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Quantifying restoration time of pipelines after earthquakes: Comparison of Bayesian belief networks and fuzzy models

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Critical infrastructures are an integral part of our society and economy. Services like gas supply or water networks are expected to be available at all times since a service failure may incur catastrophic consequences to the public health, safety, and financial capacity of the society. Several resilience strategies have been examined to reduce disaster risk and evaluate the *downtime* of infrastructures following destructive events. This paper introduces an indicator-based downtime estimation model for buried infrastructures (i.e., water and gas networks). The model distinguishes the important aspects that contribute to determining the downtime of buried infrastructure following a hazardous event. The proposed downtime model relies on two inference methods for its computation, Fuzzy Logic (FL) and Bayesian Network (BN), which are adapted for the current application. Finally, through a case scenario, a comparison of the two inference methods, in terms of results and limitations, is presented. Results show that both methods incorporate intuitive knowledge and/or historical data for defining fuzzy rules (in FL) and estimating conditional probabilities (in BN). The difference stands in the interpretation of the outcome. The output of the FL is a membership that defines how well the downtime fits the fuzzy levels while the BN output is a probability distribution that represents how likely the downtime is in a certain state. Nevertheless, both approaches can be utilized by decision-makers to easily estimate the time to restore the functionality of buried infrastructures and plan preventive safety measures accordingly.

Keywords: resilience; downtime; lifelines; infrastructure; fuzzy logic; Bayesian network; restoration

Introduction

Water and gas distribution pipes, coupled with other critical infrastructure systems, contribute to the economic development and quality of life of modern communities. During recent seismic events, such as the 1995 Kobe and 2016 Kumamoto earthquakes, the water and gas distribution networks were severely damaged [1-4]. Failures of the water distribution network can have consequences on other existing nearby infrastructures, such as gas pipes (e.g., water is required in processing plants of natural gas), potable water, and wastewater conveyance systems, leading to poor public health conditions [5, 6]. Integrity of critical infrastructures, therefore, has aroused attention to the seismic safety of lifeline systems.

Functionality of the infrastructure, under emergency conditions, can be evaluated by studying resilience of critical infrastructures that are prone to many disruptive events or inadequate maintenance [7-13]. In the seismic resilience estimation, one such matrix of interest to the decision-making is downtime. The downtime is defined as the time from the occurrence of the hazard event *(t_o)*, where there is a loss of functionality of the system, to the time when the functionality is completely restored *(t_1)* (Figure 1) [14-16].

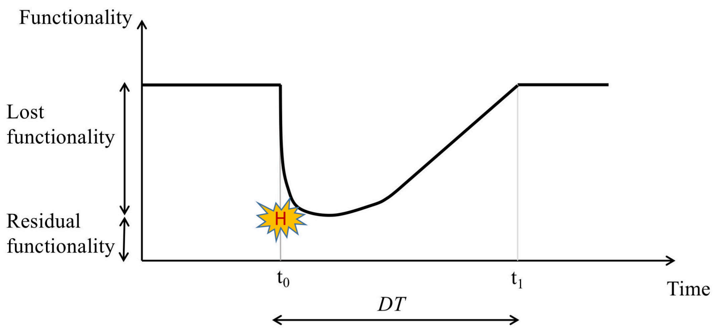

Figure 1. Conceptual Downtime (DT) of a system

Although several studies have been carried out on downtime [17-19], downtime estimation is still challenging since the data and the input parameters that are required for the estimation are not completely available, highly uncertain, and rapidly evolving in time [20-23]. The "uncertain" parameters such as the *finance* and *procurement process*, *economic* and *human resources* are important factors in the definition and estimation of the downtime. Few downtime models include the contribution of uncertain factors as they differ depending on the condition of the affected area. Therefore, the main challenge in estimating the restoration time deals with randomness, vagueness, and ignorance-type uncertainties [8, 24-26]. The typology and definition of uncertainty within the engineering community is extensive and often discordant [27]. Klir and Yuan [25] have broadly categorized uncertainty into two basic types: *vagueness* and *ambiguity* (see Table 1 for an extensive list of the uncertainty types). Besides, the uncertainties and interdependencies that exist in the downtime estimation, render rule-based systems and graphical models a viable alternative [20-22]. Interdependency, in this context, refers to the statistical relationships between the input parameters of the downtime estimation model.

Table 1. Definition of uncertainty types

Uncertainty	Definition
Imprecise	Not clear, not accurate
Vagueness	Not clearly explained or expressed, and therefore understandable in different ways. Results in uncertain or ill-defined meaning
Ambiguity	Unclear or confusing as data can have different meanings
Ignorance	Lack of knowledge, lack of reliable information about the phenomenon of interest
Inconsistent	Unpredictable and behaves differently in a situation that warrants the same behavior. Data inconsistency occurs when data is stored in different formats in two databases or if data must be matched between database
Random	Data randomness occurs when data is defined without method or conscious choice

In recent years, several techniques have been proposed and investigated based on fuzzy theory or evidence theory [21, 28-30] and Bayesian network (BN) [20, 31-33] to represent uncertainty and vagueness. A summary of recent literature on Fuzzy logic and Bayesian network applications is presented in Table 2. Fuzzy systems have been proposed to deal with vagueness, which is caused by uncertainty in observation, and to represent ambiguous data when available information is limited [34-36]. Bayesian networks, on the other hand, have long been applied as a cause-effect analysis tool for simulating the behavior of a system in situations of high uncertainty and missing data in many fields of study, ranging from social science to economics [37]. For instance, BN is efficient for handling risk assessment and decision-making under uncertainty [38] and it is typically used in risk analysis applications [39], such as seismic risk analysis [20, 40], earthquake disaster risk index [41], reliability engineering [42, 43], and safety management [44-46]. BNs have been implemented extensively to analyze and measure the resilience of critical infrastructures, such as waterspouts, supply chains, and manufacturing

[47-52]. For example, Hosseini and Barker [53] proposed a methodology to quantify resilience as a function of absorptive, adaptive, and restorative capacities through Bayesian networks with the application on an inland waterway port. In recent years, BNs have been employed in different water related issues as management tools [54-57]. Roozbahani et al. [58] developed a framework based on prediction of groundwater level using Bayesian networks model. The model was evaluated for restoring the Birjand aquifer in Iran in different hydrological conditions. A Hybrid Bayesian Networks (HBNs) was employed to develop an intelligent model for hydraulic simulation and operational performance evaluation of the agricultural water distribution system [59]. However, to this date, no downtime estimation model for pipeline networks that uses FL or BN inference methods can be found in the literature. Although the comparison among probabilistic and non-probabilistic frameworks has been addressed in several works [60-64], in most cases, the comparison is made at the theoretical level without a practical perspective [65]. Furthermore, a comparison between the two approaches focusing on the treatment and representation of the uncertainty in the recovery time estimation is still missing.

The primary goal of this paper is to introduce a system-based downtime estimation model for pipeline systems following a hazardous event. This proposed system includes important aspects of downtime and the different uncertainty types. The contribution of this paper is summarized as follows:

1) Developing a generic downtime estimation model for pipeline systems considering all relevant aspects of downtime.
2) Accounting for different types of input information and uncertainties by integrating FL and BN inference methods within the model.
3) Presenting a case scenario to demonstrate the applicability of the introduced downtime estimation model using both inference methods and considering the water network as a pipeline system.
4) Comparing the performance of both inference methods within the proposed downtime model

The downtime estimation model presented in this paper is targeted as a support tool for decision-makers to learn the overall repair time of their systems and help them prioritize the financial resources during the planning and management of disasters accordingly. It also provides a more general downtime model that adds to the existing literature. The remainder of the paper is organized as follows: Section 2 is devoted to the development of the downtime estimation model and to the description of the key indicators that are identified from past studies. Section 3 presents the case scenario that will be used to demonstrate the proposed downtime estimation approach. Sections 4 and 5 are dedicated to reviewing the basic knowledge of the FL and BN, respectively, and their implementation within the downtime estimation model. Section 6 compares the two approaches in terms of outputs and limitations. Finally, conclusions are drawn in Section 7 together with the proposed future work.

Table 2. Recent literature on Fuzzy Logic and Bayesian Network methodologies

Reference	Goal	Methodology	Results
Muller [66]	Assess the resilience of critical infrastructures	Fuzzy approach	The approach helps identifying important criteria to evaluate the resilience of infrastructures
He and Cha [67]	Modeling the recovery of critical infrastructures	Graph theory	Recovery time is sensitive to the relative importance between systems
Hosseini and Barker [46]	Evaluation of resilience-based supplier	Bayesian Network	Flexibility of variable types, inference analysis, accounting for uncertainty
Ferdous et al. [28]	Handling uncertainty in a Quantitative Risk Analysis (QRA)	Fuzzy approach	Fuzzy-based approaches properly address the uncertainties in expert knowledge
Hosseini and Barker [53]	Quantifying resilience of infrastructures	Bayesian Network	Bayesian Network can quantify resilience from qualitative variables. Backward analysis of BN provides insights to achieve a specific level of resilience for port decision-makers
This paper	Estimate recovery time of pipelines	Fuzzy approach and Bayesian Network	Downtime estimation model adaptable to any pipeline system

Downtime model for water and gas lifelines

Indicators selection and clustering

Developing the downtime estimation model for water and gas infrastructures starts by selecting the indicators that affect the downtime. All factors that contribute to the downtime estimation – geological, engineering, economic, social, and political factors – have been considered while selecting the indicators. The selection procedure starts from the target indicator, the downtime, which is decomposed into factors and sub-factors that together define it [68]. To reduce the subjectivity in selecting the downtime indicators, three criteria were considered: *validity*, *measurability*, and *coherence* [68, 69]. A total of 31 key indicators have been selected based on an extensive review of previous publications and studies [41, 68, 70, 71]. The indicators collected from the literature have been filtered to obtain mutually exclusive indicators. This has led to rejecting a number of indicators either because they are not relevant or because they overlapped with other indicators. The indicators can be classified under four main indices: (i) "Exposed infrastructure" (EI), (ii) "Earthquake intensity" (E), (iii) "Available human resources" (HR), and (iv) "Infrastructure type" (I) (Table 3-Table *6*). Figure 2 illustrates the downtime estimation model and the hierarchical relationships between the indices and the indicators. To construct the downtime model, casual and logical relationships among the downtime indicators are identified based on expert knowledge and published literature. The indicators are clustered as follows:

- Group 1: indicators referring to economic and financial reserves that support the capacity of a community to effectively respond to and recover from a disaster.
- Group 2: indicators referring to the exposure level of infrastructure. These indicators are composed of indicators related to the evaluation of the infrastructure's post-disaster condition and indicators related to the characteristics of the analyzed infrastructure.
- Group 3: Indicators related to the seismic event. These indicators represent the hazard demand a community will be subject to.
- Group 4: indicators referring to the availability of humans, composed of policy and planning indicators as well as indicators related to the affected area.

In the following, every index and its indicators are described in detail.

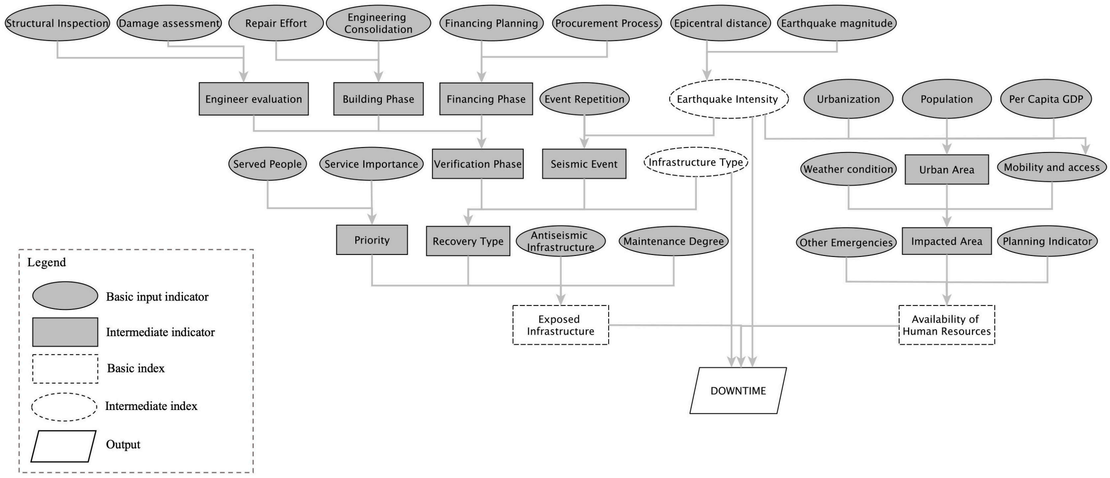

Figure 2. Downtime assessment model for water and gas infrastructure

Exposed Infrastructure (EI)

Table 3 lists the EI indicators along with their state, the performance measure, and the sources used to obtain them (when available). The EI index, describing how effectively and efficiently a community can respond to recover from short-term and long-term impacts, is quantified through the *Maintenance degree* of the infrastructure, which represents the state of deterioration of the infrastructure. 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. Therefore, in this work, it is assuming that a higher maintenance rate would lead to a lower likelihood of damage as well as a lower recovery time. The EI index also relies on the *Priority* of the infrastructure system, which is defined by the number of *Served people* and the *Service importance* of the infrastructure within the community, the *Anti-seismic technology* of the structure and the *Recovery type*. The *Recovery type* includes indicators representing the *Verification phase*, which is the sum of the time and effort required for the *Engineer evaluation*, the *Building phase*, the *Financing phase*, indicators related to the *Seismic event*, and it is also affected by the analyzed "Infrastructure type" index. The *Engineer evaluation* indicator, which is the time teams of specialists (e.g., engineers) need to define and compare the assessments and give feedback on the potentially damaged infrastructure after the inspection, is based on the *Structural inspection* process and the quantification of the damages represented by the *Damage assessment* indicator [72]. The *Building phase*, sub-classified into *Repair effort* and *Engineering consolidation*, provides all those processes of design and intervention which aim at restoring the structural characteristics of the structure. The *Financing Phase* is divided into the *Financing planning* indicator, which represents the time the expert needs to plan and distribute properly funds and resources in the right manner, and the *Procurement process*. The *Procurement process* indicator is the time required to make an offer by an individual or business for a product or service. In the aftermath of a disastrous event, it is very important to shorten the procurement process in such a way to speed up the recovery process [20]. Finally, the *Seismic event* indicator depends on the *Event repetition* indicator and on the "Earthquake intensity" index.

The indicators that are related to the "Exposed infrastructure" index are described in Table 3. Information about the "Infrastructure type" index and "Earthquake intensity" index along with their indicators are described separately in Table 5 and Table 6.

Table 3. Description of the "Exposed infrastructure" indicators

Indicator/Index	State	Performance measure/Reference
Exposed Infrastructure	Low High	Visual inspection/Expert opinion
Maintenance Degree	Poor Medium Good	Visual inspection/Expert opinion
Served people	Low Medium High	≤ 20% Population 20%<Served People<50% Population > 50% Population [73]
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 [71]
	Short	

Financing Phase	Medium Long	Visual inspection/Expert opinion [71]
Procurement Process	Reactive Emergency Accelerated	Major hazards State of emergency taken off Immediate needs [71, 74]
Building Phase	Easy Difficult Very Difficult	Visual inspection/Expert opinion [71]
Engineer Evaluation	Short Medium Long	Visual inspection/Expert opinion [71]
Structural Inspection	Short Medium Long	Visual inspection/Expert opinion [71]
Damage Assessment	Short Medium Long	Visual inspection/Expert opinion [71]
Event Repetition	Once Many	First shock Aftershocks [71]
Seismic Event	Dangerous Very Dangerous Extremely Dangerous	6<M76 7<M≤8 M>8
Financing Planning	Short Medium Long	Visual inspection/Expert opinion [71]
Repair Effort	Short Medium Long	Visual inspection/Expert opinion [71]
Verification phase	Short Medium Long	Visual inspection/Expert opinion [71]
Engineering Consolidation	Easy Difficult Very Difficult	Visual inspection/Expert opinion

Availability of Human Resources (HR)

Information on the "HR" index and its indicators is presented in Table 4. As shown in Figure 2, the "HR" index is influenced by three indicators: the occurrence of *Other emergencies* at the same time, the availability of a structured and defined *Planning indicator*, and the characteristics of the *Impacted area*. The *Planning indicator* 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 [20].

Table 4. Description of "Availability HR" indicators

Indicator/Index	State	Performance measure	Reference
Availability HR	Low High	Expert opinion	[75]
Other Emergencies	Yes No	Expert opinion	
Planning Indicator	Bad	Inadequate and inactive	[68]

	Good Excellent	Inadequate or inactive Adequate and active	[41]
Impacted Area	Small Medium Large	Visual inspection/Expert opinion	[41]
Mobility and Access	Easy Medium Hard	Visual inspection/Expert opinion	[41]
Urban Area	Small Medium Large	50.000<Population<200.000 200.000<Population<500.000 Population>= 500.000	[71] [73] [41]
Weather Condition	Very bad Bad Good	T ≤32°F or T ≥90°F 32°F<T ≤55°F and 75°F ≤T<90°F 55 °F<T < 75°F	[68] [41]
PCGDP	Low Medium High	≤5 5<PCGDP<40 >40	[41] [76]
Population	Low Medium High	<50.000 50.000<Population≤<00.000 Population>= 500.000	[73] [41]
Urbanization	Low Medium High	< 0 0 < Urbanization rate <3 > 3	[41] [77]

The *Impacted area* indicator can be divided into three sub-indicators: the *Weather condition* of the affected area, the easiness of *Mobility and access* into the area, and the characteristics of the *urban area*. The *Mobility and access* indicator is dependent on the conditions of the post-earthquake transportation system, the number of debris, and the "Earthquake intensity" index. The *Weather condition* indicator is expressed in terms of the temperature [68]. Four ranges have been selected to describe the *Weather condition* indicator, as listed in Table 4.

Besides, the *Urban area* indicator is identified by *Per Capita Gross Domestic Product* (PCGDP), which is the indicator of a nation's living standards, the *Population* density of the impacted area, and the *Urbanization* degree [76-78].

Infrastructure Type (I)

Outlined in Table 5 are the types of infrastructures that are considered in the proposed downtime model: water and gas networks. The “Infrastructure type” is a key index in the downtime evaluation since it affects the *Recovery type* indicator and the downtime output [70].

Table 5. Description of “Infrastructure Type” indicators

Indicator/Index	State	Performance measure/Reference
Infrastructure Type	Water	[8]
	Gas	

Earthquake Intensity (E)

Table 6 below presents the “Earthquake Intensity” (E) index, which expresses the severity of the earthquake to which a city will be subject. The E index influences the *Seismic event* and the *Mobility and access* indicators and directly the downtime output node. It is defined by combining the *Epicentral distance* and the *Earthquake magnitude* indicators. 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 in 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* indicator, (Strong 6-7, Major 7-8, Severe 8-9, Violent 9-10). The “Earthquake Intensity” index 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, Violent MM>MMX).

Table 6. Description of “Earthquake intensity” indicators

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

Demonstrative example

In this section, the proposed downtime model is verified with the water network of the city of

Calascibetta in Sicily, Italy (see Figure 3). Calascibetta water distribution network has been recently installed, replacing the previous one due to intensive water leakage.

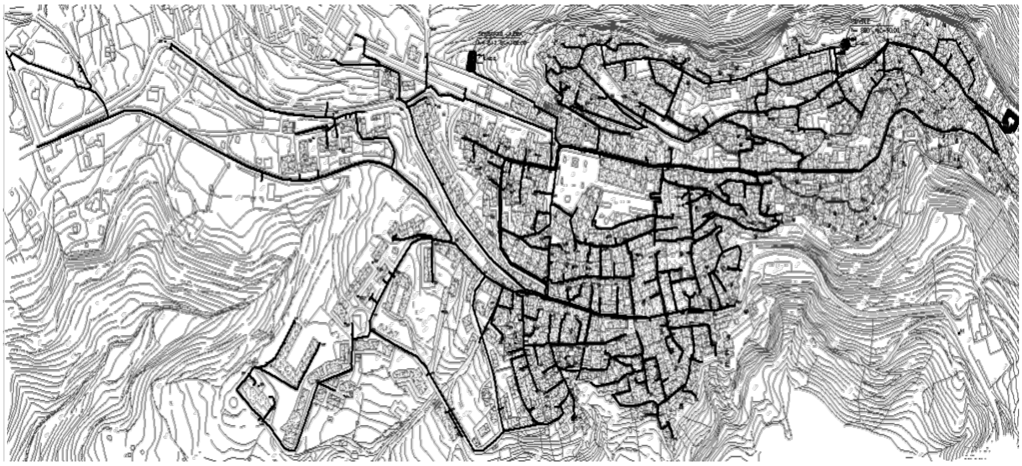

Figure 3. Calascibetta Water Distribution Network

The earthquake considered in the analysis is the 7.4 magnitude earthquake, known as "Noto valley earthquake", that hit almost the whole of eastern Sicily (Italy) on the 11th of January 1693. The earthquake caused about 60.000 injuries and affected an area of 5.600 square kilometers. Although the exact position of the epicenter remains uncertain, it is believed that it was close to the coast. The earthquake was followed by tsunamis that devasted the coastal part of the Ionian Sea and in the Straits of Messina. Simulating an emergency scenario consists of assigning a performance measure to each downtime indicator (e.g., *Procurement process*, *Service importance* of the infrastructure, *Impacted area*, etc.) of the potentially damaged infrastructures. Downtime indicators should be given qualitative judgments by an expert in the related field. In this work, some of the states of the indicators have been assumed (e.g., *Damage Assessment*, *Financing Planning*, *Repair Effort*) while others have been determined through available data (e.g., *Population*, *Per Capita GDP*, *Urbanization*). The input indicators used to quantify the downtime are summarized in Table 7. The state of each basic input indicator in Table 7 has been selected from the state ranges in Table 3-Table 6.

Table 7. Input data used to assess the downtime of water network

Basic input indicator	State
Damage assessment	Long
Structural inspection	Medium

Financing Planning	Medium
Procurement Process	Emergency
Repair Effort	Long
Engineering Consolidation	Very Difficult
Earthquake magnitude	Major
Epicentral distance	Far
Event Repetition	Many
Service Importance	High
Served People	High
Maintenance Degree	Medium
Anti-seismic Infrastructure	No
Infrastructure Type	Water
Per Capita GDP	Medium
Population	Low
Urbanization	Medium
Weather condition	Good
Other Emergencies	Yes
Planning Indicator	Bad

Table 8. Description of the downtime indicator

Output	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

Five downtime intervals (e.g., states) are introduced to discretize the downtime output see Table 8). The five ranges for the downtime indicator have been determined after observing raw data and restoration curves from a previous study [8]. That is, it has been noticed that most infrastructures take time within these ranges to recover their functionality; therefore, the different ranges for the states have been defined based on that. In the next section, the downtime of the water network of the city of Calascibetta, Sicily (Italy) is estimated using two inference methods, FL and BN.

Downtime estimation using Fuzzy Logic

This section illustrates an overview of the FL theory and the methodology adopted for estimating the downtime of buried pipelines after earthquakes for cases with high uncertainty.

Fuzzy Logic theory

The concept of fuzzy set and the theory behind it was introduced by [79] to deal with the vagueness and subjectivity of human judgment in using linguistic terms in the decision-making process [80, 81]. While in the classical binary logic a statement can be valued by an integer number, zero or one corresponding to true or false, in the fuzzy logic a variable x can be a member of several classes (fuzzy sets) with different membership grades (μ) ranging between 0 (x does not belong to the fuzzy set) and 1 (x completely belongs to the fuzzy set) [82]. Fuzzy logic became a key factor in several fields such as Machine Intelligence Quotient (MIQ) to mimic the ability of humans, industrial applications, and earthquake engineering. The fuzzy logic consists of three main steps: a) Fuzzification; b) Fuzzy inference system, and c) Defuzzification (see Figure 4).

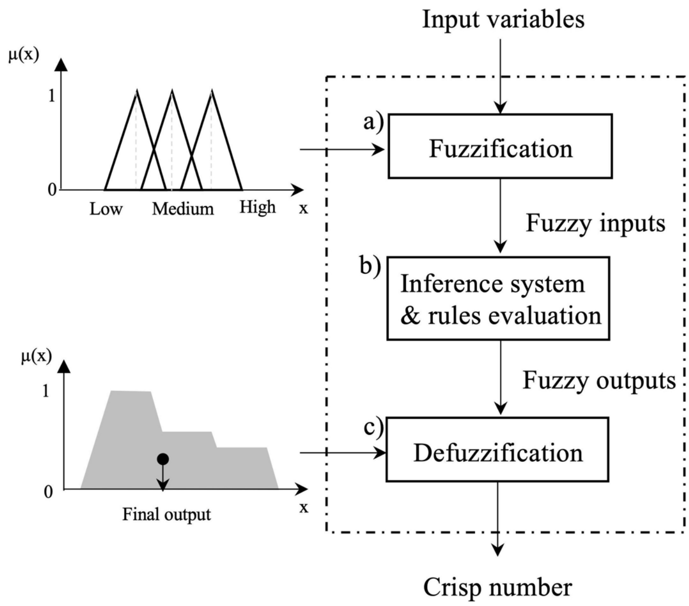

Figure 4. Fuzzy Inference System (FIS)

Step a: Fuzzification – Membership Functions

As mentioned before, the basic input indicators (i.e. those with oval shape in Figure 2) could have different states (also called linguistic quantifiers in Fuzzy logic) (see Table 3, Table 4, and Table 5). The number of states for these indicators is not constant (i.e., some have only two, some have three, and the others have four states). However, to implement the fuzzy theory in the DT model easily, the number of states is set to three states for all indicators (e.g., *low,* *medium*, and *high* or *small*, *medium*, and *large,* etc.). Taking into account more than 3 states (e.g., five states) leads to a more complicated fuzzy process. The main difficulty in designing membership functions is caused by the necessity to establish fuzzy levels and intervals. This difficulty could be increased if more states are considered since more membership functions would then be necessary to apply the fuzzy logic. In terms of fuzzy rules, a high number of states corresponds to a high number of fuzzy rules to cover all the possible permutations of the states. Consequently, designing membership functions and determining fuzzy rules become complicated. Increased number of states can, of course, make the results more specific; however, this comes at the cost of input demand: the expert would then need to provide more detailed membership functions and more rules, which could be not practical. Choosing three states is thought to provide the best balance between input demand and output clarity. Thus, in this paper, only three states are considered for every indicator. Linguistic quantifiers (i.e., states) assigned to the basic indicators are transformed into equivalent numbers (f*uzzy* numbers) on a range [0 1]. In this work, transformed values close to 0 (e.g., 0.20, 0.30) correspond to low downtime (i.e., values are closer to the *low* membership function), while values close to 1 (e.g., 0.8, 0.9) correspond to high downtime. The basic indicators and the corresponding fuzzy values are listed in Table 9.

The fuzzification step converts the input values into a homogeneous scale by assigning corresponding membership functions concerning their specified granularities [82]. The definition of membership functions is the main step on which all the other subsequent operations are based. Such functions, representing the fuzzy sets, can take different shapes (triangular, trapezoidal, and Gaussian, etc.) according to the situations, although regular shapes are commonly used [83]. There are many possible ways of selecting membership functions of fuzzy variables. Selection of membership functions can be intuitive or based on logical operations (Ross 1995), For instance, triangular or trapezoidal fuzzy membership functions are usually used to represent linguistic variables since their simplicity to apply fuzzy operations [34].

The membership functions considered in the methodology are based on triangular fuzzy numbers (TFNs). The granulation assigned to each indicator is illustrated in Figure 5. As indicated, while the membership function and the granulation of downtime indicators are represented using three-tuple membership values (μ_L, μ_M, μ_H), the downtime output is represented using five-tuple membership values (μ_{VL}^{DT}, μ_L^{DT}, μ_M^{DT}, μ_H^{DT}, μ_{VH}^{DT}) and each membership value is associated with five downtime intervals (e.g., states), *very low* (VL)*, low* (L)*, medium* (M)*, high* (H)*, and very high* (VH) to have more precise results.

Table 9. Basic input indicator and transformation

Basic input indicator	Field observation	Transformation
Damage assessment	Long	0.80
Structural inspection	Short	0.20
Financing Planning	Medium	0.50
Procurement Process	Emergency	0.50
Repair Effort	Long	0.90
Engineering Consolidation	Very Difficult	0.90
Earthquake magnitude	Major	0.35
Epicentral distance	Far	0.50
Event Repetition	Many	0.80
Service Importance	High	0.80
Served People	High	0.80
Maintenance Degree	Medium	0..50
Antiseismic Infrastructure	No	0.90
Infrastructure Type	Water	0.35
Per Capita GDP	Medium	0.50
Population	Low	0.20
Urbanization	Medium	0.50
Weather condition	Good	0.20
Other Emergencies	Yes	0.90
Planning Indicator	Bad	0.80

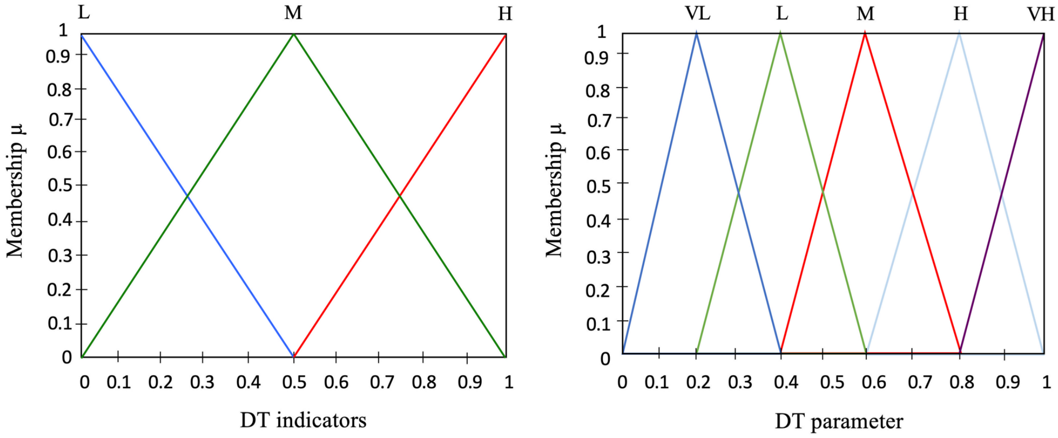

Figure 5. Membership function and granulation for the input indicators and the downtime indicator

After selecting the transformation value for each downtime indicator, one can enter the corresponding membership graph (see Figure 5) and obtain the membership degree. The results are listed in Table 10.

Table 10. Fuzzification process

Basic input indicator	Fuzzification
Damage assessment	$(\mu_S^{AD}, \mu_M^{AD}, \mu_L^{AD}) = (0, 0.38, 0.62)$
Structural inspection	$(\mu_S^{SI}, \mu_M^{SI}, \mu_L^{SI}) = (0.55, 0.45, 0)$
Financing Planning	$(\mu_S^{FP}, \mu_M^{FP}, \mu_L^{FP}) = (0, 1, 0)$
Procurement Process	$(\mu_R^{PP}, \mu_E^{PP}, \mu_A^{PP}) = (0, 1, 0)$
Repair Effort	$(\mu_S^{RE}, \mu_M^{RE}, \mu_L^{RE}) = (0, 0.15, 0.85)$
Engineering Consolidation	$(\mu_E^{EC}, \mu_D^{EC}, \mu_{VD}^{EC}) = (0, 0.15, 0.85)$
Earthquake magnitude	$(\mu_L^{EM}, \mu_M^{EM}, \mu_H^{EM}) = (0.35, 0.65, 0)$
Epicentral distance	$(\mu_L^{ED}, \mu_M^{ED}, \mu_H^{ED}) = (0, 1, 0)$
Event Repetition	$(\mu_L^{ER}, \mu_M^{ER}, \mu_H^{ER}) = (0, 0.38, 0.62)$
Service Importance	$(\mu_L^{SI}, \mu_M^{SI}, \mu_H^{SI}) = (0, 0.38, 0.62)$
Served People	$(\mu_L^{SP}, \mu_M^{SP}, \mu_H^{SP}) = (0, 0.38, 0.62)$
Maintenance Degree	$(\mu_P^{MD}, \mu_M^{MD}, \mu_G^{MD}) = (0, 1, 0)$
Anti-seismic Infrastructure	$(\mu_L^{VI}, \mu_M^{VI}, \mu_H^{VI}) = (0, 015, 0.85)$
Infrastructure Type	$(\mu_L^{IT}, \mu_M^{IT}, \mu_H^{IT}) = (0.35,0.70,0)$
Per Capita GDP	$(\mu_L^{PCGDP}, \mu_M^{PCGDP}, \mu_H^{PCGDP}) = (0, 1, 0)$
Population	$(\mu_L^{P}, \mu_M^{P}, \mu_H^{P}) = (0.55, 0.45, 0)$
Urbanization rate	$(\mu_L^{UR}, \mu_M^{UR}, \mu_H^{UR}) = (0, 1, 0)$
Weather condition	$(\mu_{VB}^{EW}, \mu_B^{EW}, \mu_G^{EW}) = (0.55, 0.45, 0)$
Other Emergencies	$(\mu_L^{OE}, \mu_M^{OE}, \mu_H^{OE}) = (0, 0.15, 0.85)$
Planning Indicator	$(\mu_B^{PI}, \mu_G^{PI}, \mu_E^{PI}) = (0, 0.38, 0.62)$

Step b: Aggregation through Fuzzy rules

The relationships between inputs and outputs are defined through the *fuzzy rule base* (FRB) that is derived from heuristic knowledge of experts or historical data. The Mamdani Fuzzy Logic inference method, known as the Max-Min method, is implemented in this work, as it is the most suitable when the fuzzy system relies on expert knowledge and experience [84]. Mamdani systems are composed of IF-THEN rules of the form "IF x is A (antecedent) THEN y is B (consequent)". Each rule delivers a partial conclusion, which is aggregated to the other rules to provide a conclusion (aggregation). The aggregation of the rules determines a rule base that is valid over the entire application domain. In general, there is no single best method to generate fuzzy rules; rather the choice is context-dependent. To determine fuzzy rules that govern the system when information is scarce or missing, expert-based knowledge (knowledge base) is used to combine all the different variables allowing the system to take care of all the different possibilities that could happen. The use of the fuzzy rule-based method allows decision-makers to express their preferences in a modular fashion and update the fuzzy inference system by using new information as it becomes available [85]. The fuzzy rules are defined using a weighting method that allows identifying the impact of the input towards the output [21, 22]. The results of the rules are then combined to get a final output through the inference process. The process is performed by using fuzzy set operations to describe the behavior of a complex system for all values of inputs. Mamdani's inference system consists of three connectives: the aggregation of the antecedents in each rule (AND connectives), implication (IF-THEN connectives), and aggregation of the rules (ALSO connectives). As Figure 2 shows, many indicators are considered in the downtime estimation model, and consequently, several fuzzy rules are required to combine them. In a fuzzy-based model, an increase in the number of input values results in an exponential increase in the number of rules [86]. Different strategies are presented to deal with the high number of rules: (i) identification of functional relationships, (ii) sensory fusion, (iii) rule hierarchy, and (iv) interpolation [87]. Magdalena [88] showed that a decomposition at the level of indicators is a proper solution. For instance, from Figure 2, it can be shown that the "Exposed infrastructure" index has four inputs: *Maintenance degree*, *Recovery type*, *Anti-seismic infrastructure*, and *Priority*. Using a three-tuple fuzzy number, which corresponds to three states (e.g., *low, medium,* and *high*), the number of rules required to combine the indicators is $3^4 = 81$. According to the process described by [88], the hierarchical structure can be decomposed at the level of indicators by introducing intermediate connections among the indicators at different levels of the hierarchy and by defining intermediate rules. Figure 6 illustrates the hierarchical fuzzy decomposition for the "Exposed infrastructure" index. As shown, pairs of indicators are aggregated through intermediate rules (temporary rules), which are TR_1, TR_2, TR_3, and TR_4. The output of the intermediate inference is then aggregated through fuzzy rule based R_1, R_2, and R_3. Thus, a new rule hierarchy is developed, and the number of rules is reduced to 7·3^2 = 63, where 7 are the rules, 3 are the fuzzy states for each indicator (e.g., *low*, *medium*, and *high*), and 2 is the number of indicators aggregated at each level of the hierarchy.

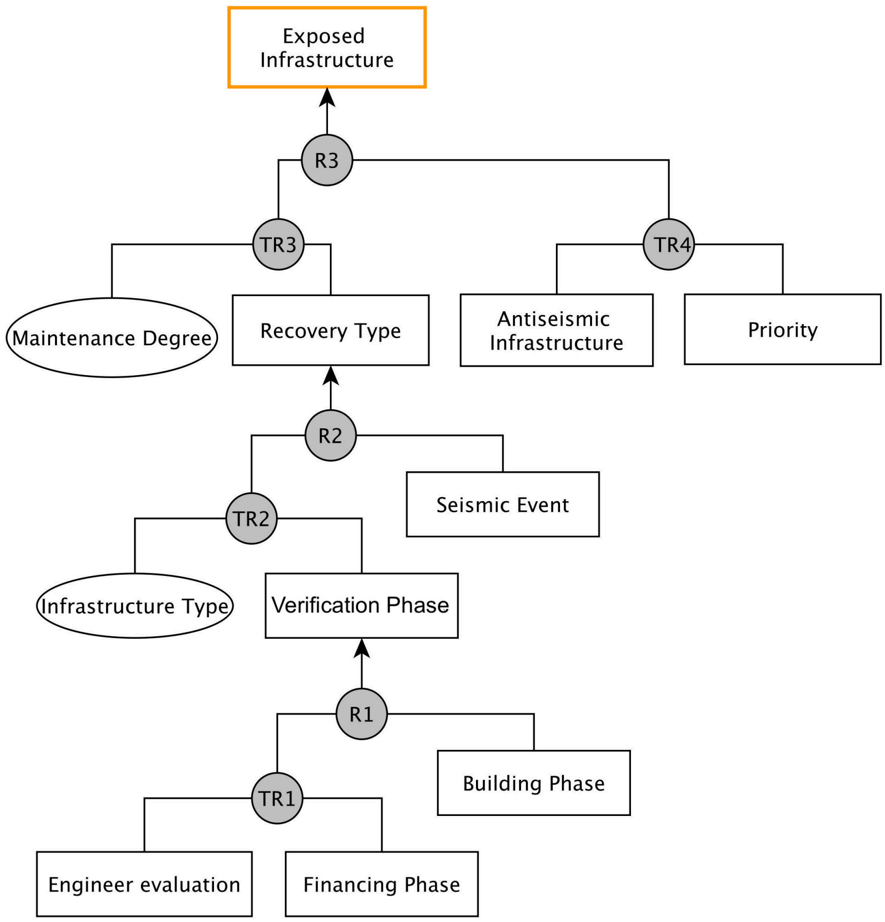

Figure 6. Hierarchical fuzzy rule base decomposition for the "Exposed Infrastructure" index

For example, the *Engineer evaluation* and *Financing phase* are aggregated through TR_1. The output of TR_1 is then aggregated with the *Building phase* indicator through R_1 to obtain the *Verification Phase*. The three-tuple fuzzy set output at each level of the hierarchical scheme is defuzzified to obtain a single crisp value. In turn, this value is fuzzified into the next level. An example of the fuzzy rule assigned for combining the *Damage assessment* and *Structural inspection* to obtain *Engineer evaluation* (see Figure 2) is given in Table 11. The indicators are combined taking into account their importance towards the output [21, 22]. Thus, in the table, every indicator (i.e., DA and SI) is assigned a weighting factor that distinguishes its importance towards the output (i.e., EE).

Table 11. Fuzzy rule for Engineer Evaluation

Rule	*DA* *W=2*	*SI* *W=1*	*EE*
1	S	S	S
2	S	M	S
3	S	L	M
4	M	S	M
5	M	M	M
6	M	L	M
7	L	S	M
8	L	M	L
9	L	L	L

Using the fuzzy rule base (Table 11), the *Engineer evaluation* is computed as follows:

$$\begin{gathered}\mu_S^{EE} = \max\left(\min(0,0.55), \min(0, 0.45)\right) = 0\\ \mu_M^{EE} = \max\left(\min(0,0), \min(0.38,0.55), \min(0.38,0.45), \min(0.38,0), \min(0.62,0.55)\right) = 0.55\\ \mu_L^{EE} = \max(\min(0.62,0.45), \min(0.62,0)) = 0.45\end{gathered} \quad (1)$$

Step c: Defuzzification to calculate corresponding crisp outputs

The last step of the FL is the *defuzzification* process that represents the inverse of the fuzzification process. The purpose of the defuzzification step is to defuzzify the output fuzzy set resulting from the inference process and obtain a final crisp number. Different defuzzification methods can be found in the literature, such as the Center-of-Gravity (CoG) and Mean of Maximum (MoM) methods. At each level of the hierarchical scheme, fuzzy outputs are defuzzified through the center of gravity (also known as the center of area) method. This defuzzification method calculates the area under the membership functions within the range of the output, then computes the geometric center of the area as follows:

$$CoA = \frac{\int_{x_{min}}^{x_{max}} f(x)\cdot x dx}{\int_{x_{min}}^{x\ max} f(x) dx} \tag{2}$$

where *f(x)* is the function that shapes the output fuzzy set after the inference process and *x* stands for the real values inside the fuzzy set support [0,1]. Using the center of gravity technique, the *Engineer Evaluation* is defuzzify as 0.54. The defuzzification of the other indicators is done in the same fashion.

The downtime of water lifeline is given through inferencing the “Availability of human resources”, the “Infrastructure type”, the “Earthquake intensity”, and the “Exposed infrastructure” indices as (μ_{VL}^{DT}, μ_{L}^{DT}, μ_{M}^{DT}, μ_{H}^{DT}, μ_{VH}^{DT}) = (0,0,1,0,0). According to the downtime membership functions, considering the highest membership value, the downtime of the water network may be classified as *medium* (11-24 days).

Sensitivity analysis of fuzzy membership functions

A sensitivity study is conducted in this work to perform a series of different simulations per type of membership function to reduce the subjectivity in the choice of membership functions and to identify the best result in terms of downtime. Such a sensitivity analysis allows understanding how the variation in the shape of the membership function affects the overall effectiveness of the system. It is performed by repeating the whole fuzzy inference procedure, modifying membership functions at a time (triangular, trapezoidal, and Gaussian membership function), keeping unvaried all the other features, thus performing 3 different simulations. From each of the 3 simulations performed, information concerning the downtime indicators and the output (i.e., the. downtime) is obtained.

By analyzing the results obtained (see Figure 7), it is possible to conclude that the investigated membership functions provide similar results for the downtime output (around 0.6). This means that membership functions do not have a high impact on the fuzzy inference procedure within the proposed downtime assessment model.

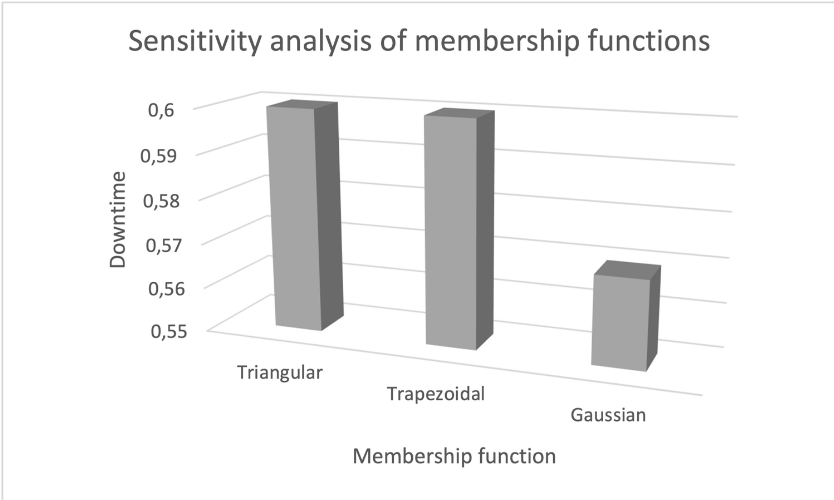

Figure 7. Histograms representing the downtime results obtained through the analyzed membership functions

Downtime estimation using Bayesian network

This section describes the BN approach and the methodology performed for quantifying the recovery time of damaged water and gas lifelines following earthquakes.

Bayesian network theory

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 structured based on Bayes' theorem that permits graphical probabilistic relationships among a set of variables [89]. Bayesian networks can update prior probabilities of some unknown variable when some evidence describing that variable exists. The uncertain variables in a BN model can be graphically represented through vertices (nodes) with an edge representing the casual relationship between two vertices and the uncertainties can be expressed through subjective probabilities [43, 89]. The ability of BN to represent graphically real-world applications where there are frequently many uncertain and unknown variables makes the approach suitable for experts' knowledge.

Let $V = (X_1, X_2, X_3)$ be the set of variables in a BN whose structure specifies a conditional relationship. An outgoing edge from X_1 to X_3 indicates that the value of variable X_3 is dependent on the value of X_1 variable. Thus, X_1 is the parent node of X_3, and X_3 is a child node of X_1. An illustrative example of BN with three variables is illustrated in Figure 8.

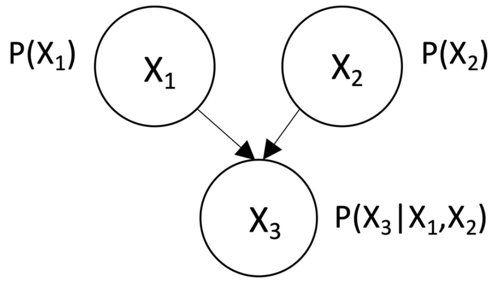

Figure 8. An example of BN with three variables

In this work, the BN includes (see Figure 9):

a) Design of BN by adding nodes that represent considered indicators and the corresponding states (e.g., *low, medium*, and *high*) and definition of parent-child relationships through causal arrows.
b) Estimation of unconditional and conditional probabilities for parent and child nodes, respectively (parameterizing the network).
c) Estimation of the downtime conditional probabilities.
d) Inference system and output evaluation (i.e., the downtime).

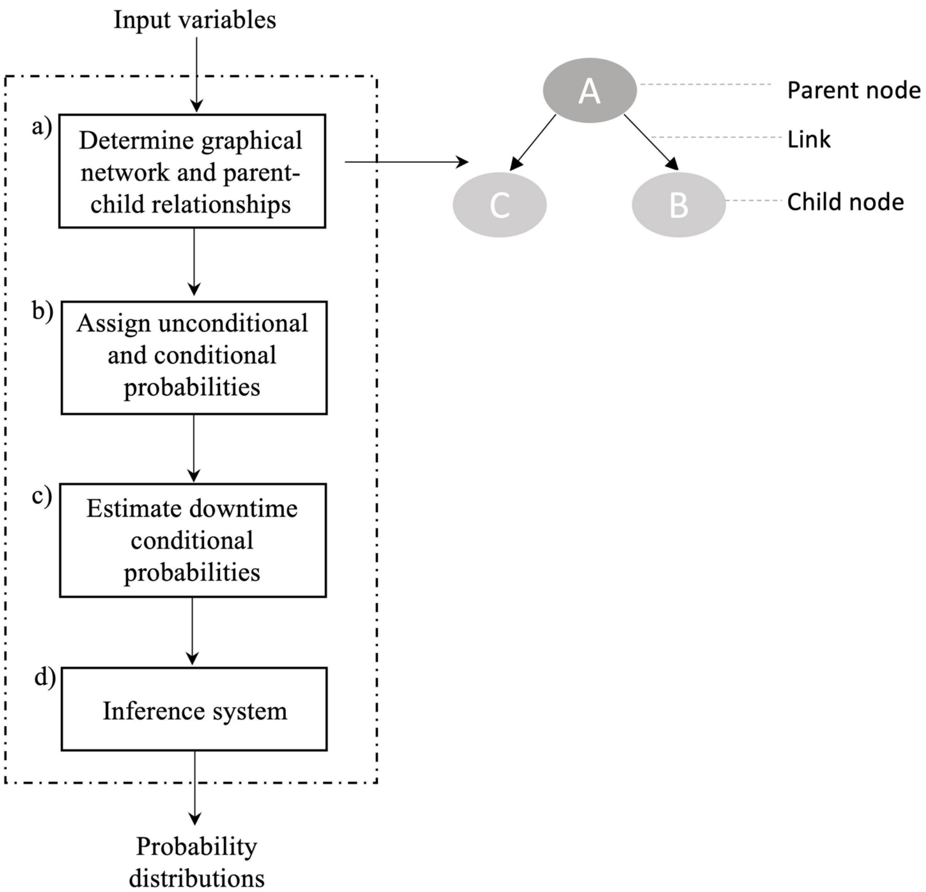

Figure 9. Steps for a Bayesian Network (BN) development

Step a: Graphical network and parent-child relationships

The graphical Bayesian Network of the proposed DT assessment model (see Figure 2) is built through Netica software [90]. A set of links are used to define parent-child relationships among the downtime indicators. Casual relationships among the downtime indicators are measured by conditional probability distributions. Conditional distributions are usually referred to as conditional probability tables (CPT). The casual relationships between indicators and corresponding CPT are established based on expert knowledge and published literature. The BN model built using Netica software is depicted in Figure 10.

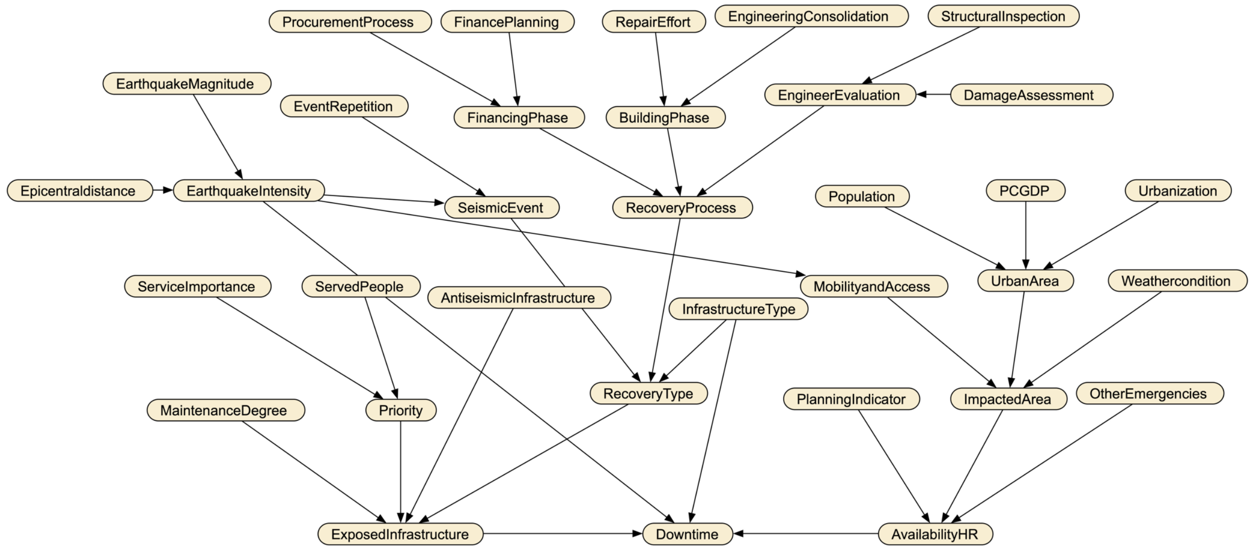

Figure 10. The Bayesian Network of the Downtime indicators using Netica software

Step b: Assigning unconditional and conditional probabilities

The main concept of BN results from the Bayes' theorem in which the relation between two nodes, hypothesis *A* (parent) and evidence *E* (child), is represented as:

$$p(A|B) = \frac{p(B|A)\ x\ p(A)}{p(B)} \tag{3}$$

where *p(A|B)* is one's belief for hypothesis *A* upon observing evidence *B*, *p(B|A)* is the likelihood that *B* is observed if *A* is true, *p(A)* is the probability that the hypothesis holds, and *p(B)* is the probability that the evidence takes place. Furthermore, *p(A|B)* is known as *posterior* probability and *p(A)* is defined as a *prior* probability.

Once the downtime indicators have been connected by a set of links defining parent-child relationships among them, 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. The specification of the parameters of the probabilistic dependence model (i.e., the cause-effect relation) represented via a Conditional Probability Table (CPT) is one of the pillars of BN. Depending on the available data (prior knowledge, expert-based information, observations, etc.), CPT can be populated in several manners [91-93]. That is, different assumptions can be made, and different methods are available, which might lead to uncertainties in the BN results [94]. In the situation where data are scarce, estimating CPTs may become challenging. A possible solution is relying on expert knowledge elicitation, which means experts are asked to give qualitative statements or relative measures. In the BN, the probabilities can be subjectively defined. The BN enable converting empirical distribution and subjective probabilities in the analysis. The approach used to estimate conditional probabilities for all nodes of the downtime network is further described in [20].

In the case of independent indicators with no parents, the CPT is reduced to an unconditional probability Table (UPT). To establish unconditional probabilities (UPs) of parent nodes, the basic inputs are assigned equal weights *1/n* following the principle of insufficient reasoning, where *n* is the number of states

However, for the downtime output itself, another procedure is adopted to come up with the conditional probabilities. The approach uses past data on infrastructure restoration in the form of restoration fragility curves [8].

Step c: Estimation of downtime conditional probabilities

The complete database used for estimating the conditional probabilities of the downtime node is listed in Table 12. This database is transformed into cumulative probability restoration curves of the analyzed lifelines.

The database was collected 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. Data used to design the restoration curves of the water and gas systems have been divided into 4 sets based on the earthquake intensity: Strong 6-7; Major 7-8; Severe 8-9; and Violent 9-10). For each lifeline, a group of restoration curves considering the four magnitude ranges have been developed. Table 13 shows the data sets considered in realizing the restoration curves, extracted from Table 12.

Table 12. Number of affected infrastructures and the corresponding total recovery time

	Water		**Gas**	
	No.	DT (days)	No.	DT (days)
Loma Prieta	10	(14), (4), (3), (1.5), (2), (1), (3), (3), (7), (4)	5	(30), (16), (11), (10), (10)
Northridge	6	(7), (2), (58), (12), (67), (46)	4	(7), (30), (5), (4)
Kobe	3	(0.5), (8), (73)	3	(84), (11), (25)

Niigata	3	(14), (28), (35)	3	(28), (35), (40)
Maule	4	(42), (4), (16), (6)	2	(10), (90)
Darfield	2	(7), (1)	1	(1)
Christchurch	1	(3)	2	(14), (9)
Napa	6	(20), (0.9), (0.75), (2.5), (12), (11)	1	(1)
Michoacán	4	(30), (14), (40), (45)	-	-
Off-Miyagi	1	(12)	3	(27), (3), (18)
San Fernando	-	-	2	(10), (9)
The Oregon Resil. Plan	1	(14)	1	(30)
LA Shakeout Scenario	1	(13)	1	(60)
Tohoku Japan	8	(4.7), (47), (1), (26), (7), (1), (47), (47)	6	(54), (2), (30), (3.5), (13), (18)
Niigata	3	(15), (4), (10)	2	(180), (2)
Illapel	1	(3)	-	-
Nisqually	-	-	-	-
Kushiro-oki	3	(6), (3), (5)	2	(22), (3)
Hokkaido Toho-oki	3	(9), (3), (5)	-	-
Sanriku	3	(14), (12), (5)	-	-
Alaska	5	(14), (5), (1), (7), (14)	3	(1), (5), (2), (14)
Luzon	3	(14), (14), (10)	-	-
El Asnam	1	(14)	-	-
Tokachi-oki	-	-	2	(30), (20)
Kanto	1	(42)	2	(180), (60)
Valdivia	1	(50)	-	-
Nihonkai-chubu	1	(30)	1	(30)
Bam	3	(14), (10)	-	-
Samara	1	(2)	-	-
Arequipa	3	(32), (34)	-	-
Izmit	2	(50), (29)	1	(1)
Chi-Chi	1	(9)	1	(14)
Alaska 2002	10	(14), (4), (3), (1.5), (2), (1), (3), (3), (7), (4)	1	(3)

Three statistical distributions are used to fit data collected in the form of restoration curves: gamma, exponential, and lognormal cumulative distributions as these are the common distributions to model the downtime. The cumulative step function of the water and gas distribution infrastructures is shown in Figure 11. Gamma, exponential, and lognormal cumulative distributions are plotted against the stepwise function to visualize the distribution fit.

Table 13. Downtime data and corresponding frequencies for water and gas networks with EM 6-7, 7-8, 8-9, and 9-10

EM 6-7	Water	DT (days)	0.5	0.75	0.9	1	1.5	2	2.5	3	4	7	8	10	11	12	14	15	20	28	30	35	46	58	67	73
		Freq.	1	1	1	1	1	3	1	4	1	2	1	1	2	2	2	1	1	1	1	1	1	1	1	1
	Gas	DT (days)	1	4	5	7	9	10	11	14	16	25	28	30	35	40	84									
		Freq.	1	1	1	1	2	3	2	1	1	1	1	2	1	1	1									
EM 7-8	Water	DT (days)	1	1.5	2	3	4	5	6	7	9	10	12	13	14	15	29	30	50							

			EM 8-9				EM 9-10			
	Gas		Water		Gas		Water		Gas	
Freq.	DT (days)	Freq.	DT (days)	Freq.	DT (days)	Freq.	DT (days)	Freq.	DT (days)	Freq.
2	1	2	3	2	10	1	1	3	1	1
1	2	1	4	1	20	1	4.7	1	2	2
2	3	3	5	1	30	1	5	1	3.5	1
4	14	1	6	1	90	1	7	2	5	1
3	18	1	9	1			14	3	13	1
2	22	1	14	1			26	1	14	1
1	27	1	16	1			47	3	18	1
2	30	1	30	1			50	1	30	2
1	60	1	32	1					54	1
2	180	1	34	1						
2			40	1						
1			42	1						
5			45	1						
1										
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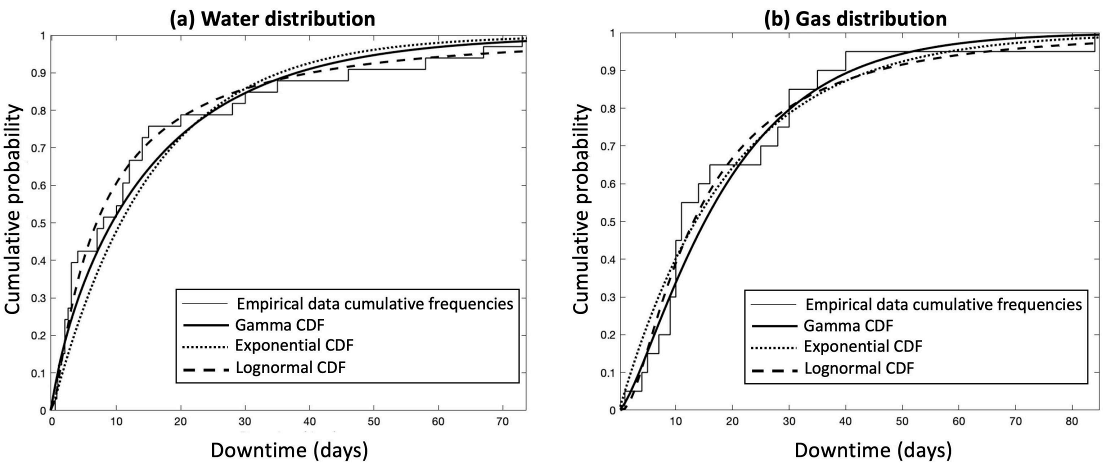

Figure 11. Cumulative frequencies with three theoretical CDF distributions for (a) water distribution infrastructure, and (b) gas distribution infrastructure for the data corresponding to EM 6-7.

Figure 12 shows the frequency histogram of the downtime data and the probability density function (PDF) of the gamma, exponential, and lognormal distributions related to (a) the water network infrastructure and (b) the gas network for earthquake magnitude range EM 6-7.

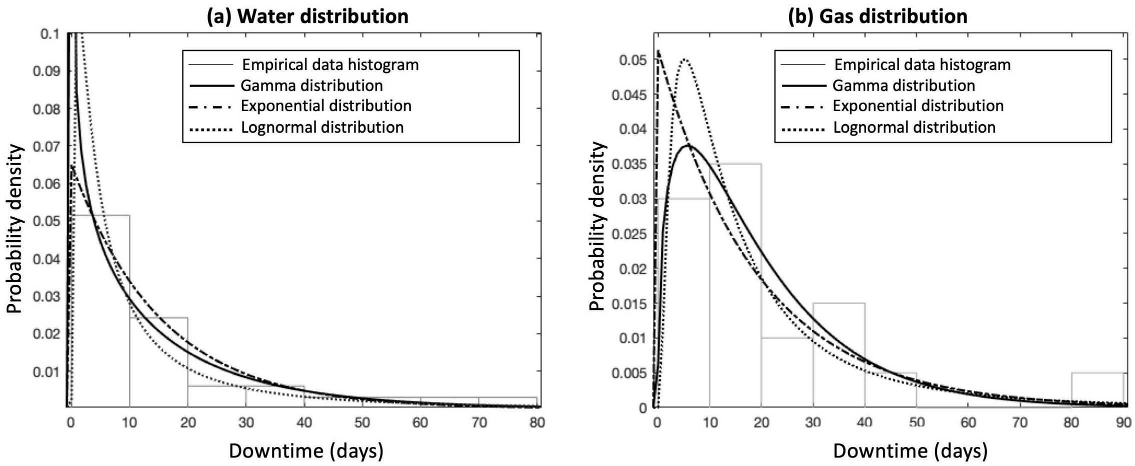

Figure 12. Histograms and PDF fitting distributions for (a) the water distribution, and (b) the gas network infrastructure for the data corresponding to EM 6-7

Since the plotted PDFs present a similar trend, it is not simple to choose the distribution with the best fit relying only on visual interpretation. Therefore, the goodness-of-fit tests (GOF) are used to identify the appropriate distribution for the empirical data [20]. Goodness-of-fit of a statistical model is a method that determines how well a model fits a set of observations. Two tests for Goodness-of-fit are used in this work the identify the distribution with the best fit: the Kolmogorov-Smirnov (K-S) and Chi-Square tests. The gamma distribution is selected to fit the downtime data of both infrastructure systems. The parameters of the chosen distribution have been determined using the Least Squares Parameter Estimation method. The restoration curves for water and gas 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: 6-7 *Strong*, 7-8 *Major,* 8-9 *Severe,* and 9-10 *Violent*, as shown in Figure 13.

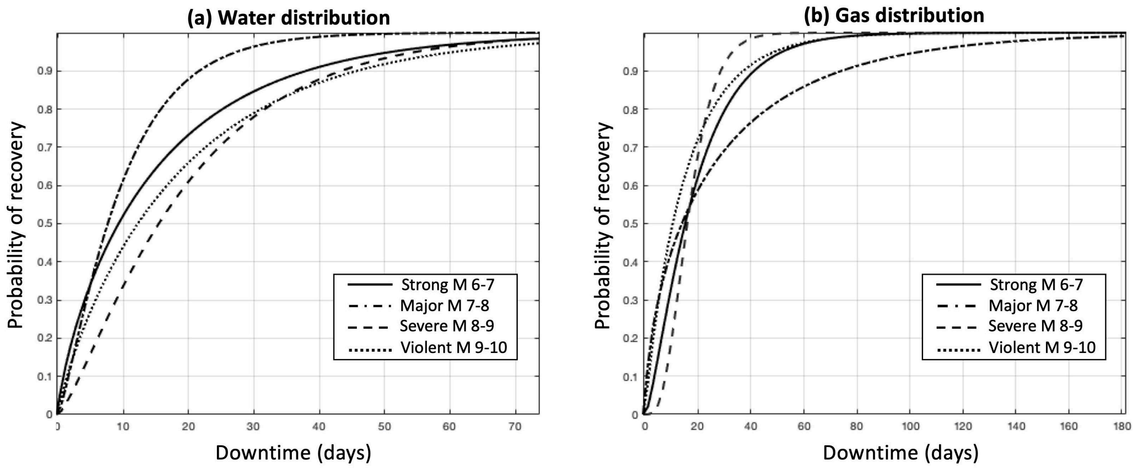

Figure 13. Restoration curves of the Water and Gas lifelines based on the earthquake magnitude

Once the restoration curves are developed, the estimation of probabilities for the downtime output is carried out. The downtime conditional probabilities obtained for every couple of "downtime state-earthquake magnitude" for the water and gas networks are listed in Table 14. The results obtained from the restoration curves are assumed to correspond to *high* infrastructure exposure and *low* available human resources, and they are considered the baselines for estimating the probabilities for other combinations in the CPT of downtime. Fragility restoration curves, designed using real data of past earthquakes, are used to calibrate the model through an iterative calibration procedure. That is, knowing the intensity of the studied earthquake, it is possible to obtain real downtime of the analyzed infrastructure system. The calibration is done by modifying the model parameters so that the downtime outcome of the model matches the real downtime from the real data. Table 15 presents a portion of the conditional probability table of the downtime indicators. In the table, the baselines resulted from the restoration curves are highlighted in bold and they are the starting point for estimating the probabilities of other combinations. The conditional probabilities of other combinations are estimated respecting that the horizontal sum must be equal to one (second probability axiom).

Table 14. Downtime probabilities of the water and gas systems given four seismic intensities

Lifeline	Time Span	Strong	Major	Severe	Violent
Water System	0-4	29%	17%	19%	20%
	5-10	23%	18%	23%	22%
	11-24	27%	28%	31%	30%
	25-40	12%	17%	16%	16%
	40+	6%	11%	7%	8%
Gas System	0-4	10%	18%	2%	20%
	5-10	23%	21%	18%	24%

	11-24	39%	30%	53%	33%
	25-40	19%	17%	22%	15%
	40+	7%	9%	4%	6%

Table 15. Conditional probability table (CPT) for the downtime output of the water and gas infrastructure

Infrastructure Type	Earthquake Intensity	Exposed Infrastructure	Av. HR	Very Low	Low	Medium	High	Very High
Water	Strong	High	High	0,2946	0,2275	0,2737	0,1355	0,0687
Water	**Strong**	**High**	**Low**	**0,2947**	**0,2289**	**0,2740**	**0,1360**	**0,0687**
Water	Strong	Low	High	0,2948	0,2291	0,2742	0,1360	0,0689
Water	Strong	Low	Low	0,2950	0,2292	0,2743	0,1369	0,0690
Water	Major	High	High	0,1826	0,2087	0,2889	0,1868	0,1330
Water	**Major**	**High**	**Low**	**0,1826**	**0,2089**	**0,2889**	**0,1869**	**0,1332**
Water	Major	Low	High	0,1826	0,2092	0,2890	0,1870	0,1340
Water	Major	Low	Low	0,1826	0,2092	0,2891	0,1870	0,1340
…	…	…	…	…	…	…	…	…
Gas	Strong	High	High	0,1035	0,2255	0,3885	0,2098	0,0726
Gas	**Strong**	**High**	**Low**	**0,1035**	**0,2255**	**0,3885**	**0,2099**	**0,0726**
Gas	Strong	Low	High	0,1036	0,2256	0,3885	0,2100	0,0727
Gas	Strong	Low	Low	0,1036	0,2326	0,3389	0,2200	0,1050
Gas	Major	High	High	0,1762	0,2171	0,3125	0,1735	0,1206
Gas	**Major**	**High**	**Low**	**0,1762**	**0,2172**	**0,3125**	**0,1735**	**0,1206**
Gas	Major	Low	High	0,1763	0,2172	0,3125	0,1736	0,1206
Gas	Major	Low	Low	0,1763	0,2173	0,3126	0,1736	0,1210
…	…	…	…	…	…	…	…	…

Step d: Inference and downtime estimation

BN's structure learning and inference for the downtime are performed using the commercial software Netica [95]. Construction of the BNs requires a list of the uncertain variables, the possible states of the discrete variables and possible ranges of the continuous variables, the relationship among the variables, and the conditional probabilities for the inference. Once the indicators and the corresponding states/ranges (see Table 7) and probabilities have been assigned, the BN is compiled. The probabilities solve the network by finding the marginal posterior probabilities that some indicators will be in a particular state given the input indicators and the conditional probabilities [96]. The DT results for the water network are shown in Figure 14. From the analysis, the downtime output shows a chance of 30.9 to be in the state *medium*.

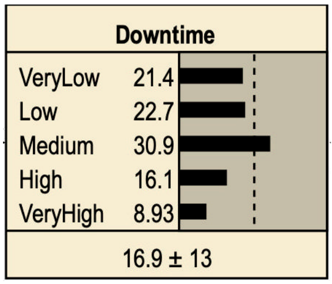

Figure 14. Downtime evaluation for water network

Sensitivity analysis

Sensitivity analysis is implemented to identify and rank critical input indicators that contribute significantly to the output result (i.e., the downtime). Sensitivity analysis allows identifying the variation in the system's reliability given a variation in the input values assuming that the inputs are uncertain [97]. In this work, two different sensitivity methods have been implemented. The first sensitivity analysis, known as Sensitivity to findings has been applied on the Bayesian network and it is based on the variance reduction and entropy reduction since the input indicators considered in the downtime model have discrete and continuous values [90, 98, 99]. The variance reduction method calculates the variance reduction of the expected real value of a query node Q (i.e., the downtime) due to a finding in a varying variable node I (e.g., *Recovery type*, *Earthquake intensity*). The variance of the real value Q given the evidence I, $V(q|i)$ is computed using the following equation:

$$(q|i) = \sum_q p(q|i)[X_q - E(Q|i)]^2 \tag{4}$$

where q = state of the query node Q, i = state of varying variable node I, $p(q|i)$ = conditional probability of q given i, X_q = value corresponding to state q, and $E(Q|i)$ = expected real value of Q after the new finding i for node I.

Entropy reduction calculates the expected reduction in mutual information of Q from a finding for variable I. The formula is provided below:

$$QR = H(Q) - H(Q|I) = \sum_q \sum_i P(q,i) \frac{log_2[P(q,i)]}{P(q)P(i)} \tag{5}$$

where $H(Q)$ and $H(Q|I)$ are the entropy before the new findings and after the new findings. 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 entropy reduction).

The results of the sensitivity analysis for the DT due to a finding at another node are provided in Figure 15. Only indicators (parent and child nodes) showing a significant contribution towards the DT output have been indicated (i.e., *epicentral distance*, *earthquake magnitude* and *intensity*, *recovery type*, *mobility and access*, and *infrastructure type*).

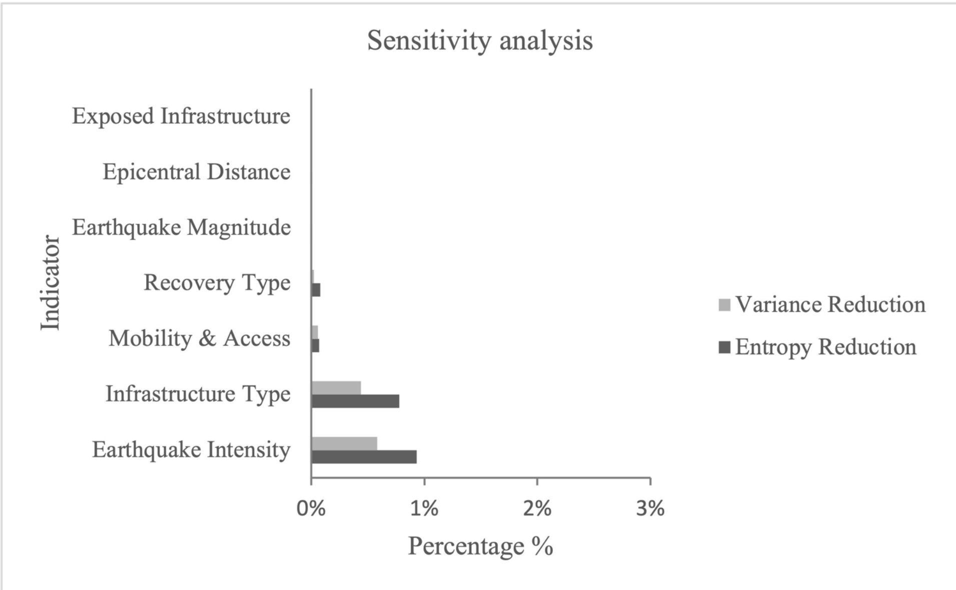

Figure 15. Sensitivity analysis of downtime node

For query node Downtime, *Earthquake Intensity* has the highest contribution (0.58% variance reduction and 0.93% entropy reduction) followed by *Infrastructure Type* (0.44% variance reduction and 0.78% entropy reduction), *Mobility and Access* (0.06% variance reduction and 0.07% entropy reduction), and *Recovery Type* (0.02% variance reduction and 0.08% entropy reduction). *Earthquake Magnitude*, *Epicentral Distance*, and *Exposed infrastructure* have very low contributions. That is, the variance reduction and entropy reduction for the three indicators are below 0.05%. The result of sensitivity analysis allows the decision-makers to identify the input parameters that affect the output most and prioritize them in the decision-making.

The second sensitivity analysis is the Sobol sensitivity method. It has been carried out by considering the basic input indicators in Fuzzy Logic. Sobol sensitivity analysis determines the contribution of each basic input indicator and their interactions to the overall model output variance. That is, it is based on variance decomposition techniques to provide a quantitative measure of the contributions of the input to the output variance. A pre-Sobol sensitivity analysis is necessary to perform the Sobol sensitivity analysis and it consists of deciding the parameters in the model to be varied and defining the parameter range, including the lower and upper bounds. After performing the pre-Sobol sensitivity analysis, the parameter sets can be generated through the Sobol sequence, and the running model output can be simulated. The outputs will be used to calculate the total and first-order sensitivity analysis. The Sobol sensitivity indices presented different features: (i) are positive values, (ii) parameters with sensitivity indices greater than 0.05 are considered significant, and (iii) the total-order sensitivity indices are greater than the first-order sensitivity indices. To implement the Sobol sensitivity method, 20 basic input indicators are investigated to identify the indicators that have a significant contribution towards the DT output. In this work, 10,000 samples per input are used for Monte Carlo-based Sobol indices. Figure 16 shows the sensitivity analysis results of the most influencing basic input indicators in the downtime estimation. The results indicate that the *Epicentral distance* indicator is the most important indicator contributing to ~90% of the model output variability, followed by the important indicators *Infrastructure type* and *Service importance*.

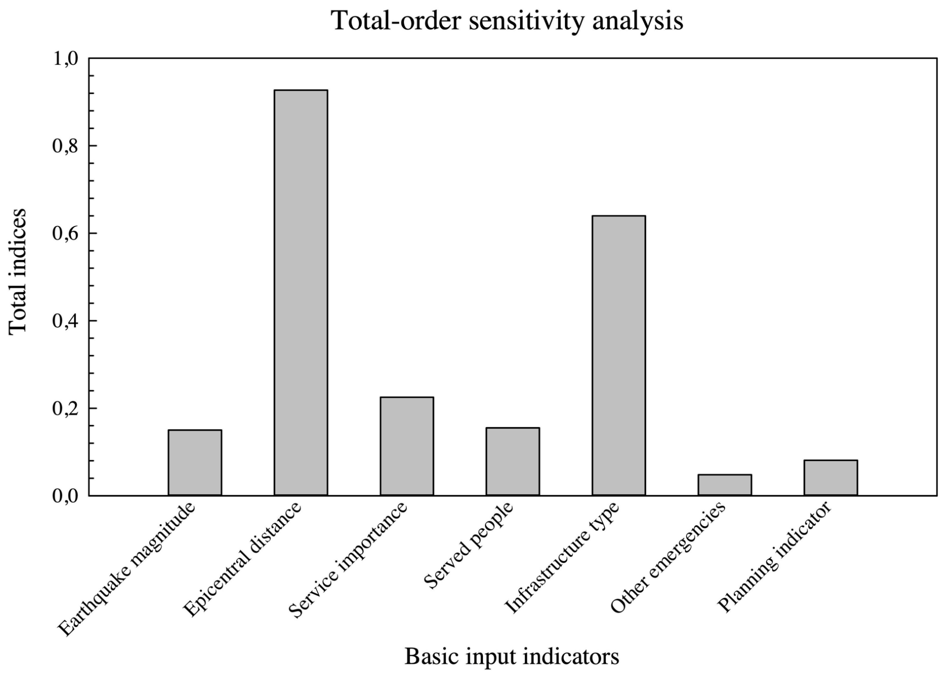

Figure 16. Total-order sensitivity analysis

Backward propagation analysis

The backward analysis (diagnostic reasoning) is a useful feature of BN that allows decision-makers to improve the performance of a system by setting a desirable state of the DT and getting the parameters that assure the predefined DT state. In backward analysis, observation is made for a specific indicator, usually a target indicator (e.g., the downtime node in this work), and then the BN calculates the marginal probabilities of unobserved indicators by propagating the impact of the observed indicator through the network in a backward fashion. For instance, if the downtime state is set to *very low (*i.e., 100% of chance to be in the state *very low*), the “Exposed infrastructure” index is 58.9% *high*, the “Availability of Human Resources” index is 54.2% *high*, and the “Earthquake intensity” index is 45% *weak.* The marginal probabilities of the other unobserved indicators are shown in Figure 17.

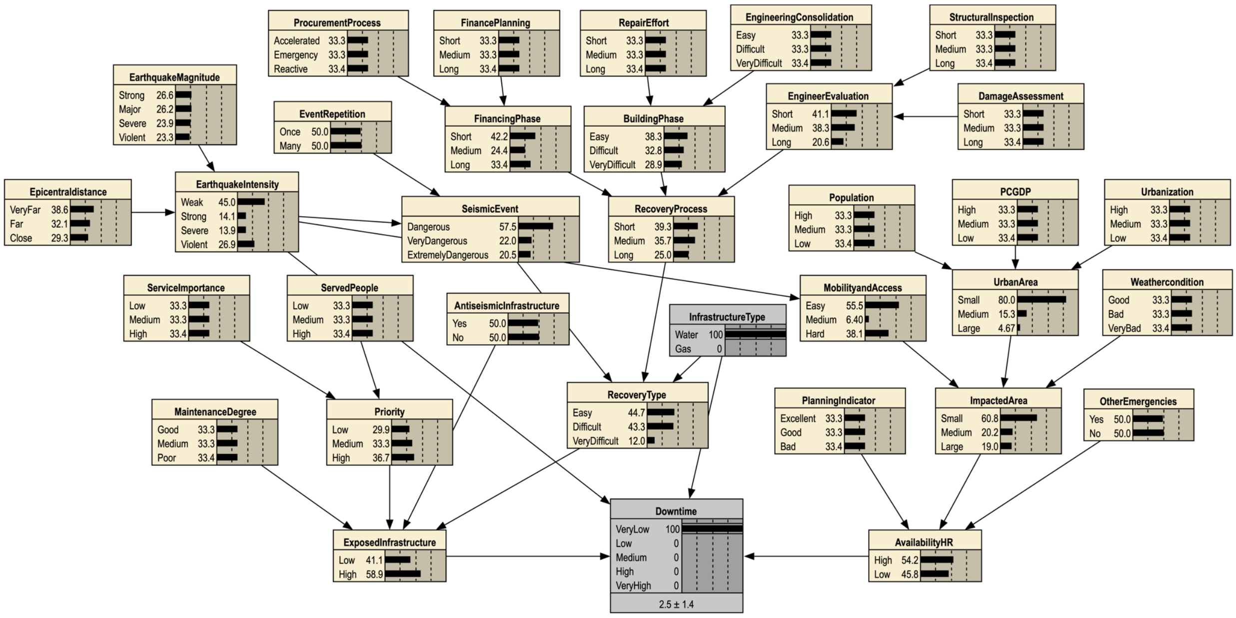

Figure 17. Backward analysis scenario when the expected downtime is set to *very low*

Results and comparison

FL and BN inference methods have been applied to estimate the downtime of the water infrastructure of the city of Calascibetta in Sicily, Italy. The application of both approaches allows performing a comparison of the modeling and quantification of the downtime. Both inference methods incorporate intuitive knowledge or historical data for defining fuzzy rules (in FL) and estimating conditional probabilities (in BN). Involving the use of experts in the generation of fuzzy rules (in FL) and probabilities (in BN) for different systems for which data are not available is a critical aspect of the downtime estimation model. In BN inference method, we can see uncertainty in the results in the form of probability dispersion (or variance) due to the basic inputs that are uncertain in the first place. That is, the principle of insufficient reasoning is applied to the basic inputs, i.e., the states of the inputs have an equal probability of occurrence. FL and BN inference methods can be implemented without being familiar with the mathematical details and probabilistic analysis. This is an important feature as complex mathematical formulations to provide direct inputs in the proper form of FL and BN are not required. Furthermore, in the definition of the input values, BN is less sensitive to less precise information than FL. That is, when the uncertainty of the inputs is significant, FL provides results less certain than BN. Both methodologies show similar results, and the recovery time output follows the same trend. FL and BN inference methods differ in their interpretation of the output. The output of the FL is a membership that defines how well the downtime fits the fuzzy levels, e.g., the downtime output for the water utility belongs to level *Very Low* with a membership degree of 0, to *Low* with a degree of membership of 0.19, to *Medium* with a degree of membership of 0.81, to *High* with a membership degree of 0, and to *Very High* with a degree of membership of 0. The BN output is a probability distribution that represents how likely the downtime is in a certain state, e.g., in the case of water lifeline shown in Figure 14, the downtime output has a 21.4 chance of being in state *Very Low*, 22.7 of being in state *Low*, 30.9 of being in state *Medium*, 16.1 of being in state *High*, and 8.93 of being in state *Very High*. Consequently, the BN output probability distribution tends to be easier to interpret as well as more intuitive than FL output, which is in the form of a fuzzy set.

One of the advantages of the proposed downtime estimation model based on BN inference method is the capability to easily update the downtime model when new data and information is available. The powerful feature of BN for generating different what-if scenarios allows running several scenarios and determining the efficient means of reducing the downtime. Another advantage of applying BN inference method to the downtime model is the diagnostic reasoning. The backward analysis of BN enables setting a desirable state of the downtime and getting the indicators that provide the predefined downtime state. By doing that, decision-makers can improve the performance of their systems. Moreover, it is possible to estimate the probability of another node if the evidence for the given nodes is known. This would provide flexibility in BN approach. Updating the downtime model based on FL requires more time since it can be done manually by adjusting fuzzy rules and changing the shape of the membership functions. Moreover, in the case of new information, fuzzy rules need to be changed. This requires a good knowledge of the system to effectively apply FL. In terms of easiness of implementing the two approaches to the downtime estimation model, both BN and FL frameworks are easy to build but estimating conditional probabilities in BN for each child node of complex systems can be challenging. To sum up, the two proposed inference systems can be implemented to cover two possible conditions: (i) data is (partially) available but uncertain, and (ii) data is not available or limited. That is, Bayesian Network is proper when statistics are available, while the Fuzzy Logic approach is a suitable solution to deal with less or unavailable data. Therefore, each approach is applicable for different cases.

The results obtained from BN and FL approaches can be used to help and support decision-makers (e.g., engineers and managers) prioritize financial resources in the planning and management of post-disaster strategies. By analyzing the downtime results, decision-makers can optimize their action by prioritizing activities and choosing proper recovery measures to assure the functionality of the infrastructures and to assign appropriate resources. Risk planners, previously concerned with protection and prevention, are now more interested in the ability of such infrastructures to withstand and recover from disruptions in the form of resilience-building strategies. Moreover, the sensitivity analysis results can be used to pinpoint which indicators are effective to reduce risk, use it for decision-maker to assign appropriate resource, and determine the most efficient and effective means of reducing risk and improving resilience. For instance, the estimated downtime values (i.e., medium downtime) of the water infrastructure of the city of Calascibetta in Sicily may be reduced by improving some sensitive and influential indicators that require special attention, such as the *Mobility and Access* and the *Recovery Type* indicators, and the "Availability of Human Resources" index. The utility managers must take appropriate preventive action (e.g., maintenance or replacement of the analyzed pipe after inspection) to avoid its failure and improve the resilience against future hazard events.

Conclusion

There is a growing interest in the infrastructure resilience concept. Ensuring appropriate performance levels of civil infrastructure systems is one of the aspects to be considered when it comes to community resilience. The key contributions of this paper are summarized as follows. First, this paper proposes an indicator-based downtime model to estimate the downtime of lifeline infrastructure, namely water and gas networks. The proposed model can be easily adapted to any pipeline system by changing the input indicators. The downtime estimation model benefits from two inference methods for its computation: Bayesian Network (BN) and Fuzzy Logic (FL). The model can accommodate different types of input as well as input uncertainties. The inference methods are considered as two alternatives that can be used in slightly different circumstances to deal with the uncertainties that affect the recovery estimation of damaged infrastructures. The downtime estimation model is applied to the city of Calascibetta in Sicily, Italy, by considering the "Noto valley earthquake" that hit Calascibetta on the 11th of January 1693 with a magnitude M 7.4 on the Richter scale. Such an illustration could help users choose the best among the two inference methods given the case they have.

The downtime estimation model presented in this paper is targeted as a support tool for decision-makers to evaluate the overall repair time and quantify the priorities of the repair activities. Results from the case scenario, in terms of probability of being in a given state (BN) and the degree of membership (FL), can be used to pursue the best strategies during the planning and management post-disaster processes, manage and minimize the impacts of seismic events, and promptly recover damaged infrastructures.

The main limitation of the proposed model is that some of the fuzzy rules in FL and conditional probabilities in BN are knowledge-based. Thus, the model development and analysis are subjective to the quality of the expert knowledge. This is unavoidable since the main feature of BN and FL is to rely on expert judgment in cases where data are sparse or not available. This can be partially addressed by asking multiple experts. Moreover, developing expert-driven Bayesian networks and Fuzzy logic systems require significant development due to the large number of variables. Although both inference systems are conceptually easy, they are not very simple to build.

Future work of this study will be oriented towards the following directions.

1. The proposed downtime estimation model can be further enhanced by merging both FL and BN in a single model. This is possible through the use of linguistic quantifiers and fuzzy number-based probabilities to assess unconditional and conditional probabilities. The BN inference is then performed to estimate the downtime of the analyzed infrastructures.
2. The downtime assessment model can be extended to include the interdependency of infrastructure networks since infrastructure systems are not isolated from each other but rely on one another to be functional.
3. A procedure to evaluate the interdependency among the downtime indicators, as well as their weighting factors, will be further addressed.

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