Analyzing Infrastructure Interdependencies Using Network-Of-Networks Modeling

Evan Scherrer
evan.scherrer@drake.edu
Drake University
Des Moines, Iowa, USA

Melissa Allen-Dumas
allenmr@ornl.gov
Oak Ridge National Laboratory
Oak Ridge, Tennessee, USA

Bharat Sharma
sharmabd@ornl.gov
Oak Ridge National Laboratory
Oak Ridge, Tennessee, USA

Abstract

Infrastructure networks play a crucial role in our day-to-day lives, and modeling these infrastructure networks can help decision-makers prepare for and respond to disruptions such as natural disasters or cyberattacks. Because these infrastructure networks depend on each other, it is not sufficient to model a single network in isolation. We build on previous single-network-modeling techniques to develop a methodology for modeling infrastructure interdependencies as a Network-of-Networks. Using distribution-level data from a real U.S. city on the power grid, road geometry, and hospital locations, we show how to apply this methodology to modeling three of the U.S. Department of Homeland Security's Critical Infrastructure Sectors: Healthcare, Transportation, and Energy. We also analyze three primary metrics before and after a simulated disaster: 1) impact on hospital access; 2) road network impact with the change in betweenness centrality; 3) electric customer outage. We simulate three different disruptions: 1) road flooding from nearby rivers; 2) a malicious actor targeting the road networks; 3) a malicious actor targeting the electric grid. Finally, we discuss how our methodology can be applied to additional infrastructure networks and types of disruption, and how Artificial Intelligence (AI) techniques may be incorporated into this methodology for further research.

CCS Concepts

• **Computing methodologies → Modeling methodologies**.

Keywords

Network Science, Modeling Robustness, Infrastructure Resilience, Artificial Intelligence, Electric Grid, Road Networks

ACM Reference Format:
Evan Scherrer, Melissa Allen-Dumas, and Bharat Sharma. 2025. Analyzing Infrastructure Interdependencies Using Network-Of-Networks Modeling. In *The 3rd ACM SIGSPATIAL International Workshop on Advances in Urban-AI (UrbanAI '25), November 3–6, 2025, Minneapolis, MN, USA.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3764926.3771946

UrbanAI '25, November 3-6, 2025, Minneapolis, MN, USA

ACM ISBN 979-8-4007-2189-2/2025/11
https://doi.org/10.1145/3764926.3771946

1 Introduction & Background

Network science can be used to describe a variety of complex relationships in both the natural world and the built environment. It can represent anything from the complex web of social connections to the ways that computers communicate with each other over the internet. Prior work utilizes network science to analyze the robustness and efficiency of modern urban infrastructure networks: Yadav et al. [14] use network science with historic flood data to analyze the London Rail Network's resiliency, and Rahimitouranposhti et al.[7] perform a similar analysis on the US's freight transportation network. Warner et al.[12] depict the cascade of infrastructure systems through networks.

However, it is important to take into account that no infrastructure network operates independently of the others, so when analyzing them, it is important to understand the complex interdependencies that tie our infrastructure networks together. Rinaldi et al. [9] describe four different types of interdependencies that should be considered when analyzing complex infrastructure networks: physical interdependencies, where one network's functionality depends on the material outputs of the other; cyber interdependencies, where one network's functionality depends on information transmitted through information technology infrastructure; geographic interdependencies, where two networks depend on each other if they are geographically colocated; logical interdependencies, which capture any type of interdependency that is not physical, cyber, or geographic; examples include financial or social connections between networks.

Lee et al. [5] describe a method, including several different heuristics, for estimating interdependencies between multiple infrastructure systems on a national scale, but their model lacks the detail of a local model of those network interdependencies. We present a network-science-based methodology for modeling interconnected systems of city infrastructure. Specifically, we choose to apply this methodology to subsets of three of the Department of Homeland Security Critical Infrastructure Sectors [10] using data for a specific city in the United States: we model the distribution-level power grid (Energy Sector), the road network (Transportation Systems Sector), and hospitals (Healthcare and Public Health Sector). Due to publicity restrictions on the data used, the city used in this report will remain anonymous.

2 Data & Methodology

This report is a case study of developing our methodology on a subset of the city's infrastructure networks. As Figure 1 shows, we model each infrastructure network individually, connect them into a network-of-networks, apply disruptions to the network-of-networks, and develop and measure metrics based on research questions we would like to answer.

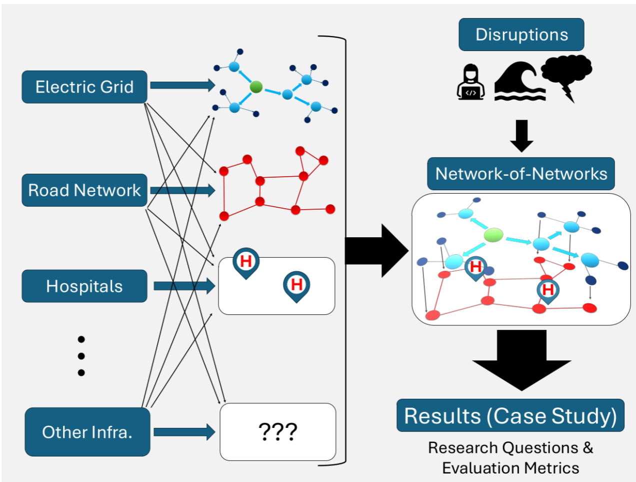

Figure 1: Our proposed methodology workflow for modeling interconnected systems of city infrastructure

2.1 Data

2.1.1 Road Geometry. The road geometry used was the U.S. Geological Survey's National Transportation Dataset[11]. The dataset was provided as a collection of Environmental Systems Research Institute (ESRI) shapefiles.

2.1.2 Electric Meter Locations and Power Line Geometry. The distribution-scale electric grid dataset was provided by a local utility company as a .mdb file containing layers for power line geometry, electric transformers, and additional information not used for the study. We used ArcGIS's [8] FeatureClassToShapefile function to open the .mdb file, aggregate three different types of primary conductors (power lines), extract the power line geometry, and export it as an ESRI shapefile.

2.1.3 Hospital and Substation Locations. Hospital and power substation locations were obtained from the U.S. Department of Homeland Security's Homeland Infrastructure Foundation-Level Data (HIFLD) dataset. The datasets were provided as ESRI shapefiles.

2.2 Methods

We first represented each infrastructure system as a separate network. Next, we identified neighboring nodes across the graphs and connected them using an adjacency list. To construct the model, we used a) GeoPandas [4] library, which is built on the popular Pandas data analysis library, to read ESRI shapefiles into tables called GeoDataFrames and to manipulate and export the GeoDataFrames into a variety of formats; b) NetworkX [3] library for creating and manipulating graphs and networks. One algorithm included in NetworkX was Brandes' edge betweenness centrality algorithm, which we used as a proxy for representing traffic; and c) Momepy (Morphological Measuring in Python) library to convert between GeoDataFrames and NetworkX graphs.

2.2.1 Road Network. To model the road network, we first read the shapefile containing road geometry data into a GeoPandas GeoDataFrame and used Momepy to convert the GeoDataFrame into a NetworkX MultiGraph while preserving intersection locations as node attributes. Once the graph was constructed, we used NetworkX's built-in measure of edge betweenness centrality as a crude model for traffic flow. Betweenness centrality answers the question: "of the shortest paths between all pairs of nodes, how many pass through this edge?"

The betweenness centrality of an edge is defined as:

$$c_B(e) = \sum_{s,t \in V} \frac{\sigma(s,t|e)}{\sigma(s,t)}$$

where V is the set of nodes, $\sigma(s,t)$ is the number of shortest (s,t)-paths, and $\sigma(s,t|e)$ is the number of those paths passing through edge e [2].

We used the edge betweenness centrality as a crude traffic model because as edges are removed, the paths that passed through those edges must use other edges instead, increasing those other edges' centrality. This process is analogous to road closures causing traffic to be redirected and increasing traffic on other roads near the closure. However, this method assumes that all destinations are equally weighted, which is not the case in the real world. This method also misses the impacts of speed limits, road capacity, etc.

2.2.2 Electric Grid. To represent the electric grid, we used a combination of three different datasets: the power line geometry; the substation locations; and the electric meter locations. As with road networks, we read the power line shapefile into a GeoDataFrame and used Momepy to convert the GeoDataFrame into an undirected graph whose nodes represent transformers and whose edges represent power lines. Since the power lines dataset had no information about the amount or direction of electricity flow, we made a few assumptions: a) the electric grid will be represented as a collection of directed, rooted trees; the root of each tree is a substation, and there is at most one path from the root to any given node in that tree; b) power only flows away from the substation (root); thus, these trees have no reciprocal edges; c) there is no power limit for substations; each substation can power all nodes connected to it simultaneously.

To convert the undirected graph of the power line geometry into a directed graph, we first made a copy of all the nodes and their locations (but not the edges between them) from the undirected graph. Then, beginning at the locations of the substations, we added edges to the directed graph in a method similar to breadth-first-search. Finally, we added a node to our directed graph for each electric meter, and an edge into each electric meter from the nearest power line.

2.2.3 Modeling Network Interdependencies. Because NetworkX has no built-in way of modeling a network-of-networks, we must implement that functionality on our own. First, we represent the road network's dependencies on the electric grid as an adjacency list L, where each road segment depends on the power line nearest to it, by Euclidian distance. These dependencies represent the reliance of a road's stoplights and emergency/night lighting on the electric grid. While this is likely an oversimplification, we do not have data on actual network dependencies; we will discuss this data limitation further in section 3. When a given node in the electric grid is disrupted, the child nodes in both the electric grid and the road network (via L) are also disrupted. Likewise, we implemented the same technique for modeling the hospitals' dependence on both the nearby roads and the electric grid. The same technique could be used to model the electric grid's dependencies on the road network (such as for maintenance access), although we did not do so.

2.2.4 Research Questions & Metrics. To test the efficacy of the modeling framework, we develop three research questions that a model such as ours could answer. For each research question, we develop a metric that can be used to quantify an answer to each of those questions.

Question I: How does a disruption to the Network-of-Networks infrastructure model impact the road network? To answer this question, we want to look specifically at how traffic flow is impacted. Since we already use edge betweenness centrality as a model for traffic flow, we can use that as a metric for how the network is impacted. In general, we expect to see the betweenness centrality of edges in the graph rise as roads close. The traffic that would have passed through them now must be redirected to other roads; thus, the betweenness centrality of those roads will rise.

Question II: How does a disruption to the Network-of-Networks infrastructure model impact the electric grid? To answer this question, we examine the number of customers without power. We express this metric as a ratio of $\frac{n}{m}$, where n is the number of customers who lost power because of the outage, and m is the total number of customers with power before the outage.

Question III: How does a disruption to the Network-of-Networks infrastructure model impact households' hospital access? To answer this question, we use electric meter locations as a proxy for households and develop two metrics: a) the number of electric meters with unobstructed road access to any hospital; and b) the average minimum distance from each household to the nearest hospital. We calculate b) by first generating a minimum-cost tree T_h for each hospital h using Djikstra's algorithm that maps electric meter nodes to their minimum-cost distance from h. Then, we compute:

$$\frac{\sum_{m \in M} min[T_{h_1}(m) \cdots T_{h_n}(m)]}{|M|}$$

where M is the set of all electric meters with a valid path to a hospital, $|M|$ is the number of electric meters in M, and $T_h(m)$ is the distance from electric meter $m \in M$ to hospital h provided by minimum-cost tree T_h.

2.2.5 Disruption & Analysis. Finally, we use the Network-of-Networks model and the metrics developed to answer the sample research questions posed in section 2.2.4. We apply a variety of different disruptions[1] to the model and measure the three metrics for each disruption. First, we use a river map of the city to draw a polygon around the most likely areas to flood. We also model a malicious actor attempting to cause the most damage to the road network by disrupting the 25 most influential edges[2], and to the electric grid by disrupting the most influential node[3]. The results of modeling each of those disruptions can be seen in Table 1. To help illustrate this operation conceptually, a sample disruption to a smaller section of the electric grid can be seen in Figure 2.

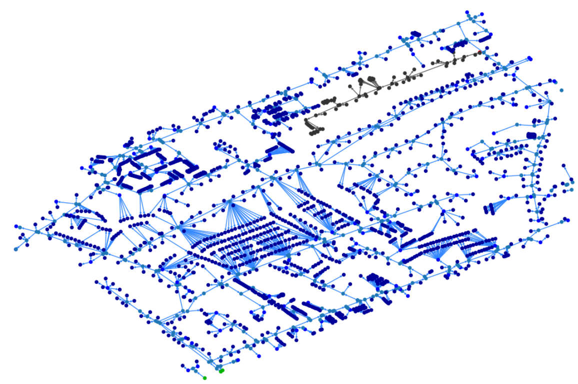

Figure 2: A graph representation of a small section of the electric grid after a disruption in the upper-right corner: blue arrows represent edges in the graph, blue nodes represent power poles and electric meters, green nodes represent power from a substation, and dark gray nodes and edges represent those impacted by the disruption

As expected, the Meters Without Hospital Access metric increased significantly for each type of disruption. However, the Average Hospital Distance did not increase as much as we expected (and in the case of a flood, it even decreased). We suspect this is because as large sections of the city - potentially far away from a hospital - are completely cut off from hospitals, they are no longer included in the average calculation, meaning that the customers remaining are on average closer to the hospital than prior to the disruption. As expected, the average road betweenness centrality increased, but the flood caused a much higher increase than expected. Finally, because in our model the electric grid was not dependent on the roads, road disruptions (flooding and a malicious actor) did not impact the number of electric meters without power. Due to modeling assumptions and data limitations, the conclusions presented in this paper should be taken with caution. Further, while the city we were examining has had floods and power outages in the past, we were unable to find data about specific power grid outages or road closures. As such, we were unable to perform external validation on this model; however, the example simulated is based on scenarios known to occur in the geographic area.

3 Conclusion & Future Work

We demonstrated a methodology for modeling interconnected networks within a city's infrastructure that can be expanded upon in the future. We used that methodology to model infrastructure

[1] on separate instances of the model - these disruptions do not compound with each other

[2] via betweenness centrality

[3] the node with the greatest number of electric meters downstream

Table 1: Key metrics for measuring the impact of a disruption to our infrastructure networks

Metric	Before Disruption	Flood	Max Road Centrality	Max Electric Grid Impact
Meters w/o Hospital Access	19	6557	422	3746
Avg. Hospital Distance	0.0172	0.0112	0.0281	0.0187
Road Btwn. Centrality	0.0140	0.6078	0.0250	0.0458
Meters w/o Power	$\frac{0}{11131}$	$\frac{0}{11131}$	$\frac{0}{11131}$	$\frac{3619}{11131}$

networks from three of the Department of Homeland Security's Critical Infrastructure Sectors: the road network, electric grid, and hospitals. We further developed some potential research questions and used the model and several potential disruption scenarios to answer those questions. As the primary focus of this paper is on the methodology, conclusions from our analysis should be taken cautiously. In the future, there are two main areas for improvement that we would like to briefly discuss: 3.1) Data & Modeling, and 3.2) Metrics & Analysis. We would also like to discuss how different AI techniques may be incorporated to enhance the work already done.

3.1 Data & Modeling

One big limitation we faced is the lack of detailed data about the traffic and electricity flow throughout their respective networks. While this doesn't change the development of the methodology, it does have a large impact on the conclusions we can justify drawing from the models we create. For a longer-term study, we would want to gather more sophisticated data about more types of infrastructure networks; this would allow for more accurate modeling.

Future modeling of these networks could take an agent-based approach instead. Agent-based modeling is an approach to modeling complex systems that involves simulating the actions and behavior of individual entities (agents) within those systems [1]. Agent-based modeling is already used to create sophisticated traffic models with software like SUMO [6], and similar work could be done with a more sophisticated electric grid model - substations and transformers are individual agents, each deciding how to route power through the rest of the grid. Neural networks and deep learning can be used for either type of agent (cars or substations/transformers) to model more sophisticated and realistic decision making.

3.2 Metrics & Analysis

Another potential avenue this project can expand is in the type of analysis we do on the model. More accurate information about the kinds of disruptions our infrastructure can face as well as the metrics we use to measure the impacts of those disruptions can enable us to answer more sophisticated research questions - which can, in turn, be used to better inform emergency responders and policymakers in the event of a real-world disruption.

Recent research involving Graph Neural Networks (GNNs) has also shown promise [13]. GNNs are a specific type of neural network that use information about a graph's nodes and edges (often in the form of an adjacency list) to make a prediction about some property (or properties) of that graph. This aligns very closely with our goals in this project - we want to predict the impact of a disruption on our interconnected networks, and the complexity of GNNs may allow us to evaluate more complex impact metrics. It should be noted that to train the GNN we would still need real-world data about disruptions and their impacts; for instance, we could use real data about flooded roads and crashes to predict crashes as a result of our simulated disruption - even if our simulation doesn't incorporate crashes directly.

Acknowledgments

This research was supported in part by the US Department of Energy, Office of Science, Office of Workforce Development for Teachers and Scientists (WDTS) under the Science Undergraduate Laboratory Internships (SULI) program hosted at Oak Ridge National Laboratory (ORNL) and administered by the Oak Ridge Institute for Science and Education (ORISE).

References

[1] Steven C. Bankes. 2002. Agent-based modeling: A revolution? *Proc. National Academy of Sciences* 99 (2002), 7199–7200. doi:10.1073/pnas.072081299
[2] Ulrik Brandes. 2008. On variants of shortest-path betweenness centrality and their generic computation. *Social Networks* 30, 2 (2008), 136–145. doi:10.1016/j.socnet.2007.11.001
[3] Hagberg, A. A. et al. 2008. Exploring Network Structure, Dynamics, and Function using NetworkX. In *Proceedings of the 7th Python in Science Conference*, Gaël Varoquaux, Travis Vaught, and Jarrod Millman (Eds.). Pasadena, CA USA, 11 – 15.
[4] Jordahl, K. et al. 2020. *geopandas/geopandas: v0.8.1.* doi:10.5281/zenodo.3946761
[5] Lee, S. M. et al. 2024. Capturing Infrastructure Interdependencies for Power Outages Prediction During Extreme Events. In *2024 IEEE International Conference on Big Data (BigData)*. 2152–2161. doi:10.1109/BigData62323.2024.10825596
[6] Lopez, P. A. et al. 2018. Microscopic Traffic Simulation using SUMO, In The 21st IEEE International Conference on Intelligent Transportation Systems. *IEEE Intelligent Transportation Systems Conference (ITSC).* https://elib.dlr.de/124092/
[7] Rahimitouranposhti, M. et al. 2025. Investigating Resiliency of Transportation Network under Targeted and Potential Climate Change Disruptions. *Transportation Research Record* (2025). doi:10.1177/03611981251355510
[8] Redlands, CA: Environmental Systems Research Institute. 2015. ArcGIS Desktop: Release 10.3.
[9] Rinaldi, S. M. et al. 2001. Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control Syst. Mag.* 21, 6 (2001), 11–25.
[10] US Department of Homeland Security. 2025. Critical Infrastructure Sectors. https://www.cisa.gov/topics/critical-infrastructure-security-and-resilience/critical-infrastructure-sectors
[11] US Geological Survey. 2025. USGS National Transportation Dataset. https://data.usgs.gov/datacatalog/data/USGS:ad3d631d-f51f-4b6a-91a3-e617d6a58b4e
[12] Warner, M. et al. 2019. Evaluation of Cascading Infrastructure Failures and Optimal Recovery from a Network Science Perspective. In *Dynamics On and Of Complex Networks III*. Springer International Publishing, Cham, 63–79.
[13] Wu, Z. et al. 2021. A Comprehensive Survey on Graph Neural Networks. *IEEE Transactions on Neural Networks and Learning Systems* 32, 1 (2021), 4–24. doi:10.1109/TNNLS.2020.2978386
[14] Yadav, N. et al. 2020. Resilience of Urban Transport Network-of-Networks under Intense Flood Hazards Exacerbated by Targeted Attacks. *Scientific Reports* (2020). doi:10.1038/s41598-020-66049-y

Received 18 September 2025; accepted 11 October 2025; revised 24 October 2025