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Review

Review on modeling and simulation of interdependent critical infrastructure systems

Min Ouyang *

School of Automation, Huazhong University of Science and Technology, 1037 Luoyu Road, Wuhan 430074, China

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ABSTRACT

Modern societies are becoming increasingly dependent on critical infrastructure systems (CISs) to provide essential services that support economic prosperity, governance, and quality of life. These systems are not alone but interdependent at multiple levels to enhance their overall performance. However, recent worldwide events such as the 9/11 terrorist attack, Gulf Coast hurricanes, the Chile and Japanese earthquakes, and even heat waves have highlighted that interdependencies among CISs increase the potential for cascading failures and amplify the impact of both large and small scale initial failures into events of catastrophic proportions. To better understand CISs to support planning, maintenance and emergency decision making, modeling and simulation of interdependencies across CISs has recently become a key field of study. This paper reviews the studies in the field and broadly groups the existing modeling and simulation approaches into six types: empirical approaches, agent based approaches, system dynamics based approaches, economic theory based approaches, network based approaches, and others. Different studies for each type of the approaches are categorized and reviewed in terms of fundamental principles, such as research focus, modeling rationale, and the analysis method, while different types of approaches are further compared according to several criteria, such as the notion of resilience. Finally, this paper offers future research directions and identifies critical challenges in the field.

Contents

* Tel.: +86 18 07 174 9645.
E-mail addresses: mouyang618@gmail.com, min.ouyang@hust.edu.cn

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1. Introduction

The economy of a nation and the well-being of its citizens depend on the continuous and reliable functioning of infrastructure systems. According to the report of the U.S. President′s Commission on Critical Infrastructure Protection (PCCIP) [164], an infrastructure system is defined as "a network of independent, mostly privately-owned, man-made systems and processes that function collaboratively and synergistically to produce and distribute a continuous flow of essential goods and services". Among all infrastructure systems, those systems "whose incapacity or destruction would have a debilitating impact on the defense and economic security" are regarded as critical. Different countries have slightly different lists detailing their critical infrastructure systems (CISs), but most contain the following systems: telecommunications, electric power systems, natural gas and oil, banking and finance, transportation, water supply systems, government services, and emergency services.

CISs are not isolated but highly interconnected and mutually interdependent [172,157,174]. For example, water and telecommunication systems need steady supply of electric energy to maintain their normal operations while electric power systems require the provision of water and various telecommunication services for power generation and delivery. Interdependencies can improve infrastructure operational efficiency, but recent worldwide events such as the 1998 storm in Canada, the 2001 World Trade Center attack, the 2003 North American blackout, the 2004 hurricane season in Florida, the 2007 UK floods and the 2010 Chile and the 2011 Japan earthquakes have shown that interdependencies can increase system vulnerability. The damage in one CIS can produce cascading failures, sending ripple effects throughout regional or national scales. Also, most CISs are becoming more congested as population and demands grow, as in the case of the U.S. electric power system. Its increasing demands have not been met by the corresponding increase in capacity and the major blackouts (affecting 1 million or more people) occur about every 4 months on average in the United States [118]. This increased vulnerability of single CIS can be easily amplified due to the interdependencies. Hence, modeling and simulation of interdependent CISs become a critical field of contemporary research and study.

The governments in different countries also recognize the increasing importance of CISs and their interdependencies. In 1996, U.S. President Clinton established the President′s Commission on Critical Infrastructure Protection (PCCIP). This commission comprehensively reviewed and recommended many national policies for protecting CISs to assure their continued operations, with the final report released in October of 1997 [164]. In 1998, the Presidential Decision Directive (PDD) no. 63 was released. It set a national goal that the United States should achieve and maintain the ability to protect the nation′s CISs from deliberate attacks by 2003. Several institutions and departments have since been founded and expanded to protect CISs, including the National Infrastructure Protection Center (NIPC), the National Infrastructure Simulation and Analysis Center (NISAC), and the U.S. Department of Homeland Security (DHS). Similarly, other countries and regions have also made some efforts to better protect their CISs, such as the European Program on Critical Infrastructure Protection (EPCIP), the Critical Infrastructure Program for Modeling and Analysis in Australia, the National Critical Infrastructure Assurance Program in Canada, the Project of Dutch Approach on Critical Infrastructure Protection in the Netherlands, the Critical Infrastructure Resilience Program in the UK, and the Critical Infrastructure Protection Implementation Plan in Germany. This increased government attention has been followed by increases in funding to universities, national laboratories, and private companies involved in the modeling and simulation of CISs interdependencies, which have further led to much innovative and diverse work.

Existing studies on interdependent CISs can be classified in different ways. Some scholars have proposed different taxonomies and compared the studies in terms of different criteria. For example, Pederson et al. [156] summarized studies up to 2006 and compared their research using six criteria: infrastructures, modeling and simulation technique, integrated vs. coupled models, hardware/software requirements, intended user and maturity level. Eusgeld et al. [71] grouped modeling and simulation techniques up to 2008 into eight categories: agent-based modeling, system dynamics, hybrid system modeling, input–output model, hierarchical holographic modeling, the critical path method, high level architecture, and petri nets. Each category was evaluated according to nine criteria: maturity, paradigm, monitoring area, data needs, course of triggered events, types of events, types of interdependencies, design strategies, and modeling focus. Satumtira and Dueñas-Osorio [190] categorized the existing studies up to 2010 according to the following attributes: the mathematical method, modeling objective, scale of analysis, quality and quantity of input data, targeted discipline and end user type. Also, there are many other review references providing classifications of the modeling approaches as well as the evaluation criteria [86,37,165,169,191,82,215,20,21,56,158,196]. Specially, [87] provided a meta-review on 12 review references in the field and suggested a list of 11 categories of criteria and 25 sub-criteria for characterizing each type of models. However, all these review references only cover a small part of the existing studies and focus more on comparisons of the modeling rationale, without carefully reviewing their extensions and applications. Also, none of these papers review existing studies from an overarching perspective, such as the emerging notion of resilience, where resilience is a relatively new yet essential concept in infrastructure engineering and is regarded as the joint ability of infrastructure systems to resist (prevent and withstand) any possible hazards, absorb the initial damage, and recover to normal operation [148,149].

This paper provides a comprehensive review in the field and groups the modeling approaches into several broad types: empirical approaches, agent based approaches, system dynamics based approaches, economic theory based approaches, network based approaches, and other approaches. Different studies of each type of the approaches are grouped and reviewed in terms of key principles, such as research focus, modeling rationale, and the analysis method, while different types of approaches are further compared according to several criteria, such as resilience as the main perspective. The paper is organized as follows: Section 2 introduces the types of interdependencies and shows their evidence under some extreme events. Section 3 summarizes the conceptual and qualitative studies in the field, which pave the way to model and simulate CISs interdependencies. Section 4 critically reviews different modeling and simulation approaches, and then Section 5 provides the comparisons across different approaches, and identifies future research directions and challenges. Finally, Section 6 offers general conclusions and insights from the literature review.

2. Types and evidence of interdependencies

CISs are dependent and interdependent in multiple ways, where dependency refers to the unidirectional relationship and interdependency indicates the bidirectional interaction [172]. Usually, dependencies are regarded as interdependencies unless they are specially referred, which is also applied in this paper. To categorize CISs interdependencies, different scholars have provided different classifications, as summarized in Table 1.

In normal operation, some interdependencies are invisible, but under some disruptive scenarios, they emerge and become obvious. To show the evidence of interdependencies and their impacts, this paper studies some extreme events and then identifies the evidence for each interdependency type defined by different scholars. The extreme events include the *1998 Ice Storm in Canada* which caused parts of Ontario, Quebec, and New Brunswick and the Northeastern United States experience one of the worst ice storms in recent history [42], the *2001 World Trade Center Attack* which led to the collapse of the twin towers and damage of numerous other buildings and utilities at the World Trade Center site [129,144], the *2003 North American Blackout* which lasted up to 4 days in various parts of the eastern USA and Canada [209], the *2004 hurricane season in Florida* which included a series of hurricanes, such as Charley, Frances and Jeanne, within a short period of approximately 2 months [133], the *2007 UK floods* which struck much of the country during June and July [22], and the *2010 Chile Mw 8.8 Earthquake* which caused coastal regions to both uplift and subside, and tsunami waves to hit the low lying Chilean coastline as well as distant shores across the Pacific Ocean [213]. All these different types of events cost billions of dollars in economic losses. Some common evidence of CISs interdependencies during and after the events is presented in the following examples:

E1: outages in power systems caused the failures of traffic signals, water supply pumping stations, and automated teller machines as well as the closure of businesses.

E2: disruptions on communication services affected the situational awareness and control of electric power (or water) systems and caused their partial failures due to lack of observability.

E3: electricity loss led to the interruption of communication services (e.g., mobile phone services), which further affected emergency communication and restoration coordination of power systems.

E4: during the restoration process, the electric power systems and the communication services were usually given repair priority relative to other infrastructure systems, and received more investment for improvement and retrofit.

E5: outages in power systems led to price changes of food and fuels.

E6: water-main breaks flooded co-located utility systems. In the case of the World Trade Center, the water flooded rail tunnels, a commuter station, and the vault containing all of the cables for one of the largest telecommunication nodes in the world.

E7: emergency services distribute emergency resources to restore various types of damaged utility systems. In the case of the World Trade Center, the New York Waterway with 24 boats dispatched some to work as floating ambulances from piers in Lower Manhattan and others to go to Hoboken, Hunts Point in Queens and the Brooklyn Army Terminal.

Table 1
Summary of interdependency types defined by different scholars and their evidence.

Authors	Interdependency Types	Definitions	Examples
Rinalidi et al., [172]	Physical	The state of one infrastructure system is dependent on the material output(s) of another infrastructure system	E1, E3
	Cyber	The state of one infrastructure system depends on information transmitted through the information infrastructure	E2, E3
	Geographic	A local environmental event can create state changes in two or more infrastructure systems	E6
	Logical	The state of one infrastructure system depends on the state of others via a mechanism that is not a physical, cyber, or geographic	E4, E5, E7, E8, E9, E10
Zimmerman [220]	Functional	The operation of one infrastructure system is necessary for the operation of another infrastructure system	E1, E2, E3
	Spatial	It refers to proximity between infrastructures systems	E6
Dudenhoeffer et al. [61]	Physical	There are direct linkages between infrastructure systems from a supply/consumption/production relationship	E1, E3
	Geospatial	There is co-location of infrastructure components within the same footprint	E6
	Policy	There is a binding of infrastructure components due to policy or high level decisions	E4, E5, E7
	Informational	There is a binding or reliance on information flow between infrastructure systems	E2, E3
Wallace et al. [212] and Lee et al. [121]	Input	The infrastructure systems require as input one or more services from another infrastructure system in order to provide some other service	E1, E2
	Mutual	At least one of the activities of each infrastructure system is dependent upon each of the other infrastructure systems	E3
	Shared	Some physical components or activities of the infrastructure systems used in providing the services are shared with one or more other infrastructure systems	E7, E10
	Exclusive or (XOR)	Only one of two or more services can be provided by an infrastructure system, where XOR can occur within a single infrastructure system or among two or more systems	E8
	Co-located	Components of two or more systems are situated within a prescribed geographical region	E6
Zhang and Peeta [218]	Functional	The functioning of one system requires inputs from another system, or can be substituted, to a certain extent, by the other system	E1, E2, E3, E10
	Physical	Infrastructure systems are coupled through shared physical attributes, so that a strong linkage exists when infrastructure systems share flow right of way, leading to joint capacity constraints	E6
	Budgetary	Infrastructure systems involve some level of public financing, especially under a centrally-controlled economies or during disaster recovery	E4
	Market and Economic	Infrastructure systems interact with each other in the same economic system or serve the same end users who determine the final demand for each commodity/service subject to budget constraints, or are in the shared regulatory environment where the government agencies may control and impact the individual systems through policy, legislation or financial means such as taxation or investment	E5

E8: debris-covered streets could not be used by both emergency response personnel and financial district workers, and lack of the latter could disrupt the financial services.
E9: most gas stations unable to pump fuel made drivers scramble to find functional gas stations, resulting in traffic congestion.
E10: closure of some metro stations increased the traffic load of the bus transportation system, resulting in long lineups at bus stops.

For each of the above examples, its associated interdependency type defined by different scholars is shown in Table 1. It can be found that some interdependency examples in practice cannot be *definitely* categorized by some classifications. For example, E4, E5, E7, E8, E9, E10 cannot be clearly sorted out according to the classification by Zimmerman [220]; other non-classified examples include E8, E9, E10 in terms of the classification by Dudenhoeffer et al. [61], E4, E5, E9 by Wallace and Lee [212,121], E7, E8, E9 by Zhang and Peeta [218]. Among these classifications, Rinaldi et al. [172] provided a self-contained classification, which can well sort out all the above interdependency examples and then is used as a criterion in this paper to compare different modeling and simulation approaches in Section 5.

3. Conceptual and qualitative studies

Before reviewing modeling and simulation approaches of CISs interdependencies, their conceptual and qualitative studies are first explored. These studies provide the definitions of CISs and their interdependencies, demonstrate the importance to account for CISs interdependencies, offer organizational and administrative strategies to better protect CISs, and also illustrate their modeling complexity. However, these studies do not provide any detailed and specific modeling and simulation approach to analyze the CISs.

Governmental reports typically belong to this type of conceptual studies. For example, the report of the U.S. PCCIP recommended a series of strategies and policies for CISs protection, such as establishing the cooperation and information sharing among infrastructure stakeholders, ingraining infrastructure protection in the culture, reforming or adding some laws, and initiating some programs of research and development on technology and tools needed for infrastructure protection [164]. The Green Paper on the EPCIP also provides some protection measures, such as establishing a critical infrastructure warning information network, using CISs expert groups at the E.U. level, sharing CISs information, and identifying and analyzing CISs interdependencies. The Critical Infrastructure Resilience Strategy in Australia recognizes that the best way to enhance the CISs resilience is to partner with owners and operators to share information, raise the awareness of interdependencies and vulnerabilities and facilitate collaboration to address any impediments. From these reports, it can be concluded that national and worldwide cooperation, information sharing, situational awareness, and better understanding and analysis of interdependencies are the consensus for effective CISs protection.

Although government reports provide detailed organizational and administrative protection strategies, they neither studied the specific techniques and means to realize them, nor discussed the modeling and simulation approaches of CISs interdependencies to assess strategies′ effectiveness and support decision makings. For the former, some scholars from universities or institutions have addressed. Bologna and Setola [24] proposed many specific recommendations to increase situational awareness, such as preparing for the worst, and identifying common mode failure events. Briere [26] recommended the establishment of a fusion center to facilitate the cooperation and coordination among different CISs, and the fusion center was able to work with public and private sector partners in a unified preparation and mitigation effort, subsequently acting as force multipliers for community stakeholder-driven rapid restoration of CISs following any type of emergency.

For the latter (modeling and simulation on CISs interdependencies), Rinaldi et al. [172] proposed six dimensions to describe interdependencies and facilitate their modeling: types of interdependencies, infrastructure environment, coupling and response behavior, infrastructure characteristics, types of failures, and state of operations. These dimensions implicated the complexity of interdependency modeling and simulation [157,173], such as topological complexity, network evolution, connection diversity, dynamical complexity, node diversity, and meta-complication. Taking the interdependent CISs as complex adaptive systems, Rinaldi et al. [173] recommended some promising modeling techniques, such as agent-based approach and system dynamics based approach.

In sum, the conceptual and qualitative studies have motivated the research on CISs interdependencies, and have paved the way to better understand the analysis, modeling, and implementation of practical protection actions for CISs. Following these efforts, many emerging studies have appeared to develop models that accurately capture CISs behavior and analyze their interdependencies and vulnerabilities. This paper groups these emerging studies in terms of their modeling approaches in the next section.

4. Modeling and simulation approaches in infrastructure interdependencies research and practice

This section groups and reviews the existing modeling and simulation approaches in the field. They are broadly categorized by the authors into six types: empirical approaches, agent based approaches, system dynamics based approaches, economic theory based approaches, network based approaches, and others. Different studies of each type of the approaches are further classified and reviewed in the following subsections.

4.1. Empirical approaches

The empirical approaches analyze CISs interdependencies according to historical accident or disaster data and expert experience. The studies with this type of approaches can identify frequent and significant failure patterns, quantify interdependency strength metrics to inform decision making, make empirically-based risk analysis, and provide alternatives to minimize the risk. Relevant studies in this type of approaches are grouped according to their research focus.

4.1.1. Identification of frequent and significant failure patterns

It is difficult to identify all interdependencies among CISs under normal operation, because some intangible interdependent relationships are undetectable by using standard data collection approaches [116] or only emerge after the occurrence of a disruptive event [113]. Hence, historical interdependency incidents can be used to uncover the interdependency structures or relationships between CISs under extreme events, such as the earthquakes in Japan [137,110], hurricanes in Florida [113,19], and some others. Establishing special databases from the incident reports and then analyzing the data can identify the frequent and significant failure patterns.

Usually, interdependency incident records are collected from newspapers, media reports, internet news outlets, official ex post assessments, and utility owners and operators [42,126–129,19].

Different scholars have constructed different databases to analyze interdependency failures. The database proposed by McDaniels et al. [127,128] and [43] can quantify the consequences of an interdependency failure under extreme events from the standpoint of societal impacts, which were characterized by an impact index (as the product of the failure duration and severity weights) and an extent index (as the product of the failure spatial extent and number of people affected). Based on these two indices, interdependency failure patterns can be classified into four quadrants, and the patterns in the first quadrant are potential important points for pre-disaster mitigation and preparedness efforts. This database has been applied to analyze several typical extreme events, such as the August 2003 northeastern North American blackout [127], the 1998 Quebec ice storm [42], a set of three 2004 Florida hurricanes [127] and 2008 Chinese Winter Storms [176]. The frequent and significant interdependency failure patterns that occur in many different extreme events are the mitigation targets from a multi-hazard perspective.

To account for mutual interdependencies, the database introduced by Luiijf [126], with 1749 CIS failure incidents in 29 European nations, showed that cascading failures due to dependencies were limited within a small number of CISs and did not cascade deeply while the interdependencies occurred far less frequently with only two cases. It is unclear whether this is due to effective management of dependencies (interdependencies) by CIS operator, or weak dependencies (interdependencies) to make cascade begin with, or invisible dependencies (interdependencies) to news report as they occurred at a more technical level. Also, to analyze the interdependency evolvement during the restoration process, the database designed by Wallace et al. [129,212] collected 3 months of incident reports following the World Trade Center (WTC) attack. The results demonstrated that banking and finance along with government and emergency services were increasingly impacted both directly and through interdependencies during the restoration process, but the CISs with physical networked layout, such as transportation and power, endured many interdependency-related incidents only during the first week of the restoration.

The above studies investigated the interdependency failures at the system level, but if detailed data is available, interdependency analysis can offer more detailed results at the component level to identify and protect key assets. The database provided by Chou and Tseng [44] collected component level failure records within and across CISs. A knowledge discovery process was employed to extract records of frequent interdependency failure patterns associated with their occurrence probabilities at component level.

The empirical approaches can help identify the potential important interdependency patterns and increase crisis managers' awareness and capabilities for responding to the future events. However, this type of the approaches has several weaknesses. First, due to the bias of reporting, there may exist underreporting of some frequent interdependency failures that may have significant impact. Second, scholars use different databases to collect failure data without a standardized data collection methodology for interdependent CIS performance. This requires a uniform data collection method, including exact definitions of CISs and their interdependencies, so that the media reporting system can follow the requirements to collect the information and support rapid analysis of the data, reducing the time to code and sort out the content of incident reports. Third, the reliance of the empirical approaches on previous failure records, which can give accurate prediction on the future similar events within the range of the collected data already in the database, may not give good predictions for new disasters. These weaknesses call for other modeling and simulation approaches for additional decision support.

4.1.2. Quantification of interdependency related indicators

Zimmerman [221] introduced several interdependency related indicators to inform mitigation and emergency decision making, such as the types of CISs that more frequently damage other CISs, the ratio of being a cause of failure to being affected by failures, combinations of failures that are most frequent, and the number of people affected. These indicators can be easily computed from the collected failure data. Some other indicators, such as interdependent strength, resilience factor, need relatively more calculation.

To quantify the interdependent strength across CISs, Mendonca and Wallace [129] used Pearson′s correlation as the metric. Results show that correlations (interdependent strength) between 50% of the pairs of CISs were statistically significant in the WTC attack. Different from the frequency analysis of the incidents, Duenas-Osorio and Kwasinski [67] exploited the time-series analysis method to reveal interdependencies across CISs from post-event restoration curves. The cross-correlations from the curves without significant lag times reflected the operational interdependencies, and those with significant lag times measured the logistical interdependencies. A synthesized coupling-strength metric incorporating both cross-correlation and lag times was further proposed to quantify the overall CISs interdependencies in 27 February 2010 Mw 8.8 Offshore Maule, Chile earthquake [205]. To quantify the resilience factors of industrial sectors (including CISs) under disruptions, [110] conducted a survey in the Tokai area based on a questionnaire, and defined the resilience factor as the proportion of production level under disruptions to the normal production level. It showed that in the manufacturing sector the resilience factor was almost zero if only the electricity supply was disrupted.

Interdependency related indicators can inform mitigation and emergency decision makings, and can be also used as the input and validation parameters to other models, such as agent-based models, input–output inoperability models and some network based models. But how to associate these indicators with other models, it is still a challenge and calls for an integration concept to link different models in a single framework, which is further discussed in Section 5.

4.1.3. Empirically-based risk analyses

According to historical failure data and the expert experiences, empirically-based risk analyses can be performed to identify the vulnerability of CISs and provide alternatives to minimize their risk of non-functionality. According to previous accidents and disasters, Utne et al. [210] plotted a cascade diagram to describe the cascading failures process across CISs under a specific initiating event. The frequency of the initiating event, the probabilities of all involved events, the number of people being affected, and the duration of each subsequent event were determined based on historical data as well as the expert judgments. Then they estimated the risk associated with the initiating event and identified the optimum strategy for risk reduction [112]. Also, by using a series of time-dependent matrices, where each of its elements (i, j) at some time (measured by experts with qualitative data, such as null, low, medium, high) corresponds to the service quality degradation of infrastructure i due to the outage of infrastructure j, Franchina et al. [79] introduced an impact-based method to construct a time-dependent cascading failure tree associated with each initial failure event to inform emergency decisions. Similar studies include the work from Ezell et al. [74,75] analyzing and managing the risk of interdependent CISs based on empirical data and the event tree, and the work from Robert [175] analyzing the specific cascading failure mechanisms between hydroelectric power generation network and a power transportation network.

The empirically-based risk analysis largely depends on the empirical data and expert judgments. A little data may bring large errors of the analysis results. But if sufficient record data for the CISs performance during adverse events are available, the errors can be reduced. Also, with sufficient data, some other methods, such as statistical learning theory [88], can be applied to directly draw conclusions from large complex data sets and provide important support for risk management both immediately before extreme events and over the longer term.

4.2. Agent based approaches

Due to the inherent complexity of CISs and the related decision-making processes, CISs are usually regarded as complex adaptive systems (CASs) [3,4,173,18,125,97,206]. To analyze the CASs, one effective way is the agent-based approaches, which adopt a bottom-up method and assume the complex behavior or phenomenon emerge from many individual and relatively simple interactions of autonomous agents [108]. Each agent interacts with others and its environment based on a set of rules, which mimic the way a real counterpart of the same type would react. Most CIS components can be viewed as agents. Hence, agent-based approaches are widely used to model the CISs interdependencies, and are mainly used by several national laboratories to study CISs interdependencies with different mature tools developed.

Sandia developed its first agent-based model called Aspen [14,15] to simulate the behaviors of economic decision-makers individually and investigate macroeconomic quantities of interest in U.S. economy. The outcome of various federal monetary policies in the model agreed qualitatively with predictions based on economic theory and practice, despite the model ignored certain important factors of the economy. In 2000, SNL developed an extended and modified model called Aspen-EE (Electricity Enhancement), which additionally included agents representing the major players in power systems, to simulate the interdependent effects of power market adjustment and power outages on other CISs [12,27]. However, Aspen and Aspen-EE both used the message-passing mechanism to realize the communication between agents without specially representing the telecommunication system. In 2004, SNL developed a new model called CommAspen, which took the telecommunication system into consideration, to simulate the interdependent effect of telecommunication disruptions on other CISs, such as banking and finance, and the power system [13]. Based on the development experiences from the above models, in 2004 SNL further developed a new model called NABLE to simulate and analyze more complex interdependencies among economic firms, households, the power system, telecommunication system and other CISs [192,69,70], and then in 2008 proposed a method to investigate the cyber and physical interdependencies by the use of a cyber-attack-consequence assessment process [111].

Argonne developed an agent-based model called SMART II in 2000 to represent the electric power marketing and the power transmission system by generation agents, consumer agents and interconnects that represented the transmission topology [138]. Different from the models in Sandia, Smart II considered the topology of the power transmission system, and then it can detect the transmission line configurations which can lead to price spikes. The avoidance of those configurations facilitated greater market price stability. Later, Argonne developed SMART II++ as an extension of SMART II [139]. This new model added a set of new agents and interconnections to represent the natural gas marketing and distribution infrastructures as well as the interconnections between the two CISs in the form of natural gas-fired electric generators. The interdependency analysis showed that emergency natural gas purchased by electric generators needed to be carefully monitored to prevent electric failures from spreading to the natural gas infrastructure. Later, ANL developed the FAST (Flexible Agent Simulation Toolkit), which included many features of SMART II+ along with improvements in detail and fidelity [140].

Idaho developed the agent-based CIMS (Critical Infrastructure Modeling System) tool to analyze the cascading effects and consequences associated with CISs interdependencies through a graphical (3D) representation of CIS component and the associated relationships [17,60–62]. CIMS modeled the CIS topologies in detail and provided the decision makers the ability to visualize interdependencies and damage effects of events. However, when the CIS sizes and complexity increase, the visual analysis methods may not suffice. Additional search and analysis methods are required to identify event–effect relationships especially across multiple CISs. Therefore the INL integrated the genetic algorithms (GA) into CIMS to help refine the search space and identify subsets of possible interactions [160]. The integration was realized by allowing the GA to access and affect the simulation agents' attribute and state values [161]. With the integration, CIMS can help determine the optimum or ranking of assets to restore or protect from attacks or other disasters.

Besides the above studies from the national laboratories, there are some other agent-based studies to enhance the modeling flexibility and extend the capacities of existing research with the integration of other modeling techniques, such as UML technique to model high-level behaviors and interactions among agents to facilitate model extension [35], engineering, and maintenance, federated simulation technique [38,39] or the generic ontology technique [52] to facilitate the reuse, share and interoperability of the existing agent-based models and reduce the development time, the Fuzzy Logic method to account for the uncertainties that characterize expert knowledge about the CISs [152,153], GIS technique to support intuitive interdependency analysis [207]. Also, some authors used the agent-based method in some specific applications associated with interdependencies, such as the interdependencies between the web system and other CISs [34], the interdependencies between changing power grid due to its deregulation and the increasing amount of distributed generators [170,171], the cyber interdependencies between information infrastructure and the power system [25], the human initiated interdependencies between the communication system and the transportation system during the evacuation process [11].

Agent-based approaches model the behaviors of decision-makers and the main system participants in the interdependent CISs, enable to capture all types of the interdependencies among CISs by discrete-event simulations, provide scenario-based what-if analysis and the effectiveness assessment of different control strategies, and can be also integrated with other modeling techniques to provide more comprehensive analysis. However, this type of methods has some weaknesses: (1) the quality of simulation is highly dependent on the assumptions made by the modeler regarding agent behaviors, and such assumptions may be difficult to justify theoretically or statistically; (2) calibrating the simulation parameters is a challenge due to lack of relevant data and the difficulties to model participant behaviors. Detailed information about each CIS is considered very sensible by CIS stakeholders due to the relevance for their business. In addition, existing models and studies usually concentrated on one aspect of the interdependent CIS, such as market structures, and system configurations. Addressing different aspects in a single framework requires an integration concept, which will be further discussed in Section 5.

4.3. System dynamics based approaches

System dynamics (SD) based approaches take a top-down method to manage and analyze complex adaptive systems involving interdependencies [78,199,115,143]. Feedback, stock and flow are the basic concepts in this type of approaches. Feedback loops indicate connection and direction of effects between CIS components. Stocks represent quantities or states of the system, the levels of which are controlled over time by flow rates between stocks. SD based approaches model the interdependent CISs by two diagrams: causal-loop diagram capturing the causal influence among different variables and stock-and-flow diagram describing the flow of information and products through the system [27,28,197]. CIP/DSS (Critical Infrastructure Protection/Decision Support System) tool is a successful application of system dynamic approach to study CISs interdependencies. This tool was developed by the joint efforts from Los Alamos, Sandia, and Argonne National Laboratories with the assistance of functional modeling and nonlinear optimization techniques [32,186,130]. CIP/DSS used nearly 5000 variables to model all CISs as defined by Homeland Security Presidential Directive 7 (e.g., water, public health, emergency services, telecom, energy, transportation) and their major interdependencies at an aggregate level. It enabled decision makers to determine what consequences might be expected from disruptions to infrastructure, explore the mechanisms behind these consequences, and evaluate mitigations for a particular risk.

Currently, CIP/DSS has been applied to a variety of specific scenarios, such as modeling an influenza outbreak and evaluating the impact of interventions and public behavior on spread of the infection [76]; analyzing the cascading effect of a power system disruption on the telecommunications infrastructure as well as the emergency service infrastructure and investigating the consequences when more and more consumer population adopt telecom services without the back-up power support [47]; investigating the impact of an infectious disease release on the metropolitan economy and analyzing the effectiveness of various responses and protective measures, such as quarantine [53]; predicting the impacts of displaced people on Baton Rouge subsequent to Hurricane Katrina [198]. Also, there were some studies extending the capacities of CIP/DSS. For example, LeClaire et al. [119] introduced a desktop simulator to help bridge the gap between the tool developer and the real decision makers.

In sum, SD based approaches model the dynamic and evolutionary behavior of the interdependent CISs by capturing important causes and effects under disruptive scenarios, capture the effects of policy and technique factors to reflect the system evolution in the long term and provide the investment recommendations, incorporate multi-attribute utility functions to compare alternative infrastructure protection strategies and help build consensus among stakeholders in a decision. The weaknesses of this type of approaches include the following: (1) as the causal-loop diagram is established based on the knowledge of a subject-matter expert, it is also a semi-quantitative method. (2) Many parameters and functions in the models require calibration, which need a huge amount of data. But in reality, data is not easily accessed due to many reasons, such as security concerns. (3) In fact, SD based approaches use a series of differential equations to describe the system-level behaviors of the CISs. They cannot analyze component-level dynamics, such as the adjustment or change of infrastructure topologies. (4) Due to the difficulty to obtain relevant data, validation efforts usually consist of conceptual validation only for important descriptive variables of each CIS to determine if the model produces a reasonable response to perturbations, so there is relatively limited validation of the model. These weaknesses call for integrating other modeling approaches in a uniform analysis framework for overall decision support.

4.4. Economic theory based approaches

In a market of an economy, there are mainly two types of players: households and producers. Households offer labor and capital to producers in exchange for income payments. The producers produce goods and services by the use of not only labor and capital, but also various types of raw and processed materials and various services, referred to as “Intermediate Goods”. CISs in an economy fall into this category of intermediate goods since they are essentially required by all procedures. Hence, the CISs interdependencies can be analyzed through models of economic interdependencies [182]. In the existing literature, two types of economic theories are employed to model CISs interdependencies: input–output (I–O) and computable general equilibrium (CGE).

4.4.1. Input–output based methods

In 1973 Nobel laureate Wassily Leontief proposed the input–output economic model [122]. It was a static and linear model of all purchases and sales between sectors of an economy based on the technological relationships of production [179].The original Leontief I–O model follows: $\mathbf{x} = \mathbf{Ax} + \mathbf{c} \Leftrightarrow \{x_i = \sum_j a_{ij}x_j + c_i\} \forall i$, the term x_i refers to the total production output from the industry i; the Leontief technical coefficient a_{ij} is the ratio of inputs of industry i to industry j in terms of the total production requirements of industry j; the notation c_i represents the industry i's total output for final consumption by end-users.

Applying the equation in interdependent CISs and interpreting the output as the risk of *inoperability* which is defined as the inability of a CIS to perform its intended functions, the first-generation physical input–output inoperability model (IIM) was proposed by Haimes and Jiang [92]. In this model, x_i was the overall risk of inoperability of the ith infrastructure that can be triggered by malicious attacks or accidental disturbances; a_{ij} was the probability of inoperability that the jth infrastructure contributed to the ith infrastructure due to their interconnectedness; c_i was the additional risk of inoperability that was inherent in the complexity of the ith infrastructure. Hence, given a perturbation from one or multiple infrastructures or industries of the economy, the IIM can estimate the ripple effects measured by infrastructure or industry inoperability.

Based on the Leontief Input–output model and the concept of *inoperability*, a series of extended IIM based models have been subsequently proposed, such as *demand-reduction IIM* defining the perturbations as the reduction of the final demand to a set of economic sectors and assessing the output reduction or inoperability of each interdependent economic sectors [187,94]; *dynamic IIM* describing the inoperability evolvement process and the temporally interdependent recovery of economic sectors after an attack or natural disaster while integrating the industry resilience coefficients to quantify and manage the improvement of various sectors [124,94,217]; *supply-side price IIM* discussing the cascading failures among interdependent economic sectors when the initial inoperability is driven by the value-added perturbations and *output-side IIM* investigating the perturbations to output levels [123], the *International Trade IIM model* considering the import activities and proposing the concept of Gross Trade Economy (GTE, sum of gross domestic products and gross imports) to analyze the international trade inoperability for all industry sectors resulting from disruptions to a major port of entry [107] and *Multiregional IIM* modeling the multi-sector and multiregional economic interdependencies and using relevant geo-spatial databases to estimate higher-order impact propagations across multiple regions and industry sectors [50,151].

These IIM based models offer intuitive interpretations of interdependencies and can be used to analyze the inoperability of CISs to different types of perturbations, which led to their successful applications in the hierarchical holographic modeling on the risks of terrorism to the homeland security [93], and the risk analysis of terrorism to Virginia′s interdependent transportation systems [48], the impact of high-altitude electromagnetic pulse (HEMP) attack on different economic sectors [95], the demand reduction of air transportation following the terrorist attacks of September 11, 2001 [188], the financial and inoperability effect of the US Northeast blackout in 2003 [5], the major impact of the US Gulf Coast hurricanes in 2005 [49], risk-based decision making under uncertainty [96,9,10], the resilience between the power delivery system and telecommunication system under Hurricane Katrina [168], the economic impact of cyber attacks on the oil and gas sector [189].

In sum, the inoperability input–output models (IIM) can easily analyze how perturbations propagate among interconnected infrastructures and how to implement effective mitigation efforts [105,33]. These models are based on the large-scale databases (Economic Analysis database of national I–O accounts and Regional Input–Output Multiplier System accounts), and measure the interdependencies among infrastructure sectors by economic relationships. Hence, the IIM based models are useful for macroeconomic-level or industry-level interdependency analysis in the aftermath of natural hazards, malicious attack or accidental events. Also, these models can provide analytical solutions so that it is easy to make the parameter sensitivity analysis. The weaknesses of this type of models include the following: (1) the input–output based models cannot analyze the interdependencies at the component levels. (2) As the interdependent matrix is derived from the economic databases, the elements in the matrix only measure the interdependent strength in normal economic operations. Actually, the interdependent strength would be non-linear and depend on the real-time infrastructure or industry outputs, so IIM based models can give a good approximate analysis on cascading the failure process and recovery process when the perturbations have small impacts on some economic sectors, but for large perturbations or new perturbations on un-recovery economic sectors caused by some old perturbations, the IIM will show large resulting errors and not be applicable any more.

4.4.2. *Computable-general-equilibrium based methods*

Computable General Equilibrium (CGE) can be viewed as an extension of the input–output model [181]. It inherits the main features of I–O models, such as the consideration of interdependencies among economic sectors, while it overcomes most of their limitations, such as linear interdependencies among economic sectors, lack of consumers′ and producers' behavioral responses to markets and prices subject to labor, resource and capital constraints [180]. In CGE, the production functions of the producers incorporate economic resilience in the equation structures, i.e. allowing for the substitution of the inputs in response to market changes. Applying the CGE, Rose and Liao [183] studied the economic resilience of the Portland, Oregon region under water system disruptions due to an earthquake as well as the effectiveness of various resilience improvement strategies, such as pre-event water pipeline replacement, and post-event increased Water Conservation and Substitution. With a similar approach, Rose et al. [184] analyzed the economic impacts of a terrorist attack on the Los Angeles power system. The economic loss was estimated as $20.5 billion without resilience strategies but reduced to $2.8 billion with the strategies, including conservation, onsite electricity generation, rescheduling of production.

Recently, by using the CGE theory and its extension spatial CGE theory, Zhang and Peeta [159,218] proposed a generalized approach to analyze various types of CISs interdependencies under a multi-layer infrastructure network (MIN) modeling platform, which uniformed different infrastructures with different operating mechanisms and flow characteristics under a single framework. MIN modeled different CISs at different network layers, where the vertical links represented the interdependencies among various CISs in the same region and the horizontal links in a layer captured the interactions or flows of a CIS across different regions. Using this modeling platform and the CGE and the spatial CGE (SCGE) theories, the approach can model the infrastructure network structure, substitutability of infrastructure commodities/services, decision-making behavior of producers and system users, and the transportation/transmission costs so that different types of CISs interdependencies, such as functional, physical, budgetary, market and economic, can be captured simultaneously. The authors also discussed and addressed the calibration, implementation, and computational issues related to deployment using available data, as well as the dynamics and disequilibrium analysis involving CISs interdependencies [219].

CGE based methods extend the capacities of the Input–output methods, capture the nonlinear interactions among CISs, provide resilience or substitution analysis of single CIS and the whole economy, and enable to capture different types of interdependencies in a single framework. The weaknesses of this type of methods include the following: (1) the calibrations of production functions and utility functions depends on the choice of the function form, and they become difficult when the relevant data is scant. (2) For the resilience analysis for the producers, it relies on external sources for some of the elasticity values required during their calibration. Studies to derive the elasticity value are scant.

4.5. *Network based approaches*

CISs can be described by networks, where nodes represent different CIS components and links mimic the physical and relational connections among them. Network based approaches model single CISs by networks and describe the interdependencies by inter-links, providing intuitive CISs representations along with detailed descriptions of their topologies and flow patterns. Performance response of CISs to hazards can be analyzed by firstly modeling the component failures from hazards at component level, and then simulating the cascading failures within and across CISs at system level. Depending on whether modeling the particle flow on CISs, this subsection groups network-based studies broadly into topology-based methods and flow-based methods.

4.5.1. *Topology-based methods*

The topology-based methods model the interdependent CISs only based on their topologies, with discrete states for each component (node or link) and usually with two states: failed and normal. Nodes can be failed directly from the hazards, or indirectly due to the disconnections from the source nodes in the same CIS [155] or due to the simultaneous failures of their dependent nodes in another CIS or due to some other factors, such as failures of back-up supports [1]. Depending on how detailed the CISs topologies are modeled, the topology-based studies can be analyzed by analytical methods and simulation methods.

4.5.1.1. Topology-based analytical methods. When CIS topologies are modeled without considering node heterogeneity, i.e. without differentiating source nodes, transmission nodes and sink nodes, each CIS can be then characterized by its node degree distribution represented by a generating function, and the giant component size of interdependent CISs under random hazards and malicious hazards can then be investigated analytically. Here, generating function is a formal power series whose coefficients encode information about a sequence that is indexed by the natural numbers [7]. Based on this definition, distribution p_k which is the probability that a randomly chosen vertex in a network has degree k has the generating function $G_0(x)=\sum_{k=0}^{\infty} p_k x^k$ [134]. The generating function method can analyze the spread of epidemic disease on networks [135,59], the breakdown of network under intentional and random attack [2,45,46], the structure of shells in networks [194], the fractal boundaries of networks [193] and the cascading failures in interdependent networks [30].

For two interdependent networks A and B with different number of nodes N_A, N_B, denote their vertex degree distributions respectively by $P_A(k)$, $P_B(k)$. Initially, remove a fraction $1-R_A$ of A nodes and $1-R_B$ of B nodes, all nodes in the giant components of networks A and B keep functional and others fail. Also, due to the interdependencies, a B (A) node can still function only if at least one of its dependent A (B) nodes is still survival. The recursive failure process proceeds between A and B until there are no further failures. In the literature, there are several following interdependent relationships. (1) The two networks have the same size $N_A=N_B=N$, and the interdependency is one-to-one correspondence $A_i \leftrightarrow B_i$, i.e. A_i depends on B_i while B_i also depends on A_i [30,103]. (2) The two networks have the same size $N_A=N_B=N$, a fraction q_A of A nodes depend on the B nodes and a fraction q_B of B nodes depend on the A nodes [154]. (3) The two networks have the same size $N_A=N_B=N$ and the identical degree distribution $P_A(k)=P_B(k)=P(k)$ with still one-to-one correspondence, but an interdependent link connects a A node and a B node with the same degree [31]. (4) The inter links between network A and network B are random and uni-directional, there are $c_0^{BA}N^A$ inter-links distributed randomly from B nodes to A nodes, and there are $c_0^{AB}N^B$ inter-links distributed randomly from A nodes to B nodes [195]. Under different interdependent relationships, the size of the giant mutually connected component of coupled networks under different hazards in the final state μ_∞ can be calculated, and the general results showed that the interdependencies increased the system vulnerability in contrast to the non-interdependency scenarios. This result was also found by applying mean-field theory in coupled regular networks [36]. Also, the interdependent networks were difficult to defend by strategies such as protecting the high degree nodes that had been found useful to significantly improve robustness of single networks. The above studies all aim at two interdependent networks, Gao et al. [80] further studied the performance response for n interdependent networks (each of them has an average degree k) under random hazards, and a general equation for the giant mutually connected component μ_∞ was found, $\mu_\infty = R_A[1-\exp(-k\mu_\infty)]^m$.

Despite the generating function method offers analytical solutions of the interdependent networks under different types of hazards, this method can only analyze the randomly constructed networks with large or infinite size under random hazards with identical failure probabilities for all components and malicious hazards by removing the nodes with largest degrees, but becomes incapable for the real infrastructure networks with spatial constraints and limited size as well as for networks under natural hazards with different component failure probabilities, which can be investigated by simulation methods.

4.5.1.2. Topology-based simulation methods. When some CISs are modeled by their topologies with additional consideration of node heterogeneity, scholars usually use the simulation-based methods to investigate the performance response of interdependent CISs under different hazards, including the natural hazards. In these studies, the performance of each network can be measured by many metrics, such as the number of normal or failed components [1,106], the inverse characteristic path length [145], the connectivity loss [65], the redundancy ratio and the cluster related metrics [66]. Also, with the number of damaged nodes or the vector of damaged nodes, incorporating some functional properties of the nodes, such as the duration of the component unavailability, the number of customers served, system-level performance can be also quantified by some functionality metric, such as lost service hour [106], the fraction of customers affected [163]. Measuring the damage level of a CIS by above performance metrics, system-level response can be further reflected by the fragility curves, which represent the probability of the system-level damage exceeding an given damage state under different hazard intensities [63,64,66,99].

Given a performance metric, the interdependent effect can be also quantified as the absolute differences between the independent and interdependent responses normalized by the maximum independent response [66,146]. This metric facilitates the assessment of mitigation actions, such as adding bypass [120], hardening individual component performance [65], the results showed that small disruptions were controlled with bypasses and large disruptions were reduced if their components were less fragile. To reduce the cascading failure effects across CISs, adjusting and designing the interface configurations (interdependent topologies) is also an effective strategy. Taking the power transmission system, water and gas system as an example, Winkler et al. [214] compared different strategy effectiveness under random failures and hurricane hazards according to a network based topological model. Those strategies were designed based on component degree, component betweenness, vertex clustering coefficient, Euclidean distance across components. Also, Hernandez-Fajardo and Dueñas-Osorio [98] investigated the cascading failure process of the interdependent CISs from transient to steady state performance and found that most of the interdependent failure propagation across the CISs occurred early.

In sum, the topology-based methods mainly capture the topological features of the interdependent CISs, identify the critical CIS components and provide suggestions on robustness improvements from the topological perspective. Despite a system topology determines its functionality, recent studies showed that the topological model alone cannot provide sufficient information about the flow performance of real CISs [100,150]. Hence, topology-based methods cannot be used alone to inform the decision-making for real-world CISs and call for integrating other modeling approaches in a uniform analysis framework for overall decision support.

4.5.2. Flow-based methods

The flow based methods take account of the services or flow made and delivered by the CISs. Nodes and edges constructing the infrastructure topologies have the capacities to produce, load and deliver the services. Based on this concept, some scholars proposed uniform network descriptions for different types of CISs and their interdependencies. Wallace and Lee [212,121] modeled different infrastructure functionalities by a uniform network flow mathematical representation. The movement of commodities corresponded to flows, and the services corresponded to a desired level of these flows. For each network, commodities flowed from node to node along arcs in the network. Each node was either a supply node, a demand node or a transshipment node and each arc had limited capacities. It also enabled mathematical representations for different types of interdependencies, and allowed users to assess the post-disruption impact and analyze the restoration process [142,41]. This model has been used in the impact analysis of CISs interdependencies in the operation of health care facilities during disaster events [6]. In addition, [201–204] modeled the CIS components by a set of response functions, which can capture the productions and consumptions of both buffered and un-buffered flows in some CISs. Also, in a much simpler case, where a failed component causes a load transferred to the loads of all other components in the same network while all loads of the components of the other network are increased by a load increment, the performance response of coupled networks under a perturbation can be then solved by applying the branch process theory [136], and results still showed the coupled networks were more susceptible to large-scale failures than single network. Instead of transferring the load to all other nodes once the failure of a node, [222,223] modeled the load redistribution only to the first neighbors of the failed node and found some similar results.

However, different CISs have different operation mechanisms, which are not suitable to be characterized by a uniform model. Using the physical rules to describe each CIS can provide more realistic modeling on interdependencies. Modeling the power system by the direct current (DC) power flow model [57,58] and the gas system by the pipeline flow model, Ouyang et al. [145] investigated their interdependent effects and found that the results were largely different from those by the topology-based method. By applying the same flow models in power and gas systems in Houston, Ouyang and Duenas-Osorio [147] modeled the multiple hazards (random hazards and hurricane hazards) and proposed a global effectiveness metric to find a global optimum strategy to design the interdependent topologies between CISs. The new models captured the network flow with approximate methods and went beyond previous studies focused only on connectivity. Also, modeling the power system by the DC power flow model and the internet by the data packet model, Rosato et al. [177] studied the variation of the internet quality of service (QoS) with respect to the QoS of the electrical network, and developed a decision support system for the fast and efficient set up of mitigation and healing strategies [178].

There are also many other flow-based studies. Bobbio et al. [23] proposed a service oriented stochastic modeling methods to investigate the availability of interdependent power grid and Telco network under the outage of critical SCADA communication links. Trucco et al. [208] defined a network node as a large functional part of a CIS and then used a dynamic functional model to assess the propagation of impacts within and across CISs at regional level in terms of disservice. Delamare et al. [54] analyzed the impact of the fast-healing telecommunication system (modeled by the router based model) on the operation of the electric power system (modeled by the maximum flow model). Nozick and Turnquist [141] modeled the interdependent gas infrastructure, the SCADA system controlling the gas pipeline flows, and the gas-fired electrical generators by the max flow model and the Markove and semi-Markove process for the holding time distribution for gas flow transition, they investigated the robustness of the gas system by simulating the time distribution for the system to recovery and satisfy all demands when all the capacities on each link was reduced to the minimum values. This approach can be also used to study the optimum restoration investment by updating the state-space, and the transition matrices [216]. To model the U.S. energy system disruption under 2005 hurricanes Katrina and Rita, Gil and McCalley [83] proposed the multi-period network flow model (linear program model) to simulate the nationwide movements of bulk energy flows through the network in the whole nation and analyzed the damage propagation among nature gas, coal, and electric systems by the variation of price [166,167]. They found that the bulk energy system was robust and able to tolerate large and multiple disruptions mainly due to coal storage. The model can also be extended to a long-term investment planning model capable of identifying what, where and when infrastructure investments should be made [104].

In sum, flow-based methods capture the flow characteristics of interdependent CISs, and provide more realistic descriptions on their operation mechanisms. This type of methods can also identify critical CIS components, and provide emergency protection suggestions on CISs. However, if the detailed operation mechanisms of CISs are modeled in detail, the computational cost is very high.

4.6. Other approaches

Besides the above approaches, there are some other approaches to model and analyze the interdependent CISs, such as the hierarchical holographic modeling (HHM) method, the high level architecture (HLA) based method, the petri-net (PN) based method, the dynamic control system theory (DCST) based method, the Bayesian network (BN) based method, and so on.

HHM is a holistic methodology aimed at capturing and representing the diverse characteristics and attributes of a CIS [91,96]. It can provide an understanding of risks at different levels and a multi-view image of a CIS with regard to identifying vulnerabilities. The basis of HHM is the overlapping among various holographic models with respect to the objective functions, constraints, decision variables, and input–output relationships of the CISs. Through HHM [91], multiple mathematical models can be developed and coordinated to capture multiple dimensions, visions, and perspectives of the interdependent CISs. However, this approach is difficult to apply in the interdependent CISs, because the structural complexity, network evolution, connection diversity, dynamical complexity, node diversity and the interdependent complexity of the interdependent CISs lead to the difficulty and infeasibility of providing a mathematical model for some dimension, or vision or perspective of the system.

Interdependent CISs can be regarded as the system-of-systems [72,114], which “consist of multiple, heterogeneous, distributed, occasionally independently operating systems embedded in networks at multiple levels that evolve over time” [55]. Based on the SoS approach, Zio and Ferrario [224] took the Muir Web as system analysis tool to analyze the contribution of interdependent power and water distribution, and transportation networks to the safety of a critical plant; Eusgeld et al. [73,72] introduced a HLA-based interdependency modeling architecture. The architecture includes three levels: the lower level includes the models of single CISs, the middle level includes the interaction model between CISs and the high level represents the global system of systems model. The HLA standard captures the interdependencies through the communication within a “system-of-systems” by a run time infrastructure in a distributed simulation environment. Applying the approach in the interdependent electric power system and its own SCADA system demonstrated its efficiency to capture the CISs interdependencies [132,131].

The Petri net (PN), proposed by Carl Adam Petri [162], can be represented by a four tuple: $PN=(P, T, I, O)$, where P stands for a set of places, T for transitions, I for input functions (a mapping from bags of places to transitions) and O for output functions (a mapping from transitions to bags of places). Another element of the Petri-Net is ‘token’ which are placed in the places. Taking the places of the net together with the tokens to represent the states or conditions of the CISs or their components, and the transitions to represent the impacts across CISs or their components, then the CISs interdependencies are simulated by the flow of the tokens throughout the network [16]. Using the petri-net based approach, Laprie et al. [117] provided a petri-net representation for the interdependencies between electricity and information infrastructure systems; Gursesli and Desrochers [89] analyzed the vulnerability and the recovery strategies for the interdependent CISs originally introduced by [173]; Sultana and Chen [200] modeled the flood-related interdependencies among CISs and their vulnerabilities with the help of fragility curves. Ge et al. [81] developed a GeoPetriNet system to simulate the complex geographical relationships between places and nodes. This method is similar to the network-based approaches, and if modeling the system in detail or having a large system size, the computation complexity is high.

The DCST based method is a quantitative method based on the use of the dynamic control system theory [68,77]. This method describes involved infrastructures and their components by the transfer functions, which express the input/output relationship of two infrastructure components into the domain of Laplace or in the domain of frequency, and then by the application of Mason′s formula, it can compute a global transfer function as well as the corresponding response along a path of interest. The interdependencies can be then quantified by the norm of the global transfer function [185]. This method has been applied in the "Methodology for Interdependencies Assessment" (MIA) EU Project [40], which aims to assess measures of inter-dependencies between the telecommunication system and the electrical system.

The BN based method uses a directed acyclic graph to model involved infrastructure systems and their interdependencies. In this graph, nodes represent random variables, which describe the status of infrastructure components and services as well as the adverse events; edges represent conditional dependencies, reflecting the causal relationships among adverse events, CISs components and infrastructure services [90]. However, the simple BN is associated with each time slice and only provides a static model of the system at each time instant. To capture the dynamic behaviors of CISs, the dynamic Bayesian networks are proposed by introducing inter-time-slice links and conditional probability tables, which represent the temporal probabilistic dependencies between variables belongs to different time slices [85,84].

5. Discussions

Section 5 introduces and reviews different modeling and simulation approaches on the interdependent CISs. This section first compares different approaches from several criteria, with resilience as the main perspective, and then identifies and concludes the future research directions and challenges.

5.1. Approach comparisons

To compare different approaches, there exist many comparison criteria in the literature, such as quantity of input data, accessibility of input data, types of interdependencies, computation complexity, maturity, CISs types, hazard types. Among these criteria, CISs types and hazard types may well differentiate each detailed study, but not for each approach introduced in Section 4, because almost all approaches can be extended to apply in other CISs and other hazard types. This paper first takes the following five criteria into consideration to compare different approaches.

(1) Quantity of input data**:** this criterion refers to the quantity of input data needed for an application of an approach. The input data historical failure reports, economic input–output quantities, the topology and geographical sites, component characteristics, policy and technical parameters and others. Three letters "S", "M", "L" rank the quantity level, and they respectively correspond to the small, medium and large amount of input data. Two or three letters may together describe one approach, which indicates the possible extensions.

(2) Accessibility of input data: this criterion judges the availability to get the required input data. The barriers to get relevant data include antitrust laws, confidentiality and privacy issues, liability issues, access to classified national security information, and reservations about sharing information with the law enforcement community [173]. Three letters "S", "M", "L" rank the accessibility level, and they correspond to the difficult, medium and easy access of input data, respectively.

(3) Types of interdependencies: this criterion describes the types of interdependencies that can be modeled by each approach. As discussed in Section 2, despite there exist many types of classifications, only Rinaldi et al. [173] provide a self-contained classification, which can sort out all the identified interdependency examples and then is used in this paper to compare different approaches. Four letters "P", "C", "G" and "L" respectively correspond to physical, cyber, geographical and logical interdependencies.

(4) Computation complexity: this criterion describes the computational cost for each approach to analyze the performance response of CISs under a disruptive event. Fast performance response analysis can support online simulation and accelerate the emergency response and decision makings. Three letters "S", "M", "L" respectively correspond to fast (less than 1 s), medium (several seconds to several minutes), and slow (several minutes to several hours to several days) computational cost.

(5) Maturity: this criterion measures the development level of each approach. The judgment is based on the number of relevant publications and applications. Three letters "S", "M", "L" respectively correspond to the low (less than 5 publications, few applications), middle (5–20 publications, prototype applications), and high level of maturity (more than 20 publications and successfully applied in real-world CISs).

Based on the above criteria, Table 2 shows the comparison results for those approaches introduced in Section 4. From the table, for the criterion of input data quantity, almost all approaches require medium or large amount of data except the topology-based analytical methods; for the criterion of input data accessibility, the input–output based methods are easy to access the required analysis data while agent-based methods and the flow-based methods are difficult to access because agent-based methods need many types of data, such as policy decision variables, human behavior variables, some of which are different to collect; the flow-based methods need the detailed information about component characteristics, which are usually related to the privacy and security issues and are then difficult to obtain. For the criterion of interdependency types, the empirical approaches, agent-based approaches, Computable-general-equilibrium theory based approaches, network based approaches, the HLA based method, the DCST based method, and the BN based method can model all four types of interdependencies; for the criterion of computation cost, empirical approaches, input–output based approaches, and the topology-based analytical methods only need small computational cost, because they all can analyze the CISs interdependencies by analytical calculation without running simulations; for the criterion of maturity, agent based approaches have been successfully used by several national libraries to apply in many real-world CISs; input–output theory based approaches have been developed well by Haimes et al. and applied in practice with a lot of publications; the network-based approaches are regarded as mature mainly based on the publications (more than 20), but in fact there still exist many challenges to use this type of approaches in practice to design or improve real-world CISs, as discussed in Section 4.4.

Recently, the concept of resilience is proposed, and the U.S. National Science Foundation committee has spent $0.15 billion in the past 6 years (from 2006 to 2012) to support the research regarding "resilient and sustainable infrastructures". Resilient CISs are expected to realize the goal of a resilient nation as claimed by the Present Obama of the United States. Regarding the definition of resilience, it varies by disciplines and applications [102,51,109,101,29,168,211]. To sum up these and other definitions, the author defined resilience as the joint ability of a system to *resist* (prevent and withstand) any possible hazards, *absorb* the initial damage, and *recover* to normal operation [148,149]. In other words, system resilience is determined by three system capacities: the resistant capacity as the ability to prevent any possible hazards and reduce the initial damage level if a

Table 2
Approach comparisons from several criteria.

Approach type	Sub-approach	Quantity of input data	Accessibility of input data	Types of interdependencies	Computation cost	Maturity	Resilience
Empirical		M, L	M	P, C, G, L	S	M	1.3,2.3, 2.4, 3.3
Agent-based		L	S	P, C, G, L	L	L	1.1, 1.2, 1.4, 1.6, 2.1, 2.5, 3.1, 3.3
SD based		M, L	M	P, C, L	M	L	1.6, 2.5, 3.3
Economic theory based	Input output	M	L	P, C	S	L	1.3, 2.3, 2.4, 3.2
	Computable general equilibrium	L	M	P, C, G, L	M	M	1.3, 1.6, 2.3, 2.4, 2.5, 3.2,
Network based	Topology-based method	S, M	M	P, C, G, L	S, M	L	1.3, 2.2, 2.3, 3.2, 3.3
	Flow-based method	L	S	P, C, G,L	L	L	1.3, 1.5, 1.6, 2.2, 2.3, 2.4, 2.5, 2.6, 3.2, 3.3, 3.4
Others	HHM	L	S	P, C, L	S	S	1.6, 2.5, 3.3
	HLA based	L	L	P, C, G, L	L	S	1.1–1.6, 2.1–2.6, 3.1–3.4
	PN	M, L	M	P	M, L	M	1.3, 1.6, 2.3, 2.4, 2.5, 3.3, 3.4
	DCST	M, L	S	P, C, G, L	M	S	1.3, 1.6, 2.3, 2.4, 2.5, 2.6, 3.3, 3.4
	BN	M, L	S	P, C, G, L	M	S	1.3, 1.5, 1.6, 2.3–2.6, 3.3, 3.4

Table 3
Sample strategies to improve CISs resilience.

Capacity type	Resilience improvement strategies (sample applications)
Resistant capacity	1.1 Adjust and improve the organizational and administrative structure to increase early-warning awareness, such as ingraining the safety culture awareness in CISs, reinforcing staff training to decrease human errors.
	1.2 Add and update safety constraints to each participant in the CISs so that the frequency of random hazards can be reduced, such as purchasing high-quality equipment and install properly, implementing strict vegetation program, placing barricades or fences.
	1.3 Harden and protect the key CISs or their components, prevent the events enabling to cause large consequences.
	1.4 Learn and improve from previous accidents using accident models, such as the System-Theoretic Accident Model and Processes approach.
	1.5 Establish an observatory network to sense, monitor, and update system states in real time along with state visualizations based on emerging infrastructure modeling techniques, such as Bayesian networks, to assess on-line risk for early warning.
	1.6 Manage consumer behaviors to keep the CISs load at a certain level to reduce the overload-induced hazards.
Absorptive capacity	2.1 Adjust and improve the organizational and administrative structure to accelerate the emergency decisions, such as sharing information among stakeholders, reinforcing staff training to accelerate the response time, ingraining the interdependency-related culture awareness, adjusting the market structures.
	2.2 Optimize and retrofit the topology of each CIS as well as the interface topologies across CISs.
	2.3 Design and prepare redundancy, backup and substitution to lower the interdependency impacts.
	2.4 Improve the absorptive capacities of some key CISs, such as the transition of the traditional power systems to smart grids.
	2.5 Manage or directly control consumer behaviors to adjust the system load in the emergent scenarios to avoid the large-scale cascading failures.
	2.6 Improve the robustness and self-configuration of the communication systems to keep the situational awareness for rapid emergency decisions.
Restorative capacity	3.1 Adjust and improve the organizational and administrative structure to accelerate restoration decisions and coordination, such as sharing information among stakeholders, establishing the fusion center to coordinate the participants during emergency scenarios.
	3.2 Design advanced decision support platform to quickly find the restoration sequences and priorities, optimum resource allocation strategies.
	3.3 Improve the restorative capacities for key CISs, such as electric power systems, communication systems.
	3.4 Increase the variety and robustness of communication channels.

hazard occurs, the absorptive capacity as the degree to which the systems absorb the impacts of initial damage and minimize associated consequences, such as cascading failures, and the restorative capacity as the ability to be repaired quickly and effectively. Based on the above concept of resilience, the author concludes a sample series of resilience improvement strategies of the interdependent CISs from each of the three capacities. The results are shown in Table 3. To assess the effectiveness of these strategies, it requires corresponding modeling and simulation approaches to support decision makings among different strategies. This paper next discusses how each type of modeling and simulation approaches introduced in Section 4 can support the effectiveness analysis of those improvement strategies listed in Table 3. The results are additionally shown in Table 2 with resilience as another perspective.

From the table, there are two interesting results. First, most of the modeling and simulation approaches only support a part of the sampled resilience improvement strategies, which indicates the overall resilience analysis and management of interdependent CISs requires different modeling approaches in a uniform framework. The HLA-based method is supposed to support all strategies because it is a hybrid approach, which can integrate all other approaches, but there still exist many challenges to apply this approach in practice and make it mature. Except the HLA-based method, the agent-based methods and network flow-based methods can support most improvement strategies, but they also require the largest quantity level of input data. Second, some strategies can be analyzed by multiple approaches. For the strategy 1.3, the critical CISs or their components can be found out not only by empirical approaches through identifying the systems or components involved in the frequent and significant failure patterns, but also by the network based methods through comparing the performance loss after the failure of each system or component. For the strategy 2.2, the optimum CIS topology can be analyzed not only by the topology-based methods, but also by the flow-based methods. Hence, in practice, how to choose an appropriate approach to support decision making? This requires a concept to integrate different approaches into a single framework and co-simulation platform to address different aspects of interdependent CISs and determine their application sequences to avoid conflictions.

5.2. Future directions and challenges

Based on the approach review in Section 4 and the approach comparisons in Section 5.1, this subsection identifies the following research directions and challenges:

A. Data access and collection
Difficult to access data or lack of precise data is a key problem in the field. To provide a detailed description and modeling of interdependent CISs, it requires a lot of relevant data, such as the topologies of single CISs, component geographical locations, interdependency relationships, operational, emergency and other procedures used by CISs owners under normal or crisis scenarios, government and corporate policies. To access these data is usually difficult due to a series of reasons including the antitrust laws, confidentiality and privacy issues, liability issues, and reservations about sharing information with the law enforcement community [172]. To find a tradeoff strategy to access detailed and high quality data needs the joint efforts from the government agencies, research communities and the utility companies. In addition, historical event data collection can not only support the empirical approaches to facilitate ex ante and ex post mitigations and decisions, but also provide the basis to validate other modeling and simulation approaches. Despite scholars have proposed different databases to collect CISs event data, there is no standardized data collection methodology for interdependent CISs. Hence, a uniform data collection method should be proposed, including exact definitions on CISs and their interdependencies, while the media reporting systems should follow some requirements to collect the data so that the time to code and sort out the incident reports is saved to support rapid analysis.

B. Comprehensive modeling and analysis
The applications of some approaches in the literature, such as agent based approaches, network based approaches, usually modeled two or only a proportion of the CISs and mainly focused on the CISs like electricity power, water, gas and communication systems. Other CISs like banking and finance, commercial facilities, and government facilities, received relatively less attentions. However, these CISs are of critical importance to disaster mitigation and recovery as well, and their integration can capture more types and more detailed descriptions of the CISs interdependencies in a comprehensive modeling framework. Also, CISs are not static but evolving due to the technological innovation, demand decrease and so on, such as the transition of traditional power systems to smart grids, the topological adjustment of physical CISs after adding new nodes and links, the capacity augment of old links, and so on. An open modeling framework to capture both short-term and long-term change and evolution of CISs is more desired for applications.

C. Integration and co-simulation
Different modeling and simulation approaches capture different aspects of interdependent CISs and sometimes may produce conflicted results, so it needs to integrate different approaches and distinct their responsibilities in a uniform framework. The systems theory may provide an integration concept. The operation and management process of interdependent CISs can be viewed as hierarchical structures where each level imposes constraints on the activity of the level beneath it, i.e., constraints at a higher level control the low-level behavior, and effective communication channels enable the feedback and control between different levels [8,225]. Numerous of feedbacks and controls among subsystems (including congress and legislatures, government agencies, utility companies, fusion center, operation and management departments, and the physical facilities of CISs) in the hierarchical structures keep the normal and stable operations of CISs. For each subsystem, to realize the systems' overall goal, such as safety, reliability and resilience, it needs to obey some constraints and fulfill some responsibilities, which may require the help of some modeling and simulation approaches. For example, for the departments of CISs planning and design, they may need to retrofit existing CISs or design new CISs, and the network based topological analysis is more appropriate to apply in this scenario. For the departments of CISs supervision and control, they may need to choose which CISs physical components are required to pay more attentions to monitor, and the network based flow analysis can be applied to identify the critical nodes. For the government agencies, they may need to decide the investment priority, and the empirical approaches can provide the critical CISs in priority. In this way, the integration of different approaches is realized through addressing different aspects of the CISs to reach an overall goal and the definitions of “critical” are various in different scenarios. However, there are still a lot of challenges for specific implementation of this concept. For example, to make a system-level decision to meet the needs of different CISs stakeholders, a co-simulation platform is required to support the decision making. Despite many studies, such as HLA-based method, have addressed these problems, the successful and comprehensive applications still require much work.

D. Validation and applications
Validation and applications are very crucial for the development of different modeling and simulation approaches. First, new models are usually validated by comparing the model outputs to the historical data and obtaining feedback from experts in the field. But it should be careful because the CISs of interest are changing with time and the historical data cannot reflect the evolution. Second, empirical approaches and other validated approaches can produce a series of risk-informed metrics, such as resilience factors, the interdependent strength across CISs, system-level fragilities, but it still exists many challenges on how to use these metrics to inform different types of decisions, such as effectiveness assessment and comparisons of mitigation, response and restoration strategies, so it requires a comprehensive and standard set of metrics and the proposal of some guidelines and standards to illustrate their applications.

6. Conclusions

The CISs are interdependent so that small failures in one CIS may spread to other CISs and lead to catastrophic event, largely affecting the economy and human beings' life. To understand performance response of interdependent CISs to different hazards and better protect them, scholars have proposed many modeling and simulation approaches to identify effective ex ante and ex post mitigation measures. This paper reviews the conceptual and qualitative studies about CISs interdependencies as well as their modeling and simulation approaches in the literature. Existing approaches are broadly grouped into six types: empirical approaches, agent based approaches, system dynamics based approaches, economic theory based approaches, network based approaches and others. For each type of the approaches, this paper organizes pertinent studies in terms of a certain principle, such as research focus, modeling rationale, the analysis method. It provides a very clear picture about the connections among these studies and presents an introduction to the new scholars interested in this field. In addition, different types of the approaches are further compared according to several criteria, with the resilience as the main perspective to position their applications and drive the proposal of a system-theory based integration framework.

Despite existing studies contribute a lot to protect and manage the interdependent CISs, there are still many challenges left, as summarized in Section 5.2. In sum, this paper not only presents an introduction about the modeling and simulation approaches of CISs interdependencies to new scholars in the field, but also identifies the future research directions and challenges to better protect and manage the interdependent CISs.

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