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An artificial neural network-based earthquake casualty estimation model for Istanbul city

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Abstract Earthquakes over the world cause serious damages for people and the economy. The establishment of an appropriate model to estimate potential losses or injuries in earthquake disasters is fundamental to decrease their impacts and losses and effectively respond and mitigate. Turkey as a country that experienced many earthquakes in the last century and had serious human and financial losses needs a comprehensive knowledge of consequences of devastating earthquakes to be able to plan for the future. Artificial neural networks (ANNs) have abilities to solve and analyse complex relations as an appropriate method to estimate number of injuries. In this study, an ANN model is built up for the earthquake casualty prediction, which takes earthquake occurrence time, earthquake magnitude, and population density as the predictors and employs 21 Mw > 5 earthquake disasters occurred in Turkey from 1975 as samples for the training of the network. The model was then tested on a study region consisting of four districts in Istanbul which is estimated to have the highest injury rate according to the earlier reports and generated estimations of the expected number of injured people. Results show that 99.9 % of the variability in the number of injured people is predictable with using this ANN model. Comparison of actual values and estimated output values in the ANN model was also found apparently very close to each other. According to the test case study results, when the value of earthquake magnitude is 6.5 Mw, number of injured people has increased in a sharp trend compared to the previous magnitude value (6 Mw) for all districts. Estimated number of injured people in daytime is obtained higher than at night when the earthquake magnitude is 5 and 5.5 Mw. The highest value in estimated number of injured people has emerged in Fatih district as 7241 for a 7.5 Mw daytime earthquake. On conclusion, it was deduced that the model can reveal accurate estimation of casualties and it can provide information in order to develop mitigation policies, especially in earthquake emergency service management.

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1 Introduction

Earthquakes over the world cause serious damages in terms of human and financial aspect. The establishment of an appropriate model to estimate potential losses or injuries in earthquake disasters is fundamental to decrease their impacts and losses and effectively respond and mitigate. Turkey has experienced many earthquakes in the last century and had serious human and financial losses (Onat et al. 2015, 2016). According to the official figures of the Marmara (17th August 1999) and Düzce (23rd November 1999) earthquakes, 18.287 people lost their lives, 46.857 people are injured, 164.711 workplaces or houses moderately damaged and 1.100.000 people became homeless (Gul and Guneri 2015a). In 23rd October 2011, an earthquake with a magnitude of 7.2 on the Richter scale struck the province of Van in eastern Turkey and 604 people lost their lives (Gul and Guneri 2015b). Between the years 1900 and 1999, 149 destructive earthquakes occurred. In these earthquakes, 97.203 people were killed and over 578.000 houses were collapsed or heavy damaged. According to these figures, a heavy-damaged earthquake occurs in every 7 months on average (Özmen 2000). When investigated the last 40 years, these earthquakes cause 531 deaths and 1474 injured on average (Fig. 1).

The city of Istanbul is situated near segments of North Anatolia Fault (NAF). In the past, the most destructive earthquakes have occurred as a result of breakage of the segments of NAF. According to the data of the Turkey Earthquake Foundation (TEF), while 58 % of Istanbul lands are under first- and second-degree earthquake risk, the remaining are under third- and fourth-degree earthquake risk (Ozmen 2002). It is expected an unavoidable large-scale earthquake event for Istanbul in the near future.

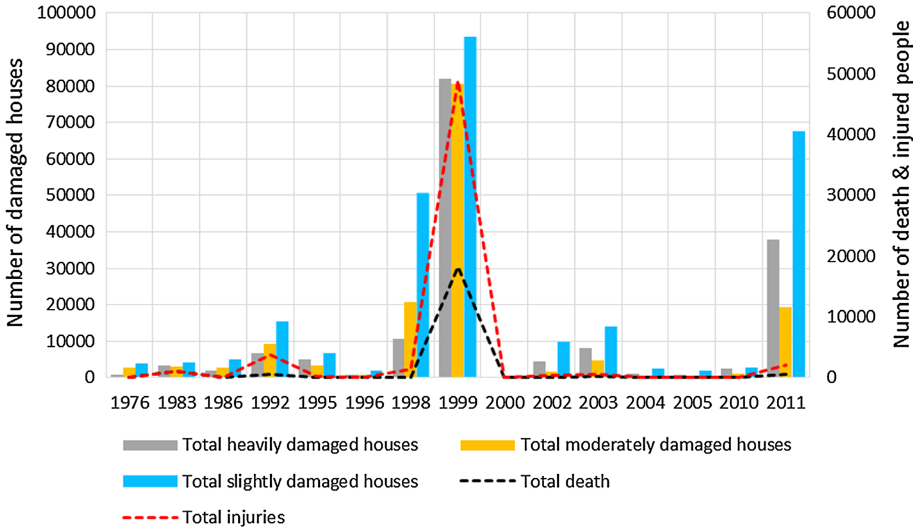

Fig. 1 Earthquakes and caused damages between 1976 and 2011 in Turkey. Total number of injured people is represented by a *dotted red line* and total number of death people by a *dotted black line*

In order to prevent human and financial losses against such an event, a comprehensive knowledge of consequences of devastating earthquakes to be able to plan for the future is required. One of the most important ways of planning the future is related with an efficient and accurate estimation of possible losses.

To this end, we aim to propose a casualty estimation model using the data of 21 Mw > 5 earthquake disasters occurred in Turkey from 1975. Earthquake occurrence time, earthquake magnitude, and population density were taken as the predictors of the model. The model was used to generate estimations of the expected number of injured people for a risky area of Istanbul city as a test case study.

The rest of the study is prepared in the following manner. Section 2 presents a review of general literature on the topic. Section 3 describes the study region. Section 4 deals with methodology including a brief overview of artificial neural networks, earthquake casualty predictors and the proposed model. Section 5 shows the results and discussion of the application case study. At last section, the conclusion and limitation of the study are provided.

2 Literature review

In the literature, researches focus on earthquake casualty estimation using apparent prediction methods and predicting factors. Aghamohammadi et al. (2013) proposed a back-propagation (BP) neural network method for modelling and estimating the severity (survivor, injured, fatality) and distribution of human loss as a function of building damage in the earthquake disaster. The data of Bam earthquake in 2003 were used to train the model. The results of the study showed that their model reveals more accurate estimation of fatalities and injuries for different earthquakes in Iran. Samardjieva and Badal (2002) estimated the expected number of killed or injured people caused by a supposed strong earthquake in Spain based on worldwide data. Badal et al. (2005) used a quantitative model that includes a correlation between earthquake magnitude and number of losses (death or injured) in order to assess the earthquake losses and damages as a function of population density. Wen-bin and Jiang (2013) developed an earthquake casualty forecasting model combining BP neural network with principal component analysis. The earthquake casualties' data of China from 1990 to 2010 were used in the model. Time of earthquake, earthquake magnitude, epicentre intensity, population density, resistance level and forecasting level were determined as predict variables. The principal components were determined using the method of principal component analysis, and then, applying the model of BP neural network analysis the earthquake casualties were forecasted. The proposed model was compared with Gauss coherence function-based forecasting model in an earthquake in China. The results showed that the forecasting accuracy was improved by 7.5 %. Xing et al. (2015) proposed a robust wavelet (RW) v-support vector machine (SVM) earthquake casualty prediction model. In the model, the data of 19 earthquakes in recent 45 years in China were used. The first 15 groups of data were used as training data; the 16th to 18th groups were used for testing; and the 19th group was used as prediction data. It was concluded that RW v-SVM prediction model gave great advantage against standard SVM and BP neural network. xia Wang et al. (2011) built up a BP neural network model for the prediction to life casualties in an earthquake, which takes earthquake magnitude, depth of hypocentre, intensity of epicentre, level of preparedness, earthquake acceleration, population density, disaster forecasting as the key factors and employs 37 severe earthquake disasters occurred in China as samples for the training of the network. Results of the study showed that the model fits for most cases of the earthquakes. Shan et al. (2005) proposed a three-layer BP network model for estimating the casualties in earthquakes. Seven evaluating indices as time of occurrence, magnitude, epicentre intensity, collapse of buildings, level of protection, population density, and disaster forecasting were taken into account. They used information of 20 past earthquake disasters as samples, in which 17 samples were used as training model and three samples as verification model.

Some researches focus on estimating casualties based on the attributes of damaged buildings apart from the abovementioned studies. Feng et al. (2013) developed a model on estimating the casualties. The number of casualties was estimated by the product of the joint casualty index (JCI) multiplied by the number of people inside the damaged buildings at the time of the earthquake. JCI was computed by the combination of damage index (DI) of buildings and the building's materials and structure index. DI was computed by a numerical damage model derived from satellite remote sensing images. The model was applied to three towns in Dujiangyan City and was found accurate in the estimation. Turkan and Özel (2014) made a comparative study for modelling destructive earthquake casualties. They used semi-parametric beta regression (SBR), semi-parametric additive regression (SAR), and beta regression (BR) models in analysing the observed casualties after destructive earthquakes. Using the data of destructive earthquakes occurred in Turkey between 1900 and 2012 having surface wave magnitudes five or more, it is concluded that SBR and SAR models can lead to more precise results than the BR and linear regression models. Shapira et al. (2015) integrated epidemiological and engineering approaches in the assessment of human casualties in earthquakes as a miscellaneous study. They provided evidence that integrating demographic and socio-economic characteristics of the population and levels of medical preparedness into the current casualty estimation models may improve the accuracy.

From this brief literature review, it is derived that neural network-based models on earthquake casualty estimation are preferred mostly since they produce more accurate predictions. Therefore, in our study, we follow an ANN-based model for the case of Istanbul. This topic is undoubtedly important but has not received much attention in Turkey in the past, although different authors have tackled this problem. The current study contributes a lot to the literature as follows: (1) Due to the common use of the BP neural network models in the literature (Aghamohammadi et al. 2013; Wen-bin and Jiang 2013; xia Wang et al. 2011; Shan et al. 2005), Levenberg–Marquardt algorithm is preferred in this study. Thus, the best networks are provided with this algorithm. (2) A new earthquake data set consisting of 21 events occurred since 1975 in Turkey that is expected to benefit for the following studies is picked out and put together from the archive of the special reports on each earthquake. (3) For the purpose of contributing to the disaster plan of Istanbul city, it is estimated earthquake casualties using our ANN-based model for four risky regions. In summary, it presents a case study in the largest city of Turkey. The ANN model performed here is the first attempt in order to decrease losses and effectively respond and mitigate.

3 Study region and data source

3.1 Description of study region

The city of Istanbul has been a major population centre with a prominent role in commercial and cultural activities. Although it is a very old city, it has grown very rapidly especially after 1950s. Its population reached 14 million today according to the official records. As an important social, economic and geopolitical centre, Istanbul has been the destination of the people emigrating from rural areas. This increased the need for housing and other infrastructural facilities. All of these factors may trigger more losses and injuries in case of a probable earthquake. According to the earthquake scenario studied by Ozmen (2002), it is estimated 81,828 casualties for Istanbul. In another report prepared by the corporation of Istanbul Metropolitan Municipality (IMM), OYO Corporation and Boğaziçi University Kandilli Observatory in 2009, earthquake-victims who need hospital treatment are estimated between 20,000 and 60,000. Also, 50,000–140,000 people are estimated to be minor injured (Istanbul Earthquake Scenario 2009). In a previous report presented by Japan International Cooperation Agency (JICA) and IMM on the disaster preparedness of Istanbul, the casualties are estimated at 120,000 (JICA report 2002). The report includes some scenario earthquake models and their possible outputs with respect to the number of casualties, deaths, and damages. According to the earthquake scenario model with a magnitude of 7 Mw or more in Istanbul, Fatih district and surrounding area are estimated to have the highest injury rate. Therefore, the region was chosen as the research area for this study. The studied region covers four different districts named Bayrampaşa, Arnavutköy, Sultangazi, and Fatih.

3.2 Data

Many factors are considered that cause human or financial loss and injury in the earthquakes. Xing et al. (2015) extracted the earthquake casualty predictors from the four dimensions of the formation of disaster, namely disaster inducing factors, disaster-formative environment, disaster-affected region and disaster-bearing capacity based on the theory of regional disaster system. Factors such as earthquake magnitude, earthquake occurrence time, status of the buildings, and population density are used as the main factors of affecting earthquake disaster casualties by the researchers (Shan et al. 2005; Wen-bin and Jiang 2013). According to the researchers, earthquake occurrence time is a significant factor affecting the casualties. Earthquake casualties occurred during the night are more than occurred in daytime (Wen-bin and Jiang 2013; Erdik et al. 2011). The earthquake data between 1900 and 2013 about fatalities show that losses during the night are more than in daytime in Turkey (Fig. 2).

One of the main factors affecting earthquake casualties is magnitude. It is defined according to international applied Richter Scaling Standard in nine magnitudes, with a score assigned to each magnitude (Xing et al. 2015). The number of injured people depending on the magnitude of the earthquake follows a trend as in Fig. 3 using the data of the last 40 years of Turkey (1976–2011). The correlation coefficient for this relation is 0.813.

Population density is another crucial factor. It is obtained by reviewing geographic information databases and regional population databases (http://tuikapp.tuik.gov.tr/nufusmenuapp). Population intensity per square kilometre is calculated by dividing total disaster area of total population in disaster area (km^2). The more densely populated an area, the more likely there are to be deaths and casualties (Ara 2013). For example, the Marmara earthquake in 1999 occurred in a densely populated area and resulted in 18,000 deaths.

In the literature, the difficulties in estimating the earthquake casualties are highlighted. They are considered as the uniqueness of earthquake, small samples to obtain data, as well as the predictors' nonlinearity. Log-linear regression, artificial neural networks, and support vector machine are the main references in estimating earthquake casualties among common use methods. Principle component analysis and correlation analysis are integrated with abovementioned methods in general.

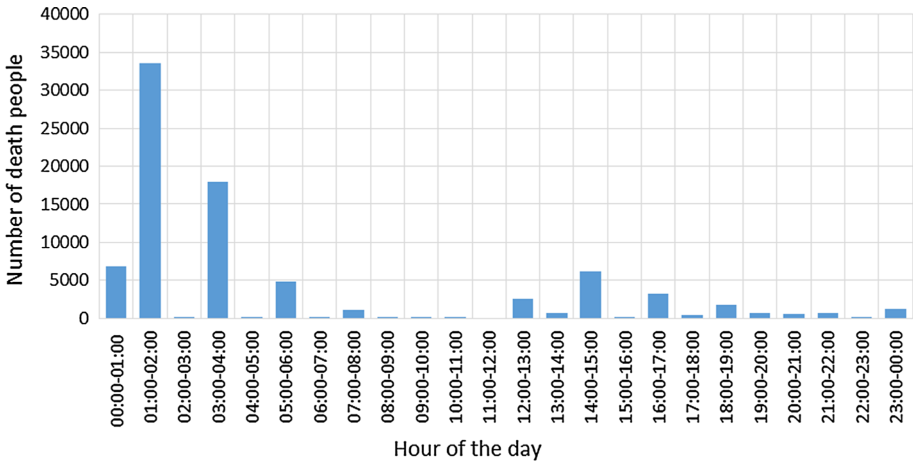

Fig. 2 Distribution of losses depending on the hour of the day. The data are based on and adapted from the official figures of the earthquakes involving death in Turkey within the periods 1900–2013

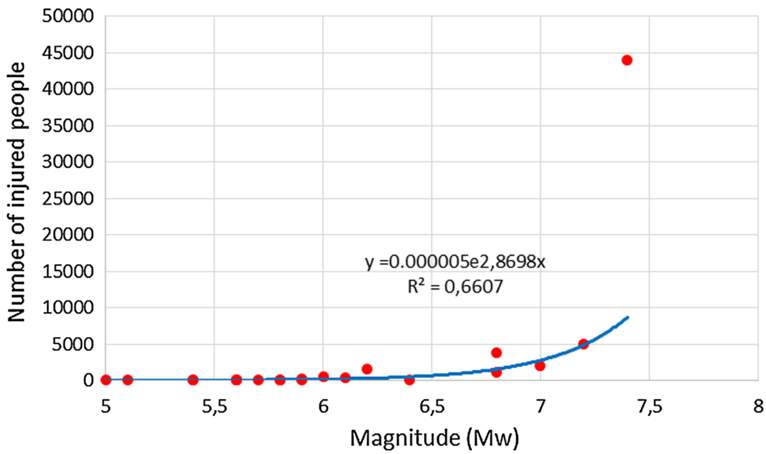

Fig. 3 Exponential trend for the number of injured people caused by the earthquakes in the 5.0–7.5 magnitude interval. The data are based on and adapted from the official figures of the recent 40 years (1976–2011) > 5 Mw earthquakes occurred in Turkey

In this study, a neural network model for the prediction of casualties in an earthquake, which employs 21 Mw > 5 earthquake disasters occurred in Turkey from 1975 as samples for the network is presented. We used a small sample data ($n = 21$) due to unavailability of complete data from past earthquakes. Sample size, methods and predictors used in the previous studies are shown in Table 1.

The data were based on and adapted from the official figures of the recent forty years (1976–2011) > 5 Mw earthquakes occurred in Turkey (as shown in Table 2). Earthquake occurrence time is denoted by the symbols 1 or 2. The earthquake time occurred at daytime is denoted by “1”, at night by “2”.

From the news archive of the special reports on each earthquake, numerical values of the related casualty factors are picked out and put together in order to build the estimation

Table 1 Related studies from the literature

Study	Sample size (n)	Method	Predictors
Aghamohammadi et al. (2013)	N/A	ANN	Building type, damage level
Samardjieva and Badal (2002)	$n = 478$	Regression	Earthquake magnitude, population density
Wen-bin and Jiang (2013)	$n = 53$	ANN	Earthquake occurrence time, earthquake magnitude, epicentre intensity, population density, resistance level, forecasting level
Xing et al. (2015)	$n = 19$	SVM	Earthquake magnitude, epicentre intensity, population density, resistance level, pre-warning level, in-building probability, location of occurrence, emergency supply support, building collapse ratio
xia Wang et al. (2011)	$n = 37$	ANN	Earthquake magnitude, depth of hypocentre, intensity of epicentre, level of preparedness, earthquake acceleration, population density, disaster forecasting
Shan et al. (2005)	$n = 20$	ANN	Earthquake occurrence time, earthquake magnitude, epicentre intensity, population density, resistance level, forecasting level

A comparison is made in terms of sample (data set) size, method, and predictors

model. Regarding earthquakes #1 to #14, the values of earthquake magnitude, earthquake occurrence time, and number of injured people were derived from the data recorded by National Strong Motion Network in Turkey (http://kyh.deprem.gov.tr/buyukdepremler). Data regarding earthquakes #15 to #21 were taken from the earthquake preliminary assessment and observation reports respectively as follows: (Doğan et al. 2004; Emre et al. 2005; Karaşin 2005; Denizlioğlu et al. 2005; Sunkar 2010; Zülfikar et al. 2011; Calayır et al. 2012; Sayin et al. 2014; AFAD 2014).

4 Methodology

4.1 Artificial neural networks

ANNs, which are generally called as "neural networks" or "neural nets", attempt to reproduce the computational processes taking place in the central nervous system (CNS) by using a set of highly interconnected processing elements (Somoza and Somoza 1993). An ANN model, which is formed of n layers, presents a different number of computational elements that function like biological neurons and intensive connections between these computational elements among layers. The computational elements used in various ANN models are named as artificial neurons or process elements (Guneri and Gumus 2008, 2009). The first layer which is called as the "input" layer and the last one which is called as the "output" layer are used to get information from inside and outside the network, respectively. The middle layers which are generally called as "hidden" layers are essential to the network in order to be able to convert certain input patterns into appropriate output patterns (Somoza and Somoza 1993). The flow of information is passed through the network by linear connections and linear or nonlinear transformations (Aghamohammadi

Table 2 Earthquake data set used in the study

#	Date (day.month.year)	Place	Earthquake occurrence time	Earthquake magnitude	Population density	Number of injured people
1	19.08.1976	Denizli	2	5	9.8	28
2	30.10.1983	Şenkaya, Erzurum	1	6.8	26.3	1142
3	05.05.1986	Sürgü, Malatya	2	5.8	38.6	24
4	06.06.1986	Sürgü, Malatya	1	5.6	38.6	20
5	13.03.1992	Erzincan	2	6.8	25.3	3850
6	01.10.1995	Dinar, Afyon	1	5.9	72.5	240
7	14.08.1996	Çorum and Amasya	2	5.4	164.7	6
8	27.06.1998	Ceyhan, Adana	1	6.2	125.2	1500
9	17.08.1999	Gölcük, Kocaeli	2	7.4	471	43,953
10	12.11.1999	Düzce	2	7.2	126.1	4948
11	15.12.2000	Bolvadin, Afyon	2	5.6	84.6	82
12	03.02.2002	Sultandağı, Afyon	1	6.1	23.9	325
13	27.01.2003	Pülümür, Tunceli	1	6.4	2.8	6
14	01.05.2003	Bingöl	2	6	31.7	515
15	25.03.2004	Aşkale, Erzurum	2	5.1	23.6	51
16	25.01.2005	Beytüşşebap and Hakkari	2	5.4	33.3	24
17	12.03.2005	Karlıova, Bingöl	1	5.6	20.7	38
18	17.10.2005	Urla and Seferihisar, İzmir	1	5.9	67	37
19	08.03.2010	Kovancılar, Elazığ	2	5.8	7.2	137
20	19.05.2011	Simav, Kütahya	2	5.7	28.2	85
21	23.10.2011	City centre and Edremit, Van	1	7	97.2	1966

The data are based on and adapted from the official figures of the 21 Mw > 5 earthquake disasters occurred in Turkey from 1975

et al. 2013). The Levenberg–Marquardt algorithm is one of the most widely used algorithms and in this study, and we reached the best solution with this algorithm. The design process of an ANN model includes three steps: selection of the predictors (variables), selection of number of layers and neurons, and selection of transfer function.

4.2 The proposed methodology

We used professional neural network-based software Alyuda Neurolntelligence®. The flow chart in Fig. 4 shows the entire model framework for casualty estimation. A study process including the phases as here data collection, data preparation, correlation analysis on the variables and modelling by ANN is followed.

One of the most important steps of data collection is predictor selection. Alam (1999) indicates that selection of predictors primarily depends on the availability of data for the construction of an ANN model. Recording and storing of historical earthquake data for Turkey is especially challenging. Hence, the analysed variables in this study solely depend on earthquake occurrence time, earthquake magnitude, and population density due to unavailability of data. Also, we have limited our data set a total of 21 earthquake events

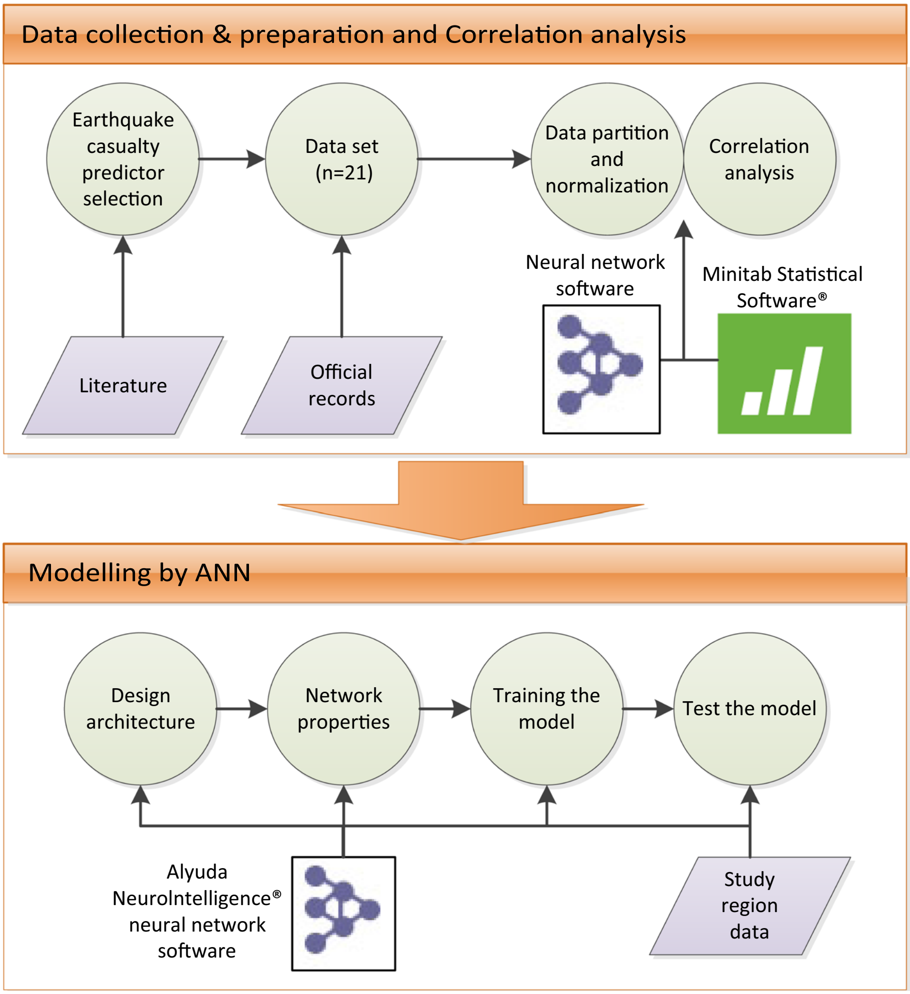

Fig. 4 Model framework for casualty estimation

with a magnitude value of higher than 5 Mw. Although many earthquakes with a MW value of lower than five have occurred since 1975 in Turkey, we have not reached any reliable data. Despite all these shortcomings, this data set put together for our model is still worth considering, because for Turkey it is not available such a gathered and combination of earthquake data up to now.

Levenberg–Marquardt is an advanced nonlinear optimization algorithm. It is the fastest algorithm available for multi-layer perceptrons. This study uses Levenberg–Marquardt since it has some features as follows: (1) it can only be used on networks with a single output unit (number of injured people in this study), (2) it can only be used with small networks because its memory requirements are proportional to the square of the number of weights in the network and (3) best solutions are obtained from this algorithm.

Each analysed variable is adjusted according to this algorithm with momentum rate. Momentum is a control parameter used by several learning algorithms, which effects the changing of weights. The greater the momentum, the more the current weight change is affected by the weight change that took place during the previous iteration. For each step of the optimization process, if performance decreases, the learning rate is increased. It is stated that this is probably the simplest and most common way to train a network (Aghamohammadi et al. 2013).

Hidden layers indicate any layer of an ANN between the input and output layers. Hidden layers provide the network's nonlinear modelling capabilities. In the literature, it is clearly stated that every neural network model with only one hidden layer is sufficient for most of the applications (Aghamohammadi et al. 2013). Therefore, a three-layer network is used in this study. The number of neurons in the hidden layer and the stopping criteria were optimized automatically by the software.

We adjust the activation function as logistic. This function has a sigmoid curve and is calculated using the following formula: $F(x) = 1/(1 + e^{-x})$. Its output range is [0.0.1]. This function is used most often in multi-layer perceptrons. We proved by trial and error to be the best for our ANN model, among a set of other options (linear and hyperbolic tangent). The software *NeuroIntelligence* supports three activation functions (logistic, linear, and hyperbolic tangent) for hidden layers and four activation functions (the same three functions for hidden layers and exponential function) for the output layer.

The parameters, namely coefficient of determination (R^2) and network error values (sum-of-squares) for training and validation sets, were used to evaluate performance of the ANN models for earthquake casualty prediction. R^2 is a statistical ratio that compares model forecasting accuracy with accuracy of the simplest model that just uses mean of all target values as the forecast for all records. The closer this ratio to 1, the better the ANN model is. Small positive values near zero indicate poor model. Negative values indicate models that are worse than the simple mean-based model. The network error function is calculated as the sum of the squared differences between the actual value (target column value) and neural network output.

5 Results and discussion

5.1 Accuracy results of the ANN model

After the data entry to the software, the system randomly selects 68 % of the data as training sets, 16 % of the data as validation sets and 16 % of the data as test sets. The software has an automatic architecture search module which selects [3–2–1] architecture for training. This means that the system selects a single hidden layer as well as two hidden neurons (Fig. 5). We make a correlation analysis using Minitab statistical software® before developing an ANN model. The correlation analysis shows that there is a higher relation between the independent variables *population density* and *earthquake magnitude* and the dependent variable *number of injured people* and a lower relation between *earthquake occurrence time* and *number of injured people* as shown in Table 3.

We used an initial learning rate of 0.1 and a momentum of 0.1. We tried alternative values for both the learning rate and momentums of (0.1), (0.2), (0.4), and (0.6) along with various learning algorithms such as Quick Propagation, Quasi-Newton, Online-Back Propagation and Levenberg–Marquardt. We run all the models within a cycle of 500 iterations. We tried 85 various models in total, and 72 of them were run under Levenberg–Marquardt algorithm. We obtained the best value with the lowest absolute error as shown

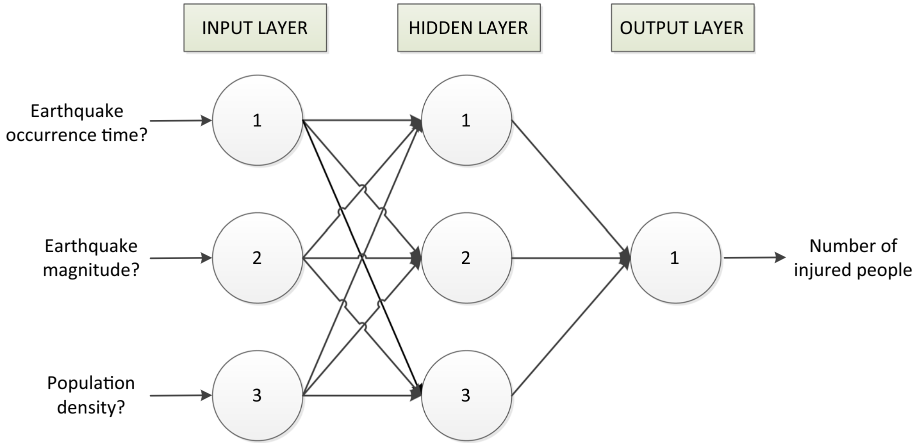

Fig. 5 General structure of developed ANN

Table 3 Results of correlation analysis

	Earthquake occurrence time	Earthquake magnitude	Population density
Earthquake magnitude	−**0.176** (0.446)		
Population density	**0.171** (0.458)	**0.503** (0.02)	
Number of injured people	**0.207** (0.368)	**0.558** (0.009)	**0.912** (0.000)

$p < 0.05$ shows significance statistically

Bolds represent Pearson correlation coefficient, and given in brackets represent *p*-values

in Table 4. The scatter plot related to the target, output values of the ANN model, and a comparison of actual and output values of the model are acquired by means of the software (as shown in Fig. 6). The coefficient of determination R^2 for all data was calculated as 0.999938. The graphs in Fig. 6a enable us to compare the target results for training,

Table 4 Best network and parameters

Summary of the ANN model	
Network architecture	[3–2–1]
Training algorithm	Levenberg–Marquardt
Hidden FX	Logistic
Output FX	Logistic
Number of iterations	110
Average training error	70.98
Average validation error	329.44
Average test error	151.09
R^2	0.999938
Learning rate	0.2
Momentum	0.1

An R^2 value of 0.999938 means that 99.9 % of the variability in the number of injured people is predictable with using this ANN model

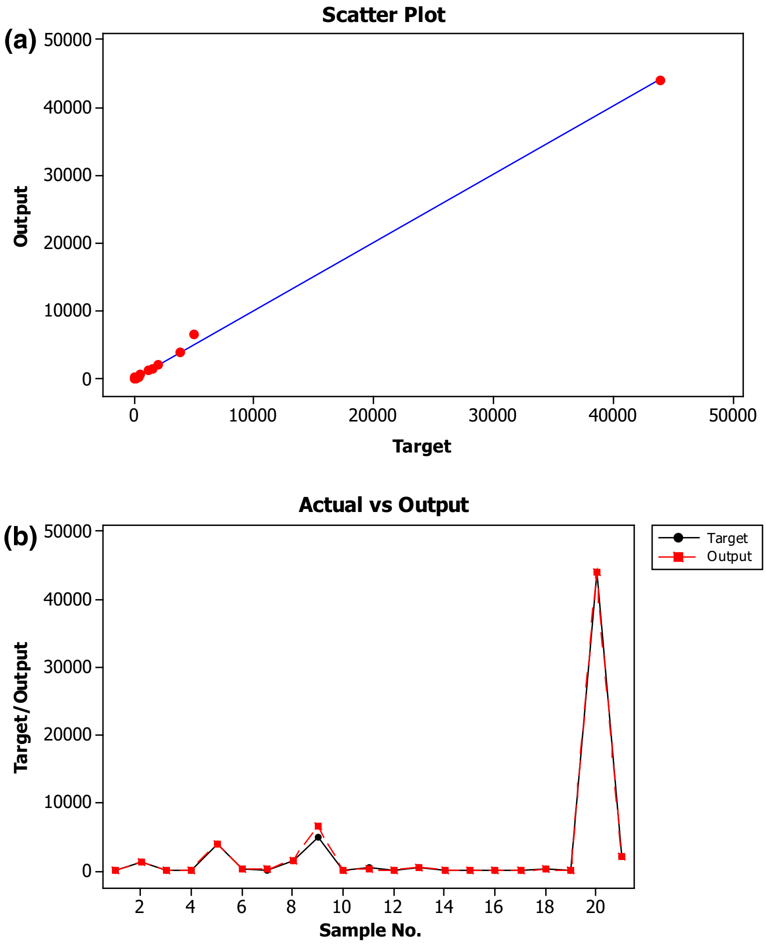

Fig. 6 **a** Scatter plot of the ANN model. **b** Comparison of actual values and estimated output values in the ANN model

validate and testing data with the outputs of the model. The horizontal axis shows the amount of target values, and the vertical axis is the amount of the output values. More points located along the diagonal axis of this graph indicate higher accuracy of designed ANN model. The output of this model is the number of injured people. Comparison between our results (Fig. 6b) and observed field data shows suitable accuracy of model for the number of injured people. Moreover, the calculated number of injured people for 15 samples extracted from designed model and from real data sets is also presented in Table 5.

5.2 Estimation results for the risky regions in Istanbul

Predicting the number of casualties for an earthquake disaster is not easy. The estimates made on a quantitative basis should be similar to the expert opinions of specialists familiar with the earthquake source regions (Wyss 2004). The city of Istanbul with its higher

Table 5 Real and calculated number of injured people for 15 samples

Earthquake ID	Number of injured people	
	Real data	Calculated data
#1	28	22
#2	1142	1142
#3	24	29
#5	3850	3850
#6	240	240
#8	1500	1500
#9	43,953	43,952
#11	82	79
#13	6	7
#14	515	515
#15	51	54
#16	24	29
#17	38	37
#19	137	134
#21	1966	1966

population nearly fifteen million is situated near the segments of North Anatolia Fault (NAF). According to the data of Turkey Earthquake Foundation (TEF), while 58 % of Istanbul lands are under first- and second-degree earthquake risk, the remaining are under third- and fourth-degree earthquake risk (Ozmen 2002). Researchers foresee that a large-scale earthquake event is unavoidable for Istanbul in the near future. The majority of Istanbul population lives in the first- and second-degree earthquake zone (Gul and Guneri 2015b). In relation to all these, an accurate estimation of earthquake casualties for the risky regions of this metropolitan city in order to be ready for a possible major earthquake expected in the following years is required. Therefore, we made estimations using our ANN-based model for four risky districts (Bayrampaşa, Arnavutköy, Sultangazi, and Fatih). The population density values for each region are 28.53, 0.29, 12.05, and 28.59, respectively, as above. We determined six groups for earthquake magnitude as 5, 5.5, 6, 6.5, 7, and 7.5 Mw in the stage of estimations for risky regions of Istanbul. Earthquake occurrence time has been divided into two groups as daytime (1) and night (2) as stated in Sect. 4. Therefore, based on the three main factors affecting earthquake disaster casualties, $4 \times 2\times 6 = 48$ different scenarios are run for four districts. Casualty estimation results in terms of the districts are presented in Fig. 7.

5.3 Discussion

Results show that when the value of earthquake magnitude is 6.5 Mw, number of injured people has increased in a sharp trend compared to the previous magnitude value (6 Mw) for all scenarios. For all regions, estimated number of injured people in daytime is higher than at night when the earthquake magnitude is 5 and 5.5 Mw. The highest estimated number of injured people has experienced in Fatih region with a value of 7241 for a 7.5 Mw daytime earthquake. The number of injured people obtained from the ANN-based model is different from the results of Model A (7.5 Mw) in JICA's (2002) report. It stemmed from that the ANN model in this study uses a more recent earthquake data and

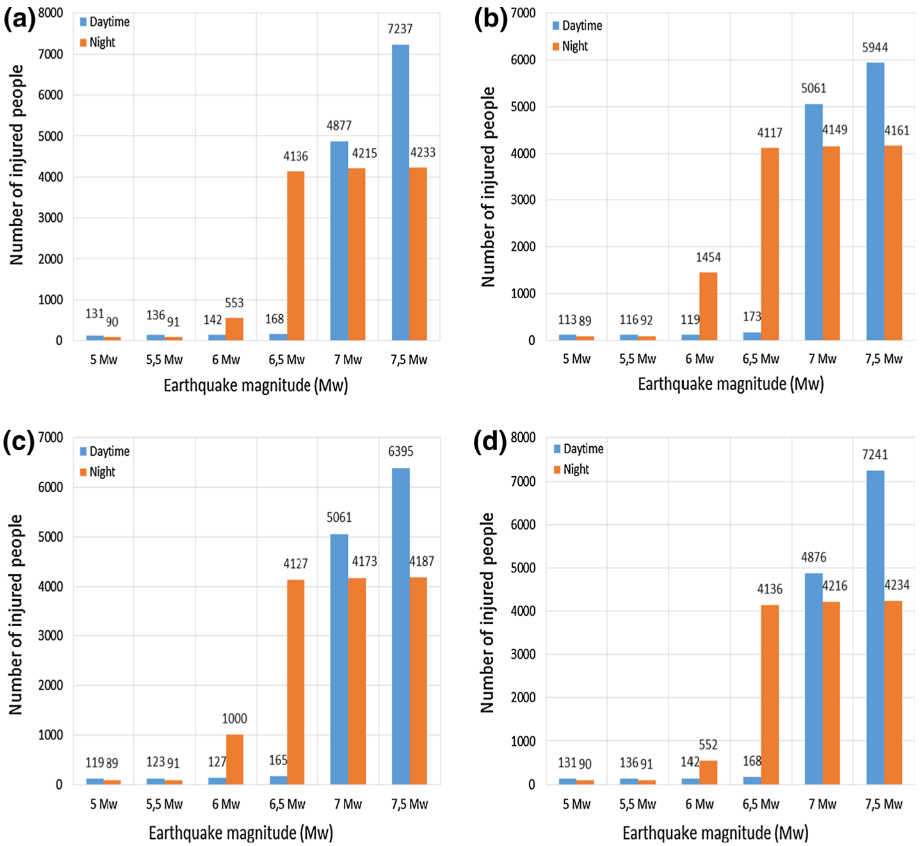

Fig. 7 Casualty estimation results of four risky regions in Istanbul. For each region, 12 earthquake scenarios are available (Daytime and night earthquakes depending on six different earthquake magnitude values); **a** for the estimated number of injured people in Bayrampaşa region; **b** Arnavutköy region; **c** Sultangazi region; and **d** Fatih region. An increasing number of injured people can be seen in all earthquake scenarios for each region after the scenarios with 6.5 Mw

has also a different model structure. In our model, nine different earthquake event data (from 2002 to 2011, see Table 2) are provided for the estimation unlike JICA's report. Thus, this model aims to consider the gap on introducing an up-to-date earthquake casualty estimation.

6 Conclusion

Earthquakes cause lots of damages to the people and economy of Turkey as well as Istanbul. So, a proper model to estimate potential number of injured people in an earthquake disaster in order to decrease their impacts and losses and effectively respond and mitigate is required. Because of different earthquakes of type and magnitude and diverse kinds of buildings, it is very difficult to find a clear relation to estimate number of casualties caused by an earthquake. Artificial neural networks have abilities to solve and analyse complex relations as an appropriate method to estimate number of injuries. In this study, an ANN-based model is proposed for the earthquake casualty estimation, which takes earthquake occurrence time, earthquake magnitude, and population density as the predictors and employs 21 Mw > 5 earthquake disasters occurred in Turkey from 1975 as samples for the network. The model generates estimations of the expected number of injured people for four risky regions of Istanbul which is the largest city of Turkey with approximately fifteen million population. Results show that the model can reveal accurate estimation of casualties, and it can provide information in order to develop mitigation policies, especially in earthquake emergency service management.

Some limitations in this study should be acknowledged. First, ANNs are considered in a sense as black boxes. ANN models present no equations defining a relationship as in regression models. So, by working with more suitable data of previous earthquakes, the neural network may be trained better and the precision and accuracy of network will be changed. The second limitation of the study concerns the casualty predictor (independent variables of the ANN model). Since recording and storing of historical earthquake data for Turkey has been yet carried out based on a regular basis for recent years, the analysed independent variables in this study solely depend on earthquake occurrence time, earthquake magnitude, and population density. Third is the potential limitation of data scarcity on building types and social structures. However, ANNs have ability to solve and analyse complicated relations stemmed from different seismotectonic properties, building types, social structures and various earthquake locations around Turkey, and the paper was not able to employ a regional effect-oriented model.

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