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Quantifying restoration time of power and telecommunication lifelines after earthquakes using Bayesian belief network model

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Abstract

Natural and human-made disasters can disrupt infrastructures even if they are designed to be hazard resistant. While the occurrence of hazards can only be predicted to some extent, their impact can be managed by increasing the emergency response and reducing the vulnerability of infrastructure. In the context of risk management, the ability of infrastructure to withstand damage and re-establish their initial condition has recently gained prominence. Several resilience strategies have been investigated by numerous scholars to reduce disaster risk and evaluate the recovery time following disastrous events. A key parameter to quantify the seismic resilience of infrastructures is the *Downtime* (DT). Generally, DT assessment is challenging due to the parameters involved in the process. Such parameters are highly uncertain and therefore cannot be treated in a deterministic manner. This paper proposes a Bayesian Network (BN) probabilistic approach to evaluate the DT of selected infrastructure types following earthquakes. To demonstrate the applicability of the methodology, three scenarios are performed. Results show that the methodology is capable of providing good estimates of infrastructure DT despite the uncertainty of the parameters. The methodology can be used to effectively support decision-makers in managing and minimizing the impacts of earthquakes in immediate post-event applications as well as to promptly recover damaged infrastructure.

Keywords: Downtime, Restoration, Lifelines, Infrastructure, Bayesian Networks

1. Introduction

Past global earthquake events, e.g. 1994 Northridge and 2016 Kaikoura earthquakes, have led to the functional disruption of power and telecommunication networks [1-3]. In the 1994 Northridge earthquake that struck Los Angeles, around 2.5 million customers lost electric power [1], with a consequent blackout of the city. Failures of electric power networks and grids can cause severe and widespread societal and economic disruption [4]. A continuous power supply is also crucial for other networks since it supplies primary and secondary energy. For example, the transportation system relies on the power network for its signals and switches; the natural gas and water systems depend on the electric power to operate their components, such as control switches and pumps, respectively; and finally, the telecommunication network relies heavily on the power network to supply power to its communication switches. The communication networks are important in post-disaster scenarios when the services are most needed to carry out relief management tasks as well as to facilitate repairs for critical infrastructure [3, 5]. Maintaining proper operation of critical infrastructures is, therefore, a primary challenge that has aroused attention to the seismic safety of lifeline systems. Furthermore, studying the resilience of critical infrastructures that are prone to many disruptive events or inadequate maintenance can be used to evaluate the functionality and the ability of an infrastructure to provide its service under emergency conditions [6, 7].

In engineering, the concept of resilience is defined as the ability of social units (e.g. organizations, communities) to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways to minimize social disruption and mitigate the effects of further earthquakes [8]. Wagner and Breil [9] defined resilience as the ability to “withstand stress, survive, adapt, and bounce back from a crisis or a disaster and rapidly move on”. In the seismic resilience assessment context, downtime (DT) can be defined as the time between the moment the hazard event occurs (t_o), where the functionality of the system $Q_{(0)}$ drops to $Q_{(1)}$, to the time when the functionality is completely restored (t_1) [10, 11] (see Figure 1). Comerio [12] described DT as “the time necessary to plan, finance, and complete repair facilities damaged by earthquake or other disasters and it is the sum of rational and irrational components”. In this paper, the downtime is defined as the period required to restore the functionality of a structure or infrastructure systems (e.g., power network, water supply, community) to its initial condition before a severe event [8].

Figure 1. Conceptual resilience function of a system highlighting Downtime (DT) (adapted from [10])

Several methodologies have been investigated in the literature to quantify the downtime of buildings and infrastructures after disruptive events [6, 12]. For example, the Federal Emergency Management Agency (FEMA) has performed several studies to estimate earthquake loss of buildings through the *Performance Assessment Calculation Tool* (PACT) [13]. PACT is an electronic tool that performs probabilistic computation and an accumulation of losses for individual buildings by using fragility and consequence data. Almufti and Wilford [14] presented the *Resilience-based Earthquake Design Initiative* (REDI™), which is a tool based on the results from PACT. Their methodology provides a framework that implements a resilience-based earthquake design to achieve much higher performance. Besides, a performance-based earthquake method to evaluate DT of infrastructures using fault trees was presented in [15]. Fault trees have long been used to estimate the probabilistic time needed to restore a facility through a database of component damageability and repair-time data.

The DT can be affected by different factors, predictable and uncertain. The predictable factors are easily quantifiable, such as construction costs and repair time, whereas the "uncertain" factors consider the time for mobilizing human and economic resources. These uncertain factors, such as *finance and bidding process, financing planning, availability of the human resource, and regulatory and economic uncertainty*, are important factors that need to be considered in the definition and estimation of the downtime [12]. Although several studies have been carried out to quantify DT, still few models take into account the contribution of uncertain factors due to the uncertainty (e.g. imprecision and vagueness) and difficulty involved in their quantification [16, 17]. Indeed, uncertain parameters could vary significantly depending on the condition of the affected area. Moreover, immediate post-event actions and decisions are often made under great uncertainty, due to the limited availability and quality of information. This leads decision-makers to act in the chaotic post-disaster environment by counting on limited and uncertain information and on their personal experience [18].

The uncertainties and interdependencies involved in the DT assessment make hierarchical/graphical models a viable alternative [19, 20]. Over the years, Bayesian networks (BNs) have been explored to account for probabilistic uncertainties and complete interaction of the decision variables. BNs are popular tools for modeling uncertainty and complex domains and for integrating different sources of information such as observed data and expert judgment [21].

The BN is efficient for handling risk assessment and decision-making under uncertainty [22]. It has been used in: risk analysis [23], resiliency modelling [24-28], reliability engineering [29, 30], and safety management [31-33]. Johansen and Tien [34] used BN to model interdependencies between critical infrastructures (such as water, power, transportation, communication, and fuel networks). Cai, Xie [25] utilized BN to quantify a resilience metric for different types of engineering systems (e.g. mechanical engineering, civil engineering, critical infrastructure, etc.). The proposed resilience metric can be used either to optimize or to design engineering systems against various hazards, such as earthquakes, floods, etc. proposed a framework to evaluate the resilience through the BN in a quantitative manner. The method allows modeling and predicting the resilience of engineering systems in the design and maintenance phases. Hosseini and Barker [26] introduced a resilience quantification methodology using BN with the application on inland waterway port. Several other examples of BN applications in engineering decision making are reported in the literature [35]. However, most of the existing BN methods for resilience quantification cannot evaluate the DT for infrastructures. The research in DT assessment of infrastructures through BN models is still at an early stage and a consistent and comprehensive methodology that considers both predictable and uncertain components for analyzing the DT of infrastructures in response to various hazards is still missing. Thus, there is a pressing need to develop a methodology to evaluate the recovery time of lifelines to restore their functionality and decrease their vulnerability to future severe events.

The main objective of this research is to develop an assessment model to evaluate the DT of lifelines following earthquakes to deal with uncertainties, including randomness and ignorance. For this purpose, this study proposes a BN-based assessment method that combines the effects of predictable and uncertain parameters, such as technical, engineering, and social components. The proposed DT model benefits of the BN potentials, including accounting for uncertainty and inference analysis to develop a general decision support framework that can be used under emergency conditions to (i) take into account those uncertain parameters that have a high impact on the recovery process and that are tricky to quantify, (ii) estimate the downtime of power and telecommunication networks damaged by earthquakes, and (ii) to help decision-makers prioritize financial resources during the planning and management post-disaster strategies through analyzing different what-if scenarios. The framework can be used to update probabilistic information of the parameters involved in the DT assessment. Updating information helps support critical decisions in the aftermath of an earthquake.

The remainder of this paper is structured as follows: Section 2 is dedicated to reviewing the basic knowledge of the BN. Section 3 illustrates the DT framework and the key variables that are identified from past studies and describes the fragility curves designed for estimating conditional probabilities. Section 4 introduces the sensitivity analysis performed to identify critical inputs. Section 5 presents an illustrative example to demonstrate the applicability of the DT framework. Finally, section 6 concludes and proposes future work.

2. BBN framework for the downtime assessment of infrastructures

2.1. The methodology

The methodology proposed in this work can be divided into the following:

- DT modeling: a BN hierarchical model is developed to quantify DT. The DT key variables and connectivity of the BN are obtained through expert knowledge and published articles.
- Conditional probabilities (CPs): CPs for the child variables are obtained from historical data, expert judgment, and published literature. For the final output (i.e. DT), conditional probabilities are obtained using restoration fragility curves derived from a database for past seismic events.
- Inference: the last step of the methodology is the combination of the key variables through the inference system of BN to obtain the final output of the network (i.e. the DT).

2.2. Background of Bayesian Network

The Bayesian Network (BN), also known as Bayesian Belief Network or Causal Probabilistic Network, belongs to the family of probabilistic *graphical models* (GMs). It is based on Bayes' theorem that permits graphical probabilistic relationships among a set of variables [36]. The uncertainties in a BN model can be expressed through subjective probabilities [30, 36], thus making the approach suitable for experts' knowledge. BNs are suitable tools for computing the probability distribution of variables conditioned on some variables that have been observed through both quantitative and qualitative information [26]. Variables of a BN can be Boolean (yes, no), continuous, or qualitative (low, medium, high)). A BN includes:

1. A set of random variables that can be linked to each other by a set of links indicated by arrows;
2. A set of mutually exclusive states assigned to each variable (e.g. L, M, and H) describing possible events that can occur;
3. A conditional probability table for each child node and an unconditional probability table for each father node.

An outgoing link from variable X to variable Y indicates a relationship that the variable Y (child) is dependent on the variable X (parent). The set of edges and nodes defines a directed acyclic graph. The relationships among the variables of a BN are usually measured by a set of Conditional Probabilities Tables (CPTs), where the likelihood of the child node to assume a certain state under a given state of its parent is assigned through expert knowledge [37, 38]. In the case of independent variables with no parents, the CPT is reduced to an unconditional probability Table (UPT).

2.3. Conditional probabilities and inference

The main concept of the BN comes from the Bayes' theorem, which defines the relationship between two nodes A (parent) and B (child), as follows:

$$P(A/B) = \frac{P(B/A)P(A)}{P(B)} \tag{1}$$

where P(A/B) is the probability of observing A given that B is true, P(B/A) is the likelihood that B is observed if A is true, P(A) and P(B) are the probabilities of observing A and B without regarding each other. P(A/B) is known as *posterior* probability and P(A) is called *prior* probability [36].

Once the variables have been connected by a set of links, unconditional and conditional probabilities are assigned. To establish unconditional probabilities (UPs) of parent nodes whose states are not known, the principle of insufficient reasoning is assumed [35, 39], i.e. the basic inputs are assigned equal weights *1/n*, where *n* is the number of states. For instance, if the variable X_1 is characterized by three states *Low* (L), *Medium* (M), and *High* (H), the UPs would be P (X_1 = L) = 1/3, P (X_1 = M) = 1/3, P (X_1 = H) = 1/3 (Kabir et al. 2015). The estimation of the conditional probabilities (CPs) can be obtained through expert knowledge elicitation and training from existing data [40, 41], and it can be divided into three steps:

1. Prioritization of parent variables: the first step consists of defining the importance of the parent variable on the child nodes by assigning a weight value to each parent node;
2. Definition of combinations: different states are identified for each variable by considering different combinations of the child nodes;
3. Estimation of conditional probabilities: the last step is the estimation of conditional probabilities for all defined combinations.

To better understand the process described above, an example is given. Consider a system with three father nodes: *Urban Area*, *Mobility and Access*, and *Extreme Weather*, and a child node: *Impacted Area* variable. Following the first step of the proposed procedure, variables are prioritized by their impact on the child node. That is, *Urban Area* is found to be more important than the other father variables, followed by *Mobility and Access* then *Extreme Weather*. This implies that the *Urban Are*a has a higher impact on the output variable (*Impacted Area*). Three different states are assigned to each of the variables. *Urban Area* (UA) is defined using three discrete states, UA^L, UA^M, and UA^S, which are related to “Large” (L), “Medium” (M), and “Small” (S) states, respectively. *Mobility and Access* (MA) is classified into three qualitative states, which are denoted as MA^H, MA^M, and MA^E corresponding to “Hard” (H), “Medium” (M), and “Easy” (E) states respectively, and *Extreme Weather* (EW) is classified into three discrete states, which are indicated as EW^{VB}, EW^B, and EW^G, corresponding to “Very Bad” (VB), “Bad” (B), and “Good” (G) states.

Figure 2 shows a partial set of combinations of the states of the three variables. The worst-case scenario is identified by the three states: Large (for *Urban Area*), Hard (for *Mobility and Access*), and Very Bad (for *Extreme Weather*). The corresponding estimated conditional probabilities for the variable “Impacted Area” are: (IA^S, IA^M, IA^L) = (0.9, 0.1, 0). Starting from the worst-case scenario, other possible combinations are implemented to come up with the full conditional probability table of the father node given the different combinations of the states of child nodes.

This approach will be used hereafter to estimate the conditional probabilities for all nodes of the DT network. However, for the DT variable itself, a different approach is used to come up with the conditional probabilities. The conditional probabilities of the DT are calculated using restoration fragility curves based on the earthquake magnitude [16]. This is introduced in detail in Section 3.

Figure 2. A three-node network with probability tables

3. Downtime Modeling using BN

3.1. Variables selection

Based on an extensive review of previous literary publications and studies on key parameters for downtime, 31 indicators are selected to develop the BN for the DT estimation [42, 43]. Indicators are selected to describe the framework's components in detail. Every indicator found in the literature has been collected and then they are filtered to obtain mutually exclusive indicators. This has necessitated rejecting a number of indicators either because they are not relevant or because they overlapped with other indicators.

The indicators refer to the implementation of processes, mechanisms, or policies intending to reduce risk and increase recovery [16]. The steps followed to create the network are:

1. Variable identification: A list of 31 key variables to build the network is provided from literature;
2. Variable clustering: after the variables are identified, they are clustered into groups to organize them appropriately;
3. Variable connection: the last step is the connection of variables using Bayesian parent-child relationships.

The DT input parameters considered in the model along with the values and the performance measure (when available) are described in Table 1, Table 2, and Table 3. Two types of variables are considered to model the DT variables: (i) discrete variables and (ii) continuous variables (i.e., DT variable). Discrete variables have a finite number of values. In the proposed framework, they are defined using two or three states, such as a *High* state that represents a positive outcome and *Low* state that represents a negative outcome. The continuous variables, on the other hand, can take infinite possible values within a given range. However, in BNs based on raw data and learned by users without a field-specific expert, it is usually assumed that variables are discrete. Continuous variables are mainly required in dynamic systems. Moreover, many BN algorithms are unable to handle continuous variables, as they are difficult to manage in a general way [44, 45]. Thus, the DT variable has been classified into intervals in such a way to treat it as a discrete one and to have a more precise DT result.

3.2. Variables connectivity

The graphical representation of the proposed DT assessment model is shown in Figure 3. As shown in Figure 3, in a hierarchical system, the child nodes become the parent nodes of other child nodes generating new child-parent relationships. For the downtime model, four downtime indices are considered: (i) exposed infrastructure (EI), (ii) earthquake intensity (E), (iii) available human resources (HR), and (iv) infrastructure type (I). In the figure, the ellipses represent the basic input indicators that determine the indicators designed by the rectangle shape. The orange color is used to highlight the four indices mentioned above. Casual relationships among the downtime indicators are established based on expert knowledge and published literature. To build the DT network, a conceptual linkage between the indicators is needed taking into account the interaction between the indicators and the effect that each indicator has on the downtime. Indicators are clustered as follows:

- Indicators referring to building financial reserves are grouped to support effective response and recovery;
- Indicators that refer to policies and plans implemented to reduce the vulnerability of the area at risk are grouped together to define the availability of human resources;
- Indicators relating to the seismic event are clustered to determine the effective recovery;
- Indicators that refer to the analyzed infrastructure are combined to carry out the exposure level of the infrastructure.

Indicators included in the DT model are described in detail in the following section.

3.2.1 Exposed Infrastructure (EI)

The exposed infrastructure (EI) index describes how effectively and efficiently a city can respond to recover from short-term and long-term impacts. It is quantified considering the maintenance degree of the infrastructure, assuming that a higher maintenance rate would lead to a lower likelihood of damages and to lower recovery time. The maintenance degree of infrastructure describes the condition the infrastructure is in. Infrastructures wear out with time and use, so proper and timely maintenance must be periodically conducted. Neglecting proper maintenance leads to a decline in the infrastructure's condition. In line with the state of infrastructure, the maintenance degree parameter is classified as *poor*, *medium*, and *good.*

EI index also depends on the number of served people, which is discretized into three states corresponding to *low, medium*, and *high* number, and on how much (*high, medium*, and *low)* the service of the structure is necessary and important in the community (a higher number of served people and higher service importance result in a higher priority of intervention following a disaster). The anti-seismic technology of the structure, and the type of the required recovery, which can be *easy*, *difficult*, or *very difficult* depending on the damage of the infrastructure and the economic processes, are assumed in the EI index evaluation. Besides, two-node states (EI^H, EI^M), corresponding to *high* (EI^H) and *low* (EI^L), are assumed to describe the Exposed infrastructure (see Table 1).

The recovery type includes indicators representing the *financing phase* (i.e. financing and procurement process), the *building phase*, the *engineer evaluation*, and the characteristic of the seismic event (i.e. the *earthquake intensity*, the *event repetition*, and the earthquake hazard). The *procurement process* is the time required to make an offer by an individual or business for a product or service. Procurement is used to determine the specifications of the project or details of the products and services to be purchased. During an earthquake condition, it is very important to shorten the procurement process in such a way as to speed up the recovery process. Given the circumstances and the immediacy of the need to respond after a seismic event, three different states of procurement are considered: reactive procurement (immediate response) in the event of a major hazard where the standard procurement procedure is not required to follow; emergency procurement is appropriate when there is no threat to loss of life and a state of emergency is taken off; finally accelerated procurement is developed to fit a specific category of procurement and immediate needs [46].

On the other side, *finance planning* represents the time required by the expert to plan and distribute properly funds and resources in the right manner. Even though it is just a matter of bureaucracy, decision making, and planning, both the *procurement process* and *financial planning* may affect strongly the downtime of a certain lifetime, even though the lifeline damage is not high. The *finance planning* variable is discretized as *long, short,* and *medium*-term. The *building phase*, sub-classified in *repair effort* and *engineering consolidation*, provides the recovery activities to follow for completing the rescue process; that is, all those processes of design and intervention which aim to restore the structural characteristics of the structure. *Repair effort* and *engineering consolidation* parent nodes are discretized in *very difficult, difficult*, and *easy*. Besides, the *engineer evaluation*, which is the time teams of specialists (engineers for instance) need to define and compare the assessments and give feedback on the potentially damaged infrastructure after the inspection, is based on the quantification of the damages and on the structural inspection process, which may require a *long*, *medium*, or *short* time.

Further information on the states of the EI parent nodes is given in Figure 3 and Table 1. With the consideration of the process outlined in Section 2, the corresponding unconditional probability table (UPT) of each parent node is defined as *1/n*, and the CPT for EI parameter and child nodes is created through subjected knowledge.

3.2.2 Earthquake Intensity (E)

The *earthquake intensity* (E) expresses the severity of the earthquake and the demand to which a city will be subjected and plays a primary role in estimating the downtime. In the downtime model, the E parameter influences both the choice of the recovery type and the result of downtime and it is defined by combining two parent nodes, the *epicentral distance,* and the *earthquake magnitude*. Distance from the epicenter is related to the observed damage such that the farther a system is located from the epicenter; the less damage is observed to the system. The *epicentral distance* is defined as *close*, *far*, and *very far*.

Four groups of Richter magnitude scale are used to classify the *earthquake magnitude* node, Strong 6-6.9; Major 7-7.9; Severe 8-8.9; and Violent 9-9.9. As *epicentral distance* and *earthquake magnitude* are parent nodes, the corresponding unconditional tables (UPTs) are defined as *1/n= 1/3* and *1/n= 1/4*, respectively.

The E node is classified into four groups of Mercalli intensity scale ranging from least perceptive to most severe: Weak MMI-MMIII, Strong MMIV-MMVI, Severe MMVII-MMX, and Violent MM>MMX (Table 2).

3.2.3 Availability of Human resources (HR)

Human resources play an important role in natural disaster planning. Liou and Lin [47] highlighted the critical role that human resource play during emergencies, through working with management, communication, and adjusting employee policies. The *Human resources* parameter is influenced by three factors: the occurrence of other emergencies at the same time, the availability of a structured and defined plan, and the characteristics of the impacted area (i.e., *large*, *medium*, and *small* impacted area). The *planning indicator* node is used in the framework to represent the emergency response and recovery planning. It can be assessed by consulting a city's local planning experts, which provide subjective assessments on three possible states of the planning indicator: *bad (minimal), good, and excellent*. According to Davidson and Shah [48], the *planning indicator* is classified as *bad* when planning is inadequate and inactive (e.g., procedures to explain what to do, how, and when are not included, roles and responsibilities of all involved parties are not established, and a plan is not practiced regularly through training); planning indicator is good when it is inadequate or inactive, then it is classified as excellent if planning is adequate and active.

The *impacted area* factor can be divided into three sub-factors: the weather conditions of the impacted area, the easiness of mobility and access into the impacted area, which depends on the condition of the post-earthquake transportation system and the amount of debris, and the characteristics of the urban area. The *extreme weather condition* parameter describes the post-earthquake weather that could limit the response effort and make hard the condition of casualties. The *extreme weather* indicator is expressed in terms of the temperature (e.g. 90°F and 32°F) [48].

The *urban area* is discretized as a *large, medium,* and *small* size according to the number of its population. That is, the urban area is large-size if the population is 1.5 million or more; medium-size urban area if its population is between 200,000 and 500,000; and small urban area if the population ranges between 50,000 and 200,000 [49]. Besides, the *urban area* parameter is identified by *Per Capita Gross Domestic Product* (PCGDP), which is the indicator of a nation's living standards, the quantity of *population* of the impacted area, and the *urbanization degree* [39, 50, 51]. Two nodes states (HR^L, HR^H), corresponding to *low* and *high* respectively, are used to describe the Availability of human resources. Further information on the states of the EI parent nodes is given in Table 3. The CPT for HR and HR sub-parameters is created in the same way described before.

3.2.4 Infrastructure Type

Another variable that should be considered is the type of affected infrastructure since DT changes according to it. It influences the required recovery type and the final output. In the proposed network (Figure 3), two types of infrastructures are considered: power network and infrastructure lifelines. The corresponding UPT for *Infrastructure type* is generated following the same procedure for the *Earthquake magnitude* node.

3.3. Inference

The downtime indicators described above can be grouped and connected through the inference process. BN's structure learning and inference for the DT are performed using the commercially available product Netica software [45]. This software can be used to classify and analyze data of a particular uncertain domain. Construction of BNs through Netica requires a list of uncertain variables, the possible states of discrete variables and possible ranges of continuous variables, the relationship among the variables, and the conditional probabilities to evaluate the dependencies. Once the variables and the corresponding states/ranges and probabilities have been assigned, it is possible to compile the network. To make a prediction, it is a simple matter of moving over parent nodes and select a state of those nodes.

The BN of the DT built using the Netica user interface is presented in Figure 3. Netica solves the network by finding the marginal posterior probabilities that some parameter will be in a particular state given the input parameters, the conditional probabilities, and the combinations of probabilities (e.g., 37.8 (*very difficult*), 41.7 (*difficult*), and 20.6 (*easy*) for Building phase node) [52].

Whenever the probability distribution in one of the root nodes is changed, the ability to quickly test many potential states and recalculate the probability distributions of all child nodes make Netica particularly useful for such analyses. Using Netica, 33 nodes (20 parent or independent nodes and 12 child or dependent nodes), 33 links, and 844 conditional probabilities are generated.

Although one BN model is designed to estimate the DT for two types of infrastructure (power and telecommunication system), different results are obtained by changing the infrastructure type node (i.e., power or telecommunication) since the conditional probabilities used in the downtime node follow the infrastructure type. Thus, changing the infrastructure type changes the model, while the other nodes remain the same in the BN model.

Figure 3. Downtime assessment model for power and telecommunication infrastructures

3.4. Data collection

In the context of this work, recovery implies returning full service to the population. Appendix A lists the complete database used to create the restoration curves of the lifelines. The database was collected only from published literature for earthquakes that have occurred after the '60s because there was little or no reliable information about the damage caused by earlier earthquakes. Infrastructure damage data is available in the literature in both qualitative and quantitative forms. However, only reports with numerical data reporting the actual time needed to restore the infrastructure service have been considered in the analysis. Qualitative data has been excluded since it refers to the degree of damage to the infrastructures and not the restoration function. The normalization of the data was not necessary since it is provided in the same scale (i.e., number of days necessary to restore the infrastructure service) and can be easily combined [16]. For instance, the raw data of the Valdivia earthquake that hit Chile in 1960 was extracted from [53]. The shock, with a magnitude of 9.5 on the Richter scale and an intensity of XI to XII on the Mercalli scale, led to a tsunami that disrupted Valdivia city. One electrical system was damaged by the earthquake and its functionality was restored in five days. The water system was also disrupted, and it took 50 days to recover its function. The gas and telecommunication infrastructures performed quite well, and no damage was reported. From Appendix A, it is evident that each earthquake has caused damage to more than one infrastructure system at the same time. For example, in the city of Loma Prieta, the earthquake caused damage to ten water, two power, five gas, and six telecommunication networks. The damaged systems needed different times to recover even when the infrastructures are of similar types. For instance, the two power plants that were affected by the Loma Prieta earthquake needed 2 and 0.5 days respectively to recover. There were some cases where either the damage information was not available, or no damage was recorded. Such cases are marked with a dash (-) inside the table. In total, the number of affected infrastructure units analyzed in this paper are 63 power systems; 84 water systems; 47 gas systems; and 34 Telecommunication systems. The seismic events considered in the study are with a magnitude range between M6 and M9.9. Most of the events considered took place in the USA, Japan, and South America.

Data used to construct the restoration curves of the Power and Telecommunication systems have been divided into 4 sets based on the earthquake intensity. Although it is not the only parameter, the earthquake intensity plays a primary role in defining the infrastructure damage and the restoration time. This classification assumes that the earthquake magnitude is fully correlated with the induced damage. The collected data has been classified under four groups of Richter magnitude scale (Strong 6-6.9; Major 7-7.9; Severe 8-8.9; and Violent 9-9.9). While in literature other intensity measures are usually used to identify the earthquake intensity (i.e., PGA, PGD, Sa, and Sd), in this work, it was not possible to know those intensity measures for all the events as such information was not published.

For each lifeline, a group of restoration curves considering the four magnitude ranges have been developed. Table 5 presents the data sets considered in the analysis, extracted from Appendix A. The parameters considered to plot the curves are: (i) the number of days required to restore full service to customers (horizontal axis) and (ii) the probability that the utility is completely restored to the customers (vertical axis).

3.5. Fitting analysis

Data gathered in the form of restoration curves are fitted with three statistical distributions: gamma, exponential, and lognormal cumulative distributions. Figure 4 shows the frequency histogram of the DT data and the probability density function (PDF) of the gamma, exponential, and lognormal distributions related to (a) the power network infrastructure and (b) the telecommunication network for earthquake magnitude range EM 6-6.9.

Figure 4. Histograms and PDF fitting distributions for (a) the power infrastructure, and (b) the telecommunication infrastructure for the data related to earthquake magnitude range M6-6.9

As shown in Figure 4, the gamma, exponential, and lognormal distributions are plotted against the empirical data to visualize the distribution fit. Since the plotted PDFs present a similar trend, it is not simple to choose the distribution with the best fist relying only on visual interpretation. Therefore, the goodness of fit tests (GOFs) are used to identify the appropriate distribution for the empirical data. GOF of a statistical model is a technique that describes how well a model fits a set of observations. It also summarizes the discrepancy between the observed values and the values coming from the model [54]. The distribution with the best fit has been identified through two tests: the Kolmogorov-Smirnov (K-S) and Chi-Square tests for Goodness-of-fit.

Results from the GOF tests are presented in Table 6 and Table 7. Results show that the gamma distribution is the distribution with the optimal fit. For the power network, the gamma distribution has the lowest values of D_n (K-S parameter) and χ^2_f (Chi-Square parameter) compared to the other distributions and these values are lower than the corresponding critical values D_n^a and $C_{1-a,f}$. In the case of the telecommunication network, all three distributions can be implemented to represent the DT data since all three distributions show lower values of D_n and χ^2_f compared to the corresponding D_n^a and $c_{1-a,f}$ where the gamma distribution has the lowest values. Therefore, the gamma distribution is selected to fit the DT data since it is suitable to represent the data of both infrastructure systems. The gamma distribution is defined using two parameters, alpha, and beta. Such parameters have been estimated for each earthquake magnitude group using the method of *maximum likelihood* (ML). ML allows identifying for a set of data the probability of obtaining that set of data given the chosen probability distribution model. The gamma parameters for the power and telecommunication lifelines are presented in Table 8.

The restoration curves for power and telecommunication infrastructures are plotted using two factors: (i) the number of days needed to restore full service (horizontal axis); (ii) the probability of a complete restoration (vertical axis). The restoration curves are classified under four groups of Richter magnitude scale: 6-6.9 *Strong*, 7-7.9 *Major*, 8-8.9 *Severe*, and 9-9.9 *Violent*, as shown in Figure 5.

Figure 5. Restoration curves of (a) the power infrastructure, and (b) the telecommunication infrastructure based on earthquake magnitude

Restoration curves are built without taking into account the attenuation function. Indeed, it is assumed that infrastructures are at an equivalent distance from the epicenter. Therefore, as mentioned before, the distance from the epicenter has been included in the downtime model as an extra node.

As shown in Figure 5, restoration curves intersect each other. In standard fragility analysis, the intersection of fragility functions for different damage states within the same data should not happen. It could happen when each fragility curve corresponding to a specific damage state is fitted independently of one another. To avoid the intersection of fragility curves, usually, the same standard deviation for all the fragility curves is assumed. In loss evaluation, however, fragility function may intersect since losses do not always follow a specific pattern (e.g. a lower damage state may require more cost to be repaired) [16]. This justifies the intersection of restoration curves in Figure 5.

3.6. Downtime conditional probabilities

Once the restoration curves are developed, the estimation of probabilities for the DT output is carried out. Five intervals (e.g. states) are introduced to discretize the DT output (see Table 4).

A conditional probability can be obtained for every couple "DT state-earthquake intensity". For instance, assume the value for the DT is classified as *High* (25-40 days), the corresponding probabilities of recovery for the power and telecommunication systems that are hit by a *Strong* earthquake (M6-6.9) are 1 and 0.97, respectively (Figure 5). The DT conditional probabilities for the power and telecommunication lifelines are listed in Table 9. In Table 9 some values overlap since restoration curves intersect each other, as is explained above.

It is important to note that in this study the DT variable is assumed to be directly influenced by four variables: *Infrastructure type*, *earthquake intensity*, *infrastructure exposure*, and *available human resources* (Figure 3). The results obtained from the restoration curves correspond to *high* infrastructure exposure and *low* available human resources, and they are considered baselines for estimating the probabilities for other combinations in the CPT of DT. Table 10 presents a portion of the conditional probability table of the DT variable. In those tables, the baselines resulted from the restoration curves are highlighted in bold and they are the starting point for estimating other combinations. The conditional probabilities of other combinations in Table 10 are estimated respecting that the horizontal sum must be equal to one (second probability axiom) (Figure 6). In Figure 6, best-case (favorable) combinations make the probability mass function (PMF) shift to the left, which implies an increase in the probability of quick recovery. The worst-case (unfavorable) combinations, on the other hand, shift the PMF to the right causing a decrease in the quick recovery probability. As shown in Figure 6, the three distributions are the same, the only difference lies in the location of the mean value of each of the three distributions that define if the scenario is favorable or unfavorable.

Figure 6. Probability mass distribution of the baseline, best-case combination, and worst-case combination.

4. Sensitivity analysis

BN analysis applies prior conditional probabilities to estimate model output in the presence of new evidence. Sensitivity analysis is carried out to identify critical input parameters that have a significant impact on the output result [35]. Sensitivity analysis assumes that the input parameters are uncertain. It allows identifying the variation in the system's reliability given a variation in the inputs values [55]. It also refers to how sensitive the performance of a model is to minor changes in the input parameters [56]. Different methods have been introduced in the literature for implementing sensitivity analysis in a BN [36, 57-60]. Since the input parameters considered in the DT framework have discrete and continuous values, the variance reduction method is utilized [36, 45, 61]. The variance reduction method allows identifying the sensitivity of a BN's output to a variation in a given input by computing the variance reduction of the expected real value of a query (target) node Q (e.g. downtime parameter, *DT*) due to a finding at varying variable node F (e.g., *Earthquake intensity*, *Infrastructure type*, *Recovery type*, and *Epicentral distance*). The variance of the real value of Q given evidence F, $V(q|f)$ is computed using the following equation [36, 45, 62]:

$$V(q|f) = \sum_{q} p(q|f)[X_q - E(Q|f)]^2 \tag{5}$$

where q = state of the query node Q, f = state of varying variable node F, $p(q|f)$ = conditional probability of q given f, X_q = value corresponding to state q, and $E(Q|f)$ = expected real value of Q after the new finding f for node F. By selecting the query node and choosing Sensitivity to Findings in Netica, a report will be displayed indicating how much the query node would be influenced by a single finding at each of the other nodes (varying nodes) through different sensitivity measures (i.e., variance reduction and percent contribution) [36, 45].

The results of the sensitivity analysis for the DT due to a finding at another node are presented in Table 11 and Figure 7. Only variables (parent and child nodes) showing a significant contribution towards the DT output have been indicated (i.e. earthquake magnitude and intensity, infrastructure type, recovery type, planning indicator, and epicentral distance). Results show that the intensity of the earthquake has the highest percent contribution towards the DT (i.e., 0.574%). The impact of the earthquake intensity is also evident in Figure 5, where the DT mostly follows the earthquake magnitude.

The type of analyzed infrastructure has also a high impact on the output. That is, the infrastructure type parameter shows a sensitivity of 0.569%. This result is reasonable, since in general the power network is the first lifeline to recover its functionality to supply other infrastructure systems, and consequently the DT is lower than other lifelines. The recovery type and the epicentral distance have lower sensitivities, 0.0428%, and 0.0327%, respectively. Having reliable data on these key indicators is crucial to reduce uncertainty.

Inference analysis is also performed to evaluate the effects on the target node (i.e., the downtime) by setting best- and worst-case scenario values of the *earthquake intensity*, *epicentral distance*, *recovery type*, and *infrastructure type*. This is helpful in decision-making to prioritize activities to best affect desirable or to avoid undesirable outcomes. In the best scenario all the indicators are set to their optimal states, while in the worst scenario the worst states are selected. Results obtained from the inference analysis are shown in Table 12. From the table, it is evident that the downtime is lower in the best-case scenario than the worst-case scenario, as expected. Moreover, the downtime for power infrastructure is always lower than telecommunication in both the scenarios. What's more, by changing the state of one node and keeping the state of the other nodes the same each time, results show that the *earthquake intensity* and the *infrastructure type* parameters have a higher impact towards the target node. Thus, the sensitivity to findings and inference analysis provide the same results.

Figure 7. Sensitivity analysis results of the DT Bayesian network model

5. Illustrative example

To demonstrate the applicability of the proposed framework, three different scenarios for the power and telecommunication infrastructures have been applied. The earthquakes considered in the analysis are:

1. Scenario 1: Napa earthquake, USA, 2012;
2. Scenario 2: Nihonkai-chubu, Japan, 1983;
3. Scenario 3: Illapel, Chile, 2015.

Napa 2014, USA: an earthquake of a magnitude of M 6.0 and a depth of 10.7 km with the epicenter located approximately 6.0 km northwest of the city of American Canyon near the West Napa Fault, in the city of Napa on the 24th of August 2014. Structural damage was generally concentrated on unreinforced masonry buildings and residential properties. Approximately 200 people were injured, and 1 person died. Lifelines performed relatively well: water infrastructure was largely restored within ten days, with the majority of breaks being in cast-iron pipes. No damage was observed to the electricity transmission network, but outages in the distribution system affected almost 70,000 customers. 99% of these faults were restored within 26 hours [63].

Nihonkai-chubu 1983, Japan: A large earthquake magnitude M7.8 occurred off the coast of Akita prefecture, Japan, on the 26th of May 1983 generating a major local tsunami that was destructive in Japan as well as in Korea. The event caused severe damage to the coastal areas of the Tohoku region. In particular, most of the earthquake damages hit buildings and lifeline facilities. Information regarding the DT of disrupted infrastructures shows that Nihonkai-chubu stayed with partial water and gas systems for around one month after the earthquake due to the severe damage to the ground pipelines. The power supply, instead, was restored the day after the seismic event [64].

Illapel 2015, Chile: a big earthquake of magnitude M8.4 shocked the Chilean town of Illapel on the 16th of September 2015. The earthquake was followed by a tsunami that killed several people on the coastline. The resilience and preparation of the country allowed the different lifelines system to perform properly [65].

The BN model built through Netica software to simulate the three different scenarios is show in Figure 8.

Figure 8. The Bayesian network of the Downtime indicators using Netica software

The input data of the three scenarios are obtained from the literature (see Table 1, Table 2, and Table 3) and summarized in Table 13 and Table 14. While in the first scenario all the input parameters could be found, the other two scenarios are implemented considering a partial availability of information. Results from the DT assessment are illustrated in Figure 9, Figure 10, and Figure 11. From the analysis, the DT output mainly depends on the infrastructure type and the intensity of the earthquake. These variables showed the highest influence on the DT output. As expected, results demonstrate that the power network requires more time to be restored when the earthquake intensity is classified as *severe* and the epicentral distance is set as *close* (scenario three). Although less time is required to restore the power network in scenario two where the infrastructure is hit by a *major* seismic event and it is placed *far* from the epicenter, results are similar to those obtained from scenario three. This can be justified considering that partial availability of information that affects scenario two and three may make results uncertain and incorrect. Moreover, interdependencies among the lifelines were witnessed and can be considered as an intrinsic characteristic of the data used to design the restoration curves. In general, the power system is always the first to recover its function after a hazard event. This is usually because all lifelines are heavily dependent on the power network as they need the power to function. Thus, it should be restored without delay. This is evident in the results as the DT of the power network is always lower than the telecommunication infrastructure in all three scenarios (i.e. probability of *very low* DT for the power network is higher than the telecommunication network in all three scenarios). Furthermore, in this work, it is assumed that a higher maintenance degree of infrastructures would result in a lower likelihood of damages, and consequently, in lower recovery time. This assumption has been confirmed by the analysis of the three scenarios. That is, the maintenance rate of infrastructures is defined as *good*, *medium*, and *poor* in the three scenarios respectively. The output from the simulation is lower in the first scenario (i.e., the maintenance degree is good) and is higher in the last two scenarios (i.e., the maintenance degree is medium and poor).

In all three scenarios, we can see uncertainty in the results in the form of probability dispersion. This is typical in BN analysis as the basic inputs are uncertain in the first place. The probability dispersion or variance can decrease when more data is available. For example, when data is not available, the principle of insufficient reasoning is applied for the basic inputs. This means that the states of the inputs are assigned an equal probability of occurrence. This, in turn, creates uncertainties that are propagated in the system and reflected on the final output (i.e. DT).

Figure 9. Downtime evaluation for a) Power network and b) Telecommunication system for Scenario 1

Figure 10. Downtime evaluation for a) Power network and b) Telecommunication system for Scenario 2

Figure 11. Downtime evaluation for a) Power network and b) Telecommunication system for Scenario 3

6. Conclusion

The importance of resilience in the context of managing infrastructure systems is indispensable. Critical infrastructures, such as power and telecommunication networks, are coping with different threats ranging from natural to man-made hazards. In this paper, a probabilistic downtime (DT) assessment and prediction framework using the Bayesian Network (BN) is provided as an initial framework for estimating the recovery time of infrastructures, highlighting how sensitivity analysis can help prepare pre-disaster strategies and assign appropriate resources. The methodology combines DT indicators through a BN-based DT assessment framework to have a first estimate of the total recovery time of power and telecommunication infrastructures that are typically damaged after earthquake events. The inclusion of the uncertain parameters that have a high impact on the recovery process and that are tricky to quantify such as *financing planning*, *availability of the human resource*, *and regulatory and economic uncertainty*, represents one of the strengths of the methodology. The quantification and characterization of the DT factors associated with power and telecommunication failures are often vague and uncertain, due to their qualitative nature rather than quantitative.

The BN-based approach used herein is based on the past data and observation of experts and can capture the knowledge uncertainty. The proposed method incorporates intuitive knowledge and engineering experience for evaluating the parameters of the framework and for estimating conditional probabilities. For instance, the conditional probabilities for each node were obtained by combining expert knowledge and past studies. To show the applicability of the model, three scenarios are introduced where data are partially available. Sensitivity analysis is performed to identify critical parameters that contribute to the DT of lifelines and to help decision-makers to pursue the best strategies for downtime reduction. Sensitivity results showed that the input parameters related to the earthquake intensity and the characteristics of the infrastructure had the highest normalized percent contribution towards the DT, i.e. 0.597% and 0.376%. The highly sensitive parameters can be used to determine parameters that require more time and effort to collect data.

The graphical interface of BNs makes the methodology a decent tool for decision-makers (e.g. engineers and managers) who may not be experts in probabilistic analysis. It is believed that the proposed approach should help the decision-makers to evaluate the overall repair time and accordingly quantify the priorities of the repair activities. Moreover, the powerful feature of BN for generating different what-if scenarios enables decision-makers to run scenarios and determine the efficient means of reducing the DT.

Results from the proposed framework would be useful in supporting decision-makers on learning about the recovery time of their system given a specific seismic event. By setting a desirable state of the DT and getting the parameters that ensure the predefined DT state, decision-makers are allowed to improve the systems' performance through the backward analysis of BN (diagnostic reasoning).

The main limitation of the proposed study is that some of the conditional probabilities are knowledge-based. Subjectivity is needed to be included during the model development and analysis, as it is one of the main features of BN for treating missing data with expert judgment. However, different conditional probabilities that are developed based on evidence data, such as historical data and analytical work, can be integrated within the methodology.

Further research will focus on the calibration of the BN model by extending the database to include more key parameters in the DT BN system and taking into account different conditional probabilities to get more accurate results. Other lifelines, such as water and gas systems, will also be analyzed considering the interdependency of infrastructure networks since infrastructure systems are not isolated from each other but rely on one another for their functionality. Finally, fuzzy logic could be applied as an alternative inference system to the BN and then compared to the proposed BN approach.

CrediT authorship contribution statement

Melissa De Iuliis: Writing – original draft, Methodology, Software, Validation. **Omar Kammouh:** Conceptualization, Supervision, Writing – review & editing. **Gian Paolo Cimellaro:** Supervision, Conceptualization, Writing – review & editing, Funding acquisition. **Solomon Tesfamariam:** Supervision, Writing – review & editing.

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Appendix A

Number of affected infrastructures and the corresponding total recovery time [16]

Earthquakes	Lifelines affected							
	Power		Water		Gas		Telecom.	
	No.	DT (days)	No.	DT (days)	No.	DT (days)	No.	DT (days)
Loma Prieta	2	(2), (0.5)	10	(14), (4), (3), (1.5), (2), (1), (3), (3), (7), (4)	5	(30), (16), (11), (10), (10)	6	(3), (4), (0.1), (3), (3), (1.5)
Northridge	3	(3), (0.5), (2)	6	(7), (2), (58), (12), (67), (46)	4	(7), (30), (5), (4)	3	(1), (2), (4)
Kobe	5	(8), (3), (2), (5), (6)	3	(0.5), (8), (73)	3	(84), (11), (25)	3	(1), (5), (7)
Niigata	4	(11), (4), (1)	3	(14), (28), (35)	3	(28), (35), (40)	-	
Maule	6	(14), (1), (3), (10), (14)	4	(42), (4), (16), (6)	2	(10), (90)	4	(17), (7), (3), (17)
Darfield	3	(1), (2), (12)	2	(7), (1)	1	(1)	3	(9), (2), (3)
Christchurch	3	(14), (0.16)	1	(3)	2	(14), (9)	2	(15), (9)
Napa	1	(2)	6	(20), (0.9), (0.75), (2.5), (12), (11)	1	(1)	-	
Michoacán	4	(4), (10), (3), (7)	4	(30), (14), (40), (45)	-	-	1	(160)
Off-Miyagi	2	(2), (1)	1	(12)	3	(27), (3), (18)	1	(8)
San Fernando	1	(1)	-	-	2	(10), (9)	1	(90)
The Oregon Resil. Plan	1	(135)	1	(14)	1	(30)	1	(30)

LA Shakeout Scenario	1	(3)	1	(13)	1	(60)	-	
Tohoku Japan	7	(45), (3), (8), (2), (2), (4)	8	(4.7), (47), (1), (26), (7), (1), (47), (47)	6	(54), (2), (30), (3.5), (13), (18)	3	(49), (21), (49)
Niigata	2	(24)	3	(15), (4), (10)	2	(180), (2)	-	
Illapel	1	(3)	1	(3)	-	-	-	
Nisqually	3	(2), (6), (3)	-	-	-	-	-	
Kushiro-oki	1	(1)	3	(6), (3), (5)	2	(22), (3)	-	
Hokkaido Toho-oki	1	(1)	3	(9), (3), (5)	-	-	-	
Sanriku	1	(1)	3	(14), (12), (5)	-	-	-	
Alaska	3	(2), (0.75), (1)	5	(14), (5), (1), (7), (14)	3	(1), (5), (2), (14)	2	(1), (2)
Luzon	3	(7), (20), (3)	3	(14), (14), (10)	-	-	3	(5), (10), (0.4)
El Asnam	-	-	1	(14)	-	-	-	
Tokachi-oki	2	(2)	-	-	2	(30), (20)	-	
Kanto	1	(7), (5)	1	(42)	2	(180), (60)	1	(13)
Valdivia	1	(5)	1	(50)	-	-	-	
Nihonkai-chubu	1	(1)	1	(30)	1	(30)	-	
Bam	1	(4)	3	(14), (10)	-	-	1	(1)
Samara	1	(1)	1	(2)	-	-	1	(1)
Arequipa	1	(1)	3	(32), (34)	-	-	-	
Izmit	1	(10)	2	(50), (29)	1	(1)	1	(10)
Chi-Chi	3	(40), (14), (19)	1	(9)	1	(14)	1	(10)
Alaska 2002	2	(2), (0.5)	10	(14), (4), (3), (1.5), (2), (1), (3), (3), (7), (4)	1	(3)	6	(3), (4), (0.1), (3), (3), (1.5)

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Tables

Table 1. Description of the Exposure infrastructure parameters

Variable	State	Performance measure/Reference
Exposed Infrastructure	Low High	Visual inspection/Expert opinion [66]
Maintenance Degree	Poor Medium Good	Visual inspection/Expert opinion
Served people	Low Medium High	< 20% Population 20%<Served People<50% Population > 50% Population [49]
Anti-seismic Infrastructure	Yes No	Earthquake resistant Earthquake non-resistant
Service Importance	Low Medium High	Visual inspection/Expert opinion
Priority of intervention	Low Medium High	Visual inspection/Expert opinion
Recovery Type	Easy Difficult Very Difficult	Visual inspection/Expert opinion [43]
Financing Phase	Short Medium Long	Visual inspection/Expert opinion [43]
Procurement Process	Reactive Emergency Accelerated	Major hazards State of emergency taken off Immediate needs [43, 46]
Building Phase	Easy Difficult Very Difficult	Visual inspection/Expert opinion [43]
	Short	

Engineer Evaluation	Medium Long	Visual inspection/Expert opinion [43]
Event Repetition	Once Many	First shock Aftershocks [43]
Seismic Event	Dangerous Very Dangerous Extremely Dangerous	6<M<7 7<M<8 M>8
Finance Planning	Short Medium Long	Visual inspection/Expert opinion [43]
Repair Effort	Short Medium Long	Visual inspection/Expert opinion [43]
Engineering Consolidation	Easy Difficult Very Difficult	Visual inspection/Expert opinion

Table 2. Description of the Earthquake intensity parameter

Variable	State	Performance measure
Epicentral distance	Close Far Very far	Visual inspection/Expert opinion
Earthquake magnitude	Strong Major Severe Violent	M 6-6.9 M 7-7.9 M 8-8.9 M 9-9.9
Earthquake Intensity	Weak Major Severe Violent	MMI-MMIII MMIV-MMVI MMVII-MMX MM>MMX

Table 3. Description of the Availability HR variables

Variable	**State**	**Performance measure**	**Reference**
Availability HR	Low High	Expert opinion	[66]
Other Emergencies	Yes No	Expert opinion	
Planning Indicator	Bad Good Excellent	Inadequate and inactive Inadequate or inactive Adequate and active	[48] [67]
Impacted Area	Small Medium	Visual inspection/Expert opinion	[67]

	Large		
Mobility and Access	Easy Medium Hard	Visual inspection/Expert opinion	[67]
Urban Area	Small Medium Large	50.000<Population<200.000 200.000<Population<500.000 Population >= 1.5 million	[43] [49] [67]
Extreme Weather	Very bad Bad Good	90°F or 35°F 80°F or 32°F 68°F	[48] [67]
PCGDP	Low Medium High	<5 5<PCGDP<40 >40	[67] [51]
Population	Low Medium High	< 50.000 50.000<Population<500.000 >= 1.5 million	[49] [67]
Urbanization rate	Low Medium High	< 0 0 < Urbanization rate < 3 > 3	[67] [50]

Table 4. Description of the DT parameter

Variable	State	Performance measure
Downtime	Very Low	0 - 4 days
	Low	5 - 10 days
	Medium	11 - 24 days
	High	25 - 40 days
	Very High	41 days and more

Table 5. Downtime data and corresponding frequencies for Power and Telecommunication networks with EM 6-6.9, 7-7.9, 8-8.9, and 9-9.9

Power	DT (days)	0.16	0.5	1	2	3	4	5	6	8	11	14	
	Freq.	1	2	2	4	3	2	1	2	1	1	1	
Telecommunication	DT (days)	0.1	1	1.5	2	3	4	5	7	9	15	90	
	Freq.	1	3	1	1	3	2	1	1	1	1	1	
Power	DT (days)	0.5	1	2	3	7	10	12	14	19	20	24	40
	Freq.	1	6	3	2	1	1	1	1	1	1	1	1
Telecommunication	DT (days)	0.1	0.4	1	2	3	4	5	8	9	10		
	Freq.	1	1	1	1	4	1	1	1	1	3		

Power	DT (days)	1	2	3	4	7	10	14	
	Freq.	3	1	3	1	1	2	2	
Telecommunication	DT (days)	3	7	17	160				
	Freq.	1	1	2	1				
Power	DT (days)	0.75	1	2	4	5	8	45	135
	Freq.	1	1	3	1	1	1	1	1
Telecommunication	DT (days)	1	21	30	49				
	Freq.	1	2	1	2				

Table 6. *Kolmogorov- Smirnov* goodness-of-fit test for Power and Telecommunication infrastructures for EM6-6.9

Theoretical distribution	Power network for EM = 6-6.9		Telecommunication network for EM = 6-6.9	
	D_n	D^{α}_{n} (α = 0.05, n = 5)	D_n	D^{α}_{n} (α = 0.05, n = 3)
Gamma distribution	0.127	0.565	0.127	0.708
Exponential distribution	0.148		0.204	
Lognormal distribution	0.218		0.182	

Table 7. *Chi-square* goodness-of-fit test for Power and Telecommunication infrastructures with EM6-6.9

Theoretical distribution	Power network for EM = 6-6.9			Telecommunication network for EM = 6-6.9		
	Chi-square χ^2_f	f = k-1	$C_{1-\alpha,f}$ (α= 0.05)	Chi-square χ^2_f	f = k-1	$C_{1-\alpha,f}$ (α= 0.05)
Gamma distribution	7.12	3	7.81	7.58	5	11.07
Exponential distribution	13.70	2	5.99	7.52	4	9.48
Lognormal distribution	13.58	3	7.81	7.55	5	11.07

Table 8. Gamma distribution parameters for Power and Telecommunication systems for the four earthquake magnitude ranges

Power system					Telecommunication system				
Parameters	1	2	3	4	Parameters	1	2	3	4
α	0.955	1.424	0.925	0.813	α	0.973	0.317	0.753	1.115
β	4.541	2.777	6.45	18.69	β	10.26	72.06	12.85	44.80

Table 9. Downtime probabilities of the power and telecommunication systems given four seismic intensities

Lifeline	Time Span	Weak	Strong	Severe	Violent
Power System	0-4	62%	52%	53%	41%
	5-10	32%	31%	34%	23%
	11-24	5%	15%	13%	23%
	25-40	0%	1%	1%	9%
	40+	0%	0%	0%	3%
Telecommunication System	0-4	43%	10%	25%	9%
	5-10	24%	43%	13%	15%
	11-24	22%	44%	17%	28%
	25-40	8%	4%	12%	20%
	40+	3%	0%	9%	14%

Table 10. Conditional Probability Table (CPT) for the downtime variable of the power and telecommunication infrastructures

Infrastructure Type	Earthquake Intensity	Exposed Infrastructure	Av. HR	Very Low	Low	Medium	High	Very High
Power	Weak	High	High	0,62394	0,32123	0,05448	0,00037	0,0000015
Power	**Weak**	**High**	**Low**	**0,62390**	**0,32119**	**0,05452**	**0,00044**	**0,0000015**
Power	Weak	Low	High	0,62387	0,32100	0,05453	0,00047	0,00009
Power	Weak	Low	Low	0,62374	0,32080	0,05454	0,00075	0,00019
Power	Strong	High	High	0,52078	0,31280	0,15198	0,01365	0,00081
Power	**Strong**	**High**	**Low**	**0,52070**	**0,31250**	**0,15214**	**0,01376**	**0,00090**
Power	Strong	Low	High	0,52065	0,31245	0,15216	0,01379	0,00091
Power	Strong	Low	Low	0,52064	0,31230	0,15151	0,01459	0,00100
…	…	…	…	…	…	…	…	…
Telecommunication	Weak	High	High	0,43050	0,24320	0,22050	0,07790	0,02790
Telecommunication	**Weak**	**High**	**Low**	**0,43000**	**0,24300**	**0,22100**	**0,07800**	**0,02800**
Telecommunication	Weak	Low	High	0,42990	0,24290	0,22150	0,07790	0,02782
Telecommunication	Weak	Low	Low	0,42989	0,24278	0,22155	0,07790	0,02789
Telecommunication	**Strong**	**High**	**High**	**0,09823**	**0,42665**	**0,43950**	**0,03510**	**0,00050**
Telecommunication	Strong	High	Low	0,09810	0,42549	0,43981	0,03560	0,00098
Telecommunication	Strong	Low	High	0,09780	0,42544	0,43990	0,03570	0,00111
Telecommunication	Strong	Low	Low	0,09500	0,42540	0,44150	0,03630	0,00180
…	…	…	…	…	…	…	…	…

Table 11. Sensitivity analysis for the *Downtime* variable due to a finding at another node (only influential variables are listed)

Node	Variance reduction	Percent contribution
Earthquake intensity	0.895	0.574
Infrastructure type	0.8865	0.569
Recovery type	0.06672	0.0428
Epicentral distance	0.05101	0.0327
Earthquake magnitude	0.02184	0.0014

Planning indicator	3.189e-05	2.05e-05

Table 12. Inference analysis results for the *Downtime* variable

Node	State
Epicentral Distance	Very Far
Earthquake Intensity	Weak
Recovery Type	Easy
Infrastructure Type	Power/Telecommunication
Downtime	14.7 ± 13/ 19 ± 12
Epicentral Distance	Close
Earthquake Intensity	Violent
Recovery Type	Very Difficult
Infrastructure Type	Power/Telecommunication
Downtime	16.8 ± 12/ 20.2 ± 10

Table 13. Input data used to assess the downtime of the power lifeline

Variables	Scenario 1	Scenario 2	Scenario 3
Anti-seismic Infrastructure	Yes	Yes	No
Assessment of the damage	Short	Medium	-
Procurement process	Emergency	-	-
Epicentral distance	Close	Far	Close
Earthquake magnitude	Strong	Major	Severe
Mobility and Access	Easy	Medium	-
Engineering Consolidation	Difficult	-	-
Event Repetition	Once	Many	Once
Extreme weather	Good	Bad	Very Bad
Finance Planning	Medium	Short	-
Infrastructure type	Power	Power	Power
Maintenance degree	Good	Medium	Poor
Other Emergencies	No	Yes	Yes
Per Capita GDP	High	Medium	Low
Planning Indicator	Excellent	Good	Bad
Population	High	High	Medium
Repair Effort	Difficult	-	-

Served People	High	Medium	High
Service Importance	High	High	Medium
Structural inspection	Short	Medium	-
Urbanization	High	Medium	Medium

Table 14. Input data used to assess the downtime of the telecommunication lifeline

Variables	Scenario 1	Scenario 2	Scenario 3
Anti-seismic Infrastructure	Yes	Yes	No
Assessment of the damage	Short	Medium	-
Procurement process	Emergency	-	-
Epicentral distance	Close	Far	Close
Earthquake magnitude	Strong	Major	Severe
Mobility and Access	Easy	Medium	-
Engineering Consolidation	Difficult	-	-
Event Repetition	Once	Many	Once
Extreme weather	Good	Bad	Very Bad
Finance Planning	Medium	Short	-
Infrastructure type	Telec.	Telec.	Telec.
Maintenance degree	Good	Medium	Poor
Other Emergencies	No	Yes	Yes
Per Capita GDP	High	Medium	Low
Planning Indicator	Excellent	Good	Bad
Population	High	High	Medium
Repair Effort	Difficult	-	-
Served People	High	Medium	High
Service Importance	High	High	Medium
Structural inspection	Short	Medium	-
Urbanization	High	Medium	Medium