Expert Systems with Applications 42 (2015) 1287–1297

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Fuzzy logic-based attenuation relationships of strong motion earthquake records

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ARTICLE INFO

Article history:
Available online 28 September 2014

Keywords:
Fuzzy logic
Ground motion
Attenuation
Earthquake records

ABSTRACT

Fuzzy logic techniques have been widely used in civil and earthquake engineering applications in the past four decades. However, no thorough research studies were conducted to use them for deriving attenuation relationships for peak ground accelerations (PGA). This paper is an attempt to fill this gap by employing a fuzzy approach with fuzzy sets for earthquake magnitude and distance from source with the objective of proposing new ground motion attenuation models. Recent earthquake records from USA and Taiwan with magnitudes 5 or greater were used; and consisted of horizontal peak ground acceleration recorded on three different site conditions: rock, soil and soft soil. The use of Fuzzy models to quantify ground motion records, which are typically characterized by a high level of uncertainty, leads to a rational analytical tool capable of predicting accurate results. Testing of the fuzzy model with an independent data set confirmed its accuracy in predicting PGA values.

1. Introduction

Earthquakes can inflict severe loss of life and property, especially when they occur in densely populated metropolitan areas (Po-Shen & Chyi-Tyi 2008). Recent earthquakes, such as Northridge (1994), Kocaeli and Düzce (1999), and Chile (2007) have alerted the community that much research studies still need to be conducted to avoid the damage caused by strong motion records. According to Sharma (2000), the estimation of peak ground acceleration in terms of magnitude, source-to-site distance, tectonic environment and source type using attenuation relationships has been a major research topic in seismic hazard estimation studies. However, prediction of ground motion characteristics far from the source for a particular region is of much importance and needs to be accurately simulated.

Earlier studies to derive ground motion models were conducted by Aptikaev and Kopnichev (1980), Campbell, 1985, Youngs, Day, and Stevens (1988), Youngs, Chiou, Silva, and Humphrey (1997), Crouse (1991), Spudich, Fletcher, and Hellweg (1997, 1999) and Ambrasseys & Douglas, 2003. A comprehensive summary of ground motion models was prepared by Douglas (2004). Lately, next generation attenuation relationships for different soil types were proposed through a research effort conducted at the Pacific Earthquake Engineering Research Center (PEER) by Abrahamson and Silva (2008), Boore and Atkinson (2008), Campbell and Bozorgnia (2008), Chiou and Youngs (2008) and Idriss (2008). These studies represent the current state of the art in ground motion modeling for shallow crustal earthquakes. Validation of these models for a series of recent California earthquake records was performed by Kaklamanos and Baise (2011). Application of these models in China was performed by Zhang, Hu, Jiang, and Xie (2012). Currently there is an on-going project conducted at PEER to develop next generation attenuation relationships for central and eastern North America. Most of these models have empirical nature and are developed based on a set of strong motion recordings from extensional tectonic environments. Because of this, their application out of the region they were developed in is limited, so that accurate seismic hazard assessment cannot be achieved. Fuzzy logic, however, offers significant advantages over this kind of approaches due to its ability to naturally represent qualitative aspect of inspection data and apply flexible inference rules (Sun, Sung, & Yong, 2002).

Fuzzy logic techniques have been previously used in earthquake engineering to evaluate seismic hazard (Lamarre & Dong, 1986), to quantify damage due to earthquake loads (Souflis & Grivas, 1986), to develop optimum systems for seismic design of reinforced concrete buildings (Yamada, Kawamura, & Tani, 2002), to evaluate structural repair methods due to seismic loads (Furuta, 1993), to

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http://dx.doi.org/10.1016/j.eswa.2014.09.035
0957-4174/

quantify the uncertainties in structural models and the subsequent response due to ground motions (Wadia-Fascetti & Smith, 1996), and to develop hybrid control systems of structures (Subramaniam, Reinhorn, Riley, & Nagarajaiah, 1996). Recently it was used to develop earthquake response spectra models (Wadia-Fascetti & Gunes, 2000), to minimize accelerations of friction pendulum base isolators (Kim & Roschke, 2006), to improve structural vibrations caused by earthquakes (Nomura, Furuta, & Hirokane, 2007), and to control seismic vibrations of small-scale buildings (Kim, Langari, & Hurlebus 2010). However, no thorough research studies were conducted to use them for deriving attenuation relationships. The objective of this study is, therefore, to develop new attenuation relationships of ground motions using fuzzy logic techniques. The data used in the study includes records from earthquakes of moment magnitude greater than 5, and site conditions characterized as soft soil, soil, and rock with closest distance less than 150 km. The fuzzy model in this study is established with inputs of earthquake magnitude and epicentral distance whereas the output is the horizontal component of peak ground accelerations (PGA).

2. A review on expert system applications

Expert systems have been applied in a variety of fields. According to Durkin (1990), expert systems have been developed in such diverse areas as science, medicine, engineering and business, to aid people engaged in these fields in increasing the quality, efficiency, and competitive leverage of their operations.

An expert system was established by Nasir, Khalil, and Sinha (1990) for inventory management. The objective of the study was on the development of a simple, user-friendly tool that can be used effectively by managers to increase the cost-effectiveness of their inventory systems. The study showed that expert system is capable of analyzing input parameters by performing statistical analyses of data bases, generating plots and graphs, implementing a set of rules for the selection of inventory models, and choosing a solution procedure.

Calvin (1991) used expert system application to clinical investigations. The DESIGN EXPERT, a prototype expert system for the design of complex statistical experiments was developed in this study. The system was designed for scientific investigators and statisticians who must design and analyze complex experiments, and it was able to (i) recognize specific types of complex experimental designs, based on the application of inference rules to non-technical information supplied by the user; (ii) encode the obtained and inferred information in a flexible general-purpose internal representation for use by other program modules; (iii) generate analysis of variance tables for the recognized design and an appropriate Biomedical Computer Programs run file for data analysis, using the encoded information.

Jo, Jung, and Yang (1997) established ramp scheduling system, called RACES (Ramp Activity Coordination Expert System), to solve complex and dynamic aircraft parking problems. RACES was developed from the domain knowledge and experience which were acquired from the domain experts. The domain knowledge and experience were taken as important factors in controlling the scheduling procedure for the development of the expert system. RACES was developed to divide the problem into sub-problems and experimental heuristics in the knowledge acquisition process, and independently processes scheduling for the divided sub-problems and shares variables and domains. It then selects or confines the search space with domain filtering techniques by exploiting the characteristics of various constraints and knowledge. The main focus of the study was to produce a user-driven near-optimal solution by means of a trade-off scheduling method using heuristics between the size of aircraft and the best-fit time. The performance evaluation of the system showed that, for 400 daily flights, RACES made parking schedules for aircraft in about 20 s compared with 4–5 h by human experts.

According to Al-Homoud and Al-Masri (1999), an expert system called Cut Slopes and Embankments Expert System (CSEES) was developed for Jordan with the objective of evaluating failure potential of cut slopes and embankments for the planning and design of roads. The expert system was designed to include a classification system for evaluating slope failure potential, and a data bank on landslides in the study area. Fuzzy set theory was used with the modified Monte Carlo simulation technique to obtain Slope Failure Potential Index (SFPI). Factors affecting slope stability, such as geology, topography, geomorphology, precipitation, vegetation, and drainage conditions were incorporated in obtaining the SFPI. The developed expert system was then applied to cut slopes and embankments in Jordan and it was proven to be successful for the areas that suffered landslides in the past.

A study made by Yang, Lim, and Tan (2005) established an expert system called VIBEX (VIBration EXpert) in order to aid plant operators in diagnosing the cause of abnormal vibration for rotating machinery. A decision table based on the cause-symptom matrix as a probabilistic method for diagnosing abnormal vibration was used in the work so as to automatize the diagnosis. Also a decision tree was used as the acquisition of structured knowledge in the form of concepts is introduced to build a knowledge base which is indispensable for vibration expert systems. The proposed system was written in Microsoft Visual Basic and Visual C++ and has been successfully implemented on Microsoft Windows environment.

Hatiboglu et al. (2010) developed a predictive tool by fuzzy logic in order to predict the outcomes of patients with intracranial aneurysm. The researchers recorded World Federation of Neurological Surgeons Scale (WFNSS), Fisher Scale and age at admission and Glasgow Outcome Score (GOS) at discharge from hospitalization for all the patients, and these were divided into appropriate classes to develop fuzzy sets. The outcomes of the patients were then calculated with these sets by fuzzy model. According to the results of study, predicted outcome by fuzzy logic approach correlated with observed outcome scores of the patients ($p > 0.05$), including 95% confidence interval. The study concluded that the outcome of the patient with intracranial aneurysm could be predicted accurately by fuzzy logic based expert system which was rarely used in medicine.

A new adaptive prediction tool termed as Geno-Kalman filtering (GKF) was established by Altunkaynak (2010b) by combining Genetic Algorithm and Kalman filtering in order to predict suspended sediment concentration. The establishment of the expert system involved three steps: relating discharge and suspended sediment concentrations by using dynamic linear model, obtaining an optimum transition matrix relating state variables by Genetic Algorithms (GAs) and calculation of an optimum Kalman gain, and prediction of suspended sediment concentration from discharge measurements by using Kalman filtering. The validation results of the proposed expert system were found to result in less errors and better efficiencies compared to perceptron Kalman filtering. The combined Geno-Kalman Filtering (GKF) technique was again used to develop predictive models for estimation of significant wave height by Altunkaynak and Wang (2012) at stations LZ40, L006, L005 and L001 in Lake Okeechobee, Florida. The results of the study showed that the GKF methodology performed better in predicting significant wave height than those from Artificial Neural Network (ANN) models.

Gudu, Gichoya, Nyongesa, and Muumbo (2012) developed an experiment system named Medical Expert System (MES) for the diagnosis and treatment of Hypertension in Pregnancy (HIP). The

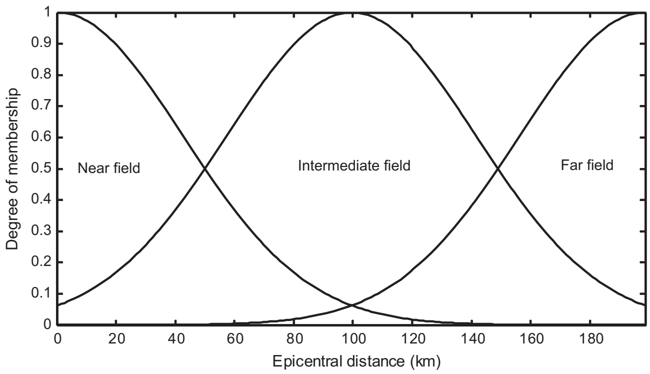

Fig. 1. Distance fuzzy sets.

main objective of the research was to develop Medical Expert System (MES) that can be used as an expert knowledge sharing tool by other medical personnel who are not specialists in diagnosis and treatment of HIP and reduce the acute shortage of specialist obstetricians. It is the belief of the researchers that the MES would be handy in sharing the much needed expert knowledge in the diagnosis and treatment of HIP since it would be used by medical officers, clinical officers and nurses in the absence of specialists.

Modirzadeh, Tesfamariam, and Milani (2012) applied an expert system in order to survey the susceptibility of buildings constructed under earlier seismic codes to seismic hazard. The researchers used soft story, weak story, and the quality of construction as performance modifiers. The evaluation of buildings was performed through a pushover analysis, and performance objective was obtained through initial stiffness of the pushover curve. Using a design of experiments technique, a reliable system input–output relation was identified and used to evaluate the performance criteria at untried design points (i.e., buildings with different modifier values). This method of performance based evaluation was demonstrated through consideration of the different structural deficiencies on a typical six-storey reinforced concrete building in Vancouver, Canada.

A hybrid expert system to spatio-temporal seismic clustering was developed by building upon a novel density based clustering scheme that explicitly takes into account earthquake's magnitude during the density estimation by Georgoulas et al., 2013. In this study, the new density based clustering algorithm is made to consider both time and spatial information during cluster formation so that clusters lie in a spatio-temporal space. Finally, time information was made to be dropped before a hierarchical agglomerative clustering algorithm acts upon the identified clusters in order to come up only with the spatial description of seismic events.

3. Fuzzy logic techniques

Fuzzy logic techniques, pioneered by Zadeh (1965), are used to define processes that are imprecise and ambiguous. Fuzzy sets are used to define membership of data that do not belong to a particular set, but rather partially to a set. As an example, fuzzy sets are used to define earthquake magnitudes that can be considered "mild", "moderate" or "severe"; and epicentral distances that are "near field", "intermediate field" and "far field". The membership degree of a set describes the level by which the data belong to that particular set. As an example, in the case of the distance from an earthquake source (Wadia-Fascetti & Gunes, 2000), it is given by:

$$m_{NEAR}(x) \in [0, 1] \quad (1)$$

where $m_{NEAR}(x)$ is the degree of membership that X has in the fuzzy set of site "NEAR the earthquake source" and x is the distance between the site and the epicentral region. The fuzzy set of distance from source is shown in Fig. 1.

The membership function indicates the membership degree of the element in the fuzzy set. The higher the likelihood that the element belongs to the set, the higher its degree of membership in the set is. Data points with membership of zero imply that the element is not a member of the fuzzy set, and membership of one implies the element belongs fully to the set. In this study, fuzzy sets are used to describe earthquake magnitude and source-to-site distance.

Attenuation relationships have a number of parameters that can be considered ambiguous or imprecise. These include the soil type that corresponds to the site under consideration, the distance of the site from the epicentral region, and the magnitude of the earthquake that can range from mild to severe. Ambiguous parameters can be expressed as fuzzy sets as in the case of earthquake magnitude shown in Fig. 2.

As stated earlier, and similar to the study by Wadia-Fascetti and Gunes(2000), epicentral distance and earthquake magnitude are the two main fuzzy variables addressed in this study. Fuzzy model sets are used to describe inputs in terms of calibration (training) process. Sites are classified as rock, soil, and soft soil; source-to-site (epicentral distance) as near field, intermediate field and far field; and earthquake magnitude as mild, moderate and severe (see Figs. 1 and 2). Membership in a set was based on expert judgment and was constructed using Gaussian membership functions. Peak ground acceleration (PGA) is a function of earthquake magnitude, epicentral distance and type of soil, among other parameters. The objective of this study is to represent the attenuation relations of PGA at sites away from the source. The study will therefore aim at characterizing the value of PGA associated with each soil type, distance from source, and earthquake magnitude.

In research studies, solutions to problems with deterministic and analytical models cannot always be performed. In this case, the solution requires uncertainty techniques. In all modeling techniques, whether analytical, probabilistic, or statistical, two parameters need to be well established: the model assumptions and the numerical data available for verification. In fuzzy techniques, however, neither crisp data nor restrictive assumptions are needed (Altunkaynak (2010a); Altunkaynak, Özger, & Çakmakçı, 2005; Dubois & Prade, 1991; Dubois & Prade, 1996; Mamdani, 1974; Özger, 2009; Russo & Jain, 2001; Uyumaz, Altunkaynak, & Özger, 2006; Wang & Mendel, 1992; Yager, 1996; Zadeh, 1968). This constitutes one of the major advantages of fuzzy logic techniques.

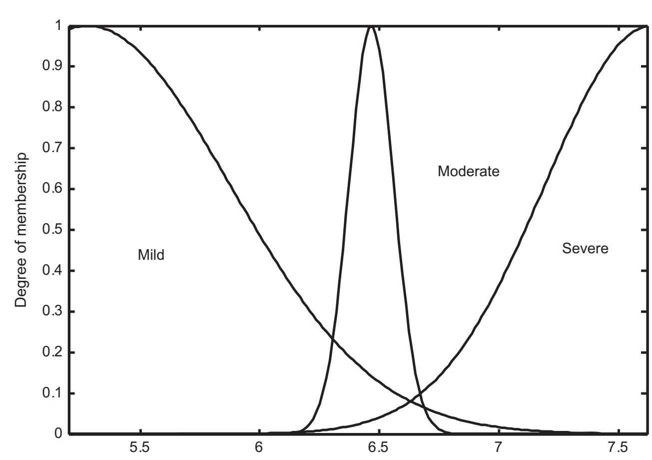

Fig. 2. Magnitude fuzzy sets.

The following steps are typically followed for application of fuzzy analysis techniques:

(i) Fuzzification of the input and output variables by considering appropriate linguistic subsets. In this study, these subsets for earthquake magnitude are mild, moderate, and severe; and for epicentral distance are near, intermediate, and far-field.
(ii) Construction of rules based on expert judgment. The rules relate the linguistic subsets of input variables to those of the output subsets. A fuzzy rule includes statements of "IF…THEN" with the first part that starts with IF and ends before the THEN referred to as the predicate or premise; and the second part that comes after "THEN" includes the fuzzy subset of the output based on the premise part. The input subsets within the premise part are typically combined with the logical "and" conjunction, while the rules are combined with logical "or".
(iii) The implication part of a fuzzy system is defined as the shaping of the consequent part based on the premise component.
(iv) The result appears as a fuzzy subset, and thus it is necessary to defuzzify the output for obtaining crisp values. Defuzzification techniques are typically conducted using the centroid method (Ross, 1995).

4. Membership functions and fuzzy rules for attenuation relationships

To establish attenuation relationships, the following steps are conducted:

(a) Fuzzification step: Earthquake magnitude and site to source distance are considered as having vague and imprecise characteristics. Therefore, all the input and output variables are initially fuzzified. The fuzzy subsets and membership degree for epicentral distance and earthquake magnitudes used in this study are shown in Figs. 1 and 2. Fuzzy subsets for other earthquake parameters, such as style of faulting, rupture depth, hanging wall effect, and soil/sediment depth effect were not considered. This is mainly to keep the model simple and reduce the number of fuzzy rules described in the next section. These effects were however indirectly accounted for through proper training of the model.
(b) Inference: This step includes many fuzzy conditional statements as rules to model the system. In this study, the two input variables are: EM (earthquake magnitude), and D (epicentral distance), and the output variable is: PGA (peak ground acceleration). The conditional statements used to relate the input to the output variables are:

$$R_1: \text{IF EM is A}(1) \text{ and D is B}(1) \text{ THEN PGA is } y_1$$
$$R_2: \text{IF EM is A}(2) \text{ and D is B}(2) \text{ THEN PGA is } y_2 \quad (2)$$

Also

$$R_N: \text{IF EM is A}(n) \text{ and D is B}(n) \text{ THEN PGA is } y_N$$

where $n = 3$, $N = 3 \times 3 = 9$, A(1), A(2), A(3) represent mild, moderate, and severe; and B(1), B(2), B(3) represent near, intermediate, and far-field. These conditions make up the input fuzzy subsets, while $y_1, y_2, \ldots, y_N$ are the output fuzzy subsets. $R_1, R_2, \ldots, R_N$ are the logical N rules that can be considered to relate the input to output variables.
Gaussian membership functions are used to construct the input fuzzy subsets (Figs. 1 and 2). Nine fuzzy rules with three fuzzy sets for each input variable were optimized based on the available data described in the next section as shown in Table 1 below.
All the rules in Eq. (2) might not be valid for the problem at hand. Each rule will be triggered in different strengths based on the available data set and input variables. Some rules might not be triggered at all, which indicates that they are irrelevant for the given problem. The final solution for the peak ground acceleration, PGA will be the union of the triggered rules of output fuzzy subsets. In this paper, Mamdani, 1974 inference is used.
(c) Defuzzification: Finally, in order to calculate the deterministic value of PGA, a defuzzification method must be employed (Kiska, Gupla, & Nikiforuk, 1985):

$$\text{PGA} = \frac{\sum_{i=1}^{9} w_i y_i}{\sum_{i=1}^{9} w_i} \quad (3)$$

where the PGA is the weighted average of all y functions with corresponding weight w_i.

5. Strong motion database

The attenuation relationships were derived using a database that was compiled for earthquakes with moment magnitudes (Mw) greater than or equal 5, and consisted of horizontal peak ground accelerations recorded on three different site conditions classified as rock, soil, and soft soil. The data used in the analysis constitutes a total of 1082 records (Table 2): 509 in soil, 549 in soft soil, and 24 in rock sites. These data were compiled from the Pacific earthquake Engineering Research Center (PEER) database.

In the data set, the earthquake intensity is characterized by moment magnitude Mw, as defined by Hanks and Kanamori (1979). The magnitudes are restricted to $\text{Mw} \geqslant 5.0$. Records for which the peak acceleration was less than 0.04 g were omitted. The soil types were divided into three groups in ascending order with respect to shear wave velocity: soft soil, soil, and rock. The average shear wave velocities for these groups are 200, 400 and 700 m/s, respectively.

6. Attenuation relationship development

The procedure used to construct the attenuation functions consists of two stages. In the first, attenuation relationships were developed for PGA through training of the values in the database. In the next stage, testing of the results was performed over the range of earthquake magnitudes considered (Mw 5 to 7.5) and distances (rcl) up to 150 km, and for all three site types.

The observed data, as well as the calculated attenuation relationships using the proposed Fuzzy approach for PGA for soft soil sites are shown in Figs. 3–5 for different magnitudes. These magnitudes are denoted as M = 5.5 for magnitude $5 \leqslant M < 6$; $M = 6.5$ for magnitude $6 \leqslant M < 7$; and $M = 7.5$ for magnitude $7 \leqslant M < 8$.

A comparison between the Fuzzy approach and the classical Boore, Joyner, and Fumal (1997) approach for soft soil is shown in Fig. 6. It is observed that Fuzzy analysis offers solution points that lead to a dynamic structure of the model rather than a static one. An important contribution is its inherent capability to capture non-linear relationships. The Boore approach is based on the following equation:

$$\ln Y = b_1 + b_2(M-6) + b_3(M-6)^2 + b_s \ln r + b_v \ln\left(\frac{v_s}{v_A}\right) \quad (4)$$

$$r = (r_{cl}^2 + h^2)^{0.5} \quad (5)$$

where Y is the ground motion parameter (peak horizontal acceleration PGA in g), M is (moment) magnitude; rcl is the closest horizontal distance from the station to a site of interest in km; Vs is the

Table 1
Fuzzy rules.

Rule description		
R_1	IF EM is Mild and D is Near field THEN	$y_1 = 41.82\text{EM} - 7.513\text{D} + 16.37$
R_2	IF EM is Mild and D is Intermediate THEN	$y_2 = 167.3\ \text{EM} - 5.079\ \text{D}-490.6$
R_3	IF EM is Mild and D is Far field THEN	$y_3 = -721.9\text{EM} - 2.993\text{D} + 5602$
R_4	IF EM is Moderate and D is Near field THEN	$y_4 = 1821\ \text{EM} - 61\text{D} - 10220$
R_5	IF EM is Moderate and D is Intermediate THEN	$y_5 = -704\text{EM} - 45.83\text{D} + 8505$
R_6	IF EM is Moderate and D is Far field THEN	$y_6 = 8680\text{EM} - 272\text{D} - 13710$
R_7	IF EM is Severe and D is Near field THEN	$y_7 = 143.5\text{EM} - 7.345\text{D} - 530.8$
R_8	IF EM is Severe and D is Intermediate THEN	$y_8 = 20.78\text{EM} - 1.441\text{D} + 79.54$
R_9	IF EM is Severe and D is Far field THEN	$y_9 = 103.8\text{EM} - 0.6304\text{D} - 560.3$

EM: earthquake magnitude.
D: epicentral distance.

Table 2
Earthquake records used in the development of PGA attenuation relationships.

Year	Month–day	Earthquake name	Earthquake magnitude	Soft soil	Soil	Rock
1987	1001	Whittier Narrows-01	5.99	56	46	4
1987	1004	Whittier Narrows-02	5.27	7	3	1
1994	0117	Northridge-01	6.69	71	71	14
1994	0117	Northridge-02	6.05	7	3	–
1994	0117	Northridge-03	5.20	2	–	–
1994	0117	Northridge-04	5.93	–	2	–
1994	0117	Northridge-05	5.13	1	3	–
1994	0320	Northridge-06	5.28	19	12	2
1999	1016	Hector Mine	7.13	33	17	–
1999	0920	Chi-Chi, Taiwan	7.62	162	160	2
1999	0920	Chi-Chi, Taiwan-02	5.90	29	80	–
1999	0920	Chi-Chi, Taiwan-03	6.20	54	–	-
1999	0920	Chi-Chi, Taiwan-04	6.20	40	–	–
1999	0922	Chi-Chi, Taiwan-05	6.20	68	68	1
1999	0925	Chi-Chi, Taiwan-06	6.30	–	44	–

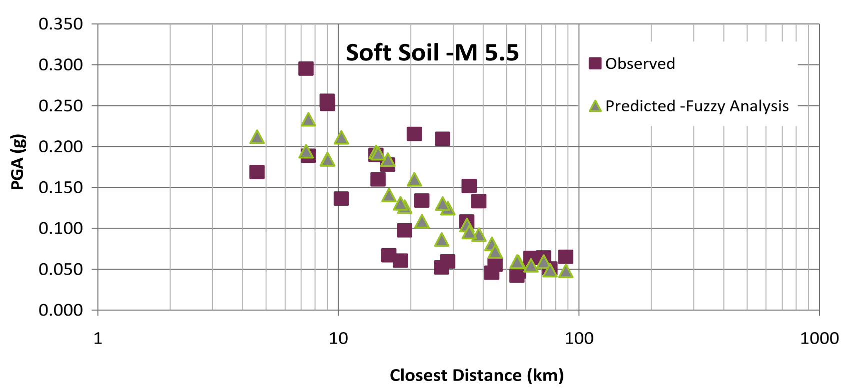

Fig. 3. Curves of peak acceleration versus distance for a magnitude 5.5 earthquake at soft soil sites.

shear wave velocity for the station in m/s; $b_1 = -0.242$, $b_2 = 0.527$, $b_3 = 0$, $b_s = -0.778$, $h = 5.57$, $b_v = -0.371$, and $V_A = 1396$ m/s.

The observed and calculated attenuation relationships for PGA for soil sites are shown in Figs. 7–9. A comparison between the Fuzzy and the Boore et al. (1997) results for soil is shown in Fig. 10. All these results show that the Fuzzy analysis proved to capture the non-linear relationship of solution points, particularly for distances greater than 10 km.

The attenuation relationships for PGA for rock sites are shown in Figs. 11–13. In this case, no records exist in the database for earthquakes with magnitudes $M > 7$.

7. Comparison with other ground motion models

The fuzzy model developed in this study for ground motion prediction is compared to those developed by Boore et al. (1997), Campbell, 1997; Spudich et al. (1999); Ambraseys, Simpson, and Bommer (1996), as well the next generation attenuation (NGA) models of Boore and Atkinson (2008) and Campbell and Bozorgnia (2008). The equations of Boore et al. and Ambraseys et al. divided the soil types into four groups according to shear wave velocities. The model by Campbell pertains to alluvium soil, soft rock and hard rock. Spudich et al. state that their equations are applicable for rock and soil sites. Boore and Atkinson's NGA model is most suitable for distances greater than 80 km, and Campbell and Bozorgnia's NGA model has complex parameterization that account for hanging wall effects, rupture-depth effects, and soil/sediment depth effects. The comparison is shown in Figs. 14 and 15 for a magnitude $6 \leqslant M < 7$ at rock sites and $7 \leqslant M < 8$ at soil sites, respectively. The comparison shows that the Fuzzy approach provides, in general, more conservative results than the other models, both for rock and soil cases.

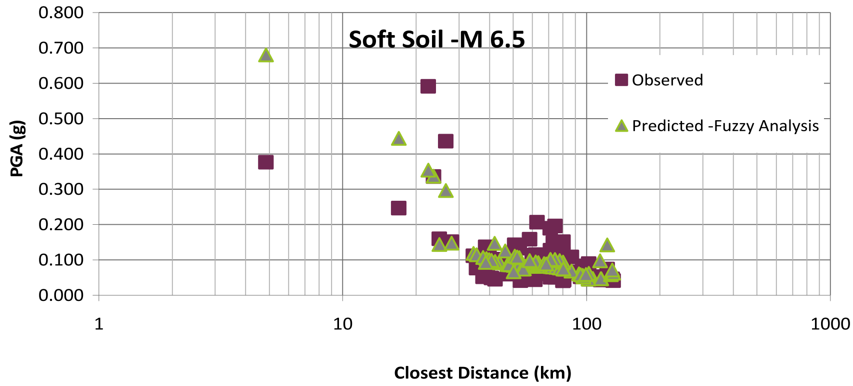

Fig. 4. Curves of peak acceleration versus distance for a magnitude 6.5 earthquake at soft soil sites.

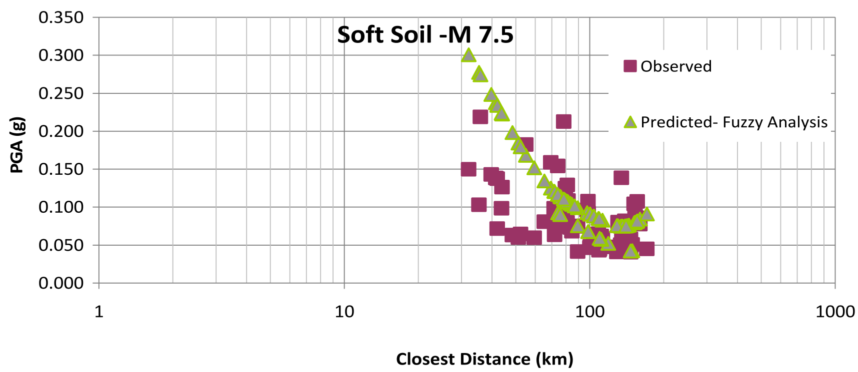

Fig. 5. Curves of peak acceleration versus distance for a magnitude 7.5 earthquake at soft soil sites.

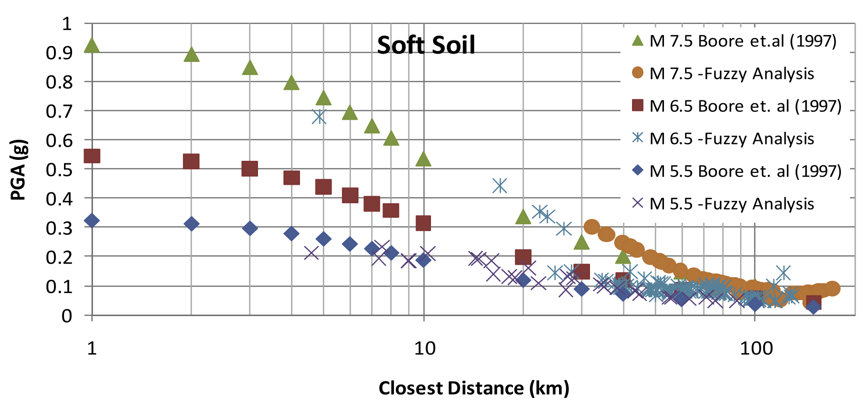

Fig. 6. Curves of peak acceleration versus distance for a magnitude 5.5, 6.5 and 7.5 earthquakes at soft soil sites.

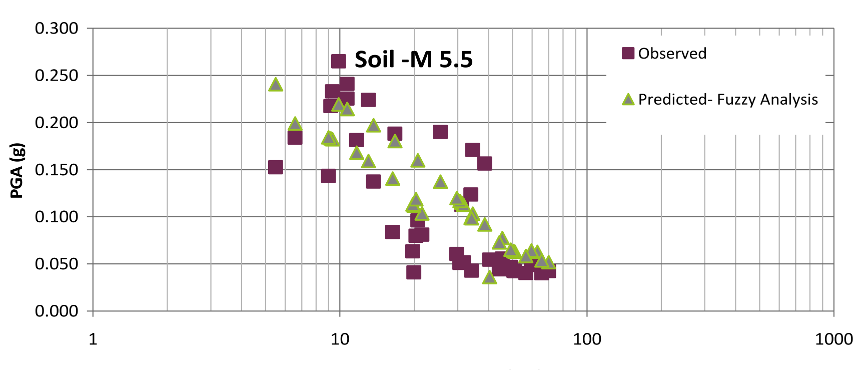

Fig. 7. Curves of peak acceleration versus distance for a magnitude 5.5 earthquake at soil sites.

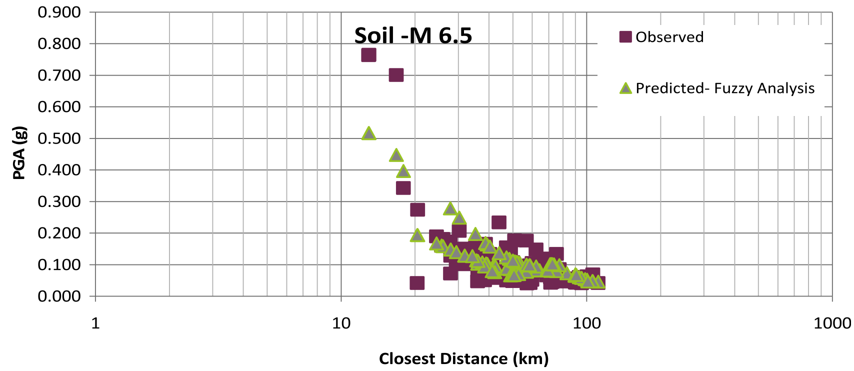

Fig. 8. Curves of peak acceleration versus distance for a magnitude 6.5 earthquake at soil sites.

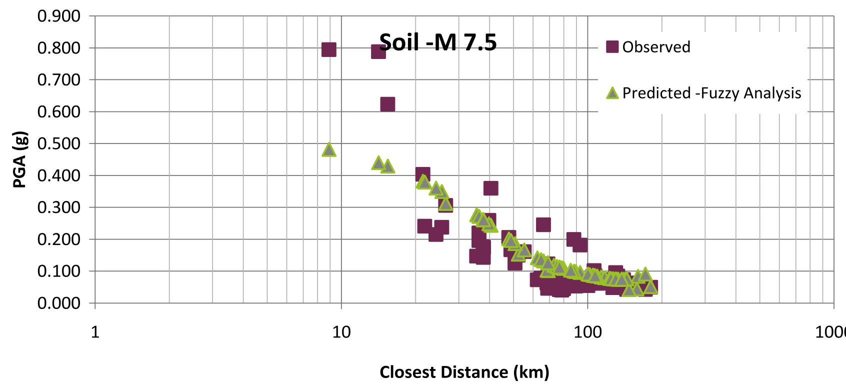

Fig. 9. Curves of peak acceleration versus distance for a magnitude 7.5 earthquake at soil sites.

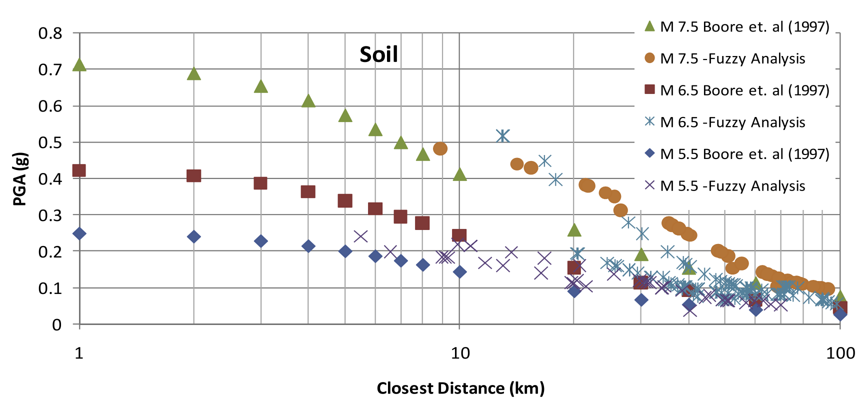

Fig. 10. Curves of peak acceleration versus distance for magnitude 5.5, 6.5 and 7.5 earthquakes at soil sites.

8. Performance evaluation of model

The main sources of uncertainty in deriving attenuation functions is due to the different geological characteristics of sites, and determination of seismic record properties at different distances from source. The fuzzy logic techniques used in this study does not eliminate these uncertainties; however it provides a better and more accurate approach to address them than do traditional physical models.

The model performance was quantitatively evaluated in terms of the mean square error (MSE) and coefficient of efficiency (CE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(J_{s,pi} - J_{s,mi})^2 \tag{6}$$

$$CE = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}(J_{s,pi} - J_{s,mi})^2}{\frac{1}{N}\sum_{i=1}^{N}(J_{s,mi} - J_{s,m})^2} \tag{7}$$

where $J_{s,pi}$, $J_{s,mi}$, $J_{s,m}$ are the predicted, measured, and mean of the specific values of attenuation relationships in observation i, respectively. N is the total number of observations.

Figs. 16 and 17 show the comparison between the measured and predicted values of attenuation relationships both for the fuzzy and the classical Boore et al. (1997) models, respectively. It is observed that the randomness and dynamism throughout these figures from the fuzzy analysis is much higher than from the Boore's analysis, and this confirms the positive contribution of the fuzzy methodology to the process. In general, there is an underestimation of observed values, particularly for large PGA,

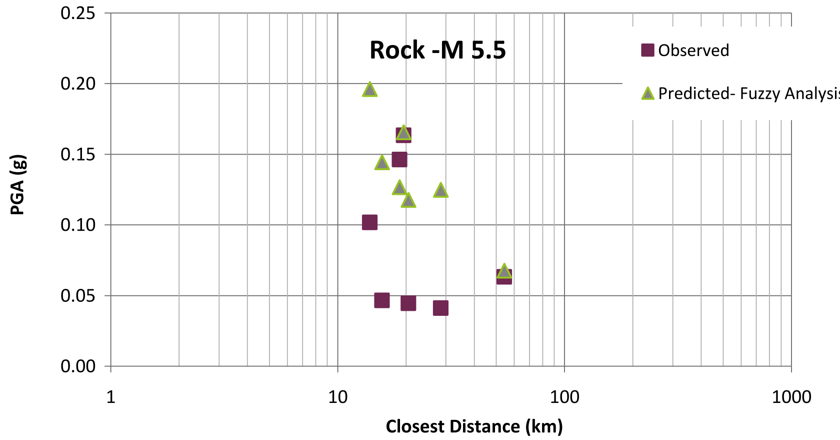

Fig. 11. Curves of peak acceleration versus distance for a magnitude 5.5 earthquake at rock sites.

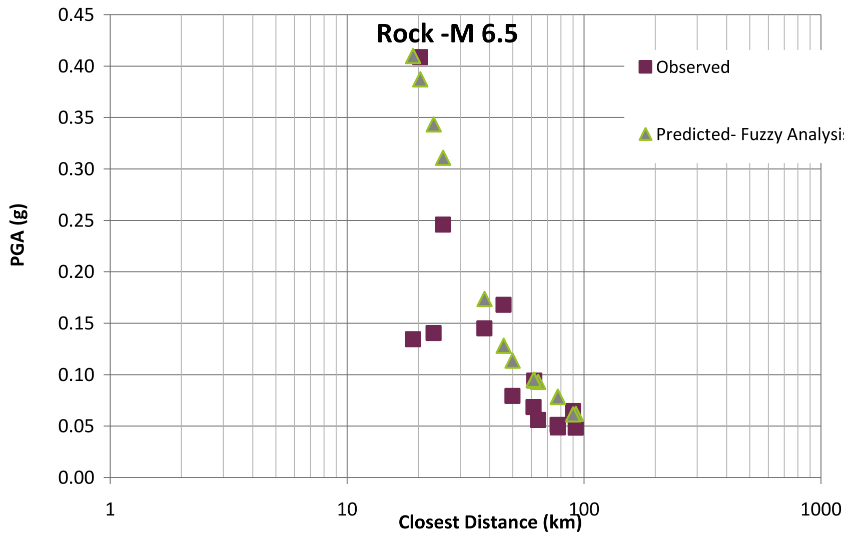

Fig. 12. Curves of peak acceleration versus distance for magnitude 6.5 earthquake at rock sites.

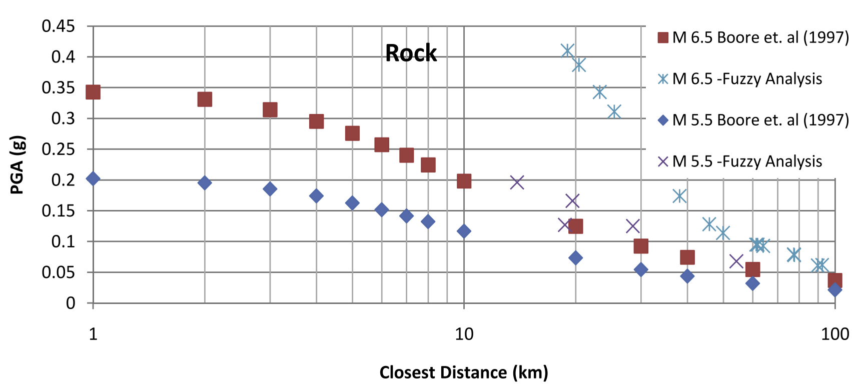

Fig. 13. Curves of peak acceleration versus distance for magnitude 5.5 and 6.5 earthquakes at rock sites.

however the deviation from the 45° diagonal line is minimum in the case of the fuzzy model. This confirms that the fuzzy analysis shows better agreement between measured and predicted values compared to Boore's analysis. These results show that the fuzzy analysis results in general in a very good prediction performance.

The coefficient of efficiency defined in Eq. (7) is typically used for quantifying the performance relative to a naive baseline, and is defined as the subtraction of the ratio of mean square error to observation variance from unity (CE = 1 − (mean square error)/(variance of observations)). The coefficient of efficiency for the fuzzy and Boore's models is obtained as 0.65 (Fig. 16) and

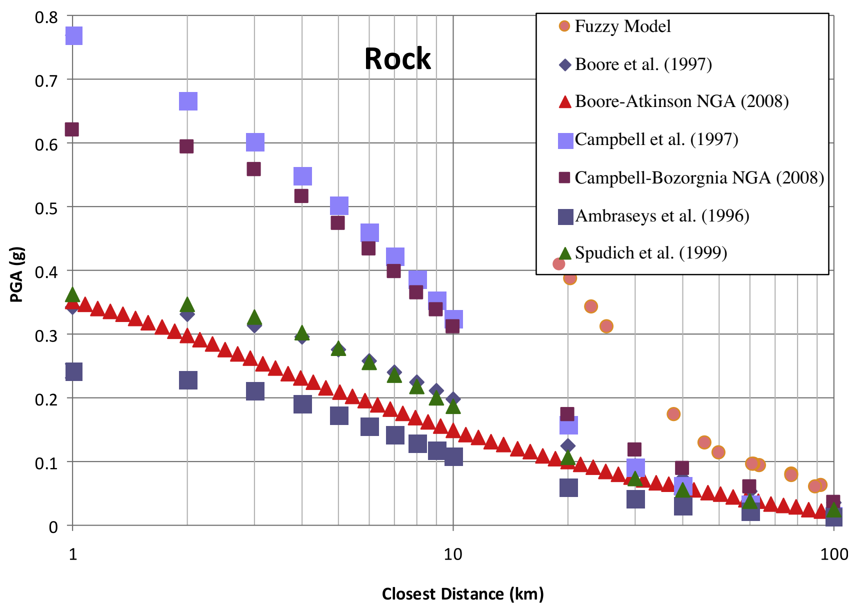

Fig. 14. Curves of peak acceleration versus distance for a magnitude 6.5 earthquake at rock sites.

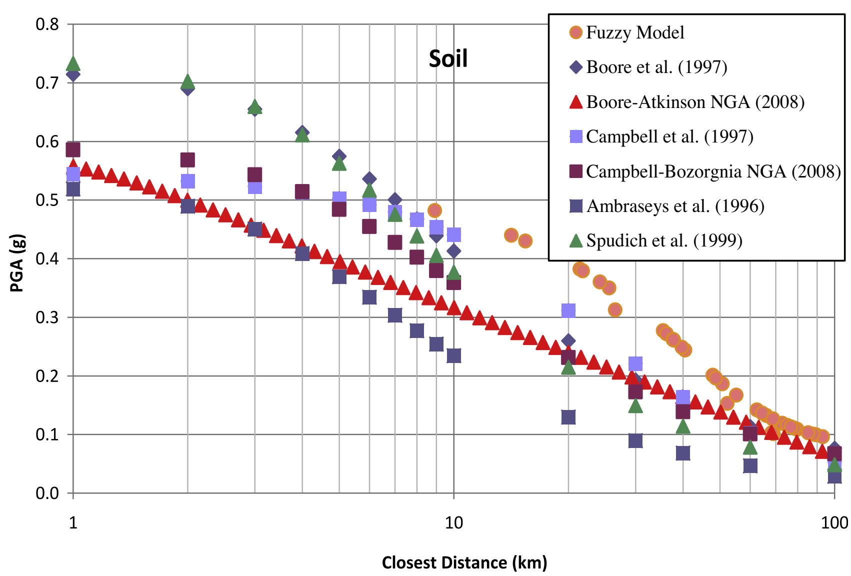

Fig. 15. Curves of peak acceleration versus distance for a magnitude 7.5 earthquake at soil sites.

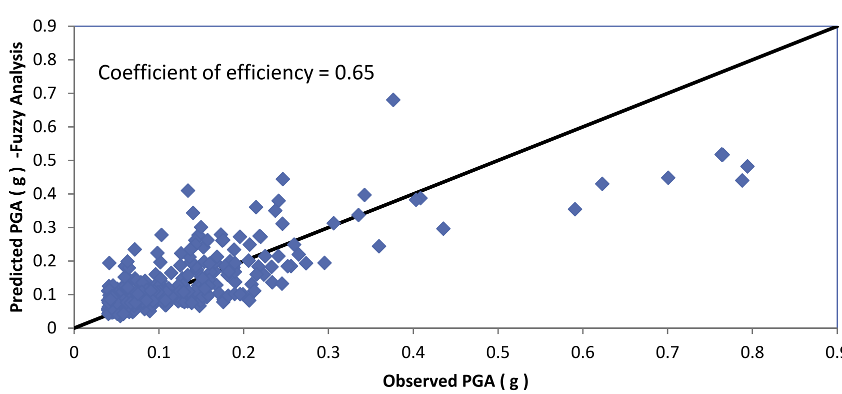

Fig. 16. Observed versus predicted (fuzzy analysis) attenuation relationships (g).

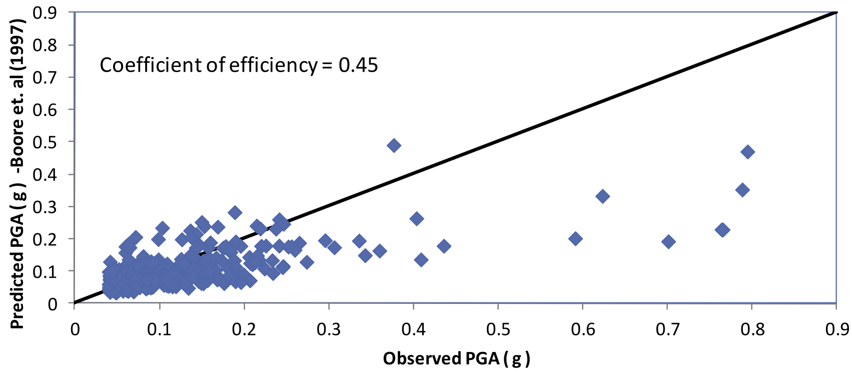

Fig. 17. Observed versus predicted (Boore et al., 1997) attenuation relationships (g).

0.45 (Fig. 17), respectively, indicating a much better agreement between observed and predicted values for the fuzzy model.

9. Discussion and conclusions

The paper presents attenuation relationships for the estimation of peak ground acceleration for earthquakes with magnitude of Mw 5 to 7.5 and *rcl* < 150 km for soft soil, soil and rock sites. A database of 1082 records was prepared and used in the study. Records with peaks of less than 0.04 g were omitted. A fuzzy logic approach was adopted to derive the attenuation relationships. Two fuzzy sets were defined, one for earthquake magnitudes categorized as severe, moderate and mild; and the other for epicentral distances defined as near, intermediate, and far. The epicentral distance and soil type proved to have a major effect on the attenuation characteristics. Comparison with previously developed physical models for attenuation functions was conducted. The study showed that the fuzzy approach results in general in a higher coefficient of efficiency. The proposed approach clearly results in a method that can accurately predict the PGA of ground motions at different distances away from the source.

While this paper represents an initial study on the use of fuzzy logic techniques to develop attenuation functions, the results obtained could be enhanced as additional records, shear wave velocities of soil profiles, and better determined distance from source data become available. Furthermore, the attenuation relationships proposed in this study can be improved and modified to account for additional earthquake parameters. The study clearly confirms that new techniques such as fuzzy methodologies can be used to improve the development of attenuation functions for use in important engineering applications. The application of the fuzzy methodology in this study demonstrates in general the use and great potential of fuzzy logic in quantifying uncertainties related to earthquake ground motions.

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