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ORIGINAL PAPER

Seismic human loss estimation for an earthquake disaster using neural network

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Abstract In Iran, earthquakes cause enormous damage to the people and economy. If there is a proper estimation of human losses in an earthquake disaster, it could be appropriately responded and its impacts and losses will be decreased. Neural networks can be trained to solve problems involving imprecise and highly complex nonlinear data. Based on the different earthquake scenarios and diverse kind of constructions, it is difficult to estimate the number of injured people. With respect to neural network's capabilities, this paper describes a back propagation neural network method for modeling and estimating the severity and distribution of human loss as a function of building damage in the earthquake disaster. Bam earthquake data in 2003 were used to train this neural network. The final results demonstrate that this neural network model can reveal much more accurate estimation of fatalities and injuries for different earthquakes in Iran and it can provide the necessary information required to develop realistic mitigation policies, especially in rescue operation.

Keywords Back propagation · Building damage · Injuries · Rescue operation

Introduction

Earthquake is one of the most destructive natural hazards for any active geological region. Earthquakes may occur at any time without any warning and can destroy buildings and infrastructures which leads to human loss and injury. In Iran, earthquake causes enormous damage to the people and economy. The high level of losses related to recent earthquake in Iran is mainly due to bad construction and urban texture. To mitigate the risk, it is essential to have a comprehensive knowledge of consequences of devastating events to be able to plan for the full cycle of disaster management. Disaster management is a time critical and collaborative activity that requires rapid assessment and decision making (Vafaeinezhad et al. 2010). If there is a good estimation of the number of injured people, we will be able to properly respond this problem and decrease its impacts and losses. Because of different earthquakes of type, magnitude and depth and diverse kinds of buildings around the world, in practice, it is very complicated to define a clear relation to estimate number of casualties caused by earthquake. Moreover, the lack of suitable data adds to the complexity of estimation and prediction of injuries (Wyss 2005).

Some researchers developed different methodologies for estimation of casualties in the earthquake disaster (HAZUS-FEMA 2003; Coburn and Spence 2003; Murakami 1992). The Coburn and Spence model uses the same four-level injury severity scale (light injuries, hospitalized injuries, life threatening injuries and deaths) and underlying concepts associated with building collapse. However, it is not in event tree format and does not account for non-collapse (damage) related casualties, nor does it account for the population not indoors at the time of earthquake. In Coburn and Spence method, the major earthquake data around the world are used for the coefficients of presented method and the number of casualties is calculated from collapsed buildings. The number of these collapsed buildings definition is also based on the MMI

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parameter which is a descriptive method to define earthquake intensity. The casualty estimation model of Coburn and Spence is based on the distribution of buildings in the complete damage state. It should also be noted that especially for cases of moderate levels of damage (i.e. those where fewer than 5,000 buildings were damaged), the casualty estimations by this method could be highly inaccurate.

The Murkami model is an event tree model that includes only fatalities caused by collapsed buildings and does not account for lesser injuries. HAZUS-Federal Emergency Management Agency (FEMA) model provides a methodology for estimating casualties caused only by building and bridge damage. This model estimates casualties directly caused by structural or non-structural damage. Although non-structural casualties are not directly derived from non-structural damage but instead are derived from structural damage output. The method excludes casualties caused by heart attacks, car accidents, falls, power failure which causes failure of a respirator, incidents during post-earthquake search and rescue or post-earthquake clean-up and construction activities, electrocution, tsunami, landslides, liquefaction, fault rupture, dam failures, fires or hazardous materials releases. On the other hand, the presented method of FEMA is specialized for USA and uses this country's building classes. This method uses four severity levels to categorize injuries, ranging from light injuries (severity level 1) to death (severity level 4). The model provides casualty rates for different structural types and damage states.

However, there is no specialized model of human causalities considering building damages, materials used for buildings, type of earthquakes and other factors for Iran. The only study of human causalities' estimation in Iran is Japan International Cooperation Agency's investigation on Seismic Microzoning of Tehran (JICA 2000). This study is based on Coburn and Spence method. However, in this study, the coefficients are somehow adopted for Iran situations. Because the used coefficients of this method are obtained from the world's earthquakes, this survey could not be convenient for Iran.

Artificial neural network (ANN) is an advanced tool stimulated by the physical and computational characteristics of the human brain. Like biological neurons, they consist of interconnected information processing neural elements, neurons, working in union to make decisions, classifications, predictions, and forecasts. Neural networks are capable to learn linear and nonlinear functions that make them influential tools to analyze complex relations. ANNs have received considerable interest in the recent years due to their wide range of applications and ability to handle problems involving imprecise and highly complex nonlinear data (Bandyopadhyay and Chattopadhyay 2007).

Neural networks have been successfully applied to assess structural damage probability due to an earthquake and such studies have been implemented by Chen and Chan (2003) and Hung and Kao (2002). Others, such as Teimori et al. (2008) and Ahadzadeh et al. (2008) used neural networks to analyze the amount of buildings' damages caused by an earthquake in Iran. Moreover, in the landslide susceptibility analysis, some researchers, such as Vahidnia et al. (2009) and Lin and Lin (2008) used neural network to classify and map earthquake induced landslide hazard. In addition, neural network methodology has been successfully applied to liquefaction potential; for example, soil liquefaction using different earthquake data assessed by Goh (2002) and Hanna et al. (2007).

Because of different earthquakes of type, magnitude and depth and diverse kinds of buildings around the world, in practice, it is very complicated to define a clear relation to estimate number of casualties caused by an earthquake. Therefore, neural network by having abilities to solve and analyze complicated relations could be a prominent method to estimate number of casualties.

Another key factor of human loss estimation is the ability to determine spatial spread of casualties which could be used to plan on search and rescue, take injured people to hospital and other disaster management activities in preparedness and response phases which could result in less human loss.

Regarding to what mentioned so far, this paper looks for a neural network based methodology for modeling and estimating the severity and distribution of human loss as a function of building damage in the earthquake disaster in Iran. Because there is lack of adequate suitable gathered data about building structure type, their damage levels and casualties and only useful data is about Bam earthquake, this study had to be confined to Bam earthquake.

Owing to the lack of data, although it was not possible to apply the presented method to other earthquakes to compare results, to show the advantages of the presented method, the number of casualties for Bam earthquake also obtained from Coburn–Spence method and finally, the results of presented method in this paper and Coburn method as compared to the reality. This research has been done in Iran, during the period February–August 2011.

Materials and methods

A neural network is composed of a large number of interconnected non linear computing elements or neurons organized in a number of layers. The first and the last layers are known as input and output layers, respectively. The layers in between are known as hidden layers.

The flow of information is passed through the network by linear connections and linear or non linear transformations. The back propagation algorithm, the most typical multi-layer feed forward, is one of the most widely used algorithms (Wang et al. 2010). A back propagation neural network (BPNN) is useful for handling real-time, non-stationary and non-linear natural phenomena (Kuok et al. 2009).

In this study, this method is being used to predict the severity and distribution of human loss in the earthquake disaster, and Gradient Descent with momentum and adaptive learning rate back propagation (GDX) algorithm is being used to train this neural network with observed data.

Feed forward neural network

Feed forward neural networks have been applied successfully in many different problems, because the advent of the error back propagation learning algorithm. This network architecture and the corresponding learning algorithm can be viewed as a generalization of the popular least-mean-square (LMS) algorithm (Haykin 1999). A multilayer perceptron network consists of an input layer, one or more hidden layers of computation neurons, and an output layer. The input signal propagates through the network in a forward direction, layer by layer. Their main advantage is that they are easy to handle, and can approximate any input/output map, as established by Hornik et al. (1989). The key disadvantages are that they are trained slowly, and require lots of training data (typically three times more training samples than network weights). Back propagation learning requires input scaling or normalization and the result may generally converge to any local minimum on the error surface, since stochastic gradient descent exists on a surface which is not flat.

GDX training algorithm

The weighting factors of the connections between the neurons are determined by training the neural network with observed data. One of the techniques for calibrating the network is to use Gradient descent with momentum and adaptive learning rate back propagation (GDX) method.

This method uses back propagation to calculate derivatives of performance cost function with respect to the weight and bias variables of the network. Each variable is adjusted according to the gradient descent with momentum. For each step of the optimization, if performance decreases the learning rate is increased. This is probably the simplest and most common way to train a network (Haykin 1999).

Design of a neural network

The design of a neural network model requires three steps: selection of the variables, selection of number of layers and neurons, and selection of transfer function.

Selection of the variables

The high level of human loss related to recent earthquakes is mainly due to bad construction; therefore, to estimate the portion of the population affected by the earthquake it is necessary to have a comprehensive knowledge about the different types of structures and the structural vulnerability levels. Therefore, in this study, the number of resident people at buildings during earthquake occurrence, the type of structure (“Steel Frame”, “Reinforced Concrete Frame” or “Brick and Steel”) and structural damaged level (“UN Damaged”, “Damaged” or “Destroyed”) are taken as input variables and the portion of the people affected by earthquake in three levels “Uninjured”, “Injured”, and “Death” is considered as output variables. Because two input variables, the type of structure and the structural damaged level, are both descriptive variables, which could not be directly used as inputs in back propagation neural network, it is necessary to quantify these variables. To make the network be able to interpolate precisely, this quantification must be applied based on the correct criteria that could correctly obtain the priority for these descriptive variables. So based on the criterion of structure resistance against earthquake, the type of structure (“Steel Frame”, “Reinforced Concrete Frame” and “Brick and Steel”) was coded from 1 to 3 respectively, and the structural damaged level (“UN Damaged”, “Damaged” and “Destroyed”) was also coded Similarly from 1 to 3.

Although increasing input values and classes (for example, the type of structures and level of injuries) increase the performance of neural network processing, the lack of suitable data imposed us to confine our input values and classes. Table 1 shows input and output layers used in our human loss model.

Selection of the number of hidden layers and neurons

It has been proven that every neural network model with only one hidden layer is sufficient for most of the applications (Haykin 1999) and a three-layer back propagation neural network can uniformly approximate any nonlinear function (Hornik et al. 1989). Therefore, a three-layer back propagation network is used in this study. The number of neurons in the hidden layer and the stopping criteria were optimized in terms of obtaining precise and accurate outputs. To determine the number of hidden layer’s neurons, the process was started with three neurons and after obtaining the results, the process were repeated for more neurons. Because the precision of achieved results did not reveal significant improvement, to decrease the complexity of processing and the required time to solve the problem, number of necessary neurons in the hidden layer was determined to be three.

Table 1 Input and output layers in human loss model

Input layers	Output layers
Resident people at buildings during earthquake occurrence	Portion of uninjured people
Type of structure	Portion of injured people
Structural damaged level	Portion of fatalities

The number of neurons in the input and output layers were also determined by the number of input and output variables, respectively.

Selection of transfer function

The transfer function is set to a hyperbolic tangent sigmoid function as this was proved by trial and error to be the best in depicting the non-linearity of the modeled natural system, among a set of other options (linear and log sigmoid).

Criteria of evaluation

Two parameters namely correlation coefficient and root mean square error (RMSE) values were used for the performance evaluation of the models and comparison of the results for prediction of human loss.

The root mean square error (RMSE) is used in order to evaluate the effectiveness of network and its ability to make precise predictions. RMSE is calculated by RMSE $= \sqrt{\frac{\sum_{i=1}^{N}(y_i - \widehat{y_i})}{N}}$ where y_i is the observed data, $\widehat{y}_i$ is the calculated data and N is the number of observations. RMSE indicates the discrepancy between the observed and calculated values.

The explanatory power of the regression is summarized by its "R-squared" value, computed from the sums of squares terms as $R^2 = 1 - \frac{\mathrm{SSE}}{\mathrm{SST}}$ R-squared, also called the coefficient of determination, is often described as the proportion of variance "accounted for", "explained", or "described" by regression. The relative sizes of the sums-of-squares terms indicate how "good" the regression is in terms of fitting the calibration data. If the regression is "perfect", all residuals are zero, SSE is zero, and R^2 is 1. If the regression is a total failure, the sum-of-squares of residuals (SSE) equals the total sum-of-squares (SST), no variance is accounted for by regression, and R^2 is zero.

Study area and data description

A large earthquake with a magnitude of Mw = 6.6 struck the city of Bam, located approximately 1,000 km southeast of Tehran, at 05:26:56 local time (01:56:56 GMT) on Friday 26th December 2003. The earthquake destroyed most of Bam city and the nearby villages. The earthquake was strongly felt in the provincial capital of Kerman, about 190 km (120 miles) Northwest of Bam; however the main damage from the earthquake was limited to a relatively small area near to Bam city, within a 20–30 km radius (Ghafory-Ashtiany and Hosseini 2006). The neural network was trained with data taken from Bam earthquake in 2003. In order to estimate the people affected by the earthquake, three levels of casualty were defined according to the Bam post-disaster field data gathered by the census center of Iran. These three levels are: "Uninjured", "Injured", and "Dead". For the city of Bam only, 55,167 were reported uninjured, 8,136 were reported injured and 22,391 people announced dead. Other information includes number of fatalities and injured people according to the location of different blocks and their resident population. Figure 1 (left) shows the distribution of injuries based on the location of blocks in Bam city and the right one displays the distribution of fatalities.

This survey data consist three major building categories namely "Steel Frame", "Reinforced Concrete Frame" and "Brick and Steel". The data also describes roughly three levels of structural loss as "UN Damaged", "Damaged" and "Destroyed". The undamaged level means that no or ignorable damage was introduced. The damaged means that the structure is repairable and destroyed means that the building must be completely replaced. The survey data are presented in 1,450 zones (building blocks) in three levels of structural damage categories, as shown in Fig. 2. The set of 590 zones were selected randomly after pre filtering (discarding) the inadequate blocks, and a large number of sample data (building block) were selected to test the results.

Results and discussion

Using the data described above, a back propagation neural network model was developed by programming in Matlab 7. Figure 3 shows this neural network with one hidden layer, consisting of three neurons, three input layers, and three output layers.

To evaluate the effectiveness and validate this network, a large number of sample data was selected to test results. RMSE was calculated between the observed data and computed values. The normalized RMSE for "# of Uninjured", "# of Injured", and "# of Dead" were calculated as 0.071, 0.042 and 0.021, respectively. These values indicate that this network can estimate the severity and distribution of human loss precisely. The coefficient of determination R^2 for training, validation, test and all data regressions were calculated as 0.9933, 0.9928, 0.9929 and 0.993, respectively.

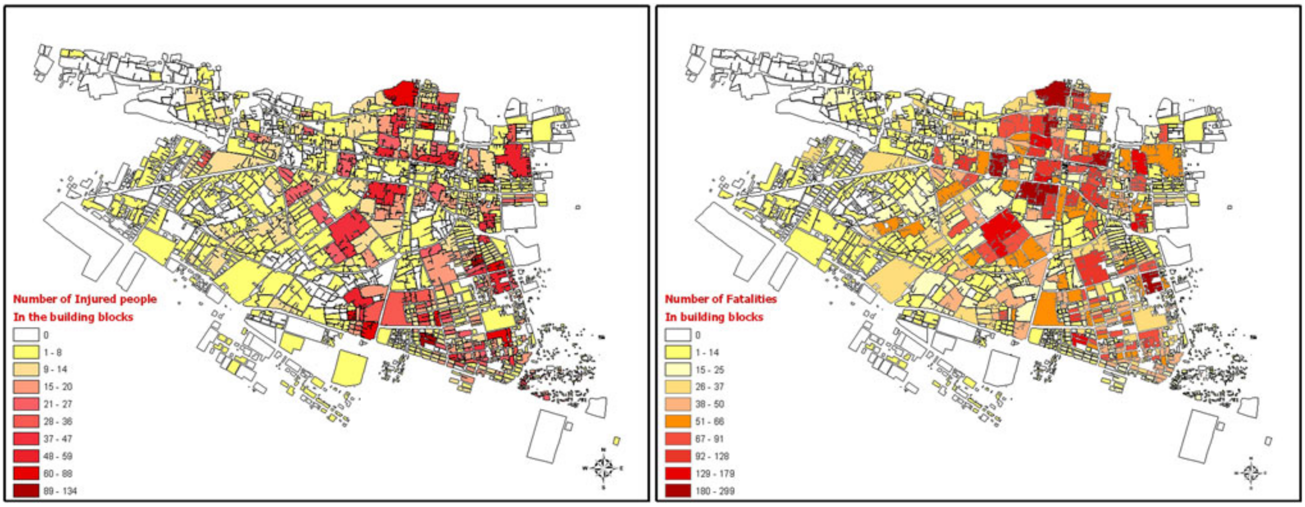

Fig. 1 Number of Injured people and fatalities in Bam earthquake

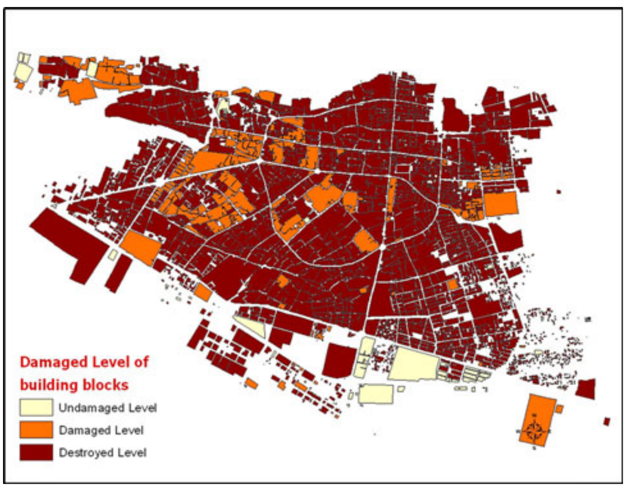

Fig. 2 The distribution of structural damage in Bam earthquake

Since the amount of determination coefficients are not far from 1, it shows the high quality of this estimating approach.

The graphs of these training, validation, test and all together of designed network have been separately depicted in Fig. 4 with regression functions superimposed to them. These graphs enable anyone to compare the target results in four situations including training, validate, testing and all data with the outputs of the model. The horizontal axis shows the amount of target output and the vertical axis is the amount of the model output. More points located along the diagonal axis of these graphs (Y = T) indicate higher accuracy of designed model. For more evaluation of the accuracy, a regression function has also been fitted to data points for each graph. The regression equation is also shown on the left side of each graph. The calculated correlation coefficient of R is also shown on top of each graph.

One of the most important capabilities of this developed model is demonstrating the spatial distribution of human

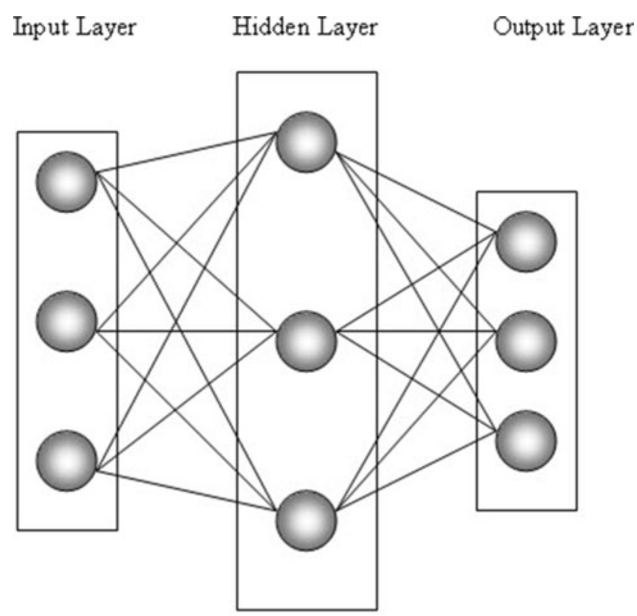

Fig. 3 Scheme of developed neural network

loss; therefore obtained results were implemented in GIS environment. The output results obtained by implementing this model for calculated injuries and fatalities of training data (Bam earthquake data) are shown in Fig. 5.

Regarding calculated RMSE values, our developed method works accurately for the whole data. The output of this model is the number of human injuries and fatalities for each building block. Comparison between our results (Fig. 5) and observed field data (Fig. 1) shows suitable accuracy of model for the number of injuries and fatalities for each building block. Moreover, the calculated number of fatalities and injured people for 15 building blocks extracted from designed model and from real data sets of Bam are also presented in Fig. 6.

To compare the developed neural network and other estimating approaches, multiple linear regression (MLR) approach was also applied for predicting the number of injured people for Bam earthquake and due to the lack of data, although it was not possible to apply our presented method to other earthquakes to compare results, to show the advantages of our presented method, the number of casualties for Bam earthquake also obtained from Coburn–Spence method.

Predicting the number of injured people for bam earthquake using MLR approach

A multiple linear regression model which implies the predicted value of the number of injured people for Bam earthquake is proposed as

$$\widehat{y} = aX_1 + bX_2 + cX_3 + dX_4 + eX_5 + fX_6 + gX_7 + hX_8 + kX_9 + L$$

where: X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9 are predictors (i.e. the resident people at un damaged, damaged and destroyed brick and steel building, the resident people at un damaged, damaged and destroyed reinforced concrete frame building, the resident people at un damaged, damaged and destroyed steel frame building, respectively). The constants a, b, c, d, e, f, g, h and k are the regression parameters computed by the method of least squares.

In the present study, the regression equation was determined to be

$$\widehat{y} = 0.17X_1 + 0.28X_2 + 0.15X_3 + 0.08X_4 + 0.35X_5 + 0.22X_6 + 0.02X_7 + 0.32X_8 + 0.21X_9 + 4.$$

The coefficient of determination calculated from this linear multiple regressions is 0.4516, which is very far from 1. Thus, this linear fitness method is not a suitable predictive model in comparison with the developed neural network approach. Because an ANN can capture many kinds of relationships, it allows the user to quickly and easily model phenomena. Therefore, ANNs provide an analytical alternative to conventional techniques which are often limited by strict assumptions of normality, linearity, variable independence etc.

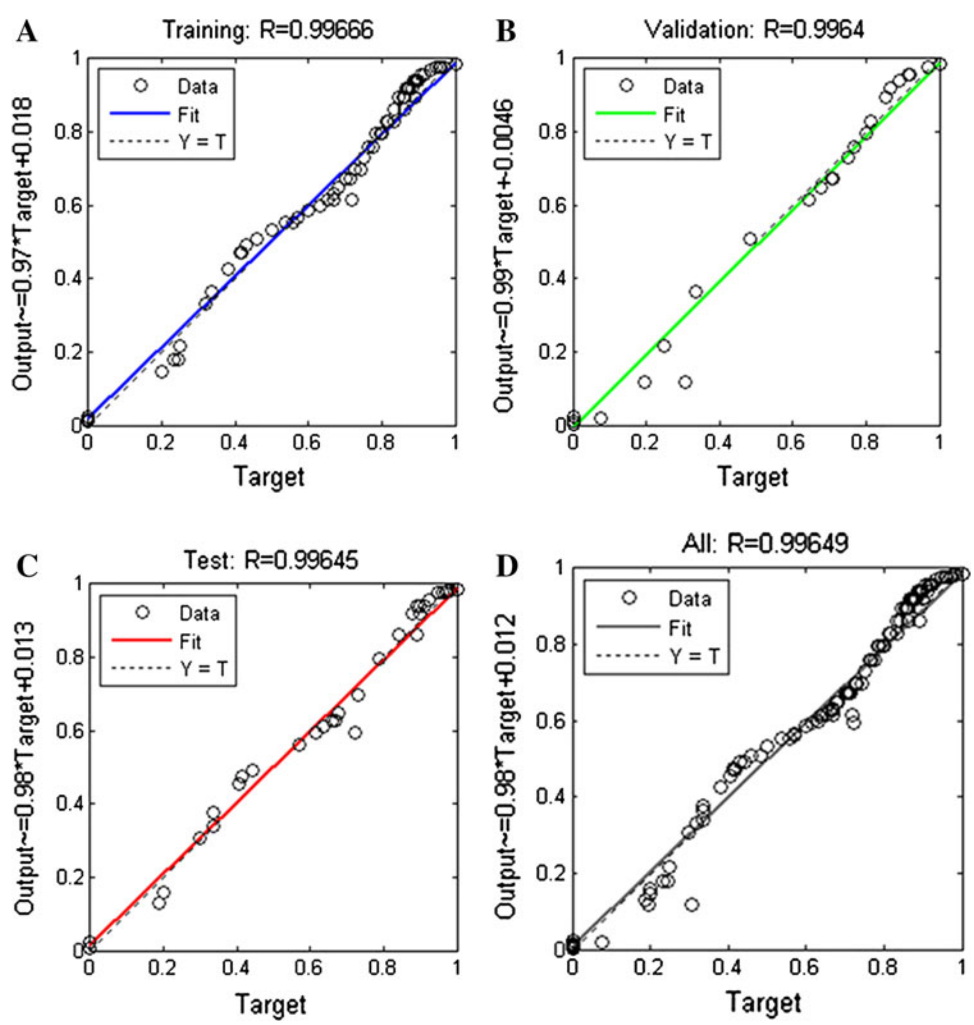

Fig. 4 Regression graphs for the training data, the validation data, the test data and the whole data

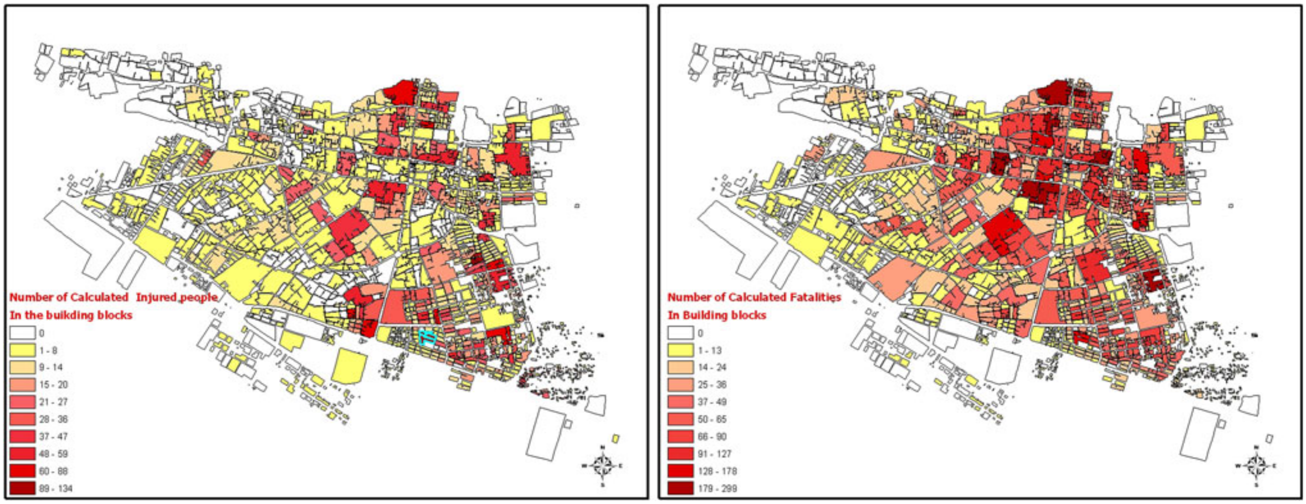

Fig. 5 Number of calculated injured and fatalities people in Bam earthquake

OBJECTID	bld_type	Damage_level	SURVIVOR	INJURED	FATALITY	SURVIVOR_Calculated	INJURED_calculated	FATALITY_calculated
1	Steel Frame	Undamaged	36	0	0	36	0	0
8	Reinforced Concrete Frame	Destryed	130	12	29	127	12	32
9	Brick and Steel	Damaged	13	0	9	14	1	7
20	Reinforced Concrete Frame	Undamaged	21	3	0	21	3	0
100	Steel Frame	Damaged	357	6	28	355	8	28
127	Brick and Steel	Destroyed	31	38	25	34	36	24
158	Brick and Steel	Damaged	12	3	6	11	4	6
168	Steel Frame	Damaged	7	4	1	6	5	1
169	Steel and Brick	damaged	3	2	0	3	2	0
190	Brick and Steel	Damaged	34	3	11	35	3	10
230	Steel Frame	Damaged	25	7	2	25	8	1
246	Brick and Steel	Destroyed	11	1	13	12	1	12
267	Brick and Steel	Destroyed	9	10	8	10	10	7
280	Brick and Steel	Destroyed	13	10	27	14	10	26
360	Reinforced Concrete Frame	Destroyed	175	78	44	177	77	43

Fig. 6 The real and calculated number of fatalities and injured people for 15 building blocks

Casualty estimation of bam earthquake using Coburn–Spence method

The study used the basic concept introduced by Coburn–Spence for the estimation of casualties. Since the concept was derived from considering worldwide earthquake damages, which includes the case of Iran as well, the concept is applicable. However, parameters used in the estimation are not necessarily suitable for the building characteristics of Iran. Consequently, the coefficients of Coburn and Spence method was adjusted to satisfy the relationship between the seismic intensity (MMI) and the death ratio in past earthquake damages in Iran based on the Japan International Cooperation Agency (JICA) study on Seismic Microzoning of Tehran (JICA 2000).

Figure 7 shows the flowchart of the human casualties estimation concept derived from Coburn and Spence method. This method explains the relationship between the death ratio and the types of rescue operations as follows:

- With regard to the people in buildings at the time of the occurrence of an earthquake, the ratio of the people who will not be able to escape from the collapsed buildings is estimated.
- Percentage of the people who will be trapped in collapsed buildings are assumed to die instantly because of the shock of falling floors and roofs, or due to suffocation by smashed bits of adobe.
- As for the people who will not die instantly, it will be almost impossible to escape by their own efforts. They will be buried under fallen furniture and/or beams, or they will be trapped in underground rooms once ground floors collapse. Some of these people will eventually die.
- The success of the emergency rescue operations will mainly depend on the time after the occurrence of the earthquake. The rescue ratio becomes almost zero at 72 h after the damage. That is, if people are not rescued within 72 h of the occurrence of the earthquake, most of them will die. Therefore, rescue operations are the

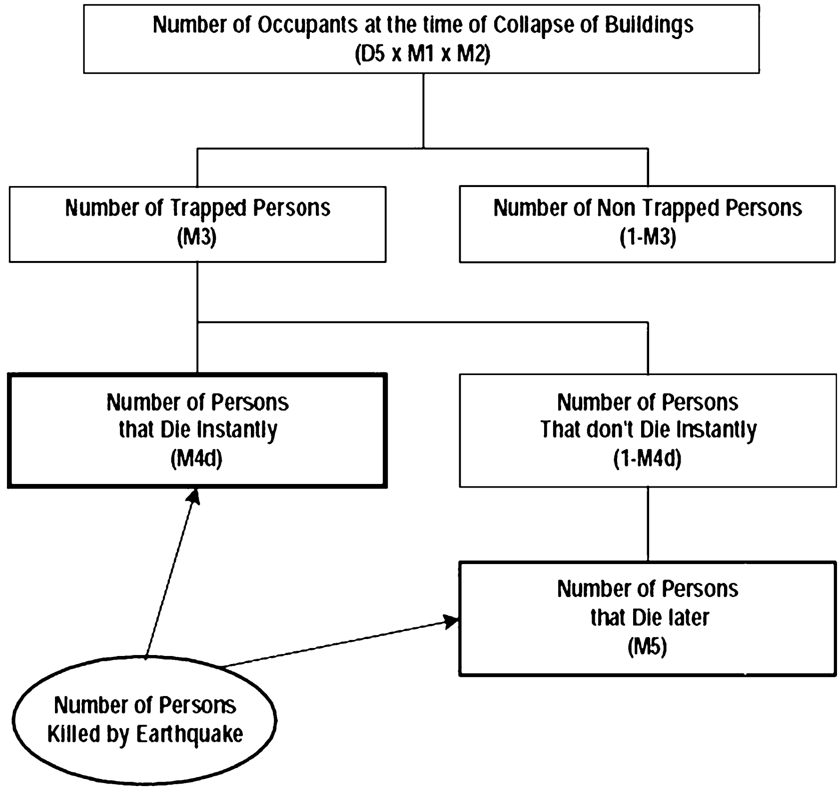

Fig. 7 Flowchart of Coburn and Spence Casually estimation method

basic factor in determining the death ratio for people who do not die immediately after the collapse of buildings.

The idea mentioned above is formulated as follows:

$$\text{Evaluation formula } Ks = D5 \times M1 \times M2 \times M3 \times (M4d + (1 - M4d) \times M5)$$

where

Ks: Human casualties
D5: Number of collapsed buildings
M1: Number of people in each building
M2: Occupancy at the time of the earthquake
M3: Number of occupants trapped by collapsed buildings
M4d: Death ratio at 0 h after the collapse of buildings
M5: Post-collapse mortality (ratio of the injuries that subsequently die before they are rescued)

Results of implementing adopted Coburn and Spence casualty estimation method

The Coburn and Spence Casualty estimation method was implemented by 2003 Bam earthquake data gathered by the census center of Iran. The parameters for the evaluation formula were determined as follows:

D5: The number of damaged residential buildings for each census zone was used as D5 coefficient. Observed data indicate that 70 percent of buildings were collapsed.
M1: The number of residents in each building was obtained from the census data. Total number of residents in the collapsed buildings was 59,594.
M2: Because the Bam earthquake occurred during night time (when the residents are in their homes.), this coefficient assumed to be 1.0

To obtain number of occupants trapped by collapsed buildings (M3), death ratio at 0 h after the collapse of buildings (M4) and post-collapse mortality (ratio of the injuries that subsequently die before they can be rescued) (M5), previous happened earthquakes in Iran and structural damages caused by these earthquakes were used. To see the amount of these coefficients with respect to the type of building, seismic intensity (MMI) and the method of their calculation, refer to the report of Japan International Cooperation Agency study on Seismic Microzoning of Tehran (JICA 2000).

Implementing this method for all of Bam city building blocks resulted in 29,491 fatalities. Meanwhile, the observed field data for Bam earthquake fatalities were 22,391 people. This means that the results of Coburn and Spence method had 32 percent of difference with reality, whereas, the results of neural network with just 2.1

percent of difference with reality shows the high performance of our developed neural network model. As it was explained in the introduction, in Coburn and Spence method, the major earthquake data around the world are used for the coefficients of presented method and the number of casualties is calculated from only collapsed buildings.

Therefore, this method could be used to estimate the number of injuries and fatalities for large occurring earthquakes all over the world with low precision. Instead, the developed neural network in this paper could be used to estimate the number of injuries and fatalities for occurring earthquakes in Iran with suitable precision because the nature of earthquakes and the type of structures in Iran are so similar.

Back propagation neural networks are in a sense the ultimate ‘black boxes’. The final product of this activity is a trained network that provides no equations or coefficients defining a relationship (as in regression) beyond its own internal mathematics. Therefore, by having more suitable data of previous earthquakes, the neural network could be trained better and the precision and validity of network will be higher.

Conclusion

Earthquakes impose lots of damages to the people of Iran. If there is a proper estimation of the number of injured people in an earthquake, its impacts and losses could be decreased. Because of different earthquakes of type, magnitude and depth and diverse kinds of buildings around the world, in practice, it is very complicated to define a clear relation to estimate number of casualties caused by an earthquake. Therefore, neural network by having abilities to solve and analyze complicated relations could be a prominent method to estimate number of casualties. In this paper, a neural network was developed to model and estimate the severity and distribution of human loss as a function of building damage in the earthquake disaster in Iran. The normalized RMSE calculated between the observed data and computed values of our work for injured and fatalities revealed high precision. Applying Coburn–Spence method on Bam earthquake data and comparison of its results with our developed method also proved high performance of our neural network based model. Another key factor of our human loss estimation method is its ability to determine spatial distribution of casualties which could be used to plan on search and rescue, take injured people to hospital and other disaster management activities in preparedness and response phases which could result in less human loss in Iran.

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