0.07. This value was chosen to limit the transportation key nodes to only the highest traffic flows. Using the conservative threshold of 0.07 ensures that only the most traveled roads are selected as key nodes. In addition, the number of key nodes in the water network is approximately the same as the number of key nodes in the transportation network. As each infrastructure comprises almost half of the nodes, the proportion of key nodes to non-key nodes remains roughly the same in both infrastructures. Table 1 provides one example subset of the total 93 coalitions in the networks. The variation in the Shapley values is due to the nature of the characteristic function. Since every coalition calculates its function based on the number of nodes in the coalition and the flow depends on the type of node, the Shapley values can vary between coalitions yet remain comparable within the coalition. Hence, although the Shapley values cannot be compared between coalitions, the coalition can still create a clear order of repair.

Table 1
Subset of Coalitions in Order of Repair from Tampa, FL

Key Node	Nodes in Coalition	Infrastructure	Shapley Value
J-103410	7324	Transportation	0.064
	A-58369	Water	0.042
	A-54531	Water	0.042
	A-66147	Water	0.00076
	A-25129	Water	0.00076
7476	A-66724	Water	1.1839
	7493	Transportation	1.1839
	7464	Transportation	1.1837
	7472	Transportation	1.1203
	7503	Transportation	1.1203
HSP	HRR	Water	0.000018
	J-87510	Water	0.000018

Under the current framework, calculating the characteristic function for the weighted graphs is limited to direct connections. Given that the coalitions only contain nodes that are directly connected to the key node, these possible paths are limited to direct connections and the potential interdependent node. The flow along the interdependent node is assumed to be the same as the maximum amount of flow on the other links. We presumed that the interdependent node is at least as important as the most important direct connection node.

A percentage of the set of all arcs was randomly selected to be disrupted. Here, we designed four scenarios with 5% disruption, 10% disruption, 12% disruption, and 15% disruption magnitudes. We also assumed that half of the selected disrupted arcs belonged to the identified coalitions. If the arc was connected to a key node or in a coalition, the proposed methodology was applied, and the order of restoration was formed. As mentioned before, the key node is always placed in the first spot of the order of repair if it is damaged. To evaluate the performance of the proposed approach, we compared the computational time to solve the optimization model for the centralized and the decentralized approaches. In order to have a fair comparison, we followed a series of steps. First, we considered identical and equal resources (maintenance crews) for both models. In all scenarios, we have two maintenance crews in each network summing up to four available repair resources overall. In addition, we allow the models to reach to the optimality for small failure scenarios, i.e., 5% and 10% disruptions. In these scenarios, we do not report any optimality gap. However, as the computational time for higher disruption scenarios increases exponentially, we restricted the models by imposing a 5% gap option, meaning that we stop the run as soon as the optimality gap reaches below 5%. It can be observed that the computational time for the 15% scenario and centralized model is more than 37 hours. Therefore, in 12% and 15% scenarios, we report the optimality gap extracted from Gurobi solver.

To improve the clarity of our experiment, we also report the average deviation from the baseline flow of interdependent networks for each disruption scenario in Table 2. As we generated the scenarios randomly, we can see that in 10% scenario, the percentage of disrupted flows decreases by 1.7% compared to the 5% disruption. This is due to the fact that nodes with higher flows (both in coalitions and outside coalitions) are randomly selected in the 5% scenario. While in 12% and 15% scenarios, we see an increase in the disrupted flow, the range does not exceed from 20% of total flow in interdependent networks. It can be observed that more extreme scenarios mirror more decision complexity and higher computational time.

Table 2 summarizes the details of failure scenarios as well as the objective function values and the computational time for both models. It can be observed that there is a significant difference between the computational time of centralized and proposed models. In addition, when the objective values are compared (see Figure 3), the proposed method reaches a higher value for restored flow. It should be noted that the objectives for the proposed model are values obtained by solving the model with the additional set of constraints in the sub-problem using Shapley values (constraints 21-24), leading to higher objective function values in terms of total met demand compared to the centralized model.

Additionally, the proposed method improves the met demand faster than the centralized approach. In 5% Scenario, both methods start at zero demand met for the water network, but the proposed method outpaces the centralized one in rapid demand growth (see Figure 4.a). In the transportation infrastructure for this scenario, the models also both start at the same demand. The met demand of the proposed model for transportation increases faster but does end up slightly below the centralized model (see Figure 4.b). However, the overall demand for the proposed method is better. A same trend is present for the extreme scenario of 15% disruption. However, the proposed model reaches far higher met demand for both infrastructures of water and transportation compared to the centralized model(see Figure 4.c & 4.d). This significant difference in the total met demand is due to the fact that coalitions, in the proposed model, are formed based on the importance of components in the networks, and the model subsequently prioritizes the restoration of the nodes and arcs which result in higher met demands. In other words, these key nodes and their respective Shapley value act as a fair proxy of flow in the networks so that their restoration will expedite the recovery performance in terms of met demand over the planning horizon. For larger magnitudes of disruptions, the role of these key elements becomes more tangible in the restoration phase of interdependent infrastructure networks.

Table 3 shows the order of repairs for water and transportation networks for the proposed and the centralized models. As the proposed model follows a different order of repairs for both disrupted networks, the met demands for this approach is different than the centralized model. It is noteworthy that there are common arcs in the order of repairs for both models, but they are restored in different sequences (for example arc (A-66721, J-49128) in water and arc (5559, 5566) in transportation network).

Table 2
Computational time and optimality gap for different disruption scenarios

Failure Percentage	Avg. Disrupted Flow	Method	Obj. Value	Time (Secs)	Optimality Gap
5%	14.43%	Centralized	3797000	2619.41	NA
		Proposed	3870000	179.23	NA
10%	12.77%	Centralized	1198000	76098.09	NA
		Proposed	1551000	231.6	NA
12%	16.95%	Centralized	1053261	28100.16	5%
		Proposed	1448000	194.28	4.76%
15%	19.64%	Centralized	750100	135676.08	5%
		Proposed	1484000	220.71	4.21%

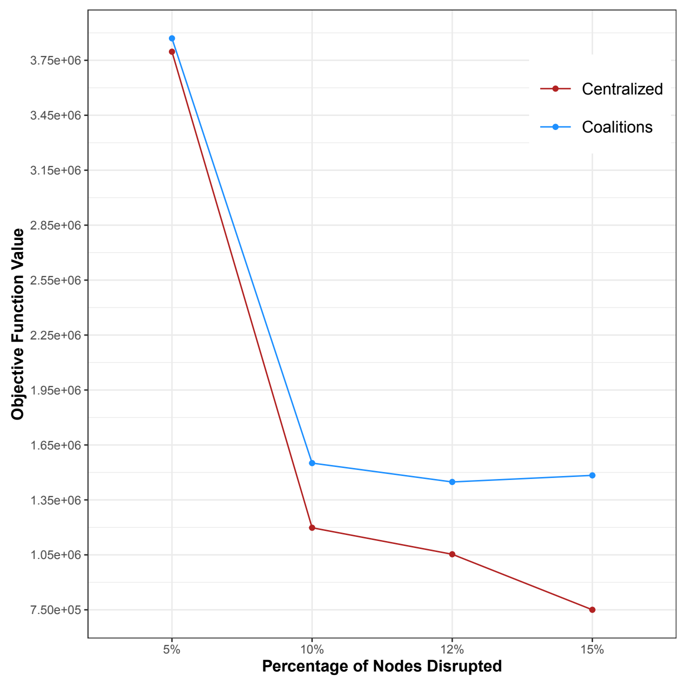

Fig. 3. Optimal Values for Both Methods

5. Concluding Remarks

We proposed a decentralized resource allocation model for interdependent infrastructure network restoration using cooperative game theory. We first identified coalitional structures in the interdependent networks and then calculated the order of restoration for the disrupted components within coalitions using Shapley values. Our proposed approach combined coalitional game theory with weighted graphs to address the fair allocation of resources in a decentralized manner. The restoration plan from coalitions were then passed on to the master optimization problem, which allocates resources to restore the

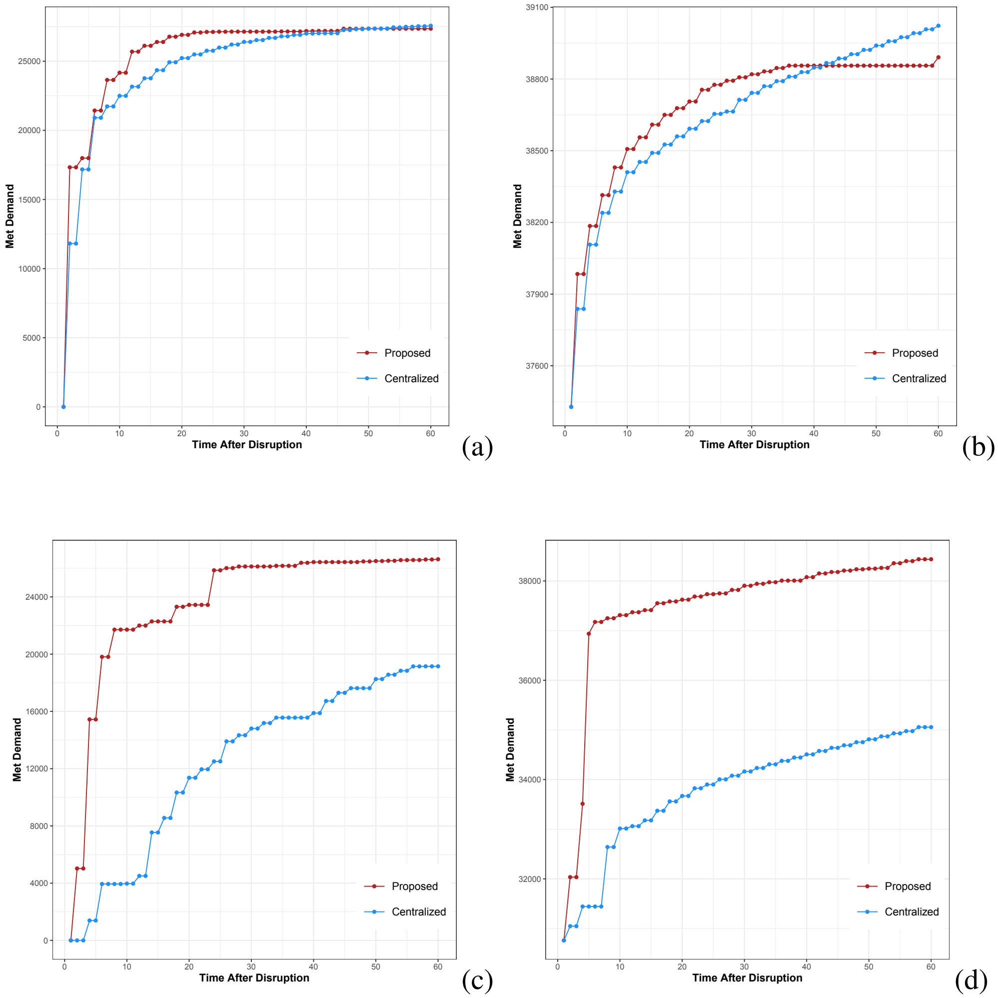

Fig. 4. Met Demand in the Water (left) and Transportation (right) Infrastructures at 5% (up) and 15% (down) disruption scenarios

whole interdependent networks. We applied our framework to water distribution and road networks in the City of Tampa, FL. We calculated and compared the computational time for both centralized and decentralized models in four scenarios to evaluate the performance of the proposed framework. We assigned identical repair resources to the centralized and proposed models to have a valid foundation for the performance comparison. We also allowed the models to reach to the optimal solutions for small disruption scenarios, and defined a 5% optimality gap for extreme failure scenarios. The results demonstrated that the decentralized model outperforms the centralized counterpart in terms of computational time and the trajectory of the system performance (met demand) over time.

In future work, more types of interdependence can be incorporated into the model, reflecting the complexity of the infrastructure networks. These additional interdependencies, such as functional in-

Table 3
Oreder of repair for 5% scenario

Water		Transportation	
Proposed	Centralized	Proposed	Centralized
A1919029, J-17012	HRR, HSP	5559, 5566	6662, 6601
A-66721, J-49128	A-66188, J-81543	8752, 6107	5182, 5173
A1848133, J-110468	A1919029, J-17012	7913, 7886	5559, 5566
J-44164, A-66687	J-121724, A-31648	6252, 8746	5986, 6025
A-66656, J-104023	A-66721, J-49128	5596, 5613	8752, 6107
J-113546, A-65192	A1848133, J-110468	6260, 6216	7812, 7828
A-66696, J-78262	J-100985, A-66492	6216, 6173	6168, 6075
A-64889, J-49929	J-44164, A-66687	7270, 7313	6918, 6913
A-66574, J-102507	A-66656, J-104023	6251, 8743	6090, 6037
A-63915, J-111809	J-43778, A-65440	5986, 6025	5596, 5613
A-66457, J-111264	J-113546, A-65192	7265, 7253	6252, 8746
J-121724, A-31648	J-115604, A-66238	5556, 5604	6063, 6073
J-48745, A-66602	A-66477, J-62660	6032, 6024	6260, 6216
A-66582, J-92739	A-66574, J-102507	6376, 6424	6216, 6173
A-66725, J-45914	A-63915, J-111809	7407, 7422	7270, 7313
A-66676, J-110923	J-87510, A1945975	8824, 8825	6251, 8743
J-81676, A-60405	A-66457, J-111264	5318, 5326	6684, 6719
J-80983, A-66422	J-78053, A-66467	7588, 7605	5843, 5733
J-23915, A1844976	A-62847, J-51783	5292, 5277	6076, 6086
A-66168, J-31363	J-54616, A-66675	6703, 6718	6514, 6337
J-115604, A-66238	A-64889, J-49929	7672, 7635	6743, 6731
J-88148, A-64810	A-66211, J-76247	6348, 6358	6716, 6730
A-66452, J-119514	J-49929, A-66211	6347, 6341	6403, 6421
J-50311, A-66351	A-60159, J-76776	8232, 8164	6350, 6404
J-113734, A-66489	J-51547, A-66298	6792, 6845	5179, 5187
A-66649, J-96263	A-66503, J-119591	5883, 5870	6786, 6779
J-120964, A-62444	J-67455, A-66503	6928, 6922	7888, 7845
J-93182, A-53105	J-48745, A-66602	8731, 7022	7265, 7253
A-40868, J-47524	A-66582, J-92739	7168, 7150	6345, 6372
J-129274, A-63752	A-66725, J-45914	7002, 6973	5180, 5186

terdependencies, will contribute to a more realistic formulation without increasing the complexity in a significant manner. Other infrastructures can also be included, such as the power infrastructure. With more extensive networks, the coalition formation procedure could be expanded, either by introducing more key nodes or relaxing the definition of the direct connections. Depending on the infrastructure and the geographical area, future work in this direction might better capture the circumstances around the disruption. The optimization problem can be expanded to include the cost to see if the proposed model could reduce the cost of restoring the networks.

As large-scale disruptions continue to change life in cities, decision-makers need a reliable and rapid way to prioritize different areas of infrastructures and eventually enhance infrastructure systems resilience. This research can further their efforts and resources toward providing a clear restoration plan.

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