Review on Empirical Quantitative Data Use in Lifeline Infrastructure Restoration Modeling

Matthew Martell[1], Scott B. Miles[2], and Youngjun Choe[3]

[1]Department of Industrial and Systems Engineering, University of Washington, Seattle.
Email: marte292@uw.edu

[2]Department of Human Centered Design and Engineering, University of Washington, Seattle.
Email: milessb@uw.edu

[3]Department of Industrial and Systems Engineering, University of Washington, Seattle.
Email: ychoe@uw.edu (corresponding author)

ABSTRACT

Disaster recovery is considered one of the less understood phases of the disaster cycle. In particular, the literature around lifeline infrastructure restoration modeling frequently mentions the lack of available data. Despite limitations, there is a growing body of research on modeling lifeline infrastructure restoration using empirical quantitative data. This study reviews this body of literature and identifies the data collection and usage patterns present across modeling approaches to inform future efforts. We classify the modeling approaches into simulation, optimization, and statistical modeling. The number of publications in this domain has increased over time with the most rapid growth of statistical modeling. Electricity infrastructure restoration is most frequently modeled, followed by the restoration of multiple infrastructures whose interdependency is increasingly considered in recent literature. Researchers gather the data from various sources, including collaborations with utility companies, national databases, and post-event damage and restoration reports. This article provides discussion and recommendations around data usage practices to facilitate a community of practice around restoration modeling and provide greater opportunities for future data sharing.

INTRODUCTION

Recovery from disasters is considered one of the less understood phases of the disaster cycle (Smith and Wenger 2007; Miles et al. 2019). Disaster recovery is a broad term with many facets, including social, economic, built, and natural environments. It is largely accepted to imply bringing each of these facets back to or better than pre-disaster levels (Kates and Pijawka 1977; Chang 2010; Lindell 2013). We follow most closely the definition of Lindell (2013). Disaster recovery is a phase of the emergency management cycle that usually overlaps with emergency response. A subsection of disaster recovery research is lifeline restoration modeling. *Restoration* refers to the short-term patching up of essential services to help facilitate longer-term recovery (Kates and Pijawka 1977; Lindell 2013; Loggins et al. 2019). Lifelines are a subset of critical infrastructures vital for communities to operate (The White House 2013), namely, electricity, natural gas, telecommunication, transportation, water, wastewater, and liquid fuel (Applied Technology Council 2016). Understanding how these systems are restored allows for more informed community resilience planning efforts (O'Rourke and Briggs 2007; National Institute of Standards and Technology (NIST) 2015). We can better understand lifeline restoration processes through modeling.

The lack of, or perceived lack of, empirical data is one of the primary challenges for the growth of the lifeline restoration modeling field (Miles and Chang 2006; Chang 2010). Ouyang (2014) identifies difficult to access data and lack of precise data as key problems for modeling lifeline systems. Lifeline modeling requires many data, frequently including system topologies, component geographical locations, and emergency procedures used by the lifeline system's owners. Data access is difficult for reasons such as security, liability, competition laws, confidentiality, and privacy. Rinaldi et al. (Rinaldi et al. 2001) also identify the volume of data required to model lifeline systems as a major challenge in the field. Ouyang (Ouyang 2014) calls for a standardized data collection method to remedy data issues, while Miles et al. (Miles et al. 2019) calls for a community of practice to develop around the broader field of disaster recovery modeling, including development of shared data sets. Consistent data collection and management strategies would allow for many more data reuse opportunities and greater access into the field for new researchers.

The need for a consistent approach to handling data in lifeline restoration modeling is apparent. It is necessary to understand the history of data usage in the field. The purpose of this study is to review the usage of empirical quantitative data to model lifeline infrastructure restoration and provide recommendations for future directions of the field. Section 2 discusses high-level trends seen in the literature and the literature search methods used. Section 3 breaks down the literature by modeling approach for an in-depth look at how various approaches utilize empirical quantitative data. Section 4 discusses topics related to lifeline restoration modeling, such as model validation and testing methods, modeling interdependent systems, benchmarking testbeds and data management best practices.

This review shows relationships between modeling approach, hazard type, lifeline system, and data set features. Additionally, it identifies trends in the field related to modeling interdependencies in the restoration process and alternative data sources, including benchmarking testbeds. The most significant contribution of this review, which separates it from existing reviews such as Ouyang et al. (2014) or Miles et al. (2019), is its focus on data and data management. There is no other review to our knowledge with this focus in the literature. Our review shows the breadth of data features and data sources used in the literature. It can guide researchers as to the many kinds of data that could be used to model lifeline infrastructure restoration. This focus on data emphasizes the importance of data collection and sharing to scholars and practitioners and hopefully encourage more of them to collect and share data.

METHODS

This section details our methods for identifying publications to include in the review, what data items we collected from each publication, and some high-level trends from the literature as a whole. We identified initial publications to include in the review by searching Web of Science. Web of Science was chosen for the search as it includes the curated reputable journals in relevant disciplines, indexed such as in Science Citation Index Expanded and Social Sciences Citation Index. This allowed us to focus on the peer-reviewed studies that meet a certain scholarly standard amid the recent increase of spurious journals. Keywords used across our searches included terms related to the phases of recovery, different hazard types, and different lifeline systems. The full list of search terms is lifeline, infrastructure, water, wastewater, electricity, power, gas, transportation, telecommunications, outage, restoration, reconstruction, recovery, disaster, hurricane, ice storm, tornado, earthquake, and data.

From these searches, publications were included only if they included a quantitative restoration model, that model was for one or more lifeline systems, and the model was grounded in empirical quantitative data in some way. Any publications published in 2019 or earlier were eligible for inclusion. Using the initial qualifying publications from Web of Science, we found older publications that fit the inclusion criteria using backward snowballing. Backward snowballing is a technique for searching the literature by proceeding backward in time through references of known publications to find older sources on a topic (Eassom et al. 2014). In total, we identified 54 publications that met the inclusion criteria for this study. Publications were identified and reviewed by the first author to determine suitability for inclusion.

As there are inconsistencies in the literature regarding the usage of key terminologies such as restoration, recovery, and response (Miles et al. 2019), and we only reviewed publications in English, this list may not be exhaustive. However, the inclusion criteria create a representative set of publications on the topic so the study's findings and insights are grounded in major literature trends. A list of all publications included in this review can be found in Table 1. The data items collected from each publication included the modeling approach(es), the hazard(s) of interest, the modeled lifeline system(s), whether the publication considered interdependencies in the restoration process, and the country of origin of the data.

The literature analyzed for this study is a subset of disaster recovery and modeling literature. It is useful to identify some excluded publications to illustrate the boundary of the reviewed literature. Nejat and Ghosh (2016) use empirical data to model housing recovery, but their work is excluded from this review since housing is not considered a lifeline. Similarly, publications that model greater community recovery, or other non-lifeline sectors, are not included in this study (Barker and Haimes 2009; Miles and Chang 2011). Works that collect restoration data without building a restoration model such as Nojima and Maruyama (2016) are also not included. Additionally, publications that work with qualitative data only, such as expert judgments (Chang et al. 2014), are not included. While qualitative data are useful for building quantitative models, the methods for collecting/generating qualitative data are substantially different from those for quantitative data and would be best served with their own review. A large body of literature omitted from this study concerns the power service restoration problem defined by the Institute of Electrical and Electronics Engineers (IEEE), as they use a specific technical definition. The problem is also known as the Fault Isolation and Service Restoration problem. Solutions to this problem try to find the fastest way to isolate a fault in the power distribution network while minimizing the number of healthy out-of-service areas (Marques et al. 2018). There are reviews of the literature in this area including Ćurčić et al. (1995) and Liu et al. (2016), so we refer readers to these articles for more information on this problem. Many publications in this domain use electricity infrastructure data, so they are a potentially valuable data source. Making exclusions of the above types allows us to keep our scope narrow while still having a significant body of research to review.

FINDINGS

An initial finding from this review is that lifeline restoration modeling is a growing field. Figure 1 shows the marked increase in publications over time. The sharp increase in publications over the last ten years (2010-2019) coincides with the proliferation of statistical models of lifeline restoration. Figure 1b shows the change in modeling approaches over time. Statistical modeling has grown markedly in the last ten years compared to other modeling approaches. This trend may be related to changes in the amount of available data and what data is being used. The availability of outage/restoration data has likely increased with the increasing number of weather-induced disasters (Kenward and Raja 2014). This increase contrasts with the availability of lifeline-specific data (e.g., topology of a networked system) typically used by simulation and optimization approaches. This type of data has not experienced the same trend in accessibility as outage/restoration data since it requires collaboration with utility companies. While statistical models can use publicly available community attributes, such as demographic information or economic data as predictors for outage duration, optimization or simulation approaches require lifeline-specific data to model the restoration process. Thus, the growth in statistical models is only natural. The data usage patterns of each modeling approach are discussed in more detail in Section 3.

Data availability is not the only factor that affects modeling decisions. Earthquake hazard research is a historically more organized and well-funded research domain than other hazards research. This is exemplified by major earthquake engineering research centers such as the Mid-America Earthquake Center, Pacific Earthquake Engineering Research Center, and the Multidisciplinary Center for Earthquake Engineering Research (MCEER). MCEER, formerly known as the National Center for Earthquake Engineering Research, alone produced hundreds of publications, some of which involve lifeline restoration modeling (Multidisciplinary Center for Earthquake Engineering Research 1986). Two of the most extensive past restoration modeling and data collection efforts are MCEER projects that involved collaborations with the Los Angeles Department of Water and Power (LADWP) and Memphis Light, Gas and Water Division (MLGW). Both partnerships resulted in multiple publications, so earthquake-related models are heavily represented in the literature as seen in Figure 2a. Another insight from Figure 2a is that there is a significant body of literature that assumes an initial damaged state without specifying a hazard type, or considers multiple hazards, to make those models more generalizable.

We separate lifeline restoration modeling into three categories for our analysis: optimization, simulation and statistical modeling. While these categories are broad, there are still enough differences in data usage between them. To facilitate our discussion of data management practices, this section discusses each modeling approach and the common data-usage practices within them. Each modeling approach subsection has three parts. Part one is focused on data set features (i.e., what types of data are being used), part two is focused on notable data sets (defined as any data set that was used in more than one publication), and part three is focused on data sources (i.e., where the data was obtained from). Statistical modeling approaches are the most common, followed by simulation, and then optimization (see Figure 2b).

There are clear connections between the modeling approaches and the types of data used.

Optimization models most often consider multiple lifeline systems and hazard types, while statistical models are typically linked to electricity restoration and simulation models to earthquakes (see Figures 3a and 3b). Optimization models are procedural and emphasize generalizability, so they tend to use data sets representing multiple systems and hazards. Statistical approaches to modeling electricity restoration are common because power outage data are more common than outage data for other lifelines. Electricity restoration models are often constructed using outage data and any data used as a predictor (e.g., electricity system features, hazard characteristics, or socioeconomic data about the surrounding community). Simulation modeling of post-earthquake restoration is common because of the MCEER research program. The long-term MCEER partnership with the Los Angeles Department of Water and Power (LADWP) yielded high-resolution simulation models of post-earthquake restoration, resulting in multiple publications.

Simulation

Overview

Simulation models have the longest history of any method in the lifeline restoration modeling domain, dating back to the 1980s (Isoyama and Katayama 1981; Isumi et al. 1985). Simulation modeling is the second most common modeling approach in the literature reviewed. In terms of data usage, simulation models are typically based on lifeline-specific data such as a connected graph representation of the system, individual component repair times, and available repair resources (e.g., maintenance crews). High fidelity simulation models require detailed data about all parts of the restoration process, so some of the largest data sets in terms of the number of features are found in this section.

Data Set Features

Data for simulation models come from many different sources. In spite of this, there is a high level of overlap in the features of the data sets. Every simulation-based publication reviewed used lifeline infrastructure data in some capacity. Lifeline systems are commonly represented as connected graphs (Isoyama and Katayama 1981; Çağnan et al. 2006; Ramachandran et al. 2015; Choi et al. 2018). Component failure rates are frequently obtained from other works (Isoyama and

Katayama 1981; Brown et al. 1997; Brink et al. 2009; Sun et al. 2015). Another common data set feature is repair crew information such as repair rate/efficiency and number of crews (Çağnan et al. 2006; Çağnan and Davidson 2007; Xu et al. 2007; Brink et al. 2009; Tabucchi et al. 2010; Luna et al. 2011; Brink et al. 2012). Lastly, information about restoration from an outage event is primarily used for model validation and testing. Validation and testing methods are discussed more in Section 4.

Notable Data Sets

Two data sets with a large number of features used for simulation modeling are those used to model the restoration of the LADWP systems (Çağnan et al. 2006; Çağnan and Davidson 2007; Xu et al. 2007; Tabucchi and Davidson 2008; Brink et al. 2009; Tabucchi et al. 2010; Brink et al. 2012). The data sets for these publications are the result of extensive collaboration with LADWP. The publications are from two separate projects, one for water restoration (Tabucchi and Davidson 2008; Brink et al. 2009; Tabucchi et al. 2010; Brink et al. 2012) and one for power restoration (Çağnan et al. 2006; Çağnan and Davidson 2007; Xu et al. 2007). The data sets include detailed network representations of the respective lifelines, locations of the various resources necessary for repair work, expected behavior of repair crews, and each repair resource's availability. Additionally, restoration and initial damage data from the 1994 Northridge earthquake serve as the basis for model validation.

Luna et al. (2011) study water supply system restoration from earthquakes using discrete event simulation and a colored Petri nets approach. They use the data set of Isoyama and Katayama (1981). The data set includes the network representation of Tokyo's trunk water supply system, damage probabilities for system components, repair crews, trucks, replacement pipes, and excavators. The authors compare their model against Isoyama and Katayama (1981); however, they do not use baseline restoration data to test the model.

Data Sources

Many data sources are used in simulation modeling studies, although some publications do not identify an original source for their data sets. Sun et al. (2015) use an IEEE Bus Test Case for their network data as well as data from HAZUS and previous works for component fragility functions. Several studies in this area (Çağnan et al. 2006; Çağnan and Davidson 2007; Xu et al. 2007; Tabucchi and Davidson 2008; Brink et al. 2009; Tabucchi et al. 2010; Brink et al. 2012) collaborate directly with LADWP and collect extensive data sets through interviews and reviewing emergency response plans. Other data sources include HAZUS, S&P Global Platts (a provider of information for commodities markets), public utility data, and government disaster reports. Easily the most common data source in the simulation literature is previous publications (Brown et al. 1997; Chang et al. 2002; Luna et al. 2011; Ouyang et al. 2012; Ouyang and Dueñas Osorio 2014; Ouyang and Wang 2015). Isumi et al. (1985) use damage and restoration reports from local government and utility companies. Lastly, Google Earth is an infrequent but inventive data source for identifying lifeline facility network structure (Ramachandran et al. 2015; He and Cha 2018).

Optimization

Overview

The purpose and data usage of optimization modeling studies differ from the other two modeling approaches. The purpose of an optimization model is typically to identify an efficient restoration sequence. In contrast, the purpose of simulation modeling is often to understand a restoration process in greater detail, while the purpose of statistical modeling is often to predict outage duration. Optimization models also distinguish themselves from other approaches by more frequently modeling interdependencies between lifelines through model constraints.

From a data usage perspective, optimization models do not put as strong of an emphasis on using empirical data. Compared to other modeling approaches, optimization models are typically focused on proving a theoretical result, which explains the lack of emphasis on data. Real-world data are not strictly necessary to prove a theoretical result, such as optimality, or show computation times. This is how data sets, such as the one used by Lee et al. (2007) arise, where a realistic representation of several lifelines is generated using empirical quantitative and qualitative data together.

Data Set Features

Optimization models are similar to simulation models in that they focus their modeling efforts on the lifeline systems and restoration processes themselves. This focus leads to data sets that take the form of connected graph representations of lifelines. These representations include location and capacity of supply nodes, node-arc lifeline interdependencies, flow capacities, flow costs, and repair costs.

Notable Data Sets

Lee et al. (2007) is one of the more frequently cited optimization restoration modeling studies, and the data set they created is reused in multiple other publications (Nurre et al. 2012; Nurre and Sharkey 2014; Çavdaroğlu et al. 2013). The authors use data from the U.S. Census, New York City Metropolitan Transit Authority, a local electric company, and Verizon to represent the lifelines in lower Manhattan. This representation includes physical layout, supplies, demands, capacities, interdependencies, and origin-destination information for the transportation and telecommunications networks.

Nurre et al. (2012) use the same data set for lower Manhattan as Lee et al. (2007), in addition to collecting data about New Hanover County, NC. The New Hanover County data set includes representations of electricity systems, wastewater systems, and emergency supply chain infrastructures. This data set was created with the infrastructure systems' managers and a county emergency manager. All systems are represented as connected graphs; restoration strategies are implemented using the input of emergency and utility managers. Sharkey et al. (2015) also use this New Hanover County data set. Iloglu and Albert (2018) use a different data set from New Hanover County, representing the road network, locations of fire and rescue stations, and locations of demand for emergency services.

In their studies, González et al. test their models on a data set representing Shelby County, Tennessee (González et al. 2016; González et al. 2017). It contains network representations of the power, water and gas systems of the county. This data set stems from an extensive partnership with a utility company, in this case, MLGW. This partnership yielded a feature-rich data set used in many subsequent studies. It dates back to an MCEER project with many contributors. This data set is discussed in more detail in Section 3.

Data Sources

The data sources for optimization models are similar to those of simulation models but less varied. Collaboration with lifeline management organizations to get data is a common method (Lee et al. 2007; Yan and Shih 2009; Nurre et al. 2012; Tuzun Aksu and Ozdamar 2014). Authors also consistently make use of data sets collected from prior studies (Nurre et al. 2012; Çavdaroğlu et al. 2013; Nurre and Sharkey 2014; Sharkey et al. 2015; González et al. 2016; González et al. 2017), frequently other lifeline restoration modeling efforts. There is less emphasis on data collection and usage than for other modeling approaches, as optimization models are frequently theoretical. Overall, optimization approaches use a similar, but smaller, set of data sources than simulation approaches.

Statistical Models

Statistical models are the most frequently used and most varied of the three modeling approaches. The goal of such a model is usually to generate a restoration time estimate (e.g., it will take four days for the lifeline to be 90% functional), or a restoration probability (e.g., there is an 80% probability the lifeline has 90% functionality in three days). The statistical modeling approaches include curve fitting (Park et al. 2006), survival analysis (Bessani et al. 2016; Davidson et al. 2017; Mojtahedi et al. 2017), various machine learning techniques (Nateghi et al. 2011; Mukherjee et al. 2018b) and econometric models (MacKenzie and Barker 2013), among others.

With the widest variety of approaches, statistical models also encompass the widest variety of data set features and sources. A commonality amongst the statistical models is lifeline restoration data used for model fitting and model validation and testing. Some larger data sets, in terms of features and the number of disaster events, include power restoration after several hurricanes in the U.S. Gulf Coast region (Nateghi et al. 2011; Nateghi et al. 2014) and a data set for power restoration after hurricanes and ice storms for three power companies covering North Carolina, South Carolina, and Virginia in the U.S. (Liu et al. 2007; Reed 2008; Davidson et al. 2017).

Data Set Features

A common feature of statistical modeling data sets is the use of restoration data from historical disaster events. Sometimes this takes the form of time series restoration data and other times a single data point representing X% restoration for a particular geographic area. Lifeline data sets are also used in many studies. Common features for power system data sets include the number of poles, transformers, switches and lines in each grid cell of a spatial data layer (Liu et al. 2007; Nateghi et al. 2011; Nateghi et al. 2014). Other common data set features include hazard data such as wind speed, rainfall, and ice accretion and geographic data such as land cover and soil depth (Guikema et al. 2010; Davidson et al. 2017). Several studies use socioeconomic data (Liu et al. 2007; Mitsova et al. 2018), including demographics, population density and poverty rates. Other data set features include commodity trade data and climate data, such as mean annual precipitation (Guikema et al. 2010; MacKenzie and Barker 2013; Mukherjee et al. 2018b).

Notable Data Sets

In two studies, Nateghi et al. (2011, 2014) use a data set representing the Gulf Coast region of the U.S. The data set includes estimates of wind gust speed, duration of wind speed exceeding 20 m/s, land cover, soil moisture, antecedent precipitation and mean annual precipitation. Power system-related features include numbers of poles, transformers, and switches; length of overhead and underground lines; and number of impacted customers. These features are mapped to 3.66 km by 2.4 km grid cells. Restoration information is available for three hurricane events. This multi-event nature combined with the number of features makes this data set one of the largest in the power restoration literature.

One of the most commonly used data sets for modeling various aspects of disaster recovery is that used in Liu et al. (2007). This data set is used for many publications, some not directly modeling lifeline restoration (Liu et al. 2005), and others extending existing restoration modeling work (Reed 2008). The data set includes outage data from three utility companies in the North Carolina area for six hurricanes and eight ice storms. The data set is collected at the county level for land cover, number of customers affected, type of device affected, population density, outage start time compared to start time of the first outage, estimated wind speed, seven-day rainfall and ice accretion. Reed (2008) uses a subset of this data set and data from the 1999 French winter storms for their model.

The work of Yu and Baroud (2019) is another that utilizes a data set from Shelby County, Tennessee. Their data set comprises outage data from fifteen storms for MLGW between 2007 and 2017. Shelby County and MLGW have provided data for research in the past that resulted in many extensive works, most notably an MCEER project in the '90s (Chang et al. 1996; Shinozuka et al. 1998). The data set presented in Chang et al. (1996) comprises layouts for water, electricity and natural gas systems, restoration data for the 1994 Northridge earthquake, utility usage data, census data, and economic data.

There are several studies that aggregate data from many events worldwide to build their models, and studies focusing on a specific geographic area for restoration data. Díaz-Delgado Bragado (2016) builds a database of restoration data for 31 earthquake events from around the world, 1923-2015, considering water, power, gas and telecommunications systems and uses it to fit gamma cumulative distribution functions. Monsalve and de La Llera (2019) also compile earthquake restoration data, encompassing six different earthquakes and various infrastructure systems. Kammouh et al. (2018) likewise bring together worldwide earthquake restoration data, including 32 earthquakes in their study. Zorn and Shamseldin (2015) is another work that brings together restoration data from multiple events, 18 total, including earthquakes, hurricanes, and other types of disasters, for electricity, water, gas, and telecommunications systems. Finally, Duffey (2019) collects power restoration data for 13 disaster events between 2012 and 2018 through "power tracker" or "outage map" websites.

Nojima et al. (Nojima and Sugito 2002; Nojima and Sugito 2005; Nojima and Kato 2012; Nojima and Kato 2014) collect data sets from Japan earthquake events as the basis for their models. These data sets include seismic intensity from the Japan Meteorological Agency, spatially distributed population data and network vulnerability data for water and gas systems. Restoration data sets for electricity, water, and gas systems are also used. The data sets are collected from the

1995 Hyogoken-Nambu earthquake and the 2011 Tōhoku earthquake.

MacKenzie and Barker (2013) use publicly available U.S. outage data, collected by the U.S. Department of Energy through form OE-417, along with state population data. The data set includes duration, location (state), and cause of the outage between January 2002 to June 2009. Barker and Baroud (2014) and Barabadi and Ayele (2018) use the same data set, while Mukherjee et al. (2018b) utilize a larger data set of OE-417 submissions, containing information from January 2000 to July 2016. They use state-level population data, climate data from the U.S. National Oceanic and Administrative Administration, electricity consumption patterns from the U.S. Energy Information Administration, Urban/Rural and Land/Water percentages from the U.S. Census Bureau, and state-level economic characteristics from the U.S. Bureau of Economic Analysis.

Data Sources

Direct collaboration with utility companies is again a common data source (Chang et al. 1996; Cooper et al. 1998; Park et al. 2006; Nateghi et al. 2011; Nateghi et al. 2014; Mitsova et al. 2018). Nateghi et al. (Nateghi et al. 2011; Nateghi et al. 2014) supplement their utility-provided data with data collected from a commercial weather forecasting service and the National Land Cover database. Mitsova et al. (2018) collect additional data from the American Community Survey for their model. Several modelers got their data sets from public U.S. government data sources (MacKenzie and Barker 2013; Barker and Baroud 2014; Mukherjee et al. 2018b; Barabadi and Ayele 2018). The most common data source is data sets from previous studies, such as the worldwide restoration data sets in Zorn and Shamseldin (2015) and Kammouh et al. (2018). Using a novel approach, Duffey (2019) makes use of "outage tracker" websites to gather restoration data after multiple disasters. Sources outside the U.S. are used in several works (Bessani et al. 2016; Mojtahedi et al. 2017; Barabadi and Ayele 2018). Finally, public outage reports are used in Duffey and Ha (2013).

FUTURE DIRECTIONS FOR RESEARCH

We identified several important topics for discussion from this literature review. These topics can be broken into thematic and methodological directions. The two thematic directions we identified were modeling interdependent systems and engagement through benchmarking testbeds. The methodological directions are alternative data sources, model validation and testing, and data management best practices. These topics have relevance to the future directions of the lifeline restoration modeling literature.

Thematic Directions

Modeling Interdependent Systems

Interdependency is increasingly recognized as an important factor to consider while modeling lifeline restoration, as seen in Figure 4a. Lifeline systems are interdependent by nature. For example, power generators require water for cooling and electricity is needed for water pumps to function. Quantifying these interdependencies regarding restoration is an ongoing challenge for modelers, but one that is actively being worked on by researchers.

There was an increase in studies of cascading failures (Hernandez-Fajardo and Dueñas Osorio 2013; Veremyev et al. 2014; Wu et al. 2016) in recent years, and there is a broad recognition that lifelines are restored in an interdependent fashion (Rinaldi et al. 2001; Sharkey et al. 2016). In contrast, our review shows that only about 25% of the reviewed literature consider interdependencies directly. Optimization models have the longest history incorporating interdependencies in their models, as seen in Figure 4b. The rest of this section discusses a few of the methods used to model interdependent restoration in the reviewed literature and promising approaches that, to our knowledge, have yet to be applied in a restoration modeling context.

Lee et al. (2007) is the oldest instance of modeling interdependent infrastructure restoration in the reviewed literature. They consider power, telecommunications, and transportation systems in modeling five types of interdependency: input dependence, mutual dependence, shared dependence, exclusive-or dependence and co-located dependence. The authors include interdependencies as constraints in their problem formulation. Çavdaroğlu et al. (2013) utilize the same data set but take the added step of determining an optimal restoration sequence for the lifeline systems. Their objective is to maximize the functionality of the lifeline services over the restoration period by balancing unmet demand costs and operating costs. They also model restoration interdependencies through their model constraints.

Yan and Shih (2009) model transportation restoration and emergency relief distribution together. While not a model of interdependent *lifeline* restoration, this work shows a way to model restoration of interdependent *systems*. They use a multi-objective optimization model to minimize the length of time for restoration and subsequent relief distribution. The authors note the connection between the transportation system and the ability to distribute relief.

MacKenzie and Barker (2013) utilize the dynamic inoperability input-output model (DIIOM) to include interdependency in their restoration model. Interdependencies in the DIIOM are quantified using commodity flow data from the U.S. Bureau of Economic Analysis. They apply the model to estimate restoration from power outages. Theirs is the earliest non-optimization approach to modeling restoration interdependency in the reviewed literature. He and Cha (2018) extend the DIIOM to calculate facility-level interdependencies as opposed to system-level interdependencies in the traditional DIIOM. This facility-level approach captures interdependencies not only *across*, but also *within* systems.

Other more recent models have a variety of approaches for modeling interdependent restoration (Ramachandran et al. 2015; González et al. 2016; González et al. 2017; Monsalve and de La Llera 2019). Monsalve and de La Llera (2019) calculate a daily restoration rate for each lifeline in their model based on the lifeline type, its interdependencies, and an additive Gaussian error term. The authors utilize a least-squares criterion that minimizes the difference between the expected value of the model and the data to estimate model parameters, including lifeline interdependencies. Their model assumes that the restoration rate of a given lifeline depends on the functionality of other lifeline systems but not on their restoration rates. González et al. (2016, 2017) define four types of interdependencies: logical, physical, cyber, and geographic. They account for these interdependencies through the constraints of their optimization model. Ramachandran et al. (2015) include interdependency in their simulation model by including constraints that some tasks cannot start until others finish (e.g., power lines cannot be repaired until the road to access those lines is free of debris).

There is a series of studies that utilize time-series restoration data and cross-correlation functions to quantify the interdependency between two lifelines (Dueñas-Osorio and Kwasinski 2012; Cimellaro et al. 2014; Krishnamurthy et al. 2016). This method of quantifying interdependencies has not been incorporated into a restoration model, but the potential is there. We believe that it could be applied in an approach similar to that of Monsalve and de La Llera (described above) (2019).

Engagement through Benchmarking Testbeds

Over the last few years, there has been significant progress creating benchmarking testbeds for recovery modeling. Two examples are Customizable Artificial Community (CLARC) County, created by Loggins et al. (2019), and Centerville, created by the Center for Risk-Based Community Resilience Planning at Colorado State University (2018). CLARC County is a GIS data set representing an artificial hurricane-prone community of 500,000. The data set contains demographic and geographic data typically reported for U.S. census tracts and physical locations and characteristics of components of civil and social infrastructure systems along with their interdependencies. The data set exists to support infrastructure and emergency management research without compromising potentially sensitive information. The Centerville community resilience testbed is a virtual city, representing a typical middle-class city in the Midwestern U.S. that is susceptible to tornadoes and earthquakes. Buildings, transportation systems, electric power, and water systems are represented in the data set, and socioeconomic features based on American Community Survey data for Galveston, Texas, and income data from Fort Collins, Colorado.

These testbeds are conducive to recovery research, as they allow for complete, albeit synthetic, data sets to be used to test and compare recovery models. The two examples provided here also show that testbeds can be constructed in various ways, ranging from being completely synthetic to being based on empirical data from a single source or an amalgamation of sources. The areas represented by the example testbeds are different, one being an individual city, while the other a U.S. county. No matter the construction, these testbeds can provide value as boundary objects for comparison if nothing else. Given how recent these efforts are, it is unclear if the development of testbeds affects the use and collection of empirical data.

The difficulty of collecting extensive data sets for lifeline restoration modeling is well documented in the reviewed literature. Loggins et al. (2019) mention an extensive data collection process they attempted for New Hanover County, NC, and how the difficulties they experienced led them to create CLARC county. The likelihood of developing complete data sets on all lifelines in a community *and* lifeline restoration data from a disaster event in that community is low. Even if such a data set were to be developed, security concerns might prevent it from ever entering the public domain. This makes testbeds the logical next step for the developing large-scale, highly detailed optimization and simulation models of interdependent recovery. However, this does not eliminate the need for the collection of empirical data.

The data collection of Loggins et al. for New Hanover County informed the creation of CLARC county (Loggins et al. 2019), and Centerville (Colorado State University 2018) was created from an amalgamation of several empirical sources. Data availability can and sometimes should inform modeling approaches depending on modelers' objectives, although models built with no empirical data can still provide useful insights and create new knowledge (e.g., what-if analysis, facilitation of discussion, and education). Examples of data availability informing model choice include the work done with LADWP. The authors had access to a feature-rich lifeline-specific data set, which made a detailed simulation model feasible. Another example of data availability informing modeling efforts/direction is the work of Mukherjee et al. (2018b). The authors had access to publicly available data at the state level, making a broader statistical model possible. Having the data set publicly available means others can duplicate and extend this work. There are also many examples of "benchmarking" in the literature where authors extend the modeling efforts of previous work using the same data set and compare results.

Methodological Directions

Alternative Data Sources

Some studies that fall outside of this review's inclusion criteria still deserve mention for their usage of data sources not seen in the reviewed literature. McDaniels and Chang characterize lifeline failure interdependencies using manual content analysis of newspapers and technical reports (Mcdaniels et al. 2007; Chang et al. 2007). In contrast, Lin et al. (2018) make use of natural language processing to analyze newspaper stories from New Zealand after the Canterbury earthquakes to track long-term recovery. Doubleday et al. (2019) use daily bicycle and pedestrian activity as an indicator of disaster recovery. Brown and Pinkerton (2019) use synthetic data for power system elements. Chang et al. (2014) use expert elicitation to characterize lifeline resilience. Expert elicitation plays an important role in statewide resilience initiatives (Washington State Seismic Safety Committee (WASSC) 2012; Oregon Seismic Safety Policy Advisory Commission (OSSPAC) 2013), and in the development of the Federal Emergency Management Agency's HAZUS (FEMA 2011).

All of the above approaches do not rely on empirical data directly related to lifelines or lifeline restoration. In particular, approaches such as those seen in Doubleday et al. (2019) are promising because they make use of empirical quantitative data that has not been used in the restoration modeling space. If data sets of this nature can be linked to lifeline restoration data, the total amount of restoration data sets available would increase. Partially synthetic power system data sets such as those used by Brown and Pinkerton (2019) also show how new data can be generated to meet an existing need. There is already a significant body of literature related to generating synthetic power system data sets (Gegner et al. 2016; Birchfield et al. 2017a; Birchfield et al. 2017b).

The approach of Lin et al. (Lin et al. 2018), using natural language processing to generate recovery data, has the potential to create many new data sets that could be used for restoration modeling. While their analysis is focused on long-term recovery, a similar approach could be used for modeling shorter-term restoration, perhaps using a different source such as Twitter data (Miles et al. 2014; Ragini et al. 2018; Zou et al. 2018). Expert elicitation is another method that can be used to develop restoration models. Models based on expert judgment can apply techniques such as Cooke's method (Cooke 1991) to create a systematic approach for eliciting expert knowledge when empirical data sets are unavailable or inaccessible.

Validation and Testing Methods

As a precursor to this section, we want to acknowledge that model validation is a contested concept with many definitions, recommendations, and best practices across disciplines (Weinstein et al. 2003; Rose et al. 2015). There is a tendency to think that every model was developed to predict, and thus every model should be validated using out-of-sample testing. However, there are many reasons for modeling outside of prediction (Epstein 2008). Given that this review aims to discuss the use of empirical quantitative data, reviewed publications use data for model calibration, validation, or application through a case study. Acknowledging that out-of-sample testing is not applicable or feasible for every modeling study, this subsection discusses what out-of-sample validation and testing techniques have been used in the field so far.

Statistical models have the widest variety of out-of-sample validation and testing approaches. Cross-validation is used in a few models for parameter fitting or model comparison (Guikema et al. 2010; MacKenzie and Barker 2013; Nateghi et al. 2014; Yu and Baroud 2019). Some modelers split their data sets into training and test sets by withholding information from some disaster events (Liu et al. 2007; Nateghi et al. 2011; Davidson et al. 2017). Park et al. (2006) fit a curve to restoration data from one event and compared the fitted parameters to that of another event.

There are several out-of-sample validation methods used by simulation models as well. For the projects that partnered with LADWP (Çağnan et al. 2006; Çağnan and Davidson 2007; Xu et al. 2007; Tabucchi and Davidson 2008; Brink et al. 2009; Tabucchi et al. 2010; Brink et al. 2012), this was to use restoration data from the 1994 Northridge earthquake. The authors perform the validation by setting model input parameters (e.g. number of repair crews) equivalent to the Northridge conditions and comparing the simulated restoration time to the actual restoration time from the Northridge event. Other studies that compare their model output to restoration data included Isumi et al. (1985) and He and Cha (2018). A comparison between model output for a theoretical disaster event and restoration data from a similar disaster event in a different location (Ramachandran et al. 2015) is one of the more inventive validation methods seen in the literature.

There are no optimization models in the reviewed literature that were tested out of sample.

However, given the nature of an optimization model, this should not come as a surprise. The goal of optimization is usually to perform better than the status quo. Thus the restoration time estimates from an optimization model would nearly always be below real-world restoration times. The contribution of an optimization model is typically a new model formulation (Nurre et al. 2012; Yan and Shih 2009) or solution approach (González et al. 2016).

Overall, the reviewed literature encompassed a wide variety of validation and testing approaches. While the authors encourage the use of out-of-sample model evaluation, we understand that this is not always possible, nor does it always make sense. However, as models continue to become more generalizable and data more available, we hope to see more out-of-sample evaluations take place in this field.

A Data Management Methodology for Reproducibility in Disaster Recovery Modeling

The research community benefits from reproducibility, which is fostered by detailed metadata and data publication. Within the analyzed publications, data descriptions are frequently lacking, and data sets are rarely published. Although it is not always possible to publish data sets for a wide variety of reasons (e.g., security and privacy), this reduces the reproducibility of any research using those data sets. As data becomes increasingly prevalent across research domains, there are more advocates for increased accessibility of data sets. Gentleman and Lang (2007) go so far as to call for the publication of "reproducible research compendiums" which include the final paper, as well as the data set, software, and any other items necessary to reproduce the research. They acknowledge that this is not feasible for all research but maintain that publishing as much information as possible is worthwhile.

More recently, the FAIR guiding principles for scientific data management and stewardship (Wilkinson et al. 2016) represent a minimal set of domain-independent data management principles. Specifically, these principles state that research objects (Bechhofer et al. 2010) should be findable, accessible, interoperable, and reusable, both for human-driven and machine-driven activities. These principles are purposefully kept minimal to make the barrier to entry as low as possible to allow for easy implementation, even in cases where data sets cannot be published in their entirety or at all.

With these principles in mind, the remainder of this section is devoted to proposing a methodology for writing the data description section of a research paper in the disaster recovery modeling domain and best practices for data publication.

González-Barahona and Robles (2012) discuss reproducibility of empirical software engineering studies and identify elements of said studies with an impact on reproducibility. We adapt their ideas to fit the disaster recovery modeling domain. We recommend all disaster recovery modeling publications using empirical data include a data description section, with at least the following components:

1. Data source(s). Where did the data set come from? This should be as specific as possible. Even if the only thing an author can share is "an unnamed utility company from the U.S. Southeast", that is still worthwhile for a reader to know. Where possible, links or citations to the original data source(s) should be included.
2. Retrieval method. How was the data set collected from the source? Examples include downloading a CSV or GIS file from a government website, receiving data via email, and using a web scraper.
3. Raw data set and metadata. Can the data set be shared or is it publicly available? If yes, we recommend linking to an online repository that includes a description of the format and features of the data set. If not, we recommend to provide the metadata of the data set and the proper procedure to gain access to the data set if there is one. We recommend following the Dublin Core (Dublin Core Metadata Initiative 2008) standards for metadata. These standards include a cross-disciplinary list of properties for use in resource descriptions designed to be machine-processable that suit modern metadata needs.
4. Data processing methods. For example, what transformations were performed on the data set to get it into a usable form? Were features standardized? How were missing entries handled?
5. Processed data set and metadata. What are the form and features of the processed data? Processed data sets should be stored separately from the raw data set in an online repository

with a link for others to access. Obtaining a Digital Object Identifier (DOI) for the data set is a best practice after publishing it on an online repository or in a peer-reviewed journal (e.g., (Mukherjee et al. 2018a)). Version-controlled documentation can track problems in the data sets as they are found and corrected. As with the raw data set, if the processed data set cannot be published, we recommend to at least provide the metadata.

6. Processed data set's summary statistics. If the data set is numerical, statistics can be presented in a table. If the data set is only a network representation of an infrastructure system, a graphical representation may be sufficient. If this information cannot be shared, it can be clearly stated with a reason (e.g., national security).

A visual depiction of this methodology can be seen in Figure 5. One example of a brief, comprehensive data description in an academic publication is from Yan and Shih (2009):

> The roadway-network information includes the roadway segments and intersections in Nantou County, the location of repair points and work stations, and the location of supply and demand points. The emergency repair resources include the work teams for each station and the average time required for a work team to repair each repair point. Note that, in practice, when scheduling the roadway repairs, information on the time needed to repair every repair point is given by the engineers. Several engineers estimate the repair time in advance based on experience and the level of damage. Decision-makers then use the average time (as was done in this research) to set the repair time. ... There are 46 intersections, 24 repair points, 8 demand points, 9 work stations, 24 work teams, 5 distribution centers, and 196 time unit lengths (3 days is the time length, with a time unit of 15 min), in the tests.

This description does not contain all the elements in our proposed data management methodology, but it shows what can be done with a small amount of space in a research publication. The authors do mention a specific data source in their acknowledgments section.

When it comes to publishing data sets, following the FAIR principles (Wilkinson et al. 2016) should be the minimum standard we strive to achieve. An emphasis on these principles is enhancing the ability of machines to find and access data sets automatically. We also would like to emphasize this point and recommend that researchers in the disaster recovery modeling domain publish their data sets on digital platforms that are easily machine-accessible. One domain-specific example of this is the National Science Foundation's Natural Hazards Engineering Research Infrastructure, DesignSafe-CI (Rathje et al. 2017). DesignSafe-CI is a cyberinfrastructure environment for research in natural hazards engineering. The features of this cyberinfrastructure include data sharing and publication, integrated data analysis tools, high-performance computing access, and collaboration tools. DesignSafe-CI has detailed data publication guidelines and guidance for writing data management plans available.

We recognize that it is not always possible to share all the information in our proposed methodology due to privacy or security concerns. Even under this constraint, it is still important to make clear data management practices for research. If the data set is private, one can still provide relevant metadatawithin the limitations of the data set provider. This creates an opportunity for future research to collect a different data set with the same features and apply the method used in the original study. Overall, there are many opportunities for increased data sharing and higher standards for reproducibility in the field of disaster recovery modeling. The proposed methodology further supports a community of practice around data management in disaster recovery modeling. Using resources like DesignSafe-CI is one way to make the disaster recovery modeling community of practice a reality.

CONCLUSION

The data sources and data features used by lifeline restoration modelers vary across modeling approaches and there is no standardized methodology for utilizing data in this research domain. This review highlights various data sets that have been used in the past to model lifeline restoration to help build a community of practice within the broader field of disaster recovery modeling. We propose a set of best practices for managing and writing about data sets used for disaster recovery modeling. These best practices rely on data access and availability. Practitioners in emergency management or infrastructure operation can significantly aid disaster recovery researchers by collecting and sharing any recovery-related data with them. A stronger partnership between the research and practicing communities is necessary for the field to move forward.

Our review shows that direct collaboration with utilities and publicly available data, usually from the government, were two of the most common data sources in the literature. Data sets are frequently reused over time to provide additional insights with new/updated modeling approaches. We discuss the usage of benchmarking testbeds as an alternative way to develop and test recovery models where relevant data sets are unavailable. Expert elicitation and large-scale text data sets are identified as additional alternative data sources. Overall, this review demonstrates the wide variety of data sources available to modelers. Some limitations of our review include that the review may not have identified every publication in this domain. This exclusion could happen due to using only one database (i.e., Web of Science) for identifying publications and the inconsistencies regarding the usage of terms such as restoration, recovery, and response. Additionally, nearly two thirds of the publications in the review used data from the U.S. Two potential causes for this include the availability of data in other countries and our inclusion of articles published in English only.

Our intent for the proposed data management practices is to cause more data sets to become publicly available. These data practices can guide modelers without much experience in disaster and hazard research to enter the research domain and open doors for disaster and hazard researchers to build models with more data than they previously had access to. With more and more data available, the goal of a generalizable model of interdependent restoration could come into view, with communities around the world as the beneficiaries.

DATA AVAILABILITY STATEMENT

All data, models, and code generated or used during the study appear in the submitted article.

ACKNOWLEDGEMENTS

This work was supported by the National Science Foundation (NSF grant CMMI-1824681).

REFERENCES

Applied Technology Council (2016). *Critical Assessment of Lifeline System Performance: Understanding Societal Needs in Disaster Recovery*. National Institute of Standards and Technology (NIST), <https://nvlpubs.nist.gov/nistpubs/gcr/2016/NIST.GCR.16-917-39.pdf>.

Barabadi, A. and Ayele, Y. (2018). "Post-disaster infrastructure recovery: Prediction of recovery rate using historical data." *Reliability Engineering and System Safety*, 169, 209–223.

Barker, K. and Baroud, H. (2014). "Proportional hazards models of infrastructure system recovery." *Reliability Engineering and System Safety*, 124, 201–206.

Barker, K. and Haimes, Y. Y. (2009). "Assessing uncertainty in extreme events: Applications to risk-based decision making in interdependent infrastructure sectors." *Reliability Engineering and System Safety*, 94(4), 819–829.

Bechhofer, S., De Roure, D., Gamble, M., Goble, C., and Buchan, I. (2010). "Research objects: Towards exchange and reuse of digital knowledge." *Nature precedings*.

Bessani, M., Zempulski Fanucchi, R., Achcar, J. A., and Dias Maciel, C. (2016). "A statistical analysis and modeling of repair data from a Brazilian power distribution system." *2016 17th International Conference on Harmonics and Quality of Power (ICHQP)*, Vol. 2016-, IEEE, 473–477.

Birchfield, A. B., Gegner, K. M., Xu, T., Shetye, K. S., and Overbye, T. J. (2017a). "Statistical considerations in the creation of realistic synthetic power grids for geomagnetic disturbance studies." *IEEE Transactions on Power Systems*, 32(2), 1502–1510.

Birchfield, A. B., Xu, T., Gegner, K. M., Shetye, K. S., and Overbye, T. J. (2017b). "Grid structural characteristics as validation criteria for synthetic networks." *IEEE Transactions on Power Systems*, 32(4), 3258–3265.

Brink, S. A., Davidson, R. A., and Tabucchi, T. (2009). "Estimated durations of post-earthquake water service interruptions in Los Angeles." *TCLEE 2009: Lifeline Earthquake Engineering in a Multihazard Environment*, Vol. 357, American Society of Civil Engineers, 1–12.

Brink, S. A., Davidson, R. A., and Tabucchi, T. H. (2012). "Strategies to reduce durations of post-earthquake water service interruptions in Los Angeles." *Structure and Infrastructure Engi-

neering, 8(2), 199–210.

Brown, R., Gupta, S., Christie, R., Venkata, S., and Fletcher, R. (1997). “Distribution system reliability assessment: momentary interruptions and storms.” *IEEE Transactions on Power Delivery*, 12(4), 1569–1575.

Brown, R. E. and Pinkerton, R. (2019). “Distribution reliability optimization using synthetic feeders.” *Energies*, 12(18), 3510.

Çağnan, Z. and Davidson, R. A. (2007). “Discrete event simulation of the post-earthquake restoration process for electric power systems.” *Int. J. of Risk Assessment and Management*, 7(8).

Çağnan, Z., Davidson, R. A., and Guikema, S. D. (2006). “Post-earthquake restoration planning for Los Angeles electric power.” *Earthquake Spectra*, 22(3), 589–608.

Çavdaroğlu, B., Hammel, E., Mitchell, J., Sharkey, T., and Wallace, W. (2013). “Integrating restoration and scheduling decisions for disrupted interdependent infrastructure systems.” *Annals of Operations Research*, 203(1), 279–294.

Chang, S. E. (2010). “Urban disaster recovery: a measurement framework and its application to the 1995 kobe earthquake.” *Disasters*, 34(2), 303–327.

Chang, S. E., Mcdaniels, T., Fox, J., Dhariwal, R., and Longstaff, H. (2014). “Toward disaster-resilient cities: Characterizing resilience of infrastructure systems with expert judgments.” *Risk Analysis*, 34(3), 416–434.

Chang, S. E., McDaniels, T. L., Mikawoz, J., and Peterson, K. (2007). “Infrastructure failure interdependencies in extreme events: power outage consequences in the 1998 ice storm.” *Natural Hazards*, 41(2), 337–358.

Chang, S. E., Seligson, H. A., and Eguchi, R. T. (1996). “Estimation of the economic impact of multiple lifeline disruption: Memphis light, gas and water division case study.” *Report no.*, NCEER.

Chang, S. E., Svekla, W. D., and Shinozuka, M. (2002). “Linking infrastructure and urban economy: Simulation of water-disruption impacts in earthquakes.” *Environment and Planning B: Planning and Design*, 29(2), 281–301.

Choi, J., Yoo, D. G., and Kang, D. (2018). "Post-earthquake restoration simulation model for water supply networks." *Sustainability*, 10(10), 3618.

Cimellaro, G. P., Solari, D., and Bruneau, M. (2014). "Physical infrastructure interdependency and regional resilience index after the 2011 Tōhoku earthquake in Japan." *Earthquake Engineering & Structural Dynamics*, 43(12), 1763–1784.

Colorado State University (2018). "Centerville community resilience testbed, <http://resilience.colostate.edu/testbed.shtml>. Accessed: 2020-01-25.

Cooke, R. M. (1991). *Experts in uncertainty : opinion and subjective probability in science*. Environmental ethics and science policy. Oxford University Press, New York.

Cooper, L., Schulz, N. N., and Nielsen, T. (1998). "Computer program for the estimation of restoration times during storms." Vol. 2, Illinois Inst of Technology, 777–780.

Ćurčić, S., Özveren, C., Crowe, L., and Lo, P. (1995). "Electric power distribution network restoration: a survey of papers and a review of the restoration problem." *Electric Power Systems Research*, 35(2), 73–86.

Davidson, R. A., Liu, H., and Apanasovich, T. V. (2017). *Estimation of Post-Storm Restoration Times for Electric Power Distribution Systems*. John Wiley & Sons, Ltd, Chapter 7, 251–284.

Díaz-Delgado Bragado, A. (2016). "Downtime estimation of lifelines after an earthquake." M.S. thesis, University of California, Berkeley, United States.

Doubleday, A., Choe, Y., Miles, S., and Errett, N. (2019). "Daily bicycle and pedestrian activity as an indicator of disaster recovery: A Hurricane Harvey case study." *International Journal of Environmental Research and Public Health*, 16(16).

Dublin Core Metadata Initiative (2008). "Dublin core metadata initiative metadata terms, <https://www.dublincore.org/specifications/dublin-core/dcmi-terms/>.

Dueñas-Osorio, L. and Kwasinski, A. (2012). "Quantification of lifeline system interdependencies after the 27 February 2010 M sub(w) 8.8 Offshore Maule, Chile, earthquake." *Earthquake Spectra*, 28(S1), S581–S603.

Duffey, R. B. (2019). "Power restoration prediction following extreme events and disasters." *Inter-*

national Journal of Disaster Risk Science, 10(1), 134–148.

Duffey, R. B. and Ha, T. (2013). "The probability and timing of power system restoration." *IEEE Transactions on Power Systems*, 28(1), 3–9.

Eassom, E., Giacco, D., Dirik, A., and Priebe, S. (2014). "Implementing family involvement in the treatment of patients with psychosis: a systematic review of facilitating and hindering factors." *BMJ open*, 4(10), e006108.

Epstein, J. M. (2008). "Why model?." *Journal of Artificial Societies and Social Simulation*, 11(4), 12.

FEMA (2011). "Hazus: FEMA's methodology for estimating potential losses from disasters. Accessed: 2020-01-25.

Gegner, K. M., Birchfield, A. B., Ti Xu, Shetye, K. S., and Overbye, T. J. (2016). "A methodology for the creation of geographically realistic synthetic power flow models." *2016 IEEE Power and Energy Conference at Illinois (PECI)*, 1–6.

Gentleman, R. and Temple Lang, D. (2007). "Statistical analyses and reproducible research." *Journal of Computational and Graphical Statistics*, 16(1), 1–23.

González, A. D., Chapman, A., Dueñas-Osorio, L., Mesbahi, M., and D' Souza, R. M. (2017). "Efficient infrastructure restoration strategies using the recovery operator." *Computer-Aided Civil and Infrastructure Engineering*, 32(12), 991–1006.

González, A. D., Dueñas-Osorio, L., Sánchez-Silva, M., and Medaglia, A. L. (2016). "The interdependent network design problem for optimal infrastructure system restoration." *Computer-Aided Civil and Infrastructure Engineering*, 31(5), 334–350.

González-Barahona, J. and Robles, G. (2012). "On the reproducibility of empirical software engineering studies based on data retrieved from development repositories." *Empirical Software Engineering*, 17(1-2), 75–89.

Guikema, S. D., Quiring, S. M., and Han, S. (2010). "Prestorm estimation of hurricane damage to electric power distribution systems." *Risk Analysis*, 30(12), 1744–1752.

He, X. and Cha, E. J. (2018). "Modeling the damage and recovery of interdependent critical infrastructure systems from natural hazards." *Reliability Engineering and System Safety*, 177, 162–175.

Hernandez-Fajardo, I. and Dueñas Osorio, L. (2013). "Probabilistic study of cascading failures in complex interdependent lifeline systems." *Reliability Engineering and System Safety*, 111, 260–272.

Iloglu, S. and Albert, L. A. (2018). "An integrated network design and scheduling problem for network recovery and emergency response." *Operations Research Perspectives*, 5, 218–231.

Isoyama, R. and Katayama, T. (1981). "Practical performance evaluation of water supply networks during seismic disaster.." *Lifeline Earthquake Engineering: The Current State of Knowledge, 1981 ; Proceedings of the Second Specialty Conference of the Technical Council on Lifeline Earthquake Engineering, Oakland Hyatt House, Oakland, California, August 20-21, 1981*, ASCE, 111–126.

Isumi, M., Nomura, N., and Shibuya, T. (1985). "Simulation of post-earthquake restoration for lifeline systems." *International Journal of Mass Emergencies and Disasters*, 3(1), 87–105.

Kammouh, O., Cimellaro, G. P., and Mahin, S. A. (2018). "Downtime estimation and analysis of lifelines after an earthquake." *Engineering Structures*, 173, 393–403.

Kates, R. and Pijawka, D. (1977). "From rubble to monument: The pace of reconstruction.." *Reconstruction following disaster*, J. E. Haas, R. W. Kates, M. J. Bowden, ed., MIT Press, Cambridge, Mass., 1–23.

Kenward, A. and Raja, U. (2014). "Blackout: Extreme Weather, Climate Change and Power Outages, <http://assets.climatecentral.org/pdfs/PowerOutages.pdf>. Accessed: 2020-06-30.

Krishnamurthy, V., Kwasinski, A., and Dueñas Osorio, L. (2016). "Comparison of power and telecommunications dependencies and interdependencies in the 2011 Tōhoku and 2010 Maule Earthquakes." *Journal of Infrastructure Systems*, 22(3).

Lee, E., Mitchell, J., and Wallace, W. (2007). "Restoration of services in interdependent infrastructure systems: A network flows approach." *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 37(6), 1303–1317.

Lin, L. H., Miles, S. B., and Smith, N. A. (2018). "Natural language processing for analyzing disaster recovery trends expressed in large text corpora." *2018 IEEE Global Humanitarian Technology Conference (GHTC)*, IEEE, 1–8.

Lindell, M. K. (2013). "Recovery and reconstruction after disaster." *Encyclopedia of Natural Hazards*, P. T. Bobrowsky, ed., Springer Netherlands, Dordrecht, 812–824.

Liu, H., Davidson, R., and Apanasovich, T. (2007). "Statistical forecasting of electric power restoration times in hurricanes and ice storms." *IEEE Transactions on Power Systems*, 22(4), 2270–2279.

Liu, H., Davidson, R. A., Rosowsky, D. V., and Stedinger, J. R. (2005). "Negative binomial regression of electric power outages in hurricanes." *Journal of Infrastructure Systems*, 11(4), 258–267.

Liu, Y., Fan, R., and Terzija, V. (2016). "Power system restoration: a literature review from 2006 to 2016." *Journal of Modern Power Systems and Clean Energy*, 4(3), 332–341.

Loggins, R., Little, R. G., Mitchell, J., Sharkey, T., and Wallace, W. A. (2019). "CRISIS: modeling the restoration of interdependent civil and social infrastructure systems following an extreme event." *Natural Hazards Review*, 20(3).

Luna, R., Balakrishnan, N., and Dagli, C. H. (2011). "Postearthquake recovery of a water distribution system: Discrete event simulation using colored petri nets." *Journal of Infrastructure Systems*, 17(1), 25–34.

MacKenzie, C. A. and Barker, K. (2013). "Empirical data and regression analysis for estimation of infrastructure resilience with application to electric power outages." *Journal of Infrastructure Systems*, 19(1), 25–35.

Marques, L. T., Delbem, A. C. B., and London, J. B. A. (2018). "Service restoration with prioritization of customers and switches and determination of switching sequence." *IEEE Transactions on Smart Grid*, 9(3), 2359–2370.

Mcdaniels, T., Chang, S., Peterson, K., Mikawoz, J., and Reed, D. (2007). "Empirical framework for characterizing infrastructure failure interdependencies." *Journal of Infrastructure Systems*, 13(3), 175–184.

Miles, S. B., Burton, H. V., and Kang, H. (2019). "Community of practice for modeling disaster recovery." *Natural Hazards Review*, 20(1), 4018023.

Miles, S. B. and Chang, S. E. (2006). "Modeling community recovery from earthquakes." *Earthquake Spectra*, 22(2), 439–458.

Miles, S. B. and Chang, S. E. (2011). "Resilus: A community based disaster resilience model." *Cartography and Geographic Information Science*, 38(1), 36–51.

Miles, S. B., Gallagher, H., and Huxford, C. J. (2014). "Restoration and impacts from the September 8, 2011, San Diego Power Outage." *Journal of Infrastructure Systems*, 20(2).

Mitsova, D., Esnard, A., Sapat, A., and Lai, B. (2018). "Socioeconomic vulnerability and electric power restoration timelines in Florida: the case of Hurricane Irma." *Natural Hazards*, 94(2), 689–709.

Mojtahedi, M., Newton, S., and Meding, J. (2017). "Predicting the resilience of transport infrastructure to a natural disaster using Cox's proportional hazards regression model." *Natural Hazards*, 85(2), 1119–1133.

Monsalve, M. and de La Llera, J. C. (2019). "Data-driven estimation of interdependencies and restoration of infrastructure systems." *Reliability Engineering and System Safety*, 181, 167–180.

Mukherjee, S., Nateghi, R., and Hastak, M. (2018a). "Data on major power outage events in the continental U.S.." *Data in Brief*, 19, 2079 – 2083.

Mukherjee, S., Nateghi, R., and Hastak, M. (2018b). "A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S." *Reliability Engineering and System Safety*, 175, 283–305.

Multidisciplinary Center for Earthquake Engineering Research (1986). "MCEER, <http://www.buffalo.edu/mceer/about.html>.

Nateghi, R., Guikema, S., and Quiring, S. (2014). "Forecasting hurricane-induced power outage durations." *Natural Hazards*, 74(3), 1795–1811.

Nateghi, R., Guikema, S. D., and Quiring, S. M. (2011). "Comparison and validation of statistical methods for predicting power outage durations in the event of hurricanes." *Risk Analysis*, 31(12), 1897–1906.

National Institute of Standards and Technology (NIST) (2015). *Community Resilience Planning Guide for Buildings and Infrastructure*, <https://www.nist.gov/topics/community-resilience/planning-guide>.

Nejat, A. and Ghosh, S. (2016). "LASSO model of postdisaster housing recovery: Case study of Hurricane Sandy." *Natural Hazards Review*, 17(3).

Nojima, N. and Kato, H. (2012). "Validation of an assessment model of post-earthquake lifeline serviceability - based on the Great East Japan Earthquake Disaster -." *Journal of Social Safety Science*, 18, 229–239.

Nojima, N. and Kato, H. (2014). "Modification and validation of an assessment model of post-earthquake lifeline serviceability based on the Great East Japan Earthquake disaster." *Journal of Disaster Research*, 9(2), 108–120.

Nojima, N. and Maruyama, Y. (2016). "Comparison of functional damage and restoration processes of utility lifelines in the 2016 Kumamoto earthquake, japan with two great earthquake disasters in 1995 and 2011." *JSCE Journal of Disaster FactSheets*.

Nojima, N. and Sugito, M. (2002). "Empirical estimation of outage and duration of lifeline disruption due to earthquake disaster." *Proc. of the Fourth China-Japan-U.S. Trilateral Symposium on Lifeline Earthquake Engineering*, 349–356.

Nojima, N. and Sugito, M. (2005). "Probabilistic assessment model for post earthquake serviceability of utility lifelines and its practical application." *Proc. of the 9th International Conference on Structural Safety and Reliability*, 279–287.

Nurre, S. G., Çavdaroğlu, B., Mitchell, J. E., Sharkey, T. C., and Wallace, W. A. (2012). "Restoring infrastructure systems: An integrated network design and scheduling (INDS) problem." *European Journal of Operational Research*, 223(3), 794–806.

Nurre, S. G. and Sharkey, T. C. (2014). "Integrated network design and scheduling problems with parallel identical machines: Complexity results and dispatching rules." *Networks*, 63(4), 306–326.

Oregon Seismic Safety Policy Advisory Commission (OSSPAC) (2013). *The Oregon Resilience Plan: Reducing Risk and Improving Recovery for the Next Cascadia Earthquake and Tsunami*, <https://www.oregon.gov/oem/Documents/Oregon_Resilience_Plan_Final.pdf>.

O'Rourke, T. D. and Briggs, T. (2007). "Critical infrastructure, interdependencies, and resilience." *The Bridge*, 37(1), 22–29.

Ouyang, M. (2014). "Review on modeling and simulation of interdependent critical infrastructure systems." *Reliability Engineering and System Safety*, 121, 43–60.

Ouyang, M. and Dueñas Osorio, L. (2014). "Multi-dimensional hurricane resilience assessment of electric power systems." *Structural Safety*, 48, 15–24.

Ouyang, M., Dueñas Osorio, L., and Min, X. (2012). "A three-stage resilience analysis framework for urban infrastructure systems." *Structural Safety*, 36-37, 23–31.

Ouyang, M. and Wang, Z. (2015). "Resilience assessment of interdependent infrastructure systems: With a focus on joint restoration modeling and analysis." *Reliability Engineering and System Safety*, 141, 74.

Park, J., Nojima, N., and Reed, D. (2006). "Nisqually earthquake electric utility analysis." *Earthquake Spectra*, 22(2), 491–509.

Ragini, J. R., Anand, P. R., and Bhaskar, V. (2018). "Big data analytics for disaster response and recovery through sentiment analysis." *International Journal of Information Management*, 42, 13–24.

Ramachandran, V., Long, S. K., Shoberg, T., Corns, S., and Carlo, H. J. (2015). "Framework for modeling urban restoration resilience time in the aftermath of an extreme event." *Natural Hazards Review*, 16(4).

Rathje, E. M., Dawson, C., Padgett, J. E., Pinelli, J.-P., Stanzione, D., Adair, A., Arduino, P., Brandenberg, S. J., Cockerill, T., Dey, C., Esteva, M., Haan, F. L., Hanlon, M., Kareem, A., Lowes, L., Mock, S., and Mosqueda, G. (2017). "Designsafe: New cyberinfrastructure for natural hazards engineering." *Natural Hazards Review*, 18(3), 06017001.

Reed, D. A. (2008). "Electric utility distribution analysis for extreme winds." *Journal of Wind Engineering and Industrial Aerodynamics*, 96(1), 123–140.

Rinaldi, S., Peerenboom, J., and Kelly, T. (2001). "Identifying, understanding, and analyzing critical infrastructure interdependencies." *IEEE Control Systems*, 21(6), 11–25.

Rose, K. A., Sable, S., Deangelis, D. L., Yurek, S., Trexler, J. C., Graf, W., and Reed, D. J. (2015). "Proposed best modeling practices for assessing the effects of ecosystem restoration on fish." *Ecological Modelling*, 300, 12–29.

Sharkey, T. C., Çavdaroğlu, B., Nguyen, H., Holman, J., Mitchell, J. E., and Wallace, W. A. (2015). "Interdependent network restoration: On the value of information-sharing." *European Journal of Operational Research*, 244(1), 309–321.

Sharkey, T. C., Nurre, S. G., Nguyen, H., Chow, J. H., Mitchell, J. E., and Wallace, W. A. (2016). "Identification and classification of restoration interdependencies in the wake of Hurricane Sandy." *Journal of Infrastructure Systems*, 22(1).

Shinozuka, M., Rose, A., and Eguchi, R. (1998). "Engineering and socioeconomic impacts of earthquakes: An analysis of electricity lifeline disruptions in the new madrid area.

Smith, G. P. and Wenger, D. (2007). *Sustainable Disaster Recovery: Operationalizing An Existing Agenda*. Springer New York, New York, NY, 234–257.

Sun, L., Didier, M., Delé, E., and Stojadinović, B. (2015). "Probabilistic demand and supply resilience model for electric power supply system under seismic hazard." *12th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP 2015*, University of British Columbia.

Tabucchi, T. and Davidson, R. (2008). *Post-Earthquake Restoration of the Los Angeles Water Supply System*. Multidisciplinary Center for Earthquake Engineering Research (MCEER).

Tabucchi, T., Davidson, R. A., and Brink, S. A. (2010). "Simulation of post-earthquake water supply system restoration." *Civil Engineering and Environmental Systems*, 27(4), 263–279.

The White House (2013). *Presidential Policy Directive 21– Critical Infrastructure Security and Resilience*. The White House, <https://obamawhitehouse.archives.gov/the-press-

office/2013/02/12/presidential-policy-directive-critical-infrastructure-security-and-resil>.

Tuzun Aksu, D. and Ozdamar, L. (2014). “A mathematical model for post-disaster road restoration: Enabling accessibility and evacuation.” *Transportation Research Part E*, 61, 56–67.

Veremyev, A., Sorokin, A., Boginski, V., and Pasiliao, E. L. (2014). “Minimum vertex cover problem for coupled interdependent networks with cascading failures.” *European Journal of Operational Research*, 232(3), 499–511.

Washington State Seismic Safety Committee (WASSC) (2012). *Resilient Washington State: A Framework For Minimizing Loss And Improving Statewide Recovery After An Earthquake*. Washington State Emergency Management Council, <https : //www.dnr.wa.gov/Publications/ger_ic114_resilient_washington_state.pdf>.

Weinstein, M. C., O’ Brien, B., Hornberger, J., Jackson, J., Johannesson, M., Mccabe, C., and Luce, B. R. (2003). “Principles of good practice for decision analytic modeling in health-care evaluation: Report of the ispor task force on good research practices—modeling studies.” *Value in Health*, 6(1), 9–17.

Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.-W., da Silva Santos, L. B., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C. T., Finkers, R., Gonzalez-Beltran, A., Gray, A. J., Groth, P., Goble, C., Grethe, J. S., Heringa, J., ’t Hoen, P. A. C., Hooft, R., Kuhn, T., Kok, R., Kok, J., Lusher, S. J., Martone, M. E., Mons, A., Packer, A. L., Persson, B., Rocca-Serra, P., Roos, M., van Schaik, R., Sansone, S.-A., Schultes, E., Sengstag, T., Slater, T., Strawn, G., Swertz, M. A., Thompson, M., van der Lei, J., van Mulligen, E., Velterop, J., Waagmeester, A., Wittenburg, P., Wolstencroft, K., Zhao, J., and Mons, B. (2016). “The fair guiding principles for scientific data management and stewardship.” *Scientific data*, 3(1), 160018.

Wu, B., Tang, A., and Wu, J. (2016). “Modeling cascading failures in interdependent infrastructures under terrorist attacks.” *Reliability Engineering and System Safety*, 147, 1–8.

Xu, N., Guikema, S. D., Davidson, R. A., Nozick, L. K., Çağnan, Z., and Vaziri, K. (2007). “Optimizing scheduling of post-earthquake electric power restoration tasks.” *Earthquake Engineering*

& Structural Dynamics, 36(2), 265–284.

Yan, S. and Shih, Y. (2009). “Optimal scheduling of emergency roadway repair and subsequent relief distribution.” *Computers and Operations Research*, 36(6), 2049–2065.

Yu, J. and Baroud, H. (2019). “Quantifying community resilience using hierarchical bayesian kernel methods: A case study on recovery from power outages.” *Risk Analysis*, 39(9), 1930–1948.

Zorn, C. R. and Shamseldin, A. Y. (2015). “Post-disaster infrastructure restoration: A comparison of events for future planning.” *International Journal of Disaster Risk Reduction*, 13, 158–166.

Zou, L., Lam, N. S. N., Cai, H., and Qiang, Y. (2018). “Mining twitter data for improved understanding of disaster resilience.” *Annals of the American Association of Geographers*, 108(5), 1422–1441.

TABLE 1. List of every publication included in review, in order of publication year. E - electricity, W - Water, G - Gas, Tel - Telecommunications, Tr - Transportation, WW - Waste Water, ESC - Emergency Supply Chain, F - Fuel, M/U - Multiple/Unspecified, OW - Other Wind.

Reference	Approach	Lifeline	Hazard Type	Country
(Isoyama and Katayama 1981)	Simulation	W	Earthquake	Japan
(Isumi et al. 1985)	Simulation	E, W, G	Earthquake	Japan
(Chang et al. 1996)	Statistical	E, W, G	Earthquake	U.S.
(Brown et al. 1997)	Simulation	E	OW	U.S.
(Cooper et al. 1998)	Statistical	E	M/U	U.S.
(Chang et al. 2002)	Simulation	W	Earthquake	U.S.
(Nojima and Sugito 2002)	Statistical	E, W, G	Earthquake	Japan
(Nojima and Sugito 2005)	Statistical	E, W, G	Earthquake	Japan
(Park et al. 2006)	Statistical	E	Earthquake	U.S.
(Çağnan et al. 2006)	Simulation	E	Earthquake	U.S.
(Liu et al. 2007)	Statistical	E	OW	U.S.
(Lee et al. 2007)	Optimization	E, Tel, Tr	M/U	U.S.
(Xu et al. 2007)	Simulation	E	Earthquake	U.S.
(Çağnan and Davidson 2007)	Simulation	E	Earthquake	U.S.
(Reed 2008)	Statistical	E	OW	U.S.
(Tabucchi and Davidson 2008)	Simulation	W	Earthquake	U.S.
(Yan and Shih 2009)	Optimization	Tr, ESC	Earthquake	Taiwan
(Brink et al. 2009)	Simulation	W	Earthquake	U.S.
(Tabucchi et al. 2010)	Simulation	W	Earthquake	U.S.
(Nateghi et al. 2011)	Statistical	E	Hurricane	U.S.
(Luna et al. 2011)	Simulation	W	Earthquake	Japan
(Ouyang et al. 2012)	Simulation	E	Hurricane	U.S.

Continued on next page

TABLE 1 – *Continued from previous page*

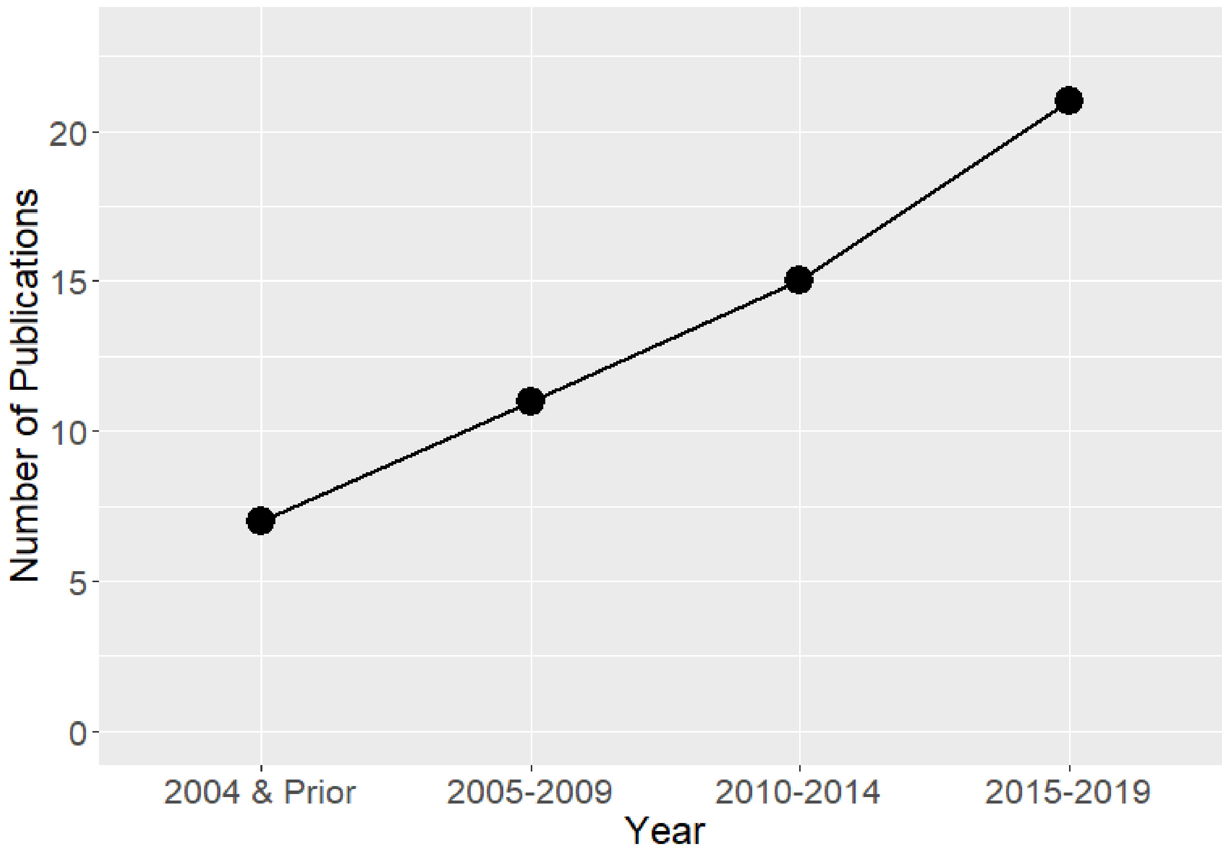
Reference	Approach	Lifeline	Hazard Type	Country
(Brink et al. 2012)	Simulation	W	Earthquake	U.S.
(Nurre et al. 2012)	Optimization	E, WW, ESC	M/U	U.S.
(Nojima and Kato 2012)	Statistical	E,W,G	Earthquake	Japan
(MacKenzie and Barker 2013)	Statistical	E	M/U	U.S.
(Çavdaroğlu et al. 2013)	Optimization	E, Tel	M/U	U.S.
(Duffey and Ha 2013)	Statistical	E	M/U	U.S., Sweden
				Belgium, France
(Nateghi et al. 2014)	Statistical	E	Hurricane	U.S.
(Barker and Baroud 2014)	Statistical	E	M/U	U.S.
(Tuzun Aksu and Ozdamar 2014)	Optimization	Tr	M/U	Turkey
(Nojima and Kato 2014)	Statistical	E, W, G	Earthquake	Japan
(Nurre and Sharkey 2014)	Optimization	E, Tel	M/U	U.S.
(Sun et al. 2015)	Simulation	E	Earthquake	U.S.
(Zorn and Shamseldin 2015)	Statistical	E, W, G, Tel	M/U	New Zealand
				Worldwide
(Ramachandran et al. 2015)	Simulation	E, W, Tel, F	OW	U.S.
(Sharkey et al. 2015)	Optimization	E, W, WW, Tel	Hurricane	U.S.
(Ouyang and Wang 2015)	Simulation	E, G	Hurricane	U.S.
(Bessani et al. 2016)	Statistical	E	M/U	Brazil
(González et al. 2016)	Optimization	E, W, G	Earthquake	U.S.
(Díaz-Delgado Bragado 2016)	Statistical	E, W, G, Tel	Earthquake	Worldwide
(Mojtahedi et al. 2017)	Statistical	Tr	M/U	Australia
(Davidson et al. 2017)	Statistical	E	OW	U.S.
(González et al. 2017)	Optimization	E, W, G	Earthquake	U.S.

Continued on next page

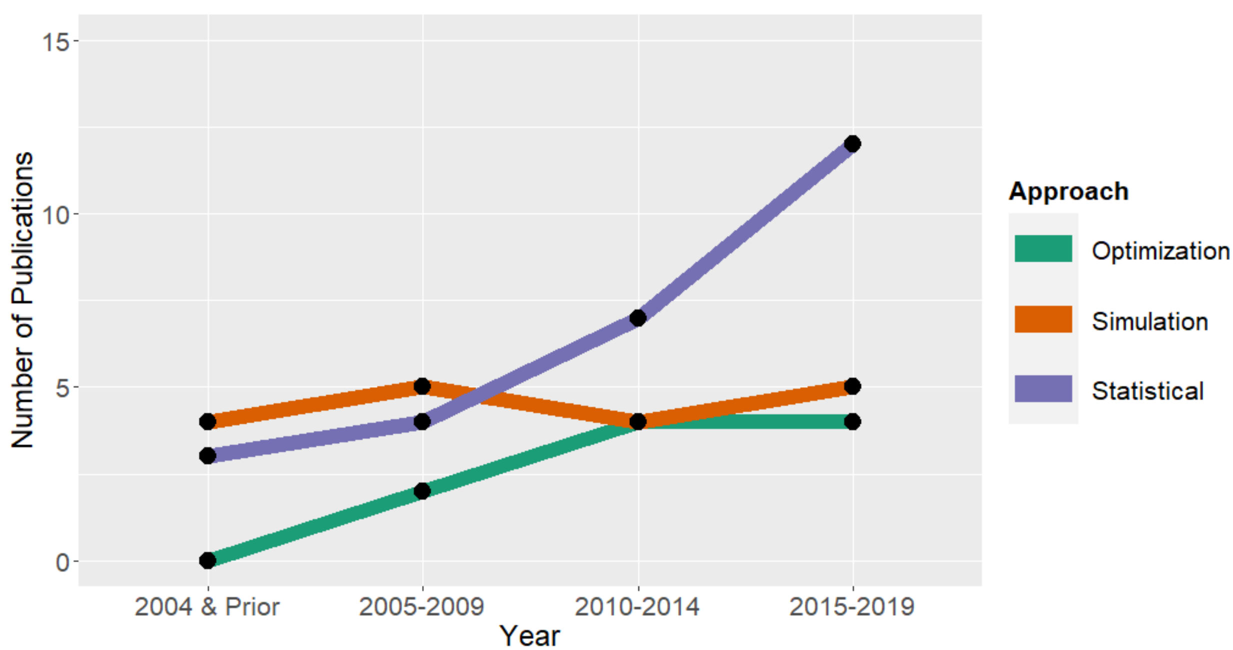
TABLE 1 – *Continued from previous page*

Reference	Approach	Lifeline	Hazard Type	Country
(Mitsova et al. 2018)	Statistical	E	Hurricane	U.S.
(Choi et al. 2018)	Simulation	W	Earthquake	South Korea
(Mukherjee et al. 2018b)	Statistical	E	M/U	U.S.
(Barabadi and Ayele 2018)	Statistical	E, Tr	M/U	Iran, U.S.
(Kammouh et al. 2018)	Statistical	E, W, G, Tel	Earthquake	Worldwide
(Iloglu and Albert 2018)	Optimization	Tr, ESC	M/U	U.S.
(He and Cha 2018)	Simulation	E, W, Tel	Hurricane	U.S.
(Monsalve and de La Llera 2019)	Statistical	E, W, G, Tel	Earthquake	New Zealand
				Japan, Chile
(Yu and Baroud 2019)	Statistical	E	OW	U.S
(Duffey 2019)	Statistical	E	M/U	Ireland, U.S.
				New Zealand

List of Figures

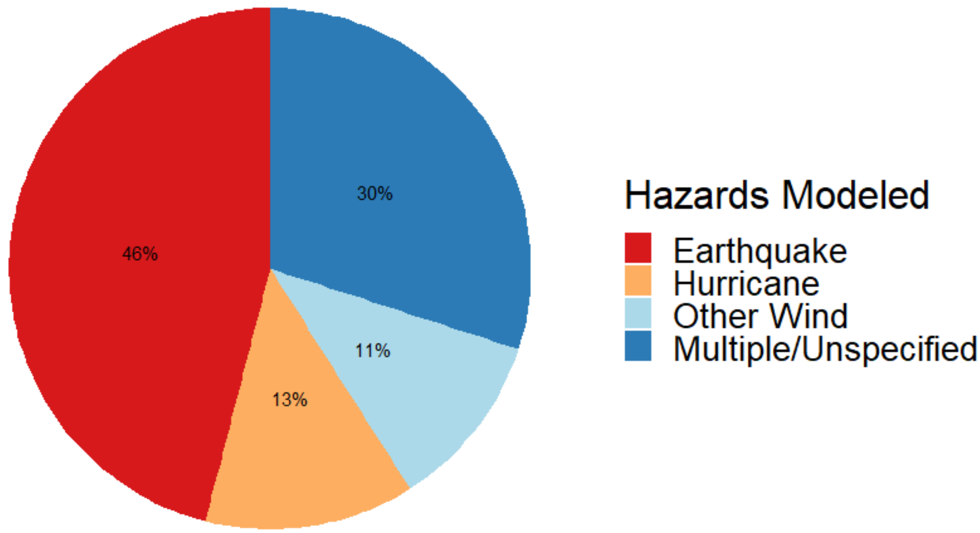


(a) Number of publications over time on modeling lifeline restoration using empirical quantitative data.

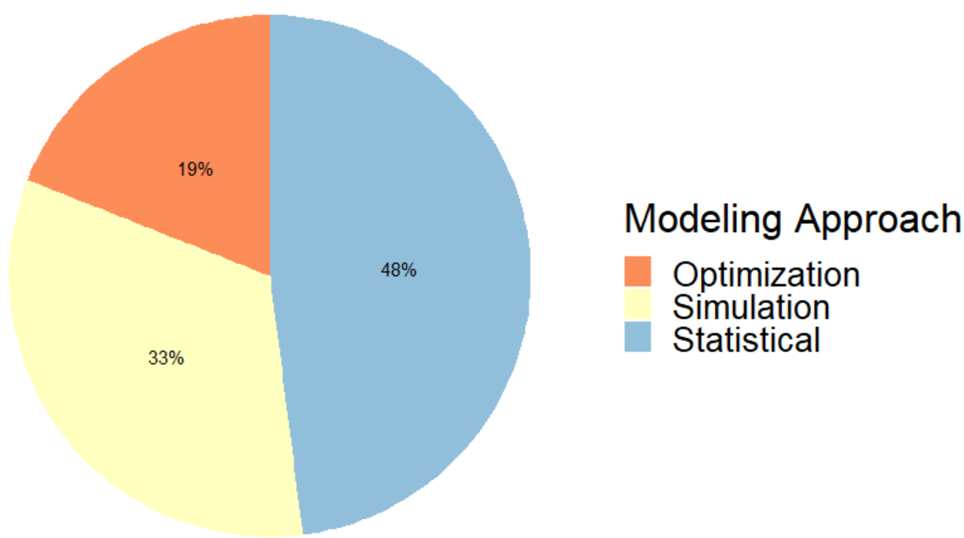


(b) Number of publications over time by modeling approach.

Fig. 1. Publication trends over time.

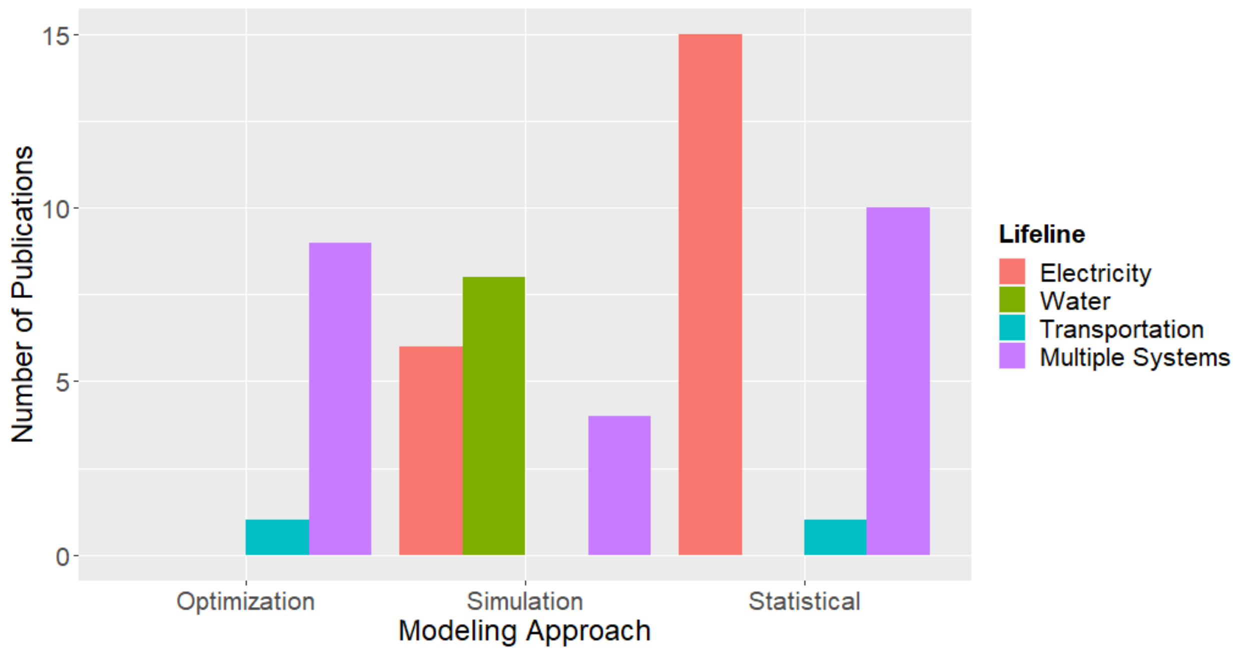


(a) Breakdown by hazard type. ‘Other Wind’ includes ice storms and tornadoes.

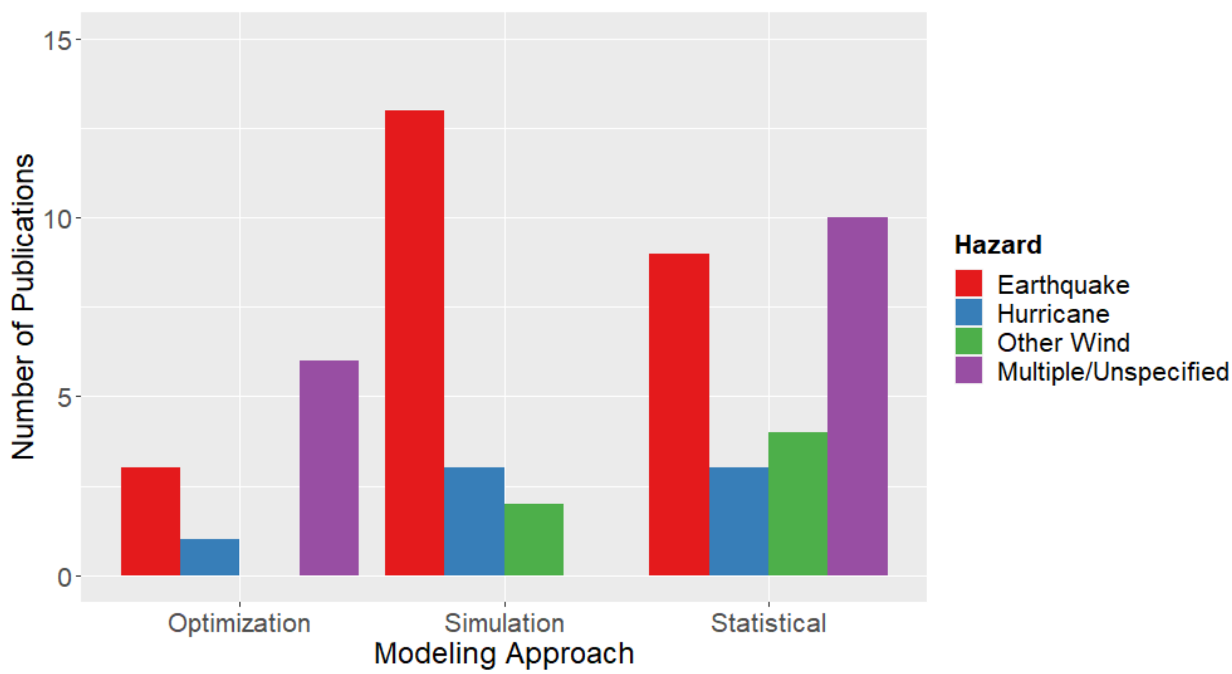


(b) Breakdown by modeling approach.

Fig. 2. Breakdown of the reviewed literature.

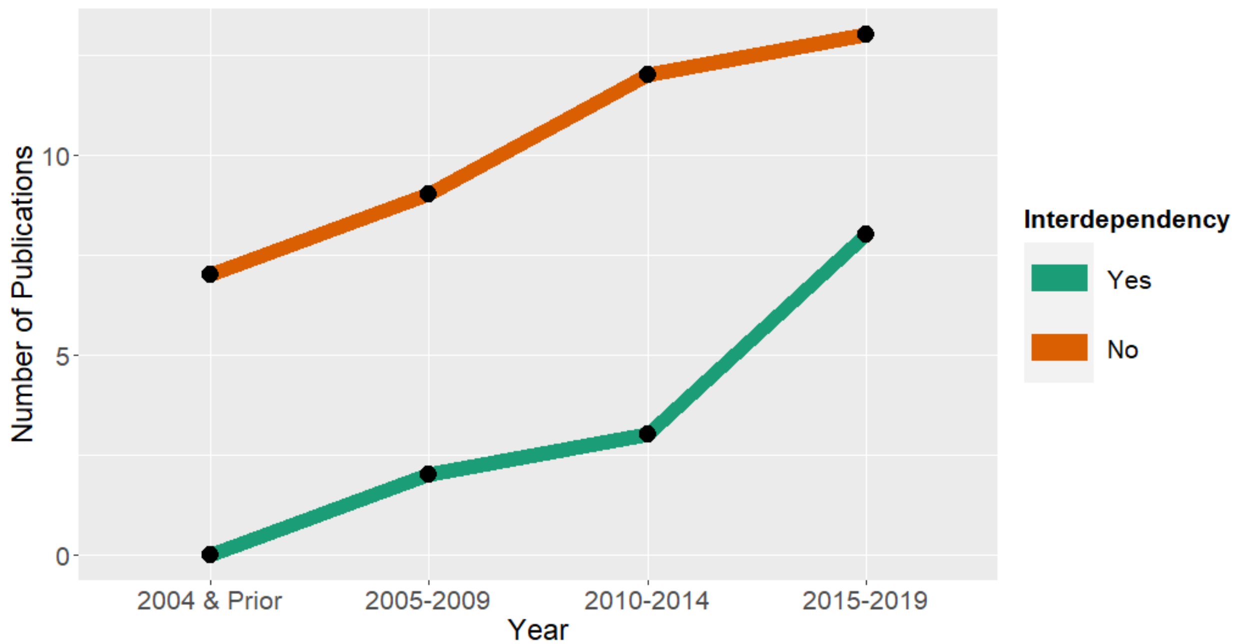


(a) Breakdown of the reviewed literature by modeling approach and lifeline system.

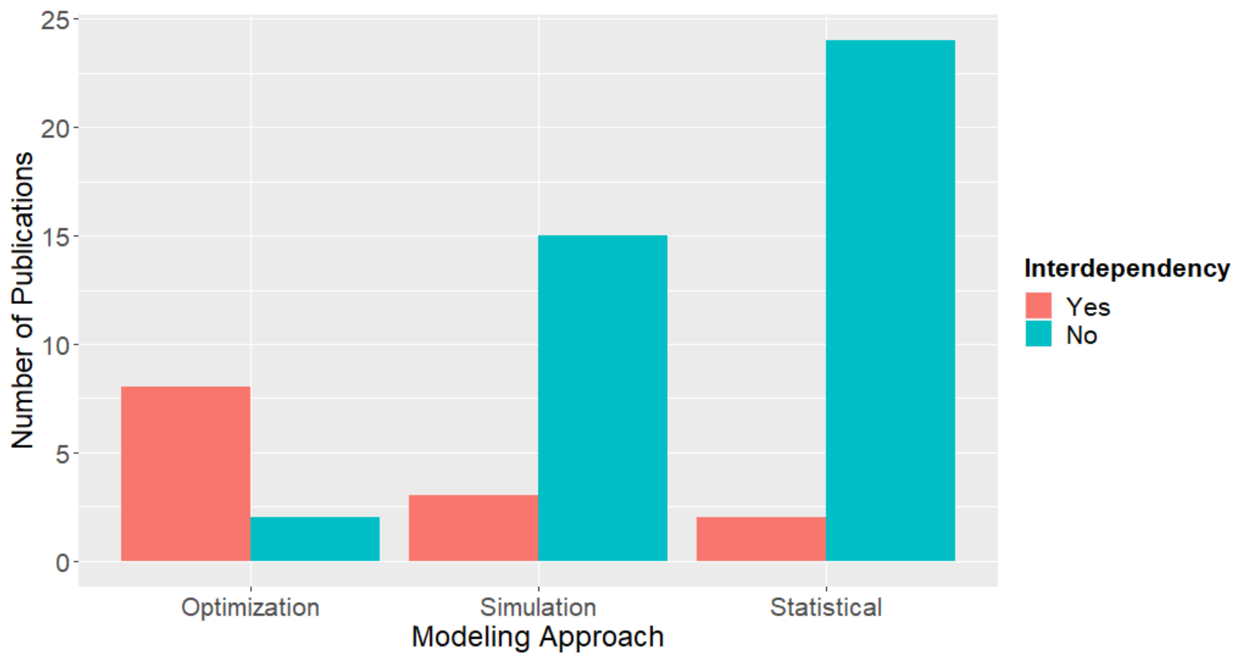


(b) Breakdown of the reviewed literature by modeling approach and hazard type.

Fig. 3. Relating modeling approach to lifeline system and hazard type.



(a) Number of publications over time that model interdependent restoration.



(b) Breakdown of publications by modeling approach on interdependent restoration.

Fig. 4. Interdependency in the reviewed literature.

Fig. 5. Graphical representation of the proposed data management methodology.