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REVIEW ARTICLE

Modeling infrastructure system interdependencies and socioeconomic impacts of failure in extreme events: emerging R&D challenges

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Abstract Greater urbanization does not only mean higher concentrations of population and economic activities, but also increasing complexity and infrastructure interdependencies in the delivery of critical urban services such as energy, water, transport and communication. This paper reviews the current literature in these areas and identifies critical research and development challenges from the perspective—and for the benefit—of key stakeholders, considering their primary decision goals and context. From this vantage point, the critical evaluation framework is extended to include a classification of disruptions and extreme events and an overview of infrastructure modeling approaches and broader socioeconomic impacts assessment methods. Mapping the range of modeling and assessment methods against different decision contexts, critical gaps in knowledge and tools are identified to support the latter. Deep uncertainties characterize the challenge as each major component in the information and decision-making chain—from the frequency and intensity of a disruptive event, to assessing the first-order and immediate impacts of an infrastructure failure, to estimating the nature, extent and impact of cascading failures—multiplies the uncertainties. The emerging research challenges to deal with these interdependencies and uncertainties are discussed.

Keywords Natural hazards · Extreme events · Systems analysis · Simulation · Infrastructure interdependency · Cascading failure

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1 Introduction

In the last decade, an increasing number of natural disasters have adversely affected regional economies and millions of people all over the world (Guha-Sapir et al. 2013; Sundermann et al. 2013). Our cities, in particular, have become more vulnerable because of the increasing rate of urban migration and greater concentration of high-value assets and critical government and business operations, many of them located in coastal and other areas naturally vulnerable to major disasters. The potential for severe and widespread impacts of extreme events has never been greater in society than today.

Critical infrastructures such as telecommunications, electric power generation and transmission, transportation, banking and finance, water supply systems and emergency services have become the components of a larger interconnected system. A disruption in one infrastructure has ripple effects into other infrastructures and eventually impacts the community and the broader economy (Rinaldi et al. 2001). There are numerous instances of interdependencies among infrastructures (de Bruijne and van Eeten 2007; Kröger 2008; Little 2002; Rübbelke and Vögele 2011; Svendsen and Wolthusen 2007; Watts 2003). Examples of cascading infrastructure failures include:

- The 2003 Northeastern America power blackout—about 50 million people in the Northeastern and Midwestern US and Ontario, Canada, lost electric power. This also shuts down water treatment plants and pumping stations. The urban water supplies in the affected areas lost water pressure contaminating urban water supplies. Major sewage spilled into waterways which forced the authorities to issue boil water orders affecting about eight million people (Wilbanks et al. 2013).
- The 2012 Hurricane Sandy in Northeastern US—caused massive failures in power supply, inundated tunnels and subway stations and streets, and stopped air transportation and financial services. About 8.7 million customers were affected by power outages causing serious damages to wireless and Internet infrastructure. Power outages also affected oil and natural gas production and transportation. Refineries were shut down and oil terminals, gas tanks and pipelines became inoperable due to power loss (Comes and Van de Walle 2014). The hurricane killed 72 people in eight states and caused a total of USD 68 billion in damages (Sundermann et al. 2013).

The nature and scope of impacts depend on the nature of the extreme event, and the primary failure type and mode of an infrastructure part or system that leads to failures elsewhere. The IPCC's fifth assessment report (Field 2012; Field et al. 2014; Revi et al. 2014) has warned about the increasing potential impacts to infrastructure systems, built environment and ecosystem services in urban areas brought by changing climate risks. Wilbanks et al. (2013) have warned the same for US cities, especially the potential for cascading failures.

A necessary first step toward better preparedness and eventually more effective loss mitigation measures is a better understanding of infrastructure interdependencies at both local and regional scales. Urban stakeholders then need to take these interdependencies explicitly into account in their policy, investment, operational and planning decisions, considering different spatial and temporal levels. Although most disaster impact assessment or hazard loss estimation (Rose 2004) mainly focuses on direct damages, the socioeconomic impacts stemming from these service disruptions can be very significant and needs serious considerations (Dore and Etkin 2000; Field 2012). Prioritized adaptation actions are needed to minimize these impacts. To implement the actions effectively and efficiently, priorities should be set based on potential impacts of the events and the expected cost-and-benefit balance of the adaptation actions toward improving infrastructure resilience.

Compounding the technical challenge, urban infrastructures are owned and operated by different stakeholders who may or may not know the forward and backward dependencies of their own infrastructure system with other systems. The choice of a particular methodology to analyze the direct and broader impacts of an extreme event on an infrastructure or a system of infrastructures depends on the context of the problem and the objectives of the analysis. A stakeholder-oriented lens is thus necessary to understand the values and limitations of each method.

This paper presents a review of the broad literature related to modeling infrastructure systems performance and assessing the socioeconomic impacts of infrastructure failures. The review specifically considers the perspectives of different decision-makers, considering the primary purpose and geographical scope of interest. The appropriateness and value of these modeling and assessment methods are assessed against these needs, and the critical research and development (R&D) gaps and directions forward are identified.

2 Background

2.1 Decision-making contexts: stakeholder concerns and geographic scopes

Different stakeholders have diverse concerns related to investment, planning, and the design and management of critical infrastructures. Understanding their primary objectives and the underlying decision-making contexts will help to evaluate the capabilities and challenges of different methodologies. The choice of an appropriate decision-support tool or scenario modeling approach should be based on this context. Table 1 lists the types of

Table 1 Typology of stakeholders (S), their primary roles (R) and geographic scopes (G)

Stakeholders	Primary roles	Geographic scopes
International (or multi-country) union (S0)	Infrastructure protection and security (R0)	Multi-national (G0)
Federal government (S1)	Regulation and policy (R1)	National (G1)
State government (S2)	Infrastructure investment and development (R2)	Regional (G2)
Local government (S3)	Infrastructure management/operation (R3)	City/town (G3)
Advocacy organizations (S4)	Infrastructure design and delivery (R4)	
Donors/financial institutions (S5)	Infrastructure services supply/provision (R5)	
Insurance (S6)	Preparedness (R6)	
Utility companies (S7)	Emergency response and management (R7)	
Business (S8)		
Households, individuals and communities (S9)		

different stakeholders and their common roles and concerns, especially in terms of primary decision objective(s) and geographic scope of interest.

An infrastructure-related decision context is based on the characteristics of the stakeholder (S), roles or objectives of decision-making (R) and the geographic scope for the infrastructure system (G). For instance, the decision-making contexts for a federal government agency (S1) making regulation and policy (R1) on a national scale (G1) might include:

- (S1/R1/G1) Developing mitigating strategies or evaluate policies to make a resilient infrastructure system against major disruptions and/or
- (S1/R1/G1) Developing regulations and standards to guide the design, delivery and/or management of built assets that are robust and resilient.

Similarly, the likely decision-making objectives for a local government agency for a city or town (S3) under a range of different roles might include:

- (S3/R2/G3) Assessing the vulnerability of the key infrastructures; develop mitigating strategies and adaptation action plans for identified critical infrastructures;
- (S3/R5/G3) Providing services delivered through infrastructure assets (e.g., people and freight transport services through airports, wharves, roads and bridges; communication services; electricity, gas, water supply, etc.);
- (S3/R3/G3) Identifying the potential risk for the local infrastructures that are critical for maintaining the crucial urban services (e.g., power supply, water supply, transportation, etc.) and identify the affected communities and/or
- (S3/R7/G3) Planning ahead for disaster scenarios and developing disaster mitigation, management and recovery plans so that disruptions in services can be minimized.

Finding an appropriate method for this diverse set of decision-making contexts is a daunting task. Later, we discuss different methodologies from the perspective of these decision-making contexts and modeling objectives.

2.2 Impacts of disruptions

A disruptive event may have impacts at different levels to a system of infrastructures and socioeconomic environments. Most broadly, these impacts can be divided into *physical* and *socioeconomic* impacts. Physical impacts are the most immediate ones observed in an infrastructure where the disruption attacks first. Thus, the disruption affects the customers or the users of this infrastructure. However, due to the interdependencies of infrastructures, this disruption will create more effects to other infrastructures dependent on the first infrastructure. Therefore, a sequence of disruptive events will follow with impacts to different sectors. For instance, energy crisis in a region can disrupt many vital services propagated from the initial disruptions created in electric power generation. This higher-order effect of disruptions in infrastructure systems is well depicted in Rinaldi et al. (2001) (see Fig. 1).

Socioeconomic impacts of a disruptive event may include: social, demographic, economic and political impacts. Lindell and Prater (2003) included psychosocial, sociodemographic, socioeconomic and sociopolitical impacts under social impacts. The reason we use an alternative convention is that the term “socioeconomic” can represent the broader-level impacts of disruptions to society and economy. These impacts may occur over short-term and/or long-term periods of time. Of these, the economic impacts including the direct and indirect economic losses are comparatively well studied using various economic

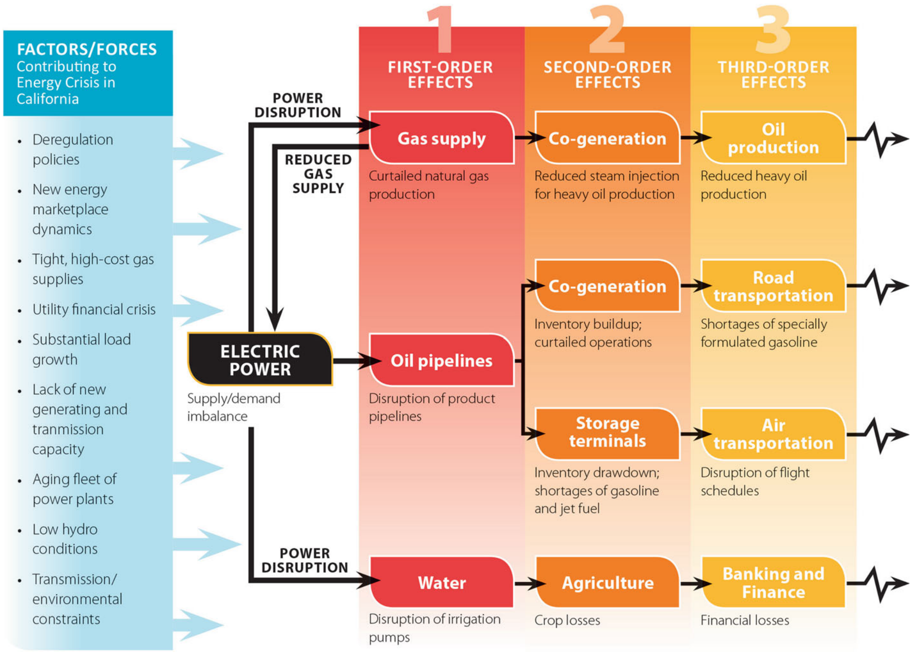

Fig. 1 An example of *n*-th-order infrastructure interdependencies (adapted from Rinaldi et al. 2001)

theory-based approaches. A modeling approach aiming to support decision-making capabilities should, however, capture all of these physical and social impacts in an integrated manner so that the ultimate impacts of the disruptions can be studied well.

Figure 2 presents a conceptual view of the overall problem of understanding the impacts of a disruption in infrastructure systems. The major elements of this point of view include: the type and nature of the disruptive event(s), decision-makers' primary role and objective(s), interdependency layers and characteristics of infrastructure systems, and the scope of impacts considered (i.e., local and higher-order effects of disruptions). On the onset of a disruptive event, the interdependencies of infrastructure systems influence the extent of direct physical impacts. The impacts to other sectors and their economic consequences are next to follow. Eventually, this disruptive event will have broader-level socioeconomic impacts. A cohort of decision-makers with a range of different decision-making contexts has to understand the potential sequence of events, assess the potential impacts of those events and make appropriate decisions at different stages.

2.3 Typology of disruptive events

The type of the disruptive event plays an important role when analyzing its impacts to infrastructure systems. We categorize disruptive events based on two dimensions: time available to prepare for the event and the duration of the actual event. Figure 3 shows a schematic representation of the idea of classifying disruptions based on these two dimensions. The nature of system modeling and the duration of simulation required to inform a given decision will depend on the type and duration of the disruptive event. In addition, the required technical detail or resolution of the analysis will depend on the time available

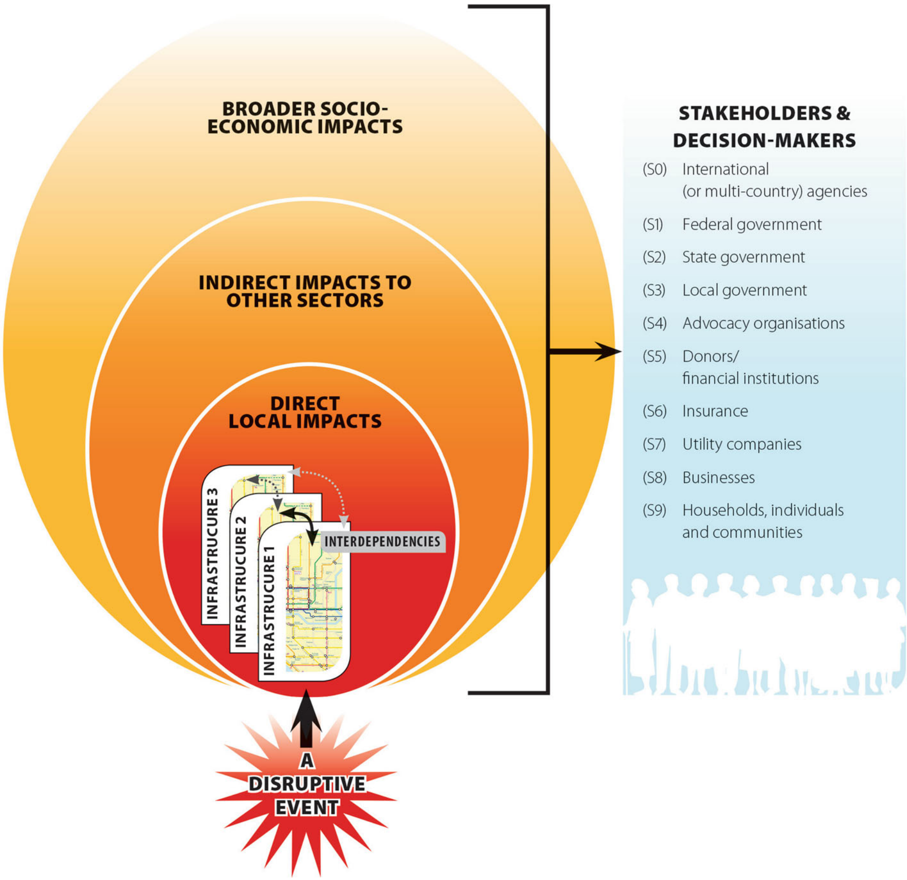

Fig. 2 Different levels of impacts of infrastructure disruptions

for the stakeholder to prepare/plan for the disruption. Also, implicit in the figure is the size of the affected area (by nature of disruption), both primary/directly and secondary. An important element is the post-event recovery period, which does not necessarily depend on the disruptive event itself but may heavily depend on stakeholders' decisions and actions, and the adaptive capacity of the affected community.

Extreme events are typically characterized by the low probabilities and high consequences of the events. This has traditionally been addressed in a risk context (Aven 2012). However, recently, there has been much focus on *deep uncertainties* involved in the extremely unlikely events such as those called "perfect storms"—a rare conjunction of known events (Junger 2009)—and "black swans"—an extreme surprising event relative to the present knowledge (Aven 2013b; Taleb 2009, 2010, 2014). These two types of events represent uncertainties of two different types. Perfect storms represent mostly aleatory uncertainties (randomness) in the joint occurrence of rare, but known events and black swans represent epistemic uncertainties reflecting incomplete knowledge or lack of knowledge—e.g., about the distribution of the parameters involved or even the occurrence of the event (Paté-Cornell 2012). In the real world, most events involve both types of uncertainties.

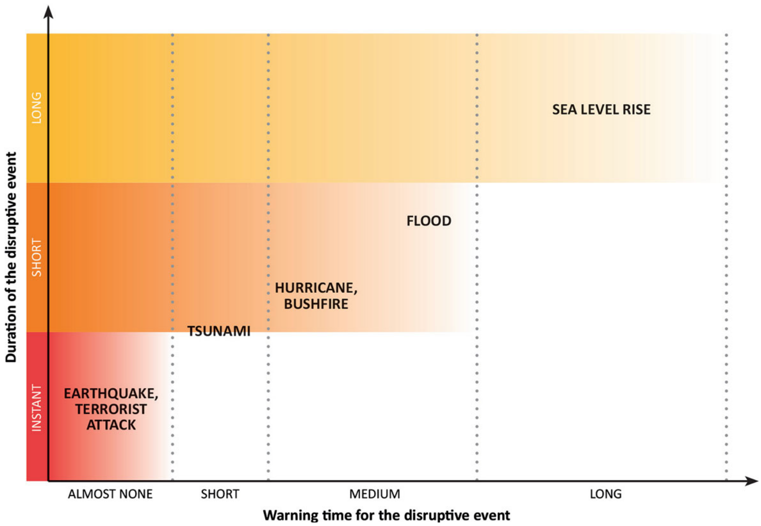

Fig. 3 Typology of disruptive events

An initiating or primary event may also trigger a critical combination of events. For example, the severity of the 2009 Black Saturday bushfires in Victoria, Australia, was exacerbated by the conjunction of high temperature, high wind speed, low humidity and sustained period of dry weather, albeit the fact that only weak correlations exist among the occurrences of these weather variables. During Hurricane Katrina and the Fukushima nuclear disaster, the levee infrastructures failed due to multiple hazards occurring at once (Quinn and Taylor 2014). The Fukushima nuclear disaster in Japan was caused by a rare conjunction of a magnitude 9 earthquake and a 14-m high tsunami. Although such combinations of events did not occur in recent times, at least two occurrences (in the 9th and 17th centuries) of similar events are found in the historical records of the region. The Fukushima reactors were designed for 5.7 m of wave height (Paté-Cornell 2012).

3 Approaches to assess infrastructure interdependencies

There are many modeling and simulation approaches to study infrastructure performance. One basic way to divide them is whether a single infrastructure or a system of interdependent infrastructure is being modeled. We mainly focus on the methods to study a system of infrastructures rather than a single infrastructure, and issues particularly related to interdependencies among different infrastructures. An infrastructure system can be defined as: "a network of independent, mostly privately owned, man-made systems and processes that function collaboratively and synergistically to produce and distribute continuous flow of essential goods and services" (PCCIP 1997).

The following methodological approaches are reviewed based on stakeholder roles and decision-making contexts:

1. Empirical approaches
2. Agent-based simulation approaches
3. System dynamics approaches

4. Economic theory-based approaches
5. Network-based approaches

A number of earlier studies (Bloomfield et al. 2009; Eusgeld et al. 2008; Griot 2010; Ouyang 2014; Pederson et al. 2006; Rinaldi 2004; Satumtira and Dueñas-Osorio 2010; Yusta et al. 2011) reviewed the methodological approaches to model infrastructure interdependencies. These studies, however, reviewed the approaches mechanistically without explicitly considering the modeling objectives and the stakeholder concerns. Based on a review of interdependency studies, Rinaldi (2004) noted that the diverse set of stakeholder concerns drive the principal requirements of a model. Our experience working with all the identified stakeholders in Table 1 in workshops, project consultancies and collaborative research (Bakens et al. 2005; Balouktsi et al. 2015; Foliente 2002) confirm this statement. Thus, the present review adopts an alternative approach to map these methods over an extensive range of decision-making contexts. The objective is to identity the appropriate method(s) among a range of different approaches to model infrastructure interdependencies for specific contexts.

3.1 Empirical approaches

Empirical analyses have been performed to identify the vulnerability of infrastructure systems and provide alternative risk mitigating strategies. Many of these analyses are predominantly based on historical failure data and expert judgments. For instance, using an event tree, Ezell et al. (2000a, b) demonstrated the application of risk analysis for a small municipal water distribution system. An alternative methodological approach is suggested by Guikema (2009) based on statistical learning theory. Franchina et al. (2011) proposed an impact-based approach to model the cascading effects. Based on probabilistic elicitation approaches and expert judgments, Chang et al. (2014) characterized infrastructure vulnerability and community resilience focusing on infrastructure interdependencies. Most of these studies are conducted to assess the risk and vulnerability of the infrastructure systems (see Table 2).

One of the major limitations of these empirical analyses is their heavy dependence on empirical data and expert judgments. Thus, the findings might be biased toward specific cases often analyzed based on small-scale data. Such biases can be alleviated by gathering comprehensive data in large scale. Another limitation of these approaches is that, because of their dependence on empirical data, they are hardly applicable to future scenarios making it difficult for scenario-based what-if analyses.

3.2 Agent-based simulation approaches

An agent-based model adopts a bottom-up approach to analyze the complex architecture and adaptive behaviors of the components of infrastructure systems. Agent-based approaches have the capability to model down to the level of a single component of an infrastructure system as well as the behavior of a decision-maker. Through discrete-event simulations, such methods can capture all kinds of the interdependencies among infrastructure systems (Ouyang 2014). One of the major advantages of using agent-based methods is that they can provide flexible scenario-based what-if analyses assessing the effectiveness of different strategies. They can be also integrated with other modeling techniques providing a detailed analysis. Our review suggests that agent-based methods can be applied to a range of decision contexts involving a host of stakeholder concerns (Table 3).

Table 2 Studies based on empirical approaches

Study	Objective	Major stakeholders	Infrastructure modeled	Geographic scope	Method used
Chang et al. (2007), McDaniels et al. (2007) and Zimmerman and Restrepo (2006)	Risk mitigation	Government	Multiple	National/ city	Based on societal impacts
Ezell et al. (2000a, b)	Risk and vulnerability assessment and risk management	Local government	Water supply and treatment system	Small city/town	Event tree
Robert (2004)	Risk and vulnerability assessment	Utility company	Hydroelectric power generation network and electric power transmission network	Not available	Based on experts' judgments on consequences
Kjølle et al. (2012) and Utne et al. (2011)	Risk and vulnerability assessment and risk management	Emergency preparedness group of a municipality, utility companies	Electricity supply, transport, and ICT	City	Cascade diagram
Huang et al. (2014)	Identification of critical infrastructure and their dependency relationships	Government	Most of the infrastructure sectors	National	Based on experts' opinions

However, agent-based approaches have a few limitations: (1) the modeler needs to make some strong assumptions about the behavior of an agent, and in some cases, such assumptions are hard to justify; (2) to properly calibrate the parameters of a simulation model, agent-based methods require a large set of detailed data about infrastructure systems and agent behavior; it is sometimes difficult to collect such detailed information on infrastructure performance particularly when the relevant infrastructures have data sensitive to public safety and/or stakeholder interests.

3.3 System dynamics-based approaches

System dynamics is a widely used method to analyze and understand the behavior and structure of a complex system over time. Based on nonlinear theory and feedback controls, it represents a top-down approach to analyze complex systems. This approach was initially developed by Forrester (1961) and later extended by Sterman (2001). System dynamics has three central concepts, which include: stocks (the accumulation of resources in a system), flows (the rates of change that alter those resources) and feedback (information that

Table 3 Studies adopting agent-based simulation approaches

Study	Objective	Major stakeholders	Infrastructure modeled	Geographic scope
Aspen-EE (Barton et al. 2000; Brown et al. 2004)	Impacts of disruptions (Chang et al. 2007) or policy changes on the economy	Government, utility companies	Electric power market and consumer behavior	National
CommAspen (Barton et al. 2004)	Economic impacts of disruptions in telecommunications	Government, utility companies	Power, communication, banking and finance	National
Smart II (North 2001a) SmartII + (North 2001b)	System planning and operation	Utility companies	Electric power market Electric power and natural gas markets	Regional
CIMS (Becker et al. 2011; Dudenhoeffer et al. 2006)	Visualization	Utility companies		National
Barrett et al. (2010)	Evacuation planning	Emergency response organization	Cell phone, transportation network and social calling network	City or region

determines the values of the flows). The simulation of a system based on a system dynamics approach gives important insights on causes and effects leading to a better understanding of the dynamic behavior of the system. A simplified example of a system dynamics model representing the traffic present in a road network is shown in Fig. 4. The volume of traffic present on the road network is a stock controlled by flows determined by the entry and exit rates of vehicles, which are dependent on a number of other variables not pictured. A feedback loop can be set up between population and entry rate determining the number of vehicles entering the road network. Another feedback loop can be set up between traffic and the entry rate decreasing entry to the roads under heavy traffic conditions. The number of people successfully completing trips depends on the exit rate and the number of occupants per vehicles.

Under a disruptive event, an infrastructure responds in a dynamic manner. System dynamics-based approaches can model this evolutionary behavior of the interdependent systems by capturing important cause–effect relationships. These approaches can be applied to answer a range of questions related to infrastructure performance and designs (see Table 4). However, system dynamics-based approaches need assumptions or expert knowledge to establish the causal relationships; require extensive data to calibrate the parameters and functions; lack the ability to capture component-level dynamics; and can be validated only at the conceptual level because of data requirements.

3.4 Economic theory-based approaches

3.4.1 Input–output models

Nobel laureate Wassily Leontief first proposed the input–output (I–O) economic model (Leontief 1951) which has been widely used in economics to predict the flow of commodity or information between economic sectors. Leontief's I–O model was later extended

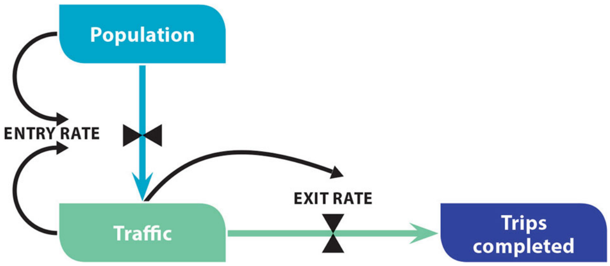

Fig. 4 Simplified example of a system dynamics model [adapted from (Steinberg et al. 2011)]

Table 4 Infrastructure studies utilizing system dynamics approach

Study	Objective	Major stakeholders	Infrastructure modeled	Geographic scope
CIP/DSS (Bush et al. 2005; Santella et al. 2009; Steinberg et al. 2011)	Consequence of disruptions to infrastructure, risk and vulnerability assessment, guide risk mitigation strategies, identify risk propagation	Government (federal, state and local) and industry	Water, information and telecommunications, energy, transportation, banking and finance and others	National, regional and city level
EVA-INFRA-SD (Tonmoy and El-Zein 2013)	Vulnerability assessment	Local government	Water and waste water network	Local community

to describe the ripple effects of disruptions in interdependent systems (Haimes and Jiang 2001).

Based on I–O modeling, Haimes and Jiang (2001) first proposed a model known as the inoperability input–output model (IIM) for interconnected infrastructure systems. In the IIM, they introduced the term *inoperability*—the inability of a system to perform its intended functions. Caused by internal failures or external disruptions, inoperability of a system represents the reduction in the delivery compared to the system's intended output. Inoperability may be denoted by the extent to which a system is dysfunctional, expressed as a percentage of the system's original production level. The formulation of IIM as follows:

$$x = Ax + c \Leftrightarrow x_i = \sum_j a_{ij}x_j + c_i$$

In this model, x_i is the overall risk of inoperability of the ith infrastructure caused by a disruption; a_{ij} represents the probability of inoperability that the jth infrastructure contributed to the ith infrastructure due to their interconnectedness; and c_i is the additional risk of inoperability inherent in the complexity of the ith infrastructure. Hence, given a disruption from one or multiple infrastructures or industries of the economy, the IIM can estimate the ripple effects measured by infrastructure inoperability.

IIM has been used to analyze how a disruption propagates among interconnected infrastructures, how to assess the risks and vulnerability of different sectors due to a disruptive event and what are the impacts of risk management strategies (see Table 5). These models are applied to large-scale databases such as the Economic Analysis database of national I–O accounts and regional I–O multiplier system accounts, and measure the interdependencies among economic sectors. As such, the IIM-based models are useful for macroeconomic-level or industry-level interdependency analysis.

Since these models are based on I–O modeling from economics, they also suffer from the limitations common to I–O approaches. These limitations include linearity assumption, lack of behavioral content, lack of interdependence between price and output, lack of explicit resource constraints and lack of input and import substitution possibilities (Rose 2004). Of these limitations, the most relevant ones, for IIMs, are due to the assumptions related to linearity, equilibrium and deterministic point of view (Santos 2006). This model assigns the contributions of a sector to other sectors linearly which may not be true in some cases. I–O models assume equilibrium among economic sectors implying that industry inputs and outputs will balance with the final consumption of the sectors' outputs. While this condition may be true in the long run, during the transient times following a major disruption in economic activities, nonequilibrium conditions could dominate. By assigning deterministic coefficients, these models lack content related to the uncertain response of an infrastructure system due to a disruption. Another major limitation of I–O models for infrastructure analysis is the lack of spatial representation of the infrastructure systems in the modeling framework, while most of the critical infrastructure networks (e.g., transportation, energy, water distribution) are spatially embedded. In addition, IIMs cannot account for the interdependencies at the level of individual component of an infrastructure or economic sector. Consequently, I–O models cannot handle decisions such as whether to invest or specifically where to invest in an infrastructure system for improving resilience.

Table 5 Economic theory-based approaches

Study	Objective	Major stakeholders	Infrastructure modeled	Geographic scope	Method used
Leontief-based Inoperability input–output model—IIM (Cagno et al. 2011; Crowther and Haimes 2010; Haimes and Jiang 2001; Jung et al. 2009; Leung et al. 2007; Lian and Haimes 2006; Santos 2006; Santos and Haimes 2004)	Risk and vulnerability assessment and management	NA	Most of the Economic sectors	National	I–O models
Zhang and Peeta (2011)	Analyzing system resilience and coordinated disaster recovery	Government	Transportation, telecommunication, energy and Power	National	Spatial computable general equilibrium

To mitigate some of the issues of I–O modeling, Resurreccion and Santos (2013) developed a dynamic inoperability I–O model (DIIM) to assess the propagation of direct and indirect impacts of disruption over time.

3.4.2 Computable general equilibrium (CGE)

CGE-based methods extend the capacities of the I–O methods (Rose 2004), 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. This method, however, requires selecting a form of the utility functions for calibrating production functions, which sometimes may be difficult to apply for limited data. Zhang and Peeta (2011) formulated an equilibrium problem to study the interdependency issues using a multilayer infrastructure network concept and the spatial extension of the CGE models.

3.5 Network-based approaches

Infrastructure systems can be represented by networks where nodes or vertices represent different components of a system and links or edges represent relationships among them. Network-based approaches can analyze interdependencies through different analytical techniques. Through network-oriented approaches, intuitive representations of critical infrastructures are possible by providing the detailed descriptions of their structures and flow patterns. In these approaches, individual component failures of a single infrastructure under a disruption can be modeled and the performance response of the infrastructure system can be analyzed. Network-based approaches can be divided into two groups: (a) topology-based approaches and (b) flow-based approaches.

The topology-based approaches can be used for vulnerability assessment from large-scale datasets of infrastructure systems (see Table 6). However, such approaches are limited since they ignore the functional relationships among the different elements of the network missing vital information about infrastructure performance. Flow-based methods, on the other hand, can capture the flow characteristics of interdependent infrastructures, and provide more realistic descriptions on their operation mechanisms. However, these approaches are not scalable since when the network is modeled in detail, the computational cost to analyze it is very high.

4 Approaches to assess the socioeconomic impacts of disruptions

Estimation of economic and social impacts of a disaster has been an important topic of research because of interests to assess the vulnerability of individuals and communities, evaluate adaptation and mitigation options, improve decision-making capacities for recovery operations and finding the required level of disaster assistance, and inform insurers of their potential liability (Rose 2004). Assessment of socioeconomic impacts of a major disaster can serve the following purposes (Rose 2004):

- assess the risk and vulnerability of a geographic region and population
- evaluate alternative adaptation and risk mitigation strategies
- improve decision-making capacities for disaster preparedness and management operations

Table 6 Network-based approaches

Study	Objective	Major stakeholders	Infrastructure modeled	Geographic scope	Method used
Buldyrev et al. (2010)	Risk and vulnerability assessment and network design	National governments, Utility companies	Power transmission network and internet	National	Complex network theory
Dueñas-Osorio et al. (2007)	Risk and vulnerability assessment	Utility companies	Power system and water distribution system	Local Community	Topological analysis
Wang et al. (2012)	Risk and vulnerability assessment	Utility companies	Power and water systems	City	Complex network theory
Rahman et al. (2008) and Rahman et al. (2011)	Risk and vulnerability assessment	Utility companies, emergency managers	Power and water systems	Local community	Matrix partition-based technique
Holden et al. (2013)	Simulate the operation of interdependent infrastructures	Local governments	Water distribution and power generation	Local community	Network flow models

- find the required level of assistance
- inform insurers of their potential liability.

4.1 Assessing the economic impacts of disruptions

Many empirical studies (Alesch et al. 1993; Dacy and Kunreuther 1969; Dahlhamer and D'Souza 1997; Durkin 1984; Gordon and Richardson 1995; Hallegatte 2008; Kroll et al. 1991; Lindell and Perry 1998; Nigg 1995; Tierney 1997) have been conducted to estimate the economic impacts of disasters in general. However, only few of them have focused to measure the economic impacts of infrastructure disruptions due to disasters. Modeling approaches for this purpose are mainly based on economic theories broadly divided into two categories:

- I–O models
- Computable general equilibrium (CGE) models.

4.1.1 Input–output (I–O) models

I–O modeling is the most common method to analyze the regional impacts of a disruption because of its strong theoretical foundation in economics. This model considers production interdependencies making it suitable for measuring how the impacts of a disruption in one sector can ripple throughout the economy. The I–O model is used in the HAZUS loss estimation methodology (Brookshire et al. 1997; Schneider and Schauer 2006) which is one of the most comprehensive methodologies to estimate the losses of a natural hazard. In addition to estimating the immediate economic and social losses of natural hazard, HAZUS estimates the long-term effects upon the regional economy. The Indirect Economic Loss

Module of the HAZUS is based on I–O models (Brookshire et al. 1997; Schneider and Schauer 2006). HAZUS is intended primarily for use by state, regional and community governments. Initially, HAZUS was developed for estimating losses due to an earthquake to provide a basis for decisions with several objectives including disaster preparedness and planning for disaster response, assistance and mitigation (Kircher et al. 2006). HAZUS was later extended to estimate the losses for floods (Scawthorn et al. 2006) and hurricanes (Vickery et al. 2006). Kim et al. (2002) estimated the direct and indirect economic impacts of disruptions in the regional transport networks due to an earthquake considering the interindustry relationships through an integrated regional I–O model and network assignment model. Although not based on I–O models, Chang (2003) developed a methodology based on life cycle cost analysis for estimating the direct economic losses caused by infrastructure disruptions.

As mentioned earlier, the disadvantages of an I–O model include its linearity, lack of behavioral content, lack of interdependence between price and output, lack of explicit resource constraints, limitation in spatial representation and lack of input and import substitution possibilities (Rose 2004).

Based on an I–O modeling framework, Hallegatte (2008) proposes a new model, to assess the indirect effects of disasters at a regional scale. This model can be extended to measure the impacts of infrastructure disruptions as well. The proposed model considers sector production capacities and both forward and backward propagations within the economic system and the adaptive behaviors. Hallegatte (2008) used the method to model the response of Louisiana economy after the landfall of hurricane Katrina and found that economic processes exacerbate direct losses and estimated the total costs of hurricane Katrina as $149 billion including the direct losses equal to $107 billion.

4.1.2 Computable general equilibrium (CGE) models

Computable general equilibrium (CGE) models have gained popularity to estimate losses of hazards because of the inherent limitations of I–O models. Applications of CGE models include studying synthetic scenarios (Boisvert 1992; Brookshire and McKee 1992) and real-world case studies (Rose and Liao 2005; Rose et al. 2005). Applying the CGE model, Rose and Liao (2005) studied the economic resilience of the Portland, Oregon region for disruptions in water systems due to an earthquake. Effectiveness of various resilience improvement strategies including pre-event water pipeline replacement and post-event increased water conservation and substitution were evaluated. With a similar approach, Rose et al. (2005) analyzed the economic impacts of a terrorist attack on the Los Angeles power system.

4.2 Assessing the social impacts of disruptions

Although considerable efforts are made to assess the physical and economic impacts of a disaster, explicit social impact analysis is typically absent in the disaster impact assessments or hazard loss estimations reports. This is mainly due to the difficulty in quantifying social impacts. Only few studies have attempted to measure the social impacts of disasters. Social impacts may include loss of lives, displaced populations, disruptions in healthcare services, psychological impacts and political impacts (Chang et al. 2009; Lindell and Prater 2003; Scawthorn et al. 2006).

Lindell and Prater (2003) presented a conceptual model to assess the social impacts of natural disasters. They presented the complex process of assessing disaster impacts based on a number of dependency relationships—for instance, while the physical impacts of a disaster depend on the characteristics of the disaster and the hazard mitigation and emergency preparedness of the affected community, social impacts of a disaster depend on the physical impacts of the disaster and available community recovery resources and extra-community assistance.

HAZUS loss estimation methodology (Scawthorn et al. 2006) includes social losses by estimating the number of individuals who need shelters. Specific models are used to estimate the number of displaced households in the affected areas. Displaced households also include those who evacuate during a disaster.

Chang et al. (2009) investigated social impacts of infrastructure disruptions including impacts due to displaced individuals seeking public shelter and functionality losses for health-care facilities. They developed a model to estimate the demand for public shelter considering household decision-making behavior and socioeconomic and location characteristics in addition to building damage and infrastructure failures. They also modeled operational performance of a hospital's interacting systems including structural, non-structural, lifeline and personnel in an earthquake.

5 Discussion

Table 7 presents a mapping between the approaches to model infrastructure performance in disruptions and possible decision-making contexts. We use the stakeholder group (S), their primary roles (R) and possible geographic scopes (G) to represent a few specific examples of decision-making contexts. The appropriateness of a method is judged based on our understanding of the types of decisions faced by the different stakeholders, our knowledge of the fine technical features and capability of the different approaches, and the applications of the methods in similar contexts, as reviewed herein.

A federal government agency may be interested in developing regulation and policy; a specific decision-making context may be to develop standards, at a national level, to guide the design and management of robust and resilient built assets. In such cases, approaches based on agent-based simulation or system dynamics modeling have been applied before to model infrastructure performance. Hence, for this context, such methods could be preferred to other approaches.

Similarly, a local government agency may be interested to develop an emergency management and recovery plan so that disruptions in lifeline services are minimized. For such contexts, agent-based simulation approaches, system dynamics approaches and network theory-based approaches have been applied before.

In normal practice, the government/policy-maker or the industry decision-maker does not need to run any of the models presented in Table 7; their analysts (in-house or external consultants) do. Unfortunately, some analysts and researchers tend to see every problem as "a nail that can be fixed with a hammer" (or use the same tool/model that they know, rather than the one that is more/most appropriate for a given problem). The above discussion shows that Table 7 can help guide both the decision-makers and their analysts/consultants to determine, in the first instance, the most appropriate tool(s) for a given decision context.

An alternative approach to identify the stakeholder decision contexts is through a broad survey across all the stakeholders in Tables 1 and 7. However, we would expect that such a survey would not necessarily lead to a much different list of decision contexts as presented

Table 7 Decision-making contexts: stakeholder groups and their roles, geographic scopes and appropriate methods

	Stakeholder group	Primary roles	Geographic scope	Specific decision-making context	Appropriate methods
Government	S0. International (multi-country) union	R1. Regulation and policy	G0. Multi-national	S0/R1/G0: Develop regulations coordinating policies for infrastructure development in the member states	NA
		R2. Infrastructure investment and development		S0/R2/G0: Set major infrastructure cross-border projects	NA
	S1. Federal government	R0. Infrastructure protection and security	G1. National	S1/R0/G1: Provide protection and security to critical national infrastructures	M1
		R1. Regulation and policy		S1/R1/G1: Develop mitigating strategies or evaluate policies to make a resilient infrastructure system against major disruptions	M2, M3, M4
				S1/R1/G1: Develop regulations and standards to guide the design, delivery and/or management of built assets that are robust and resilient	M2, M3
		R2. Infrastructure investment and development		S1/R2/G1: Make prioritized investment decisions to mitigate the risks of major disruptions	M1, M3
		R5. Infrastructure services supply/provision		S1/R5/G1: Provide services delivered through infrastructure assets (e.g., people and freight transport services through airports, wharves, roads and bridges; communication services; electricity, gas, water supply, etc.)	M2, M3, M5
	S2. State government	R2. Infrastructure investment and development	G2. Regional	S2/R2/G2: What major investments should be made in a region to adapt to a disruption such as sea level rise	M2, M3
		R5. Infrastructure services supply/provision		S2/R5/G2: Provide services delivered through infrastructure assets (e.g., people and freight transport services through airports, wharves, roads and bridges; communication services; electricity, gas, water supply, etc.)	M2, M3, M5
		R3. Infrastructure management and operation		S2/R2/G2: Understand the potential number and value of assets at risk against major disruptions and develop mitigating strategies in a major metropolitan region	M2, M3, M5
		R7. Emergency response and management		S2/R7/G2: Develop regional response operations under a major disaster	M2
	S3. Local government	R2. Infrastructure investment and development	G3. City/town	S3/R2/G3: Assess the vulnerability of key infrastructures; develop mitigating strategies and adaptation action plans for identified critical infrastructures.	M3, M5
		R5. Infrastructure services supply/provision		S3/R5/G3: Provide services delivered through infrastructure assets (e.g., people and freight transport services through airports, wharves, roads and bridges; communication services; electricity, gas, water supply, etc.)	M2, M3, M5

Table 7 continued

	Stakeholder group	Primary roles	Geographic scope	Specific decision-making context	Appropriate methods
		R3. Infrastructure management/operation		S3/R3/G3: Identify the potential risk for the local infrastructures that are critical for maintaining the crucial urban services (e.g., power supply, water supply, transportation, etc.) and identify the affected communities	M1, M5
		R7. Emergency response and management		S3/R7/G3: Plan ahead for disaster scenarios and develop disaster mitigation, management and recovery plans so that disruptions in services can be minimized	M2, M3, M5
Nongovernment organizations	S4. Advocacy organizations	R3. Infrastructure management/operation	G2. Regional	S4/R3/G2: Develop response operations in a region in case of a major disruption	M2
	S5. Donors/financial institution	R2. Infrastructure investment and development		S5/R2/G2: Evaluate different alternative investment options of a region to mitigate potential risks	M3, M4
		R7. Emergency response and management		S5/R7/G2: Estimate required relief and evaluate disaster recovery funding	M4
Industry	S6. Insurance	R2. Infrastructure investment and development	G1. National; G2. Regional; G3. City/town	S6/R1/G1: Assess the risks and impacts of a major disruption	M3, M4
		R1. Regulation and policy		S6/R1/G1: Develop regulations and standards to guide the design, delivery and/or management of built assets that are robust and resilient	M4
	S7. Utility companies	R2. Infrastructure investment and development	G2. Regional; G3. City/town	S7/R2/G2: Plan, design, and build new utility infrastructures and evaluate alternative options	M2, M4, M5
		R3. Infrastructure management and operation		S7/R3/G2: Design risk mitigating measures preventing cascading failures and protecting assets	M1, M2, M3, M5
		R5. Infrastructure services supply/provision		S7/R5/G2 & G3: Provide services delivered through infrastructure assets (e.g., people and freight transport services through ports, roads and bridges; communication services; electricity, gas, and water supply etc.)	M2, M3, M5
	S8. Business	R2. Investment and development	G2. Regional; G3. City/town	S8/R2/G2: Develop business strategies and evaluate investment options	M2, M4, M5
		R3. Management and operation		S8/R3/G2 or G3: Assess the risks of an operation under a major disruption	M1, M2, M5
Public/community	S9. households or individuals	R6. preparedness	G1. national; G2. regional; G3. City/town	Plan and prepare (appropriately) to preserve life and property in extreme events	M1, M2

M1—empirical approaches, M2—agent-based simulation approaches, M3—system dynamics approaches, M4—economic theory-based approaches and M5—network-based approaches herein. Rather, it will lead to domain-specific concerns, which will be very difficult to map over a common set of dimensions and methodological approaches. These can be confirmed in future studies, including detailed analyses of stakeholder concerns and comparison of the appropriateness of selected methodological approaches for a common decision-making context.

5.1 Trends and gaps

The present review highlights the lack of appropriate integrated approaches to assess the broad socioeconomic impacts of disruptions to interdependent infrastructures. Our findings are summarized below:

- Various objectives and goals have been identified to study infrastructure interdependencies, in general, and the impacts of disaster to infrastructure, in particular. A method's appropriateness should be judged under the decision-making contexts for which the model is developed. Future applications and/or further development of a method depend on the specific decision-making context. Thus, the lens of decision-making contexts is absolutely necessary to assess the appropriateness of a model.
- A major issue in assessing infrastructure performance and socioeconomic impacts of disruptions is the lack of comprehensive datasets and/or access to relevant datasets. Modeling approaches have a wide range of data requirements in terms of coverage and extent. Required datasets include characteristics of disruptive events, topologies and locations of infrastructure components, nature of interdependencies, procedures to manage and operate during disruptions, and actual social and economic costs of the events. Collecting this wide range of data is usually difficult due to a number of concerns including difficulty to monitor the real-time performance of infrastructures due to failure of internet, assembling and maintaining databases, and privacy, security and proprietary issues (Rinaldi et al. 2001). There are infrastructures that are privately owned and operated and often have a restricted policy to collect and share data. There is also lack of a benchmark dataset to compare different methods to assess infrastructure system performance during a specific disruption scenario.
- Although many studies determined the direct and indirect economic impacts of disasters, there is a paucity of rigorous studies assessing the broader-level socioeconomic impacts of disruptions.
- Most of the impact studies determine the direct and indirect economic impacts of a disruption based on I–O relationships among economic sectors. However, different interdependencies (including physical, logical and geographical) among the infrastructure systems have not been considered.
- From methodological perspective, two clear directions have emerged. On one hand, methods that are used to address the interdependencies incorporating the details of the infrastructure systems have rarely been used for impact assessment of disruptions; on the other hand, methods used to estimate the losses of hazards are mainly based on economic theories with limitations to capture the details of the systems. While these two directions might be suitable for certain decision-making contexts, there are cases where these methods are simply not adequate. For instance, to evaluate alternative mitigating options of a disruption, one needs to incorporate sufficient details. However, traditional economic theory-based models have inherent limitations to incorporate such details. Only few models of estimating the direct economic impacts of disruptions (Chang 2003) can address this gap to some extent.

- At present, there is a paucity of studies investigating infrastructure system interdependency issues at a local scale. However, local governments commonly face such issues related to the management and planning for potential disruptions.
- There is a gap in the literature in understanding extreme events such as black swans and perfect storms described in Sect. 2.3. Particularly, the uncertainties involved, including the aleatory and epistemic, need to be considered in the modeling process. Infrastructure performance during disruptions may involve many forms of uncertainties from determining the frequency and intensity of a disruptive event, to assessing first-order and immediate impacts of an infrastructure failure, to understanding the nature and extent of the interdependencies among the components of infrastructure systems and to estimating the impacts of the cascading failures in those systems. Paté-Cornell (2012) and Aven (2013a, b) have highlighted the meaning and importance of black swans in risk assessment and management context. Aven (2013a, b) also discussed the limited capabilities of traditional risk assessment to identify and predict the black swans.

6 Future directions and challenges

The seemingly simple question "how can we assess the impacts of disruptions on our interdependent infrastructure systems?" turns out to be a wicked problem, which is underpinned by major challenges in three overlapping areas (Fig. 5).

Major research questions that need to be addressed include:

- When does one primary event trigger a critical combination of events and how should one deal with the deep uncertainties involved in an extreme event?
- How can we introduce the vast range of stakeholder concerns into the infrastructure modeling process particularly addressing the interdependency issues and assessing socioeconomic impacts?
- What are the physical and socioeconomic impacts of specific disruptions at a given location, and how can we design and build our complex infrastructure systems in those locations to be well prepared for those disruptions?
- Is it possible, or even appropriate, to develop one super-tool that can satisfactorily address all the key issues and impact areas, or will it be more worthwhile and effective developing an ensemble of tools with properly designed interfaces allowing information/data interoperability among various tools?
- How can we create a comprehensive methodological approach with a platform of linked models and data interoperability for modeling infrastructure interdependencies for a range of different stakeholder concerns and decision contexts?

Because of the vast extent of the decision-making contexts and the stakeholder concerns and a diverse range of methodological approaches, it will be a nearly impossible task to build a super-tool to support a wide range of decision-makers. Instead, a more pragmatic approach will be to build interfaces among different aspects of the problem linking models and outputs. Such a linked or interoperable modeling approach will be able to fit different methodological approaches in the framework depending on the stakeholder concerns, geographic scopes and infrastructures to be modeled.

Potential research challenges to answer these questions include:

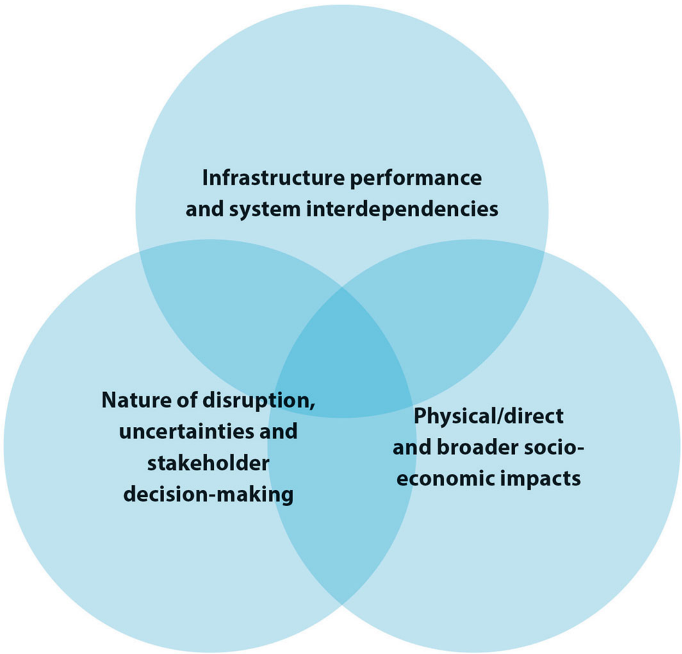

Fig. 5 Intersection of major research themes involving infrastructure disruptions

- A comprehensive methodological framework, consisting of linked models, supported by an extensive database of information involving various infrastructures, features of disruptive events and detailed social and economic costs will be needed. Emerging technologies such as the internet of things can help to monitor infrastructure components before, during and after disasters (Akyildiz et al. 2002; Yen-Kuang 2012). Data interoperability and information systems platform need to support a range of modeling and analysis tools and different workflows.
- The need to model infrastructures and assess the socioeconomic impacts in a harmonized framework. Such a framework is necessary to understand the role of interdependency issues when measuring the impacts of a disruption.
- The need for a consistent benchmark and relevant datasets to evaluate different methodologies of estimating socioeconomic impacts. To judge critically and rigorously the appropriateness of the applications, a set of methods should be applied over a common decision-making context and their performance and accuracy evaluated.
- The need to better understand the broader and extensive impacts of infrastructure disruptions on people and communities.

Finally, a major challenge will be how to deal with the deep uncertainties involved in the occurrence and the consequences of the disruptive events and internalize the uncertainties into the decision-making process. Aven (2013a) highlighted the limitations of common analytical approaches to support decision-making for scenarios with deep uncertainties. To deal with these uncertainties, in a risk assessment and management context, Aven (2013a) suggested managerial review and judgment that can go beyond the analytical methods typically used. Similar approaches involving stakeholders' judgment are needed when making decisions based on the assessment of the infrastructure performance and the socioeconomic impacts of disruptions. Infrastructure risk management and decision-making can potentially be explored also based on convex functions and "antifragility" concepts (nonlinear response to stressors) and various heuristics to detect model error or limitations (Taleb 2014; Taleb and Douady 2013).

7 Conclusions

A stakeholder-oriented framework has been presented to assess the opportunities and value of different approaches of modeling the direct and broader socioeconomic impacts of an extreme event to an infrastructure system, especially focusing on system interdependencies. The strengths and limitations of different methodological approaches for modeling infrastructure systems and their interdependencies, and for assessing the socioeconomic impacts of failure were assessed from the perspective of a decision-maker with a range of concerns. A diverse set of methodologies, spanning from economics to risk engineering, is mapped over a wide range of decision-making objectives and geographic scope. This framework provides practical guidance for analysts and policy-makers in selecting or narrowing the choice of appropriate methods for a specific purpose related to broad impact assessment of infrastructure disruptions.

We have identified critical R&D needs to address: (a) the lack of comprehensive datasets and/or access to a large volume and the diverse sets of data needed to support different modeling approaches and analysis workflows; (b) the lack of an integrated methodological approach to model an infrastructure system and assess the impacts of disruption or harmonized ways to link a specific approach or method to another considering the wide range of stakeholder objectives; and (c) the development of meaningful (i.e., purpose-driven or contextual) and practical approaches to deal with perfect storms and black swans to guide action/decisions designed to minimize future losses.

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