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Vulnerability Assessment of Constructions by Intelligent System Means

Hichem. Noura[1] & Mohamed. Abed[2]
[1] Civil Engineering Department, University of Khemis Miliana, Algeria, hichem.noura@hotmail.fr
[2] Civil Engineering Department, University of Blida, Algeria, abedmed@yahoo.fr

SUMMARY:
North Algeria is subjected to a frequent strong seismic activity. The estimation of the vulnerability of constructions, especially the ancient ones constitute a challenge for the public authorities. The results of such studies are important in the reduce of material and human losses under future seismic events as they allow strengthening intervention and also improve the disaster management plans. In this context, we expose in this paper an approach based on neural networks to assess the vulnerability of concrete structures. First, an artificial neural network associated with a set of 130 appraised constructions, is utilised to constitute a learning phase. In a second period, another set of buildings is utilised to measure the vulnerability and compare it with the expert assessment. A validation study permits to conclude acceptable the results estimated with the neural network system.

Keywords: Building vulnerability, Expertise, Accelerogram, Artificial Neural networks, Damage

1. INTRODUCTION

A great number of constructions in the North of Algeria date back to French and Turkish colonial period. These buildings are still exploited; some of them have undergone reinforcement actions in view of their importance (e.g. hospitals). Paradoxically, this north of Algeria strip is facing a strong recurring seismic activity. To predict the consequences for these post-seismic constructions which do not obey the current seismic code requires determination and mastery of the parameters affecting their vulnerability to earthquake. The ability to measure more accurately vulnerability is now one of the most critical challenges faced by structural engineers. In this context, the results of such studies are important in reducing human and material losses while allowing actions to strengthen existing structures and better management of post-seismic crisis.

The important earthquake of May 21, 2003, with 6.8 Magnitude that struck mainly the province of Boumerdes and the eastern part of Algiers province has resulted in very high toll of human losses (more than 2300 dead and 10000 injured people) and in very important damage to built environment (more than 100.000 dwellings or constructions collapsed or more or less seriously damaged).

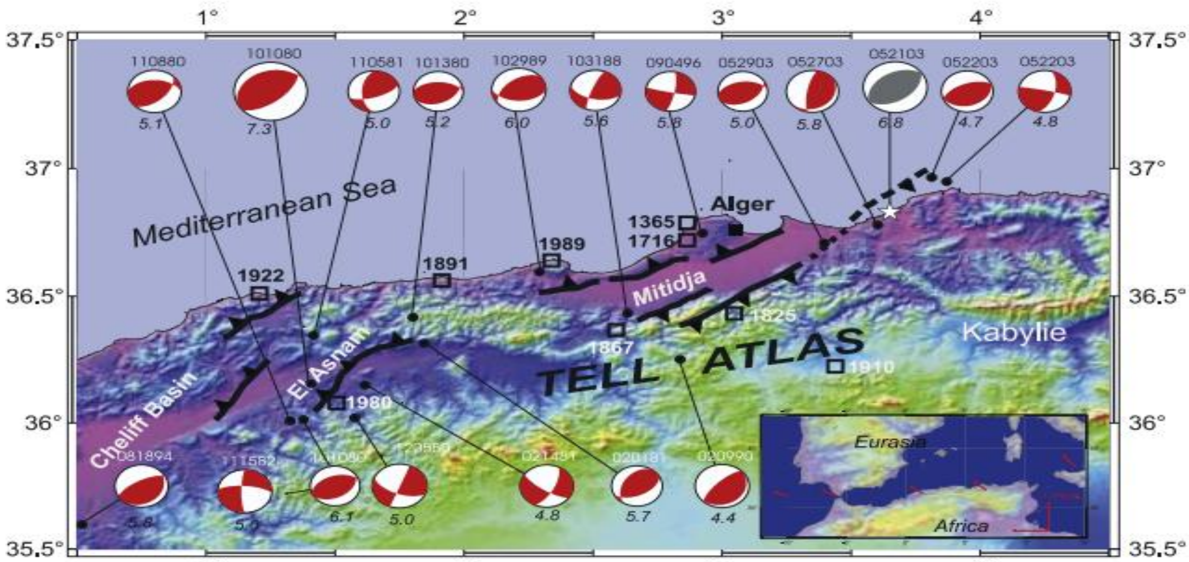

Figure 1.Seismicity and focal mechanisms in northern Algeria.

Table 1. Main earthquakes in Algeria (1365-2005)

Location	Date	*I*/M	M	Victims
Alger	03/01/1365	X		several
Alger	10/03/1673			
Mitidja	03/02/1716	X		20 000
Oran	09/10/1790	X		2000
Blida	02/03/1825	X		7000
Djidjelli	22/08/1856	x		-
Aurès	16/11/1869	IX		30
Gouraya	15/01/1891	X		38
Aumale	24/06/1910	VIII	6.6	81
Orléansville	09/09/1954	X	6.7	1243
El Asnam	10/10/1980	X	7.3	2633
Constantine	27/10/1985	VIII	6.0	10
Tipaza	29/10/1989	VIII	6.0	12
Boumerdes-Alger	21/05/2003	X	6.8	2300

Seismic vulnerability analysis of existing buildings requires basic information on their structural behavior. In the current methods such as HAZUS or Risk-UE, these parameters are collected by visual screening or estimated among generic values of physical parameters. Even for more complete diagnosis, the experts have to deal with the lack of structural plans, the unknown quality of material, ageing and damaging of the structure. The ambient vibrations of buildings and the modal parameters (frequencies, damping ration and modal shapes) that can be extracted from them naturally include all these parameters in the linear elastic part of their behavior. The aim of this work is to use this modal information to help the vulnerability assessment.

The estimated damage from future earthquakes depends on several factors. In fact, the quantity of buildings, the variability of structure types and the lack of describing information are the main difficulties encountered. Most actual methods for estimating the vulnerability are established considering post-seismic observations, registering the level of damage observed depending on the nature of construction. These methods are related to countries with high seismicity (USA, Japan, Turkey, Italy ...). They are based on the structural features observation with the aim to assign a global vulnerability index (IV). Based on available information, different accuracy levels are provided, which leads to variability of the vulnerability estimation. Relevant parameters, the coefficients assigned to them in computing the vulnerability index (IV) and the relationship between IV and the damage is determined from the feedback produced by experts on post-seismic missions. Unfortunately, in some situations the ground motion that generated the observed damage is usually not known because it was not registered.

Different methodologies are proposed to measure the structural seismic vulnerability (index method for example). These techniques are obviously empirical as they are based on the engineers' expertise and visual inspections. Among these methods, we can mention the Italian method of GNDT Benedetti (vulnerability index), the FEMA 273-274 and HAZUS 99 programs.

Development of decision tools systems to assist engineers in estimating the vulnerability can be a positive experience. The computer has become ubiquitous in the study and consideration of natural hazards. Many experiments have proved the benefits of using computer technologies to meet various needs such as management, modelling, inference, numerical calculation and prediction of phenomena. In this paper we present an approach based on artificial neural networks (ANNs) systems to assess the vulnerability of a building. In fact, a system of ANNs associated with a set of appraised buildings can be set up to form a first learning phase. In a second phase, this system can be used to predict the vulnerability of another set of constructions.

2. PRINCIPLE OF THE PROPOSED APPROACH:

Vulnerability characterizes the fragility of a component exposed to the natural phenomenon. It is expressed by a relationship between damage levels and levels of seismic attack. One can distinguish a physical vulnerability (or structural), human, functional, economic, social, etc. A construction is composed of a supporting framework (structure), and secondary equipment which will ensure the main functions (coverage, closure, separations, corridors, various technical materials, etc.). Thus the structure connected to the ground by the foundation must ensure stability under the influence of gravity (the masses resulting from all facilities are supported by the structure), the effects associated with climate (wind, snow, temperature variations) and seismic zone earthquakes.

Analysis of seismic vulnerability of buildings requires the determination of parameters characterizing the dynamic behaviour of structures. In common methods, this information is collected by visual expertise or chosen from standard values. Other methods are based on measuring dynamic modal parameters (Michel et al., Earthquake Engineering and Structure, 2011). The approach for estimating the vulnerability of reinforced concrete structures is to identify structural or non-structural parameters that influence the seismic response of the structure. Some of these parameters are extracted from records of damage assessments, called post seismic evaluation forms saved for different regions in Algeria.

2.1. The selected parameters and their classifications

Parameters for estimating the vulnerability of buildings are selected from the seismic evaluation forms for different regions in Algeria with different accelerogram. These parameters are classified using the methods of vulnerability analysis, developed in countries with high seismicity.

Each structural or non structural parameter can affect the seismic response of building and can take only one vulnerability value, this represents the class to which the construction belongs.

Table 2. Vulnerability class of the different structural criteria

#	Meaning of Parameters	Classes				
P1	Soil problem around the construction	1 (no)			5 (yes)	
P2	Foundations	1 (no)			5 (yes)	
P3	Substructure	1	2	3	4	5
P4	Bearing elements (vertical loads)	1	2	3	4	5
P5	Elements resisting to horizontal loads	1	2	3	4	5
P6	Roof floor	1	2	3	4	5
P7	Non structural elements	1	2	3	4	5
P8	Influence of adjacent constructions	1 (no)			5 (yes)	
P9	Symmetry plan	1 (good)		3 (medium)		5 (bad)
P10	Elevation regularity	1 (good)		3 (medium)		5 (bad)
Accelerogram		**Magnitude (1 -9)**				

Based on GNDT method (Benedetti and Petrini 1984, GNDT 1994), and European level EMS98, we propose a table setting out the parameters for estimating the vulnerability of reinforced concrete structures. For each parameter, a value between 1 and 5 is assigned. The least vulnerable (1) reflects the compliance of this parameter with the integrity of the structure, the more vulnerable (5) reflects the worst situation while Classes 2, 3 and 4 represent intermediate situations.

This particular model is validated with the records of earthquakes that occurred in Algeria, an instrumented by accelerogram network was used structure in our study.

2.2. Classification of the structure

A structure is classified according to its resistance to earthquakes as follows:
- Class 1: very good resistance to earthquake (moderate damages)
- Class 2: good resistance to earthquake (moderate damages)
- Class 3: a medium strength earthquake (significant damages to heavy)
- Class 4: poor resistance to the earthquake (very heavy damages)
- Class 5: a very bad earthquake resistance (collapse)

Table 3. Classifications of buildings according the damage evaluation form.

Class	1	2	3	4	5
Colour to use					

3. ARTIFICIAL NEURAL NETWORKS (ANNS)

The ANNs are biologically inspired and represent a mathematical model of the functioning of the biological neuron (Jodouin, 1994). Taking into account an ANNs architecture, the input and output data, the first phase is to master the relationship between input and output by a process called learning. The aim of this stage is to minimize the error by adjusting the model parameters.

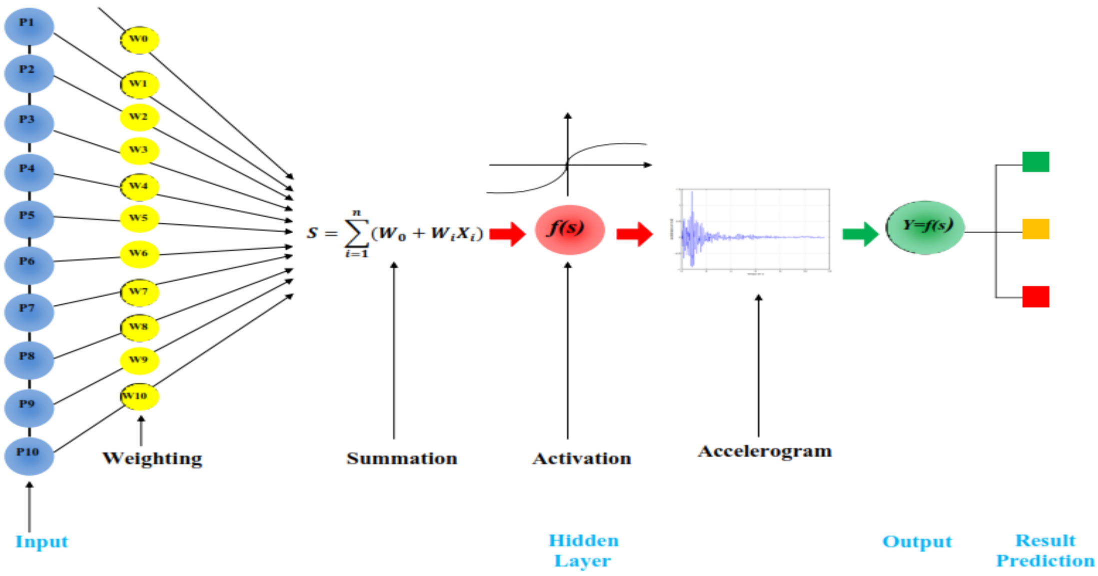

Figure 2. Network architecture RPG

The ANNs offer an alternative to mathematical modelling and are a part of non parametric and non linear statistical models suited to meet the challenges of decision support, diagnosis, prediction, etc. The application of this model type only appeared in early 1990 and their advantage lies in their ability to generalisation.

The artificial neural networks (ANNs) are widely used in civil engineering. The great interest in neural networks comes from their ability to learn, giving them the possibility to approximate any function with a desired precision. Nevertheless, the results predicted by such tools depend on the number of cases presented during the learning phase. Indeed, the higher the number, the higher the accuracy is better. The ANNs are used in many application areas such as pattern recognition, signal processing, learning, memorisation and especially the generalisation.

The network architecture multilayer backpropagation (RPG) used in this study consists of a layer of input neurons, one or more hidden layers of neurons, an output layer, and a set of parameters that control the learning process as the learning parameter (n), and the maximum allowable square error (E^2). Figure 3.1 shows the network architecture of RPG. The different steps to follow during learning phase with the «Back propagation» algorithm are as follows:

Step 1: Initialise the weights of connections between neurons. Often a value between 0 and 1, randomly determined, is assigned to each of the weights.

Step 2: Application of a vector input-output learning.

Step 3: Calculation of the ANNs outputs from inputs that are applied and calculating the error between the outputs and the real outputs to learn.

Step 4: Fix the weights of connections between neurons in the output layer and the first hidden layer considering the error occurring in the output.

Step 5: Error Propagation of the previous layer and adjusting the weights of connections between neurons in the hidden layer and those in entry.

Step 6: Completing the second stage with a new vector Input-Output so much as performance of the ANNs (error on the outputs) is not satisfactory.

The back propagation algorithm of the gradient is to perform a gradient descent on the cost function already used for the single neuron:

$$\varepsilon(\vec{w},k) = \frac{1}{2}\left(d(k) - y(k)\right)^2 \quad (3.2)$$

4. APPLICATION OF ANNS (RPG) FOR THE ESTIMATION OF VULNERABILITY

For the case we deal with, a base of 130 cases of appraised buildings is used in an architecture of ANNs to compose the learning phase by the software MATLAB 7.8 (DATA / NETWORK MANAGER). These cases are selected from the evaluation forms of post-seismic damage corresponding to important earthquakes that have affected Algeria (El Asnam 1980, Boumerdes 2003, etc.). We have deliberately diversified the types of construction (masonry, reinforced concrete with / without shear walls, date of build, etc.) and the implantation sites in order to contain all possible cases during the learning phase.

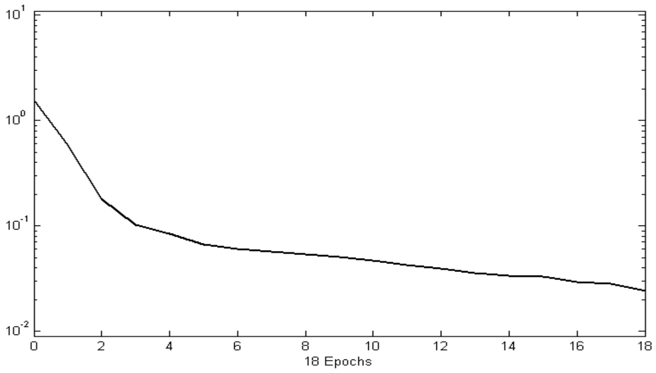

Figure 3. Performance results (performance=0.039)

4.1. Performance results

The learning curve indicates that the performance of the network converges faster during the first iterations and reaches an error limit of about 0.039. Learning outcomes and test of the network RPG are shown in Figure 4.2 This figure shows significantly improved learning outcomes and test, for all values of the parameters for estimating the vulnerability validation.

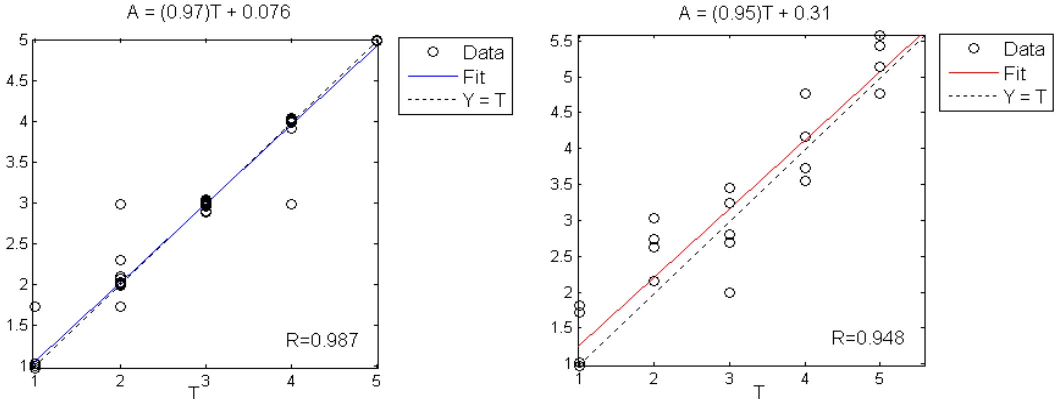

Figure 4. Comparing the output given by the ANNs (RPG) and the output target.

To check the quality of the network that forms a linear regression between the network response and the desired output, a correlation rate (R assesses) is calculated between the network response and the calculated output. A line that approximate all pairs of the desired output of the network (A) and the calculated output (T) is shown in figure 4.2. For a perfect network formed, it is necessary that all data points are aligned along the diagonal (A = T) and the value of R will be equal to one (R = 1).

The learning results and the testing of network vulnerability assessment are given in Figure 4.2. This figure shows significantly improved test results for all parameter values for estimating the vulnerability validation.

4.2. Validation of the ANNs RPG

To judge the reliability of results proposed by the system, we conducted a validation study. Indeed, another base of 10 appraised constructions which didn't take part in the set of "learning data" is used to compare the results predicted by the system (ANNs RPG) with effective expertise results (targets results) see Table 4.1. It should be noted that these constructions are selected from the evaluation forms of post-seismic damages for El Asnam and Boumerdes earthquakes.

Table 4. Parameters for estimating the vulnerability with the effective output

Parameter	Form # 131	Form # 132	Form # 133	Form # 134	Form # 135	Form # 136	Form # 137	Form # 138	Form # 139	Form # 140	Form # 141
P1	1	1	1	1	1	1	1	1	1	1	1
P2	1	1	1	1	1	1	1	1	1	1	1
P3	2	1	1	1	2	2	2	1	1	1	1
P4	5	2	1	1	3	4	2	1	1	1	1
P5	5	2	1	1	4	4	2	1	1	1	1
P6	3	2	1	1	3	3	2	1	1	1	1
P7	5	2	2	2	5	5	2	2	2	1	1
P8	1	1	1	1	1	1	1	5	1	1	1
P9	3	1	3	1	3	3	1	3	1	3	3
P10	3	1	3	1	1	1	3	3	1	3	3
Colour											
Effective result	5	2	2	2	4	4	3	3	2	1	1

This validation procedure is performed in the tool Network / Data Manager software MATLAB. After importing the data stored in the workspace neural network RPG which represent the parameters P1 to P10, an activation of the simulation process (figure 4.3) produce results that correspond to the estimation of vulnerability (figure 4.4).

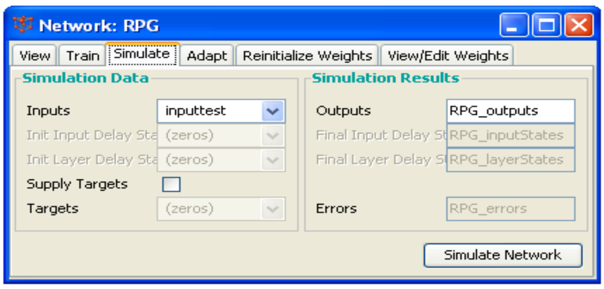

Figure 5. Simulation panel

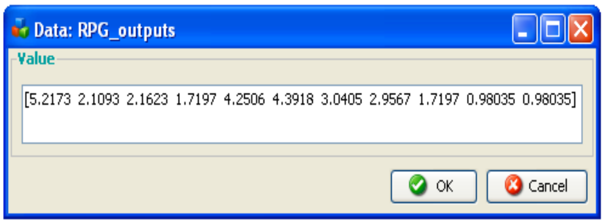

Figure 6. Viewing window of the output calculated by the ANNs (RPG)

The results obtained are summarized in the window Network / Data Manager; we can see a new variable in the menu (RPG_outputs) which represents the output computed by the neural network (see Figure 4.4). These values represent the rate of damage or the building vulnerability.

At the end comparing the two outputs, output calculated by the neural network and the effective output shown on the appraised construction forms, we can see that the predicted results calculated by the neural network RPG are satisfactory. We can therefore construct models of neural networks that provide a fast, convenient and very beneficial for estimating the vulnerability of buildings.

Table 5. Comparison of effective output and the predicted output calculated by the ANNs (RPG)

	Form # 131	Form #132	Form #133	Form # 134	Form # 135	Form # 136	Form # 137	Form # 138	Form # 139	Form # 140	Form #141
Effective output	5	2	2	2	4	4	3	3	2	1	1
Colour											
Output by ANNs	5.21	2.10	2.16	1.71	4.25	4.39	3.04	2.95	1.71	0.98	0.98

5. CONCLUSION

The technique of artificial neural networks applied in this study was done using the application NETWORK / DATA MANAGER MATLAB 7.8. The neural network chosen RPG gave satisfactory results. The mean error of the estimate of the vulnerability of reinforced concrete structures was 5% with a regression coefficient (R) of 0.98. These results confirm that the approach for a rapid and inexpensive assessment of vulnerability can be conducted. To be extended to other sites, knowledge of earthquake hazards is required. In our opinion, two approaches could be followed. The first one is to proceed in the same manner as above, that is to say, include new data sets for learning for other new areas. This means that a new parameter is added which account for a seismic zone. A second approach would be to measure the impact of seismic hazard for the new area and adjust the predicted results accordingly.

Neural networks require a large amount of data to be driven properly and to reach a satisfactory statistical convergence. However, in this study, the number of available data was unfortunately limited. Consequently, this restricts us somewhat in our conclusions. Nevertheless, the results indicate that neural networks could be an interesting alternative in the making of a support tool for estimating the vulnerability of buildings. Certainly, further investigation by an increase and diversification of the type of construction in the learning phase could strengthen this last conclusion.

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