Multilayer critical infrastructure network modeling for equitable resilience

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1 Introduction

The frequency and magnitude of extreme events have significantly increased all over the globe during the past two decades (Kermanshah and Derrible, 2017). The performance of ~~transportation~~ critical infrastructure networks can be seriously affected by these extreme events (Ilbeigi, 2019). Transportation systems, in particular, are vulnerable to a widespread range of natural events and disruptions such as such as hurricanes, tornadoes, earthquakes, wildfires, traffic incidents, snowing, flooding, infrastructure failures, among others (Bhavathrathan and Patil, 2018), (Twumasi-Boakye and Sobanjo, 2018). For example, Ilbeigi (2019) ~~has~~ developed a quantifying resilience framework for the 2012 Hurricane Sandy, which ~~has~~ hit urban areas in New York City and ~~h~~was identified as the fourth costliest hurricane in U.S. history. He has evaluated transportation dataset for a period of four weeks (two weeks before the hurricane and two weeks after it) and considering the closeness centrality index, he found out that the New York City transportation network was affected by the hurricane for 135 hours. The proposed framework helps decision makers to identify more vulnerable parts of the network, which are more likely to fail first (Ilbeigi, 2019).

In order to develop a more reliable framework for quantifying resilience in our communities, the focus of the resilience studies should be shifted from transportation network to a more comprehensive view in which all critical infrastructures elements are included. For instance, one of the most vulnerable elements in road transportation systems are bridges which can highly affect robustness of the transportation network as a whole (Zhang, Wang, and Nicholson, 2017). Moreover, it is critical to have a resilient transportation network during and after a disaster, to ensure emergency services, rescue operations, and access to major population and activity centers in a city (Ilbeigi, 2019). Although it is very important to make decisions regarding restoration of transportation networks in a short period after event, these decisions have to be made ~~in a way that~~ with regard to various decision-making criteria and resource constraints have been made in to account (Liu et al., 2020). So it is of vital importance for decision makers to have access to a promising decision making framework able of quantifying transportation network resilience. This way, they can ensure availability of a promising transportation network with the optimum capacity, when a disaster occurs.

Network analysis has long been considered an effective approach to studying the behavior of complex systems, such as social, biological and transportation systems. Representing transportation networks through graphs, is one of the primary steps in quantifying transportation networks, which have been conducted by many resilience studies. There are different approaches in modelling transportation networks from considering cities as nodes and traffic roads as edges (Ip and Wang, 2009), and considering potential traffic bottlenecks in a city as nodes and streets as edges (Das, 2020) to considering intersections and state bridges as nodes and interstates, highways or spurs as edges (Antony, 2017). Traditional network analyses, however, fail to provide a comprehensive overview of a complex system, as they ignore the presence of multiple type of edges of a system in which entities have a different set of neighbors in each layer (Domenico et al., 2013). Focusing on multilayer networks in the field of network resilience is very important due to the criticality and complexity related to these infrastructures. Transport processes in a multilayer framework reveal complex interdependencies compared to those in a single layer representation (Wu et al., 2020), yielding important insights for better decision-making.

Moreover, one important criterion, which has been neglected in quantifying critical infrastructure resilience, is social equity. People's vulnerability is affected by their exposure to hazards and their ability to avoid or manage the effects of the hazard (Cutter, 1995). Studies have shown that class, race and ethnicity, gender, disability, political power, personal wealth, age, housing ownership and occupation can affect vulnerability against hazards (Bolin and Kurtz, 2018; Cutter, 1995). Although there are many studies that consider social equity in planning transportation networks, there is a significant gap in including social equity as an important factor in developing resilience approaches in the overall critical infrastructure systems of a community and their interdependencies. Given that these systems as the main foundation for national security, economy, public welfare and individuals' daily activities (Qiang and Xu, 2019), it is critical to develop a comprehensive quantifying framework for network resilience. Although previous studies provide valuable insights about transportation network resilience, there is an urgent need to broaden this concept by considering equity metrics and also by encompassing critical infrastructure systems including bridges, buildings, etc as a multilayered network to develop a decision making framework for restoration of a transportation infrastructure in case of a disaster.

2 Network resilience modeling

Recently, the focus of transport infrastructure management has switched from protection to resilience (Das, 2020). Moreover, as a result of the developments in resilience engineering studies, the definition of system resilience has shifted from a system's ability to deal with threats to a system's ability to adjust its functionality (Hollnagel et al., 2010). Based on this new definition, a system is resilient when it can respond to what happens, monitor critical developments, anticipate future threats and sustain required functions (Hollnagel et al., 2010). More formally, the resilience of a network or system refers to its capability to withstand, adapt to and recover fully or partially after a disruptive event (Aydin et al., 2018), (Almoghathawi and Barker, 2019), which can be natural or man-made (Ahmed and Dey, 2020). Weilant et al. (2019) have suggested three different aspects associated with the concept of resilience:

- Decreasing the probability of a disaster and increasing the ability of a community to resist a disaster
- Increasing the adaptability of a system while maintaining functions in the pres-

ence of a disaster

- Decreasing the needed time for the system to recovery to normal functioning

Ten dimensions of resilience in transportation systems have been identified. These dimensions are redundancy, diversity, efficiency, components' dependency, strength, stakeholders' collaboration (Ahmed and Dey, 2020), adaptability, mobility performance, safety performance, and the ability to recover quickly (Ahmed and Dey, 2020), (Murray-tuite, 2006).

2.1 Modeling approaches

Critical infrastructure are those that if destroyed or rendered unavailable will significantly impact social or economic welfare or affect national security, national public health or safety. (Škrlj et al., 2019). Having a resilient critical infrastructure is vital for a society in order to resist, respond to, and recover from disruptive events (Tingting and Yu, 2020). Transportation infrastructure has been identified as one of critical infrastructure systems essential to the well-being of modern societies (Zhang and Wang, 2016).

Research on transportation system resilience began in the 1990s (Ahmed and Dey, 2020). Since the concept of resilience engineering has emerged, different related concepts and methods has been addressed by many scholars and most of the studies on transportation system resilience studies focused on the resilience of the roadway-based transportation system (Ahmed and Dey, 2020). At the beginning of this journey, most of the studies focused on providing qualitative overview of resilience (Baroud et al., 2014), (Bhatia et al., 2015) but providing a quantitative overview of resilience is attracting more attention during past years and several quantifying framework for transportation networks resilience have been proposed by scholars (Adjetey-Bahun et al., 2014), (Cavallaro et al., 2014), (Bhatia et al., 2015), (Donovan and Work, 2017).

Network system resilience can be modelled considering two phases: pre-disaster phase and post-disaster phase (Ahmed and Dey, 2020). Some studies have further categorized the post-disaster phase into two sub-phases: response and restoration. The response phase is shortly after the disruptive event and restoration phase follows the response phase. During restoration phase the infrastructure is waiting for repair, but daily travel demand has recovered to a relatively normal level, although some demand cannot be satisfied by the degraded infrastructure network (Tingting and Yu, 2020). Optimal recovery strategies to a disaster within a given network may differ by hazard, community /cluster/neighborhood or objective (Bhatia et al., 2015). So it is critical to develop a decision making framework, which is capable of reflecting changes per phases and modifying itself based on the situation. As a result, developing a dynamic model, which considers multiple efficient measures for quantifying resilience and the effect of different kinds of disasters from mild to sever, becomes more and more important.

In order to come up with an efficient model, it is critical to evaluate all relevant historical data. With increasing availability of data, machine learning technique is applying in many areas. Machine learning is a technique to predict the behaviour of a system based on an analytical model build upon learning from the latest patterns of historical data (Tizghadam et al., 2019). One of the most prevalent application of machine learning techniques, is in time prediction based on current and past data. A significant number of studies have focused on predicting future delays in transportation networks (Chandramouleeswaran et al., 2018; Takeichi et al., 2017; Choi et al., 2016).

Machine learning is also applied in many other areas such as smart transportation, intelligent transportation networks, car sharing placement, public transport locationing (Tizghadam et al., 2019), traffic assignment, predicting behavior of an individual driver in various traffic flow conditions, providing driving decision algorithm for self-driving cars and predicting speed in roadways (Bhavsar et al., 2017). Machine learning techniques have also been employed toward system resilience. For example, there is a study that focus on estimating clearance time after an incident is investigated (Tang et al., 2020). This way, there can be a real-time decision support for incident management, which helps saving lives and reducing incident recovery time (Bhavsar et al., 2017).

2.2 Modeling approaches

Different methods have been applied in studying the resilience of a transportation system. Ahmed and Dey (2020) have categorized modeling framework for quantifying transportation resilience studies into two different categories:

- Step-wise assessment (qualitative assessment, simulation)
- optimization

Bhavathrathan and Patil believe that resilience in a system can be quantified by evaluating the magnitude of faults that a network can survive before collapsing from a state of normal operation. Considering this fact, they have presented a weighted fictitious game theory based algorithm for solving the critical state identification problem (Bhavathrathan and Patil, 2018).

Serulle et al. have applied fuzzy logic to develop a quantifying resilience framework. Their fuzzy-based model, allows recognizing different values (estimates, lower quality data, linguistically captured data) and assigns a measurement range to each qualitative or quantitative resilience metric and combines them into a resilience index for transportation infrastructure (Serulle et al., 2011).

Antony (2017) has presented a disaster restoration framework through modelling a road transportation network with bridges as nodes and interstates or highways as edges using graph theory analytic and Eigen-vector centrality applying open source Python package of OSMnx (Antony, 2017).

Chen et al(2018) have investigated strategic investments on enhancing transportation network resilience against man-made emergency events applying network game theory approach, through which, the interactions among neighbour players in a pre-hinterland container transportation network have been evaluated (Hong et al., 2018).

Aydin et al (2018) have applied topology-based simulation using graph-based connectivity metric of Giant Connected Component(GCC) to evaluate road recovery strategies in rural transportation networks following geohazards specially earthquakes. They have also used Monte Carlo to simulate recovery time and quantifying the uncertainty during the recovery process to each strategy (Aydin et al., 2018).

Tingting and Yu (2020) have developed a bi-objective bi-level optimization framework for transportation system restoration plan to balance measures of unmet demand and travel time and determine optimal resource allocation for roadway restoration (Tingting and Yu, 2020).

2.3 Network-based resilience metrics

The first step in developing a decision-making framework for restoration of transportation networks, is to define relevant resilience metrics in order to reflect the ability of a multilayered network including transportation system and critical infrastructures to respond to and recover from a disaster. Different resilience metrics have been considered for transportation network resilience. These are summarized in Table 1.

TABLE 1 Transportation network resilience metrics

Multilayer network item	**References**
The mean recovery time [1]	Aydin et al. (2018); Ahmed and Dey (2020); Fang et al. (2016); Almoghathawi and Barker, 2019; Baroud et al. (2014); Zhang, Wang, and Nicholson (2017); Ilbeigi (2019); Pant et al. (2014)
Vulnerability/ reliability/ network robustness/ probability of failure [2]	Aydin et al. (2018); Ahmed and Dey (2020); Jenelius et al. (2006); Almoghathawi and Barker (2019); Zhang and Wang (2016)
Unmet travel demand	Ahmed and Dey (2020); Jenelius et al. (2006); Bhatia et al. (2015); Kermanshah and Derrible (2017); Tingting and Yu (2020)
Average transmission time	Ahmed and Dey (2020); Wu et al. (2020); Tingting and Yu (2020); Jenelius et al. (2006)
Change in network capacity	Wu et al. (2020); Ahmed and Dey (2020); Jenelius et al. (2006)
Restoration costs	Aydin et al. (2018); Ahmed and Dey (2020); Baroud et al. (2014)
Components' dependency, Connectivity and accessibility	Ahmed and Dey (2020); Bhatia et al. (2015); Jenelius et al. (2006); Mattsson and Jenelius (2015)
Efficiency of the recovery process	Aydin et al. (2018); Zhang, Wang, and Nicholson (2017)
loss of service cost	Fang et al. (2016); Baroud et al. (2014)
Accessibility to resources	Aydin et al. (2018); Ahmed and Dey (2020)
Safety performance	Ahmed and Dey (2020)
Shortest path	Ahmed and Dey (2020)
Size of population affected by blockages at each node	Aydin et al. (2018)
Road hierarchy	Aydin et al. (2018)
Average transmission speed	Aleta et al. (2017)
Travel cost [3]	Jenelius et al. (2006)
Change in the performance of network [4]	Ilbeigi (2019)
The time averaged level of operability [5]	Pant et al. (2014)
Maximum loss of functionality [6]	Pant et al. (2014)

We define six domains to organize existing critical infrastructure resilience metrics (Figure 1). They are: safety, restoration, performance, equity, network and infrastructure. The gap in equity-related metrics is evident.

Table 2 provides an overview from all researches which have been reviewed in section 3 and compares them based on applied resilience metrics, case studies, applied method, and provides a brief explanation from their results.

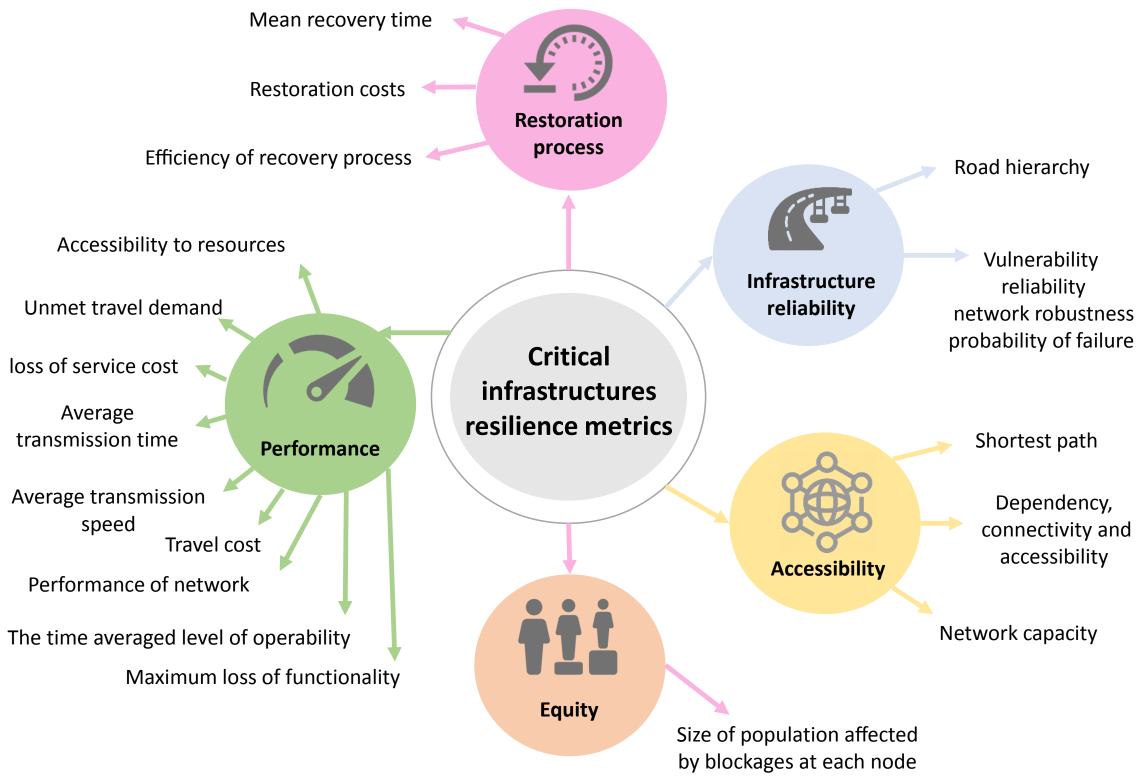

FIGURE 1 Currently used metrics

3 Overview of multilayer networks

Multilayer networks are networks that contain at least two types of nodes or two types of edges (Škrlj et al., 2019). Multilayer networks are widespread in real world systems such as communication systems, social systems, transportation systems, and biological systems (Wu et al., 2020). As shown in Table 3, several components can be considered in modeling multilayer networks:

3.1 Multilayer modeling of transportation networks

There are different approaches in modelling transportation networks as a multilayer network. (Wu et al., 2020) describes two typical multilayer network models:

- Multilayer model with a logical layer and a physical layer
- Multilayer model with abstraction of real multilayer networks, in which entities can travel across multiple network layers (for example a high speed layer and a low speed layer)

Kurant and Thiran (2006) have proposed a generalized multilayer network model in which the lower layer represents the physical infrastructure and the upper layer represents the traffic flows and applied it to three transportation systems. This generalized framework facilitates description, comparison and analysis of complex systems such as transportation networks (Kurant and Thiran, 2006). Ip and Wang (2011) have represented transportation networks by an undirected graph with the nodes as cities and edges as traffic roads and calculated the network resilience of a city node by the weighted average number of reliable passageways with all other city nodes in the network (Ip and Wang, 2011). Aleta et al. (2017) have presented a model for representation of the transportation system of an entire city by considering each line of each mode of transport (bus, metro, and tram) as a single layer and each stop as a node. Based on their multilayer model, there will be a weighted link (based on distance) between two nodes on a layer if the corresponding line passes through both of them. They have also added a new layer which represents the land to introduce the possibility of moving through the city by walking. This model has been applied to study the interconnected structure of 9 different cities in Europe (Aleta et al., 2017). Li et al. (2019) have developed an innovative approach in resilience planning of multilayer transportation networks by simulating the network dynamics of inter-organizational coordination among interdependent infrastructure systems including transportation, flood control, emergency response, community development, and environmental conservation. They have examined their model to 35 organizations from five infrastructure systems within Texas, based on the data gathered from a Hurricane Harvey and evaluated the weaknesses in coordination between entities (Li et al., 2019). Asgari et al. (2016) proposed an unsupervised mapping algorithm (CT-Mapper) to map sparse cellular trajectories and modeled a transportation network by a large multilayer graph, in which there are three different layers of train, subway and road. In this multilayer model, nodes are metro/train stations or road intersections and edges are connections between them (Asgari et al., 2016).

3.2 Multilayer network approaches for critical infrastructure resilience

This is where we need to highlight a gap

4 Multilayer network model for an equitably resilient system: a conceptual framework

5 Conclusion

References

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TABLE 2 Overview of the researches

Reference	Resilience index	Methods	Multi-layer	Disaster	Case study	Results
Serulle et al (2011)	Road available capacity, Road density, Alternate infrastructure proximity, Level of intermodality, Average delay, Average speed reduction, Personal transport cost, Commercial–industrial transport cost, Network management	Fuzzy logic	No	Flooding	Santo Domingo, Dominican Republic	Identifying available capacity, alternate infrastructure proximity, and network management as the most important metrics
Antony (2017)	Centrality measures	Graph theory analytic	No	natural or man-made disaster	Air and road transportation system of the U.S	Identifying nodes with highest Eigen-vector centrality measures as the most important nodes to restore.
Chen et al(2018)	Vulnerability	Network game theory	No	Man-made emergency events (labor strikes)	China's pre-hinterland container transportation network	Providing behavioral analysis of different players in strategic investment decisions
Aydin et al (2018)	proximity to the main research center, time to recovery	Topology-based simulation using graph-based connectivity metric of Giant Connected Component(GCC) and Monte Carlo simulation	No	geohazards specially earthquakes	Sindhupalchok District in Nepal	Providing a framework for evaluating road recovery strategies
Bhavathrathan and Patil (2018)	travel time at an upper envelope of operable disruptions	Game theory	No	-	Anaheim city road network	Developing a quantifying resilience framework based on the magnitude of distruptions
Tingting and Yu (2020)	Unmet demand, Total travel time	bi-objective bi-level optimization framework	No	Hurricane, Earthquake, Flood	Road network in Sioux Falls	Determining optimal resource allocation framework for roadway restoration

Multilayer network item	**References**
Roads Bridges	Antony (2017); Zhang, Wang, and Nicholson (2017)
Walkways Bike paths Private roads	Antony (2017)
High speed and low speed as different layers in a multilayer network	Wu et al. (2020)
Public transit Passenger and freight car transportation systems	Ahmed and Dey (2020)
Railway	Bhatia et al. (2015)

Table 3 Multilayer network components