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Research Article

Neural Network Techniques for Post-Earthquake Assessment of Buildings

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Abstract

After a strong earthquake the damage in the affected area can be so extended that it is not possible to make all building evaluations only by expert engineers. It is common the tendency of non-expert inspectors to aggravate or to underestimate the real level of damage. But, due to the fact that the damage levels are usually linguistic qualifications such as light, minor, moderate, average, severe, etc., an expert system implemented in a computer for post-earthquake evaluation of building damage has been developed using an artificial neural network and fuzzy sets technique. This expert system allows performing the building damage evaluation by non-experts that participate in a massive survey of buildings. The model considers different possible damages in structural and architectural elements and potential site seismic effects in the ground. It takes also into account the pre-existing conditions that can make the building more vulnerable, such as the quality of construction materials, plant and height irregularities and bad structural configurations. The system makes decisions about the building habitability and reparability applying fuzzy rule bases to the available building information. The global level of the building damage is estimated taking into account the structural and non-structural damage. The global building state is determined adding the rule base on ground conditions, obtaining thus the habitability of the building. The building reparability also depends on other fuzzy rule base: the pre- existent conditions. Thus, the expert system aids to make decisions on habitability and reparability of each building that are basic in the emergency response phase after the occurrence of a strong earthquake.

Keywords: *Damage assessment, Expert system, Fuzzy rule, post-earthquake evaluation of buildings, neural network.*

1. Introduction

In case of a strong earthquake, the damage evaluation process must be made by a broad group of professionals related to building construction. It is highly desirable that people involved in this process have expertise and experience in these tasks. Nevertheless, the professionals having these skills are usually only a few and it is necessary to involve inexperienced voluntary engineers or architects. As a consequence, the damage underestimation or overestimation is common. Therefore, this work proposes the use of the computational intelligence as support to this task, developing an expert system for supporting the building damage evaluation process, using artificial neural networks and fuzzy sets.

2. Damage evaluation after an earthquake

As a result of earthquakes occurred in different countries located in seismic areas, the development of guidelines to damage evaluation in buildings has been necessary, with the aim of deciding as soon as possible whether the buildings may continue being used or not. After a strong earthquake, the identification of the constructions which suffered serious damage, and that can represent thus a danger for the community, is crucial. The identification of the safe constructions that can be used as temporary shelters for evacuated people is also necessary. Some countries have developed systematic guidelines and procedures to evaluate the building damage, namely Mexico, Japan, United States, Italy, Macedonia, and Colombia, among others. Damage evaluations are useful to improve the effective earthquake-resistant construction codes, by identifying the type of failure of the structural systems. ATC, (1985, 2001).

2.1. Problems with the damage evaluations

When the damage in the area struck by an earthquake is extensive, local experts in earthquake engineering are always insufficient to make all the evaluations on the state of the buildings. Professionals with little or no

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experience must be part of the evaluation teams. According to the findings of risk perception researchers, the tendency of inexpert inspectors is to aggravate or to underestimate the damage level. The information on the damage evaluation is highly subjective and depends on heuristic criteria and the biases of introduced by the inspectors in each case. The damage levels are defined in all evaluation guidelines using linguistic qualifications like light, moderate, severe or strong; these concepts may have different meanings according to the judgment of each person and a defined limit between these assessments does not exist clearly. ATC (2005)

3. Computational modeling for post-earthquake damage evaluation

The problems that appear in the process of damage evaluation suggested to the author to look for new tools that facilitate the work. The proposed model uses the fuzzy logic approach motivated by the incomplete and subjective character of the information. Post-earthquake damage evaluations use qualitative and linguistic expressions that are appropriately handled by the fuzzy sets approach. On the other hand, an artificial neural network (ANN) is used to calibrate the expert system using the criterion of specialists. This enables the use of computational intelligence for the evaluation of damage by neophytes. For the model development, several building damage evaluation guidelines were taken into account. In addition, several members of the Colombian Association for Earthquake Engineering technically supported this work. The model has been implemented as a Visual BASIC 6.0 computer program, and has been called Earthquake Damage Evaluation of Buildings, EDE.

3.1. Artificial Neural Network structure.

The ANN has three layers. The variables in the input layer of the neural network are grouped in four types, namely Structural Elements (SE), Non-structural Elements (NE), Ground Conditions (GC), and Pre-existent Conditions (PC). Each one contributes with information to neurons in the intermediate layer; they only affect the intermediate neurons in the group to which they correspond. The number of input neurons or variables in the model is not constant; it depends on the class of the structural system that will be evaluated and on the importance of the different groups of variables selected for the evaluation. The number of neurons of the input layer of the structural elements group changes according to the class of building. Table 1 presents the structural elements or variables considered according to the structural system. A qualification is assigned depending on the observed damage, using five possible damage levels that are fuzzy sets. For structural and non- structural elements, the following linguistics damage qualifications are used: None (N), Light (L), Moderate (M), Heavy (H) and Severe (S). Figure 1 illustrates the membership functions for these qualifications. The fuzzy sets are based on selected damage indices (section 3.2). Damage in the non-structural elements do not endanger the stability of building, but may represent a hazard for the occupants. The non-structural elements are classified in two groups: common and optional elements. Table 2 illustrates the groups.

The variables of the ground and pre-existent conditions are valuated through the qualification of their state at the evaluation moment. The linguistic qualifications are: Very Good (VG), Good (G), Medium (M), Bad (B), and Very Bad (VB). The ground conditions comprise the occurrence of landslides and soil liquefaction. Preexistent conditions are related to the quality of the materials of construction, plane and vertical shape irregularities of building, and the structural configuration. In the intermediate layer, one index is obtained by defuzzification of each group of variables. Taking into account the four available indices, it is possible to define in the output layer the building damage using fuzzy rules with the structural and nonstructural evaluations. The building habitability is obtained also involving the assessment of the ground conditions. Finally, using the pre-existent conditions it is possible to define the required level of reparability.

Table 1 Structural elements according to the structural System

Structural System	Structural Elements
RC frames or (with) shear walls	Columns/walls, beams, joints and floors
Steel frames	Columns, beams, connections and floors
Unreinforced/Reinforced /Confined masonry	Bearing walls and floors

Table 2 Non-Structural elements.

Common elements	Partitions
	Elements of façade
	Stairs
Optional elements	Ceiling and lights
	Installations
	Roof
	Elevated tanks

3.1.1. Input layer of the ANN

The fuzzy sets for each element or variable i (for instance columns or walls), in the input layer, are obtained from the inspector's linguistic qualifications of damage Dj in each level j and its extension wj . The damage extension (percentage of each damage level in

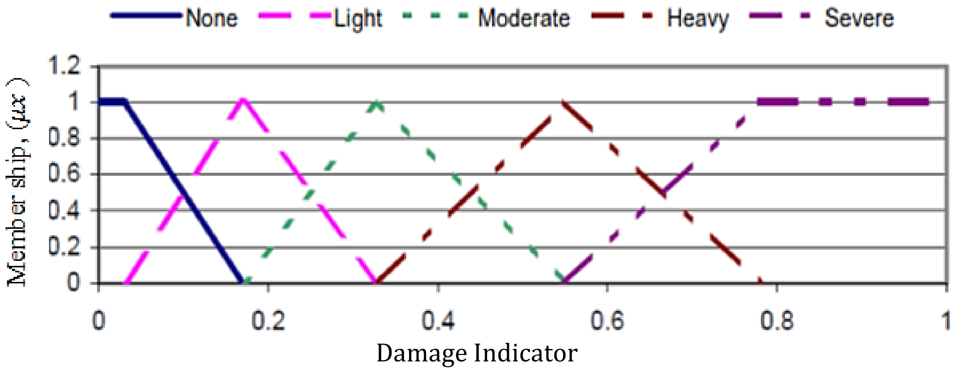

Fig.1 Membership functions for linguistic qualifications

each element) varies from 0 to 100 and it is normalized.

$$w_j = \frac{D_j}{\sum_N D_j} \;, \sum_N w_j = 1 \qquad (1)$$

The aggregated qualification of damage D_i for each variable is obtained with the union of the scaled fuzzy sets, taking into account the damage membership functions
$\mu D_j\ (D_j))$ and its extensions or weights assigned by the inspector

$$D_i = (D_N \cup D_L \cup D_M \cup D_H \cup D_S) \qquad (2)$$

$$\mu_{Di}(D) = \max(w_{N,i} * \mu_{D_N}(D_{N,i}), \dots, w_{S,i} * \mu_{D_S}(D_{S,i})) \qquad (3)$$

Union in the theory of the fuzzy sets is represented by the maximum membership or dependency. By means of defuzzification, using the Centroid of Area method (COA), a qualification index *Ci* is obtained for each variable of each group of neurons

$$C_i = \left[max.\left(w_{N,i} * \mu_{D_N}(D_{N,i}), \dots\dots, w_{S,i} * \mu_{D_{S,i}}(D_{S,1})\right)\right]_{Centroid} \qquad (4)$$

3.1.2. Intermediate layer of ANN

In this layer, there are four neurons corresponding to every group of variables: structural elements, non-structural elements, ground conditions, and pre-existent conditions. Figure 2 shows a general scheme of the evaluation process. In this model of neural network, the inputs of the four neurons are the qualifications C_i obtained for each variable of the each group of neurons and its weight W_i, or degree of importance on the corresponding intermediate neuron introduced by the inspector according to its own criteria. These weights are normalized and are calibrated by means of a learning function (section 3.2). The initial values and the training process of theses weights have been defined and made by the participation of experts in earthquake damage evaluation. Using these qualifications and weights of each variable *i*, a global index could be obtained, for each group k, from the defuzzification of the union or maximum membership of the scaled fuzzy sets. The membership functions $\mu C_{ki}(C_{ki})$ and their weights W_{ki}

$$\mu\mu_{CSE}(C) = \max\left(W_{SE1} * \mu_{C_{SE1}}(C_{SE1}), \dots., \ W_{SE1} * \mu_{C_{SEi}} * (C_{SEi})\right) \qquad (5)$$

$$I_{SE} = \left[max\left(W_{SE1} * \mu_{C_{SE1}}(C_{SE1}), \dots, W_{SEi} * \mu_{C_{SEi}}(C_{SEi})\right)\right]_{\text{Centroid}} \qquad (6)$$

Show the notation for the group of structural elements. The groups of variables related to ground and pre-existing conditions are optional then they can be or cannot be considered within the evaluation. If this happens, the habitability and reparability of building is assessed only with the structural and non-structural information.

3.1.3. Output layer of the ANN

In this layer the global indices obtained for structural elements, non-structural elements, ground and pre-existent

Conditions correspond to one final linguistic qualification in each case. The damage level is obtained according to the "proximity" of the value obtained to a global damage function of reference. In this layer, it takes place also the process of training of the neural network. The indices that identify each qualitative level (center of cluster) are changed in agreement to the indices calculated in each evaluation and with a learning rate.

Once the final qualifications are made, it is possible to determine the global building damage, the habitability and reparability of the building using a set of fuzzy rules bases.

3.2. Learning process of the ANN

The output layer of the neuronal network is calibrated when the damage functions are defined in relation to the damage matrix indices. In order to start the calibration, a departure point is defined, that means the initial indices of each level of damage.

Table 3 Comparative table for damage indicators

Damage Level	Park, Ang and Wen	Sanchez-Silva	Proposed
Very light	< 0.1	0.10	0.07
Light	0.10-0.25 (0.175)	0.20	0.17
Moderate	0.25-0.40 (0.325)	0.35	0.33
Severe	0.40-0.80 (0.60)	0.60	0.55
Destruction	>0.80	0.90	0.76

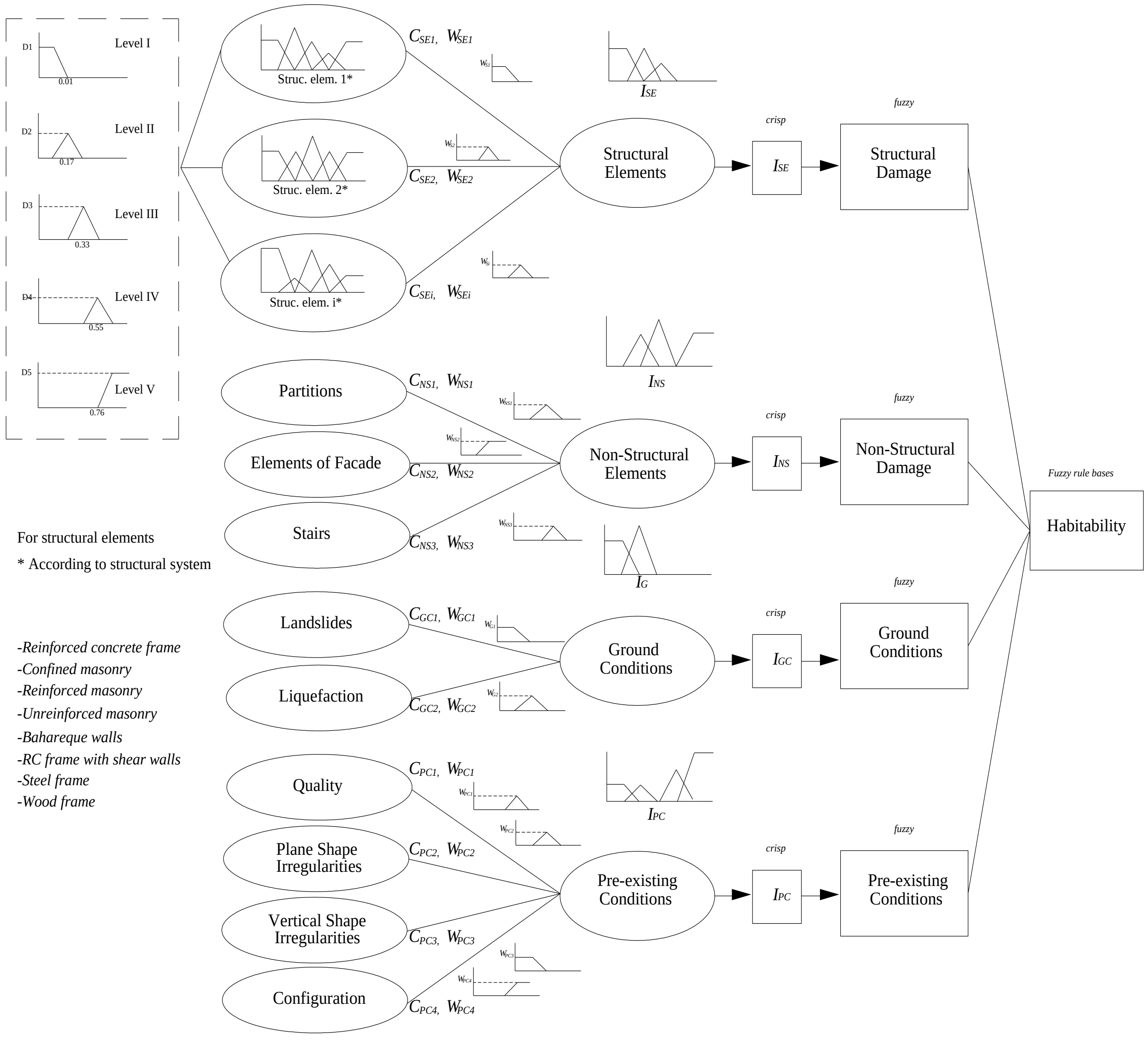

Fig.2 Structure of the proposed ANN

The indices proposed by the ATC-1310, Park *et al*., (1984), the fragility curves used by Goretti , (2005), and the indices used by Sanchez-Silva, *et al*., (2001) have been considered. The values of these indices correspond to the area of the centroids of each membership function related to each damage level. Table 3 shows the indices proposed in this work, which can be compared with those proposed by Park, Ang and Wen and Sanchez-Silva. The selection of the initial indices is based on those of Park; this choice can be justified on the basis that they have been calibrated with information of several studies. Those authors consider that collapse occurs in 0.8, although Stone *et al*., (1993) propose a collapse threshold of 0.77. Considering this, 0.76 is the selected index for the destruction level or collapse. In the selection of the damage index, the authors decided to be conservative, since the Indices corresponding to severe and moderate damage have been highly discussed, and doubts exist on whether they should be smaller.

The calibration is performed for each damage level and only the indices corresponding to the groups of variables considered in each evaluation are calibrated. The network learning is made using a Kohonen network

$$I_{kj}(t+1) = I_{kj}(t) + \alpha(t)\left[I_{kj}(t) - I_{kj}\right] \quad (7)$$

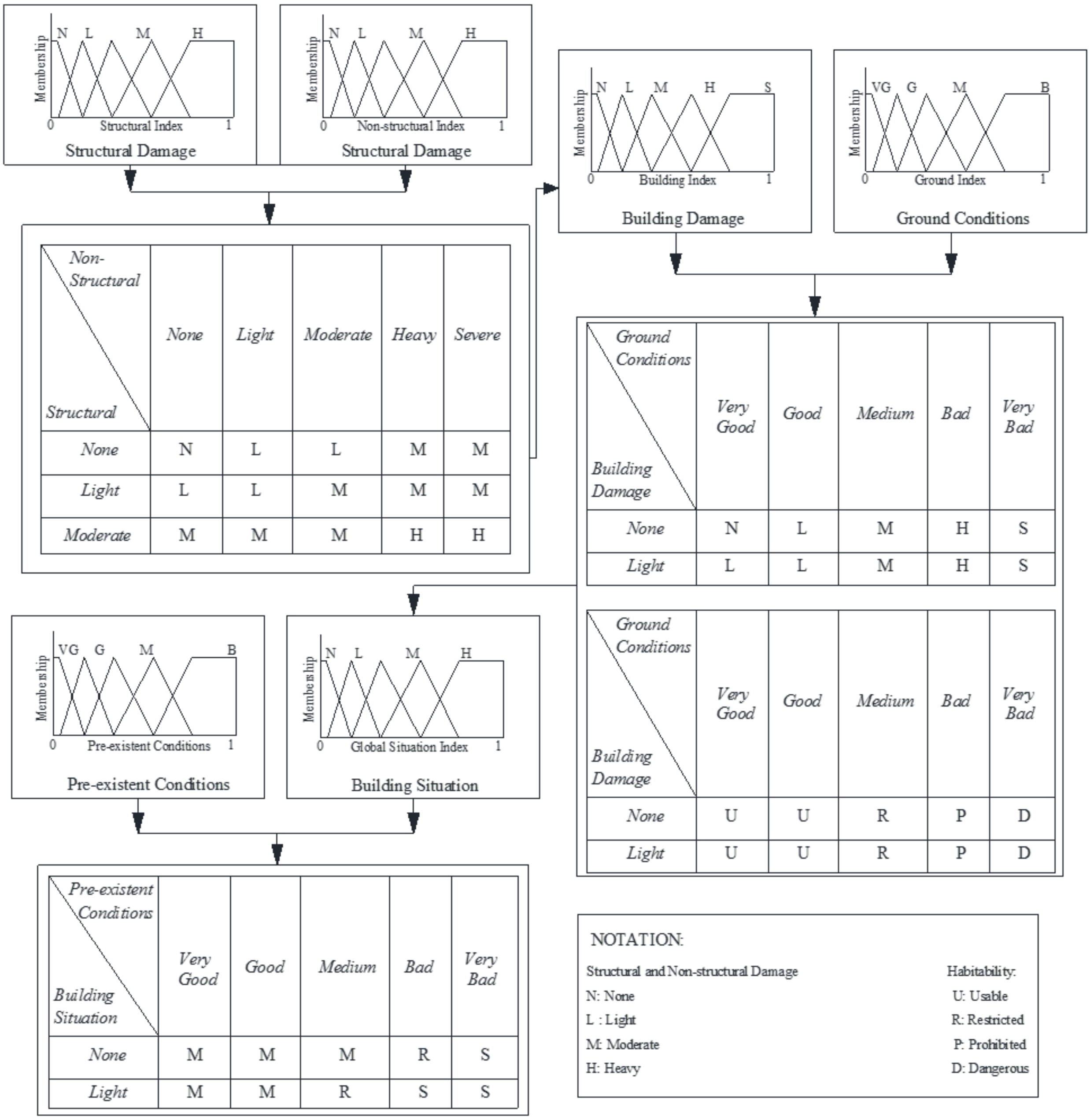

Fig. 3 Method for building habitability and reparability

Where I_{kj} is the value of the index of a group of variables k recalculated considering a learning rate α and the difference between the resulting index of the present evaluation and the previous indices in each level of damage j. The learning rate is defined by

$$\alpha(t) = 0.1 * Exp(-0.1 * t) \qquad (8)$$

Where t is the number of times that has been used the index or weight that is calibrated. For training, the damage evaluations made during the Quindío's earthquake in Colombia (1999) were used. The neural network has been calibrated for reinforced concrete framed buildings, however more information is necessary to complete the network training for other structural classes, such as the wood and steel frame structures, because these building classes are not common in that area struck by the earthquake. Reinforced concrete frames with shear walls were only a few also, therefore the number of building evaluations to calibrate this structural system were insufficient.

Fuzzy rule bases

Once obtained the damage level of the structural and non-structural elements, the state of the ground and pre-existent conditions, the habitability and the reparability of the building are assessed. Figure 3 displays the fuzzy rule bases used. The global level of building damage is estimated with the structural and non-structural damage results. This has five possible qualifications: none, light, moderate, heavy and severe damage. The global building state is determined taking into account the rule base of ground conditions and thus the habitability of the building. The linguistic qualification for the building habitability has four possibilities: usable, restricted, prohibited and dangerous. They mean habitable immediately, usable after reparation, usable after structural reinforcement, and non-usable at all. Besides, the building reparability depends on another fuzzy rule base: the pre-existent conditions. The building reparability has also four possibilities: not any or minor treatment, reparation, reinforcement, and possible demolition.

Conclusions

After a review of different guidelines for post-earthquake building damage evaluation, an innovative expert system has been proposed. The distinct advantages and disadvantages of each method were considered for the development of the tool.

The expert system was developed by using artificial neural networks and fuzzy logic approach in order to improve the existing field methodologies. This type of tool is very appropriate in the practice, due to the subjective nature of the building damage evaluations and the incomplete information.

The evaluations made by expert engineers after the earthquake of Quindío, Colombia, in 1999, have been very useful for the expert system training. FEMA (1999).

The use of AI tools in Civil Engineering has very little diffusion until present, thus it is recommended to promote their use to provide suitable and versatile solutions to different problems in this field of knowledge.

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