Modeling the Post-disaster Recovery of Interdependent Civil Infrastructure Network

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ABSTRACT: Modeling the post-disaster performance of interdependent infrastructure systems contributes to strategic community resilience planning. The normal operation of the facilities in different infrastructure systems are dependent upon each other for product input or information sharing. However, when disaster happens, these dependencies would aggravate the initial damage caused by the hazards and lead to cascading failures. Thus, incorporating the dependencies among infrastructure facilities in modeling the damage and recovery of infrastructure systems under disruptive events is essential to guide the strategic pre-disaster risk mitigation and post-disaster recovery planning. The Dynamic Integrated Network (DIN) model is proposed in this study to simulate the damage and recovery of infrastructure network while considering the facility-level dependencies. The DIN model first assesses the inoperability of the network nodes and links over time to simulate the damage and recovery of the dependent civil infrastructure facilities, and then assesses the recovery and resilience of the individual infrastructure systems and the integrated network utilizing some network performance metrics. The proposed DIN model is illustrated with a hypothetical infrastructure network, consisting of interdependent power, water and telecommunication systems under a scenario hurricane hazard. The recovery simulation result from the proposed model is compared to with no interdependency considered, and with only system-level interdependencies considered. This comparative study suggests that the recovery time would be underestimated if no interdependency was considered, or be overestimated if only system-level interdependencies were considered, both of which would lead to poorly informed decision making. The DIN model is then validated through simulating the recovery of the interdependent power, water and cellular systems of Galveston City, Texas after Hurricane Ike (2008). The simulated power system recovery time is comparable to the actual time, which demonstrates that the proposed DIN model can produce comparable results to physical reality.

KEYWORDS: Dynamic Integrated Network; hurricane; infrastructure; interdependency; recovery.

1. INTRODUCTION

Understanding the post-disaster performance of interdependent infrastructure systems contributes to strategic community resilience planning. Recent natural and manmade disasters such as 9/11 terrorist attack (2001), Hurricane Sandy (2012) and Mexico Earthquake (2017) witnessed severe damages to the infrastructure systems, which impaired the normal operation of the society and caused significant economic losses. The interdependencies among civil infrastructure systems and facilities would aggravate the initial damage caused by the disasters and lead to cascading failures. Therefore, modeling the damage and recovery of the civil infrastructure network with considering these interdependencies is essential to support strategic pre-disaster risk mitigation and post-disaster recovery planning.

Recent catastrophic events led to several funded projects on assessing the post-disaster performance of interdependent infrastructure systems, such as the European project SYNER-G (Franchin, 2014), NSF-funded PRAISys project (Karamlou & Bocchini, 2016), and NIST-funded Center for Community Resilience Planning (Ellingwood et al., 2016). The awareness of the infrastructure network vulnerability under disasters also led to many studies on developing methodologies to simulate the damage and recovery of interdependent infrastructure systems. Some methodologies use mathematical formalisms such as hierarchical holographic modeling, Input-output models, Markov chains or Petri nets (Ezell et al., 2000; Haimes & Jiang, 2001; Gursesli & Desrochers, 2003). Other approaches utilize quantities in graph theory, such as the network-based approach or agent-based approach (Dueñas-Osorio et al., 2007; Folga et al., 2009; Santella et al., 2009). In general, the existing approaches to model the performance of interdependent infrastructure systems under disruptive events can be grouped into six types: empirical-based, agent-based, system dynamics-based, economic-based, network-based and others (Ouyang, 2014; Hasan & Foliente, 2015).

The infrastructure interdependency can be classified into three levels depending on the resolution: system-to-system level, system-to-facility level and facility-to-facility level. While considerable studies exist on modeling the performance of interdependent infrastructure systems after disruptions, the majority of them only consider the system-to-system level interdependency. This study proposes the Dynamic Integrated Network (DIN) model which increases the resolution of the interdependency modeling by incorporating the facility-to-facility and system-to-facility level interdependencies for more refined recovery estimation.

Modeling the damage and recovery of critical infrastructure systems with considering different levels of interdependencies is essential for community resilience planning against catastrophic events. However, infrastructure damage and recovery are not deterministic process due to their inherent uncertainties. It is important to reflect these uncertainties and report the variations in the infrastructure performance estimation to better guide the strategic disaster risk management.

In the following sections, the damage and recovery modeling methodologies of the DIN model are first introduced. The application of the model to a hypothetical infrastructure network under hurricane hazard is discussed next. Then, model comparison and validation are presented.

2. DYNAMIC INTEGRATED NETWORK MODEL

The Dynamic Integrated Network (DIN) model is developed to simulate the damage and recovery of the infrastructure network under disruptive events for community resilience planning. The network nodes represent critical infrastructure or end-user facilities while the links represent the dependency relationships between the nodes. The framework of the DIN model is shown in Figure 1.

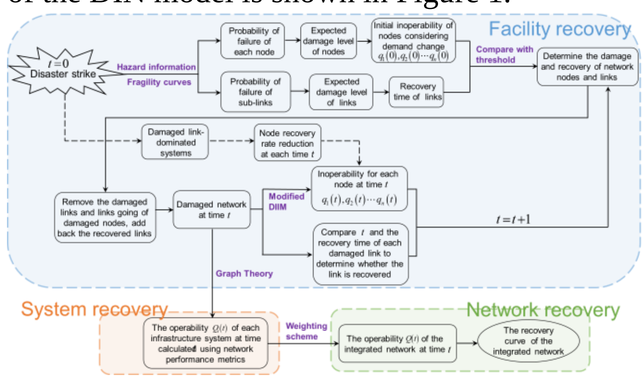

Figure 1: The framework of the DIN model.

2.1. Damage and Recovery of Network Nodes

The damage and recovery of network nodes (representing facilities) over time are measured using inoperability (i.e. the complement of operability). The inoperability of a facility is defined as the inability of the facility to perform its intended functions, which can be calculated as the percentage of the unrealized level of output to the as-planned level of output of that facility to meet its demand (MacKenzie & Barker, 2012). In the DIN model, the initial inoperability of a facility is assumed to be proportional to the physical damage level determined from probability of damage state curves for the corresponding facility structural type. The conditional cumulative distribution function (CDF) of damage states can be obtained for each given hazard intensity and each structural type (MRl, 2011). These CDFs are used to simulate the damage states and estimate the initial inoperability of network nodes with considering the uncertainties.

The recovery of the network nodes is measured by the propagation of inoperability over time, which can be calculated using Eq. (1):

$$\underline{q}(t+1)-\underline{q}(t)=\underline{\underline{r}}\cdot\underline{\underline{B}}\left[\underline{\underline{A}}^{T}\cdot\underline{q}(t)-\underline{q}(t)\right] \qquad (1)$$

where $\underline{q}(t)$ = the inoperability vector at time t; $\underline{\underline{B}}$ = the diagonal recovery coefficient matrix; $\underline{\underline{r}}$ = the diagonal recovery coefficient ratio matrix; $\underline{\underline{A}}$ = the dependency matrix.

The recovery coefficient matrix, $\underline{\underline{B}}$, represents the recovery rate of infrastructure facilities. It can be determined through expert estimation or regression analysis based on empirical data (MacKenzie & Barker, 2012).

The facility-to-facility level dependencies between network nodes are modeled using the dependency matrix, $\underline{\underline{A}}$. Each element in the dependency matrix, A_{ij}, measures the importance of node i to the successful recovery of node j among all the suppliers of node j during the post-disaster recovery phase. It can be calculated as the product of output matrix, $\underline{\underline{O}}$, and the input matrix, $\underline{\underline{I}}$. Each element, O_{ik}, in the output matrix represents the importance of the i^{th} node in producing the k^{th} PIS. Since each PIS is defined for each link and thus has only one supplier node, the importance value of the i^{th} node in producing the k^{th} PIS is either 0 or 1. Each element, I_{kj}, in the input matrix measures the relative importance of the k^{th} PIS in the successful operation of the j^{th} node among all the PISs that the j^{th} node would receive during the recovery phase.

The system-to-facility level dependencies are also considered in the DIN model to reflect the interaction of the systems with different natures. Some infrastructure systems, such as the transportation system (refers to the road network in this paper) and the natural gas and oil system, mainly consist of link components (e.g. roads, pipelines). The dependency of the critical facilities in the other systems on the link-dominated systems can be modeled using the recovery coefficient ratio matrix, $\underline{\underline{r}}$, which quantifies the recovery rate reduction of the facilities in the other systems due to the damage of the link-dominated systems. Besides, some systems, such as food services, agriculture or manufacturing, do not have a network topology but still contribute to the community resilience. The dependency of the facilities in the systems which can be modeled as a network on these systems are implicitly considered in the DIN model. One effect of the damage of these systems that do not have network topology is the demand change of other systems. If the post-disaster demand of a facility i changes from $\tilde{x}_i(0)$ to $\tilde{x}_i^*(0)$, its initial inoperability should be updated to Eq. (2):

$$q_i^*(0)=1-\frac{\tilde{x}_i(0)}{\tilde{x}_i^*(0)}\cdot\left[1-q_i(0)\right] \qquad (2)$$

where $q_i(0)$ = the initial inoperability of facility i based on the pre-disaster demand; $q_i^*(0)$ = the updated initial inoperability of facility i based on the post-disaster demand (He & Cha, 2019).

2.2. Damage and Recovery of Network Links

Network links provide passages to send products, information or services (PISs) from one node to another. Since a link has length and can experience multiple physical damages along its length, the physical damage level of a link is modeled using Bernoulli process. A link would be damaged if failure occurs at any location of the link along its length. The link would not be physically recovered until all causes of failures are resolved and the PIS can flow on this link as is in the normal state.

2.3. Damage and Recovery of Individual Systems and the Integrated Network

The damage and recovery of network nodes and links change the network topology over time, which can be used to measure the operability of each infrastructure system and the integrated network. Assume that each node or link has a threshold operability level below which the corresponding facility or line is damaged and requires repair. The damaged links or links going out of the nonfunctioning nodes are removed from the network. A node would be recovered when its operability first becomes higher than the threshold value. A link would be added back to the network when both its tail node and the link itself are recovered.

The network topology can be reflected using some network performance metrics, such as connectivity, efficiency, accessibility, etc. In this study, the values of the parameters at each time step are normalized by the value calculated from the pre-disaster network and used to describe the operability, $Q_i(t)$, of the i^{th} infrastructure system at time t. Then, the operability of the integrated network, $Q(t)$, can be determined by combining the operability of individual systems using some weighting scheme. A plot of $Q_i(t)$ or $Q(t)$ over time shows the recovery process (i.e. recovery curve) of the i^{th} infrastructure system or the integrated network, which can be used to measure the vulnerability, recovery time or resilience of the system or network (Reed et al., 2009; He & Cha, 2018a). An example output of the DIN model is shown in Figure 2.

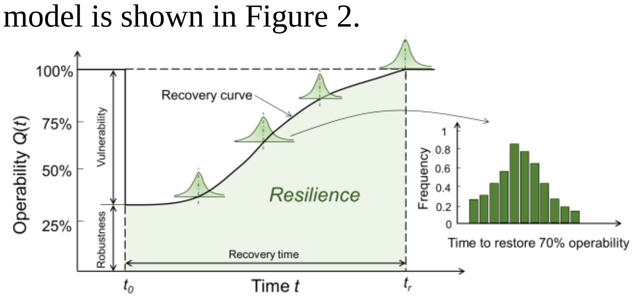

Figure 2: An example output of the DIN model.

3. MODEL APPLICATION AND COMPARISON

3.1. Model Application

The DIN model is illustrated with a hypothetical interdependent power, water and cellular network located in the coastal area in Texas. The critical facilities and their dependencies were identified based on existing literatures (Germanopoulos, 1985; Liu et al., 2005; Kwasinski et al., 2009; He & Cha, 2018b). Building upon the dependency relationships, the hypothetical study region is populated with 2 power plants, 2 raw water collection points, 2 cellular central offices, 6 end-user groups, and several critical facilities between the source nodes of each system and the end-users. In total, 67 nodes and 174 links are modeled in the integrated network, as is shown in Figure 3.

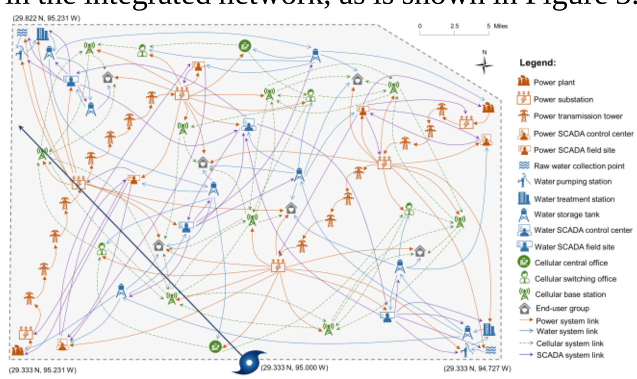

Figure 3: Critical nodes and links in the hypothetical infrastructure network.

The study region is hit by a Category 2 hurricane making landfall at (29.333 N, 95.000 W) with approach angle of -44.64°, as is shown in Figure 3. The gradient wind speed at different locations of the study region was developed using the modified Georgiou's model (Georgiou et al., 1983). The maximum wind speed experienced by each facility location ranges from 40.48 m/s to 45.30 m/s.

The damage and recovery of the infrastructure network subjected to the scenario hurricane hazard were assessed using the DIN model. The input matrix used to calculate the dependency matrix was determined by first assessing the relative importance of the PISs from the modeled systems among all the PISs that a node needs during the recovery phase, then equally distributing the relative importance value among all the modeled systems, since the node could not function properly without any of them. The initial inoperability of a node is calculated as the expected damage level and varies between 0.0095 and 0.7050 based on the type and location of the corresponding facility. The inoperability is updated using Eq. (1) over time to simulate the whole recovery process. The recovery coefficients for different types of nodes were determined using simple linear regression analysis with data samples obtained from HAZUS®-MH2.2 analysis and ATC-13 report (Applied Technology Council, 1985; MRI, 2011; He & Cha, 2018a). The recovery times of links with different damage levels were determined using empirical data from ATC-13 and linear interpolation. The threshold inoperability level of 0.3 was used to determine the nonfunctioning network nodes and links, since an inoperability above 0.3 is regarded as *extensive damage requiring major repairs* according to ATC-13 (Applied Technology Council, 1985). The network efficiency, E, was used to measure the operability of each infrastructure system and the integrated network over time, which is defined as the average of the reciprocals of the shortest path lengths between every two vertices in a graph (Dueñas-Osorio et al., 2007). The recovery curves for each system and the integrated network measured by E is shown in Figure 4.

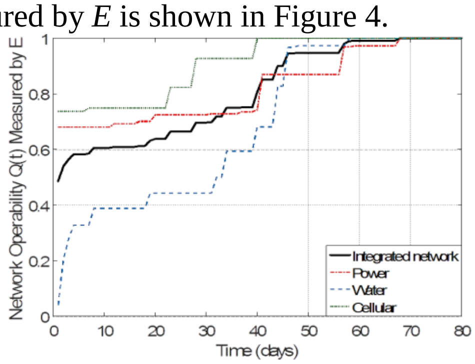

Figure 4: The recovery curves for each system and the integrated network measured by efficiency.

It can be learned from Figure 4 that the vulnerability, recovery time and resilience vary by system. The cellular system has the highest resilience among all three systems since only 4 out of 15 cellular nodes are damaged and could be fully recovered after 39 days. Water system has the highest vulnerability and lowest resilience with 10 out of 18 water system nodes and 51 out of 59 water system links damaged. The full recovery time for the water system is 57 days. Although the vulnerability of the power system is not as high as the water system (2 out of 28 power nodes and 16 out of 60 power links are damaged), the recovery time (67 days) is the longest, which drags down the recovery of the integrated network. The simulation results can be used to support disaster risk management decision making. For example, if this community wants to achieve faster recovery, more repair crews and resources should be allocated to enhance the performance of the water and/or power system.

3.2. Model Comparison

To highlight the importance of incorporating facility-level dependencies in the recovery modeling, the recovery estimation from the DIN model was compared with that using two other types of conventional models, one without considering dependencies between different systems, and another considering only the system-to-system level interdependencies. All the parameters and assumptions used in section 3.1 still apply to the analyses in this section.

For the case where no dependencies between systems are considered, a counterpart infrastructure network was developed by eliminating the inter-system links in Figure 3, as is shown in Figure 5. The recovery curves of the network with and without considering interdependencies between systems measured by E are shown in Figure 6. The result shows that the recovery time would be underestimated (23 days shorter) and the resilience would be overestimated if interdependencies between different systems are not considered. This trend seems to be reasonable since without considering the inter-system interdependencies, a damaged node is assumed to be able to get everything it needs from other systems for its operation during the recovery process. If the interdependency between the systems is taken into account, however, insufficient supply of necessary PISs from other systems could slow down the recovery process of a damaged node. The underestimation of the recovery time and overestimation of the resilience may lead to an underestimation of potential losses and risks, which will result in poorly-informed recovery planning decisions.

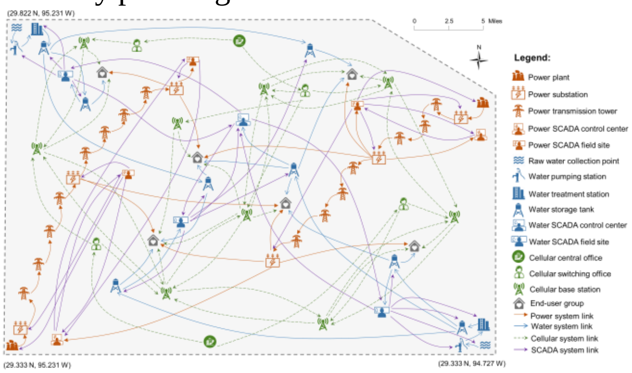

Figure 5: The counterpart infrastructure network without considering inter-system interdependencies.

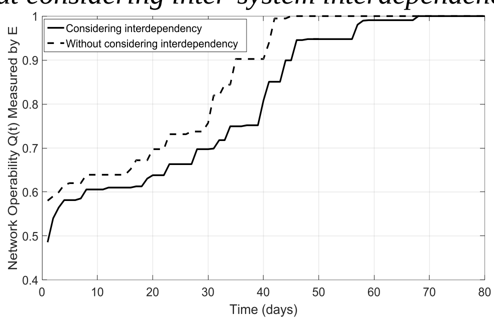

Figure 6: The recovery curves of the integrated network with and without considering interdependencies between systems measured by E.

In the second case, only the system-to-system level interdependencies are considered, just like the case in some existing studies (Haimes & Jiang, 2001; Reed et al., 2009). Figure 7 shows the hypothetical infrastructure network modified from Figure 3 by combining all the facilities in one system as one node. The initial inoperability of a system node in Figure 7 was assumed to be the maximum initial inoperability of all the nodes in the original system. The recovery assessment result in Figure 8 indicates that the recovery time of the integrated network would be overestimated and resilience would be underestimated if only system-level interdependencies are considered. Besides, the recovery of the network is described in a more refined way when the facility-level dependency is considered. These trends are reasonable since by considering the dependencies in facility-level, each system can be partially damaged, the nodes in each system can recover at different time. However, if we view each system as one node, each system at a given time can only have the states of damaged or not damaged, which simplifies the modeling of the whole recovery process and overestimates the overall damage severity of each system. This overestimation may cause the waste of resources due to the over-preparation of the recovery tools and materials, unnecessary social disruptions due to the expected longer recovery time and poorly-informed decisions for disaster risk management.

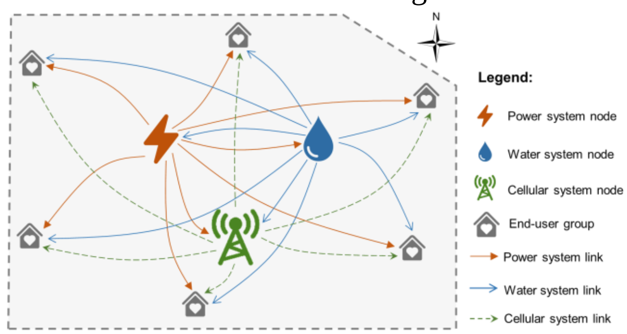

Figure 7: The counterpart infrastructure network with considering only system-level interdependencies.

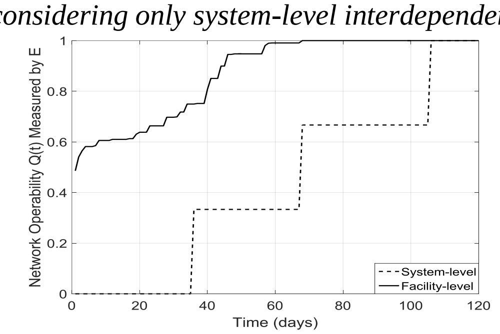

Figure 8: The recovery curves of the integrated network with considering system-level or facility-level dependencies measured by E.

4. MODEL VALIDATION

To validate the model with physical reality, the DIN model was applied to simulate the recovery of interdependent power, water and cellular systems in Galveston City, TX after Hurricane Ike (2008). In total, there are 353 nodes and 578 links in the network, as is shown in Figure 9. Hurricane Ike wind speed in different locations of Galveston range between 120.84 m/s and 174.60 m/s. The range of the flood depth caused by heavy rainfall is between 0.14 m to 4.71 m (He & Cha, 2019).

In this analysis, two types of system-to-facility level dependencies were incorporated. First, the recovery rates of the damaged facilities in power, water and cellular systems were reduced because of the transportation system damage. Second, it was assumed that the post-disaster demand of the facilities reduced to 74.14% of their pre-disaster demand, which is proportional to the post-Ike population drop of Galveston City.

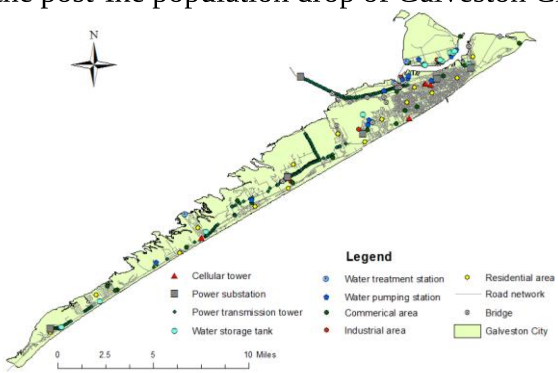

Figure 9: Critical facilities in power, water and cellular systems and road network in Galveston City.

The uncertainties in some of the modeling variables were considered, such as the initial damage level and recovery coefficients of network nodes, the recovery time of the damaged network links and so on. The probabilistic models of the random variables considered in this study can be found in He & Cha (2019). The Monte Carlo Simulation with Latin Hypercube sampling was run for 1,000 times until the mean and standard deviation of the network recovery time converge. The variations of the recovery curve for the power system measured by *E* is shown in Figure 10. The information on the variations provides whole picture of risk, which could better guide the risk-informed community resilience decision-making.

The simulated power system recovery time was then compared with the actual time for validation purpose. The actual power system recovery time for Galveston City after Hurricane Ike was 23.17 days (Department of Energy, 2008), which is within the mean (29.94 days) minus/plus one standard deviation (7.76 days) of the simulated time. It shows that the proposed DIN model can produce comparable result with the physical reality.

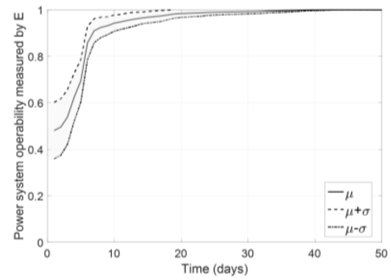

Figure 10: The variations of the recovery curve for the integrated network measured by E.

5. CONCLUSION

This paper presents the methodology and application of the DIN model in simulating the post-disaster damage and recovery of the interdependent infrastructure systems. The following three features of the DIN model make it a superior tool to guide the community resilience planning. Firstly, different levels of dependency relationships between infrastructure systems and/or facilities are incorporated, which makes the DIN applicable to model the recovery of infrastructure systems with various natures. Secondly, uncertainties in the infrastructure recovery process are considered probabilistically to better support the risk-informed decision making. Thirdly, the DIN model could produce the recovery estimation for individual facilities, systems or the integrated network to support the infrastructure resilience planning work at different resolutions. The results of the DIN model is useful in guiding the strategic community resilience planning, such as determining the risk mitigation investment priorities in the pre-disaster phase, or optimizing the recovery scheduling in the post-disaster phase. The DIN model is applicable to any infrastructure systems under any hazard types. The modeling results could be more accurate if more data on the infrastructure performance under disasters are available in the future.

6. ACKNOWLEDGEMENT

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