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Comparison of Bayesian belief networks and fuzzy models**

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1 **Quantifying restoration time of pipelines after earthquakes:**

2 **Comparison of Bayesian belief networks and fuzzy models**

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

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

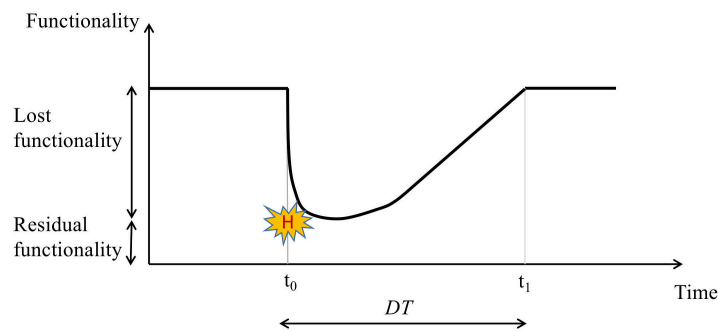
36 Keywords: resilience; downtime; lifelines; infrastructure; fuzzy logic; Bayesian  
37 network; restoration

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44 **Introduction**

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

53         Functionality of the infrastructure, under emergency conditions, can be evaluated by  
54 studying resilience of critical infrastructures that are prone to many disruptive events or  
55 inadequate maintenance [7-13]. In the seismic resilience estimation, one such matrix of interest  
56 to the decision-making is downtime. The downtime is defined as the time from the occurrence  
57 of the hazard event ( $t_0$ ), where there is a loss of functionality of the system, to the time when the  
58 functionality is completely restored ( $t_1$ ) (Figure 1) [14-16].



59  
60 **Figure 1.** Conceptual Downtime (DT) of a system  
61

62         Although several studies have been carried out on downtime [17-19], downtime  
63 estimation is still challenging since the data and the input parameters that are required for the  
64 estimation are not completely available, highly uncertain, and rapidly evolving in time [20-23].  
65 The “uncertain” parameters such as the *finance* and *procurement process*, *economic* and *human*  
66 *resources* are important factors in the definition and estimation of the downtime. Few downtime  
67 models include the contribution of uncertain factors as they differ depending on the condition of  
68 the affected area. Therefore, the main challenge in estimating the restoration time deals with

69 randomness, vagueness, and ignorance-type uncertainties [8, 24-26]. The typology and  
70 definition of uncertainty within the engineering community is extensive and often discordant  
71 [27]. Klir and Yuan [25] have broadly categorized uncertainty into two basic types: *vagueness*  
72 and *ambiguity* (see Table 1 for an extensive list of the uncertainty types). Besides, the  
73 uncertainties and interdependencies that exist in the downtime estimation, render rule-based  
74 systems and graphical models a viable alternative [20-22]. Interdependency, in this context,  
75 refers to the statistical relationships between the input parameters of the downtime estimation  
76 model.

77 **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

78

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

92 [47-52]. For example, Hosseini and Barker [53] proposed a methodology to quantify resilience  
93 as a function of absorptive, adaptive, and restorative capacities through Bayesian networks with  
94 the application on an inland waterway port. In recent years, BNs have been employed in  
95 different water related issues as management tools [54-57]. Roozbahani et al. [58] developed a  
96 framework based on prediction of groundwater level using Bayesian networks model. The  
97 model was evaluated for restoring the Birjand aquifer in Iran in different hydrological  
98 conditions. A Hybrid Bayesian Networks (HBNs) was employed to develop an intelligent  
99 model for hydraulic simulation and operational performance evaluation of the agricultural water  
100 distribution system [59]. However, to this date, no downtime estimation model for pipeline  
101 networks that uses FL or BN inference methods can be found in the literature. Although the  
102 comparison among probabilistic and non-probabilistic frameworks has been addressed in  
103 several works [60-64], in most cases, the comparison is made at the theoretical level without a  
104 practical perspective [65]. Furthermore, a comparison between the two approaches focusing on  
105 the treatment and representation of the uncertainty in the recovery time estimation is still  
106 missing.

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

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

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

131 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

132

133 **Downtime model for water and gas lifelines**

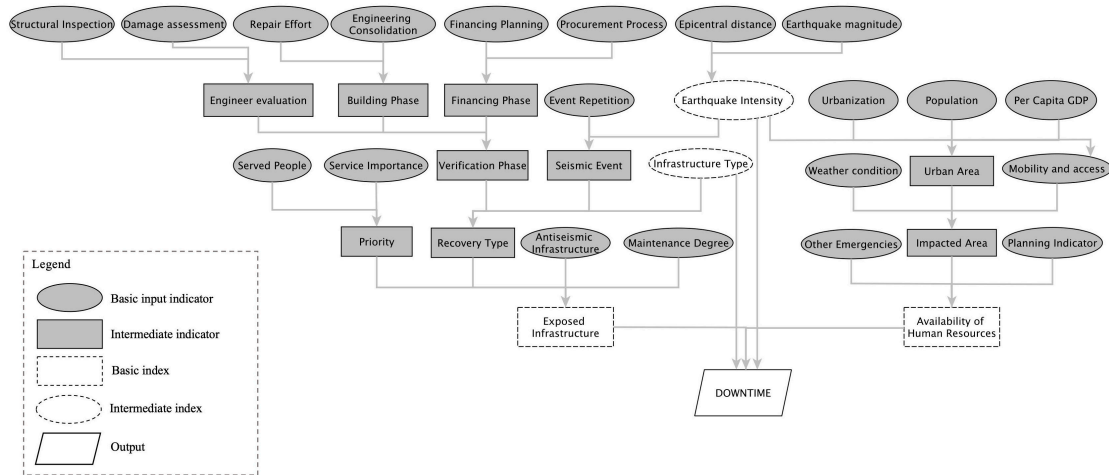
134 ***Indicators selection and clustering***

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

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



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



162

163 **Figure 2.** Downtime assessment model for water and gas infrastructure

164

165 *Exposed Infrastructure (EI)*

166

Table 3 lists the EI indicators along with their state, the performance measure, and the

167

sources used to obtain them (when available). The EI index, describing how effectively

168

and efficiently a community can respond to recover from short-term and long-term

169

impacts, is quantified through the *Maintenance degree* of the infrastructure, which

170

represents the state of deterioration of the infrastructure. Infrastructures wear out with

171

time and use, so proper and timely maintenance must be periodically conducted.

172

Neglecting proper maintenance leads to a decline in the infrastructure's condition.

173

Therefore, in this work, it is assuming that a higher maintenance rate would lead to a

174

lower likelihood of damage as well as a lower recovery time. The EI index also relies on

175

the *Priority* of the infrastructure system, which is defined by the number of *Served*

176

*people* and the *Service importance* of the infrastructure within the community, the *Anti-*

177

*seismic technology* of the structure and the *Recovery type*. The *Recovery type* includes

178

indicators representing the *Verification phase*, which is the sum of the time and effort

179

required for the *Engineer evaluation*, the *Building phase*, the *Financing phase*,

180

indicators related to the *Seismic event*, and it is also affected by the analyzed

181

“Infrastructure type” index. The *Engineer evaluation* indicator, which is the time teams

182 of specialists (e.g., engineers) need to define and compare the assessments and give  
183 feedback on the potentially damaged infrastructure after the inspection, is based on the  
184 *Structural inspection* process and the quantification of the damages represented by the  
185 *Damage assessment* indicator [72]. The *Building phase*, sub-classified into *Repair effort*  
186 and *Engineering consolidation*, provides all those processes of design and intervention  
187 which aim at restoring the structural characteristics of the structure. The *Financing Phase*  
188 is divided into the *Financing planning* indicator, which represents the time the expert  
189 needs to plan and distribute properly funds and resources in the right manner, and the  
190 *Procurement process*. The *Procurement process* indicator is the time required to make an  
191 offer by an individual or business for a product or service. In the aftermath of a  
192 disastrous event, it is very important to shorten the procurement process in such a way  
193 to speed up the recovery process [20]. Finally, the *Seismic event* indicator depends on the  
194 *Event repetition* indicator and on the “Earthquake intensity” index.  
195 The indicators that are related to the “Exposed infrastructure” index are described in  
196 Table 3. Information about the “Infrastructure type” index and “Earthquake intensity”  
197 index along with their indicators are described separately in Table 5 and Table 6.

198 **Table 3.** Description of the “Exposed infrastructure” indicators

Indicator/Index	State	Performance measure/Reference
Exposed Infrastructure	Low	Visual inspection/Expert opinion
	High	
Maintenance Degree	Poor	Visual inspection/Expert opinion
	Medium	
	Good	
Served people	Low	≤ 20% Population
	Medium	20% < Served People < 50% Population
	High	> 50% Population [73]
Anti-seismic Infrastructure	Yes	Earthquake resistant
	No	Earthquake non-resistant
Service Importance	Low	Visual inspection/Expert opinion
	Medium	
	High	
Priority of intervention	Low	Visual inspection/Expert opinion
	Medium	
	High	
Recovery Type	Easy	Visual inspection/Expert opinion [71]
	Difficult	
	Very Difficult	
	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

199

200 *Availability of Human Resources (HR)*

201 Information on the “HR” index and its indicators is presented in Table 4. As shown in Figure 2,  
202 the “HR” index is influenced by three indicators: the occurrence of *Other emergencies* at the  
203 same time, the availability of a structured and defined *Planning indicator*, and the  
204 characteristics of the *Impacted area*. The *Planning indicator* is used in the framework to  
205 represent the emergency response and recovery planning. It can be assessed by consulting a  
206 city’s local planning experts [20].

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

208

209 The *Impacted area* indicator can be divided into three sub-indicators: the *Weather condition* of  
210 the affected area, the easiness of *Mobility and access* into the area, and the characteristics of the  
211 *urban area*. The *Mobility and access* indicator is dependent on the conditions of the post-  
212 earthquake transportation system, the number of debris, and the “Earthquake intensity” index.  
213 The *Weather condition* indicator is expressed in terms of the temperature [68]. Four ranges have  
214 been selected to describe the *Weather condition* indicator, as listed in Table 4.  
215 Besides, the *Urban area* indicator is identified by *Per Capita Gross Domestic Product*  
216 (PCGDP), which is the indicator of a nation’s living standards, the *Population* density of the  
217 impacted area, and the *Urbanization* degree [76-78].

218 *Infrastructure Type (I)*

219 Outlined in Table 5 are the types of infrastructures that are considered in the proposed

220 downtime model: water and gas networks. The “Infrastructure type” is a key index in the  
 221 downtime evaluation since it affects the *Recovery type* indicator and the downtime output [70].

222 **Table 5.** Description of “Infrastructure Type” indicators

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

223

224 *Earthquake Intensity (E)*

225 Table 6 below presents the “Earthquake Intensity” (E) index, which expresses the severity of the  
 226 earthquake to which a city will be subject. The E index influences the *Seismic event* and the  
 227 *Mobility and access* indicators and directly the downtime output node. It is defined by  
 228 combining the *Epicentral distance* and the *Earthquake magnitude* indicators. Distance from the  
 229 epicenter is related to the observed damage such that the farther a system is located from the  
 230 epicenter, the less damage is observed in the system. The epicentral distance is defined as  
 231 (close, far, and very far). Four groups of Richter magnitude scale are used to classify the  
 232 *Earthquake magnitude* indicator, (Strong 6-7, Major 7-8, Severe 8-9, Violent 9-10). The  
 233 “Earthquake Intensity” index is classified into four groups of Mercalli intensity scale ranging  
 234 from least perceptive to most severe: (Weak MMI-MMIII, Strong MMIV-MMVI, Severe  
 235 MMVII-MMX, Violent MM>MMX).

236 **Table 6.** Description of “Earthquake intensity” indicators

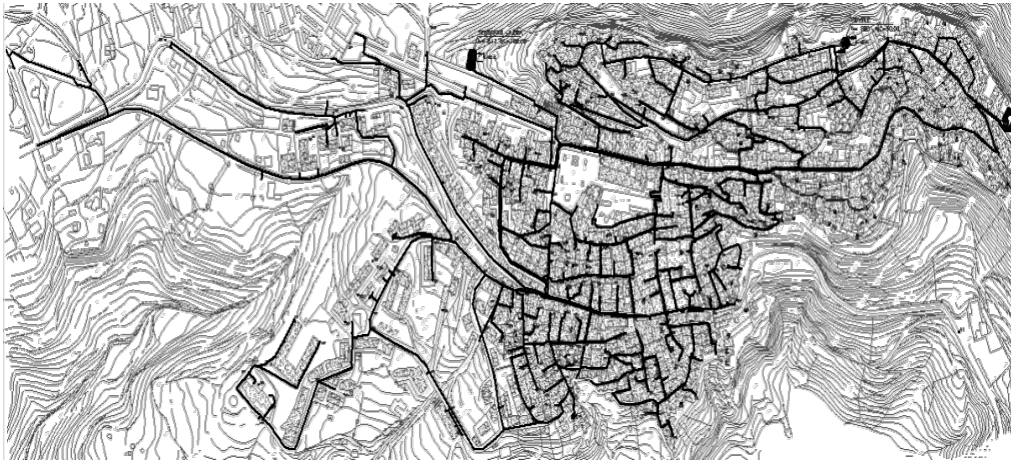
Indicator/Index	State	Performance measure
Epicentral distance	Close	
	Far	Visual inspection/Expert opinion
	Very far	
Earthquake magnitude	Strong	M 6-6.9
	Major	M 7-7.9
	Severe	M 8-8.9
	Violent	M 9-9.9
Earthquake Intensity	Weak	MMI-MMIII
	Major	MMIV-MMVI
	Severe	MMVII-MMX
	Violent	MM>MMX

237

238 **Demonstrative example**

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

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



242  
 243 **Figure 3.** Calascibetta Water Distribution Network

244 The earthquake considered in the analysis is the 7.4 magnitude earthquake, known as “Noto  
 245 valley earthquake”, that hit almost the whole of eastern Sicily (Italy) on the 11<sup>th</sup> of January  
 246 1693. The earthquake caused about 60.000 injuries and affected an area of 5.600 square  
 247 kilometers. Although the exact position of the epicenter remains uncertain, it is believed that it  
 248 was close to the coast. The earthquake was followed by tsunamis that devastated the coastal part  
 249 of the Ionian Sea and in the Straits of Messina. Simulating an emergency scenario consists of  
 250 assigning a performance measure to each downtime indicator (e.g., *Procurement process*,  
 251 *Service importance* of the infrastructure, *Impacted area*, etc.) of the potentially damaged  
 252 infrastructures. Downtime indicators should be given qualitative judgments by an expert in the  
 253 related field. In this work, some of the states of the indicators have been assumed (e.g., *Damage*  
 254 *Assessment*, *Financing Planning*, *Repair Effort*) while others have been determined through  
 255 available data (e.g., *Population*, *Per Capita GDP*, *Urbanization*). The input indicators used to  
 256 quantify the downtime are summarized in Table 7. The state of each basic input indicator in  
 257 Table 7 has been selected from the state ranges in Table 3-Table 6.

258 **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

259

260

**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

261

262

Five downtime intervals (e.g., states) are introduced to discretize the downtime output see

263

Table 8). The five ranges for the downtime indicator have been determined after observing raw

264

data and restoration curves from a previous study [8]. That is, it has been noticed that most

265

infrastructures take time within these ranges to recover their functionality; therefore, the

266

different ranges for the states have been defined based on that. In the next section, the downtime

267

of the water network of the city of Calascibetta, Sicily (Italy) is estimated using two inference

268

methods, FL and BN.

269

### **Downtime estimation using Fuzzy Logic**

270

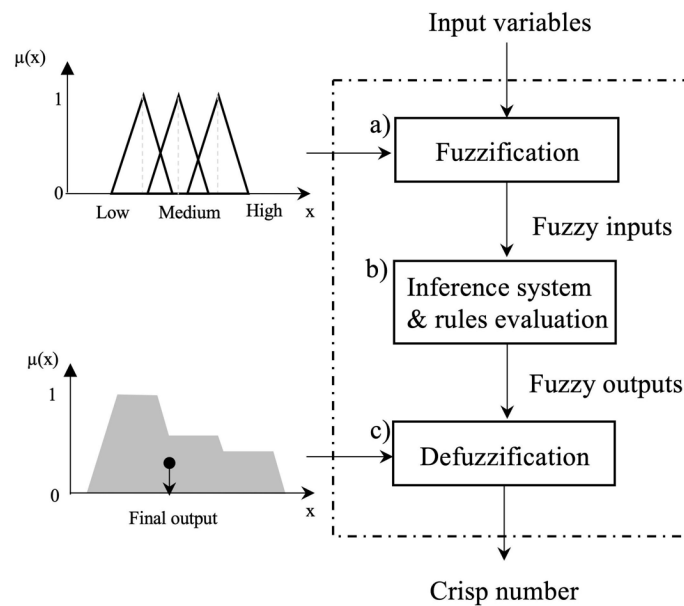
This section illustrates an overview of the FL theory and the methodology adopted for

271

estimating the downtime of buried pipelines after earthquakes for cases with high uncertainty.

272 **Fuzzy Logic theory**

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



283

284 **Figure 4.** Fuzzy Inference System (FIS)

285 **Step a: Fuzzification – Membership Functions**

286 As mentioned before, the basic input indicators (i.e. those with oval shape in Figure 2) could  
287 have different states (also called linguistic quantifiers in Fuzzy logic) (see Table 3, Table 4, and  
288 Table 5). The number of states for these indicators is not constant (i.e., some have only two,  
289 some have three, and the others have four states). However, to implement the fuzzy theory in  
290 the DT model easily, the number of states is set to three states for all indicators (e.g., *low*,



291 *medium*, and *high* or *small*, *medium*, and *large*, etc.). Taking into account more than 3 states  
292 (e.g., five states) leads to a more complicated fuzzy process. The main difficulty in designing  
293 membership functions is caused by the necessity to establish fuzzy levels and intervals. This  
294 difficulty could be increased if more states are considered since more membership functions  
295 would then be necessary to apply the fuzzy logic. In terms of fuzzy rules, a high number of  
296 states corresponds to a high number of fuzzy rules to cover all the possible permutations of the  
297 states. Consequently, designing membership functions and determining fuzzy rules become  
298 complicated. Increased number of states can, of course, make the results more specific;  
299 however, this comes at the cost of input demand: the expert would then need to provide more  
300 detailed membership functions and more rules, which could be not practical. Choosing three  
301 states is thought to provide the best balance between input demand and output clarity. Thus, in  
302 this paper, only three states are considered for every indicator. Linguistic quantifiers (i.e., states)  
303 assigned to the basic indicators are transformed into equivalent numbers (*fuzzy numbers*) on a  
304 range [0 1]. In this work, transformed values close to 0 (e.g., 0.20, 0.30) correspond to low  
305 downtime (i.e., values are closer to the *low* membership function), while values close to 1 (e.g.,  
306 0.8, 0.9) correspond to high downtime. The basic indicators and the corresponding fuzzy values  
307 are listed in Table 9.

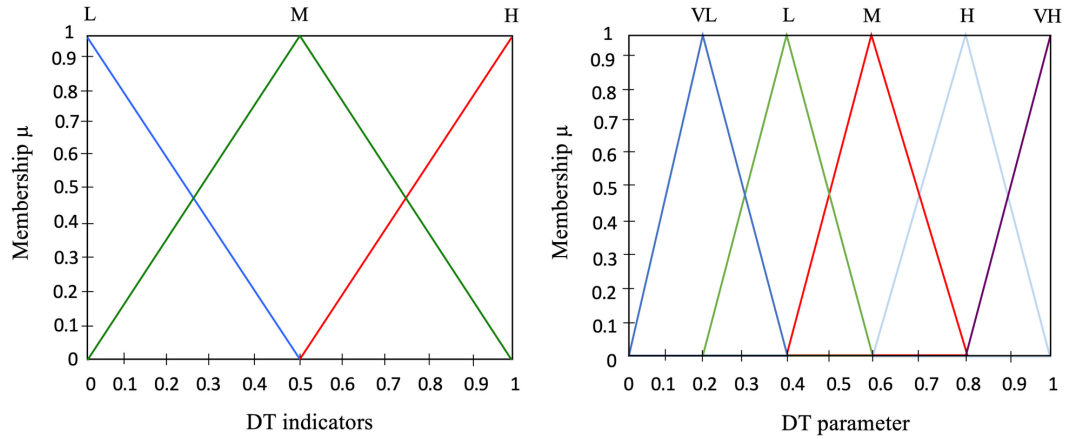
308 The fuzzification step converts the input values into a homogeneous scale by assigning  
309 corresponding membership functions concerning their specified granularities [82]. The  
310 definition of membership functions is the main step on which all the other subsequent  
311 operations are based. Such functions, representing the fuzzy sets, can take different shapes  
312 (triangular, trapezoidal, and Gaussian, etc.) according to the situations, although regular shapes  
313 are commonly used [83]. There are many possible ways of selecting membership functions of  
314 fuzzy variables. Selection of membership functions can be intuitive or based on logical  
315 operations (Ross 1995), For instance, triangular or trapezoidal fuzzy membership functions are  
316 usually used to represent linguistic variables since their simplicity to apply fuzzy operations  
317 [34].

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

325 **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

326



327  
 328 **Figure 5.** Membership function and granulation for the input indicators and the downtime indicator  
 329 After selecting the transformation value for each downtime indicator, one can enter the  
 330 corresponding membership graph (see Figure 5) and obtain the membership degree. The results  
 331 are listed in Table 10.

332 **Table 10.** Fuzzification process

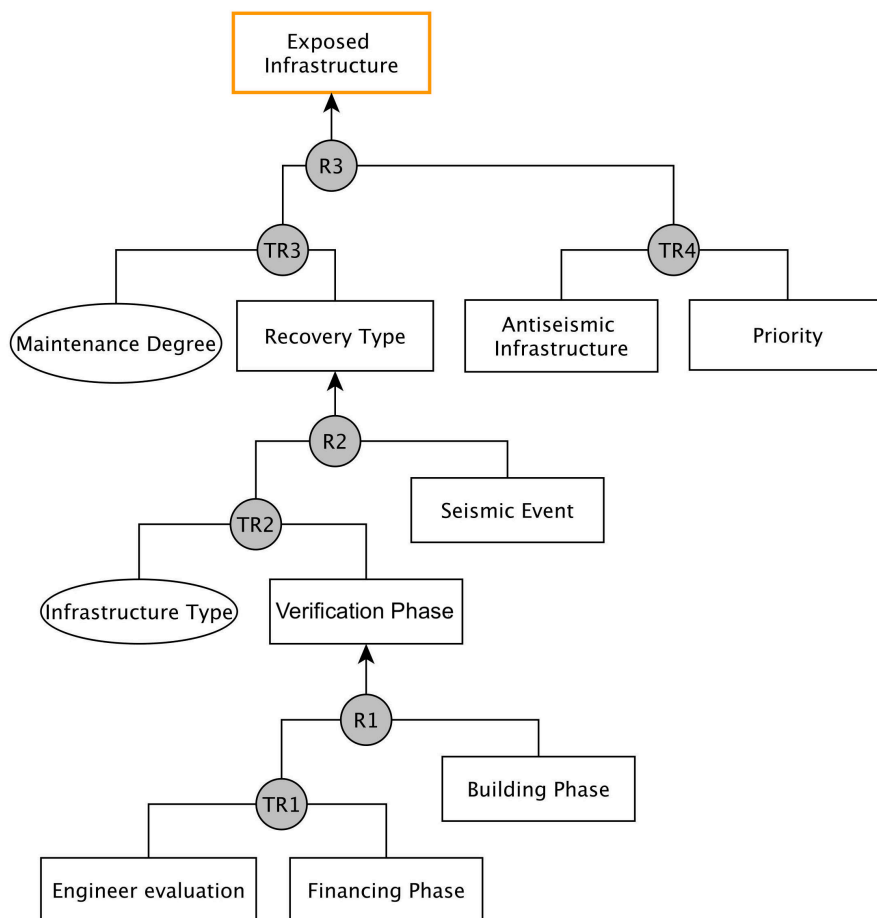
Basic input indicator	Fuzzification
Damage assessment	$(\mu_S^{AD}, \mu_M^{AD}, \mu_L^{AD}) = (0, 0.38, 0.62)$
Structural inspection	$(\mu_S^{SI}, \mu_M^{SI}, \mu_L^{SI}) = (0.55, 0.45, 0)$
Financing Planning	$(\mu_S^{FP}, \mu_M^{FP}, \mu_L^{FP}) = (0, 1, 0)$
Procurement Process	$(\mu_R^{PP}, \mu_E^{PP}, \mu_A^{PP}) = (0, 1, 0)$
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	$(\mu_L^{VI}, \mu_M^{VI}, \mu_H^{VI}) = (0, 0.15, 0.85)$
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	$(\mu_B^{PI}, \mu_G^{PI}, \mu_E^{PI}) = (0, 0.38, 0.62)$

333

334 ***Step b: Aggregation through Fuzzy rules***

335 The relationships between inputs and outputs are defined through the *fuzzy rule base* (FRB) that  
336 is derived from heuristic knowledge of experts or historical data. The Mamdani Fuzzy Logic  
337 inference method, known as the Max-Min method, is implemented in this work, as it is the most  
338 suitable when the fuzzy system relies on expert knowledge and experience [84]. Mamdani  
339 systems are composed of IF-THEN rules of the form “IF  $x$  is A (antecedent) THEN  $y$  is B  
340 (consequent)”. Each rule delivers a partial conclusion, which is aggregated to the other rules to  
341 provide a conclusion (aggregation). The aggregation of the rules determines a rule base that is  
342 valid over the entire application domain. In general, there is no single best method to generate  
343 fuzzy rules; rather the choice is context-dependent. To determine fuzzy rules that govern the  
344 system when information is scarce or missing, expert-based knowledge (knowledge base) is  
345 used to combine all the different variables allowing the system to take care of all the different  
346 possibilities that could happen. The use of the fuzzy rule-based method allows decision-makers  
347 to express their preferences in a modular fashion and update the fuzzy inference system by  
348 using new information as it becomes available [85]. The fuzzy rules are defined using a  
349 weighting method that allows identifying the impact of the input towards the output [21, 22].  
350 The results of the rules are then combined to get a final output through the inference process.  
351 The process is performed by using fuzzy set operations to describe the behavior of a complex  
352 system for all values of inputs. Mamdani’s inference system consists of three connectives: the  
353 aggregation of the antecedents in each rule (AND connectives), implication (IF-THEN  
354 connectives), and aggregation of the rules (ALSO connectives). As Figure 2 shows, many  
355 indicators are considered in the downtime estimation model, and consequently, several fuzzy  
356 rules are required to combine them. In a fuzzy-based model, an increase in the number of input  
357 values results in an exponential increase in the number of rules [86]. Different strategies are  
358 presented to deal with the high number of rules: (i) identification of functional relationships, (ii)  
359 sensory fusion, (iii) rule hierarchy, and (iv) interpolation [87]. Magdalena [88] showed that a  
360 decomposition at the level of indicators is a proper solution. For instance, from Figure 2, it can  
361 be shown that the “Exposed infrastructure” index has four inputs: *Maintenance degree*,

362 *Recovery type, Anti-seismic infrastructure, and Priority*. Using a three-tuple fuzzy number,  
 363 which corresponds to three states (e.g., *low, medium, and high*), the number of rules required to  
 364 combine the indicators is  $3^4 = 81$ . According to the process described by [88], the hierarchical  
 365 structure can be decomposed at the level of indicators by introducing intermediate connections  
 366 among the indicators at different levels of the hierarchy and by defining intermediate rules.  
 367 Figure 6 illustrates the hierarchical fuzzy decomposition for the “Exposed infrastructure” index.  
 368 As shown, pairs of indicators are aggregated through intermediate rules (temporary rules),  
 369 which are TR<sub>1</sub>, TR<sub>2</sub>, TR<sub>3</sub>, and TR<sub>4</sub>. The output of the intermediate inference is then aggregated  
 370 through fuzzy rule based R<sub>1</sub>, R<sub>2</sub>, and R<sub>3</sub>. Thus, a new rule hierarchy is developed, and the  
 371 number of rules is reduced to  $7 \cdot 3^2 = 63$ , where 7 are the rules, 3 are the fuzzy states for each  
 372 indicator (e.g., *low, medium, and high*), and 2 is the number of indicators aggregated at each  
 373 level of the hierarchy.



374

375 **Figure 6.** Hierarchical fuzzy rule base decomposition for the “Exposed Infrastructure” index

376

377 For example, the *Engineer evaluation* and *Financing phase* are aggregated through TR<sub>1</sub>.  
 378 The output of TR<sub>1</sub> is then aggregated with the *Building phase* indicator through R<sub>1</sub> to obtain the  
 379 *Verification Phase*. The three-tuple fuzzy set output at each level of the hierarchical scheme is  
 380 defuzzified to obtain a single crisp value. In turn, this value is fuzzified into the next level. An  
 381 example of the fuzzy rule assigned for combining the *Damage assessment* and *Structural*  
 382 *inspection* to obtain *Engineer evaluation* (see Figure 2) is given in Table 11. The indicators are  
 383 combined taking into account their importance towards the output [21, 22]. Thus, in the table,  
 384 every indicator (i.e., DA and SI) is assigned a weighting factor that distinguishes its importance  
 385 towards the output (i.e., EE).

386 **Table 11.** Fuzzy rule for Engineer Evaluation

Rule	$\frac{DA}{W=2}$	$\frac{SI}{W=1}$	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

387

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

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

390 **Step c: Defuzzification to calculate corresponding crisp outputs**

391 The last step of the FL is the *defuzzification* process that represents the inverse of the  
 392 fuzzification process. The purpose of the defuzzification step is to defuzzify the output fuzzy set  
 393 resulting from the inference process and obtain a final crisp number. Different defuzzification  
 394 methods can be found in the literature, such as the Center-of-Gravity (CoG) and Mean of  
 395 Maximum (MoM) methods. At each level of the hierarchical scheme, fuzzy outputs are

396 defuzzified through the center of gravity (also known as the center of area) method. This  
397 defuzzification method calculates the area under the membership functions within the range of  
398 the output, then computes the geometric center of the area as follows:

$$399 \quad CoA = \frac{\int_{x_{min}}^{x_{max}} f(x) \cdot x dx}{\int_{x_{min}}^{x_{max}} f(x) dx} \quad (2)$$

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

404 The downtime of water lifeline is given through inferencing the “Availability of human  
405 resources”, the “Infrastructure type”, the “Earthquake intensity”, and the “Exposed  
406 infrastructure” indices as  $(\mu_{VL}^{DT}, \mu_L^{DT}, \mu_M^{DT}, \mu_H^{DT}, \mu_{VH}^{DT}) = (0,0,1,0,0)$ . According to the  
407 downtime membership functions, considering the highest membership value, the downtime of  
408 the water network may be classified as *medium* (11-24 days).

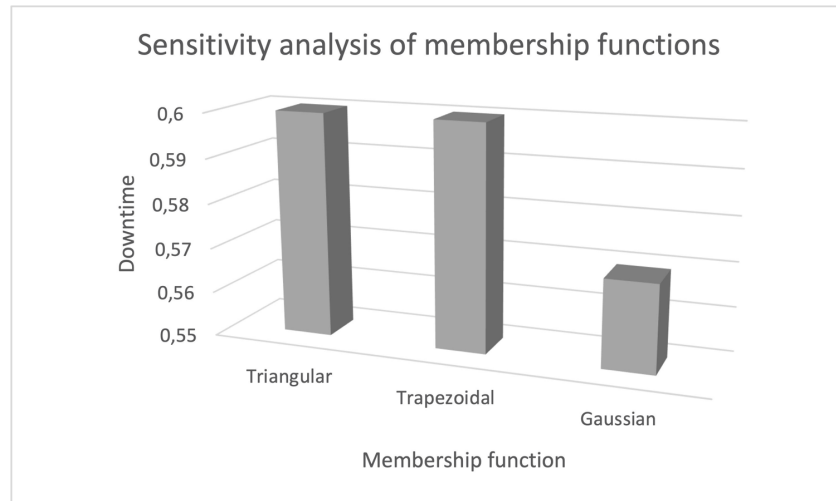
#### 409 ***Sensitivity analysis of fuzzy membership functions***

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

419 By analyzing the results obtained (see Figure 7), it is possible to conclude that the investigated  
420 membership functions provide similar results for the downtime output (around 0.6). This means

421 that membership functions do not have a high impact on the fuzzy inference procedure within  
422 the proposed downtime assessment model.

423



424

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

427

#### 428 **Downtime estimation using Bayesian network**

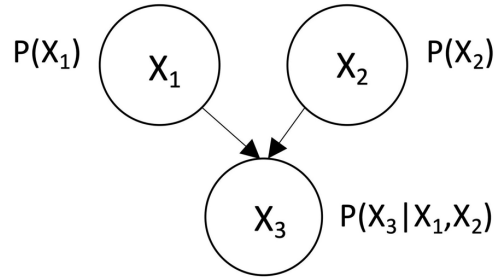
429 This section describes the BN approach and the methodology performed for quantifying the  
430 recovery time of damaged water and gas lifelines following earthquakes.

#### 431 ***Bayesian network theory***

432 The Bayesian network (BN), also known as Bayesian Belief Network or Causal Probabilistic  
433 Network, belongs to the family of probabilistic *graphical models* (GMs). It is structured based  
434 on Bayes' theorem that permits graphical probabilistic relationships among a set of variables  
435 [89]. Bayesian networks can update prior probabilities of some unknown variable when some  
436 evidence describing that variable exists. The uncertain variables in a BN model can be  
437 graphically represented through vertices (nodes) with an edge representing the casual  
438 relationship between two vertices and the uncertainties can be expressed through subjective  
439 probabilities [43, 89]. The ability of BN to represent graphically real-world applications where  
440 there are frequently many uncertain and unknown variables makes the approach suitable for  
441 experts' knowledge.



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

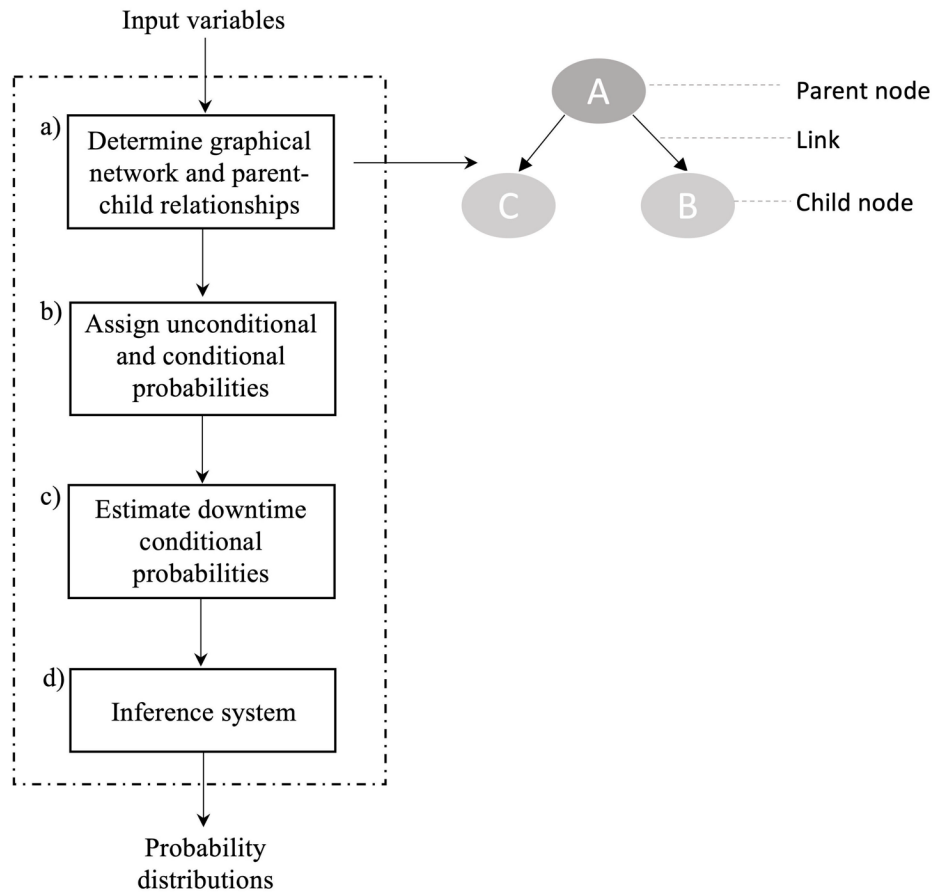


446

447 **Figure 8.** An example of BN with three variables

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

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



456  
457

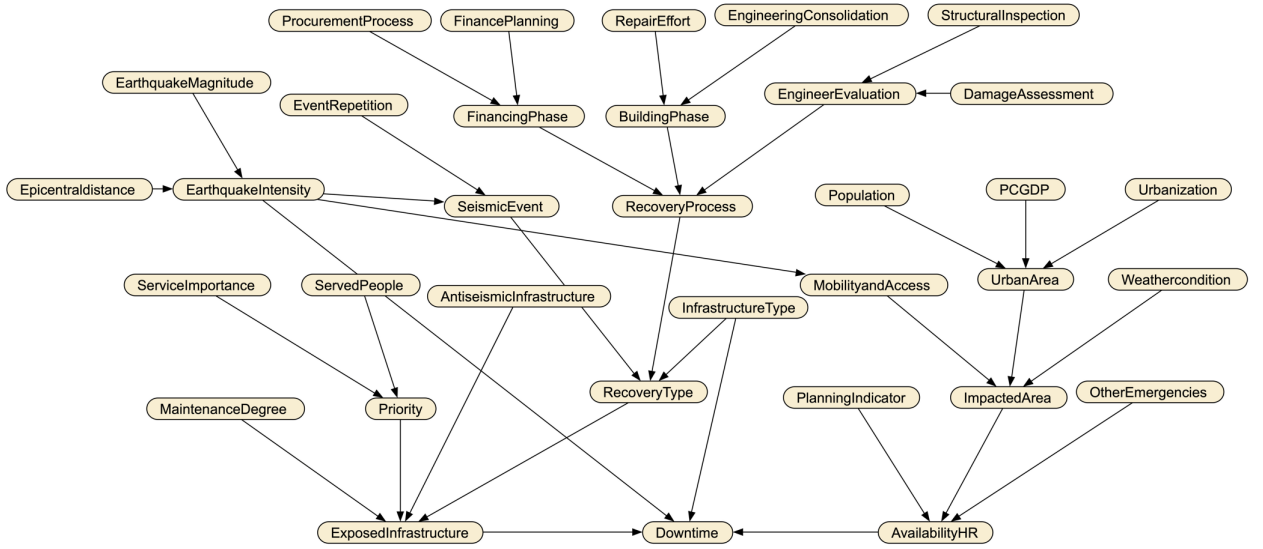
458 **Figure 9.** Steps for a Bayesian Network (BN) development

459

460 ***Step a: Graphical network and parent-child relationships***

461

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



469

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

471 ***Step b: Assigning unconditional and conditional probabilities***

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

474 
$$p(A|B) = \frac{p(B|A) \times p(A)}{p(B)} \quad (3)$$

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

479 Once the downtime indicators have been connected by a set of links defining parent-child  
 480 relationships among them, a set of Conditional Probabilities Tables (CPTs), where the  
 481 likelihood of the child node to assume a certain state under a given state of its parent, is  
 482 assigned. The specification of the parameters of the probabilistic dependence model (i.e., the  
 483 cause-effect relation) represented via a Conditional Probability Table (CPT) is one of the pillars  
 484 of BN. Depending on the available data (prior knowledge, expert-based information,  
 485 observations, etc.), CPT can be populated in several manners [91-93]. That is, different  
 486 assumptions can be made, and different methods are available, which might lead to uncertainties  
 487 in the BN results [94]. In the situation where data are scarce, estimating CPTs may become

488 challenging. A possible solution is relying on expert knowledge elicitation, which means  
 489 experts are asked to give qualitative statements or relative measures. In the BN, the probabilities  
 490 can be subjectively defined. The BN enable converting empirical distribution and subjective  
 491 probabilities in the analysis. The approach used to estimate conditional probabilities for all  
 492 nodes of the downtime network is further described in [20].

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

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

500 ***Step c: Estimation of downtime conditional probabilities***

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

504 The database was collected from published literature for earthquakes that have occurred after  
 505 the '60s because there was little or no reliable information about the damage caused by earlier  
 506 earthquakes. Data used to design the restoration curves of the water and gas systems have been  
 507 divided into 4 sets based on the earthquake intensity: Strong 6-7; Major 7-8; Severe 8-9; and  
 508 Violent 9-10). For each lifeline, a group of restoration curves considering the four magnitude  
 509 ranges have been developed. Table 13 shows the data sets considered in realizing the restoration  
 510 curves, extracted from Table 12.

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

	<b>Water</b>		<b>Gas</b>	
	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)

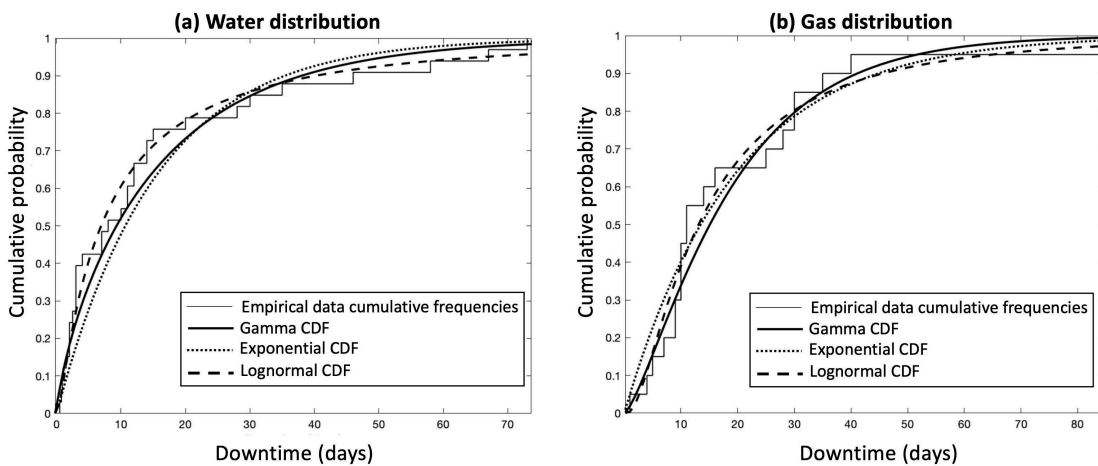
512

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

518 **Table 13.** Downtime data and corresponding frequencies for water and gas networks with EM 6-7, 7-8, 8-  
519 9, and 9-10

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

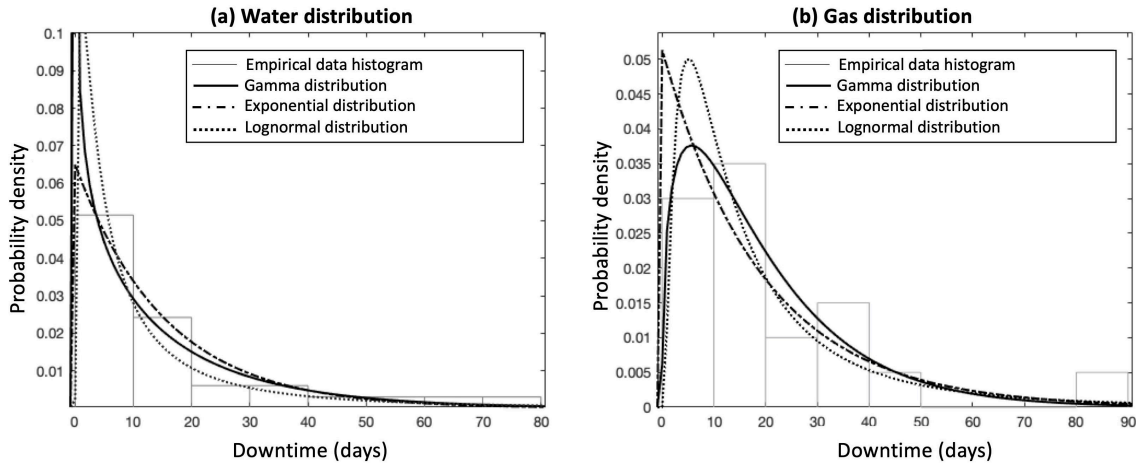
		EM 8-9				EM 9-10			
		Water		Gas		Water		Gas	
		Freq.	DT (days)	Freq.	DT (days)	Freq.	DT (days)	Freq.	DT (days)
	Gas	2	1	1	10	3	1	1	1
	Gas	1	2	1	20	1	4.7	1	2
	Gas	3	3	1	30	1	5	1	3.5
	Gas	4	14	1	90	2	7	1	5
	Gas	3	18	1		3	14	1	13
	Gas	2	22	1		1	26	1	14
	Gas	1	27	1		3	47	1	18
	Gas	2	30	1		1	50	2	30
	Gas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



520

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

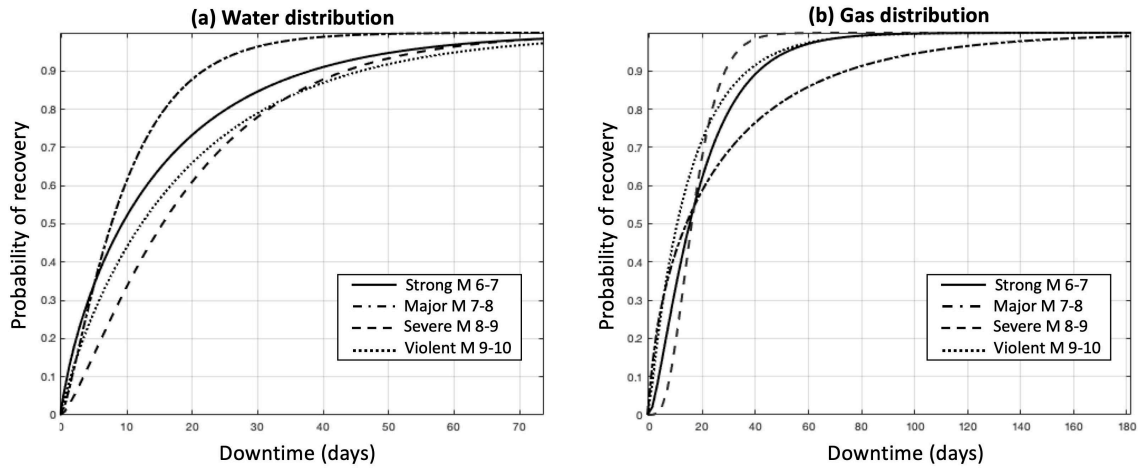
523 Figure 12 shows the frequency histogram of the downtime data and the probability density  
 524 function (PDF) of the gamma, exponential, and lognormal distributions related to (a) the water  
 525 network infrastructure and (b) the gas network for earthquake magnitude range EM 6-7.



526

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

529 Since the plotted PDFs present a similar trend, it is not simple to choose the distribution with  
 530 the best fit relying only on visual interpretation. Therefore, the goodness-of-fit tests (GOF) are  
 531 used to identify the appropriate distribution for the empirical data [20]. Goodness-of-fit of a  
 532 statistical model is a method that determines how well a model fits a set of observations. Two  
 533 tests for Goodness-of-fit are used in this work the identify the distribution with the best fit: the  
 534 Kolmogorov-Smirnov (K-S) and Chi-Square tests. The gamma distribution is selected to fit the  
 535 downtime data of both infrastructure systems. The parameters of the chosen distribution have  
 536 been determined using the Least Squares Parameter Estimation method. The restoration curves  
 537 for water and gas infrastructures are plotted using two factors: (i) the number of days needed to  
 538 restore full service (horizontal axis); (ii) the probability of a complete restoration (vertical axis).  
 539 The restoration curves are classified under four groups of Richter magnitude scale: 6-7 *Strong*,  
 540 7-8 *Major*, 8-9 *Severe*, and 9-10 *Violent*, as shown in Figure 13.



541  
542 **Figure 13.** Restoration curves of the Water and Gas lifelines based on the earthquake magnitude

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

558 **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%

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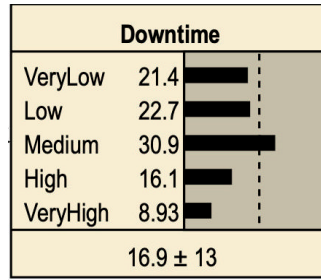
**Table 15.** Conditional probability table (CPT) for the downtime output of the water and gas infrastructure

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
<b>Water</b>	<b>Strong</b>	<b>High</b>	<b>Low</b>	<b>0,2947</b>	<b>0,2289</b>	<b>0,2740</b>	<b>0,1360</b>	<b>0,0687</b>
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
<b>Water</b>	<b>Major</b>	<b>High</b>	<b>Low</b>	<b>0,1826</b>	<b>0,2089</b>	<b>0,2889</b>	<b>0,1869</b>	<b>0,1332</b>
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
<b>Gas</b>	<b>Strong</b>	<b>High</b>	<b>Low</b>	<b>0,1035</b>	<b>0,2255</b>	<b>0,3885</b>	<b>0,2099</b>	<b>0,0726</b>
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
<b>Gas</b>	<b>Major</b>	<b>High</b>	<b>Low</b>	<b>0,1762</b>	<b>0,2172</b>	<b>0,3125</b>	<b>0,1735</b>	<b>0,1206</b>
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
...	...	...	...	...	...	...	...	...

561

562 **Step d: Inference and downtime estimation**

563 BN's structure learning and inference for the downtime are performed using the commercial  
564 software Netica [95]. Construction of the BNs requires a list of the uncertain variables, the  
565 possible states of the discrete variables and possible ranges of the continuous variables, the  
566 relationship among the variables, and the conditional probabilities for the inference. Once the  
567 indicators and the corresponding states/ranges (see Table 7) and probabilities have been  
568 assigned, the BN is compiled. The probabilities solve the network by finding the marginal  
569 posterior probabilities that some indicators will be in a particular state given the input indicators  
570 and the conditional probabilities [96]. The DT results for the water network are shown in Figure  
571 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

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573  
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### 576 *Sensitivity analysis*

577  
578

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:

$$589 \quad (q|i) = \sum_q p(q|i)[X_q - E(Q|i)]^2 \quad (4)$$

590 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  $I$ .

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

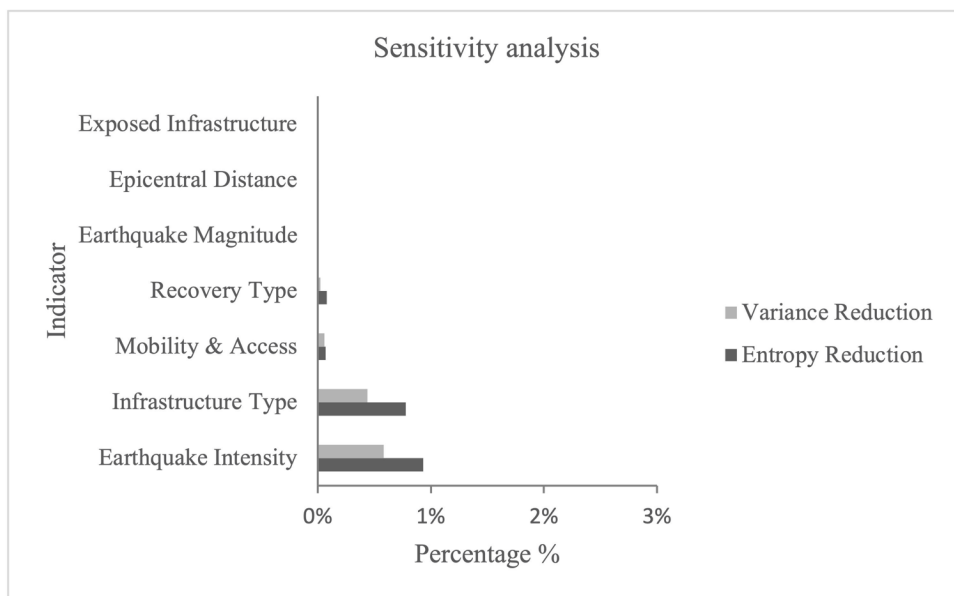
$$595 \quad QR = H(Q) - H(Q|I) = \sum_q \sum_i P(q, i) \frac{\log_2[P(q,i)]}{P(q)P(i)} \quad (5)$$

596 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

598 displayed indicating how much the query node would be influenced by a single finding at each  
599 of the other nodes (varying nodes) through different sensitivity measures (i.e., variance  
600 reduction and entropy reduction).

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

605



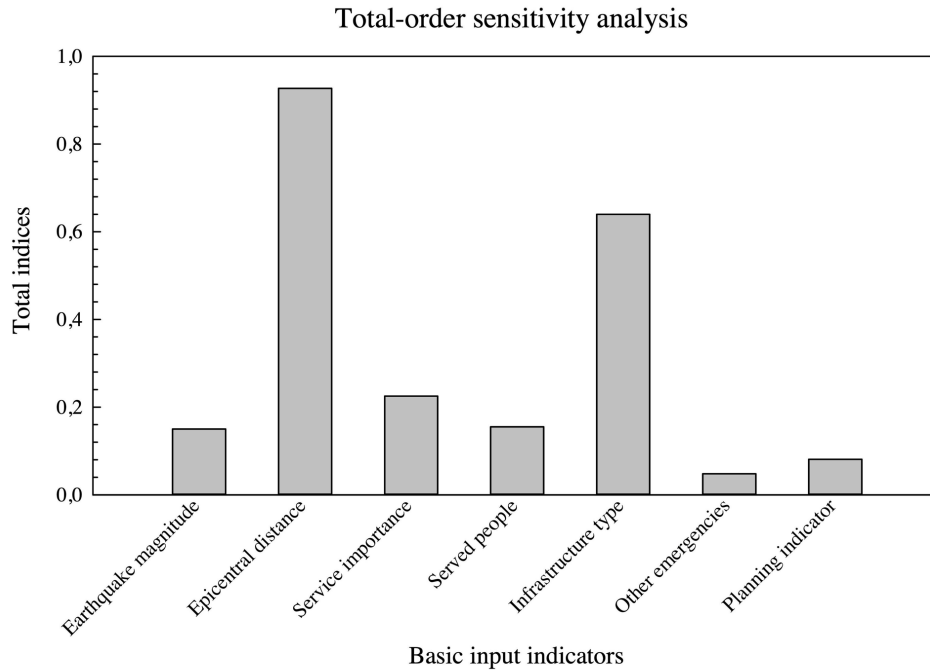
606

607 **Figure 15.** Sensitivity analysis of downtime node

608

609 For query node Downtime, *Earthquake Intensity* has the highest contribution (0.58% variance  
610 reduction and 0.93% entropy reduction) followed by *Infrastructure Type* (0.44% variance  
611 reduction and 0.78% entropy reduction), *Mobility and Access* (0.06% variance reduction and  
612 0.07% entropy reduction), and *Recovery Type* (0.02% variance reduction and 0.08% entropy  
613 reduction). *Earthquake Magnitude*, *Epicentral Distance*, and *Exposed infrastructure* have very  
614 low contributions. That is, the variance reduction and entropy reduction for the three indicators  
615 are below 0.05%. The result of sensitivity analysis allows the decision-makers to identify the  
616 input parameters that affect the output most and prioritize them in the decision-making.

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

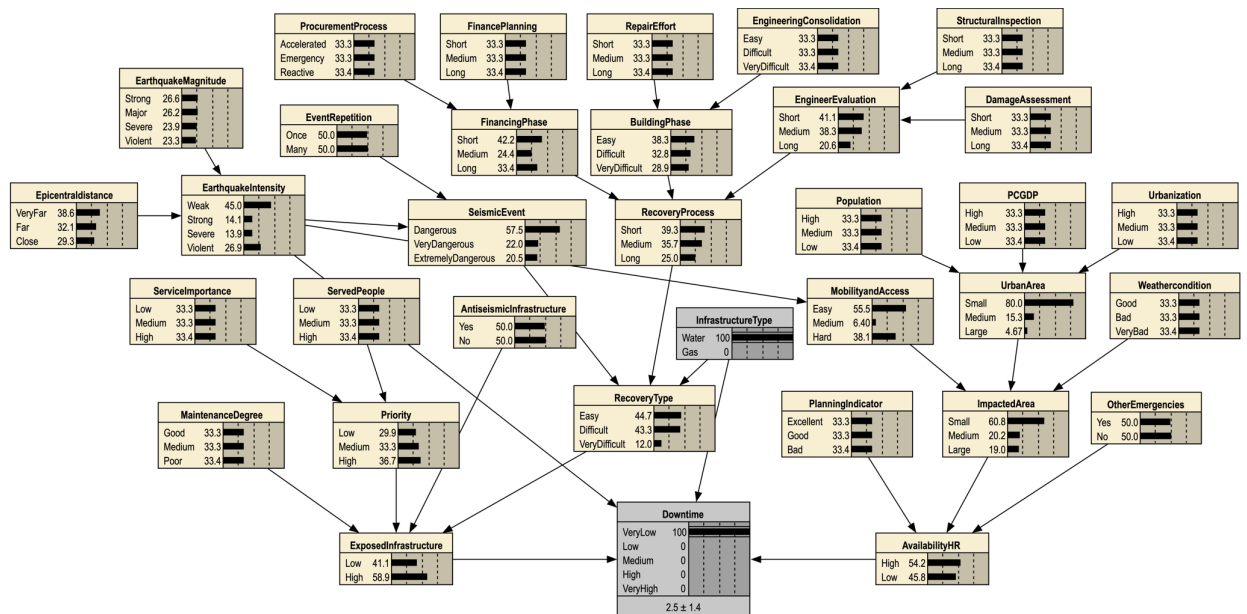


637

638 **Figure 16.** Total-order sensitivity analysis

639 ***Backward propagation analysis***

640 The backward analysis (diagnostic reasoning) is a useful feature of BN that allows decision-  
 641 makers to improve the performance of a system by setting a desirable state of the DT and  
 642 getting the parameters that assure the predefined DT state. In backward analysis, observation is  
 643 made for a specific indicator, usually a target indicator (e.g., the downtime node in this work),  
 644 and then the BN calculates the marginal probabilities of unobserved indicators by propagating  
 645 the impact of the observed indicator through the network in a backward fashion. For instance, if  
 646 the downtime state is set to *very low* (i.e., 100% of chance to be in the state *very low*), the  
 647 “Exposed infrastructure” index is 58.9% *high*, the “Availability of Human Resources” index is  
 648 54.2% *high*, and the “Earthquake intensity” index is 45% *weak*. The marginal probabilities of  
 649 the other unobserved indicators are shown in Figure 17.



650

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

652 **Results and comparison**

653 FL and BN inference methods have been applied to estimate the downtime of the water  
654 infrastructure of the city of Calascibetta in Sicily, Italy. The application of both  
655 approaches allows performing a comparison of the modeling and quantification of the  
656 downtime. Both inference methods incorporate intuitive knowledge or historical data  
657 for defining fuzzy rules (in FL) and estimating conditional probabilities (in BN).  
658 Involving the use of experts in the generation of fuzzy rules (in FL) and probabilities (in  
659 BN) for different systems for which data are not available is a critical aspect of the  
660 downtime estimation model. In BN inference method, we can see uncertainty in the  
661 results in the form of probability dispersion (or variance) due to the basic inputs that are  
662 uncertain in the first place. That is, the principle of insufficient reasoning is applied to  
663 the basic inputs, i.e., the states of the inputs have an equal probability of occurrence. FL  
664 and BN inference methods can be implemented without being familiar with the  
665 mathematical details and served probabilistic analysis. This is an important feature as complex  
666 mathematical formulations to provide direct inputs in the proper form of FL and BN are  
667 not required. Furthermore, in the definition of the input values, BN is less sensitive to

668 less precise information than FL. That is, when the uncertainty of the inputs is  
669 significant, FL provides results less certain than BN. Both methodologies show similar  
670 results, and the recovery time output follows the same trend. FL and BN inference  
671 methods differ in their interpretation of the output. The output of the FL is a  
672 membership that defines how well the downtime fits the fuzzy levels, e.g., the  
673 downtime output for the water utility belongs to level *Very Low* with a membership  
674 degree of 0, to *Low* with a degree of membership of 0.19, to *Medium* with a degree of  
675 membership of 0.81, to *High* with a membership degree of 0, and to *Very High* with a  
676 degree of membership of 0. The BN output is a probability distribution that represents  
677 how likely the downtime is in a certain state, e.g., in the case of water lifeline shown in  
678 Figure 14, the downtime output has a 21.4 chance of being in state *Very Low*, 22.7 of  
679 being in state *Low*, 30.9 of being in state *Medium*, 16.1 of being in state *High*, and 8.93  
680 of being in state *Very High*. Consequently, the BN output probability distribution tends  
681 to be easier to interpret as well as more intuitive than FL output, which is in the form of  
682 a fuzzy set.

683 One of the advantages of the proposed downtime estimation model based on BN  
684 inference method is the capability to easily update the downtime model when new data  
685 and information is available. The powerful feature of BN for generating different what-  
686 if scenarios allows running several scenarios and determining the efficient means of  
687 reducing the downtime. Another advantage of applying BN inference method to the  
688 downtime model is the diagnostic reasoning. The backward analysis of BN enables  
689 setting a desirable state of the downtime and getting the indicators that provide the  
690 predefined downtime state. By doing that, decision-makers can improve the  
691 performance of their systems. Moreover, it is possible to estimate the probability of  
692 another node if the evidence for the given nodes is known. This would provide

693 flexibility in BN approach. Updating the downtime model based on FL requires more  
694 time since it can be done manually by adjusting fuzzy rules and changing the shape of  
695 the membership functions. Moreover, in the case of new information, fuzzy rules need  
696 to be changed. This requires a good knowledge of the system to effectively apply FL. In  
697 terms of easiness of implementing the two approaches to the downtime estimation  
698 model, both BN and FL frameworks are easy to build but estimating conditional  
699 probabilities in BN for each child node of complex systems can be challenging. To sum  
700 up, the two proposed inference systems can be implemented to cover two possible  
701 conditions: (i) data is (partially) available but uncertain, and (ii) data is not available or  
702 limited. That is, Bayesian Network is proper when statistics are available, while the  
703 Fuzzy Logic approach is a suitable solution to deal with less or unavailable data.  
704 Therefore, each approach is applicable for different cases.

705 The results obtained from BN and FL approaches can be used to help and support  
706 decision-makers (e.g., engineers and managers) prioritize financial resources in the  
707 planning and management of post-disaster strategies. By analyzing the downtime  
708 results, decision-makers can optimize their action by prioritizing activities and choosing  
709 proper recovery measures to assure the functionality of the infrastructures and to assign  
710 appropriate resources. Risk planners, previously concerned with protection and  
711 prevention, are now more interested in the ability of such infrastructures to withstand  
712 and recover from disruptions in the form of resilience-building strategies. Moreover, the  
713 sensitivity analysis results can be used to pinpoint which indicators are effective to  
714 reduce risk, use it for decision-maker to assign appropriate resource, and determine the  
715 most efficient and effective means of reducing risk and improving resilience. For  
716 instance, the estimated downtime values (i.e., medium downtime) of the water  
717 infrastructure of the city of Calascibetta in Sicily may be reduced by improving some



718 sensitive and influential indicators that require special attention, such as the *Mobility*  
719 *and Access* and the *Recovery Type* indicators, and the “Availability of Human  
720 Resources” index. The utility managers must take appropriate preventive action (e.g.,  
721 maintenance or replacement of the analyzed pipe after inspection) to avoid its failure  
722 and improve the resilience against future hazard events.

723

## 724 **Conclusion**

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

741 The downtime estimation model presented in this paper is targeted as a support tool for  
742 decision-makers to evaluate the overall repair time and quantify the priorities of the  
743 repair activities. Results from the case scenario, in terms of probability of being in a

744 given state (BN) and the degree of membership (FL), can be used to pursue the best  
745 strategies during the planning and management post-disaster processes, manage and  
746 minimize the impacts of seismic events, and promptly recover damaged infrastructures.

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

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

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

## 766 **Acknowledgment**

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