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Pre-earthquake fuzzy logic and neural network based rapid visual screening of buildings

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Abstract. When assessing buildings that may collapse during a large earthquake, conventional rapid visual screening procedures generally provide good results when identifying buildings for further investigation. Unfortunately, their accuracy at identify buildings at risk is not so good. In addition, there appears to be little room for improvement. This paper investigates an alternative screening procedure based on fuzzy logic and artificial neural networks. Two databases of buildings damaged during the Athens earthquake of 1999 are used for training purposes. Extremely good results are obtained from one database and not so good results are obtained from the second database. This finding illustrates the importance of specifically collecting data tailored to the requirements of the fuzzy logic based rapid visual screening procedure. In general, results demonstrate that the trained fuzzy logic based rapid visual screening procedure represents a marked improvement when identifying buildings at risk. In particular, when smaller percentages of the buildings with high damage scores are extracted for further investigation, the proposed fuzzy screening procedure becomes more efficient. This paper shows that the proposed procedure has a significant optimisation potential, is worth pursuing and, to this end, a strategy that outlines the future development of the fuzzy logic based rapid visual screening procedure is proposed.

Keywords: fuzzy logic; artificial neural networks; rapid visual screening; seismic vulnerability; vulnerability assessment; damage.

1. Introduction

Large earthquakes can cause great damage to manmade structures. When a large earthquake occurs, there may be loss of life, many injuries and substantial financial loss. Globally, the average annual losses due to earthquakes are not as high as when considering other natural hazards such as wind and flood. In addition, much higher risks of loss of life or injury are accepted when driving a car. However, large earthquakes have a major psychological impact, as their effects are instantaneous and devastating.

At the present moment, it is not possible to predict the occurrence of a large earthquake. In general, the best that can be done is a statistical approach by stating that there is a certain probability that a certain size earthquake will occur in a certain time span. That is, the certain size earthquake could happen tomorrow, at any time in the specified time span or may not happen at all.

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Even if it was possible to predict an earthquake, all that could be done is to evacuate the population and accept the inevitable infrastructure damage.

Given the uncertainty in predicting earthquakes, a second approach would be to identify the structures and buildings that would suffer during a large earthquake. A starting point would be to screen the structures and buildings that would play an important role after a large earthquake. Examples of such important buildings are hospitals, telecommunication buildings, emergency service buildings, government buildings and schools. The overall object would be to identify buildings at risk so that remedial measures can be considered or, at least, the residents of a building should be aware of the risks involved in living or working in a particular building should a large earthquake occur. It is known that older buildings are more vulnerable than new buildings and codes have been revised and improved as knowledge has increased. Following significant code revisions, much research has been performed to investigate remedial measures to strengthen the weak elements of a structure, such as columns and beam-column joints (for example, Tsonos 2002, Vandoros and Dritsos 2006).

Most countries in earthquake regions have introduced some form of a pre-earthquake assessment of existing structures in order to identify buildings at risk. The rapid visual screening procedure (RVSP) is the first stage of some of these pre-earthquake assessment procedures. Screeners collect structural characteristic information and other parameters that are used to determine if a further investigation is required. This paper investigates the fuzzy logic based rapid visual screening procedure (FL RVSP) as an alternative to conventional RVSPs and the object is to investigate if the FL RVSP can replace conventional RVSPs when identifying buildings at risk. Two databases of earthquake-damaged buildings are investigated. Through the use of artificial adaptive neural networks, the first database is used to train the FL RVSP and the second database is used to first check the results and then to extend the training process. It is recognised that the use of existing databases has limitations but it is not the object of the present work to build the final fuzzy logic software system for rapid visual screening assessment. The object is to examine the capability of the method to give good results after the collection of specific data needed to train the method and to investigate if it is worthwhile pursuing the FL RVSP as an alternative to conventional RVSPs.

2. Rapid visual screening procedures

The object of a RVSP is to quickly inspect buildings in order to assess their susceptibility to earthquake damage without performing structural analysis calculations. Information is collected with the aim to allocate a numerical value that should indicate if a building requires further investigation. Buildings are ranked depending on the numerical value allocated.

The Federal Emergency Management Agency (FEMA) first introduced a rapid visual screening procedure in America (FEMA 154 1988, FEMA 155 1988) and it was revised (FEMA 154 2001) to include more recent seismic risk information. For the FEMA procedure, any relevant information available in records, databases and building construction documents is initially collected. After this process, trained screeners, with an engineering background and the assistance of a quick reference guide, go out into the field to confirm any collected information and fill in any gaps in the record. Depending on the degree of seismic activity, one of three data collection forms are used. To obtain a final score, a basic structural hazard score is initially allocated, which depends on the structural type of the building. Score modifiers are then added to or subtracted from the basic score. The allocation of a score modifier depends on the number of storeys, the occurrence of vertical irregularities (including inclined walls, building on a hill, soft storey and short columns), the occurrence of plan irregularities, the age of the building and the soil type. The age of the building is important as it indicates if the building was constructed before the introduction of seismic codes or after significant improvements in these codes. The final score indicates if a detailed evaluation is required. Other information collected on site is a sketch of the building, a photograph, the occupancy load and the possibility of falling hazards. The FEMA rapid visual screening procedure is typically performed from outside the building but the reliability of and the confidence in the record will increase if an internal inspection is performed. Countries that have pre-earthquake assessment procedures based on the FEMA procedure include Canada, Greece and India. A possible problem with the FEMA procedure is that it uses gross empirical values to describe structural characteristics and parameters, which may be difficult to transform to the structural characteristics and parameters of other countries.

The Japanese introduced a first level screening procedure for reinforced concrete buildings as early as 1977. A detailed English Language description of the method has been presented by Otani (2003). It is not a true RVSP, since the process involves the measurement of element dimensions and the estimation of concrete strengths so that a gross calculation of a building's seismic capacity can be performed. Access to buildings is required. To obtain a final score, the Japanese method then uses multiplication factors for other parameters that may affect a building's susceptibility. Many other countries (such as New Zealand, Turkey and Italy for masonry buildings) follow the method's philosophy. Because more information is required and due to the different approach, it could be estimated that the Japanese method would take up to five times longer to perform when compare to FEMA based RVSPs.

In Greece, the Earthquake Planning and Protection Organization (OASP) has introduced a rapid visual screening procedure (OASP 2000) that is almost the same as the original FEMA procedure (FEMA 154 1988, FEMA 155 1988). The only difference between the original FEMA procedure and the FEMA based OASP procedure is that the structural characteristics reported differ slightly because various structural properties are different in Greece. In addition, the OASP RVSP is typically performed inside the building. One data collection form is used and a basic score is initially allocated depending on the structural type. Score modifiers for parameters that are considered to affect the structural performance are then added to or subtracted from the basic score. These parameters are the seismic region, the age of the building (as in seismic code used for the design), the soil type, the condition of the building (as in a lack of maintenance) and if the building is high-rise. Additional parameters are if the building has a soft storey, short columns, a regular layout of infill walls, any previous damage, vertical or plan irregularities and the possibility of torsion or pounding. Again, as for the FEMA method, the final score indicates if a detailed evaluation is required and other information is collected on site. The FEMA based OASP RVSP is a well-accepted method that generally provides good results. The method is tried, tested and has been developed through expert examination over many years but there appears to be little room for further improvement.

The basic problem with rapid visual screening procedures is that they assume that the factors that may affect the effectiveness of the structural system act individually on the structural system. In addition, the engineer performing the procedure has the difficult task of making yes-no decisions when the truth may be closer to varying degrees of maybe. Rapid visual screening procedures are not perfect and it would be sensible to look into ways of improvement. In simple terms, any enhancement directly converts into saved lives, injury and financial loss. For the above reasons, the FL RVSP is being developed at the University of Patras with the aim of accurately ranking buildings in the order of susceptibility to earthquake damage. In addition to the work being carried out at the University of Patras, Sanchez-Silva and Garcia (2001) have performed a similar earthquake damage assessment based on fuzzy logic and neural networks. Sanchez-Silva and Garcia (2001) reported that their model was highly reliable and provided a good representation of experts' opinions.

3. Fuzzy logic

Professor Lotfi Zadeh of the University of California, Berkeley is considered to be the founder of fuzzy logic (Zadeh 1965). It is not the intention of this paper to describe fuzzy logic in detail. The intention is to describe the basic principles involved. Further detailed information can be found elsewhere (Zadeh 1973, Mamdani and Assilian 1975, Sugeno 1975, Levrat *et al.* 1996).

Fuzzy logic is a mathematical process that attempts to describe human reasoning. Human reasoning processes imprecise information with the object of making a decision or drawing a conclusion.

The basic concept of fuzzy logic is a fuzzy set. Fuzzy sets differ from classic sets (Boolean or Aristotelian logic) where an element either belongs to or does not belong to a set. A fuzzy set is a superset of Boolean logic and does not have a clearly defined boundary. An element can have a partial membership of the fuzzy set ranging from 0, or non-membership, to 1, or full-membership. Fuzzy sets are used to describe various imprecise states of linguistic variables. For example, as shown in Fig. 1, fuzzy sets for the states poor, medium and good describe the linguistic variable maintenance, where maintenance is defined as a value between 0 and 1. Fuzzy sets of imprecise information are input to a fuzzy inference system.

A second basic concept of fuzzy logic is the conditional statement or the fuzzy if-then rule. Fuzzy if-then rules take the form if x is A and y is B then z is C. The operators 'and' and 'or' are used in fuzzy if-then rules. These operators are from standard truth tables, which define the numbers 1 (true) and 0 (false). Once the values 1 and 0 are defined, values other than 1 and 0 can be considered. The operator 'and' corresponds to the function min (the fuzzy intersection) and the

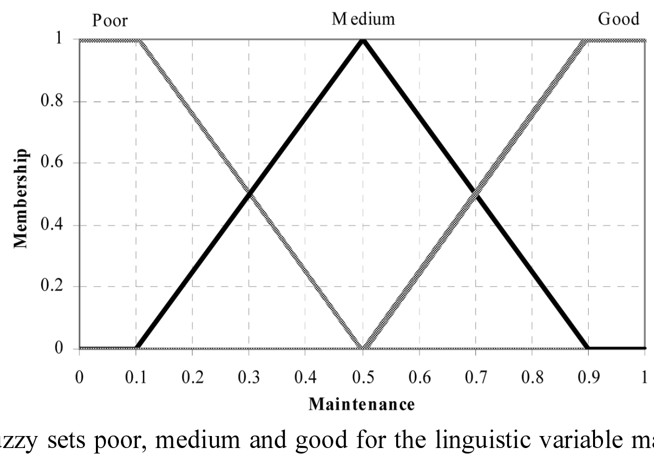

Fig. 1 Fuzzy sets poor, medium and good for the linguistic variable maintenance

operator 'or' corresponds to the function max (the fuzzy union). That is, poor 'and' medium is min (poor, medium) and is the intersection of poor and medium from Fig. 1 (the area inside the coordinates (0.1, 0), (0.3, 0.5) and (0.5, 0)). Similarly, poor 'or' medium is max (poor, medium) and is the union of poor and medium from Fig. 1 (the area inside the coordinates (0, 1), (0.1, 1), (0.3, 0.5), (0.5, 1) and (0.9, 0)). It should be noted that there are other operators but the operators 'and' and 'or' are the ones used in the present paper. Fuzzy if-then rules are used to map fuzzy set input to an output or a conclusion.

There are two main types of fuzzy inference systems depending on the form of the output. If the output is a fuzzy set, the system is called Mamdani-type system (Mamdani and Assilian 1975). If the output is a constant value or a polynomial function, then the system is called Sugeno-type system (Sugeno 1985).

4. Adaptive network based fuzzy inference system (ANFIS)

It is not the intention of this paper to describe the ANFIS procedure in detail. The intention is to describe the basic concepts that are involved. Further detailed information can be found elsewhere (Jang 1993, Kartalopoulos 1995).

Artificial adaptive neural networks are inspired by the structure and operation of the human nervous system. Through neurons, the human nervous system receives signals, processes the information and then redistributes the processed information to other neurons and so on. By comparing the output to an existing set of patterns within the system, the system adapts its structure to include the new information. That is, the system learns.

The ANFIS is an adaptive network that corresponds to a Sugeno-type fuzzy inference system. Once a fuzzy inference system has been set up, information can be input into the system to obtain an output. If the output is already known, the fuzzy output can be compared to the known output and the ANFIS is able to adjust its structure to minimise the error. After a forward pass through the fuzzy inference system, a least squares estimate of the output error is performed. A back-propagation algorithm, in the form of the gradient descent rule (Jang 1993), is then used to adjust the structure of the fuzzy inference system. The process is repeated until a minimal error is obtained.

The use of artificial adaptive neural networks is the fundamental advantage of the FL RVSP over conventional RVSPs. Without adaptive neural networks, the FL RVSP does not have the potential of enhancement. It must be noted that the network described above is not the only adaptive network. For example, Sanches-Silva and Garcia (2001) used weighted unsupervised competitive learning for their adaptive neural network.

5. Fuzzy logic based rapid visual screening procedure

In its present form, the FL RVSP has only been applied to buildings constructed from reinforced concrete. Reinforced concrete buildings make up the vast majority of the building stock in Greece. The FL RVSP is based on the OASP RVSP, insomuch as the same structural characteristic information gathered by the OASP RVSP is used as input information for the FL RVSP. Where the FL RVSP differs is that the state of each structural characteristic is described through linguistic terms. In addition, collected information is analysed by a computer as advances in computer technology have eliminated the difference between performing simple and complicated routines. For this reason, the FL RVSP does not provide an immediate on site result.

The initial variable definition and formulation the fuzzy rules have been presented by Mandas and Dritsos (2004). Demartinos and Dritsos (2006) have previously described how the existing Mamdani-type system was converted to a Sugeno or ANFIS type system so that the FL RVSP could be trained. These authors have also presented the linguistic terms used for the definition of each variable and the respective fuzzy sets. As an example, Fig. 1 above is based on the linguistic terms and corresponding fuzzy sets for the definition of the variable maintenance, as presented by Demartinos and Dritsos (2006). As for all RVSPs, the FL RVSP in its present form may not describe all the features required to predict the damage a structure may suffer. For example, it is known that, during construction, a high level of supervision can greatly improve the quality of a building. It is difficult to see how the level of supervision can be identified during a RVSP.

Since the number of rules equals the number of all possible fuzzy set combinations, a direct combination would have lead to an extremely large system with over three million rules. Such a system would be difficult to define and would be highly demanding in terms of computational requirements. Therefore, the intermediate variables seismic hazard, basic structural strength, regularity and structure's condition were used to group the input variables and reduce the size of the system. A total of 366 rules were defined of which 60 rules were used to describe seismic hazard, 216 rules were used to describe basic structural strength, 81 rules were used to describe regularity and 9 rules were used to describe structure's condition. Table 1 gives examples of how structural characteristic information was used to derive fuzzy input data. It should be noted that Table 1 only gives an indication of the relationship between structural characteristic information and fuzzy input data as other factors, such as the shape of the fuzzy sets, can influence the results. Table 2 lists which variable was used to derive the intermediate variables and Fig. 2 presents the fuzzy sets used

Table 1 Fuzzy input variable examples

Ground motion					
Seismic zone	I	II	III	IV	
Specified ground acceleration (g)	0.12	0.16	0.24	0.36	
Linguistic term	Light	Moderate	Intense	Very intense	
Maximum membership variable value	0	0.33	0.67	1	
Soil quality					
Soil category	A	B	Γ	Δ	X
Linguistic term	Very good	Good	Moderate	Poor	Very poor
Maximum membership variable value	0	0.25	0.5	0.75	1
Soft storey					
Linguistic term	No infill walls	Infill walls partially exist	infill walls exist		
Maximum membership variable value	0	0.5	1		
Wall and infill wall layout					
Linguistic term	Non symmetric	Partially symmetric	Symmetric		
Maximum membership variable value	0	0.5	1		

Table 2 Input and intermediate variables

Seismic hazard	Basic structural strength	Regularity	Structure's condition
Ground motion	Building height	Plan regularity	Previous damage
Soil quality	Soft storey	Torsion	Maintenance
Building height	Short columns	Height regularity	
	Year of construction	Pounding	
	Infill wall layout		

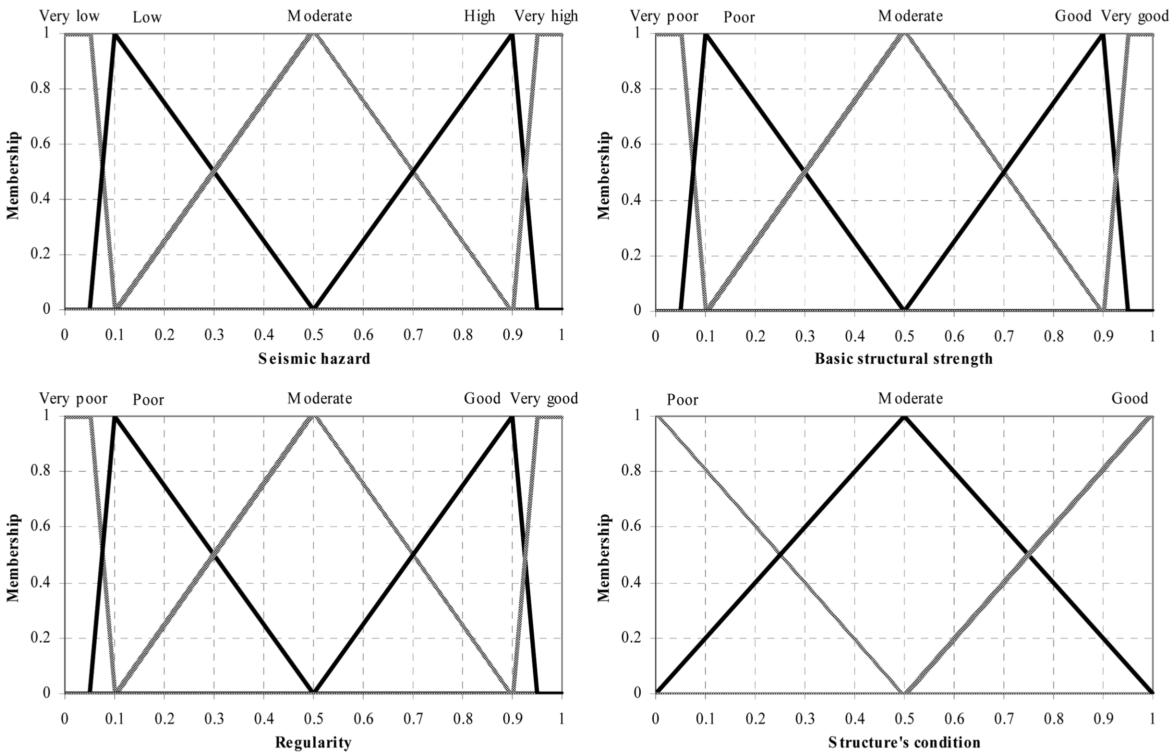

Fig. 2 Fuzzy definition of intermediate variables

Table 3 Fuzzy rule examples

Premise	Conclusion
IF 'ground motion' is intense AND 'soil quality' is very poor AND 'building height' is short	THEN 'seismic hazard' is high
IF 'building height' is short AND 'soft storey' is no infill walls AND 'short columns' is existence AND 'year of construction' is very old AND 'infill wall layout' is non-symmetric	THEN 'basic structural strength' is very poor
IF 'plan regularity' is complex layout AND 'torsion possibility' is large AND 'height regularity' is regular AND 'pounding possibility' is small	THEN 'regularity' is very poor
IF 'previous damage' is none AND 'maintenance' is medium	THEN 'structure's condition' is good
IF 'seismic hazard' is high AND 'basic structural strength' is very poor AND 'regularity' is very poor AND 'structure's condition' is good	THEN 'damage score' is severe

to define the intermediate variables. Table 3 gives a fuzzy rule example from each intermediate variable and an example linking the intermediate variables to the final damage score.

When determining a fuzzy rule conclusion, expert opinion was managed by asking the experts to arrange the input variables in order of importance. Once the importance of each variable was determined, the rules for each intermediate variable could be sorted into an order. Each rule was then given a rank number between 0 and 1 and then, with reference to Fig. 2, a linguistic variable conclusion could be applied to each rule. This process was repeated for the final damage score outcome. The input variables of Table 2 have been arranged in order, with the expert opinion determined most important variables at the top. The similarly determined importance of the intermediate variables of Table 2 is from left to right.

Once the intermediate variables were evaluated, the values obtained became input values for a fuzzy inference system to evaluate the output variable damage score. Demartinos and Dritsos (2006) have previously defined the damage score as an output variable that represents the possibility that a structure will suffer a certain type of damage. This definition of the damage score was based on the damage type descriptions of BSSC (2000). In addition, the damage type was related to numerical values that represent a central damage factor (ATC 13 1985). That is, the five damage type classes of very light, light, moderate, severe and collapse are related to central damage factors of 0.0 to 0.1, 0.1 to 10, 10 to 30, 30 to 60 and 60 to 100 respectively. A total of 375 fuzzy rules were defined in order to evaluate the damage score output variable.

6. Application of the FL RVSP method

The object of a RVSP is to rank assessed buildings in terms of possible vulnerability to seismic hazard. Consequently, by selecting a percentage of the highest ranked buildings, a high priority subset of vulnerable buildings can be identified for further investigation and possible intervention. The FL RVSP ranks buildings in terms of the damage score output variable. Higher damage score values should indicate a higher possibility of damage during a strong earthquake. An identified high priority subset should be made up of particularly vulnerable buildings. Unfortunately and at times tragically, a building's vulnerability can only be observed after a powerful earthquake.

Existing databases of buildings whose vulnerability has been assessed after a major seismic event can be used as hypothetical building sets for pre-earthquake evaluation. Information collected can be used to assess the method's efficiency and precision when considering the expected damage. The method would be efficient if the procedure ranked buildings correctly in the order of observed damage. That is, buildings that collapsed should have the highest damage score and buildings that were not damaged should have the lowest damage score. The method would be accurate if the observed damage corresponded to the predicted damage, expressed in terms of the possibility that a certain type of damage would occur. Information gathered relating to the effects of major earthquakes on structures can be used to validate the efficiency and precision of the FL RVSP. In addition, as the output is already known, building sample databases and ANFIS can be used to train the FL RVSP. Matlab® software (Mathworks Inc. 2002) was used to perform the fuzzy logic inference process and system training.

It is believed that the FL RVSP could be applied to other earthquake prone regions of the world. In order to tailor the input variables to another earthquake region, some input variables may need to be removed, while others may need to be added. In addition, the shape and number of fuzzy sets may need to be changed. An example of how fuzzy logic and neural networks have been applied in other earthquake regions is the work of Sanchez-Silva and Garcia (2001). These authors used different fuzzy sets and slightly different input and intermediate variables. In addition, Sanchez-Silva and Garcia (2001) applied their method to a mixture of structural types.

6.1 Building sample databases

Two building databases (Halkia 2006) were used for the present study. These databases were compiled from raw data collected from buildings that had suffered damage during the Athens earthquake of 1999. These databases do not represent data specifically collected for FL RVSP use. It must be accepted that the use of such databases is not the best way to train the FL RVSP but other suitable information is not available. The collection of the information used for the databases was commissioned by the OASP in order to investigate reasons for structural damage. Two independent teams of experts collected the information on site by assessing each building's damage. Information collected related to the structural type, the design code used, the building's shape, the building's regularity, the building's on site observed damage type description (BSSC 2000) and other parameters concerning structural characteristics and strength.

For structural design purposes, Greece is divided into four seismic hazard zones and different ground accelerations are specified for each seismic zone. It has been determined that there is a 10% probability of exceeding these accelerations during a 50-year period. The specified effective ground acceleration for the Athens region is 0.16 g. The epicentre of Athens earthquake was outside the city at Mount Parnitha, to the northwest of the city. Peak ground accelerations recorded near the city centre ranged from 0.12 g to 0.30 g at distances of 15 km to 17 km from the epicentre (Anastasiadis *et al.* 1999). Therefore, as the actual peak ground acceleration at the epicentre would have been higher than these quoted values, the 1999 Athens earthquake was deemed a major seismic event. It should be noted that the raw data used for this study was collected in Athens suburbs near the epicentre.

The first database consists of 102 buildings of which 26 were moderately damaged, 42 were severely damaged and 34 buildings that collapsed. These damage descriptions meet definitions provided by BSSC (2000).

The second database consists of 215 buildings of which 49 buildings had light damage, 40 buildings had moderate damage, 33 buildings had severe damage and 93 buildings had collapsed. Again, these damage descriptions meet definitions provided by BSSC (2000).

The collected raw data could not be directly used to evaluate damage scores. With the exception of building height and year of construction, the raw data is in the form of yes-no answers, whereas the FL RVSP requires a numerical input somewhere between 0 and 1. Therefore, an interpretation of facts took place according to input variable definitions provided by the FL RVSP. A subsequent record was thereby formed, which included values for the input variables. Registered recorded values were then used to evaluate damage scores. It must be pointed out that the initial interpretation of facts was an approximate procedure and was not easy to perform, as a visual inspection of each building was not possible. That is, the input variables must have been present to some degree but it was difficult to decide to which degree when the only information available was a yes or a no answer. Therefore, irregularities and errors may have been introduced.

It should be noted that both databases do not cover all five classes of damage, as they do not include information on buildings that did not suffer any damage. This is a limitation of the present study. The first database includes buildings with the damage types of moderate, severe and collapse, while the second database includes buildings with the damage types of light, moderate, severe and collapse. If buildings with no damage had been assessed, they may have received damage scores corresponding to the five classes of damage. That is, any study that looks only at damaged or collapsed buildings is bias and is valid only for damaged or collapsed buildings. Because of this limitation and as the databases do not represent data specifically collected for FL RVSP use, a real training of the system could not be expected. Having said this, the alternative would be to screen a set of buildings and then wait for a major earthquake to occur.

6.2 The training process

The ANFIS damage score was trained in two different stages. Firstly, 102 input desired output pairs from the first database were used to initially train the system. Secondly, 215 input desired output pairs from the second database were used to first test and then retrain the system. This method was adopted because the first database may not fully represent the features of the system to be modelled. In order to validate the system, a testing data set that was not used for the initial training is required to test the trained system. Therefore, the second database was used to check if the initial trained system was valid. As the initial trained system was found to be not valid, the system was retrained.

The desired values were specified by a procedure that took two steps. For the first step, the building samples were separated into categories depending on the damage that had occurred. These categories were buildings that had suffered light, moderate or severe damage or buildings that had collapsed. This imposed the requirement that the damage score should fall within the intervals of 0.1 to 10, 10 to 30, 30 to 60 and 60 to 100 for the preceding categories respectively, according to the definition of the damage score variable. The second step was to rank the buildings within each damage group category based on the experience and knowledge of experts.

For the system under consideration, the number of consequent and premise parameters respectively amounted to 375 and 60. For sufficient tuning of the system, ANFIS requires that the training data should be greater than the sum of the parameters to be modified. Therefore, the system was underdetermined. This fact indicated that there would be a poor convergence between actual and desired outputs. Regardless of this fact, the training process was applied to give an idea of how gathered information relating to a structure's earthquake performance could be used to improve this fuzzy approach to RVSP. The obtained root mean square errors were 12.4 and 25.6 for the first and second databases respectively. As larger values of root mean square error indicate greater errors, it would be expected that results from the second database would be less accurate than that results from the first database.

7. FL RVSP enhancement

7.1 First training

Fig. 3 presents charts relating to the efficiency of the method trained through the first database. The upper charts of this figure represent the percentage distribution of buildings for each damage group.

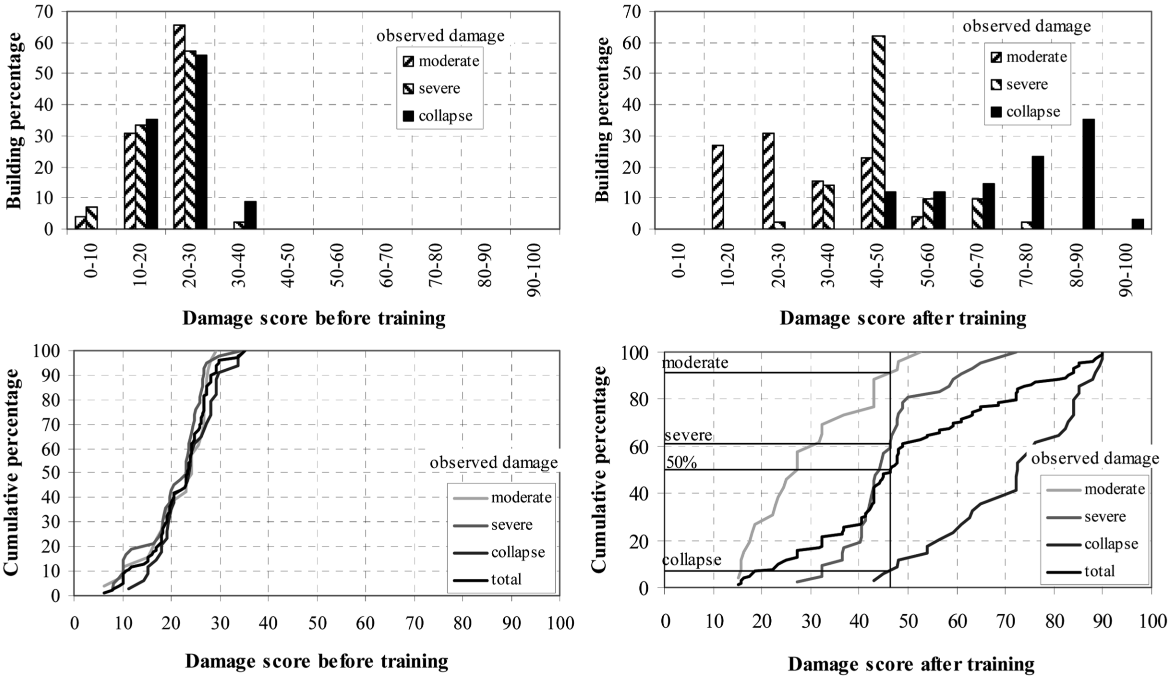

Fig. 3 First database FL RVSP results

From the top left chart of Fig. 3, the building sample before training was concentrated within the interval of 0 to 40 and a distinction between the groups is difficult to see. This indicates that either the initial fuzzy rule formulation or the interpretation of facts was not good, as damage groups and damage score ranges do not correspond. Having said this, the buildings that collapsed generally received higher damage scores while the buildings with moderate damage generally received lower damage scores. There is a clear improvement after training as the building sample was correctly distributed over the range of 10 to 100, clear distinctions between the groups can be seen and individual groups are distributed around the correct damage score ranges.

Cumulative percentage graphs are presented in the lower charts of Fig. 3. Before training, no real difference between the plots can be seen. After training, there is a clear distinction between the groups and the plots are arranged in the correct order.

If the 102 buildings of this database had been assessed for potential hazard by the FL RVSP before the earthquake strike, then the buildings with high damage scores would have been selected for further investigation. Therefore, by selecting a percentage of the buildings with high damage scores, high priority subsets can be formed. For this analysis, 50%, 20% and 10% of the total buildings were selected for the high priority subsets. For example, for the 50% subset and with reference to the lower right hand chart of Fig. 3, a horizontal line is first drawn from the 50% mark on the cumulative percentage axis to the total plot. Then a vertical line is drawn where this horizontal line meets the total plot. The percentages of the moderate, severe and collapse groups that make up the 50% subset can now be read off the cumulative percentage axis (that is, 100 minus group cumulative percentage) by noting where the vertical line crosses the individual plots. The procedure can then be repeated to extract the 20% and 10% subsets. Table 4 presents the results of the selection procedure before and after the training procedure.

Table 4 First database high priority sets

Damage group	50% of the total		20% of the total		10% of the total	
	Before training	After training	Before training	After training	Before training	After training
Moderate	53%	9%	20%	0%	4%	0%
Severe	44%	39%	7%	0%	4%	0%
Collapse	53%	93%	32%	57%	21%	30%

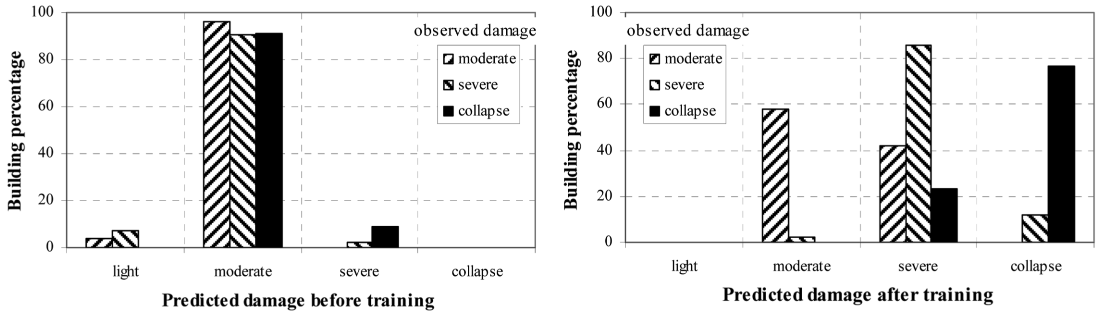

Fig. 4 First database predicted and observed damage

By comparing the before and after training percentages of Table 4, the improvement in the method's efficiency after training is clearly demonstrated as either a very high percentage of the buildings that actually collapsed were identified or the high priority subsets consist exclusively of collapsed buildings.

Fig. 4 presents the association between the FL RVSP's predicted damage before and after training and the observed damage (BSSC 2000) as reported by experts on site. Clearly, there is little precision before training, as the majority of the collapsed or severely damaged buildings were associated with the possibility of moderate damage. In addition, no building that collapsed was associated with the possibility of collapse. On the other hand, the training procedure clearly improved the precision, as the majority of the collapsed and severely damaged buildings were correctly associated. The only disadvantage was that the correctly associated moderately damaged buildings before training were incorrectly distributed between the severe and moderate damage ranges after training.

The above discussion has clearly demonstrated that, for the first database, training through the FL RVSP potentially offers significant efficiency and precision improvements when predicting the damage that may be caused by a large earthquake.

7.2 Checking and second training

Charts relating to the efficiency of the method for the second database are given in Fig. 5 and the upper charts of this figure present the percentage distribution of the buildings for each damage type.

From the upper left hand chart of Fig. 5, the initial assessment of building sample was mainly concentrated within the ranges of 0 to 10 and 30 to 60. As this figure bears little resemblance to the upper right hand chart of Fig. 3 above, it can be concluded that there are major differences between the first and second databases. That is, although both databases were compiled from data collected

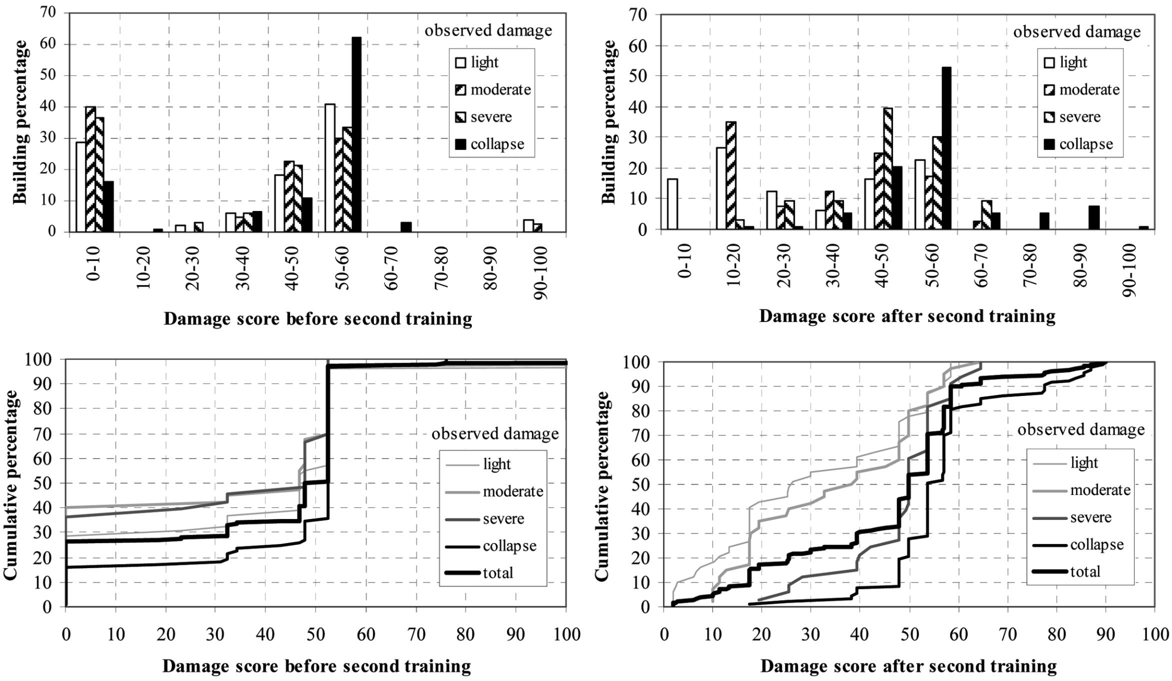

Fig. 5 Second database FL RVSP results

in the same region after the same seismic event, the two sets of raw data are not comparable. For this reason, the first database trained fuzzy inference system did not capture the characteristics of the second database. After the second training procedure, from the upper right hand chart of Fig. 5, the building sample was correctly distributed over the range of 0 to 100 and the groups appear to be distributed in the correct order.

Cumulative percentage graphs are presented in the lower charts of Fig. 5. Before second training, no real difference can be seen between the plots and the plots are not in the correct order. When comparing the lower left hand charts of Figs. 5 and 3, it can be seen that training from the first database improved the initial assessment results. After second training, there is a distinction between the groups and the plots are generally arranged in the correct order.

As performed for the first database above, three possible high priority subsets can be extracted that consist of 50%, 20% and 10% of the total amount of buildings from the second database. The results of the selection process, before and after the training procedure, are presented in Table 5.

Table 5 Second database high priority sets

Damage group	50% of the total		20% of the total		10% of the total	
	Before second training	After second training	Before second training	After second training	Before second training	After second training
Light	45%	22%	20%	8%	10%	0%
Moderate	33%	25%	20%	5%	10%	2%
Severe	33%	49%	20%	16%	10%	7%
Collapse	66%	75%	20%	33%	10%	19%

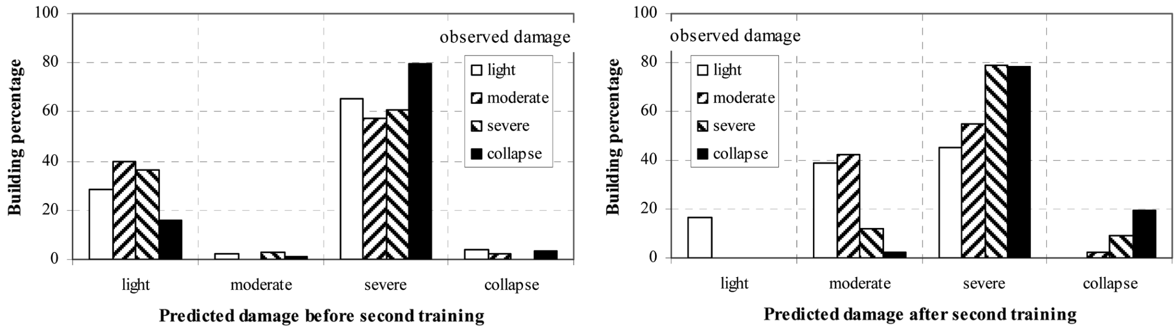

Fig. 6 Second database predicted and observed damage

From Table 5, there is a clear improvement in the percentages for all groups when comparing the results before and after the second training procedures.

The association between the FL RVSP's predicted damage before and after the second training process and the observed damage (BSSC 2000) as observed by experts on site is given in Fig. 6. Before second training, only 3% of the buildings that collapsed were associated with the possibility of collapse and 65% of the light damage group was associated with the possibility of severe damage. In general, most buildings were placed in the light or severe damage groups, regardless of the damage.

After the second training, 19% of buildings that collapsed produced outputs that denoted the possibility of collapse. Unfortunately, the buildings with light damage were distributed to the light, moderate and severe damage groups and the largest percentage of the moderately damaged or collapsed buildings were associated with the severe damage range.

It can be concluded from the above discussion that the first trained FL RVSP based on the first database produced poor results for the second database. After second training, the results show a marked improvement but the improvement was not as dramatic as was observed when solely looking at the first database.

8. OASP RVSP and FL RVSP comparisons

The relative efficiency and precision of the FL RVSP can be further investigated by drawing comparisons with the FEMA based OASP RVSP. To draw comparisons, it has been assumed that OASP structural scores less than unity correspond to probable collapse.

8.1 First database

Fig. 7 presents the relationship between the expected and on site observed collapses for the OASP RVSP and the FL RVSP. Fig. 7 shows that, for the FEMA based OASP RVSP, many buildings with moderate or severe damage had structural scores that indicated probable collapse. For the FL RVSP, the probable collapse group is almost exclusively made up of buildings that collapsed. Therefore, the OASP RVSP has low accuracy when predicting the degree of damage and only gives an indication of the possibility of collapse.

The distribution of the buildings in each damage group in relation to the structural score is

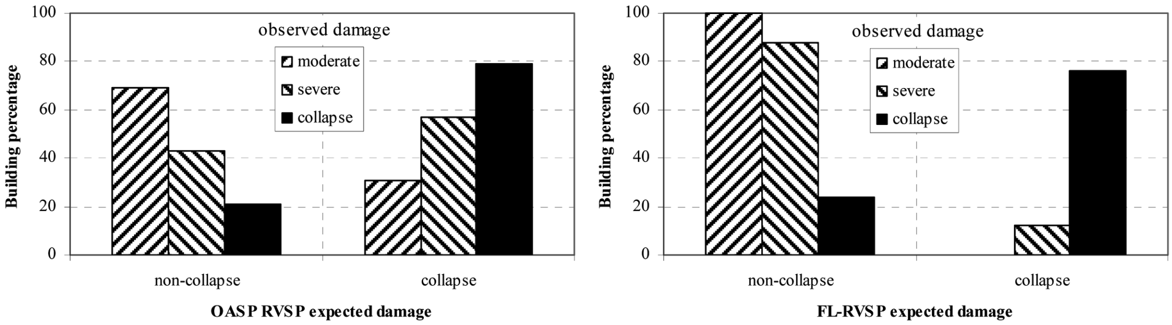

Fig. 7 First database expected and observed damage

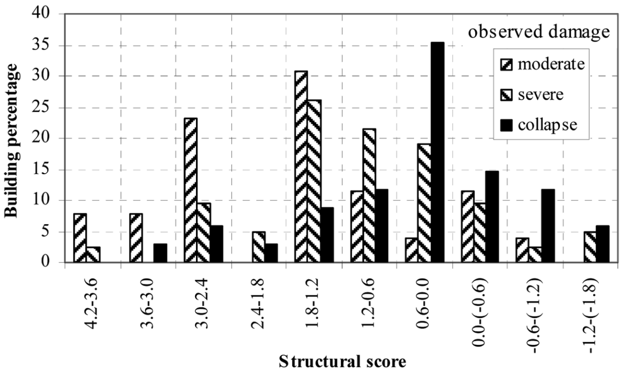

Fig. 8 First database OASP RVSP distribution chart

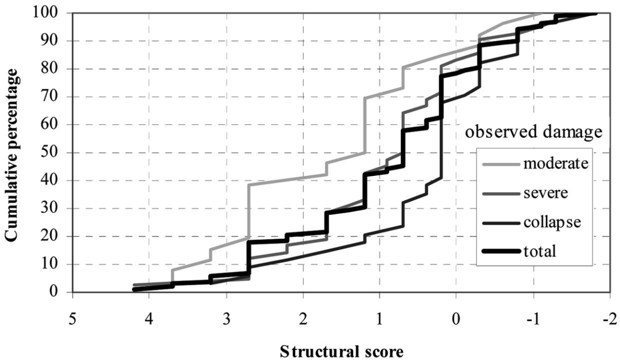

Fig. 9 First database OASP RVSP cumulative percentage chart

presented in Fig. 8. The structural score scale of Fig. 8 has been reversed (high numbers first) in order to draw comparisons with the top right chart of Fig. 3 above.

Reliable conclusions concerning the efficiency of the OASP RVSP method cannot be drawn as Fig. 8 shows that the OASP RVSP distributed all damage groups virtually over the full range of the structural score scale. On the other hand, the top right chart of Fig. 3 above shows that the FL RVSP distributed each damage group into distinct intervals over the damage score scale.

Fig. 9 presents the cumulative percentage chart for the FEMA based OASP RVSP. The structural score scale of Fig. 9 has been reversed so that this figure can be compared to the lower charts of

Table 6 Comparison of first database 50%, 20% and 10% high priority subsets

Method	50% (51 buildings)				20% (20 buildings)				10% (10 buildings)			
	M	S	C	E	M	S	C	E	M	S	C	E
FL RVSP before training	14 53%	19 43%	18 53%	35%	5 20%	3 7%	12 32%	60%	1 4%	2 4%	7 21%	70%
FL RVSP after first training	2 9%	17 39%	32 93%	63%	0 0%	0 0%	20 57%	100%	0 0%	0 0%	10 30%	100%
FEMA based OASP RVSP	6 23%	19 45%	26 73%	51%	3 12%	7 15%	10 28%	50%	1 3%	3 7%	6 15%	60%

Fig. 3 above. A further measure of each method's efficiency can be obtained by comparing 50%, 20% and 10% high priority subsets from Figs. 9 and 3. Table 6 presents the composition of the extracted high priority subsets in terms of the number of buildings of each group in the high priority subset and their respective group percentage.

From Table 6, it can be seen that the FL RVSP after training is far more efficient at identifying buildings at risk, especially when the size of the subset is reduced. For example, the OASP RVSP 20% high priority subset includes 12% of the moderately damaged buildings and only 28% of the collapsed buildings were identified. In contrast, for the FL RVSP after training, when the high priority subset consisted of 20% or 10% of the buildings, the sets are exclusively made up of buildings that had collapsed.

A quantitative measure of the efficiency would be the percentage of buildings in each high priority subset that did actually collapse. Higher percentages would indicate better efficiency. The efficiency percentages (E) for each method are also presented in Table 6.

The efficiency percentages from Table 6 demonstrate the relative advantage of the trained FL RVSP over the FEMA based OASP RVSP. In all cases, the efficiency percentages from the trained FL RVSP are higher than the percentages from the FEMA based OASP RVSP. In particular, when 20% or 10% of the buildings are selected, the FL RVSP has 100% efficiency. The respective efficiency percentages for the OASP RVSP are only 50% and 60%. In addition, even before training, the FL RVSP represents an improvement when compared to the OASP RVSP when looking at the 20% and 10% subsets.

8.2 Second database

Fig. 10 presents the relationship between the expected and observed collapses for the OASP RVSP and the FL RVSP. Fig. 10 shows that, when compared to the FEMA based OASP RVSP, the FL RVSP identified fewer buildings that collapsed but the collapse group contains fewer buildings that suffered light, moderate or severe damage. When compared to the results from the first database (Fig. 7 above), a reduction in the effectiveness of the FL RVSP method can be seen.

Fig. 11 presents the distribution of the buildings in each damage group in relation to the structural score. The structural score scale of Fig. 11 has been reversed (high numbers first) in order to draw comparisons with the top right chart of Fig. 5 above.

Fig. 11 shows that the OASP RVSP distributed all damage groups over most of the range of the structural score scale. Therefore, reliable conclusions concerning the efficiency of the OASP RVSP

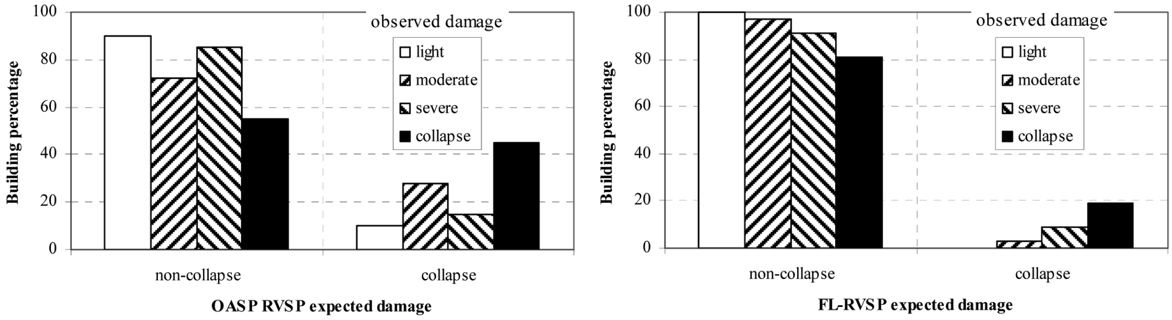

Fig. 10 Second database expected damage and observed damage

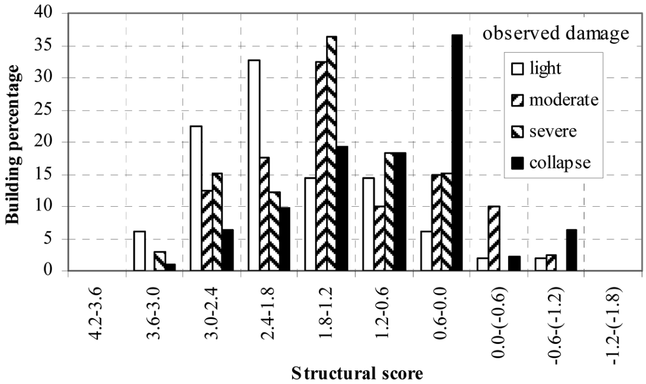

Fig. 11 Second database OASP RVSP distribution chart

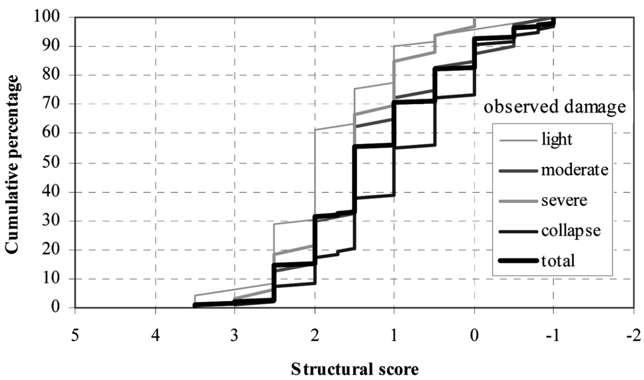

Fig. 12 Second database OASP RVSP cumulative percentage chart

method cannot be drawn. On the other hand, the top charts of Fig. 5 above shows that the FL RVSP was better at distributing the damage groups into distinct intervals over the damage score scale.

Fig. 12 presents the cumulative percentage charts for the FEMA based OASP RVSP. The structural score scale of Fig. 12 has been reversed so that this figure can be compared to the lower charts of Fig. 5 above. As for the first database, high priority subsets can be extracted to further investigate the efficiency of each method in identifying high-risk buildings. Table 7 presents the composition of the extracted 50%, 20% and 10% high priority subsets.

Table 7 Comparison of second database 50%, 20% and 10% high priority subsets

Method	50% (108 buildings)					20% (43 buildings)					10% (22 buildings)				
	L	M	S	C	E	L	M	S	C	E	L	M	S	C	E
FL RVSP before second training	22 45%	13 33%	11 33%	62 67%	57%	10 20%	8 20%	6 20%	19 20%	44%	5 10%	4 10%	3 10%	10 10%	45%
FL RVSP after second training	11 22%	10 25%	16 49%	71 75%	66%	4 8%	2 5%	5 16%	32 33%	74%	0 0%	1 2%	3 7%	18 19%	82%
OASP RVSP	14 29%	18 45%	14 42%	62 67%	57%	3 6%	8 20%	3 9%	29 32%	67%	2 4%	5 13%	0 0%	13 13%	58%

As for the first database above, the percentage of buildings in each high priority subset that did actually collapse would give an alternative measure of the efficiency. Table 7 also presents the efficiency percentages for each method.

The efficiency percentages from Table 7 demonstrate that, before second training, the FL RVSP was not as good as the OASP RVSP at identifying buildings at risk. After second training, there is a marked improvement in the FL RVSP when compared to the FEMA based OASP RVSP. In particular, when 10% of the buildings are selected, the FL RVSP has 82% efficiency while the respective efficiency percentage for the OASP RVSP is only 59%. Again, the FL RVSP after training is more efficient at identifying buildings at risk, especially when the size of the subset is reduced.

Overall, as stated before, the small number data led to an underdetermined system and the use of small data sets led to a biased training of the system, which did not allow for the actual response of all building cases. Considering these problems, the indication is that the FL RVSP represents the possibility of distinct improvement in identifying buildings at risk when compared to the OASP RVSP. That is, the FL RVSP has the potential for improvement while conventional RVSPs have little room for improvement. Therefore, it would be worthwhile to collect information during a RVSP that would be specifically tailored to the requirements of the FL RVSP.

The results of this study emphasise the optimisation potential of the FL RVSP. Larger specific databases are required for training purposes and these databases should include all cases of buildings, damaged or not.

9. Proposed strategy

It has been demonstrated that the FL RVSP offers an improvement over conventional RVSPs. In addition, through adaptive neural networks, the FL RVSP has the potential for continual enhancement only if specific large databases of information are collected. Therefore, it would be of interest to propose a strategy outlining the future direction of the FL RVSP. The proposed strategy is as follows:

1. The specific structural characteristic and parameters to be inspected should be defined and adopted. It is envisaged that these structural characteristics would be more or less the same as those for the OASP RVSP,
2. Specific information collection forms must be produced so that trained experts can record the

structural characteristics required for the FL RVSP. The data collection forms must be easy to fill in and it would not be necessary for the trained experts to have a background in fuzzy logic or artificial neural networks,
3. The basic software for use by the FL RVSP should be adopted,
4. In order to aid consistency when collecting information, a training programme should be developed to teach screeners and a reference guide should be produced,
5. Regions affected by strong earthquakes should be visited in order to collect information from undamaged buildings and new databases should be complied from existing information concerning the repair of buildings damaged by earthquakes and from information concerning buildings that collapsed during earthquakes,
6. Structural characteristic building information should be collected from building samples from the most earthquake prone areas and, after the occurrence of a sizable earthquake in one of these areas, trained experts should collect information reporting the damage level of sample buildings,
7. The information collected from steps 5 and 6 should be used to train the FL RVSP and
8. Steps 6 and 7 should be repeated after every new earthquake.

The FL RVSP method should be permanently trained. Training could be considered complete when the results before and after training do not differ by more than 5%.

To end on an optimistic note, steps 1 to 3 have already been completed at the University of Patras. As part of a project to assess the seismic vulnerability of the buildings of Western Greece, the above strategy is underway and is being funded by the governing body of the Region of Western Greece.

10. Conclusions

When considering possible earthquake damage, it is well known that conventional RVSPs provide great benefit when identifying buildings for further investigation. RVSPs are well-accepted methods that generally give good results. RVSPs are tried, tested and have been developed through expert examination over many years. The problem is that there is little room for further improvement. Any improvement directly converts into saved lives, injury and financial loss.

The FL RVSP, as alternative to conventional RVSPs, has been described and investigated in this paper with the object of looking into ways of improving the accuracy of RVSPs when identifying buildings at risk. As for conventional RVSPs, the collection of data for the FL RVSP is easy. Although the FL RVSP uses complex software, it is as easy to use and provides a rapid result.

Two databases of earthquake-damaged buildings have been used for this investigation. The first database was used to first train the FL RVSP and the second database was used to check and then extend the training process. Results before and after the fuzzy logic based artificial neural network training process have been examined, compared to each other and compared to the FEMA based OASP RVSP. The databases investigated did not cover all classes of damage, buildings with no damage were not considered and the databases examined did not represent data specifically collected for FL RVSP use. In addition, the system was underdetermined and the FL RVSP is still being developed. Regardless of these limitations, the training process was applied to give an idea of how gathered information relating to a structure’s earthquake performance could be used to improve this fuzzy approach to RVSP. Quite remarkable improvements in efficiency and precision were produced when the FL RVSP was applied to the first database while less remarkable improvements were produced when the FL RVSP was applied to the second database.

When compared to the existing FEMA based OASP RVSP, this study has demonstrated that the trained FL RVSP represents a distinct improvement in identifying buildings at risk. In some cases, the FL RVSP was better at predicting the damage a set of buildings would suffer during a large earthquake even before the training process. In particular, when the size of a high priority subset is reduced, the FL RVSP after training becomes more efficient at identifying buildings at risk. It can be concluded that the FL RVSP could replace conventional RVSPs when identifying buildings at risk.

The results of this study emphasise the optimisation potential of the FL RVSP and it has been demonstrated that it is worthwhile pursuing the FL RVSP as an alternative to conventional RVSPs. As the training process is of fundamental importance to the process, large databases of specific information tailored to the requirements of the FL RVSP must be collected. To this end, a strategy has been proposed and a project is underway in Western Greece to collect specific data to permanently train the FL RVSP.

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