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DETERMINISTIC AND FUZZY-BASED METHODS TO EVALUATE COMMUNITY RESILIENCE BASED ON THE PEOPLES FRAMEWORK

ABSTRACT

Community resilience is becoming a growing concern for authorities and decision makers. This paper introduces two indicator-based methods to evaluate the resilience of communities based on the PEOPLES framework. PEOPLES is a multi-layered framework that defines community resilience using seven dimensions. Each of the dimensions is described through a set of resilience indicators collected from literature and they are linked to a measure allowing the analytical computation of the indicator's performance. The first method proposed in this paper requires data on previous disasters as an input and returns as output a performance function for each indicator and a performance function for the whole community. The second method exploits a knowledge-based fuzzy modeling for its implementation. This method allows a quantitative evaluation of the PEOPLES indicators using descriptive knowledge rather than deterministic data including the uncertainty involved in the analysis. The output of the fuzzy-based method is a resilience index for each indicator as well as a resilience index for the community. The paper also introduces an open source online tool in which the first method is implemented. A case study illustrating the application of the first method and the usage of the tool is also provided in the paper.

Keywords: *Deterministic approach, resilience indicators, Fuzzy method, , PEOPLES framework, Earthquake resilience*

1. INTRODUCTION

The number of natural disasters and the corresponding number of people affected, with related economic losses, have shown an upward trend in the last years. This implies that communities are often not sufficiently resilient to natural catastrophes. Consequently, the concept of resilience has been deepened in the engineering field to assess the ability of a community to recover after an undesirable event. Indeed, since the adoption of the Hyogo framework in Manyena (2006), strategies involved in hazard planning and disaster risk reduction have experienced a paradigm shift from a vulnerability assessment approach to a resilience-based approach (Mayunga, 2007).

Since the concept of resilience is applicable in several disciplines, different definitions are available in the literature. Cimellaro et al. (2016a) have conducted a comprehensive review on this topic. In their work, the resilience definition provided by Bruneau et al. (2003) emerges: resilience is "the ability of social units to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways to minimize social disruption". This definition has been later improved by Cimellaro et al. (2010) who define resilience as: "a function indicating the capability to sustain a level of functionality or performance for a given building, bridge, lifeline network, or community, over a period defined as the control time (T_C) that is usually decided by owners, or society (usually is the life cycle, life span of the system etc.)". Thus, resilience can be defined analytically as the area under the serviceability performance curve $Q(t)$ of a system, normalized accordingly to the considered control time (T_C):

$$R = \int_{t_1}^{t_r} \frac{Q(t)}{T_C}\, dt \tag{1}$$

where R is the resilience index, $Q(t)$ is the system functionality at time t, t_1 is the moment when the disturbance occurs and the system functionality drops, t_r is the moment when the initial serviceability is completely recovered; T_C is the control time. The serviceability $Q(t)$ ranges between 0% and 100% to indicate the complete absence of functionality of the service and its complete effectiveness, respectively.

Several solutions for measuring resilience are available in the literature (Abeling et al., 2014, Cutter et al., 2008, Cimellaro et al., 2016b, Cimellaro et al., 2015, Cimellaro et al., 2014). Liu et al. (2017) introduced a method that combines dynamic modeling with resilience analysis. Interdependent critical infrastructures have been analyzed in terms of design, operation, and control using this method by performing a numerical analysis. Kammouh et al. (2017b) have introduced a quantitative method to assess the resilience at the state level based on the Hyogo Framework for Action (UNISDR, 2011). The approach introduced was an evolution of the risk assessment concept. The resilience of 37 countries has been evaluated and a resilience score between 0 and 100 has been assigned to each of them (Kammouh et al., 2017c). Cutter et al. (2014) clarified that research on measuring community resilience is still in the early stages of development. Although many attempts have been made to consolidate research on community resilience, no accepted method exists so far and there are still difficulties in developing concrete assessment approaches and reliable indicators.

Here, community resilience is evaluated exploiting two novel methodologies, which benefit from the PEOPLES framework (Cimellaro et al., 2016a, Renschler et al., 2010). PEOPLES is a layered framework: each dimension is divided into components. However, the framework does not identify a clear procedure to quantitatively compute resilience, but rather a qualitative assessment and description of resilience. The goal of this paper is to use the structure of PEOPLES framework to come up with a quantitative framework that allows evaluation of the resilience of communities. To do so, two different new methodologies to analytically quantify the resilience of communities are proposed. The first method is deterministic and requires data on past earthquake events in the form of indicators. This method turns a resilience index and a performance function for the community as an output. However, in specific scenarios, some indicators may be difficult to obtain and quantify, as well as the interdependency among them. In order to track and represent such uncertainties, another method based on a fuzzy-logic modeling is proposed. This method does not require deterministic data but rather expert knowledge to determine the different parameters involved in the resilience evaluation. It also accounts for the uncertainties involved in the assessment process. This method returns a resilience index for each indicator and a resilience index for the analyzed community. This paper also introduces a free open source tool in which the deterministic resilience method is implemented. A case study illustrating the use of the tool is also presented.

2. PEOPLES: A COMPREHENSIVE MULTI-LAYERED RESILIENCE FRAMEWORK

PEOPLES is a framework for identifying the different resilience characteristics of a community (both in time and space) and for providing new ways through which decision makers can take actions under emergencies (Cimellaro et al., 2016a). The framework allows modeling possible responses of a community considering the interdependency between the different community layers. The acronym PEOPLES stands for seven community dimensions including:

1. Population and demographics: it includes parameters that describe the social-economic composition of the community. This dimension measures the social vulnerability that could hinder the functionality of the emergency and recovery systems (e.g. population density, age distribution, presence and integration of minorities and socio-economic status).
2. Environment and ecosystem: it estimates the capability of the environment and of the ecosystem to get back to its pre-hazard conditions. It includes water, air and soil assessments as well as a measure of the biodiversity and the sustainability relations.
3. Organized government services: it covers the services that the government guarantees before and after an extreme event. A great importance is given to the mitigation and recovery processes, which include the preparedness to hazards and all disaster risk reduction measures.
4. Physical infrastructure: it considers the buildings and facilities that are the prevalent interests of civil engineers and traditional resilience analysis. Particularly, two different aspects are analyzed in this dimension: facilities, which includes housing and services which are not crucial for the emergency response, and lifelines, which instead consists of the services that are of vital importance for the management of critical situations.
5. Lifestyle and community competence: this dimension takes into account the capability of a community to face problems by means of political partnerships. This includes both the abilities of a community (i.e. the

skills of their components) and its perceptions (i.e. the judgements and feelings that a community has on itself).

6 Economic development: it describes the economic situation of the community. It can be easily divided in two terms, a static component, which measures the present economic condition, and a dynamic one, which instead takes into account the development and economic growth of the community.

7 Social-cultural capital: this last dimension contains an evaluation of the community's attitude to react to disasters and to return to the pre-event conditions. It includes a lot of subcategories that measure the people's commitment in the community and the social-cultural heritage.

3. METHOD 1: INDICATOR-BASED DETERMINISTIC APPROACH

3.1 PEOPLES' hierarchy: dimension, components, indicators, and measures

PEOPLES is a multi-layered framework containing seven dimensions, each of which is divided into a set of components. To quantify the PEOPLES framework, a list of 115 resilience indicators describing the different aspects of a community has been identified and allocated to the PEOPLES' components. A full list of the components and indicators is provided in the free tool web page (more details are provided later in the paper). Each indicator is accompanied with a *measure* to allow the analytical evaluation of the indicator's performance. The measures are presented in the form of continuous functions instead of scalar values (crisp values). This allows identifying the performance of the indicator during an interval of time (i.e. the period following the disaster) rather than at a specific instance of time. Each measure is normalized with respect to a fixed quantity, the standard value (*SV*). The standard value is an essential quantity that provides the baseline to measure the resilience of a system. The system's existing serviceability at any instance of time is compared with the standard value to know how much serviceability deficiency is experienced by the system. In addition, measures are classified in two different categories: "static measures (*S*)", assigned to the measures that are not affected by the disastrous event, and "dynamic measure (*D*)" or event-sensitive measures, assigned to the measures whose values change after a hazard takes place.

3.2 Interdependency factor

Interdependencies between the different variables of PEOPLES framework can highly affect the resilience result. Generally, the interdependency depends on several factors such as the disaster event and the type of analyzed community (rural, urban and industry). To include interdependencies, weighting factors are allocated to each variable through an interdependency analysis. In the analysis, the variables of PEOPLES are classified in three major groups as follows:

1. Indicators that fall within a component are considered as a group (totally 29 groups);
2. Components classified under a dimension are taken as a group (totally 7 groups);
3. PEOPLES seven dimensions fall in one group (totally 1 group).

A square matrix for each group of variables is created (Figure 1), where each cell in the matrix represents the level of interdependency between two variables. Each cell (a_{ij}) can take the values *0* or *1* indicating full independence and full interdependence, respectively. This value can be identified either using descriptive knowledge in the form of a questionnaire filled by a group of experts or by relating to past data on previous events. Figure 2 shows a sample questionnaire to portray, as an example, the interdependencies that exist among the indicators under the component "lifeline". This questionnaire form can be filled at least by one expert who has enough knowledge about the dynamics that exist between the variables. The expert responsibility is to identify whether two indicators have "low" or "high" correlation. These descriptors are translated to 0 and 1 respectively in the matrix cells.

[Figure 1. near here]

[Figure 2. near here]

The interdependency matrix is not symmetrical because if a variable *i* is dependent on a variable *j*, the reverse is not necessarily true. The interdependency factor of a variable *i* is obtained by normalizing the summation of the cells' values in column *i* with respect to maximum value among all the columns' summations. The interdependency factor for a variable *i* is mathematically calculated as follows:

$$\lambda_i = \frac{\sum_{j=1}^{n} a_{ji}}{\max(\sum_{j=1}^{n} a_{j1}, ..., \sum_{j=1}^{n} a_{jn})} \quad (2)$$

where λ_i is interdependency factor for variable *i*, a_{ji} is the interdependency level that variable *j* has on a variable *i*, *n* is the number of variables in the studied group. To better consider the uncertainties and reduce the subjectivity, the questionnaire can be filled by a group of experts. In this case, a statistical analysis is carried out. A probability distribution function (PDF) is considered for each variable based on the data collected from the experts (Figure 2), and three values are used in the subsequent analysis to address the uncertainties in final resilience output: (1) the mean (σ), (2) mean + standard deviation, (3) mean – standard deviation (Figure 3). A total of 37 matrices are needed to perform a complete interdependency analysis at a community level using the hierarchy of PEOPLES framework.

[Figure 3. near here]

3.3 Importance factor

Variables do not contribute equally to the overall resilience output. Thus, each of the dimensions, components and indicators is given an importance factor (*I*) ranging from 1 to 3, where 1 means low importance and 3 means high importance. This factor represents the extent to which a variable (component, sub-component, or indicator) contributes towards achieving resilience. This factor can be chosen by experts or decision makers.

3.4 Weighting factor

The final weighting factor for each variable (w_i) is calculated considering both interdependency and importance factors. Equation 3 translates an interdependency factor (λ_i) and importance factor (I_i) of variable *i* into a final weighting factor (w_i).

$$w_i = \frac{\lambda_i . I_i}{mean(\lambda_1 . I_1, ..., \lambda_n . I_n)} = \frac{\lambda_i . I_i}{\sum_{j=1}^{n} \lambda_j . I_j} n \quad (3)$$

where w_i is weighting factor of variable *i*, I_i is importance factor of variable *i*, λ_i is interdependency factor of variable *i*, *n* is the number of variables in the studied group.

3.5 Deriving the final resilience curve

After obtaining weighting factors for the variables of the PEOPLES framework, a serviceability function is built for each variable: uniform function for event-non-sensitive measures "static measures", and non-uniform function for event-sensitive measures "dynamic measures", as shown in Figure 4. The serviceability function can be defined using a set of parameters that mark the outline of the serviceability function (e.g. initial serviceability q_0, post disaster serviceability q_1, restoration time T_r, recovered serviceability q_f). These parameters can be obtained from the past events and/or by performing a hazard analysis specific to each variable. In addition, the shape of restoration curve (sometimes referred to as *slope* or *rapidity*) during the recovery affects the resilience quantity and therefore it should be taken into account in the resilience computation. However, the restoration rapidity depends on many variables such as the spatial dimension, the temporal dimension, the hazard type, the available resources (including financial and human resources), the restoration plan, etc. Thus, modeling the restoration curve of a single system is complex and it could be defined graphically in countless shapes (Kammouh et al., 2017b). Different types of restoration curves such as linear, exponential, step function, trigonometric and random function can be selected based on the available system information. For example, the exponential shape can be selected when the initial speed recovery is high due to an initial inflow of resources and it decreases as the recovery reaches the end (Kafali and Grigoriu, 2005). HAZUS (FEMA, 2011) adopted the linear trend as a restoration curve that is generally used when there is not enough available data regarding the system resources and recovery plans (Whitman et al., 1997). In this study, as not much information about the restoration rapidity is available, the linear shape for restoration curve is selected to build the serviceability function. All serviceability functions are weighted using the weighting factors described before.

[Figure 4. near here]

Prior to obtaining the weighted serviceability function for each indicator, the final resilience function is obtained through a hierarchical aggregation procedure (Figure 5). The average of the weighted serviceability functions of the variables in the same group is considered to move to an upper layer. That is, to obtain the serviceability function of component *i*, the average of the weighted serviceability functions of the indicators under component *i* is considered. Similarly, to obtain the serviceability function of dimension *j*, the average of the weighted serviceability functions of the components under dimension *j* is considered. Finally, the serviceability function of the community is the average of the weighted serviceability functions of the seven dimensions. The resilience index of the community is then evaluated as the area under the final serviceability function using Equation 1.

[Figure 5. near here]

3.6 Open source online tool

The use of the open source online tool (http://borispio.ddns.net/PEOPLES/login.php) is illustrated here. A Login/Register window appears when accessing the tool (Figure 6a). The user must register prior to using the tool. Once registered, the user can start a new scenario for which the resilience is to be evaluated (Figure 6b). The scenario is composed of two main parts: (1) the analyzed community (i.e. city, country, etc.), and (2) the hazard considered (e.g. earthquake, tsunami, fire, etc.).

[Figure 6. near here]

After defining the scenario, a data-entry page that displays the various variables of the PEOPLES framework appears (Figure 7). On the left side of the webpage, the seven dimensions of PEOPLES are listed. A separate page for each dimension can be accessed by clicking on the dimension. For each dimension, a list of components and indicators is shown with blank spaces to insert the data of the parameters required for the resilience evaluation. A pop-up description is triggered when hoovering the mouse over a parameter in the window. This is to get extra information that helps the user identify what kind of information they need to insert. The parameters involved in the resilience evaluation are:

- Importance factor (I): a value between 1 and 3 representing the weight of the indicator towards the resilience output (Note: in the current version of the tool only the importance factor procedure is implemented. The new version will include the interdependency analysis described above)
- Indicator nature (Nat): the indicators are classified according to their nature: "Static (S)", assigned to the measures that are not affected by the disastrous event, and "Dynamic (D)" or event-sensitive measures, assigned to the measures whose values change after a hazard takes place;
- Un-normalized serviceability before the event (q_{0u}): is the un-normalized initial serviceability of the measure;
- Standard value (SV): represents the optimal quantity for the indicator in order to be considered as fully resilient;
- Normalized serviceability before the event (q_0): is the normalized initial serviceability of the measure. It is obtained automatically by the tool by dividing the un-normalized serviceability q_{0u} over the standard value SV;
- Serviceability after the event (q_1): The residual serviceability after the disaster. This quantity should be normalized by the user with respect to SV;
- Serviceability after recovery (q_r): it is the recovered serviceability, which can be equal, higher, or lower than the initial serviceability (q_0). In this paper. The recovered serviceability q_r is assumed equal to the

initial serviceability $q_{0;}$

- Restoration time (T_r): it is the time needed to finish the recovery process. This value is usually determined using probabilistic or statistical approaches.

A list of importance factors (I) has been set as default in the tool; however, the user can change the numerical values in the list according to their preference. The importance factors can be set all to "1" in case the user finds no justification to assign weights to the indicators; in this case, the indicators will be equally weighted. The nature of the indicator "*Nat*" can also be changed by the user because this parameter depends on the type of hazard and type of community considered in the analysis. If the indicator is *Static 'S'*, it is enough for the user to insert data about the initial serviceability of the system q_{0u}, and the standard value *SV*. If otherwise the indicator is *Dynamic 'D'*, the user should proceed and insert data about the post-event damage q_1, serviceability level after restoration q_r, and restoration time T_r. The parameter q_{0u} is inserted as un-normalized value while the other serviceability parameters q_1 and q_r have to be normalized by the user with respect to *SV* (divide over *SV*). A serviceability curve for each component is shown at the bottom of the page after inserting the indicators' data. The serviceability curve of the analyzed dimension, which is the weighted average of all serviceability functions of the components, is also shown on the same graph.

After inserting the required data for all PEOPLES seven dimensions, the user will be able to see the serviceability curve of the community by clicking on the 'The community resilience curve' on the left side of the screen. For each of the serviceability curves, the tool automatically evaluates the *LOR*, which is an indicator for the serviceability loss incurred during the event.

[Figure 7. near here]

3.7 Case study

The resilience of the city of San Francisco is evaluated using the proposed method. The case study shows the applicability of the proposed methodology and not the actual evaluation of the resilience of San Francisco. The 1989 Loma Prieta earthquake, which characterized by a moment magnitude of 6.9 M_w, is considered as the disaster event. The introduced tool has been used to carry out the case study, but only the 'Physical Infrastructure' dimension is considered in the case study. Table 1 shows the list of the components and indicators that are grouped under the dimension 'Physical Infrastructure'. Each indicator is linked to a measure that describes the indicator numerically using a set of parameters. In this study, the parameters have been obtained using open database sources (see notes under Table 1). The case study can be replicated by inserting the data in Table1 in their corresponding online fields (see Figure 8).

In Table 1, q_{0u} is the un-normalized initial serviceability of the measure. The normalization of this quantity is necessary to combine it with the other measures that fall in a same group. This is done by dividing the un-normalized serviceability q_{0u} over the standard value *SV* described before. Right after the disaster, the serviceability function of a dynamic measure drops to q_1 (see Figure 4b). In this example, the recovered serviceability q_r is assumed equal to the initial serviceability q_0. It is worth to note that not all facilities can be restored immediately after the disaster due to limitation of resources (financial, man power, etc.) and due to the lack of recovery plans. In addition, restoring some facilities is sometimes done in series with (after the completion of) other facilities, which poses some delay to the restoration process. The restoration time T_r is usually determined using probabilistic or statistical approaches. In this case study, the restoration fragility curves recently developed have been used to determine the restoration time for the different variables (Kammouh and Cimellaro, 2017a). In their work, they have introduced an empirical probabilistic model to estimate the downtime of the lifelines following an earthquake. Different restoration functions were derived for different earthquake magnitudes using a large earthquake database that contains data on the downtime of the infrastructures. The functions were presented in terms of probability of recovery versus time. The downtime corresponding to 95% of exceedance probability of recovery has been used as a deterministic downtime for the considered infrastructure. As for the rate of restoration, in this paper a linear interpolation is assumed for all the measures.

[Table 1. near here]

[Figure 8. near here]

Data collection was the most challenging part of the analysis since data about the serviceability of community systems is scares and not shareable with the public. However, this does not imply that data is not available but rather is not accessible. Interested parties, such as decision makers and authorities, can use the framework with its full potential since data is usually available to them.

The tool combines the serviceability functions as described, while it evaluates the loss of resilience of the physical infrastructure using Equation 1. The time interval for the calculation of resilience is considered from the time that the event occurs (t_0=0) until full recovery is achieved (i.e. the time corresponding to the instance where the curve reaches its pre-disaster level, which coincides with the maximum restoration time among all indicators; t_r=700 days). The control time T_c is determined based on the user's period of interest and so it can take any value. In the tool, T_c is set equal to t_r automatically. Figure 9 shows the resilience curve of the case study obtained using the tool. The obtained *LOR* value (25.6%) corresponds only to the physical infrastructure dimension of the community. In order to have a resilience index for the whole community, the serviceability functions of other dimensions have to be similarly evaluated and combined in the same way. It is also interesting to compare the resilience of the two components *facilities* and *lifelines* shown in Figure 9. It is clear that the city of San Francisco has more problems in facilities (*LOR*=31.29%) than lifelines (*LOR*=21.85%); therefore, it is suggested that the authority focuses more on enhancing their facilities.

[Figure 9. near here]

4. METHOD 2: SIMPLIFIED FUZZY LOGIC RESILIENCE FRAMEWORK

The methodology previously described can serve as a tool in preliminary decision-making processes related to natural catastrophic events. Nevertheless, this method is operable only if indicators can be numerically quantified, which may not be the case in some scenarios. In this section, a method that does not require deterministic data to compute the resilience of a community is proposed. The method exploits a fuzzy logic-based modeling of PEOPLES indicators to deal with uncertainties and missing knowledge. In the following sections, the fuzzy modeling of PEOPLES indicators and the evaluation of community resilience using information gathered through the fuzzy inference system are discussed. Different approaches are proposed to match different levels of complexity, starting from a two- and four-parameter approaches and ending with a full translation of the PEOPLES framework. The proposed methodologies are not fully interchangeable and so only one of them should be selected in accordance with the level of details needed.

4.1 Fuzzy logic

Zadeh (1965) introduced the concept of fuzzy set and the theory behind it. This theory comes with the absence of any mathematical framework that is able to describe the complexity and vagueness included in processes where human intervention is significant. While in the crisp logic the variables belong only to one class, in the fuzzy logic a variable x can be a member of several classes (fuzzy sets) with different membership grades (μ). Thus, each fuzzy set is characterized by a membership function that associates to any input x a real number (μ) ranging between 0 (x does not belong to the fuzzy set) and 1 (x completely belongs to the fuzzy set) (Zadeh, 1965). The strength of inference systems based on fuzzy logic relies on the following two main aspects:

- fuzzy inference systems can handle both descriptive (linguistic) knowledge and numerical data;
- fuzzy inference systems exploit approximate reasoning algorithm to formulate relationships between inputs by which uncertainties can be propagated throughout the whole process (Tesfamariam and Saatcioglu, 2008a)

Designing a fuzzy logic-based system follows two fundamental steps: 1) defining the membership functions and the fuzzification process; 2) designing the fuzzy inference system. Fuzzy methods have been widely developed and applied in several fields (Ross, 2009). In the context of earthquake engineering, fuzzy methods have been exploited in different applications (e.g. Tesfamariam and Saatcioglu, 2008b, Tesfamariam and Saatcioglu, 2010, Tesfamariam and Wang, 2011). Fuzzy methods have been widely used also for developing structural control systems. A clear procedure for the application of fuzzy logic can be found in Tesfamariam and Saatcioglu (2008a, b).

A fuzzy logic system (FLS) can be defined as the nonlinear mapping of an input data set to a scalar output data. A FLS consists of four main parts: fuzzifier, rules, inference engine, and defuzzifier (Figure 10). The process of fuzzy logic is: a crisp set of input data are gathered and converted to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms and membership functions. This step is known as fuzzification. Afterwards, an inference is made based on a set of rules. Lastly, the resulting fuzzy output is mapped to a crisp output using the membership functions, in the defuzzification step.

[Figure 10. near here]

4.1.1 Fuzzification

The basic input parameters have a range of values that can be clustered into linguistic quantifiers, for instance, very low (VL), medium low (ML), medium (M), medium high (MH) and very high (VH). The process of assigning linguistic values is a form of data compression and it is called *granulation*. The fuzzification step converts the input values into a homogeneous scale by assigning corresponding membership functions with respect to their specified granularities (Tesfamariam and Saatcioglu, 2008b).

Membership functions are used in the fuzzification and defuzzification steps of a FLS, to map the non-fuzzy input values to fuzzy linguistic terms and vice versa. A membership function is used to quantify a linguistic term. Note that, an important characteristic of fuzzy logic is that a numerical value does not have to be fuzzified using only one membership function. In other words, a value can belong to multiple sets at the same time. There are different forms of membership functions such as triangular, trapezoidal, piecewise linear, Gaussian, or singleton. The most common types of membership functions are triangular, trapezoidal, and Gaussian shapes. The type of the membership function can be context dependent and it is generally chosen arbitrarily according to the user experience (Mendel, 1995).

4.1.2 Fuzzy rules

The fuzzy rule base (FRB) is derived from heuristic knowledge of experts or historical data to define the relationships between inputs and outputs. The most common type is the *Mandami* type, which is a simple *if-then* rule with a condition and a conclusion. For instance, considering two inputs, the i[th] rule has the following formulation:

$$R\text{: if } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } A_2 \text{ then } y \text{ is } B \tag{4}$$

where R *is the rule number*, x_1 and x_2 are the inputs variable, A_1 and A_2 are input sets, y is the output and B is the output set. The completeness of a fuzzy model is determined by the description of the behaviour for all possible input values and requires a large number of rules. The rule base is the union of all the rules:

$$R = \bigcup_{i=1}^{n} R_i = R_1 \text{ also } R_2 \text{ also} \ldots \text{also } R_n \tag{5}$$

In some cases it is possible to regulate the degree of influence of each rule on the final output. This can be done by adding weightings based on priority or consistency, in a static or in a dynamic way.

4.1.3 Fuzzy inference system (FIS)

After evaluating the result of each rule, the results are combined to obtain a final output. This process is called *inference*. Several accumulation methods can be used to combine the results of the individual rules. The maximum algorithm is generally used for accumulation. The evaluations of the fuzzy rules and the combination of the results of the individual rules are performed using fuzzy set operations. The operations on fuzzy sets are different with respect to the operations on non-fuzzy sets.

4.1.4 Defuzzification

After the inference step, the overall result is a fuzzy value. This result should be defuzzified to obtain a final crisp output. This is the purpose of the defuzzifier component of an FLS. The defuzzification represents the inverse of the fuzzification process. It is performed according to the membership function of the output variable. There are several techniques to perform the defuzzification such as centre of gravity, centre of area, and mean of maximum methods.

4.2 Two- parameter approach

This approach adopts only two of the four serviceability parameters described before, namely serviceability initial drop q^* (previously referred to as q_0) and recovery time T^* (previously referred to as t_0). Fuzzy parameters have been chosen based on the research by Bruneau et al. (2003) who describes the resilience of a system using the following three indicators: reduced failure probability; reduced consequences from failure; reduced time to recovery. The reduced failure probability has not been taken into account as it is not easily related to the herein adopted mathematical definition of resilience, which considers only the failure consequence q^* and the repair time T^*. Figure 11 presents a hierarchy of the two-parameter approach where both *time* and *initial drop* variables are used as inputs for the fuzzy system. The inputs are combined using a set of rules to obtain the output variable *fuzzy resilience*. The fuzzy output is defuzzified to get a crisp value that serves as a resilience index for the corresponding indicator.

[Figure 11. near here]

4.2.1 Evaluating initial serviceability drop (q^*)

Two trapezoidal membership functions can be reasonably adopted in the present case. They are termed as "High" and "Low". The fuzzification used for q^* is [High; Low] → [(0, 0, 0.3, 0.7); (0.3, 0.7, 1, 1)]. The membership functions are graphically shown in Figure 12.

[Figure 12. near here]

4.2.2 Evaluating recovery time (T^*)

When speaking of recovery, the intention is *full* recovery. Outperforming, or non-complete recovery, as indicated by Cimellaro et al. (2010), are not generally predictable and therefore they are not included here. For the time variable T^*, three membership functions are suggested by the authors, namely: "short"; "long"; and "very long". The time variable is normalized based on a 3-year time span, which is normally the time reference for civil applications (i.e., 3 years corresponds to 1 on the horizontal axis). Figure 13 shows the membership functions chosen by the authors. The membership functions are not symmetrical as they have been constructed to the favor of the "Long" and "Very Long" memberships. That is, high range of values of the restoration time T^* variable corresponds to the membership functions "Long" and "Very Long".

[Figure 13. near here]

The aim is to translate the given input variables ($q^*$and T^*) into one resilience measure R. This measure is itself fuzzy and so it is defined by a membership function. The chosen membership functions are depicted in Figure 14. Following the fuzzy approach, it is possible to define an output value calculated from the provided inputs on basis of a set of rules. The rules adopted in this study to relate the inputs and the output are shown in Table 2.

[Figure 14. near here]

[Table 2. near here]

4.2.3 Defuzzification

The fuzzy output variable is translated (defuzzified) into a numerical value that serves as a measure for resilience. Different methods for defuzzification can be used (Manyena, 2006) such as center of gravity, weighted average, mean-max, center of largest area etc. The use of one method rather than another is dependent on the application. Here, the center of gravity method given in Equation 6 is used.

$$CoA = \frac{\int_{X_{\min}}^{X_{\max}} f(x).x\,dx}{\int_{X_{\min}}^{X_{\max}} f(x)\,dx} \tag{6}$$

where $f(x)$ is the function that shapes the output fuzzy set after the aggregation process and x stands for the real values inside the fuzzy set support ([0, 1]). Practical examples on the application of the fuzzy method to several case studies can be found in Tesfamariam and Saatcioglu (2008a,b).

4.2.4 Importance factor

The fuzzy logic introduced above applies to each indicator apart. It is often the case to aggregate different indicators into a single measure (i.e. community resilience) through a hierarchical structure. Usually, indicators are not equally important because they contribute differently towards resilience and this necessitates weighting them according to their contribution. The weighting scheme used in Kammouh et al. (2017d) is here adopted. It can be performed by simply allocating an importance factor (I) ranging between 1 and 3 to each indicator then applying the weighted average rule, as follows:

$$R = \frac{\sum_{i=1}^{N} I_i R_i}{\sum_{i=1}^{N} I_i} = \sum_{i=1}^{N} w_i R_i \tag{7}$$

where R is the community resilience measure, R_i is the resilience measure of the i^{th} indicator, I_i is the corresponding importance factor (which can be scaled to preference), and w_i is the weighting factor of the i^{th} indicator. The difference with what has been proposed previously in the paper or in Kammouh et al. (2017d) is that in this methodology the serviceability functions are translated into resilience values before applying the weighting method (Figure 15). This simplifies the fuzzy system as it reduces the number of variables that need to be handled.

[Figure 15. near here]

4.2.5 Interdependency factor

While the next step of the research is to inject an interdependency methodology within the fuzzy system (with its own membership functions); currently, interdependencies are accounted for as weighting factors that increase or decrease the contribution of each variable according to the level of interdependency of the variable with other variables. Since the introduced fuzzy-based method deals with indicators, the interdependency methodology presented previously in this paper can be applied in full potential. The interdependency coefficient can be combined with the importance factor to obtain one single weighting factor for each indicator. This can be done using Equation 3 or by simply taking the average of the two coefficients.

4.3 Four-parameter approach

Considering only two parameters to represent a resilience indicator may in some cases be insufficient, thus affecting the mentioned benefits of using the Fuzzy approach. Moreover, this may oversimplify the problem especially when specific information about the structure itself is available and to be added. For this reason, in certain cases it may be beneficial to build up the resilience curve from fuzzy parameters other than the recovery time and the initial drop. In fact, it has been pointed out by Comerio (2006) that further distinction in the repair time is possible. According to his work, the following parameters should be taken into account:

- Construction repair time;
- Mobilization time;
- Economic conditions of the interested region;

The mobilization time in particular, labeled as "irrational" in Comerio (2006) (e.g. financing, workforce availability, relocation of functions or regulatory changes), is often not properly accounted for and therefore it should be given a special attention when evaluating downtime. These three indicators may be fuzzyfied with a structure similar to the one adopted for the recovery time T^*. The result is similar to what shown previously with the only difference that new rules and membership functions are to be assigned to the new variables. When resilience measures are calculated, weighting is performed to obtain the system (community) resilience.

4.4 Full PEOPLES

Most of the concepts described previously remain valid here. The only difference is that the approach introduced in this section includes the weighting of the variables within the fuzzy system. Normally, choosing adequate weighting factors is subjective and includes uncertainty. Although the inclusion of the weighting factors within the fuzzy system may add additional complexity as more variables are considered, it is certainly beneficial as it solves the uncertainty problem related to the weighting factors. To do that, two alternatives are proposed:

- Include the importance factor in the definition of the rules governing the fuzzy logic. In other words, assign rules such that the output is strongly related to the indicators with highest importance;
- Translate the importance factor into a fuzzy variable itself and include rules for it.

In both cases, rules have to be adapted to account for the importance factors. In the former case, rules are firmly tight to the particular application (i.e. hard to modify and not flexible); the latter case is, in this respect, more flexible but at the cost of additional complexity since additional rules have to be added to include the effect of the importance factor. This approach will be further developed and case studies will be added in future work. Figure 16 shows the logic flow where the weighting process is included as a separate variable in the first step before fuzzification.

[Figure 16. near here]

5. DISCUSSION

The two methodologies, although applied in the same context, are used under two different conditions. The first "deterministic" method is used only when data on a previous disaster is available. Applying the methodology to a real disaster allows the user to assess the loss of resilience following that particular disaster, which may help to prepare for future disasters by focusing on the weak aspects. This method also has the potential of being probabilistic when data on many previous events are available. However, this goes beyond the scope of the paper since the methodology will be the same regardless if the data are deterministic or probabilistic. The second methodology is used for both assessment and planning when data does not actually exist (which is often the case). Of course, this method would yield less accurate results since it relies on expert judgments instead of actual data.

Choosing between the two methods depends on what we really need. If it is an actual assessment for a previous disaster then the first method should be used (given that data is available). If the goal is to plan for future events without having data on previous events then the fuzzy-based method should be used. The results of the first method are more accurate but it can be rather challenging to obtain data.

6. CONCLUDING REMARKS

This paper introduces two methods to compute the resilience of communities based on the PEOPLES framework. An indicator-based approach has been implemented as the core engine of both methodologies. The significance of the first resilience method lies in its graphical representation, which helps decision makers take proper actions to improve their resilience. While all previous works generally provide a single index to measure community resilience, the proposed method indicates in detail whether the resilience deficiency is caused by the system's lack of robustness or by the slow restoration process. It identifies where exactly resources should be spent to efficiently improve resilience. This method has been implemented in a user-friendly tool that allows the user to insert data of the different community indicators and get a resilience curve as output. On the other hand, the second method does not need deterministic data for its implementation but rather descriptive knowledge, which can come in the form of a questionnaire. This method makes use of the fuzzy logic modeling to account for the uncertainty involved in the resilience parameters assessment. Choosing between the two methods depends on the availability of data and on the level of complexity sought. The interdependency among the resilience variables in both methods has been considered by performing an interdependency analysis, which resulted in an importance factor allocated to each variable.

ACKNOWLEDGEMENTS

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FIGURES

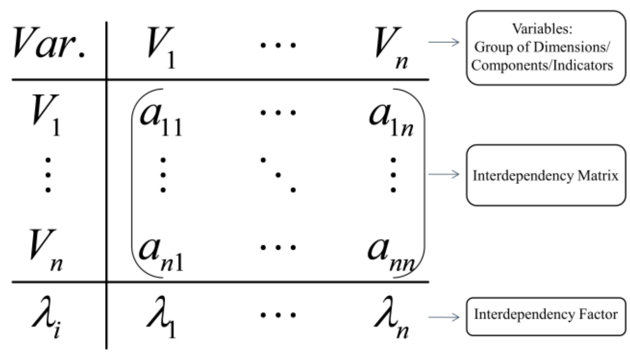


Figure 1. Interdependency matrix for the variables in a same group.

Name:
Designation:
Company:
Date:

Question: please fill the following table based on your expertise. Each cell represents the level of interdependency and its cascading effect of each indicator upon the other one (across each raw). Please use “L” for Low level of interdependency and “H” to display High level of interdependency.

The level of interdependency on other indicators (read across each row)

Indicator	Telecommunication	Mental health support	Physician access	Medical care capacity	Evacuation routes	Industrial re-supply potential	High-speed internet infrastructure	Efficient energy use	Efficient Water Use	Gas	Access and evacuation	Transportation	Waste water treatment
Telecommunication	H												
Mental health support		H											
Physician access			H										
Medical care capacity				H									
Evacuation routes					H								
Industrial re-supply potential						H							
High-speed internet infrastructure							H						
Efficient energy use								H					
Efficient Water Use									H				
Gas										H			
Access and evacuation											H		
Transportation												H	
Waste water treatment													H

Figure 2. Sample questionnaire to build the interdependency matrix for indicator under component “lifeline”.

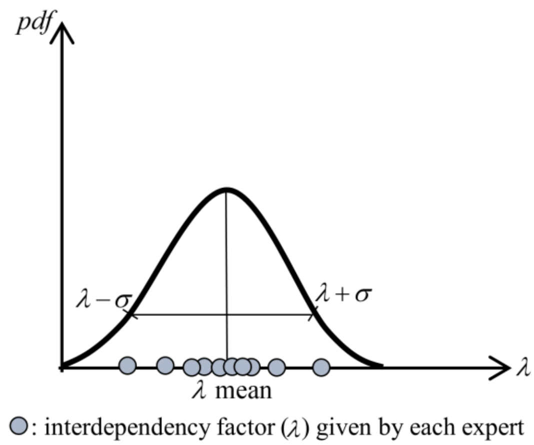


Figure 3. Statistical analysis for the expert responses about the interdependency factor of each variable.

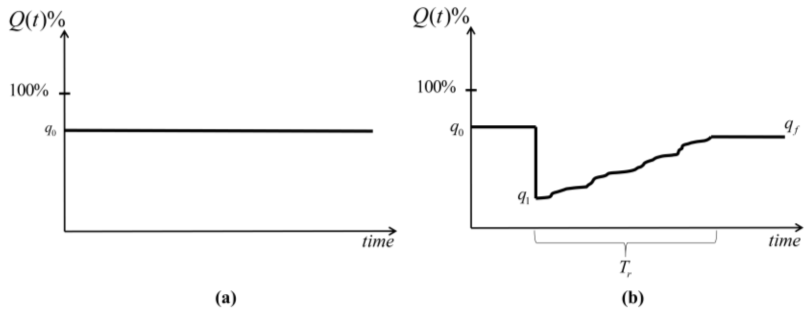


Figure 4. Serviceability functions (a) static, (b) dynamic.

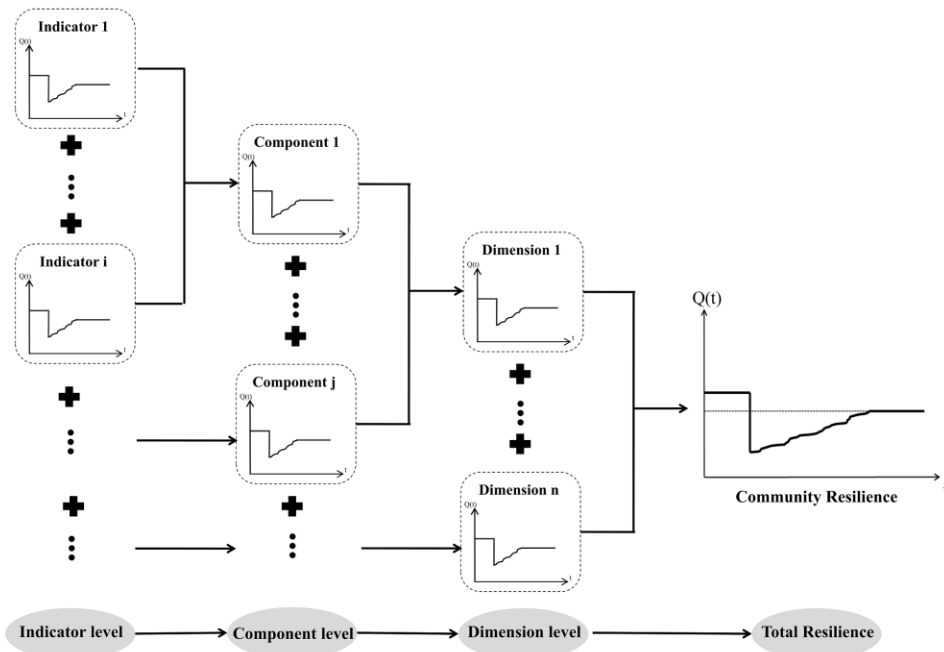
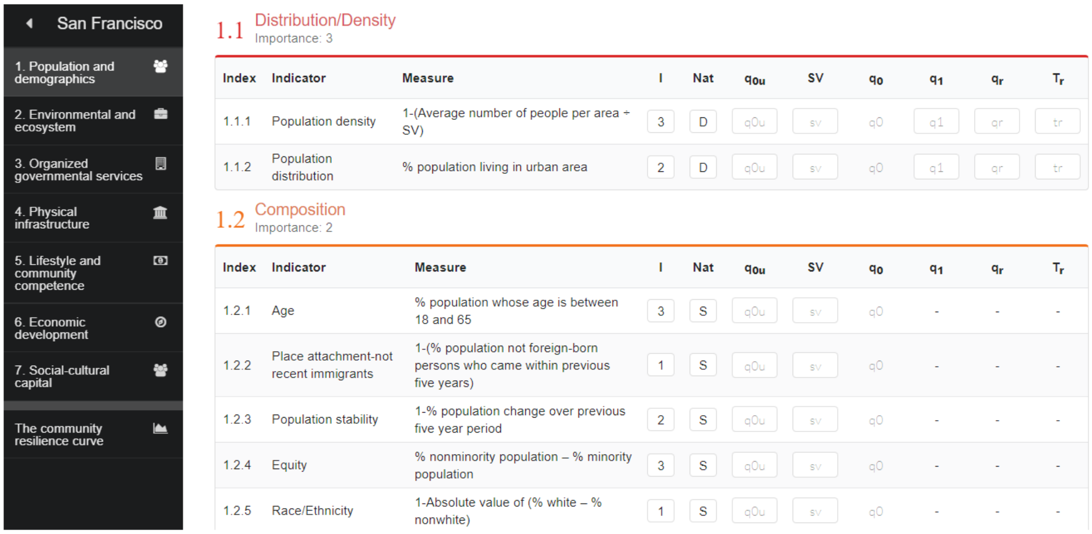


Figure 5. Hierarchical scheme of the adopted indicator-based resilience methodology.

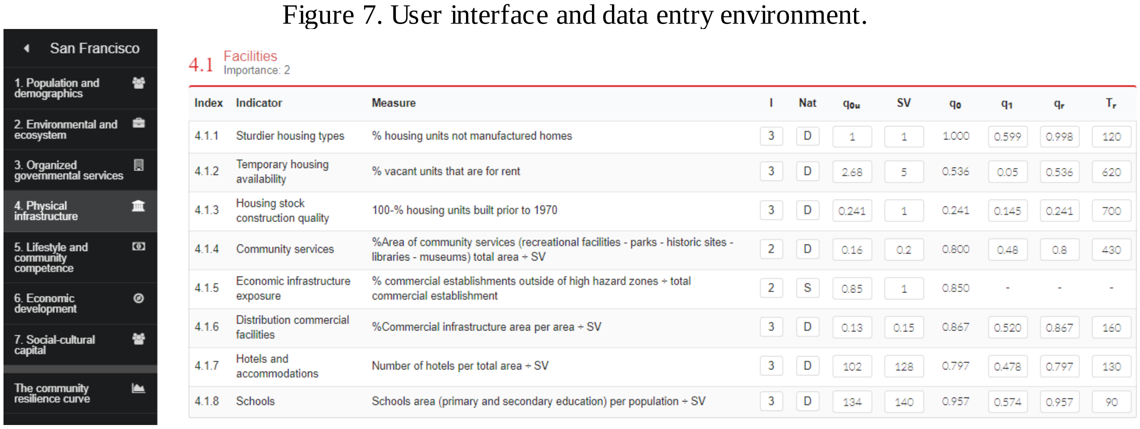
Figure 6. (a) Registration/login page, (b) new scenario definition/load scenario.



Index	Indicator	Measure	I	Nat	q_{0u}	SV	q_0	q_1	q_r	T_r
1.1.1	Population density	1-(Average number of people per area ÷ SV)	3	D	q0u	sv	q0	q1	qr	tr
1.1.2	Population distribution	% population living in urban area	2	D	q0u	sv	q0	q1	qr	tr

Index	Indicator	Measure	I	Nat	q_{0u}	SV	q_0	q_1	q_r	T_r
1.2.1	Age	% population whose age is between 18 and 65	3	S	q0u	sv	q0	-	-	-
1.2.2	Place attachment-not recent immigrants	1-(% population not foreign-born persons who came within previous five years)	1	S	q0u	sv	q0	-	-	-
1.2.3	Population stability	1-% population change over previous five year period	2	S	q0u	sv	q0	-	-	-
1.2.4	Equity	% nonminority population – % minority population	3	S	q0u	sv	q0	-	-	-
1.2.5	Race/Ethnicity	1-Absolute value of (% white – % nonwhite)	1	S	q0u	sv	q0	-	-	-

Figure 7. User interface and data entry environment.



Index	Indicator	Measure	I	Nat	q_{0u}	SV	q_0	q_1	q_r	T_r
4.1.1	Sturdier housing types	% housing units not manufactured homes	3	D	1	1	1.000	0.599	0.998	120
4.1.2	Temporary housing availability	% vacant units that are for rent	3	D	2.68	5	0.536	0.05	0.536	620
4.1.3	Housing stock construction quality	100-% housing units built prior to 1970	3	D	0.241	1	0.241	0.145	0.241	700
4.1.4	Community services	%Area of community services (recreational facilities - parks - historic sites - libraries - museums) total area ÷ SV	2	D	0.16	0.2	0.800	0.48	0.8	430
4.1.5	Economic infrastructure exposure	% commercial establishments outside of high hazard zones ÷ total commercial establishment	2	S	0.85	1	0.850	-	-	-
4.1.6	Distribution commercial facilities	%Commercial infrastructure area per area ÷ SV	3	D	0.13	0.15	0.867	0.520	0.867	160
4.1.7	Hotels and accommodations	Number of hotels per total area ÷ SV	3	D	102	128	0.797	0.478	0.797	130
4.1.8	Schools	Schools area (primary and secondary education) per population ÷ SV	3	D	134	140	0.957	0.574	0.957	90

Figure 8. Case study input data for Physical Infrastructure component.

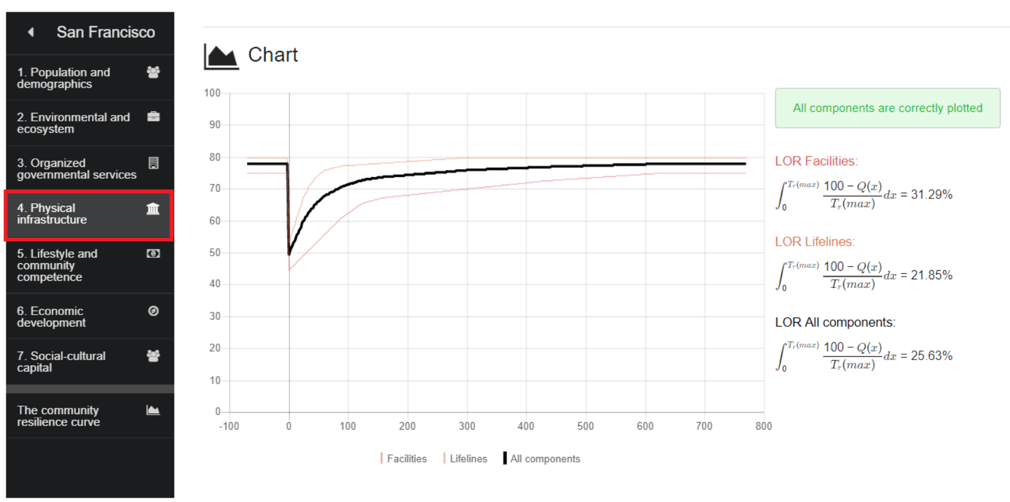


Figure 9. Serviceability curves of the components “Facilities” and “Lifelines” of the dimension “Physical Infrastructure”.

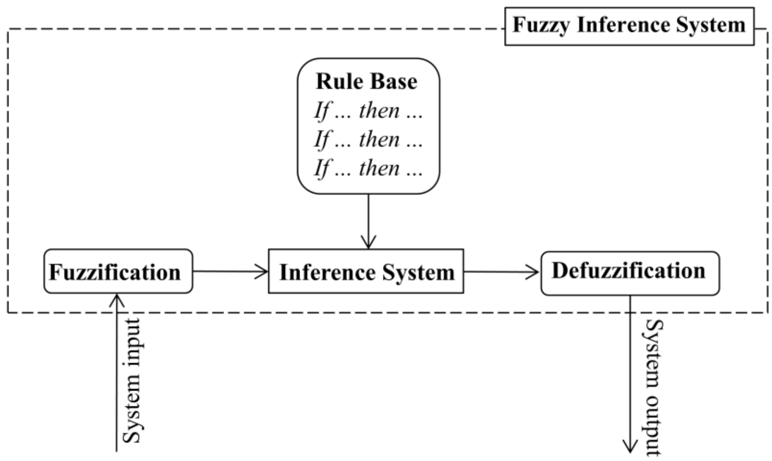


Figure 10. Fuzzy inference system.

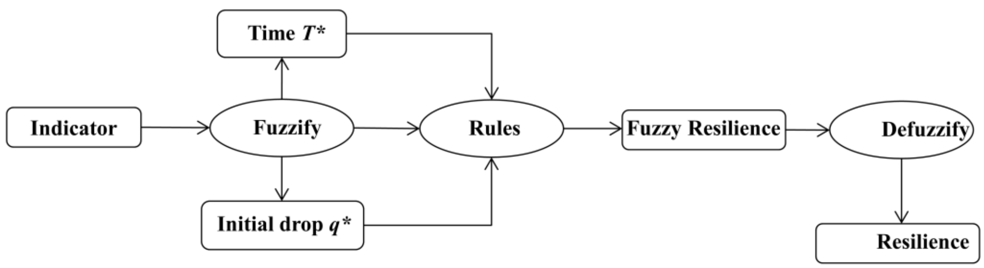


Figure 11. Schematic representation of the two-parameter approach.

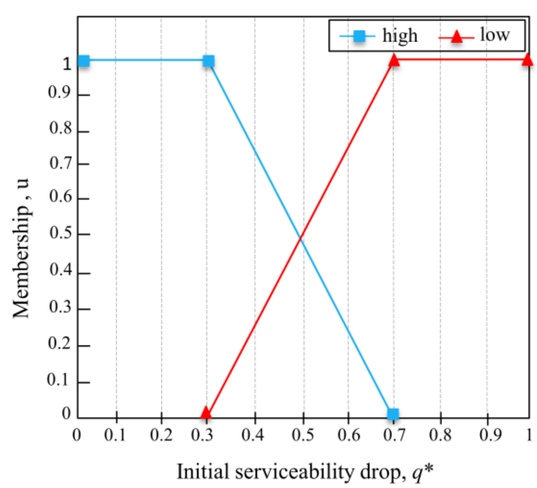


Figure 12. Membership functions for the serviceability variable $q*$.

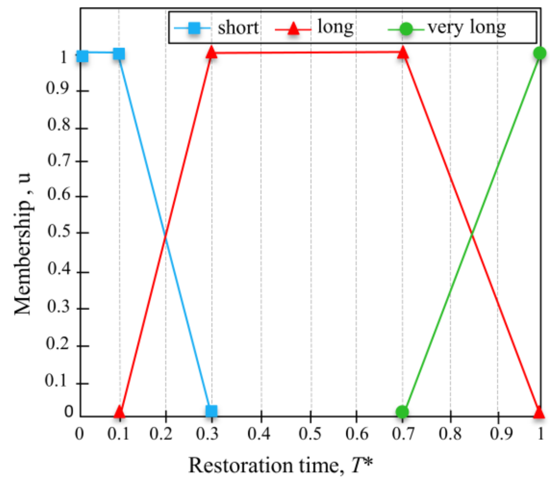


Figure 13. Membership functions for the downtime variable T^*.

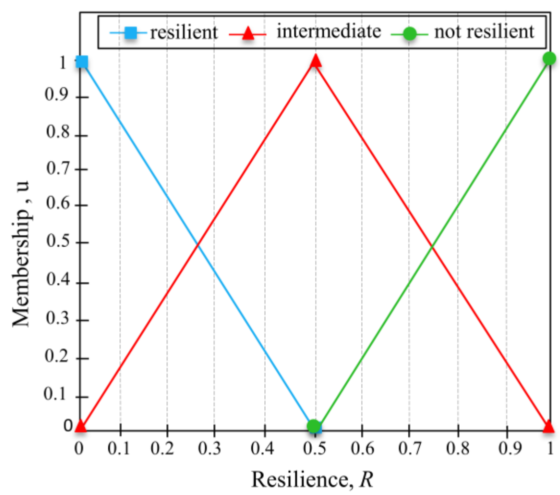


Figure 14. Membership functions for the resilience variable R.

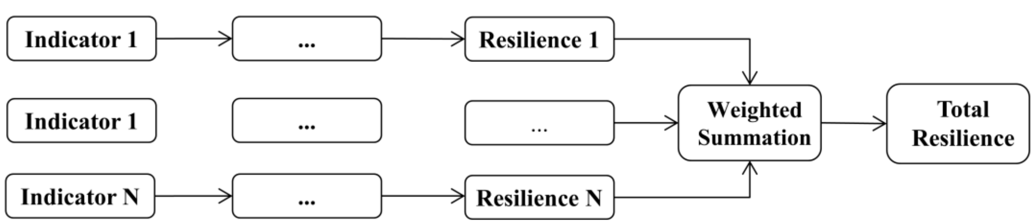


Figure 15. Hierarchical scheme of the fuzzy system with the weighting process.

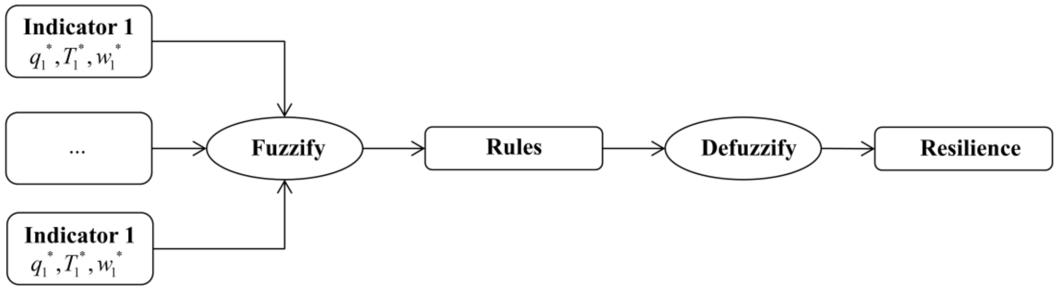


Figure 16. Full PEOPLES approach general hierarchical scheme with the weighting process included in the fuzzy system as a separate variable.

TABLES

Table 1. Serviceability parameters of the indicators within the Physical Infrastructure dimension for the city of San Francisco after the Loma Prieta earthquake.

4- Physical infrastructure									
Component/indicator	**Measure**	***w***	**Nat**	q_{0u}	***SV***	q_0	q_1	q_r	T_r **(days)**
4.1 Facilities	-		-						
4.1.1 Sturdy (robust) housing types	% housing units that are not manufactured homes	3	D	1	1	1	0.599	0.998	120
4.1.2 Temporary housing availability	% vacant units that are for rent	3	D	2.68	5	0.536	0.050	0.536	620
4.1.3 Housing stock construction quality	100-% housing units built prior to 1970	3	D	0.241	1	0.241	0.145	0.241	700

4.1.4 Community services	%Area of community services (recreational facilities, parks, historic sites, libraries, museums) total area ÷ SV	2	D	0.16	0.2	0.800	0.480	0.800	430
4.1.5 Economic infrastructure exposure	% commercial establishments outside of high hazard zones ÷ total commercial establishment	2	S	0.85	1	0.850	-	-	-
4.1.6 Distribution commercial facilities	%Commercial infrastructure area per area ÷ SV	3	D	0.13	0.15	0.867	0.520	0.867	160
4.1.7 Hotels and accommodations	Number of hotels per total area ÷ SV	3	D	102	128	0.797	0.478	0.797	130
4.1.8 Schools	Schools area (primary and secondary education) per population ÷ SV	3	D	134	140	0.957	0.574	0.957	90
4.2 Lifelines									
4.2.1 Telecommunication	Average number of Internet, television, radio, telephone, and telecommunications broadcasters per household ÷ SV	3	D	5	6	0.833	0.500	0.833	90
4.2.2 Mental health support	number of beds per 100 000 population ÷ SV	2	D	69	75	0.920	0.644	0.920	35
4.2.3 Physician access	Number of physicians per population ÷ SV	2	S	2.5	3	0.833	-	-	-
4.2.4 Medical care capacity	Number of available hospital beds per 100000 population ÷ SV	3	D	544	600	0.907	0.635	0.907	35
4.2.5 Evacuation routes	Major road egress points per building ÷ SV	2	S	0.67	1	0.670	-	-	-
4.2.6 Industrial re-supply potential	Rail miles per total area ÷ SV	3	D	5412	6000	0.902	0.631	0.902	45
4.2.7 High-speed internet infrastructure	% population with access to broadband internet service	3	D	0.9	1	0.900	0.450	0.900	300
4.2.8 Efficient energy use	Ratio of Megawatt power production to demand	3	D	0.8	1	0.800	0.160	0.800	25
4.2.9 Efficient Water Use	Ratio of water available to water demand	3	D	1	1	1.000	0.240	1.000	60
4.2.10 Gas	Ratio of gas production to gas demand	3	D	0.1	1	0.100	0.050	0.100	70
4.2.11 Access and evacuation	Principal arterial miles per total area ÷ SV	3	D	172138	200000	0.861	0.602	0.861	45
4.2.12 Transportation	Number of rail miles per area ÷ SV	3	D	5412	6000	0.902	0.631	0.902	72
4.2.13 Waste water treatment	Number of WWT units per population ÷ SV	3	D	3	4	0.750	0.300	0.750	65

- Note: q_{0u} = initial serviceability; *SV* = standard value; q_0 = initial normalized serviceability; q_1 = post disaster serviceability; q_r= recovered serviceability; T_r = restoration time.
- Source: City Data, Census Data, This Study, City Assessor's Data, Dept of Numbers, SF Indicator Project, Data World Bank, Dot Ca, SF Bos, Arcadis, SF Wáter, Energy Ca.

Table 2. Fuzzy rule base for resilience.

T^*	q^*	R
short	high	resilient
Long	high	resilient
Very long	high	intermediate
Short	low	intermediate
long	low	not resilient
Very long	low	not resilient