Downtime Estimation of Buildings and Infrastructures Using Fuzzy Logic

DOWNTIME ESTIMATION OF BUILDINGS AND INFRASTRUCTURES USING FUZZY LOGIC

M. De Iuliis[(1)], G.P. Cimellaro[(2)], M. Domaneschi[(3)], S. Tesfamariam[(4)]

[(1)] *PhD student, Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Italy, email: melissa.deiuliis@polito.it*
[(2)] *Associate Professor, Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Italy, email: gianpaolo.cimellaro@polito.it*
[(3)] *Assistant professor, Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Italy, email: marco.domaneschi@polito.it*
[(4)] *Professor, School of Engineering, The University of British Columbia, Kelowna, BC, Canada, Email: solomon.tesfamariam@ubc.ca*

Abstract

Extreme natural events (e.g. earthquakes, floods, fire) are the major sources of threat to society and infrastructure. Communities that are able to absorb the impacts, recover quickly after disasters, and adapt to adverse events are fairly resilient communities. Economic and public health consequences from natural disasters have increased over time and motivated discussion of a new resilience management worldwide. The key parameter to estimate the resilience of buildings and infrastructures is the downtime (DT). Several strategies have been investigated to reduce disaster risk and evaluate the recovery time of buildings and infrastructures following dangerous events. However, the estimation of the DT is still challenging due to the uncertainty and vagueness of the data available.

This paper introduces a method to predict the DT of buildings and infrastructures following earthquakes through a Fuzzy Logic hierarchical scheme. The use of expert-based systems can be helpful to deal with uncertainties, randomness, and limited data availability in the context of risk analysis and management. Fuzzy theory describes the behavior of a complex system through linguistic variables and it is based on deterministic functions.

Two different DT models are introduced in this work for residential buildings and infrastructures, since different are the input parameters involved in the estimation process. In the first model, the DT can be divided into three main components: downtime due to the actual damage (DT1); downtime caused by irrational delays (DT2); and downtime due to utilities disruption (DT3). DT1 is evaluated by relating the building damageability to given repair times of the building's components. A rapid visual screening survey is filled out by an expert to acquire information about the analyzed building. Then, fuzzy logic is implemented to determine the building vulnerability, which is combined with a given earthquake intensity to obtain the building damageability. DT2 and DT3 are estimated using the REDI[TM] Guidelines. DT2 considers irrational components through a specific sequence, which defines the order of components repair, while DT3 depends on the site seismic hazard and on the infrastructure vulnerability. The downtime of the building is finally estimated by combining the three components above, identifying three recovery states: re-occupancy, functional recovery, and full recovery.

For estimating the recovery time of buried infrastructures, 31 indicators have been selected from previous publications and studies referring to programs and policies intending to reduce risk and increase recovery. The DT model is designed by aggregating four downtime indices: exposed infrastructure, earthquake intensity, human resources, and infrastructure type. The collected information on the potentially damaged lifelines are aggregated into a fuzzy hierarchical scheme and combined to obtain the DT.

The methodology can be used to effectively support decision-makers in managing and minimizing the impacts of earthquakes and to recover damaged infrastructure promptly.

Keywords: downtime, damages, buildings, infrastructures, fuzzy logic

1. Introduction

Residential buildings and critical infrastructures (CI) systems, which contribute to the economic development and quality of life of modern communities, are subjected to degradation due to aging, aggressive environmental factors, and natural and human-made disasters (e.g., earthquakes, floods, and terrorist attacks).
During recent seismic events, such as the 1995 Kobe earthquake and 2016 Kunamoto earthquake, severe building and lifeline damages have occurred, especially to water distributions and gas networks whose damage brings along disastrous fire events [1-3].
The functionality and the ability of a system to provide its service under emergency conditions can be evaluated by studying the resilience of buildings and critical infrastructures that are prone to many disruptive events or inadequate maintenance [4-6].
In engineering, the concept of resilience is "the ability of social units (e.g. organizations, communities) to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways to minimize social disruption and mitigate the effects of further earthquakes" [7, 8]. Wagner and Breil [9] defined resilience as the ability to "withstand stress, survive, adapt, and bounce back from a crisis or a disaster and rapidly move on". In the seismic resilience estimation, the concept of downtime (DT) is defined as the time between the moment the hazard event occurs *(t_o)*, when the of the system $Q_{(0)}$ drops to $Q_{(1)}$, and the time when the functionality is completely restored *(t_1)* [10-12] (see Fig. 1).

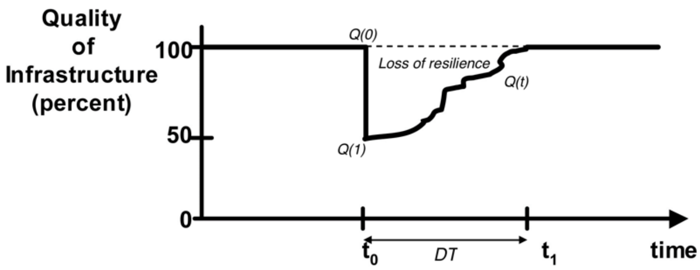

Fig. 1 – Conceptual resilience function of a system highlighting Downtime (DT)

Although several studies have been carried out on DT, the data and the input parameters that are required for the estimation are subject to imprecision and vagueness uncertainties [13]. Parameter uncertainty could happen in data acquisition in the chaotic aftermath of a hazard event. Soon after a disastrous event, the available information is usually incomplete, highly uncertainty, and rapidly evolving in time. Therefore, the main challenge in restoration time estimation is dealing with randomness, vagueness, and ignorance-type uncertainties [6]. Several techniques have been proposed and investigated based on fuzzy theory or evidence theory [14, 15]. Recently, fuzzy systems have been increasingly proposed to deal with vagueness, which is caused by unclear concepts in observation, and to represent ambiguous and uncertainty data when available information is limited, mainly coming from expert judgements.

In this context, the present study is aimed at estimating the restoration time of damaged buildings and infrastructures following earthquakes by implementing a DT model and an expert-based system: Fuzzy Logic. The remainder of this paper is structured as follows: Section 2 is dedicated to reviewing the basic knowledge of FL. Section 3 describes the DT estimation through FL, Section 4 illustrates the DT methodology for critical infrastructures. A scenario analysis is provided in Section 5 to demonstrate the applicability of the methodology. Finally, Section 6 draws conclusion and proposes future research work.

2. Fuzzy Logic theory

The concept of fuzzy set and the theory behind it was introduce by [16] to deal with vagueness and subjectivity of human judgement in using linguistic terms in decision-making process [17, 18]. 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) [19]. Later on, fuzzy sets were implemented to new approaches in which linguistic variables were used instead of or in addition to numerical variables [20]. Fuzzy logic became a key factor in several fields such as Machine Intelligence Quotient (MIQ) to mimic the ability of human, industrial applications, and earthquake engineering.

The fuzzy logic consists of three main steps (see Fig. 2): 1) Fuzzification; 2) Fuzzy inference system; and 3) Defuzzification.

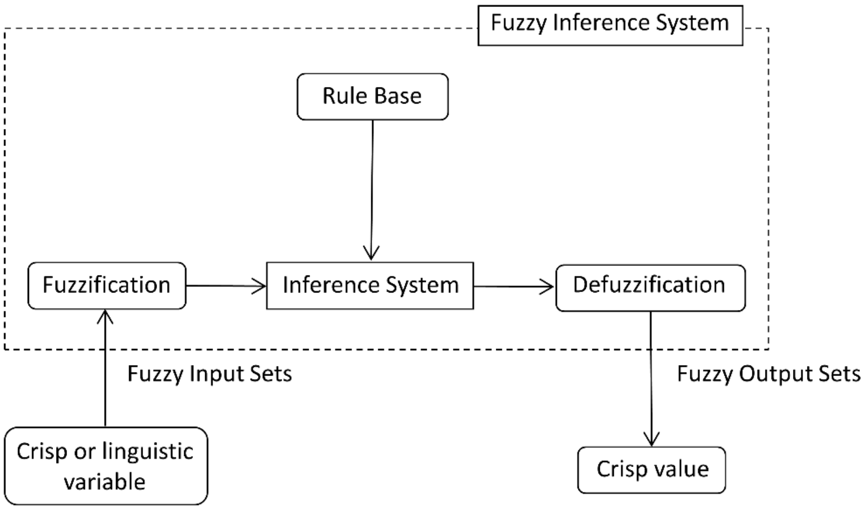

Fig. 2 – Fuzzy Inference System (FIS)

2.1 Fuzzification

The basic input parameters have a range of values that can be grouped into linguistic quantifiers according to the number of the states. However, to implement fuzzy theory in the DT model easily, only three states are assigned to the DT variables (e.g., *low*, *medium*, and *high* or *small*, *medium*, and *large*, etc.). The fuzzification step converts the input values into a homogeneous scale by assigning corresponding membership functions with respect to their specified granularities [19]. Different forms of membership functions are defined in fuzzy theory such as triangular, trapezoidal, and Gaussian shapes. Triangular or trapezoidal fuzzy membership functions are usually used to represent linguistic variables since their simplicity to apply fuzzy operations [21].

2.2 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 most common type is the Mamdani type, which is a simple IF-THEN rule with a condition and a conclusion. The fuzzy rules are defined using a weighting method that allows to identify the impact of the input towards the output [22, 23]. 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. That is, intersection, minimum, product, union, maximum, and summation aggregation procedures are available to define a complex system. For instance, 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).

2.3 Defuzzification

The last step of the FL is the *defuzzification* process. Many different techniques to perform defuzzification are available in the literature, such as: the center of the area (COA), the center of gravity, bisector of area, etc. [24]. The purpose of the defuzzification step is to defuzzify the fuzzy output and obtain a final crisp output.

3. DT evaluation of buildings through FL

The Downtime assessment for buildings can be performed following five steps, which are:

1. Performance of a Rapid Visual Screening (RVS) of the potentially damaged buildings;
2. Creation of a hierarchical scheme, in which information obtained from the RVS is used as input;
3. Translation of the RVS results into numerical data through the use of Fuzzy system. The numerical data are used to define the Building Damageability membership (BD) following the defined hierarchical scheme;
4. Evaluation of the repairs (rational components), delays (irrational components), and utilities disruption considering the damage memberships that are greater than zero;
5. Defuzzification of the downtimes obtained from the analysis to quantify the total repair time.

In the following, each step will be expounded.

The evaluation of the downtime can be handled through a comprehensive hierarchical structure (Fig. 3), which follows a logical path combining the parameters that contribute in the downtime analysis. The methodology starts with a Rapid Visual Screening (RVS) of the buildings based on a survey form performed by an expert. A Fuzzy system is implemented in the procedure to translate the RVS results from linguistic terms into numerical data. Building information from the RVS is incorporated through a hierarchical structure, which follows a logical order for combining specific contributors (e.g. site seismic hazard and building vulnerability modules) to estimate the building damage [25]**.** The building damageability is carried out as five-tuple membership values (μ_{VL}^{BD}, μ_{L}^{BD}, μ_{M}^{BD}, μ_{H}^{BD}, μ_{VH}^{BD}) and each membership value is associated with five damage states, *very low* (VL), *low* (L), *medium* (M), *high* (H), *and very high* (VH). The building membership can be considered as the limit state in which the structure may be for a given site seismic hazard and building vulnerability. Thus, the downtime analysis is carried out for the degrees of damage membership that are greater than zero, which represents the possibility of the building being in a limit state. For instance, if the damage membership is (μ_{VL}^{BD}, μ_{L}^{BD}, μ_{M}^{BD}, μ_{H}^{BD}, μ_{VH}^{BD}) = (0, 0, 0.37, 0.63, 0), the downtime is quantified for damage = *Medium (0.37)* and damage = *High (0.63)* [26]. These fuzzy numbers describe the damage expected as a result of a given earthquake and are used to calculate the *repairs*, *delays*, and *utilities disruption*. To estimate the downtime due to *repairs*, it is necessary to define the repair time for each component of the analyzed building and the number of workers assigned for the repair. Downtime due to *delays* is based on irrational components. The irrational components considered in the methodology are a selection from the components introduced in REDI™: post-earthquake inspection, engineering mobilization, financing, contractor's mobilization, and permitting [27]. Downtime due to *utilities* depends on the infrastructure systems that are likely to be disrupted after an earthquake (e.g. electricity, water, gas, etc.). The evaluation of utilities disruption is necessary since functional and full recovery of the building cannot be reached while utilities are disrupted.

Finally, once the rational components, the irrational components, and the utilities disruption are known, the downtime can be estimated. A downtime value is computed for each damage membership as follows:

$$DT = \sum_{i=1}^{n} DT_i * \mu_i \tag{1}$$

where DT_i is the downtime for a certain granulation, i is the granulation assigned to the damage membership, μ_i is the damage membership degree of granulation i.

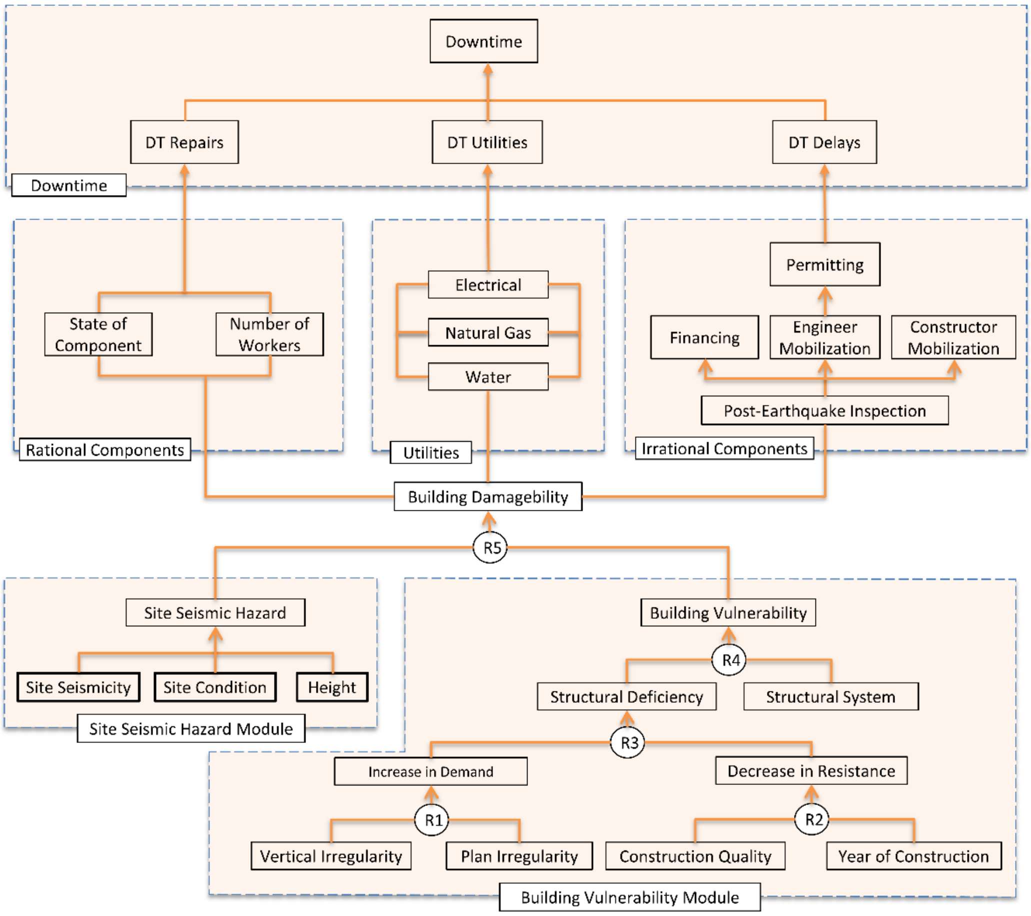

Fig. 3 - The building damageability hierarchical scheme, adapted from Tesfamaraim and Saatcioglu [28]

3.1 Damage estimation

The building damage is estimated through a hierarchical scheme that includes all variables contributing to the building damage (Fig. 3). The proposed hierarchical scheme for the building damageability is an adaptation from Tesfamariam and Saatcioglu [19], in which aggregation of the variables is done through the fuzzy model described before, and the granularity assigned to the fuzzification is associated with the level of damage state. Furthermore, a heuristic model to assign membership values starting from linguistic information is employed in this paper. The membership functions considered in the methodology are those introduced by Tesfamariam and Saatcioglu [19], which are based on triangular fuzzy numbers (TFNs). The weighting method introduced before is used to define the fuzzy rules and to connect the inputs and the outputs of the system. Finally, at each level of the hierarchical scheme, the weighted average method is used for the defuzzification to obtain an index I, as follows:

$$I = \sum_{i=1}^{n} q_i * \mu_{R,i} \tag{2}$$

where q_i is the quality-ordered weights, $\mu_{R,i}$ is the degree of membership, i is the tuple fuzzy set. The 1991 Northridge Earthquake damage observations are used to calibrate the quality-ordered weights in the methodology [19].

The defuzzification process is not required for the Building Damageability. Each damage membership grade that is greater than zero is used independently in the downtime analysis. The resulting downtimes corresponding to the different memberships are combined to obtain a final downtime value, as described before. The granulation assigned to each parameter is shown in Fig. 4.

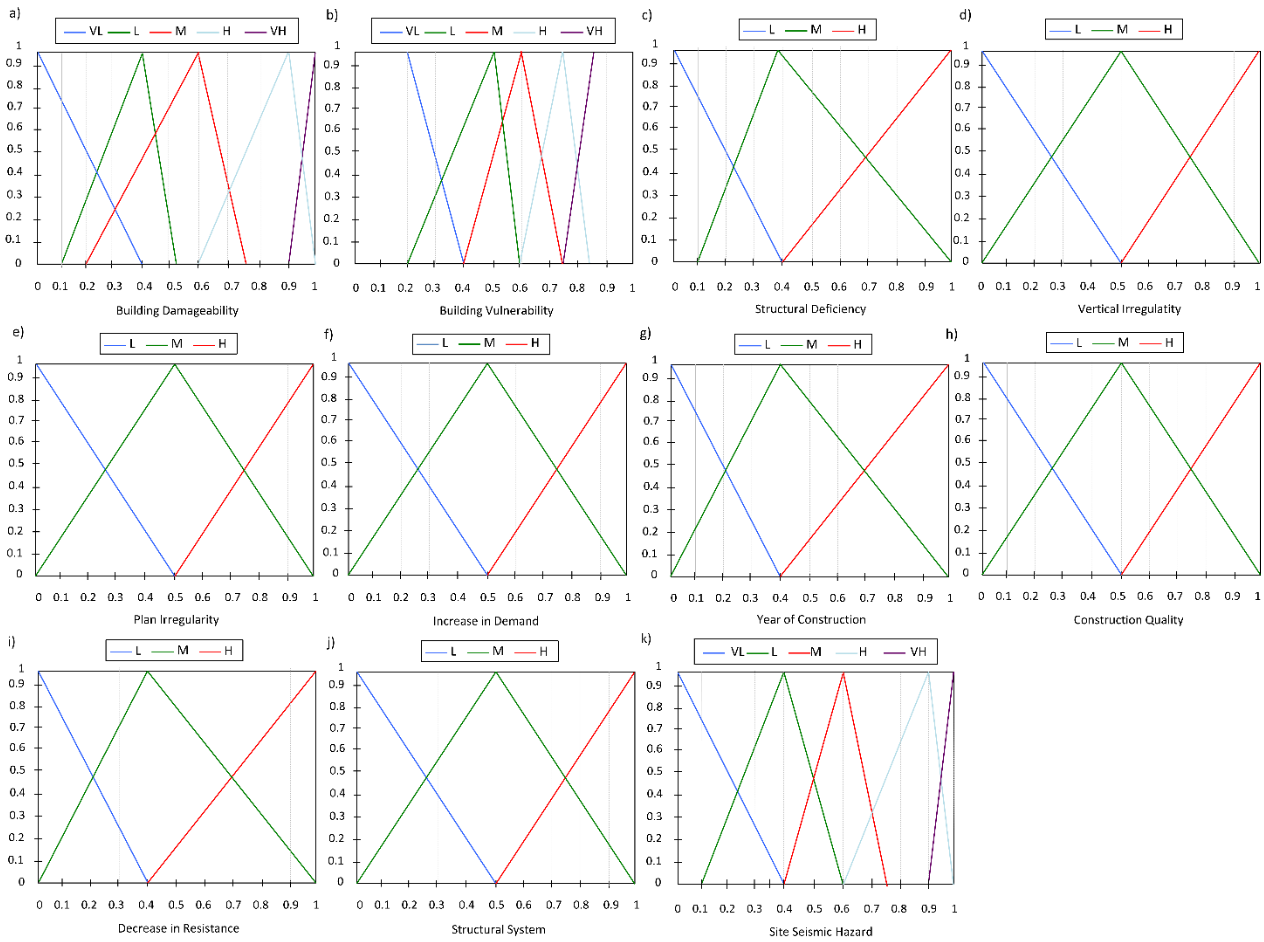

Fig. 4 - Membership functions and granulation for: a) building damageability; b) building vulnerability; c) structural deficiency; d) vertical irregularity; e) plan irregularity; f) increase in demand; g) year of construction; h) construction quality; i) decrease in resistance; j) structural system; k) site seismic hazard

3.2 Downtime due to repairs

In general, the Downtime (*DT*) is the combination of the time required for *repairs* (*DT repairs*, rational components), *delays* (*DT delays*, irrational components), and the time of *utilities* disruption, as follows:

$$DT = max((DT repairs + DT delays); DT utilities) \tag{3}$$

The combination of the three components depends on the chosen recovery state (i.e. re-occupancy recovery, functional recovery, and full recovery) [29]. For example, in the re-occupancy recovery state, consideration of *utilities* disruption is not required, thus the downtime is the result of the time required for *repairs* and *delays* only. Downtime due to repairs considers rational parameters: the state of the damaged components and the number of workers assigned.

3.3 Downtime due to delays

Downtime due to delays is derived from irrational components introduced by Comerio [27]. The irrational components used in the methodology are a selection from the components presented in REDI™: Financing, Post-earthquake inspection, Engineer mobilization, Contractor mobilization, and Permitting. Downtime due to delays is largely based on the building damage. For instance, in buildings where the expected damage state is *Low*, less downtime due to delays is likely to occur. In the following, irrational components are examined.

3.4 Downtime due to utility disruption

Utilities are likely to be disrupted after an earthquake event of certain intensity. Since utility service is required for functional and full recovery, delays due to utility disruption need to be considered for those recovery states. Utilities disruption times are defined from data about past earthquakes Kammouh and Cimellaro [30]. Generally, the disruption of utilities should be considered only in *functional* and *full recovery* states when the maximum membership value of the site seismic hazard is greater than or equal to *Medium* [31-33].

4. Recovery time evaluation of infrastructures

Developing the downtime model for critical infrastructures starts by selecting the variables and parameters (indicators) that affect the DT. The indicators refer to the implementation of processes, mechanisms, programs for emergency response, or policies intending to reduce risk and increase recovery [6]. A total of 31 key indicators have been selected based on an extensive review of previous publications and studies. The DT is modelled by aggregating four downtime indices: (i) exposed infrastructure (EI), (ii) earthquake intensity (E), (iii) available human resources (HR), and (iv) infrastructure type (I). Casual and logical relationships between the downtime indicators are based on expert knowledge and published literature. The graphical representation of the proposed DT assessment model is shown in Fig. 5.

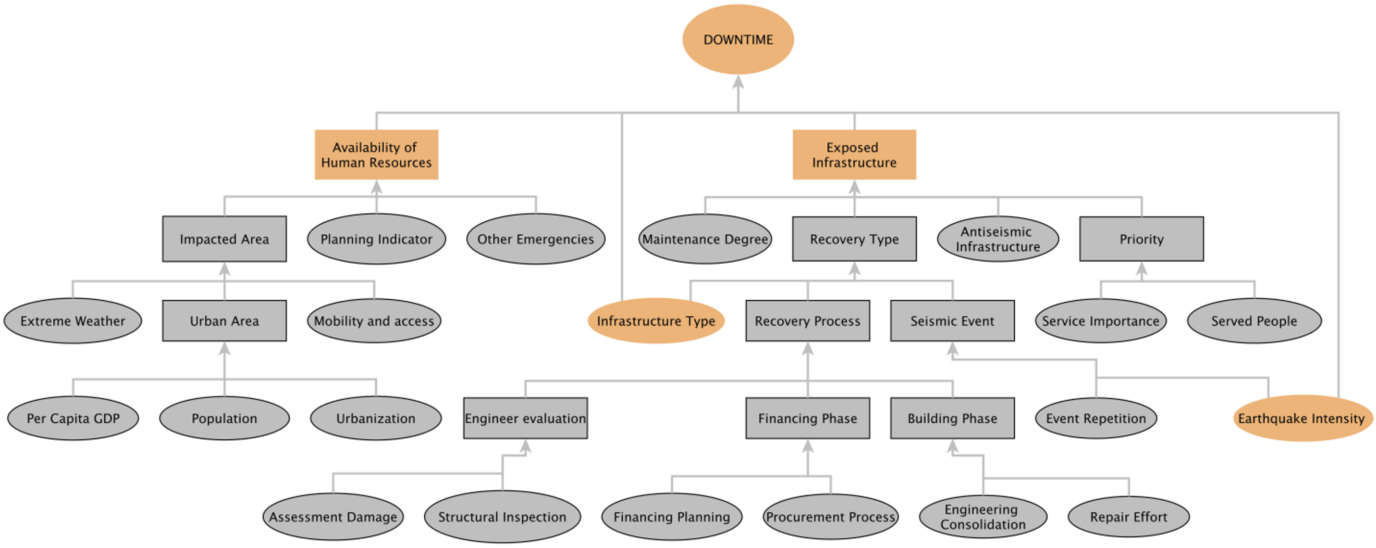

Fig. 5 - DT evaluation model for infrastructures

The downtime evaluation for water and gas lifelines damaged by earthquakes through FL consists of four main steps, which are:

- Step 1: Evaluation of the DT indicators for the potentially damaged lifelines;
- Step 2: Creation of a hierarchical scheme through the gathered indicators;
- Step 3: Application of the Fuzzy theory and the aggregation of the input values.

- Step 4: Defuzzification of the combined input values to obtain the downtime membership function.

Collecting information on the DT indicators (e.g., procurement process, characteristics of the exposed infrastructure, impacted area, etc.) of the potentially damaged infrastructures is the first step of the proposed methodology. Soon after a disastrous event, the available information is usually incomplete, highly uncertainty and is can be affected by subjective and qualitative judgments [34], which can be handle through the fuzzy theory. As Fig. 5 shows, many parameters are considered in the downtime 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 [35]. Magdalena [36] showed that a decomposition at the level of indicators is a proper solution. For instance, from Fig. 5**Errore. L'origine riferimento non è stata trovata.**, it can be shown that exposed infrastructure has four inputs: maintenance degree, recovery type, anti-seismic infrastructure, and priority. Using a three-tuples fuzzy number, which corresponds to three states (e.g., low, medium, and high), the number of rules required to combine the parameters is 34 = 81. According to the process described by [36], the hierarchical structure can be decomposed at the level of indicators by introducing intermediate connections among the parameters at different levels of the hierarchy and by defining intermediate rules.
Starting from linguistic information, membership values are assigned through the implementation of a heuristic model, which can generate membership functions using human intelligence. The membership functions considered in the methodology are based on triangular fuzzy numbers (TFNs). The inference step of fuzzy logic is carried out through the definition of the fuzzy rules that are used to connect input and output values of the system. Fuzzy rules are defined by the implementation of a weighting method, which allows determining the impact (i.e. weight) of the input towards the output [22, 23].

5. Scenario analysis

In this section, an illustrative example of scenario for water and gas networks is provided to demonstrate the applicability of the proposed downtime methodologies. The earthquake considered in the analysis is the 6.0 magnitude earthquake that hit Napa (USA) on the 24th of August 2014. The earthquake with the epicenter located approximately 6.0 km northwest of the city of American Canyon near the West Napa fault, caused about 200 injured people and 1 dead person. Lifelines performed relatively well: water infrastructure was largely restored within ten days, with the majority of breaks being in cast iron pipes. There was minor damage to roads and natural gas lines. The input data used in the methodology are obtained from literature (see Fig. 5) and they are combined through FL. In the following, the steps of the FL approach are illustrated.

Transformation: The first step of the FL methodology to quantify the DT is to transform the basic items into comparable numbers. To do that, artificial numbers and expert knowledge are used. Three states (i.e., low, medium, and high) have been assigned to the inputs to simplify the fuzzy logic procedure. An example of transformation values is listed in Table 1.

Table 1. Basic items and transformation

Basic item	Field observation	Transformation
Assessment Damage	Long	0.20
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 intensity	Strong	0.85
Event Repetition	Once	0.30
Service Importance	High	0.70

Fuzzification: this step consists of fuzzifying the transformed values with respect of their granulation. After selecting a transformation value for each DT parameter, one can enter the corresponding membership graph and obtain the membership degree. Some of the results are illustrated in Table 2.

Table 2. Fuzzification process

Basic item	Fuzzification
Assessment Damage	$(\mu_S^{AD}, \mu_M^{AD}, \mu_L^{AD}) = (0.60, 0.27, 0)$
Structural inspection	$(\mu_S^{SI}, \mu_M^{SI}, \mu_L^{SI}) = (0.60, 0.27, 0)$
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	$(\mu_S^{RE}, \mu_M^{RE}, \mu_L^{RE}) = (0, 0.20, 0.75)$
Engineering Consolidation	$(\mu_E^{EC}, \mu_D^{EC}, \mu_{VD}^{EC}) = (0, 0.20, 0.75)$
Earthquake intensity	$(\mu_L^{EI}, \mu_M^{EI}, \mu_H^{EI}) = (0, 0.5, 0.70)$
Event Repetition	$(\mu_L^{ER}, \mu_M^{ER}, \mu_H^{ER}) = (0.40, 0.52, 0)$
Service Importance	$(\mu_L^{SI}, \mu_M^{SI}, \mu_H^{SI}) = (0, 0.56, 0.40)$

Inference: Mamdani's inference system is performed through the DT hierarchical scheme in Fig. 5**Errore. L'origine riferimento non è stata trovata.**. An example of inference for the engineer evaluation input is shown in this section. The inference step for the other DT parameters is carried out in a similar manner. The engineer evaluation (IE) index is the combination of assessment damage and structural inspection. Using the fuzzy rule base, the engineer evaluation is computed as follows:

$$\begin{gathered} \mu_S^{EE} = \max(\min(0.60,0.60)\,,\min(0.60,0.27)) = 0.60 \\ \mu_M^{EE} = \max(\min(0.60,0)\,,\min(0.27,0.60)\,,\min(0.27,0.27)\,,\min(0.27,0)\,,\min(0,0.60)) = 0.27 \\ \mu_L^{EE} = \max(\min(0,0.27)\,,\min(0,0)) = 0 \end{gathered} \tag{4}$$

Defuzzification: using the mentioned quality-ordered weights factors, qi (i = 1,2,3) = [0.25, 0.5, 1], the engineer evaluation factor is defuzzified as follows:

$$EE = \sum_{i=1}^{n} q_i \cdot \mu_i = 0.25\ \times 0.60 + 0.5 \times 0.27 + 1 \times 0 = 0.285 \tag{5}$$

Defuzzification of other DT parameters is done similarly. The membership of DT is given through inferencing the availability of human resources, the infrastructure type, the earthquake intensity, and the exposed infrastructure as $(\mu_{VL}^{DT}, \mu_L^{DT}, \mu_M^{DT}, \mu_H^{DT}, \mu_{VH}^{DT}) = (0,0.04,0.89,0,0)$ for gas infrastructure and $(\mu_{VL}^{DT}, \mu_L^{DT}, \mu_M^{DT}, \mu_H^{DT}, \mu_{VH}^{DT}) = (0.32,0.51,0,0,0)$ for water lifeline. According to the DT membership functions, the DT may be classified as Medium and Low for gas and water networks, respectively. Results show that the water lifeline requires less time to restore its functionality to the community than gas infrastructure. In most cases the gas distribution system is the service that takes longest to be completely restore. This is probably due to the mandatory tests and investigations necessary after a sever event that make the utility inoperative for more days [6].

6. Conclusion

This paper introduces a new methodology for estimating the downtime of residential buildings and critical infrastructures (CIs) (e.g., power network, water, gas, and telecommunication lifelines) against earthquake events through Fuzzy Logic. The presented work illustrates how the fuzzy approach can be applied to deal with uncertainties and limited data that are typical in the aftermath of a sever event. FL-based expert system incorporates intuitive knowledge or historical data for evaluating the parameters of the framework and for defining fuzzy rules.

Two different DT models are proposed for residential buildings and infrastructures, respectively. The proposed method combines DT indicators through a FL DT assessment framework to have a first estimation of the total recovery time. The use of FL allows a fast and simple estimation of the DT through a hierarchical scheme in which the parameters that mainly affect the recovery time are aggregated. The hierarchical scheme provides a clear and logical organization of the system combining specific contributors at every level of the system. To show the applicability of the model, a scenario is provided for water and gas networks is provided. The earthquake considered in the analysis is the 6.0 magnitude earthquake that hit Napa (USA) on the 24th of August 2014. Results show that FL is a suitable approach in cases with limited knowledge to support decision-makers in managing and minimizing the impacts of earthquakes and to recover damaged infrastructures promptly.

Future work will be oriented towards developing a methodology in which FL and BN are integrated. That is possible through the use of linguistic variables and fuzzy number-based probabilities to assess unconditional and conditional probabilities. The Bayesian inference is then performed for estimating the DT of damaged infrastructures. Moreover, the interdependency of infrastructure networks will be considered in the restoration time estimation since infrastructure systems are not isolated from each other but rely on one another to be functional.

7. Acknowledgements

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