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Overview of Interdependency Models of Critical Infrastructure for Resilience Assessment

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ABSTRACT

Critical infrastructure systems are interdependent to ensure normal operations for supporting a national economy and social well-being. In the wake of a disaster, such interdependencies may introduce additional vulnerability and cause cascading failures. Therefore, understanding interdependencies and assessing their impact are essential to mitigate such adverse consequences and to enhance disaster resilience in the long term. There have been various models developed to capture dependencies and interdependencies across infrastructure systems. However, problems of inconsistent usage and a lack of technical guidance hinder practical applications of interdependency models. Therefore, this study presents a new classification of interdependency models based on the implementation methods: dependency tables, interaction rules, and data-driven approaches. For every class of interdependency model, fundamental assumptions and detailed implementation methods are described, with discussion of appropriate application areas, advantages and limitations. This study also compares different types of models to facilitate analysts in choosing models based

on their needs. Due to the intrinsic complexity of dependencies and interdependencies, there are many challenging modeling issues; this study discusses future research directions to address such challenges.

***Keywords*—** Interdependencies; Dependencies; Interdependency models; Resilience; Disruption; Infrastructure systems

INTRODUCTION

Critical infrastructure, such as electric power, telecommunication, transportation, and healthcare, support the national economy and social welfare, with complex interdependencies embedded (Rinaldi et al. 2001). Under normal service conditions, these interdependencies can usually improve the reliability and efficacy of infrastructure services. In case of a major disruption, either a natural hazard, a man-made disaster or a pandemic, these interdependencies often cause cascading failures and restoration delays, introducing additional vulnerability of the combined infrastructure systems (Ouyang 2014; Sun et al. 2020b; Sun et al. 2020d). The need for reducing infrastructure vulnerability during disruptions calls for resilience enhancement efforts with consideration of complex interdependencies. The concept of *resilience* was proposed in ecology by Hollings (1973), and then gradually adopted in other fields (Bruneau et al. 2003; Bocchini et al. 2014). Resilience is the ability of an entity to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions (PPD 2013). When performing community resilience assessments, interdependencies among infrastructure systems are an important component to consider, and failure to do so may yield inaccurate results (Koliou et al. 2020; Sun et al. 2020d). To enhance infrastructure resilience of interdependent infrastructure systems, decision makers need to develop efficient mitigation strategies by eliminating the adverse impact of interdependencies in disruptions. Therefore, it is crucial to carefully understand complex interdependencies and evaluate their impact on the performance and resilience of critical infrastructure via rigorous models.

Many models have been developed to address infrastructure interdependencies either descriptively or quantitatively. Requiring particular assumptions and certain data as input, these models can capture interdependencies from different aspects, which makes it challenging for analysts to choose an appropriate method for performing interdependency analyses of their own interest. In this respect, a comprehensive summary of available models can provide a general guide for analysts. There are multiple studies reviewing computational models for capturing interdependencies. Ouyang (2014) classified interdependency models in a general sense according to the modeling approach and discussed challenging issues in this field. Hasan and Foliente (2015) discussed interdependency models for failure analyses in extreme event, mainly focusing on the socioeconomic impact. Tøndel et al. (2018) reviewed methods for capturing interdependencies between the power system and the communication system, based on the impact of interdependencies on reliability. Wei et al. (2019) summarized interdependency models for transportation and power distribution systems. While the aforementioned studies have reviewed interdependency modeling methods from different perspectives, there are still inconsistencies in the classifications of interdependency models for critical infrastructure, as they lack a holistic view. The inconsistent usage and the absence of guidance hinder the practical application of these models.

For this reason, this study provides a new classification of interdependency models simply based on how dependencies and interdependencies are implemented, which represents preliminary findings of the effort for preparing a chapter in the upcoming ASCE "Objective Resilience: Manual of Practice" (Sun et al. 2021). In what follows, this study briefly describes popular classifications of interdependencies. Afterwards, it presents our new classification of interdependency models, by discussing fundamental assumptions, implementation methods, and application areas. It then compares different types of interdependency models, in terms of input data, advantages, limitations, computational complexity and development maturity, and identifies challenges in the field with future research recommendations. This new classification of interdependency models can facilitate researchers' understanding of different ways of implementing interdependencies and identifying research gaps for future improvements. Analysis results from interdependency models can benefit practitioners to identify interdependencies with the most adverse impact and develop effective management plans for resilience enhancement.

REVIEW OF PREVIOUS INTERDEPENDENCY CLASSIFICATIONS

There have been various classifications of dependencies and interdependencies proposed. This section summarizes several popular ones, shown as Figure 1. Zimmerman (2001)'s classification considers two categories: functional and spatial. Functional dependencies refer to dependencies of one system on another in operations, such as mass rapid transit relying on electric power and telecommunication systems. Consequently, a functionality perturbation in one infrastructure may potentially affect the functionality of another infrastructure. Conversely, spatial interdependencies refer to the fact that the geospatial proximity of multiple components tends to lead to simultaneous damage by the same disaster and impossibility of simultaneous repair activities, which is very common for urban utility pipelines.

Rinaldi et al. (2001) proposed a different classification: physical, cyber, geographic, and logical dependencies. Physical dependencies and interdependencies refer to the fact that the functionality of a system depends on the material output(s) of another system via a physical linkage. For instance, a water distribution network and a nuclear power plant are physically interdependent, with water pumps using the electricity for lifting and the power plant using water for cooling. Cyber dependencies and interdependencies represent the fact that the functionality of a system depends on information flow from the communication system. For instance, subways manage the flow of trains via Supervisory Control and Data Acquisition (SCADA) systems and computerized systems for electric power and communication. Geographic interdependencies represent that two systems are interdependent on each other due to spatial proximity. Logical interdependencies cover all other types of interactions. Comparing this classification to Zimmerman (2001)'s classification, geospatial interdependencies have the same meaning as spatial interdependencies; physical and cyber interdependencies fall into functionality dependencies.

Dudenhoeffer et al. (2006b) classified dependencies into physical, informational, geospatial, and policy. Comparing this classification to Rinaldi et al. (2001)'s, it can be found that physical and geospatial interdependencies have the same meanings in both classifications, informational dependencies correspond to cyber dependencies; policy dependencies represent interactions between infrastructure components due to policies or high-level decisions, falling into Rinaldi et al. (2001)'s logical dependencies.

Heavily emphasizing economic interactions, Zhang and Peeta (2011)'s classification is physical, functional, budgetary, market, and economic. Compared to Rinaldi et al. (2001)'s classification, Zhang and Peeta (2011)'s physical dependencies only consider coupling interactions due to physical attributes. Functional interdependencies represent two aspects: (i) the need of external functionality inputs, which is similar to Rinaldi et al. (2001)'s physical dependencies, and (ii) the possibility of being functionally substitutable to some extent, which no other classifications have considered. Budgetary interdependencies represent shared budgets for resource allocations due to financial constraints. Market and economic interdependencies represent an integration of infrastructure sectors due to shared market and shared customers.

Based on which management phase interdependencies are affecting, Sharkey et al. (2016) presented a different classification: operational interdependencies, infrastructure failure interdependencies, and restoration interdependencies. Operational interdependencies represent the fact that a component in an infrastructure system requires services provided by other infrastructure system(s) to be functional. Infrastructure failure interdependencies are failures in interdependent systems triggered by the initial failure of one of them due to an extreme event (Chang et al. 2005; McDaniels et al. 2007). Sharkey et al. (2016)'s restoration interdependencies represent the fact that a restoration activity or process in an infrastructure system is impacted by a restoration activity or process in another infrastructure system.

Focusing on the role of dependepencies and interdependencies in the various phases of resilience analysis, Sun et al. (2020c) proposed a new classification: hazard-related, damage-related, restoration related, and functionality-related. Hazard-related interdependencies represent the fact that there are correlations in the intensity measure at multiple locations and correlations between multiple intensity measures for describing the same event. Damage-related interdependencies represent correlated damage and failures within a system and across systems during an event. Restoration-related dependencies and interdependencies are similar to Sharkey et al. (2016)'s restoration interdependencies. Functionality-related dependencies represent the fact that a component/system requires functionality support from other component(s)/system(s) to be properly functional.

While some previous studies often use the terms "*dependency*" and "*interdependency*" interchangeably, this paper differentiates them using the following definitions. *Dependencies* represent unidirectional relations, describing the case when a first component influences the functionality or recovery of a second, whereas this second component does not necessarily influence the first in the same way. For example, a telecommunication tower uses the electricity from a nearby electric substation, indicating functionality dependency of the telecommunication tower on the substation. Conversely, *interdependencies* represent bidirectional relationships between two interconnected components/systems, whose functionality or restoration impact each other. Interdependencies often result from a long chain of dependencies among intermediate components. For instance, the local failure of a leg member in a telecommunication tower may lead to misalignment of microwave devices on top, causing communication service disruptions; such service disruptions hinder restoration coordination for fixing damaged distribution lines, which may in turn cause longer power outage for the telecommunication system.

Based on how interactions are acting within or across systems, dependencies and interdependencies can be classified into two categories: *intra-system* and *inter-system* (Sun et al. 2020c). Dependencies and interdependencies between components within the same system are considered as *intra-system dependencies and intra-system interdependencies, respectively*. For instance, in case of power outages, *resource-sharing interdependency* may represent the sharing of a limited number of linemen for repairing damaged power lines at multiple damage sites; within a transportation network, *compositional functionality dependency* represents the fact that the network functionality is related to the functionality of individual road segments. Conversely, *inter-system dependencies and interdependencies* refer to interactions between components from different systems. Examples include *inter-system functionality dependency* of a water pump on a nearby substation for using the electricity and *inter-system precedence dependency* of rebuilding a damaged bridge prior to replacing cracked utility pipes underneath it.

PROPOSED CLASSIFICATION OF INTERDEPENDENCY MODELS

Based on how they capture dependencies and interdependencies, this study classifies interdependency models into three major categories: dependency-table-based models, interaction-rule-based models, and data-driven approaches, as shown in Figure 2. While the previous classifications presented in Figure 1 have strong similarities and partially overlap, because they are all connected to what causes the interdependencies or how they manifest themselves. In contrast, it is easy to notice how distinct the new three categories proposed in Figure 2 are, this is because they are based on a completely different classification criterion: how dependencies and interdependencies can be modeled by engineers and other practitioners. The following content describes our classification of interdependency models, by discussing implementation mechanisms and application areas. While this classification may not be exhaustive, potentially with other techniques falling outside of these classes, it incorporates major trends of interdependency modeling in the research community at the time of writing.

Dependency Tables

Qualitative tables

Qualitative tables use descriptive terms to summarize the existence and the coupling strength of interdependent relations between two infrastructure systems. Such tables are usually derived from expert judgements that are collected from tabletop exercises, surveys, and interviews (Bigger et al. 2009; Tang et al. 2004), or derived from published reports and newspapers (Ouyang 2014). Descriptive terms in such tables can also represent the infrastructure dependencies and interdependencies in the normal service phase (Pederson et al. 2006), damage phase (McDaniels et al. 2007; Rong et al. 2010) and restoration phase (The Lifeline Council 2014). Descriptive dependency tables can assist decision-makers in gaining a general assessment of dependencies for preliminary planning. The interpretation of these tables is intuitive and they are easy to use, requiring no computation at all, with many successful applications for assessing system-level interactions. However, descriptive terms can not quantify infrastructure interactions. Additionally, describing component-level interactions with descriptive terms would be cumbersome. To address these limitations, quantitative dependency tables can be used, as described below.

Quantitative tables

Numerical coefficients in a quantitative table can represent the existence, the strength, and the impact level of an interaction between two components/systems under a hazard scenario. Based on how the coefficients are determined in interdependency models, quantitative dependency tables can be further classified into survey-based tables, correlation-based tables, graph-theory-based adjacency matrices and weight tables, conditional-probability-based tables, as well as economic-theory-based tables.

Using surveys to collect experts' judgments about dependencies and interdependencies is a popular method in practice. Coefficients are calculated from statistics of the survey data, in the form of the total count and consequences of cascading failures, as well as the number of restoration tasks in every infrastructure system (Kelly 2015; Luiijf et al. 2008; Chang et al. 2014; Singh et al. 2014; Mitsova et al. 2020). The most critical interdependent relation is expected to correspond to either the greatest (positive or negative) coefficient. Oftentimes, a survey collects expert judgments under a specific event of a certain type at a certain intensity level for a community with specific infrastructure, socioeconomic, and environmental features. As a result, quantitative dependency tables determined from a survey may not be applicable to interdependencies for another community, or the same community under another type of hazard at a different intensity level. Moreover, dependencies and interdependencies may change over time and space, due to varying environment and deterioration. Some studies have tried to address these issues by using dependency tables that are related to event, time, and space (Franchina et al. 2011; Laugé et al. 2015).

Correlation-based tables represent dependencies and interdependencies by using coefficients from correlation analyses. At the current stage, correlation-based tables typically represent system-level dependencies and interdependencies. Popular correlation coefficients include Pearson correlation coefficient and cross-correlation coefficient. For example, Pearson correlation coefficients are used to indicate the degree of interdependency based on the number of failure incidents in every infrastructure system over a certain time period (Mendonça and Wallace 2006; Wallace et al. 2003). Some other studies derive dependency metrics based on the cross-correlation analysis of historical recovery data, indicating the coupling strength of dependencies in the recovery process (Cimellaro et al. 2014; Dueñas-Osorio and Kwasinski 2012; Gonzalez et al. 2016). Correlation-based tables have three limitations. First, being derived from failure incidents or recovery data, correlation coefficients can infer dependencies and interdependencies in the damage phase or the restoration phase for a community suffering from a certain event, which may not be applicable to the same community in normal service conditions, or another community subjected to a different event. Second, the type of interdependency (such as operational and logistical) is interpreted by experienced analysts, and this is very difficult to validate and calibrate. Third, dependencies imply a relation of causality, which is different from poor correlation, potentially leading to the common "post hoc ergo propter hoc" fallacy. Despite these shortcomings, dependency tables are used by modelers in several ways. For instance, when simulating random functionality recovery curves, the degree of correlation can be used in the random sampling algorithm, to ensure that the recovery curves capture the trends observed in reality.

Many infrastructure systems are physically interconnected with network features. For studying networks of nodes (also called vertices) connected by lines (also called edges), graph theoretical models are a popular and effective choice. The most basic model uses binary coefficients in the adjacency matrix to represent the presence or absence of a pairwise connection among two nodes in a network. To represent link characteristics, specific coefficients are collected in a weight matrix, such as the link length or the flow capacity. For this reason, graph theory can be used to represent network topological connectivity for interdependency modeling of infrastructure systems, with nodes representing critical components and links representing physical connections. Under a hazard scenario, both nodes and links are subject to failure, with binary functionality (ATC 1985; Guidotti et al. 2017; Sun et al. 2020b), continuous functionality (Karamlou and Bocchini 2017b; Thurner et al. 2018), or discrete functionality (Shinozuka et al. 2003; Bocchini and Frangopol 2011a; Karamlou and Bocchini 2017a). The system functionality is usually defined based on the network topology or network flow, such as connectivity (Dueñas-Osorio and Vemuru 2009; Bocchini and Frangopol 2011b), number of functional/failed/repaired components (Johansson and Hassel 2010; Karamlou and Bocchini 2016), flow capacity (Bocchini and Frangopol 2011b; Bocchini and Frangopol 2012a; Bocchini and Frangopol 2012b), number of customers with service (Mitsova et al. 2018; Sun et al.

2020b; Sun et al. 2020c), and network flow (Lee II et al. 2007; Ma et al. 2019). In addition to physical dependencies, the link concept can be generalized to describe other types of dependencies across systems, and a joint adjacency matrix can be used to describe both physical connectivity and other dependencies. When modeling cascading failures with uncertainty, the uncertain dependency relation can be described by a probability, such as the failure probability of a component from interdependent fragility analyses (Dueñas-Osorio et al. 2007), and the conditional failure probability of a component given the failure of another component from a different system (Guidotti et al. 2016). Following the format of a joint adjacency matrix, a joint probability matrix of the same size can be constructed, with every coefficient as the cascading failure probability of a component due to the failure of another component, given an event intensity, or given the failure of the second component. Finally, a dependency matrix of the same size can be computed by multiplying coefficients in the joint adjacency matrix by coefficients in the joint probability matrix in the same positions. With graph-theory-based matrices, network models can rigorously capture interdependencies and simulate both cascading failures and interdependent system recovery. Major limitations of network models include requiring the compete knowledge of the network topology and the characteristics of its nodes and links. Moreover, network analyses are usually associated with large computational costs for networks of realistic size.

In fact, critical infrastructures are interconnected in economics, in terms of inter-sector transactions. Economic-theory-based tables can be used to capture dependency and interdependency relations from the economic perspective. Economic-theory-based tables have been used in input-output (I-O) models, inoperability input-output models (IIM), dynamic inoperability input-output models (DIIM), and computable general equilibrium (CEG) analyses. The I-O model was initially proposed to quantify the interactive nature of production and consumption processes among infrastructure sectors (Leontief 1951). With input-output tables describing monetary flows across sectors within a chosen time period, economic interdependencies are represented by inter-sector transactions with a set of linear equations (Leontief 1951). Basic input-output models have been successfully applied to develop economic policies (Beaumont 1990). The IIM has been developed to capture the disrupted infrastructure service as a result of a disruption in demand and supply (Haimes and Jiang 2001; Haimes et al. 2005a; Haimes et al. 2005b; Santos and Haimes 2004). In addition to using the same principles as those in the basic I-O model, the IIM uses a perturbation vector to capture the inoperability of a disrupted system due to cascading effects. IIMs can investigate cascading failures

(Santos et al. 2008; Kelly 2015) and system inoperability (Crowther and Haimes 2005; Liu and Xu 2013), to support decision making in disaster planning by allocating limited resources to sectors and interactions with the most financial impact (Anderson et al. 2007). One step further, to consider the economic impact throughout the recovery process, the DIIM is developed to capture the temporal evolution of the economic impact from interdependencies (Lian and Haimes 2006; Orsi and Santos 2010). These three I-O based models are computationally efficient because of their linear mathematical nature. However, they have four major limitations. First, data collection and preprocessing become cumbersome for a large number of sectors. Second, these models only capture economic impacts due to interdependencies at the system-level rather than at the component-level. Third, these models cannot capture influencing factors, such as market trends and human-related factors, which often lead to significant variations in economy. Fourth, these models may fail in capturing either system redundancies and contingency plans or dynamic economic interactions for interdependency modeling under extreme events (Santos 2005). Conversely, CGE analyses can capture nonlinear inter-sector relations by building upon I-O models along with two additional assumptions of equilibrated economy and optimal behaviors (Rose 1995). While I-O models assume infinite resources available, CGE models consider maximal profits under constrained resources in decision-making. CGE analyses have successful applications to economic resilience assessment (Rose and Liao 2005; Rose et al. 2007). However, CGE analyses strongly depend on production functions and utility functions and may suffer the drawback of misleading interpretations of economic interdependencies when only limited data are available (Ouyang 2014).

Interaction Rules

Discrete event simulation

Discrete event simulations use models to represent complex dependencies as an ordered sequence of defined events through sequential and conditional logic as well as causal relations, and to evaluate the probability of failure under a specific condition. Typical discrete event simulation models include fault tree analysis (FTA), event tree analysis (ETA), and Petri net analysis. Both FTA and ETA can visualize a chain of events, including dependency relations. Developed by H. Watson (Watson 1961; Lee et al. 1985), FTA is a top-down deductive analysis method to explore causes of system-level failures. A fault tree consists of events, gates, and transfer symbols for visualizing deductive logical relations between a system failure and all contributing causes, with Boolean logic. The events are associated with statistical probabilities, and gates represent logical interactions of the sequences of component failures. FTA can resolve primary causes of an undesired event, with successful applications to the analyses of progressive failure, reliability and risk in the engineering field. Conversely, ETA is a logic modeling method for both success and failure responses under an initial event scenario. An event tree uses logical induction and forward chaining to move the specific case to a general case, presenting clear visualization of event agents (Nivolianitou et al. 2004). ETA has been widely used for system risk analyses (Chou and Tseng 2010). FTA and ETA are often coupled together to assess infrastructure dependencies under damage scenarios (Teodorescu 2015). To consider temporal variations of complex interdependencies due to dynamic evolution of the disaster event and infrastructure system in disaster management, dynamic fault tree and dynamic event tree have been developed by integrating Markov models and dynamic programming (Rao et al. 2009; Wheeler et al. 2017). Alternatively, Petri nets can also visualize causal relations and temporal sequences, as an event evolves. Petri nets graphically visualize stepwise processes, with nodes representing transitions and places, and arrows describing pre-conditions and post-conditions. Petri nets have been applied to risk analyses of deterministic events and stochastic events, and even human actions in the accident model can be integrated to predict the corresponding consequences (Nivolianitou et al. 2004), and they can be integrated with fault trees and event trees (Wu et al. 2010; Nývlt and Rausand 2012). Dynamic Petri nets have also been developed, which can replace fault trees, event trees, and Markov chains in the risk and safety analyses (Codetta-Raiteri 2005).

Agent-based models

Agent-based models were initially developed at Sandia National Laboratories in the 1990s to simulate individual decision-makers for investigating the economy in the United States (Barton et al. 2000; Basu et al. 1998). As a bottom-up approach, agent-based models assume that complex interdependencies originate from individual agents and agent interactions. Agents represent human operators and major infrastructure components, and agent interactions are simulated based on a set of prescribed rules (Farmer and Foley 2009). Under a given scenario, agents are assumed to be rational and act in their own interests, with predefined rules for performing learning, adaptive, and decision-making activities. In this way, agent-based models can simulate simultaneous operations and complex interactions of multiple agents obeying simple rules, aiming to explain the collective agent behaviors and the impact of individual agent behaviors on system performance. The first agent-based model was Aspen (Basu et al. 1996), and then a modified model named Aspen-EE was developed for simulating interdependent effects of power outage and electricity price (Barton et al. 2000). Afterwards, further improvements have been continuously made to agent-based models, such as SMART II for modeling electric networks at the transmission-level (North 2001b; North 2001c), SMART II++ for simulating interactions of electric power and natural gas systems (North 2001a), CommAspen for simulating the interactions of the communication system with other systems (Barton et al. 2004), and CIMS (Critical Infrastructure Modeling Systems) for analyzing cascading failures and visualizing event damage effects (Dudenhoeffer et al. 2006a; Permann 2007). Agent-based models have been applied to various disciplines to explain social segregation, stock crash, supply chain optimization, traffic congestion, and so forth (Campbell and Cochrane 1999; Casalicchio et al. 2008; Crooks 2010; van Hillegersberg et al. 2004; Logi and Ritchie 2002; Macal 2016). Sometimes, in interdependency modeling analyses, agent-based models are used along with other methods, such as reinforcement learning (Sun and Zhang 2020). Because of the simplification in representing a complicated system and the initial assumption of complex interaction behaviors, using agent-based models to achieve a good representative model of complicated interactions would be challenging for large complex systems (Fagiolo et al. 2007). In this case, it is common to build and validate agent-based models by expert judgments (Coates et al. 2019), or by comparing with results from other models, such as multi-agent system approaches (Makowsky 2006) and discrete event simulations (Fortino et al. 2005).

System dynamics approach

Proposed by Forrester (1958), system dynamics is a bottom-up approach for understanding the nonlinear behaviors of complex systems over time. For this reason, it has become a popular approach for capturing the dynamic and evolution of interdependencies. In system dynamics, dependency relations can be represented by two types of diagrams: causal-loop diagrams representing cause-effect relations, and stock-flow diagrams representing the flow of information and commodities. While suitable to understand system interactions and behaviors, system dynamics usually does not capture component-level interdependencies. System dynamics approaches have been applied to simulating operation states, disruption consequences, and commodity consumption for interconnected infrastructures. For example, CIP/DSS (critical infrastructure protection/decision support system) is a decision support tool for understanding possible consequences under different disruption scenarios in infrastructure management (Bush et al. 2005; LeClaire and Hirsch 2009; Santella et al. 2009). Hwang et al. (2015) developed a system dynamics model to assess the effectiveness of government plans on post-disaster recovery efforts of the built environment. Links et al. (2018) applied system dynamics to predicting the community functionality evolution at the county-level in the United States. Minato and Morimoto (2017) used system dynamics to model interactions between airlines and airports. Sutley and Hamideh (2018) applied system dynamics to understand interdependencies in post-disaster house recovery. In addition, system dynamic approaches are often used along with other modeling methods, such as optimization (Min et al. 2007) and graph-theory-based matrices (LeClaire and O'Reilly 2005). However, system dynamics approaches have inherent limitations in uncertainty quantification; Bayesian networks can address this limitation very well, as described below.

Bayesian-network-based approach

Bayesian networks use Bayesian inference to model conditional dependencies in the form of directed probabilistic graphs. Therefore, Bayesian networks can assess causation, i.e., the consequences of different options under different uncertain drivers, suitable for interdependency modeling. Bayesian networks have advantage of being able to properly address uncertainties related to data, by providing a unified framework to allow the input of very different data (such as expert surveys, field measurements, and simulation data) and the update of data at different stages (Bromley et al. 2005; Johansen and Tien 2018). Applying Bayesian networks for interdependency modeling may face the following two limitations. First, a Bayesian network uses discretized variables rather than continuous variables, which may not be the case in practical applications (Kelly et al. 2013). To address this limitation, dynamic Bayesian networks have been proposed to consider both discrete and continuous variables, as well as time-based variables (Di Giorgio and Liberati 2011). Second, the computational complexity of Bayesian networks grows sharply with the number of nodes, making their application to large and complex systems challenging. Developing efficient algorithms may alleviate this limitation (Tien and Der Kiureghian 2016; Applegate and Tien 2019). Despite these challenges, Bayesian networks have been successful in interdependency modeling applications (Haraguchi and Kim 2016; Johansen and Tien 2018), especially when used along with other models, such as economic-theory-based matrices (Aung and Watanabe 2009) and graph-theory-based matrices (Hossain et al. 2019; Dong et al. 2020).

Optimization

Optimization models are used to minimize or maximize certain objective(s) under a set of constraints. When applied to disaster management of interdependent systems, optimization models can simulate the optimal planning decision of retrofit and restoration. Moreover, different types of interdependencies related to the restoration process can be implemented in optimization models as (Sun et al. 2020b). Resource constraints represent resource-sharing interdependencies, i.e., sharing a limited supply of available manpower, materials, and equipment when conducting specific restoration tasks. Construction precedence relations between restoration tasks can be enforced as precedence constraints in an optimal sequencing algorithm, representing precedence dependencies. Functionality dependencies, including both compositional functionality dependencies and inter-system functionality dependencies, can be represented by rigorous restoration functions (Karamlou and Bocchini 2017a; Sun et al. 2019; Sun et al. 2020b; Liu et al. 2020). In applications of dependencies and interdependencies, optimization models are often integrated with other models, such as network models (Karamlou and Bocchini 2016; Ouyang 2017; Zlotnik et al. 2017; Almoghathawi et al. 2019; Ma et al. 2019; Karakoc et al. 2019) and agent-based models (Permann 2007; Kizhakkedath et al. 2013). For instance, optimization models have been applied to identifying effective recovery decisions on network resilience enhancement (Vugrin et al. 2014; Ouyang and Wang 2015; Zhang et al. 2018; Sun et al. 2020b). To simulate decision-making of joint restoration planning and scheduling, the interdependent network design problem can be framed into an optimization model (Cavdaroglu et al. 2013; Sharkey et al. 2015; Gonzalez et al. 2016).

Population mobility models

To develop efficient disaster management plans, understanding the mobility patterns of population and commodities under different hazard scenarios is essential. Population mobility models can serve this purpose well by examining the movement of interdependent entities and generating and consuming commodities in the mobility process (Morrison 1972; Kang et al. 2015; Yan et al. 2017; Barbosa-Filho et al. 2018). Typically, population mobility models are built on survey data. These mobility models can provide insights on the spatial distribution of population and service demands (such as traffic, power, water, and natural gas), supporting decision-making in developing policies for traffic management and land use. They have successful applications to estimating the resident mobility and assessing the impact of interdependencies on urban multimodal transportation networks (Kim et al. 2009; Lee and Waddell 2010), electric power grids (Bayram et al. 2013), water systems (McPherson and Witkowski 2005), and epidemiology (Vazquez-Prokopec et al. 2013).

Aggregate supply and demand models

Aggregate supply and demand models explain the relationship between price level and output through total supply and total demand from the economic perspective. The total demand is the total quantity of output that a nation or a company needs, and the total supply is the total quantity of output that a nation/company produces and sells at a price level (Greenlaw 2014). The equilibrium level is reached when the total supply matches the total demand. Aggregate supply and demand models can represent interdependencies through interactions between the demand for commodities and services from infrastructure systems and the capability to provide the commodities or services for infrastructure systems. For example, aggregate supply and demand models can capture how much additional infrastructure assets are required to recover the consequences and cascading effects due to an initial disruption (Rinaldi 2004). For instance, aggregate supply and demand models have been applied to investigating the interactions between economics and energy supply, oil industry, or agriculture under different scenarios (Chambers 1984; Elwood 2001; Messner and Schrattenholzer 2000).

Data-driven Approaches

Given the advancement of technology, huge amounts of data, such as news reports and social media data, are rapidly generated and easily accessible by the general public. The growing availability of big data provides opportunities for applying data-driven approaches to resilience analysis and disaster management (Barker et al. 2017; Kuang and Davison 2020; Sun et al. 2020a; Pilkington and Mahmoud 2020). Among them, a promising application is to identify infrastructure interdependencies and assess their impact on community resilience. For instance, Zhou et al. (2020) collected data from multiple newspapers and applied text mining to identify interdependent failures of infrastructure systems in terms of incidents of bursting water pipes in Hong Kong. Roy et al. (2020) analyzed social media data with supervised learning models to find the co-occurrence of multiple service disruptions and tried to infer interdependencies accordingly. In terms of input data, the aforementioned studies have successfully used online news and social media data to train models for interdependency analyses. We foresee that other types of real data, such as remote sensing data and mobile phone data, which have been widely used in disaster-related analyses, are likely to be used for inferring the existence of dependencies and interdependencies and determining their coupling strength in future studies. When real data are not available, simulation data may be used. For instance, Lopez et al. (2018) simulated the decision-making process in emergency responses for interdependent systems with the i2Sim simulator and then trained the agent model with simulation data with reinforcement leaning for predicting emergency responses of interdependent systems. Ghaneshvar (2019) used optimization models of interdependent water, gas, and power systems under different attack scenarios to generate recovery simulation data and applied supervised learning models to predict recovery time. Data-driven approaches require large amounts of training data to establish useful models for diagnostics and predictions (Zaidi et al. 2018) and they provide no physical insights with potential biases in prediction results (Yang et al. 2019; Heglund et al. 2020).

DISCUSSION

Comparison of Interdependency Models

Table 1 compares the aforementioned models, in the aspects of input data, interdependeny representation, advantages, disadvantages, computational complexity, and development maturity. Among them, computational complexity refers to the computational cost required when using a method for modeling interdependencies, not the difficulty level of implementing such models in computational algorithms. Development maturity describes the degree to which a method is ready for practical applications. These models can capture infrastructure interdependencies in various ways, supporting decision-makers in identifying vulnerable and sensitive interactions and developing management plans to mitigate dependencies and interdependencies with the most adverse impacts. Based on this comparison, analysts can choose one of these models or integrate multiple models together for interdependency modeling analyses based on their needs.

Dependency tables can represent complex interdependencies at the component- and/or system-level in a qualitative or quantitative manner. With descriptive terms intuitively representing system-level interdependencies according to expert judgment, descriptive dependency tables for qualitative assessment are popular among practitioners, such as city planners and emergency managers, because of ease of use, no computational cost, and high development maturity. In contrast, quantitative tables can capture and measure infrastructure interdependencies. For example, correlation analysis can quantify the coupling strength between infrastructures at system-level, requiring low computational effort; network models can represent interdependencies at both component-level and system-level, requiring more sophisticated computations.

Interaction rules can capture complex infrastructure interdependencies as well. For instance, discrete event simulations and system dynamics simulations can assess causal relations to identify interactions and components with the strongest impact, requiring medium to high computational cost. Being able to capture interdependencies at both component- and system-levels, optimization models can evaluate the impact of mitigation and restoration decisions on system resilience, with the drawback of expensive computational cost for large problems (Sun et al. 2020b). Bayesian networks can quantify large uncertainties to assess the system resilience in a probabilistic manner. Population mobility models help us understand dynamic processes associated with human displacement, useful for urban planning and disaster response.

So far, there are only a small number of studies applying data-driven approaches to interdependency analyses. This indicates that this category of interdependency modeling method is still in its infancy, with low development maturity. Depending on the method adopted, data-driven approaches can range from computationally cheap to computationally expensive. Despite the limitations of no physical insights and potentially biased results, the availability of big data provides promising opportunities for using data-driven approaches to understand dependencies and interdependencies among infrastructure systems from different perspectives and ultimately support decision-making in disaster management in the coming decades.

Challenges and Recommendations

This study presents a new classification of interdependency models, simply based on how complex infrastructure interactions are implemented, in the hope of promoting research in this area. While interdependency modeling has raised research attention, there are some challenging issues remaining, which may hinder practical applications. This study focuses on four challenges described below.

The first challenge is the difficulty of collecting data. To begin with, many of these models require large amount of input data, which may not be always available. Data are generally scarce in this field due to various reasons, such as national security, commercial competitiveness, legal ramifications, privacy and ethical issues. In practice, such data may come from expert surveys, field measurements, remote sensing, social media, longitudinal studies, and high-fidelity simulation models, to name a few. Even if required input data are available, there are often issues related to data incompleteness and data ownership. To address this challenge, regulations and standards need to be established for appropriate data collection, cleaning, protection, and management. Many efforts have been made in this direction. For instance, various open databases have been established to collect and share data in a standardized form, such as Open Government (Open Government 2018), Homeland Infrastructure Foundation-Level Data (HIFLD 2018), Open Infrastructure Map (OpenStreet 2020), DesignSafe (Rathje et al. 2017), and Bureau of Economic Analysis data (BEA 2020). With an increasing amount of data available, interdependency models are expected to be calibrated and validated better, supporting more accurate resilience assessment and informed decision-making.

The second challenge is the difficulty of developing accurate and comprehensive interdependency models. That is mainly because dependencies and interdependencies are often conditional on the hazard type and the infrastructure characteristic, related to the socioeconomic background and evolving over time and space (Sun et al. 2019; Sun et al. 2020b). At the current stage, many interdependency models cannot fully capture such influencing factors. By developing and implementing disaster management plans with the consideration of the aforementioned features, more efficacious decisions are expected to be made for different communities, with fewer conflicts between current and future needs. Therefore, future research efforts should develop more realistic and comprehensive interdependency models to consider these features, such as implementing dependency relations that are functions of time and space, as well as other influencing factors.

The third challenge is the difficulty of directly applying interdependency modeling conclusions to practical decision-making. Previous evidence shows that the same type of dependency and interdependency may yield very different impact on system performance and resilience for a different system or community, subjected to a different type of hazard, within a different management time horizon (Sun et al. 2020b; Sun et al. 2020c). For this reason, the findings about the impact of interdependencies on resilience drawn for a specific community under a specific disaster scenario often cannot be directly applied to a different community/disaster. This means that the impact of dependencies and interdependencies should be assessed case by case, using appropriate interdependency models. Additionally, the current models for prediction of recovery and quantification of resilience may not be accurate and robust enough to have high confidence in the exact value of their numerical results, but they can be proficiently used in a comparative way to assist decision making, for instance to identify the components of a system that are most likely to hinder recovery, to prioritize preventive disaster mitigation actions, or to allocate budget among multiple vulnerable communities.

The fourth challenge is the difficulty of calibration and validation. Available interdependency models are often build on very different computational theories and input data, applicable to different scenarios, and generating results using different metrics. These factors make analysis results using different interdependency models incomparable, leading to challenges in further calibration and validation of these interdependency models. In current research and practice, calibration and validation are usually made by comparing to historical data and expert judgment (Ouyang 2014). Since historical data and expert judgment are typically limited to certain communities and infrastructure systems, or certain types of hazards within a limited time frame, they may be inapplicable to cases when dependencies and interdependencies are involved in conditions falling out of the range. Therefore, guidelines and representative testbeds should be established to facilitate calibration, validation, and practical applications of interdependency models.

CONCLUDING REMARKS

Focusing on their implementation method, this study presents a new classification of interdependency models: dependency tables, interaction rules, and data-driven approaches. For every class of interdependency model, it describes the implementation method with a short discussion of application examples. Based on expert surveys, descriptive dependency tables are suitable for the preliminary interdependency assessment because of intuitive and straightforward representations and ease of use, with no computational cost and a moderate data collection effort. For quantitative assessments, quantitative dependency tables and interaction rules are recommended. For example, correlation analyses can infer the coupling strength in the post-disaster recovery process at the system-level based on correlation analyses of historical data. Economic theory-based models can evaluate economic relations between sectors within a certain time period at the national-scale. Discrete event simulations can model individual components and interconnected systems and address uncertainties, suitable for assessing potential damages at different confidence levels and comparing optional retrofit and restoration plans. Network models implement graph-theory-based matrices to represent dependencies from the bottom up, particularly suitable for assessing network vulnerability. Agent-based models can consider human behaviors and their interactions with critical components by following predefined rules. Population mobility models can help urban planners understand population displacements across regions and nations. With an increasing amount of data generated daily, data-driven approaches are expected to become more popular in applications of interdependency modeling.

This study also compares the advantages and limitations, computational cost, and development maturity between different types of interdependency model. Because of the complex nature of dependencies and interdependencies, there are some challenges in interdependency modeling, related to data, model establishment, practical application, calibration and validation. This study discusses future research recommendations for addressing such challenges. Previous experience shows that interdependency models can help in assessing the impact of different interdependencies on community resilience, allowing decision-makers to develop efficient disaster management plans and deploy effective disaster response operations with limited resources at hand by decoupling the interdependencies with the most adverse impact. With the increasing attention on this topic, the growing availability of data, and the rapid development of computational power, more advanced interdependency models are expected to be developed and applied to support informed decision-making for resilience management.

DATA AVAILABILITY STATEMENT

No data, models, or code were generated or used during the study.

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TABLE 1. Comparison of interdependency models

Category	Model	Input	Interdependency representation	Advantage	Disadvantage	Complexity	Maturity
Dependency tables	Descriptive table	Expert judgement	Descriptive terms; system-level	• Intuitive representation • Easy implementation	• Requiring sufficient experience • Depending on the hazard scenario • Potentially biased	Very low	High
	Survey-based matrix	Survey data	Coefficients; system-level	• Simple representation	• Requiring calibration • Potentially biased	Low	Medium to high
	Correlation analysis	Historical data	Pearson correlations; cross correlation coefficients; system-level	• Interpreting interdependencies with coupling strength and time lag	• Requiring functionality recovery data • Assuming stationary in time-series analyses	Low	Low to medium
	Network model	Topology; capacity; flow	Adjacency matrix; weight matrix; etc.; component-level and system-level	• Intuitive representation • Capturing interdependencies at component- and system- levels	• Requiring the complete knowledge of network features • Computationally expensive for large networks	Medium to high	High
	Input-output model	Inter-sector transaction data	Interdependency coefficient matrix; system-level	• Evaluating economic cascading impacts • Simple linear modeling	• Only economic impact • No representation of redundancy • Not applicable to forecasting	Medium	Medium to high
	Computable generalized equilibrium	Inter-sector transaction; elasticity	Interdependent coefficient matrix; system-level	• Capturing statis and dynamic nonlinear socioeconomic interdependencies	• Requiring a large amount of data • Limited to economic impact only	High	Medium to high
Interaction rules	Discrete event simulation	Expert judgment; simulation data	Possible scenarios and associated probabilities; component-level and system-level	• Explicit cause-consequence analysis	• Requiring expert knowledge and assumptions for setting up causal relations	High	Medium to high
	Agent-based model	Expert experience and judgment	Predefined rules; component-level	• Dynamic model • Considering decisions and consequences	• Modeling reactions after a perturbation rather than a whole picture • Difficult to calibrate agent behavior	Medium to high	Medium
	System dynamics simulation	Expert knowledge	System dynamics diagrams; component-level	• Dynamically simulating causes and effects in a evolving process with feedback	• Requiring expert knowledge and assumptions to establish relations and diagrams	Medium to high	Medium
	Bayesian network	Simulation data; field measurements	Directed graphs; component-level	• Generalized framework for handling data with large uncertainties	• Requiring variable discretization • Computationally expensive for large systems	Medium to high	Medium
	Optimization	Mathematical formulation from operations research	Constraints of resource, precedence, budget, and time, etc.; component-level and system-level	• Generalized framework for simulating mitigation and restoration decisions	• Computationally expensive for large problems	High	Medium to high
	Population mobility model	Empirical data; simulation data	Logit model; gravity model, random walk algorithm; system-level	• Capturing human mobility and location choices	• Assuming certain mobility decisions • Requiring a large amount of travel data	Medium	Medium
	Aggregate supply and demand model	Profit data; spending data; price	Multi-attribute utility model; system-level	• Comprehensive assessment of commodity flow	• Limited to system-level interdependencies only	Medium	Medium
Data-driven approaches		Social media data; news; simulation data	Artificial intelligence; system-level	• Processing big data effectively and efficiently	• No physical insights • Potentially biased	Low to high	Low

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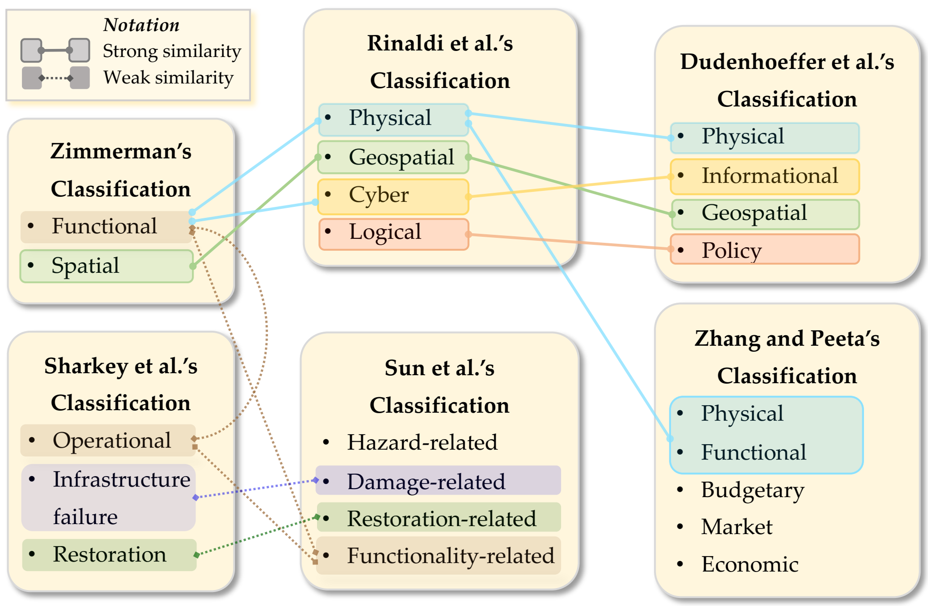

Fig. 1. Popular classifications of interdependencies and their similarity.

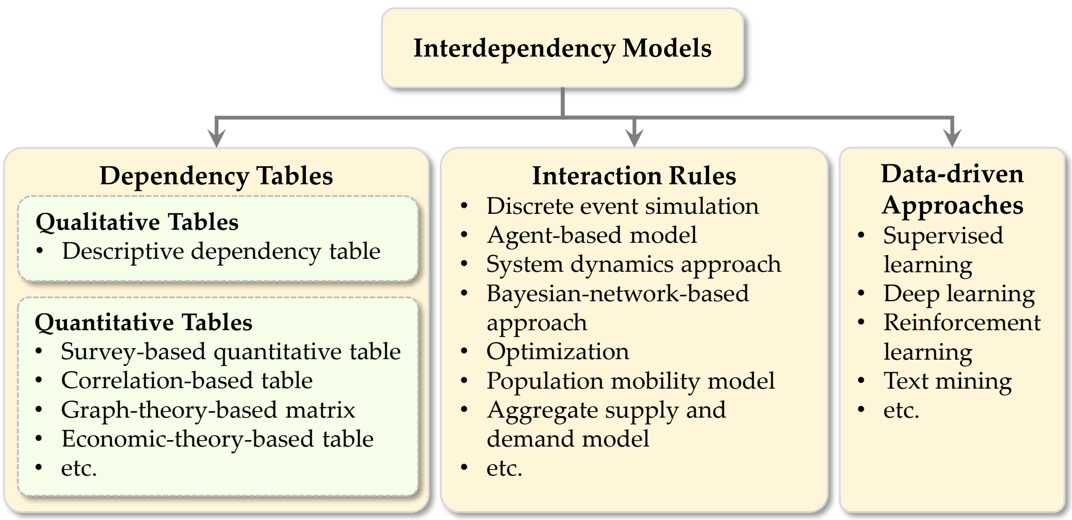

Fig. 2. Classification of interdependency models based on the implementation method.