Interdependent Infrastructure Network Restoration Optimization from Community and Spatial Resilience Perspectives

Deniz Berfin Karakoc
School of Industrial and Systems Engineering
University of Oklahoma
Norman, Oklahoma, USA
denizberfinkarakoc@ou.edu

Kash Barker
School of Industrial and Systems Engineering
University of Oklahoma
Norman, Oklahoma, USA
kashbarker@ou.edu

Yasser Almoghathawi
Systems Engineering Department
King Fahd University of Petroleum and Minerals
Dahran, Saudi Arabia
moghathawi@kfupm.edu.sa

ABSTRACT

Modern societies rely on the critical infrastructure networks to ensure their operability and existence. Most of the recent research and government planning revolves around maintaining the proper and continuous functioning of these critical infrastructure networks. However, these critical infrastructure networks do not exist on their own, but they perform interdependently. Thus, the study of forming resilient interdependent infrastructures against natural or man-made large-scale disruptions and planning the restoration of these critical networks becomes a more complex challenge. As such, the frequency of large-scale disruptions appears to be increasing and devastating for the surrounding communities in the long-term, the social and geographic aspects of these disruptions should be emphasized in the restoration planning studies so that resilience and well-being of the served community is also optimized. In this work, we integrate (i) a resilience-driven multi-objective mixed-integer programming formulation that schedules the restoration of disrupted components in each network with (ii) a geographically distributed social vulnerability index and population density ratio and (iii) a spatial risk measure to assign the impact of the surrounding environment to the system. This model is illustrated with an example study in Shelby County, TN in the United States.

1 INTRODUCTION

Critical infrastructure networks, such as power, natural gas, and water distribution, form the backbone of modern societies to provide their daily needs and ensure their safety, high socio-economic standards, and quality of life. However, these critical infrastructures have experienced various disruptions in the past and continue to be subject to both external and internal stressors such as aging-induced system failures, natural disasters, and malevolent attacks. Hence, given the inevitability of these large-scale disruptions, an ability to adapt and quickly recover from these disruptions is extremely crucial for both the interdependent infrastructure networks and their surrounding communities.

Moreover, these networks have become more dependent on each other where they contain a bi-directional relationship to operate properly and more efficiently [30]. This type of a complex coordination that is caused by physical, spatial, cyber, or logical interdependencies can increase performance efficiency and reduce the resource consumption of these networks since the output of one network could be the input of another. However, due to the existence of such complex coordinations, there is a possibility of chain reactions of dysfunctionality between the interdependent components due to disruption in a single network. Hence, this type of bi-directional relationships could enhance the overall network vulnerability since complete system failure could be caused by a disruption in a single network. Therefore, the study of recovery planning to ensure a desired level of resilience in these highly vulnerable networks become a crucial challenge [7, 22, 36]. Hence, the importance of addressing risks associated with the interdependencies among the critical infrastructures through building secure and resilient networks is highlighted in many governmental planning documents [28] and examined in recent literature work [1, 4, 18].

Further, the socio-economic status and the demographics of the served community, as well as the spatial risks related to the surrounding environment and the location of these networks, could increase the impact of disruptions [24] over the system performance, thus system resilience. Therefore, resilience and recovery planning studies for the interdependent infrastructure networks should take social and spatial vulnerabilities into account to reveal more reliable and comprehensive guidance to decision makers.

In this work, we study the problem of interdependent infrastructure network restoration after the occurrence of a disruptive event with a focus on the vulnerability of society that interacts with the network and additional hazard risk of the surrounding environment. As for the results, we observe that when additional community and spatial resilience measures are included in the problem, both the optimal restoration schedule of disrupted components and the performance of networks through the restoration process show changes. Therefore, the overall system resilience through time differs when community and spatial vulnerability measures are taken into account.

2 BACKGROUND

2.1 Network Resilience

The term resilience is defined as the ability to withstand, adapt to, and recover from a disruption [27]. Even though the definition is commonly agreed, many different approaches are introduced in the literature to formulate and quantify the resilience of a network. Some of the proposed measurement methods include (i) describing the resilience as the normalized area underneath the performance graph [11], (ii) representing the resilience as a function of topological measures [32], and (iii) quantifying resilience as the probability of recovery [21].

As shown in Figure 1, two primary dimensions of resilience, vulnerability and recoverability, help characterize network resilience [5]. The vulnerability of a network states the magnitude of damage in the performance of a network due to a stressor [19], where the recoverability of a network refers to the speed at which the network reaches to its desired performance level [31]. Hence, resilience is measured in this work as the of network recovery over network loss through complete recovery period [17].

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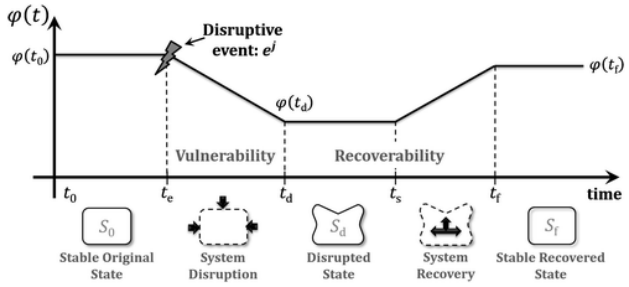

Figure 1: The Network Performance $\phi(t)$ across the Before, During and After States of a Disruptive Event [17].

2.2 Recovery of Infrastructure Networks

The study of optimally scheduling the restoration of infrastructure networks is emphasized in the last decade especially due to the high frequency of both natural disasters and the malevolent attacks. In the literature, a mixed-integer programming is developed with an objective of minimizing the total cost associated with the flow and unmet demand in the network system [20]. Another optimization model is for the restoration of disrupted components in the interdependent networks is formulated in such a way that each component is assigned with a recovery due date that should be satisfied [15]. A different mixed-integer programming model is proposed that (i) determines the set of disrupted components that should be restored and (ii) assigns the related work crews through the restoration that would ensure the minimum total cost of flow, unmet demand and restoration activities [33]. More recently, an interdependent infrastructure network design problem is introduced in the literature that schedules the restoration activities of the disrupted components under certain budgetary and resource-based constraints [16]. Finally, a different approach is defined as a two-phase recovery for physically interdependent critical infrastructures that includes both a linear and a mixed-integer programming with the objectives of minimizing the flow cost and maximizing the total amount of commodity deliveries in the system [35].

In this study, we extend a previously proposed approach for the restoration scheduling of interdependent infrastructure networks [2] in such a way that the modified resilience-driven multi-objective mixed integer programming model would account for the additional risk and vulnerability measures of the surrounding environment. Hence, the newly optimal restoration schedule of disrupted components would prioritize the community and spatial resilience perspectives.

2.3 Social Vulnerability

Social vulnerability is defined by the set of characteristics of a group or individual that influence their capacity to anticipate, cope with, resist, and recover from the impact of a hazard [6]. Many studies propose to identify the behavioral aspects, human occupancy, and response level of societies that are shaped by these different socio-economic characteristics.

The social vulnerability of a community is often defined by the number and the availability of recovery resources. Such resources for a disrupted region include the number of work crews, restoration equipment, number of physicians, their dispatch locations [26], shelter number and capacity [34], and medical capacity [3]. However, some of the proposed studies revolve around the idea that certain social and economic characteristics, namely inequalities and differences in the society, have an effect on vulnerability and recoverability. Some of the most commonly considered demographics are racial and technical inequalities [26], and educational inequalities [25, 26] where according to the way that these socio-economic characteristics are defined, they either contribute to or counteract the resilience of the communities against disruptive events.

A common algorithm to quantify social vulnerability is the Social Vulnerability Index (SoVI), which is a measure that is formulated by the different levels of age, gender, race, wealth, and occupation of the citizens [12]. This proposed algorithm considers multiple socio-economic characteristics to define vulnerability levels based on the cumulative effect of all the demographics. These socio-economic characteristics are utilized to identify the 42 variables that are grouped into 11 factors to be used in the SoVI algorithm [12]. These 11 factor groups that are listed in Table 1, are used to measure the social vulnerability index of communities to accurately estimate their recoverability, resilience capacity and response level against a possible stressor.

Table 1: Social Vulnerability Index Factors

Personal wealth	Ethnicity (Native-American)
Age	Occupation
Ethnicity (Hispanic)	Infrastructure dependence
Race (African-American)	Housing stock and tenancy
Race (Asian)	Density of the built environment
Single-sector economic dependence	

In this study, we utilize a reduced version of the SoVI algorithm, the SoVI-Lite approach [14]. The SoVI-Lite approach contains less technical implementation but efficient data compilation [14]. An overview of the SoVI-Lite implementation is as follows:

1. Calculate the ratio of the population that is included in the all possible 42 socio-economic variables
2. Standardize the percentages of variables to the z-scores
3. Assign signs to the z-scores according to the influence of a higher percentage level of the variables on social vulnerability concept
4. Sum all the z-scores

We also normalize the final sum of z-scores for each geographic region such that a SoVI of 0 suggests the least socially vulnerable and of 1 suggests the most socially vulnerable community.

2.4 Spatial Risk

In addition to social demographics, the surrounding environment and changes in spatial conditions also affect the impacts of a disruption as experienced by a community [14]. These spatial conditions refer both the type of the local region (e.g., village, sub-district) [37] and the geographic location (e.g., island, coastal area, volcanic risk area, seismic hazard zone). [9].

In this study, we consider the geographic location as the spatial risk indicator where risk is caused by the high possibility of being subjected to a specific natural disaster, an earthquake. To quantify earthquake risk, we use the peak ground acceleration (PGA) measure to formally express the expected seismic hazard impact due to a ground shake [13].

Additionally, we scale the PGA measures of different geographic regions to be between 0 and 1. For the PGA measures, similar to the SoVI scores, 0 represents spatially the least risky location and 1 represents spatially the most risky location.

3 PROPOSED MODEL

We extend a multi-objective resilience-driven restoration optimization model for restoration scheduling of interdependent infrastructure networks in such a way that differing levels of community and spatial resilience measures are taken into account while planning the recovery process optimally after a disruption. We integrate social vulnerability, population density, and spatial risk measures into the resilience maximization and total restoration cost minimization objectives to ensure that the restoration scheduling is driven by community and spatial resilience perspectives.

3.1 Model Assumptions

In the proposed multi-objective resilience-driven mixed-integer programming model, the following assumptions hold: (i) each network consists of nodes and links that are either not disrupted or fully disrupted, (ii) the recovery duration can vary for each component in each network, (iii) disrupted components are not operational unless their restoration is completed, (iv) the demand and supply of the nodes and the flow of the links are known in advance, (v) a known unmet demand penalty, restoration, and flow cost is associated with component in each network, (vi) for a component to be functional all the physically interdependent components must be functional as well,(vii) a fixed number of work crews are assigned to each network for restoration, and finally (viii) a specific disrupted component could be restored by a single work crew at a certain time period.

3.2 Model Notation

The sets, parameters, and the decision variables of the proposed optimization model for interdependent infrastructure network restoration problem are listed in Table 2, 3 and 4, respectively.

Table 2: Sets of Restoration Model

Notation	Explanation
T	Available recovery time horizon, $T = \{1, \ldots, \tau\}$
K	Interdependent infrastructure networks, $K = \{1, \ldots, \kappa\}$
N	Nodes of the networks
L	Links of the networks
N'	Disrupted nodes
L'	Disrupted links
N^k	Nodes in network $k \in K$
L^k	Links in network $k \in K$
R^k	Restoration work crews for network $k \in K$
N_s^k	Supply nodes in network $k \in K$, $N_s^k \subseteq N^k$
N_d^k	Demand nodes in network $k \in K$, $N_d^k \subseteq N^k$
N'^k	Disrupted nodes in network $k \in K$, $N'^k \subseteq N^k$
L'^k	Disrupted links in network $k \in K$, $L'^k \subseteq L^k$
Ψ	Interdependent nodes

3.3 Objectives of Model

The total amount of unmet demand in the network states the system loss that is caused by the disruptive event. Thus, decreasing the amount of total unmet demand to a desired level refers to enhancing system performance and represents the effectiveness of the restoration process. Hence, the resilience of the system would be formalized by the cumulative recovery of the interdependent infrastructure networks over the total system loss through a certain time horizon as in Eq. 1.

Table 3: Parameters of Restoration Model

Notation	Explanation
b_i^k	Amount of maximum flow at node $i \in N^k$
$SoVI_i^k$	Social vulnerability index for demand node $i \in N_d^k$
V_i^k	Social vulnerability score for demand node $i \in N_d^k$
P_i^k	Population density for demand node $i \in N_d^k$
PGA_i^k	Peak ground acceleration measure for demand node $i \in N_d^k$
G_i^k	Peak ground acceleration score for demand node $i \in N_d^k$
Q_i^k	Unmet demand of node $i \in N_d^k$ after disruption
μ^k	Weight of each network $k \in K$
fn_i^k	Restoration cost for disrupted node $i \in N'^k$
fl_{ij}^k	Restoration cost for disrupted link $(i,j) \in L'^k$
c_{ij}^k	Unitary flow cost for link $(i,j) \in L^k$
p_i^k	Unmet demand penalty cost for demand node $i \in N_d^k$
dn_i^k	Restoration duration of the disrupted node $i \in N'^k$
dl_{ij}^k	Restoration duration of the disrupted link $(i,j) \in L'^k$
u_{ij}^k	Flow capacity of link $(i,j) \in L^k$

Table 4: Decision Variables of Restoration Model

Notation	Explanation
s_{it}^k	Amount of unmet demand at node $i \in N_d^k$ at time $t \in T$
x_{ijt}^k	Flow through link $(i,j) \in L^k$ at time $t \in T$
y_i^k	Restoration status of node $i \in N'^k$
z_{ij}^k	Restoration status of link $(i,j) \in L'^k$
α_{ijt}^k	Operational status of link $(i,j) \in L'^k$ at time $t \in T$
β_{it}^k	Operational status of node $i \in N^k$
γ_{it}^{kr}	Work crew assignment to node $i \in N'^k$ for restoration
δ_{ij}^{kr}	Work crew assignment to link $(i,j) \in L'^k$ for restoration

$$\max \sum_{k\in K} \mu^k \sum_{t=1}^{\tau} \Bigg(\frac{t\Big[\sum_{i\in N_d^k}\Big(Q_i^k V_i^k P_i^k G_i^k\Big) - \sum_{i\in N_d^k}\Big(s_{it}^k V_i^k P_i^k G_i^k\Big)\Big]}{\sum_{i\in N_d^k}\Big(\tau Q_i^k V_i^k P_i^k G_i^k\Big)} - \frac{(t-1)\Big[\sum_{i\in N_d^k}\Big(Q_i^k V_i^k P_i^k G_i^k\Big) - \sum_{i\in N_d^k}\Big(s_{i(t-1)}^k V_i^k P_i^k G_i^k\Big)\Big]}{\sum_{i\in N_d^k}\Big(\tau Q_i^k V_i^k P_i^k G_i^k\Big)} \Bigg) \tag{1}$$

The second objective of the proposed model takes the total cost associated with the (i) restoration process that includes the recovery of the disrupted nodes and links, (ii) the flow cost, and (iii) the penalty cost of the leftover unmet demand in the system which fluctuates by both the social and geographical vulnerability levels of the service areas of the demand nodes. Therefore, the minimization of the total cost objective would be formulated as in Eq. 2.

$$\min \sum_{k\in K} \Bigg(\sum_{i\in N'^k} fn_i^k y_i^k + \sum_{(i,j)\in L'^k} fl_{ij}^k z_{ij}^k + \sum_{t\in T} \Bigg[\sum_{(i,j)\in L^k} c_{ij}^k x_{ijt}^k + \sum_{i\in N_d^k} p_i^k V_i^k P_i^k G_i^k s_{it}^k \Bigg] \Bigg) \tag{2}$$

3.4 Mathematical Model

The explained objectives are subject to the following constraints.

$$\sum_{(i,j)\in L^k} x^k_{ijt} - \sum_{(j,i)\in L^k} x^k_{jit} = 0, \quad \forall i \in N^k \setminus \{N^k_s, N^k_d\}, k \in K, t \in T \tag{3}$$

$$\sum_{(j,i)\in L^k} x^k_{jit} + s^k_{it} = b^k_i, \quad \forall i \in N^k_d, k \in K, t \in T \tag{4}$$

$$x^k_{ijt} - u^k_{ij}\beta^k_{it} \le 0, \quad \forall (i,j) \in L^k, i \in N^k, k \in K, t \in T \tag{5}$$

$$x^k_{ijt} - u^k_{ij}\beta^k_{jt} \le 0, \quad \forall (i,j) \in L^k, j \in N^k, k \in K, t \in T \tag{6}$$

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

$$\beta^{\bar{k}}_{\bar{i}t} \le \beta^k_{it}, \quad \forall \Big((i,k),(\bar{i},\bar{k})\Big) \in \Psi \tag{8}$$

$$z^k_{ij} = \sum_{r\in R^k} \sum_{t\in T} \delta^{kr}_{ijt}, \quad \forall (i,j) \in L'^k, k \in K \tag{9}$$

$$y^k_i = \sum_{r\in R^k} \sum_{t\in T} \gamma^{kr}_{it}, \quad \forall i \in N'^k, k \in K \tag{10}$$

$$\sum_{(i,j)\in L'^k} \sum_{l=t}^{min(\tau, t+dl^k_{ij}-1)} \delta^{kr}_{ijl} + \sum_{i\in N'^k} \sum_{l=t}^{min(\tau, t+dn^k_i-1)} \gamma^{kr}_{il} \le 1 \quad \forall k \in K, r \in R^k, t \in T \tag{11}$$

$$\beta^k_{it} \le \sum_{r\in R^k} \sum_{l=1}^{t} \gamma^{kr}_{il}, \quad \forall i \in N'^k, k \in K, t \in T \tag{12}$$

$$\alpha^k_{ijt} \le \sum_{r\in R^k} \sum_{l=1}^{t} \delta^{kr}_{ijl}, \quad \forall (i,j) \in L'^k, k \in K, t \in T \tag{13}$$

$$\sum_{t=1}^{dl^k_{ij}-1} \alpha^k_{ijt} = 0, \quad \forall (i,j) \in L'^k, k \in K \tag{14}$$

$$\sum_{t=1}^{dn^k_i-1} \beta^k_{it} = 0, \quad \forall i \in N'^k, k \in K \tag{15}$$

$$\sum_{r\in R^k} \sum_{t=1}^{dl^k_{ij}-1} \delta^{kr}_{ijt} = 0, \quad \forall (i,j) \in L'^k, k \in K \tag{16}$$

$$\sum_{r\in R^k} \sum_{t=1}^{dn^k_i-1} \gamma^{kr}_{it} = 0, \quad \forall i \in N'^k, k \in K \tag{17}$$

$$s^k_{it} \ge 0, \quad \forall i \in N^k_d, k \in K, t \in T \tag{18}$$

$$x^k_{ijt} \ge 0, \quad \forall (i,j) \in L^k, k \in K, t \in T \tag{19}$$

$$y^k_i \in \{0,1\}, \quad \forall i \in N'^k, k \in K \tag{20}$$

$$z^k_{ij} \in \{0,1\}, \quad \forall (i,j) \in L'^k, k \in K \tag{21}$$

$$\beta^k_{it} \in \{0,1\}, \quad \forall i \in N^k, k \in K, t \in T \tag{22}$$

$$\alpha^k_{ijt} \in \{0,1\}, \quad \forall (i,j) \in L'^k, k \in K, t \in T \tag{23}$$

$$\gamma^{kr}_{it} \in \{0,1\}, \quad \forall i \in N'^k, k \in K, t \in T, r \in R^k \tag{24}$$

$$\delta^{kr}_{ijt} \in \{0,1\}, \quad \forall (i,j) \in L'^k, k \in K, t \in T, r \in R^k \tag{25}$$

In the proposed mathematical model, the first two constraints, Eqs. (3) and (4), govern the flow conservation of node $i \in N^k$. In Eqs. (5) to (7), capacities of the network components are formulated. Eq. (8) governs the physical interdependency between nodes. In Eqs. (9) to (18), the restoration process of disrupted components is formulated, where Eqs. (9) and (10) ensure the work crew assignment for to be restored components, Eq. (11) ensures that a single work crew can restore at most one disrupted component in network $k \in K$ at a specific time $t \in T$, Eqs. (12) and (13) ensure the operability of a component when its restoration is completed, and Eqs. (14) to (18) ensure that for a disrupted component to be functional, its restoration should be completed. Finally, the nature of decision variables in the optimization model is represented in Eqs. (18) to (25).

4 ILLUSTRATIVE EXAMPLE

The proposed model is applied to data collected for Shelby County, Tennessee in the United States, whose geographic location is the epicenter of the New Madrid Seismic Zone [16].

The three distinct critical interdependent infrastructure networks, water, gas and power distribution systems, are represented in Figure 2. There is a total of 124 nodes, 37 of which are demand nodes, and a total of 176 links in the three networks. We implement a single scenario with 19 disrupted demand nodes and assign two work crews separately for each network to complete the restoration process simultaneously for all three networks in 28 time periods.

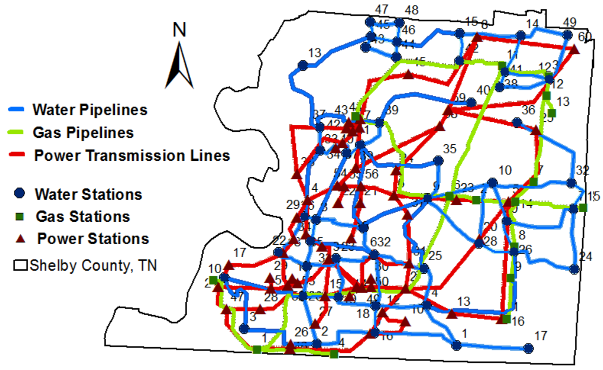

Figure 2: Layout of Interdependent Water, Gas and Power Infrastructure Networks over Shelby County [16].

In Figure 3, the geographic location of the demand nodes of all three infrastructure networks, i.e. water, gas and power, and the PGA measures that are specific to each region due to the New Madrid Seismic Zone is illustrated [13].

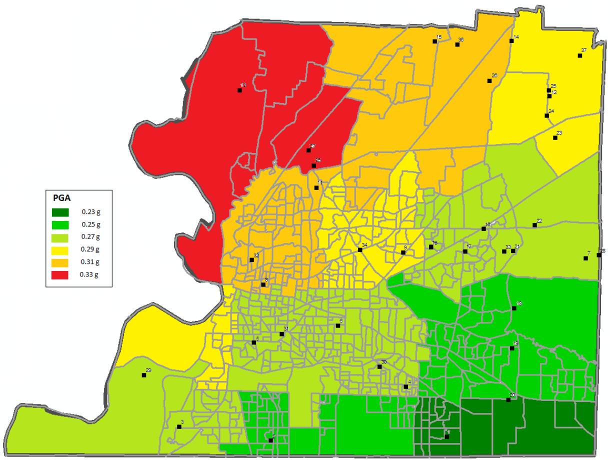

Figure 3: Distribution of Regional PGA Measures among Shelby County [13].

For the SoVI-Lite approach, the eight variables from Table 5 are used in the block group level for Shelby County, TN, where block groups are formed by multiple adjacent blocks with a total of 300 to 6000 residents [8].

To assign the social vulnerability scores and the proportional population densities that are calculated in block group level to each demand node, the block groups are distributed among them according to their location to represent the specific service area of demand nodes. For this distribution process, Voronoi diagram method is utilized [29]. The Voronoi diagram method calculates the distance from predetermined input points to any point in the sample space. Later, it sets the boundaries for the coverage area of input points in such a way that any point in the sample space is covered by its closest input point.

Table 5: SoVI-Lite Variables for Block Groups

Percentage of households that earn less than \$75.000 annually
Percentage of population that is African-American
Percentage of population that is Asian
Percentage of population that is Hispanic
Percentage of population that is over age 65
Percentage of population that is under age 5
Percentage of single-female based households
Percentage of households that live under the poverty line

Also, the social vulnerability indices $SoVI_i^k$ are normalized and relatively more importance is given to the demand nodes that are highly vulnerable by implementing an exponential effect to formulate the social vulnerability scores V_i^k, [23]. Also, a similar approach is utilized to enhance the emphasize on demand nodes with higher peak ground acceleration measure, PGA_i^k. The exponential formulation of the social vulnerability scores and the peak ground acceleration scores are represented in Eq. 26 and in Eq. 27, respectively.

$$V_i^k = e^{a*SoVI_i^k}, \quad \forall i \in N_d^k, a \in Z^+ \tag{26}$$

$$G_i^k = e^{a*PGA_i^k}, \quad \forall i \in N_d^k, a \in Z^+ \tag{27}$$

To account for the social expectations and the human occupancy levels of the service areas of demand nodes, we include the population density measure in the proposed approach as we adopted the idea that the size of the population that is represented by each demand node could also be an effective aspect in the community-resilience perspective. The population density measure is formulated as the ratio of the population that is served by demand node $i \in N_d^k$, over the total population of all service areas.

After the distribution of the block groups to demand nodes, an average of the social vulnerability scores is taken and the population density of block groups proportional to their layout in the Voronoi cells is calculated to assign these measures to the demand nodes. The visualization of the social vulnerability scores among the block groups is illustrated in Figure 4.

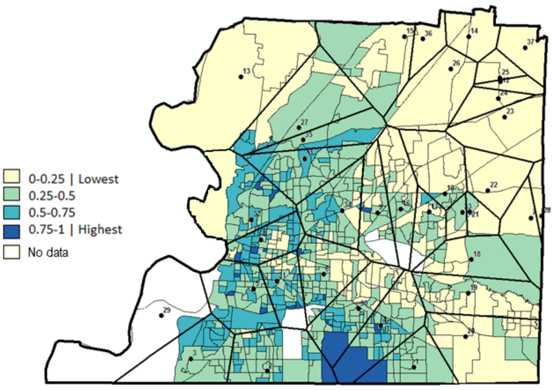

Figure 4: Distribution of Block-Group Social Vulnerability Scores and Demand Node Service Areas among Shelby County [12, 14].

The ϵ-constraint method is used in the resilient objective to transform it into a constraint with the assigned values such that $\epsilon \in [0, 1]$, to solve the multi-objective problem [10]. As the resilience levels are $\in [0, 1]$, the consistent ϵ-constraint formulation is in Equation 28.

$$\sum_{k \in K} \mu^k \sum_{t=1}^{\tau} \left(\frac{t \left[\sum_{i \in N_d^k} \left(Q_i^k V_i^k P_i^k G_i^k \right) - \sum_{i \in N_d^k} \left(s_{it}^k V_i^k P_i^k G_i^k \right) \right]}{\sum_{i \in N_d^k} \left(\tau Q_i^k V_i^k P_i^k G_i^k \right)} \right.$$
$$\left. \frac{-(t-1) \left[\sum_{i \in N_d^k} \left(Q_i^k V_i^k P_i^k G_i^k \right) - \sum_{i \in N_d^k} \left(s_{i(t-1)}^k V_i^k P_i^k G_i^k \right) \right]}{\sum_{i \in N_d^k} \left(\tau Q_i^k V_i^k P_i^k G_i^k \right)} \right) \leq \epsilon \tag{28}$$

The following Table 6 represents a subset of disrupted nodes in each network and the change in the restoration schedule. The second column, titled as 'With' states recovery scheduling results when social vulnerability and spatial risk measures are taken into consideration, i.e. the defined parameters of V_i^k, P_i^k and G_i^k are included in the model whereas the third column labeled as 'Without' states the restoration order without these measures. The disrupted node which is scheduled earliest in the restoration process is ranked 1 where the disrupted node that is ordered latest in the restoration process is ranked 4. Lastly, Figure 5 represents the change in the network performance for three infrastructure networks when community and spatial resilience measures are considered and not considered in the optimization model.

Table 6: A Subset of Restoration Schedule Comparison for Critical Infrastructure Networks

Water Node ID	With	Without	Gas Node ID	With	Without	Power Node ID	With	Without
45	1	2	1	1	2	34	1	4
10	2	1	15	2	4	14	2	2
48	3	4	13	3	3	5	3	1
27	4	3	9	4	1	20	4	3

Note the difference in the ranking of disrupted nodes when the additional social and environmental measures are included in restoration problem of interdependent infrastructure networks. Not only the recovery order of demand nodes is changed, that is assigned with social vulnerability and spatial risk scores as their importance measure, but also ranking of the transshipment nodes and supply nodes that are effective in the delivery of the commodity and responsible from providing the needs of these relatively more important demand nodes differ.

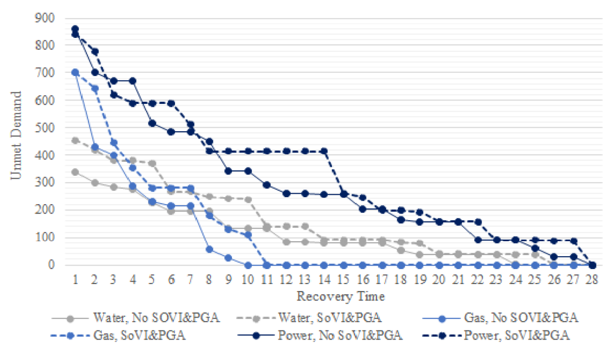

Figure 5: Illustration of the Change in the Network Performance

In this study, we encounter when additional social vulnerability and spatial risk measures are considered, optimum restoration schedule differs for each network. As the restoration schedule differs, the total unmet demand in each network hence the network performance through time differ when the results of both models are compared.

5 CONCLUSION

Modern day societies heavily depend on the continuous and proper functioning of critical infrastructure networks in terms of maintaining their existence and day-to-day operability. These physical infrastructures contain an interdependency such as they would be attached to each other logically, physically, geographically or informatively. Additionally, there exists a bi-directional relationship between the community networks and physical infrastructure networks for supply and demand manners. Therefore, the critical infrastructure networks become more vulnerable against external stressors where any disruption that would occur in these networks would impact the societies and the resilience and vulnerability levels of the societies would effect the performances of these networks.

In this study, to achieve more comprehensive understanding of the interdependent infrastructure network resilience we proposed a resilience-driven multi-objective mixed-integer programming model that is integrated with the vulnerability levels of its surrounding environment. To plan accordingly with the social expectations against disruptions and the geographical risks associated with the spatial location of these networks, the proposed approach takes into account a geographically distributed (i) social vulnerability index to represent the behavioral responses of the various socio-economic dynamics in the society, and (ii) geographic risk index measure to illustrate the differing potential disruption levels of a spatial hazard.

As for the results of our proposed study, we observe that considering the social vulnerability, population density measures of the surrounding community and the potential geographic risk of the spatial location of these networks requires a different restoration scheduling to recover from external stressors in a timely manner. The newly achieved restoration schedule of the disrupted components, and the performance of critical networks through time are both planned based on the resilience enhancement of both surrounding community and the physical networks. For future work, we believe that as more aspects of vulnerability is considered additionally in the proposed study, more extended research with higher humanitarian motivation would be accomplished.

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