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Literature review on modeling and simulation of energy infrastructures from a resilience perspective

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ABSTRACT

Recent years have witnessed an increasing frequency of disasters, both natural and human-induced. This applies pressure to critical infrastructures (CIs). Among all the CI sectors, the energy infrastructure plays a critical role, as almost all other CIs depend on it. In this paper, 30 energy infrastructure models dedicated for the modeling and simulation of power or natural gas networks are collected and reviewed using the emerging concept of resilience. Based on the review, typical modeling approaches for energy infrastructure resilience problems are summarized and compared. The authors, then, propose five indicators for evaluating a resilience model; namely, catering to different stakeholders, intervening in development phases, dedicating to certain stressor and failure, taking into account different interdependencies, and involving socio-economic characteristics. As a supplement, other modeling features such as data needs and time scale are further discussed. Finally, the paper offers observations of existing energy infrastructure models as well as future trends for energy infrastructure modeling.

1. Introduction

1.1. Critical infrastructure (CI) protection

A nation's health, wealth, and security rely on the production and distribution of goods and services. The array of physical assets, processes and organizations through which these goods and services move are called infrastructures [1]. Among all infrastructure systems, the critical infrastructures (CIs) are those systems "*whose incapacity or destruction would have a debilitating impact on the defense and economic security*" [2]. Presidential Policy Directives 21 *Critical Infrastructure Security and Resilience* (PPD-21) identified 16 critical sectors of infrastructures including: chemical, commercial facilities, communication, critical manufacturing, dams, defense industrial base, emergency services, energy, financial services, food and agriculture, government facilities, healthcare and public health, information technology, nuclear reactors, materials, and waste, transportation systems, and water and wastewater systems.

However, human-induced and natural disasters, such as the 9/11 terrorist attacks [3] in 2001 and Hurricane Katrina [4] in 2005, further highlighted the vulnerability of CI systems and raised the awareness about their protection. In the United States, the National Infrastructure Simulation and Analysis Center (NISAC) and the Department of Homeland Security established in 2001 and 2002, respectively, aim at improving CI protection. PPD-8 and PPD-21 specifically addressed the national preparedness of CI systems.

Similar organizations and programs have also been developed in other regions and countries, such as the European Program on Critical Infrastructure Protection, the Critical Infrastructure Protection Implementation Plan in Germany and the Critical Infrastructure Resilience Program in the UK [5]. In Asia, recovering from the earthquake and tsunami at Tokushima, the National Resilience Program of Japan dedicated $210 billion worth investment in 2013 to increase the overall resilience of energy, water, transportation and other CIs [6]. Being aware that the majority of outages have roots in the distribution system, the Chinese National Energy Administration allocated 20 trillion CNY for the distribution renovation during 2015–2020 to increase reliability, power quality, and resilience to disruptions. The modeling and simulation of CIs for protection and resilience purposes have thus received significant interests among universities, national laboratories and private companies.

1.2. The concept of resilience

Resilience, as an emerging concept in the area of engineering, was

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first introduced in 1973 by Holling into the fields of ecology and evolution [7]. This concept was first used to describe the ability of an ecosystem to continue functioning after changes. Nowadays, resilience has been broadly applied across many fields, including natural disaster and risk management [8], civil infrastructure studies [9–11], system engineering [12], energy systems [13,14], etc.

Though consensus on resilience definition is lacking [15], the essence of resilience definitions is generally the same, that is, it is an overarching concept that encompasses the system performance before and after disastrous events. Francis and Bekera [16] reviewed various approaches to defining and assessing resilience and identified three resilience capacities: adaptive capacity, absorptive capacity, and recoverability. Resilience therefore can be defined as "*the ability of an entity to anticipate, resist, absorb, respond to, adapt to and recover from a disturbance*" [17].

Resilience is a multi-dimensional concept. Its qualitative and quantitative studies often involve interdisciplinary efforts. Meerow et al. [18] reviewed the literature on urban resilience and concluded that "*applying resilience in different contexts requires answering: Resilience for whom and to what? When? Where? And Why?*" They, thus, pointed out the key considerations in the application of resilience: the stakeholder, the stressor, the temporal and spatial scale, and the motivation. Shaw and IEDM Team [19] developed a Climate Disaster Resilience Index to measure the existing level of climate disaster resilience of targeted areas. This index utilizes 25 variables in five resilience-based dimensions: natural, physical, social, economic and institutional. Carlson et al. [17] and McManus et al. [20] provided frameworks for system-level and region-level resilience overview to address personal, business, governmental, and infrastructure aspects of resilience. Roege et al. [21] formulated a scoring matrix to evaluate the system's capability to plan, absorb, recover and adapt from the perspective of physical, information, cognitive and social.

In this work, reviewing energy infrastructure models from a resilience perspective implies utilizing different resilience-based dimensions and considerations during the evaluation of the selected models. Consequently, the models' ability to promote resilience in energy infrastructures against short-term disruptions and long-term degradations is addressed, not only from a physical perspective, but also socio-economically.

1.3. Energy infrastructure resilience

Energy infrastructures include electric power, natural gas, and fuel networks. Among all the CI sectors, energy infrastructure might be identified as the most crucial one due to the enabling functions they provide across all other CI sectors (PPD-21). For example, water supply and sewer systems rely on electric power systems to operate their pump stations. Information and telecommunication systems rely on power networks to carry out information transmission tasks. Transportation systems rely on fuel networks to obtain power for all kinds of vehicles. The dependence of other critical infrastructures on the energy network can lead to its vulnerability: Disruptions in the energy system may transverse to other dependent infrastructure systems and possibly even back to itself, where the failure originated [22,23]. This cascading and escalating characteristic of failure adds to energy network's vulnerability. Energy infrastructures are also vulnerable to climate change. For example, the rising sea level and increasing frequency of major storms lead to severe floods in coastal areas, where a lot of energy infrastructures are located [24], such as power plants, natural gas facilities, and oil and gas refineries. Moreover, high-impact low-probability events, such as hurricanes and terrorist attacks, further threaten the operation of energy infrastructures.

Based on the above-mentioned importance and vulnerability, the study of energy infrastructure resilience has become an urgent and significant research topic. Different researchers approach this problem in various ways. Many scholars simulate energy infrastructure resilience as an optimal operation problem [25–30]. Some adopt agent-based modeling (ABM) technique to reveal the complex interactions among energy system components [31–34]. Others improve traditional topological metrics of power grids by embodying its physical behavior [35]. Also, in response to the emergence of "big data" resources, some researches apply large-scale data analysis in the energy resilience studies, especially for power grid studies [36,37].

Although some researches consider resilience and reliability of energy infrastructures in the same topic [38,39], it is to note that resilience and reliability are not the same. While reliability is the ultimate goal that system designers and providers strive for, resilience is the way to achieve it by recovering fast from and adapting to disruptions [40]. The focus of this review paper is the modeling and simulation of energy infrastructure resilience.

1.4. Work scope and highlights

The modeling and simulation of CIs has been the topic of a few critical reviews. Eusgeld et al. [41] reviewed eight modeling and simulation techniques for interdependent CIs; namely, agent-based modeling, system dynamics, hybrid system modeling, input-output-model, hierarchical holographic modeling, critical path method, high level architecture and petri nets. They also proposed seven model evaluation criteria concerning modeling focus, methodical design strategies, type of interdependencies, types of events for simulation, event consequences, data needs and monitoring field. More recently, Ouyang [05] reviewed existing approaches for CI modeling and simulation grouping them into six types: empirical approaches, agent-based approaches, system dynamics based approaches, economic theory based approaches, network based approaches, and others. Existing studies were categorized and reviewed in terms of fundamental principles. Different approaches were further compared concerning the inclusion of sampled resilience improvement strategies.

However, both aforementioned studies had a working scope of general CI systems rather than focusing on energy infrastructures. The work of Eusgeld et al. [41] only compared different modeling approaches against each other without reviewing the details of specific models. The work of Ouyang [05] adopted several resilience improvement strategies to evaluate the modeling approaches but did not address other important issues of resilience such as the stakeholder or the temporal scale.

In this paper, we conduct a comprehensive review of 30 energy infrastructure models collected from open literature. In the overview part, we first summarize the modeling scenarios and the problems tackled by the models, as well as their typical assumptions. Based on the literature review, typical approaches to study energy infrastructure resilience are introduced with exemplary models. As the next step, we propose five selected resilience indicators; namely, catering to different stakeholders, intervening in development phases, dedicating to certain stressor and failure, taking into account different interdependencies and involving socio-economic characteristics. Other features are further discussed such as model type, data needs, etc. This review highlights the features and trends of existing models concerning their ability to address the multi-dimensional aspects of energy infrastructure resilience while stressing the characteristics of different modeling approaches. From reading the paper, the readers could gain knowledge of: (1) what are the differences among major energy infrastructure models, (2) what are the modeling needs from a resilience perspective through the proposed resilience indicators, (3) what kind of energy infrastructure model is needed in the future to better equip energy infrastructure resilience studies.

The remainder of the paper is organized as follows: Section 2 introduces the model-collection procedure, provides an overview of the models and summarizes typical modeling approaches.Sections 3 proposes the resilience indicators, as well as other selected modeling features. Section 4 gives a discussion based on the proposed indicators and modeling features. Finally, concluding remarks and future trends in the field are stated in Section 5.

Table 1
Keywords for literature search.

				Model*
Energy		Infrastructure		Simulat*
Power				Resilien*
Electric*	+	Network	+	Vulnerab*
Gas				Protect*
Fuel		System		Secur*
				Risk

2. Reviewing existing energy infrastructure models

2.1. Collection of models

The review focus of this paper are models aiming at energy infrastructure operation, protection, or resilience enhancement. Three model collection methods have been applied: (1) searching literature with a variety of keywords, (2) checking the references and citations of the papers identified through method 1, (3) referring to the publications of selected research groups in the field.

The keywords used in the literature search are listed in Table 1. The search strings accounted for the fact that different literature may use different terms for the same object (i.e. protection and security). As a result, 210 journal and conference papers from reliability, infrastructure and energy related journals were initially collected. Related papers citing or cited by the papers found in the first stage were reviewed as well.

Models were also collected by reviewing the work done by active research groups in CI modeling and simulation field such as NISAC, ANL, Los Alamos National Laboratory (LANL), etc. NISAC experts use advanced modeling and simulation capabilities to address CI interdependencies, vulnerabilities, and complexities in the U.S. Scientists at ANL use the ABM technique to study various aspects of energy network resilience. They also developed models for the natural gas and petroleum fuel networks [34]. The Interdependent Energy Infrastructure Simulation System [42] developed by LANL is an actor-based model that helps decision-makers understand and assess intrinsic vulnerabilities in CIs.

Through the above-mentioned procedure, this study identified 30 models for energy infrastructures. In the selected models, 17 are applied on power networks, 3 on natural gas networks, 4 on both power and natural gas networks, and the remaining 6 are applied on other energy infrastructure systems. When looking at the detailed scenarios of the models, most models for power networks focus on power transmission networks. Nonetheless, the research on distribution systems is emerging. Some of the models integrate financial networks, human activity, or supervisory control and data acquisition (SCADA). The natural gas network models mainly focus on the analysis and restoration of natural gas transmission pipelines. The models for both power and natural gas networks are dedicated to studying the interdependencies between the two systems. Other models include energy generation and storage system model [43], coal distribution network model [44], crude oil and petroleum product transport pipeline model [34], and integrated urban energy systems model [32].

2.2. Model overview

To understand what problems the research community of energy infrastructure resilience is trying to tackle and how the researchers are approaching these problems, this section first summarizes the research problems of the selected models and their corresponding key assumptions. Then, in the following section, the modeling approaches adopted by these models are introduced, representing typical methods for conducting energy infrastructure resilience studies.

Given that resilience describes a system's ability to sustain disruptions and to recover quickly from them, energy infrastructure resilience models concentrate on solving two major problems: (1) resource allocation and hardening planning in the preparation stage, (2) power outage management and service restoration in the immediate aftermath and recovery stage. Due to the limitation of budgets, how to identify the most vulnerable components in the system, harden them with minimized economic costs and gain the most effects out of the hardening measures is one main topic the research community cares about. The second topic aims to mitigate the impacts of the disasters and to recover the services quickly. Typical implementations include models that simulate the restoration process or that abstract the restoration process as an optimal control problem [25]. Common restoration measures include repair crew dispatch, distributed generation (DG), switch device remote control, etc.

Since the energy infrastructure sector is closely related to other CI sectors, an emerging number of researches focus on the study of interdependencies within the energy infrastructure sector and across CI sectors. Within the energy infrastructure sector, the interaction between the natural gas system and the power grid system is studied [45]. Across different sectors, researchers try to involve energy, water, transportation and communication systems into the same modeling and simulation framework and find resilient solutions on a more holistic scale.

For different application focuses, the models are usually developed under various assumptions of the real world. In models of distributed generation or microgrid technologies, it is typically assumed that the remotely controlled automatic switch devices are available in the distribution network so that lines can be opened/closed and loads can be connected/disconnected to form multiple microgrids. The switches are assumed to have local communication capabilities to exchange information with its neighboring switches [27]. In most resilience models that simulate the defender and attacker activities, the decision maker has a budget to harden a maximum of power lines and to place a maximum of DG units and the system operators are aware of the status of all the components after the occurrence of the outage [30]. The worst-case attack scenario occurs and the hardened lines and nodes are assumed to be able to survive the disasters. For models that study the weather impact, it is usually assumed the system is exposed to the same weather conditions at any given time by modeling the weather event as a standstill event, which reduces the complexity of the modeling procedure because no regional weather aspects are considered. The restoration time during high and extreme wind speed events is equal to the restoration time during normal wind speeds [46,47]. For models studying interdependencies between power and gas systems, it is usually assumed that electricity generation consumes gas and gas compressors consumes electricity [30]. Other specific assumptions depend on the modeling objectives and the scale of the model.

Table 2 summarizes basic information for the selected models including name, developer/author, scenario, and purpose/problem tackled. “Scenario” gives the specific modeling object of a model. “Purpose/problem tackled” describes the targeted problem the model was developed to solve. Among all the models, 15% are for power outage management and service restoration, 21% are for vulnerability and reliability analysis, 18% are for resource allocation and hardening planning, 12% are for infrastructure interdependency analysis. The rest address problems such as electricity market studies, weather event impact studies, general presentation and analysis, etc.

2.3. Modeling approaches

In this section, we introduce typical modeling approaches for energy infrastructure resilience problems. The models collected in this paper adopt a variety of modeling approaches including optimal operation modeling, topological network modeling, agent-based modeling, probabilistic modeling, system dynamics modeling, empirical modeling, etc. Table 3 lists the modeling approaches and the corresponding models that were collected in this paper.

The most common four approaches will be introduced in detail in the following subsections. The rest approaches are introduced briefly in “other approaches”. It should be noted that since the review object of this paper is

Table 2
Basic information of the selected models.

	Name	Developer/Author	Scenario	Purpose/ Problem Tackled
1	Two-stage outage management model (2018)	Arif et al.	Power distribution systems	Improve the computational efficiency in solving outage management problems for large distribution systems, co-optimize the repair, reconfiguration, and DG dispatch to maximize the picked-up loads and minimize the repair time.
2	Microgrids formation scheme (2016)	Chen et al.	Power distribution systems	Create a microgrid operation scheme to restore critical loads from the power outage by controlling the ON/OFF status of the remotely controlled switch devices and DG.
3	Sequential service restoration framework (2018)	Chen et al.	Power distribution systems	Generate a sequential service restoration framework for distribution systems and microgrids in large-scale power outages. A sequence of control actions includes coordinating switches, distributed generators, and switchable loads to form multiple isolated microgrids.
4	Multiple energy resilient operation model (2015)	Manshadi and Khodayar	Electricity and natural gas systems	Identify the vulnerable components and ensure the resilient operation of coordinated electricity and natural gas infrastructures considering multiple disruptions within the microgrid by improving the resilience of generation and demand scheduling.
5	Two-stage robust optimization model (2016)	Yuan et al.	Power distribution systems	Resilient distribution network planning to coordinate the hardening distributed generation resource allocation with the objective of minimizing the system damage.
6	A risk optimization model (2017)	Nezamoddini et al.	Power transmission networks	Determine the optimal investment decision for the resilient design of transmission systems against physical attacks. The investment costs are minimized such that the load curtailment does not exceed a certain threshold value.
7	The planner-attacker-defender model (2017)	Fang et al.	Power transmission networks	Study the combination of capacity expansion and switch installation in electric systems that ensures optimum performance under nominal operations and attacks. The planner-attacker-defender model is adopted to develop decisions that minimize investment and operating costs, and functionality loss after attacks.
8	Attack structural vulnerability model (2010)	Chen et al.	Power transmission networks	Propose a hybrid approach for structural vulnerability analysis of power transmission networks, in which a DC power flow model with hidden failures is embedded into the traditional error and attack tolerance methodology.
9	CitInES (2013)	Page et al.	Energy generation, storage, transport, distribution systems and demand	Present a multi-energy modelling environment to simulate and optimize urban energy strategies. Energy demand is modeled to consider the costs and impacts of demand-side measures. Optimization techniques are involved to provide answers to urban energy infrastructure planning issues.
10	An improved model for structural vulnerability analysis (2009)	Chen et al.	Electric power systems	Structural vulnerability analysis of power networks. Depicting a typical power network as a weighted graph based on electrical topology by introducing its bus admittance matrix.
11	Graph Model (2006)	Holmgren	Electric power systems	Model electric power delivery networks as graphs, calculate values of topological characteristics of the networks, and evaluate different strategies to decrease the vulnerability of the system.
12	Tri-level defender-attacker-defender model (2018)	Lin and Bie	Power distribution systems	Find the best hardening plan under malicious attacks given the available defending resources and operational restoration measures for a distribution system. Resilient operational measures include optimal DG islanding formation and topology reconfiguration.
13	A "proof-of-concept" model (2011)	TU Delft	The 380 kV power network in the Netherlands	Explore the adaptation of energy infrastructures to climate change.
14	Electricity Market Complex Adaptive System (2006)	ANL	Electric power and financial networks	Modeling and simulation of operations in restructured electricity markets.
15	Natural Gas Infrastructure Toolset (2006)	ANL, Infrastructure Assurance Center	Natural gas networks	Provide an analyst with a quick method to access, review, and display components of the natural gas network; perform varying levels of component and systems analysis, and display analysis results.
16	Critical Infrastructure Modeling System (2006)	INL	Electric power system, human activity and SCADA	Provide decision makers with a highly adaptable and easily constructed 'wargaming' tool to assess infrastructure vulnerabilities including policy and response plans.
17	Critical Infrastructure Simulation by Interdependent Agents (2006)	University Roma Tre	Electric power system and SCADA	Analyze short term effects of failures in terms of fault propagation and performance degradation.
18	Integrated energy system reliability evaluation model (2016)	Li et al.	Electricity distribution network, distributed renewable energy system, gas system, cooling, and heating systems	Present a new reliability evaluation approach, in which Smart Agent Communication is based system reconfiguration is integrated into the reliability evaluation process.
19	SynCity (2010)	Imperial College London	Urban energy systems	Provide an integrated, spatially and temporally diverse representation of urban energy use within a generalized framework across all the design steps and in a variety of problem environments.

(*continued on next page*)

Table 2 (*continued*)

	Name	Developer/Author	Scenario	Purpose/ Problem Tackled
20	Resilience evaluation model (2017)	Panteli and Pierluigi	Electric power systems	Provide a conceptual framework for gaining insight into the resilience of power systems with focus on the impact of severe weather events. The effect of weather is quantified with a stochastic approach. The resilience of the critical power infrastructure is modeled and assessed within a context of system-of-systems that also include human response as a key dimension.
21	Multi-microgrid reliability assessment framework (2017)	Farzin et al.	Multi-microgrid distribution system	Develop a general framework for reliability assessment of multi-microgrid (MMG) distribution systems. Investigate reliability impacts of coordinated outage management strategies in a MMG distribution network.
22	Critical Infrastructures Interdependencies Integrator (2002)	ANL	Natural gas pipelines	Infrastructure restoration time and/or cost estimation considering an interdependency analysis.
23	Restore (2011)	ANL	Natural gas pipelines	Estimate the time and cost of Infrastructure restoration.
24	A framework for reliability/availability assessment (2017)	Cadini et al.	Electric power transmission networks	Combine an extreme weather stochastic model to a realistic cascading failure simulator based on a direct current power flow approximation and a proportional re-dispatch strategy. Dynamics of the network is completed by the introduction of a restoration model accounting for the operating conditions that a repair crew may encounter during an extreme weather event.
25	Interdependent Energy Infrastructure Simulation System (2006)	LANL	Electric power and natural gas infrastructures	Assist individuals in analyzing and understanding interdependent energy infrastructures.
26	Framework for Electricity Production Vulnerability Assessment (2009)	Shih et al.	Coal distribution network	Use data warehousing and visualization techniques to explore the interdependencies between coal mines, rail transportation, and electric power plants.
27	Critical Infrastructure Protection Modeling and Analysis (CIPMA) Program (2006)	Australian Government - Attorney General's Department	CI networks and high priority precincts	Support business and government decision making for CI protection, counter-terrorism and emergency management, especially with regard to prevention, preparedness, and planning and recovery.
28	Petroleum Fuels Network Analysis Model (2006)	ANL, Infrastructure Assurance Center	Crude oil and petroleum product transport pipelines	Perform hydraulic calculations of pipeline transport of crude oil and petroleum products. Introduction of pipeline component dependencies into critical infrastructure analyses.
29	Critical energy infrastructures (2014)	Erdener et al.	Electricity, natural gas and oil systems	Analysis of the impacts of interdependencies between electricity and natural gas systems. Propose an integrated simulation model that reflects the dynamics of the systems in case of disruptions and takes the cascading effects of these disruptions into account.
30	Fast Analysis Infrastructure Tool (2006)	Sandia National Laboratory (SNL)	Electric power, natural gas, and waterway systems	Determine the significance and interdependencies associated with elements of the nation's CI.

Table 3
Modeling approaches for energy infrastructure resilience problems.

	Modeling approach		Model name
1			Two-stage outage management model [25]
2			Microgrids formation scheme [27]
3			Sequential service restoration framework [26]
4	**Optimal operation modeling**		Multiple energy resilient operation model [29]
5			Two-stage robust optimization model [30]
6			A risk optimization model [48]
7			The planner-attacker-defender model [49]
8			Attack structural vulnerability model [50]
9			CitInES [43]
10	**Topological network modeling**		An improved model for structural vulnerability analysis [51]
11			Graph Model [52]
12			Tri-level defender-attacker-defender model [53]
13			A "proof-of-concept" model [24]
14			Electricity Market Complex Adaptive System [34]
15			Natural Gas Infrastructure Toolset [34]
16	**Agent-based modeling**		Critical Infrastructure Modeling System [31]
17			Critical Infrastructure Simulation by Interdependent Agents [34]
18			Integrated energy system reliability evaluation model [33]
19			SynCity [32]
20			Resilience evaluation model [47]
21			Multi-microgrid reliability assessment framework [54]
22	**Probabilistic modeling**		Critical Infrastructures Interdependencies Integrator [55]
23			Restore [56]
24			A framework for reliability/availability assessment [46]
25		Actor-Based Modeling	Interdependent Energy Infrastructure Simulation System (IEISS) [42]
26		Empirical Modeling	Framework for Electricity Production Vulnerability Assessment [44]
27	**Other approaches**	System Dynamics Modeling	CIPMA Program [34]
28		Physical Modeling	Petroleum Fuels Network Analysis Model [34]
29		Integrated Simulation Platform	Critical energy infrastructures [45]
30		Integrated Simulation Platform	Fast Analysis Infrastructure Tool [34]

numerical models that could conduct simulations and predict system performance in the real world, no surveys or qualitative studies were included. In the remaining part of this section, each modeling approach is introduced with exemplary models to address their characteristics.

2.3.1. Optimal operation modeling

Optimal operation modeling is one of the most widely used method in the research area of energy infrastructure resilience. In this method, when the system is interrupted, achieving resilience can be interpreted as an optimization problem to restore the system within a short time while minimizing the load shedding ratio.

Arif et al. [25] solved the outage management problem by co-optimizing the repair, reconfiguration, and DG dispatch to maximize the picked-up loads and minimize the repair time considering reconfiguration and repair crew scheduling. Chen et al. [27] and Ding et al. [28] proposed a microgrid formation mechanism to restore critical loads after major faults at the grid caused by natural disasters. In this scheme, a mixed-integer linear program was formulated to maximize the total prioritized loads restored while satisfying self-adequacy and operation constraints of each microgrid. Similarly, Chen et al. [26] formulated a mixed-integer linear program model for the sequential service restoration problem. This model can generate the optimal restoration sequences to coordinate dispatchable DGs and switchgears to energize the system on a step-by-step basis. Manshadi and Khodayar [29] proposed a bi-level optimization methodology which took into consideration the interdependency between natural gas and electricity infrastructures. Through this model, the identification of most vulnerable components in the system, as well as the resilient generation and demand scheduling could be achieved. Yuan et al. [30] proposed a model for resilient distribution system planning with hardening and DG based on two-stage optimization. In this model, a multi-stage and multi-zone-based uncertainty set was used to capture the uncertainty of natural disasters.

To sum up, existing optimal operation models share common object functions such as maximizing picked-up loads, minimizing repair time and economic investments. For restoration strategy development purpose, frequently considered measures include topology reconfiguration, DG dispatch, microgrid formulation, repair crew dispatch and switch device control. The problem is usually represented by mathematical models with equilibrium equations and certain constraints, including self-adequacy and operation constraints. An emerging number of researches focus on solving problems of demand scheduling and load flexibility in response to the adoption of building-to-grid, vehicle-to-grid technologies.

However, this type of model is usually focused on one single problem, either protection resource allocation or restoration, which are two separate stages of energy infrastructure resilience. On the other hand, the occurrence of the disaster is usually not simulated. If all these characteristics are coupled together, the optimization problem might get very complicated and the computational time problem will arise. Nezamoddini et al. [48] compared the computational time of different scales of test systems. The computational time increases from 3 seconds to 4.2 hours when the system upgrades from IEEE 6-bus to IEEE 57-bus test system.

2.3.2. Topological network modeling

Power networks have been studied as a typical example of real-world complex networks [51]. They can be modeled by extracting their topology. In this type of models, the power networks are represented by a set of vertices connected by a set of edges, where the vertices represent buses and the edges represent transmission lines. This type of model is typically applied in the structural vulnerability analysis of power networks.

Topological network models are easy to analyze due to their high level of abstraction and simplification. Buldyrev et al. [22] used the topology of the interdependent power system and communication system to demonstrate the cascading fault evolving between the two systems. Page et al. [43] proposed a simplified energy network modeling approach. Based on the topology of the original network, they used clusters that were aggregations of network nodes to build a less detailed model and calibrated it with detailed simulations. In this way, the number of variables was significantly reduced.

However, purely topological approaches fail to capture the physical properties and operational constraints of power systems and, therefore, can sometimes provide too optimistic analyses [35]. Hines et al. [57] compared purely topological network models and higher fidelity models in the vulnerability modeling of electricity infrastructures. They used three measures of vulnerability: characteristic path lengths, connectivity loss, and blackout sizes. Their conclusion was that evaluating vulnerability in power networks using purely topological network models can be misleading. Chen et al. [50] proposed a hybrid model for structural vulnerability analysis of power networks. Their approach embodied the traditional topological methodology and took into account important characteristics of power transmission networks such as the power flow distribution. Consequently, their hybrid model better approximated real power grids compared with a traditional topological network model.

Topology modification, or known as reconfiguration, plays an important role in the study of electric power system resilience, as a section can be reconnected to another power supply when an outage happens. Lin and Bie [53] proposed a tri-level defender-attacker-defender model to harden the distribution system under malicious attacks. In this model, resilient operational measures such as topology reconfiguration and DG were simulated to study their impact on distribution system resilience.

2.3.3. Agent-based modeling

Agent-based models consist of dynamically interacting, rule-based agents [58,59]. A general definition of agent is: "*an entity with a location, capabilities and memory. The entity location defines where it is in a physical space… What the entity can perform is defined by its capabilities… the experience history (for example, overuse or aging) and data defining the entity state represent the entity's memory.*" [60]. An agent-based model can exhibit complex behavior patterns [61] and provide valuable information about the dynamics of the simulated real-world system [60].

The application of ABM in the modeling and simulation of energy infrastructures mainly focuses on the analysis of the interactions between interdependent systems. Casalicchio et al. [62] used ABM to model a system composed of a power grid and a communication network with agents representing the entire infrastructure, its subsystems and the humans involved in the scenario. In this model, an agent is described by its attributes, the services it provides to other agents, and the services provided by other agents. Li et al. [33] modeled the integrated energy system of electricity and natural gas system. A two-hierarchy smart agent model is built as the basis for the system reliability analysis. The lower hierarchy are the component smart agents which represent the power lines, transformers, and electricity loads while the higher hierarchy are the zone agents which form the system topology.

Another important application of ABM is to simulate the socio-economic activities, such as the electricity market and human activities within the energy infrastructure framework. Zhou et al. [63] simulated an electricity market with demand response from commercial buildings. In this model, agents were used to model different participants of the market such as power generation companies, load-serving entities, commercial building aggregators, and an independent system operator. SynCity [32] is a tool developed by Imperial College London for integrated modeling of urban energy systems. This tool adopts agent-based micro-simulations to simulate the daily-activities of citizens of the city. Each citizen makes stochastic decisions based on the pre-defined rules and according to the environment around him/her. Solanki et al. [64,65] used agents to model different operators in restoring the electric system.

The ABM technique has proved its advantages in the following aspects: (1) It can capture complicated interdependencies by simulating physical or economic flows among different infrastructures. (2) It enables the study of large-scale problems by avoiding complicated theoretical analysis. (3) It allows behavior analysis of customers or decision-makers by making certain rules. However, ABM still has limitations in that it is difficult to validate, and not all types of interdependencies can be included in one single model. Most existing agent-based models can only simulate one type of interdependencies such as the physical or logical interdependency [66].

2.3.4. Probabilistic modeling

In energy infrastructure resilience modeling, probabilistic algorithm is necessarily applied to capture the uncertain characteristics of the system failure. Many models adopt sequential Monte Carlo simulation method [46,54,47]. A Monte Carlo simulation uses repeated sampling to determine the properties of some phenomenon or behavior [67]. The essential idea is to use randomness solving problems that might be deterministic in principle. It is useful for gathering information about random objects, estimating certain numerical quantities, and optimizing complicated objective functions [68].

Monte Carlo simulation in the field of energy infrastructure modeling is often employed for the simulation of weather events due to their high stochasticity. Panteli and Mancarella [47] developed a time-series simulation model based on sequential Monte Carlo method to assess the impact of weather events on power-system resilience. With the knowledge of the hurricane occurrence frequency and its impact on power system components, Li et al. [69] developed an algorithm to evaluate the risks of the power system in face of hurricanes. This method can be expanded to systems under other stochastic natural disasters. Similarly, Cadini et al. [46] used a sequential Monte Carlo simulation scheme to simulate historical failures caused by both normal and extreme weather events. The simulation results were then used to evaluate the reliability of the studied power transmission system.

Another common application of Monte Carlo simulation in energy infrastructure modeling is to simulate the restoration process of disrupted infrastructures. For example, the software tool Critical Infrastructures Interdependencies Integrator [55] developed by ANL used Monte Carlo simulation to estimate the time and cost required to restore a given infrastructure component, a specific infrastructure system, or a set of interdependent infrastructures.

It should be noted that Monte Carlo simulation can be integrated into other modeling frameworks, such as optimization-based models, to simulate the performance of energy systems. For example, Farzin et al. [54] evaluated the role of outage management with Monte Carlo simulation, while considering the optimal power flow problem of the electric distribution system.

2.3.5. Other modeling approaches

Actor-based modeling: Similar to an agent-based model, an actor-based model is composed of actors that can make local decisions, create more actors, send messages and determine how to respond to messages received. The Interdependent Energy Infrastructure Simulation System (IEISS) [42] developed by LANL is an actor-based infrastructure modeling, simulation, and analysis tool designed to understand interdependent energy infrastructures. The actors can realistically simulate the dynamic interactions within each of the infrastructures, with a specialization in simulating the interdependent electric power and natural gas infrastructures.

Empirical modeling: Empirical models are built based on historical data or expert experience. Shih et al. [44] adopted data warehousing technique to conduct vulnerability assessment of interdependencies between coal mines, rail transportation, and electric power plants. A data warehouse is a system used for reporting and data analysis. It has the capability of bringing various datasets together and managing historical data. In this case, the data warehouse allowed an interactive analysis of historical and multi-dimensional data of varied granularities.

System dynamics modeling: System dynamics is a method for studying the behavior and the underlying structure of a complex system over time [70]. It is widely used in the analysis of CI interdependencies. For example, the CIPMA program [71] in Australia adopts the system dynamics model to examine the relationships and dependencies within and between CI systems, and to demonstrate how a failure in one sector can greatly affect the operations of other CI sectors.

Physical modeling: Petroleum Fuels Network Analysis Model (PFNAM) [34] is a physical model developed by ANL to perform hydraulic calculations of pipeline transport of crude oil and petroleum products. Main outputs of the model include pressure and pipeline capacity estimates along the pipeline.

Integrated simulation platform: Some models are implemented in a way that several approaches are adopted for component models and then coupled together. Erdener et al. [45] proposed an integrated simulation model for electricity and gas systems. The electricity and gas systems are first modeled separately and then linked by an (MATLAB-based) interface. The Fast Analysis Infrastructure Tool (FAIT) developed by SNL [34] consists of a dependency model and an economic model. The dependency model is an object-oriented expert system model of infrastructure interdependencies. The economic model utilizes the input-output method for estimating the economic consequences of the disruption of an asset. An input-output model is a quantitative economic technique that represents the interdependencies between different branches of a national economy or regional economies [72]. This economics-based method has been applied on CIs to capture the cascading economic effects of a disruption across different sectors [66].

3. Proposed resilience indicators and other features

3.1. Resilience indicators

To address energy infrastructure resilience, a model should take into account certain dimensions of resilience. Sharifi [73] proposed a framework for the analysis of community resilience assessment (CRA) tools. Within this framework, six criteria were proposed to evaluate the selected CRA tools. These include comprehensiveness in addressing multiple dimensions of community resilience, considering connections between different spatial scales, ability to measure changes across temporal scales, developing suitable measures for capturing uncertainties, collaboration with stakeholders, and leading to action plans. Cutter et al. [08] measured the inherent resilience of counties in the United States according to six capitals identified in the extant literature: social, economic, housing and infrastructure, institutional, community, and environmental. Hosseini et al. [15] identified four domains of resilience: organizational, social, economic, engineering.

Although different researchers may emphasize various aspects when assessing resilience, they do share some common grounds. Based on literature review, this paper proposes five indicators for energy infrastructure models from the resilience perspective. A model that successfully helps enhance energy infrastructure resilience should: be dedicated to certain stakeholders, intervene in one or more resilient infrastructure development phases, be able to simulate a certain stressor and the failure it caused, address interdependencies within or between infrastructure sectors, and integrate socio-economic characteristics.

Indicator 1 – Catering to different stakeholders: Urban infrastructures are owned and operated by different stakeholders who may not be aware of the interdependencies between their own infrastructure system and other systems [74]. Different stakeholders tend to have different priorities and considerations, when making decisions related to infrastructure investment, protection, or restoration. Hence, it is necessary to identify the stakeholder of a selected model before diving into further details. A stakeholder-oriented lens helps better understand a model's values and limitations. Francis and Bekera [16] included stakeholder engagement as a key component in the analysis framework of engineered and infrastructure systems. Hasan and Foliente [74] classified stakeholders according to their scales and roles into: international union, federal/state/local government, advocacy organizations, donors/financial institutions, insurance, utility companies, business, and households, individuals and communities.

Indicator 2 – Intervening in development phases: This indicator evaluates in which phase of infrastructure development a model can be employed. Four phases are distinguished: design, operation, restoration, and adaptation. Compliance with this indicator is decided as follows. If the model helps designers recognize the most vulnerable components in an infrastructure system and enhance the infrastructure resilient design, then the model is dedicated to the design phase. If the model focuses on the modeling and simulation of CI operational status, then the model is dedicated to the operation phase. If the model simulates restoration processes and helps develop restoration strategies, then the model is dedicated to the restoration phase. If the model integrates resilience enhancement techniques and considers the long-term adaptation of CIs to certain stressors, then the model is dedicated to the adaptation phase.

Indicator 3 – Dedicating to certain stressor and failure: In the research field of resilience, a stressor represents the source that causes the system to change its original status. For CIs, there are generally two kinds of stressors: human-induced stressors such as terrorism and maloperations, and nature-induced stressors such as the climate change and extreme weather events. Identifying the stressor that a model is dealing with helps further evaluate the failure mode.

There are three types of infrastructure failures; namely, cascading failure, escalating failure, and common cause failure [55,75,76]. The cascading failure refer to the disruption of one single infrastructure that is caused by a component failure, which is common in power grid disruptions. An escalating failure is a disruption in one infrastructure that exacerbates independent disruptions in other infrastructures. This kind of escalating effect is due to the complex interdependencies among infrastructure sectors and often leads to a longer time of restoration. A common cause failure is a disruption of two or more infrastructures at the same time resulted from a common cause. Existing models typically don't distinguish between “cascading failure” and “escalating failure”, englobing them all under the concept of “cascading failure”. In this paper, they are distinguished to investigate a models’ temporal scale and the feature in simulating escalating effects of disasters. For example, a model for escalating failure not only simulates the immediate effects of a disruption, but also the propagated effects of a disaster among different sectors.

Indicator 4 – Taking into account different interdependencies: The interdependency between CIs is defined by Rinaldi et al. [77] as “*a bi-directional relationship between two infrastructures through which the state of each infrastructure influences or is correlated to the state of the other.*” Due to the complex relationships among different CI sectors, the vulnerability of CI systems is raised. The failure of one single component can lead to the failure of the entire system, even of the systems that rely on it. Some research results have proved the necessity to consider interdependencies between infrastructure systems when evaluating resilience and reliability [45,33].

There are four types of interdependencies: physical, cyber, geographic, and logical [77]. Physical interdependency expresses the physical reliance on material flow from one infrastructure to another. Typically, the output of one infrastructure may be the input of another infrastructure for operation. Cyber interdependency expresses the reliance on information transfer between infrastructures. An infrastructure has cyber interdependency if its state depends on information transmitted through the communication infrastructure. Geographic interdependency exists if a local environmental event can affect multiple infrastructures. That is, elements of multiple infrastructures are in close spatial proximity. Logical interdependency is a dependency that exists if two infrastructures depend on each other via a mechanism that fall into none of the above categories. It may be more closely linked to a control schema that links one infrastructure to another infrastructure without any direct physical, cyber, or geographic connection. Compliance with this indicator is confirmed if a model considers any of the four types of interdependencies inner the energy sector, or between energy and other sectors.

Indicator 5 – Involving socio-economic characteristics: Socio-economic characteristics are significant aspects of resilience. According to the City Resilience Framework [78], economy and society is one of the four basic elements of resilience, which is also recognized as the organizational resilience. The other three categories include the health and wellbeing of individuals, urban systems and services and, finally, leadership and strategy, which emphasize the role of people, place and knowledge in constructing a resilient city. When evaluating the resilience of energy infrastructures, a place-based perspective considering the people, as well as the socio-economics is more comprehensive. Many researchers point out that the socio-economic impacts resulting from the infrastructure disruptions can be very significant and needs serious considerations [79,80]

This indicator examines if a selected energy infrastructure model considers the socio-economic impacts of the infrastructure failures or involves socio-economic activities in the simulation. Typical socio-economic characteristics include age, ethnic, religion, income, disaster insurance, and community resources.

3.2. Other modeling features

In order to further evaluate the models and gain insights into the characteristics of different modeling approaches in the context of energy infrastructure modeling, some more features of the models are discussed in this section; namely, data needs, model type, and time scale. Furthermore, whether the model is dynamic or static and whether the damage and restore processes are endogenous or exogenous are also discussed.

Data needs: The input data of a model usually include information about the layout of the simulated system, commodity flows, functioning, as well as numerical values for modeling parameters [41]. Data needs can vary largely according to the modeling approaches. A model with high data needs relies on high quality and large quantity of input data to provide reasonable outputs. On the contrary, a model with low data needs can provide plausible outputs, even when little data is accessible. This indicator analyzes the data needs of modeling approaches for energy infrastructures. For example, if a model requires databases as inputs, then the data demand level is high. If a model only has a few input variables, or only requires a small amount of profile data, then the data demand level is low. If the situation lies in between, then the demand level is regarded as medium.

However, it should be noted that there is a trade-off between a model's data need and its accuracy. High-fidelity models that reproduce the state and behavior of the real world better will rely more on high quantity and quality of data [41]. On the other hand, a model with lower data need might sacrifice its accuracy due to more assumptions. The data need of a model from a developer's angle is dependent on the development purpose. In the context of energy infrastructure resilience, for example, a model intended for impact analysis of weather events on the energy system will require more data than an optimization model that is developed for restoration strategy design. At last, a model's data need is also highly dependent on the data availability. Sometimes, developers have to make reasonable assumptions to compensate for the inaccessible data.

Model type: This indicator evaluates the computational mechanism of the models. Three types of models are distinguished: white box, black box, and grey box, which is their combination. In the white-box approach, the model uses governing laws of physics and the detailed knowledge of the underlying process [81]. In the black-box approach, the system performance data is collected under normal use or under a specific test and a relationship is found between the input and output variables using mathematical methods [82]. In the grey-box approach, the model structure is formed using physics-based methods and the parameters are determined using estimation algorithms based on the measured data [81].

Time scale: The simulation time step and time horizon vary with the purpose and scenario of the energy infrastructure model. Holmgren [52] simulated different hazard scenarios and gave their time scales. For major technical failure that disables a station in the sub-transmission or distribution grid, the corresponding vertices in the model are removed for 10 hours. For human factors and regular technical failures, the time scale is 1 to 2 hours. For snowstorm and lightning, the time scales are 8 hours and 0.5 h, respectively. As for the repair time, it usually lasts hours depending on the damaged component in the system. Li et al. [33] studied the reliability problem of integrated energy systems and gave the repair time of different components. Each kilometer of gas or heat pipeline will take 5 hours to repair. However, for gas-fired boiler, steam turbine, or absorption cooling plant, it will take 200 to 300 hours to repair. This indicator examines the time scale each model is designed to simulate over. Time step and time horizon are distinguished.

Dynamic or static: Dynamic models simulate the system performance in a time-dependent way, while static models calculate the system in equilibrium. Given the dynamic characteristics of energy infrastructure systems and the time-dependent instinct of resilience problems, most energy infrastructure resilience models are built dynamically. However, there do exist some static models. Manshadi and Khodayar [29] simulated the resilient microgrid operation problem in a static way to identify the vulnerable components and the optimal operation plan considering the interdependency between power and gas systems. Nezamoddini et al. [48] solved a resilient distribution network planning problem in equilibrium to coordinate the hardening and distributed generation resource allocation with the objective of minimizing the system damage. The physical model Petroleum Fuels Network Analysis Model (2006) conducts the hydraulic calculation of fuel pipelines in an equilibrant way.

Endogenous or exogenous damage/restore: The simulation of damage and restore processes are dealt with either endogenously or exogenously in resilience models. Models that don't obtain the disruption signal from outside but rather embed the disruptions inside the model are endogenous. Typically, the damage of the energy infrastructure is represented by the disconnection of lines, open switch devices, or randomly or intentionally removed nodes. Specially, in some agent-based models, different types of faults are propagated by agents. In exogenous models, the damage is generated by external random or non-random events, such as unit outages or system disruptions. Li et al. [33] adopted

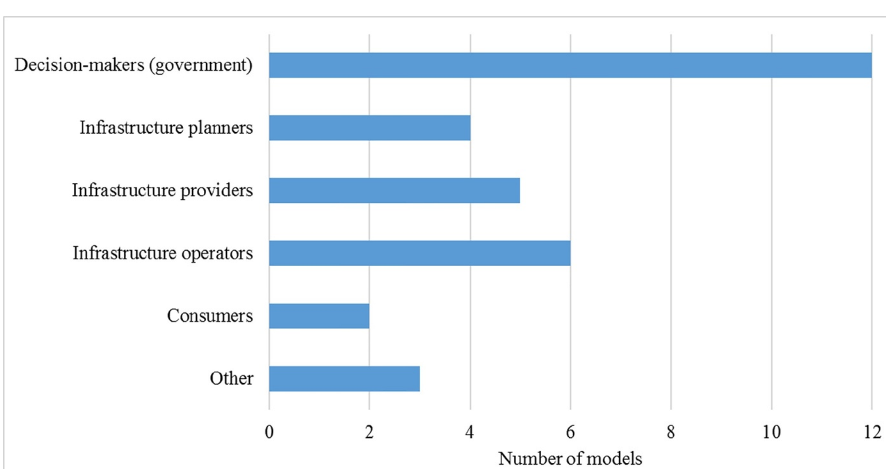

Fig. 1. Number distribution of models with different stakeholders.

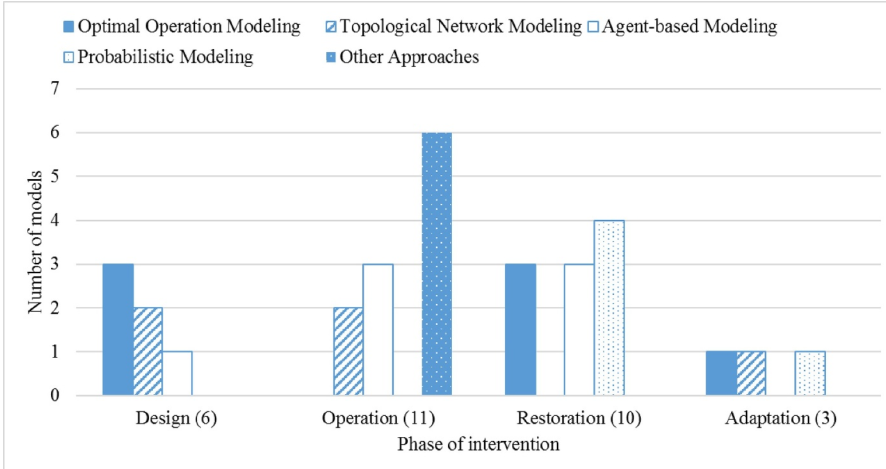

Fig. 2. Number distribution of modeling approaches intervening in different phases.

Monte Carlo simulation to evaluate power system reliability by generating stochastic errors. The Fast Analysis Infrastructure Tool (FAIT) (2006) couples with other models to get the duration and magnitude of the disruption and recovery and conducts regional economic analysis.

4. Discussions

This section applies the above-proposed resilience indicators and other modeling features to evaluate the collected energy infrastructure models. The evaluation results can be found in Appendices 1 and 2. Findings regarding the resilience-related performance of the models and comparisons between different modeling approaches are discussed in the following text.

Stakeholder: Regarding “resilience for whom”, Fig. 1 shows the number of models with different stakeholders revealing that the stakeholders taken into account by most selected models are the decision-makers, including the government. They serve the decision-makers during the infrastructure protection tasks, investment-related procedures, or when faced with infrastructure emergencies. The second most common stakeholders are infrastructure providers and operators, as over one third of the selected models were developed for their needs. Infrastructure providers and operators have significant impact on energy infrastructure resilience as they take charge of the operation and maintenance of infrastructures. Only two models include the consumers as relevant stakeholders. Although both decision-makers (especially the government), as well as providers and operators are in the service of consumers, surprisingly little attention has been paid to energy consumers when developing energy infrastructure models. Given that the ultimate goal of energy infrastructure resilience promotion is to better serve the consumers, it would be beneficial to consider their demands on energy supply and their response to energy infrastructure emergencies when seeking a holistic solution of energy resilience. Other stakeholders include research institutes, emergency responders, and engineers.

Intervention phase: Regarding the infrastructure development phase in which a model is employed, most models in this study are found to be dedicated to the operation phase (Fig. 2). Another considerable proportion of models conduct restoration simulations of the energy infrastructures. The least number of models take adaptational evolutions of energy infrastructures into account. This distribution indicates that existing energy infrastructure models for resilience studies have been focusing on the operation phase. On the other hand, they are limited in integrating long-term adaptation strategies into the modeling framework, which should be an important dimension of resilience enhancement.

Stressor: Nearly 40% of the models simulating general disruptions of energy infrastructures. Instead of identifying a specific cause, these models focus on the failure of the infrastructure after the occurrence of a disaster and are generally applicable for disruption studies. 28% of the models are developed against intentional attacks while 19% are against extreme weather events such as natural disasters. Only 3% of the selected models take economic disruptions as the stressor.

Failure: 40% of the models simulate cascading failures of energy infrastructures while 27% are for common cause failures, where several locations of disruptions occur together. However, only 16% of the models are able to simulate escalating failures of the critical infrastructures

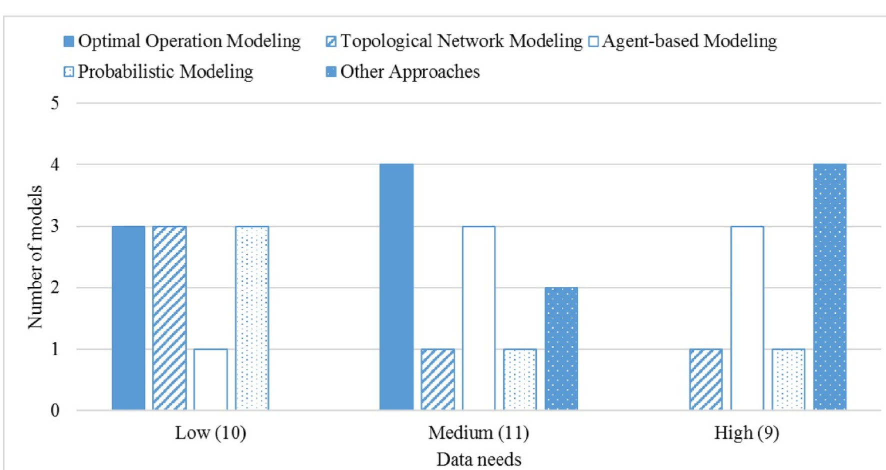

Fig. 3. Number distribution of modeling approaches with different data needs.

revealing that most existing energy infrastructure models don't account for the escalating effects of a failure. They tend to only focus on the immediate effects of a disruption. The varying temporal scale in the aftermath of disasters have been neglected by most selected models.

Interdependency: Regarding CI interdependencies, 43% of the selected models consider some types of interdependencies. The model “Critical energy infrastructures” [45] studies the interdependency inner the energy sector between the natural gas and electric power system. Other models consider interdependencies between energy and other sectors such as transportation ([32,43,44,55,56]) and telecommunication ([34,55,56]). The rest of the models do not consider interdependencies but rather focus on the energy sector.

Socio-economic characteristics: 50% of the selected models involve socio-economic characteristics during the modeling and simulation process. However, most of these models only consider economic characteristics, such as economic impacts of infrastructure disruptions [83,34] and investment optimization [49,48,43]. Only four of all the selected models consider social impacts of a disaster, such as public hazards [25] or effects on population and housing [24,32,34].

Data needs: Fig. 3 depicts the number distribution of modeling approaches with different data needs. Agent-based models tend to have the highest data needs, as 86% of them fall in medium and high data need columns. As for optimal operation models, topological network models and probabilistic models, most of them fall in the columns of low or medium data needs. This phenomenon is consistent with the characteristics of ABM, as historical data and attribute data will be needed to define each agent and certain interaction rules,

Model type: Concerning the model type, 93.3% of the selected models are white box. Only 3.3% of them are grey box and 3.3% are black box. In the grey box model [47], historical weather data are used to first determine the frequency distribution of certain weather events. The weather profile is then used as an input of the physics-based model. In the black box model [44], data warehousing and visualization techniques are used to manage non-spatial historical data which are then merged with geospatial data to model the potential impacts of a disruption to one or more mines, rail lines, or power plants.

Other features: When looking at other features of the models, the time horizon varies from the short term of several hours to the long term of several years, depending on the problem tackled. Accordingly, the time step ranges from 1 minute or 1 h to 1 week. Most models deal with energy infrastructure resilience problems dynamically. 63.3% of the models have endogenous damage or restoration while 16.7% have exogenous. For more details, the reader could refer to Appendix 2.

5. Conclusions

Energy infrastructures are becoming more vulnerable due to the rising frequency of both nature- and human-induced disasters. Hence, the resilience of energy infrastructures has gained much attention in recent years. This paper reviewed 30 energy infrastructure models from a resilience perspective. Through the review, research problems tackled by the models and typical modeling approaches adopted by researchers were summarized. Specifically, the authors proposed five resilience-based indicators to comprehensively address a model's capability in promoting energy infrastructure resilience. At last, other modeling features such as data needs and time scale were discussed to further evaluate the models.

The models collected in this work involve representative state-of-the-art energy infrastructure models implemented through various approaches. The addressed problems include optimal resource allocation and hardening planning, interdependency analysis, outage management and restoration, weather impact study, etc. The models intervene across planning, operation, restoration and adaptation phases of energy infrastructures. Based upon the review, the following observations are gained: The dominant stakeholder of the models are decision-makers, including government and regulators. Most selected models serve energy consumers indirectly as little attention is paid to energy consumers during the development stage. Most selected models focus on the operation and restoration phases of energy infrastructures. Long-term adaptation strategies are not integrated into the modeling framework by most models. Existent models tend to only consider immediate effects of system disruptions. The study on the propagated effects of the failure among different sectors is typically neglected. Although many selected models involve economic impact evaluation, only a few models take into account social parameters or consider social impacts of disasters. Concerning other modeling features, physics-based models are still the trend in energy infrastructure modeling, rather than data-driven techniques. Among others, agent-based models tend to have higher data needs than topological models and optimal operation models. The time horizon and time step vary significantly among the models, ranging from several hours to several years.

Based on the discussions above, future trends in the modeling and simulation of energy infrastructures are as follows:

Addressing larger temporal and spatial scale: As most existing energy infrastructure models focus on immediate effects of disruptions but are limited in capturing the dynamic behavior during longer terms, it remains to be explored how the models could be scaled over a larger temporal scale. Also, including the complex interactions across multiple CI sectors over different spatial scales helps making the model more realistic. However, the challenge of scalability lies in the computational time. How to employ more complexity in the model while reducing the computational time remains a challenge for future researchers.

Integrating more human and social aspects: Though existent models serve mostly the needs of decision-makers, energy consumers’ behavior and potential in helping achieving energy infrastructure resilience would be more considered in the future. The emerging focus on human-in-loop control and demand response technologies also implies this trend. Also, since the impact of disasters eventually take place on the human and the society, it would be drawing more attention to integrate social characteristics in the modeling frameworks and study the social impacts of CI disruptions. However, the uncertainty in human behavior and the quantification of social factors remain a challenge.

Employing more smart resources and solutions: It was noticed from the review that smart technologies such as energy storage, demand response with flexible loads (e.g. electrical vehicles, flexible building loads) are integrated by some models to explore future possibilities of energy resilience. In the future, as these technologies develop and become more accepted, involving them in energy infrastructure models would be a trend.

Due to the limited number of models collected in this paper, there are certain limitations of the work: only four of the commonly used modeling approaches are deeply analyzed and the working scope is limited to the energy sector. In the future, the same evaluation methodology could be applied to transportation, water supply and sewer, communication and other CI sectors.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ress.2018.11.029.

Appendices

Appendices 1 and 2.

Appendix 1. Proposed resilience indicators and the evaluation results of selected models.

	Modeling approach	I1 Stakeholder	I2 Phase of intervention	I3 Stressor	Failure type	I4 Interdependencies	I5 Socio-economic characteristics
1		N/A	Restoration	General disruptions	Common cause failure	None	Yes
2		N/A	Restoration	Extreme weather events	Common cause failure	None	None
3		N/A	Restoration	Storms and cyber-physical attacks	Common cause failure	None	None
4	**Optimal operation modeling**	Infrastructure planners and operators	Design	Intentional attacks	Common cause failure	Yes	Yes
5		N/A	Design	Extreme weather events	Common cause failure	None	Yes
6		Government and infrastructure operators and consumers	Adaptation	Intentional attacks	Cascading	None	Yes
7		Infrastructure planners	Adaptation	Intentional attacks	Cascading	None	Yes
8		N/A	Operation	Random and intentional attacks	Cascading	None	None
9		Infrastructure planners	Design	None	None	Yes	Yes
10	**Topological network modeling**	N/A	Operation	General disruption	Escalating	None	None
11		N/A	Adaptation	Intentional attacks	Cascading	None	None
12		N/A	Design	Intentional attacks	Common cause failure	None	Yes
13		Policy makers	Restoration	Overload	Cascading	None	Yes
14		Policy makers, research institutes and infrastructure providers	Operation	General disruption	Cascading	None	Yes
15		Infrastructure providers and consumers	Operation	General disruption	Cascading	None	None
16	**Agent-based modeling**	Decision-makers	Operation	General disruption	Cascading	Yes	None
17		Infrastructure providers, planners and emergency responders	Operation	None	None	Yes	None
18		NA	Restoration	General disruptions	Cascading	Yes	None
19		Policy makers and engineers	Design	None	None	Yes	Yes
20		Electrical utilities, system operators, regulators and policy makers	Adaptation	Extreme weather events	Common Cause failure	None	None
21	**Probabilistic modeling**	NA	Restoration	General disruptions	Cascading	None	None
22		Infrastructure providers	Restoration	General disruption	None	Yes	Yes
23		Government	Restoration	General disruption	None	Yes	Yes
24		Infrastructure operators	Restoration	Extreme weather events	Cascading	None	None
25		Government internal analysts	Operation	Terrorist attack or natural disaster	Cascading	Yes	Yes
26		Infrastructure operators and decision-makers	Operation	General disruption	Escalating	Yes	None
27	**Other modeling approaches**	Infrastructure operators, business and government decision-makers	Operation	Terrorist attack	Escalating	Yes	Yes
28		Government	Operation	General disruption	Escalating	None	None
29		N/A	Operation	General disruption	Escalating	Yes	None
30		Government internal analysts	Operation	Economic disruptions	Common cause failure	Yes	Yes

(a) Yes: addressed.
(b) None: not addressed.
(c) N/A: not enough information provided.

Appendix 2. Other modeling features and the evaluation results of the selected models.

	Modeling approach	Data needs	Model type	Output format	Time scale	Dynamic or static	Endogenous or exogenous damage/Restore
1		Medium	White box	Data charts	Several-hour time horizon	Dynamic	Endogenous
2		Low	White box	Plan	N/A	Dynamic	Endogenous
3	**Optimal operation modeling**	Medium	White box	Plan	N/A	Dynamic	Endogenous
4		Medium	White box	Plan	N/A	Static	Endogenous
5		Medium	White box	Data and plan	N/A	Dynamic	Endogenous
6		Low	White box	Data and plan	N/A	Static	Endogenous
7		Low	White box	Plan	N/A	Static	Endogenous
8		Low	White box	Data charts	N/A	Dynamic	Endogenous
9		High	White box	Potential costs and CO_2 emission	N/A	Dynamic	N/A
10	**Topological network modeling**	Low	White box	Data charts	N/A	Dynamic	Endogenous
11		Low	White box	Data charts	Several-hour time horizon	Dynamic	Endogenous
12		Medium	White box	Plan	N/A	Static	Endogenous
13		Medium	White box	Metrics	1-week time step	Dynamic	N/A
14		Medium	White box	Economic impacts	1-hour time step	Dynamic	Exogenous
15		Low	White box	GIS	N/A	Dynamic	Exogenous
16	**Agent-based modeling**	High	White box	3D visualized model	N/A	Dynamic	Endogenous
17		High	White box	Graphic models	N/A	Dynamic	Endogenous
18		Medium	White box	Data charts	1-minute or 1-hour time step	Dynamic	Exogenous
19		High	White box	Map	1-year time horizon	Dynamic	N/A
20		Low	Grey box	Index	10-hour to 50-hour time horizon	Dynamic	Endogenous
21	**Probabilistic modeling**	Medium	White box	Plan	1-hour time step	Dynamic	Endogenous
22		Low	White box	Graphs and tables	N/A	Dynamic	Endogenous
23		Low	White box	Graphs	N/A	Dynamic	Endogenous
24		High	White and grey box*	Data charts	1 year	Dynamic	Endogenous
25		High	White box	Map	N/A	Dynamic	N/A
26	**Other modeling approaches**	High	Black box	GIS	Between 1-month and 5-year time horizon	Dynamic	Endogenous
27		High	White box	GIS	N/A	Dynamic	N/A
28		High	White box	Graphs and tables	N/A	Static	N/A
29		Medium	White box	Data charts	N/A	Dynamic	Exogenous
30		Medium	White box	Reports	1-week to 1-month time horizon	Dynamic	Exogenous

N/A: not enough information provided.

* :This model has two sub-models that adopt different modeling methods. The restoration model is white box and the cascading failure model is grey box.

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