ISSN: 0974-2115
www.jchps.com Journal of Chemical and Pharmaceutical Sciences

Earthquake Magnitude Prediction for Andaman-Nicobar Islands: Adaptive Neuro Fuzzy Modeling with Fuzzy Subtractive Clustering Approach

R.S. Kamath[1] and R.K. Kamat[2]
[1]Department of Computer Studies, Chhatrapati Shahu Institute of Business Education and Research, University Road, Kolhapur 416004
[2]Department of Electronics, Shivaji University, Kolhapur 416 004
Corresponding author: E-Mail: rskamath@siberindia.edu.in

ABSTRCT

We report computational intelligence approach for predicting earthquake magnitude in Andaman-Nicobar Islands by applying Adaptive Neuro Fuzzy Inference System (ANFIS). Proposed model is the fusion of computing paradigms artificial neural network (ANN) and fuzzy inference (FIS) systems to create a successful synergic effect.The earthquake dataset is obtained from European-Mediterranean Seismological Centre. The major features such as latitude, longitude, depth and magnitude of past seismic events are considered here for computing future earthquakes' magnitude. ANFIS model encompassed with phenomenal learning capacity using ANN and fuzzy rating for changing over numerical estimations of characteristics into linguistic grades. ANFIS architecture, thus derived entails fuzzy subtractive clustering with 70 nodes, eight fuzzy rules and hybrid algorithm for training the model. The reported ANFIS model provides faster computation with accurate results in light of the inputted dataset. The present study measured performance of the model with reference to Root Mean Squared Error (RMSE).

KEY WORDS: earthquake, ANFIS, European-Mediterranean Seismological Center, prediction, model learning, FIS, ANN.

1. INTRODUCTION

ANFIS for Earthquake Magnitude Prediction: Earthquake forecasting and prediction is a dynamic theme in the arena of geological research and of late it has emerged as an exclusive branch of the study of seismology concerned with the particular of the time, area, and magnitude of future quakes inside stated confidence limits but with sufficient precision so that a warning can be issued (Kamat, 2017). Literatures in soft computing reveals that soft computing is more powerful in providing practicable answer for the problems that deal with uncertainties (Kamath, 2014). Fuzzy logic handles uncertainty in a natural manner by providing a human oriented knowledge representation and ANN plays a major role in self learning and generalization of rules (Demuth, 2015). In ANFIS, both the learning abilities of a neural system and reasoning capacities of fuzzy logic are combined in order to give improved prediction capabilities, as compared to using a single methodology alone (Bystrov, 2016). Though the expectation of earthquakes is not easy, many research groups are striving hard to monitor the possibility of an earthquake so as to come out with the likelihood of the next quake that might occur in the region.

Zamani (2013), have demonstrated application of ANN and ANFIS for earthquake incidence in Iran. Their study scrutinized the spatial-temporal varieties in seismicity parameters in south Iran. The supervised Radial Basis Function system and ANFIS model were executed on the grounds that they have demonstrated the productivity in order and prediction problems. Mirrashid (2014), have reported the prediction of future earthquakes using adaptive neuro-fuzzy inference system. The earthquake data of Iran between 1950 and 2013 that had been used for this purpose. ANFIS modeling is carried out using algorithms including grid partition, subtractive clustering and fuzzy C-means. Shibli (2011), has presented an ANFIS way to deal with anticipate the area, event time and the extent of seismic tremors in light of the principle of conservation of energy and momentum of annual earthquakes. In this ANFIS training, the area of the earthquake is treated as an input, and the moment of the earthquake is selected as the output. Mittal (2011), have carried out the comparison of ANN and ANFIS for the prophecy of Peak Ground Acceleration in Indian Himalayan Region.

Different research groups have applied soft computing techniques for evaluating features of earthquake related research, though not much work is done towards using these techniques for prediction purpose. Karmi (2006), have reported earthquake risk assessment system using fuzzy-probabilistic technique. Kalita (2012), have adopted a soft computing approach for recognition of Earthquake Precursor from low scope adds up to electron content profiles. Yet another paper reports utilization of the remote sensing technique combined with the soft computing approach for damage mapping post-earthquake hazards (Mansouri, 2015).

In the backdrop of the research endeavors portrayed above, this paper reports ANFIS for predicting earthquakes' magnitude. The present investigation is simulated in MATLAB environment (Natick, 2009). ANFIS, a combination of fuzzy logic and ANN helps to model the framework for prediction of future earthquakes' magnitude. Contrasted with neural systems, an imperative favorable position of neuro-fuzzy systems is its reasoning capacity of a specific state.

The rest of paper is structured as follows; after a brief introduction, second section deals with the theory of ANFIS. The third section details out learning model and inference of proposed ANFIS model. The results and discussion are reported in the fourth section. The conclusion at the end divulges aptness of the ANFIS for predicting earthquake magnitude.

2. METHODS & MATERIALS

ANFIS: Theoretical Considerations: Defining effective membership function is a major issue in fuzzy inference system (FIS). Neuro-fuzzy systems provide a method for the fuzzy modelling strategy to learn data about a dataset, keeping in mind the end goal to process the membership function parameters that best permit the related FIS to track the given input/output information. This learning strategy works comparatively to that of neural systems. ANFIS achieves this membership function parameter adjustment. It improves fuzzy if-then rules acquired from human knowledge to explain the input-output performance of a system by employing a hybrid learning procedure (Bystrov, 2016). ANFIS uses first-order Takagi-Sugeno type FIS and a typical rule set has the form shown in equation (1).

$$\left.\begin{array}{l}\text{if } x \text{ is } A1 \text{ and } y \text{ is } B1 \text{ then } f1 = p1x + q1y + r1 \\ \\ \text{if } x \text{ is } A2 \text{ and } y \text{ is } B2 \text{ then } f2 = p2x + q2y + r2\end{array}\right\} \quad (1)$$

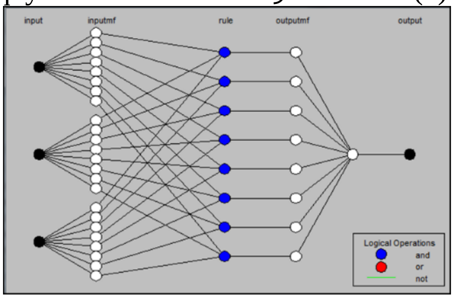

Figure.1. Schematic representation of ANFIS model

Combining both neural network and fuzzy logic, ANFIS is used to handle complex and nonlinear problems. The high speed of training, the effective learning algorithm and the simplicity of the software give ANFIS big advantages over the other ones. A graphic representation of ANFIS model designed in the present study is shown in fig. 1. ANFIS structure maps inputs through input membership functions and related parameters, and after that through output membership functions and related parameters to outputs, can be utilized to decipher the input/output outline. ANFIS has fixed five layers. The parameters of the network are the standard deviation and mean of the membership functions which are antecedent parameters and the coefficients of the output linear functions called consequent parameters.

Model Learning and Inference through ANFIS: This experiment of predicting earthquake magnitude in Andaman Nikobar islands is simulated in MATLAB environment. The ANFIS model is conceived as a Multi-Input Single-Output (MISO) configuration. In the present study, we have evaluated on a catalog of 956 earthquake events, which took place between 1st Oct, 2004 and 20th Feb, 2016 in the area of Andaman Nikobar Islands. Each seismic event specifies year, month, day, time, latitude, longitude, magnitude, depth. Date and time are more complex data typefor our ANFIS model and our focus is to envisage the magnitude of the next earthquake rather than the time of the earthquakewhich means keeping the date and time is not necessary. Therefore the proposed model works basically with three inputs latitude, longitude and depth.

The model learning is administered by splitting dataset into following three types using random sampling method:

- Training data set that contains preferred input/output data pairs of the target system to be modeled.
- Testing data set that can check the generalization capability of the resulting FIS.
- Checking data set for the purpose of model over fitting during the training.

Optimized ANFIS architecture is determined by experimenting ANFIS with various parameters as mentioned in figure.2. The ANFIS provides the different form of output when the properties are changed. In the present study, subtractive clustering and grid partition are experimented to establish initial FIS. Membership function parameters are tuned using backpropagation and hybrid algorithm (Demuth, 12). This allows fuzzy systems to learn from the data used for modelling. Triangular and Gaussian shapes are used for the membership function distribution for the input variables. The parameters related with the membership functions will change through the learning process. The calculation of these parameters or their change is encouraged by an gradient vector, which gives a measure of how well the FIS is demonstrating the input/output information for a given set of parameters. The learning algorithm and the RMSE are used to identify ANFIS parameters. Figure 3(a-d) presents the FIS models generated in the present study per variation in the properties. The experiment revealed that the fuzzy subtractive clustering with 70 nodes, eight fuzzy rules and hybrid algorithm is efficient for training the ANFIS model. Table.1, presents the details of ANFIS properties for present modelling.

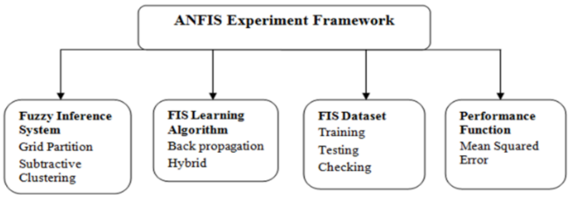

Figure.2. ANFIS modeling experiment framework

Table.1. Optimized ANFIS architecture for earthquake prediction

ANFIS Modelling Description	Values
FIS Generation	Subtractive Clustering
Nodes	70
Range of influence	0.2
Squash factor	1.25
Linear parameters	32
Nonlinear parameters	48
Training data pairs	715
Checking data pairs	100
Fuzzy rules	8
Learning Algorithm	Hybrid
Max. Epochs (Stopping Criterion)	50
Error tolerance (Training Error Goal)	0

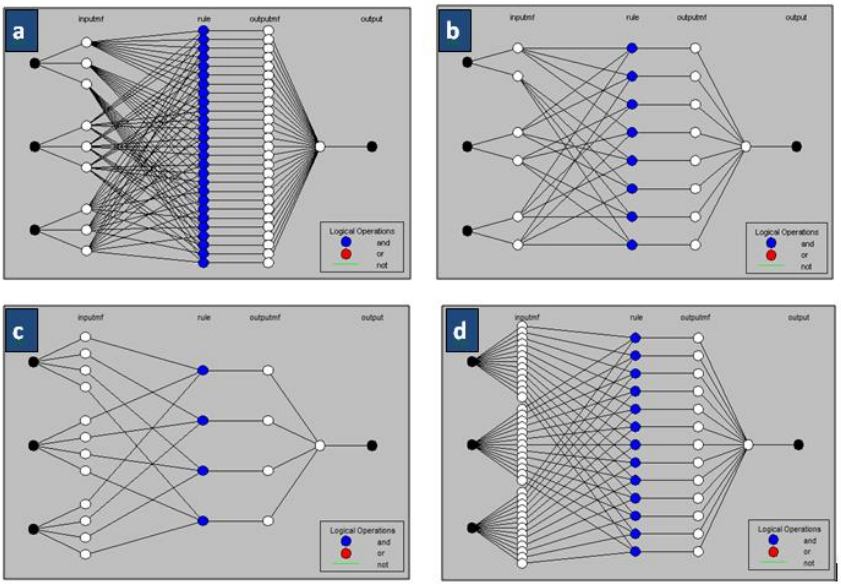

Figure.3. Structure of ANFIS Models. Fig.(a)ANFIS-Grid partition clustering with membership functions 3; Fig.(b)ANFIS-Grid partition clustering with membership functions 2; Fig.(b)ANFIS-Subtractive clustering with membership functions 4; Fig.(d)ANFIS-Subtractive clustering with membership functions 13

3. RESULTS AND DISCUSSIONS

We explored ANFIS modeling with different combinations FIS and ANN. This section explains predicting earthquake's magnitude in Andaman-Nicobar Islands. MATLAB is used to analyze FIS structure, ANN learning and RMSE for quality assessment.

Figure.3(a-d), presents the FIS models generated in the present study per variation in the properties. We have demonstrated FIS generation with two types of clustering such as subtractive and grid partition. Corresponding analysis is presented in Table 2. Grid partition is experimented with varying number and types of membership functions. A detail of this experiment conducted is summarized in table 3. Subtractive clustering is experimented with varying range of influence and squash factor, where as accept ratio and reject ratio are kept as constant. In order to find the optimal model, the parameters of the subtractive clustering technique were 0.2-0.8 for range of influence and 1, 1.25 and 1.5 for squash factor. The value of accept ratio and reject ratio were fixed based on MATLAB defaults (0.5 and 0.15, respectively). A detail of this experiment with subtractive clustering is summarized in table.4. Membership function parameters are attuned using backpropagation and hybrid algorithm. The present investigation measured performance of the model with reference to Root Mean Squared Error computed for training, testing and checking dataset. Figures.4(a-d), presents analysis of RMSE for ANFIS-Grid partition clustering with triangular membership function and backpropagation learning experiment conducted.

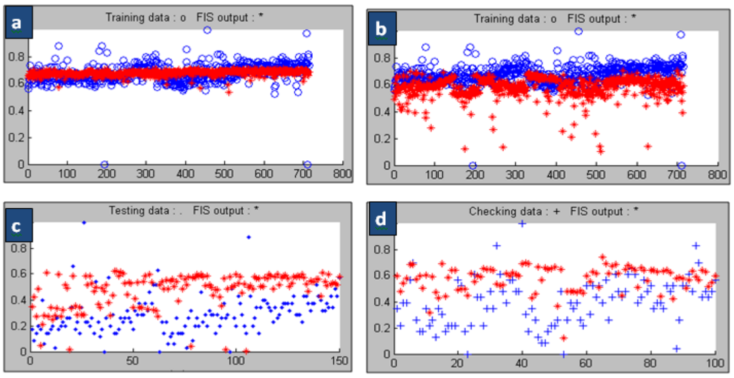

Figure.4. Analysis of RMSE for ANFIS-Grid partition clustering with triangular membership function and backpropagation learning, (a). Training RMSE 0.065219 for 3 membership function; (b). Training RMSE 0.13381 for 2 membership function; (c). Testing RMSE 0.20886 for 5 membership function; (d). Checking RMSE 0.25283 for 2 membership function

The optimized ANFIS structure selected for the earthquake magnitude prediction has fuzzy subtractive clustering (range of influence: 0.2, squash factor: 1.25, accept ratio: 0.5, reject ratio: 0.15) with 70 nodes, eight fuzzy rules and hybrid algorithm is efficient for training the ANFIS model. The performance of ANFIS modelling pertaining to this is shown in figures.5(a-c). Fig.5(a), portrays the RMSE 0.059778 between output of training data and FIS generated output, fig. 5(b) reveals the RMSE 0.40872 between output of testing data and FIS generated output, fig.5(c), reveals the RMSE 0.3214 between output of checking data and FIS generated output which indicates that the application of ANFIS achieved much satisfactory results for predicting earthquakes' magnitude. Using a given input/output dataset, the ANFIS constructed with subtractive clustering whose membership function parameters are adjusted using either a back-propagation algorithm.

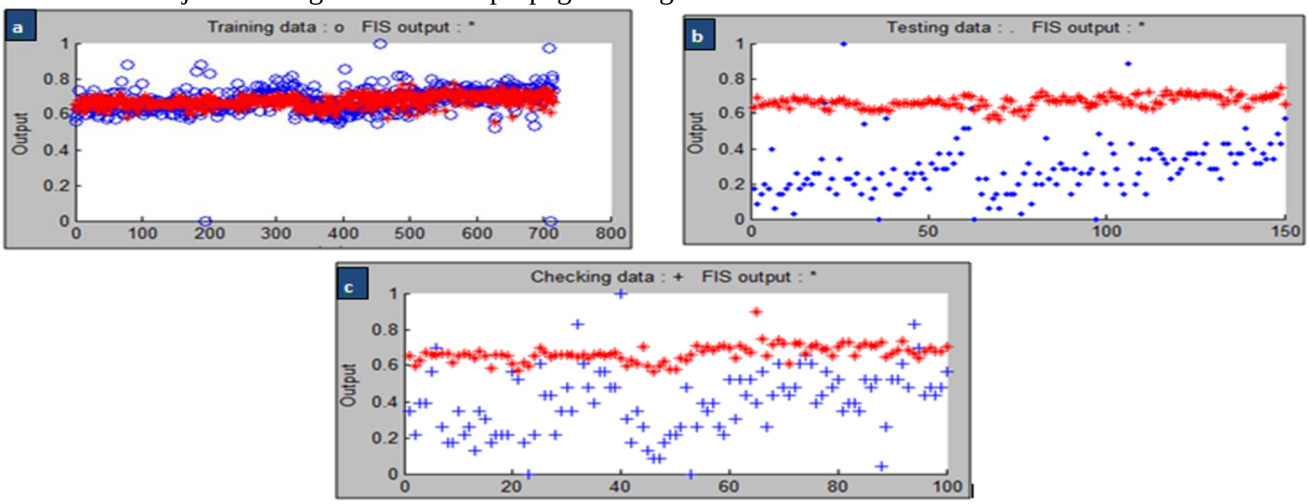

Figure.5. Performance of selected ANFIS modeling. (a) Training error 0.059778; (b)Testing error 0.40872; (c)Checking RMSE 0.3214.

Thus derived ANFIS architecture efficiently predicts future earthquake's magnitude with very less error. We have tested network model with known earthquake events. Table.5, shows the result obtained by applying the new dataset on the derived neural network model. Actual magnitude of the earthquake events and ANFIS computed magnitude are compared. Result concludes that ANFIS prediction is a suitable approach since the resulting analysis is much more accurate and precise.

Table.2. ANFIS description for FIS generation with grid partition and subtractive clustering

ANFIS Info	**Grid Partition**			**Subtractive clustering**				
Number of Membership functions ->	**3**	**5**	**2**	**3**	**4**	**2**	**8**	**13**
Nodes	78	286	34	30	38	22	70	110
Linear parameters	108	500	32	12	16	8	32	52
Nonlinear parameters	18	45	18	18	24	12	48	78
Fuzzy rules	27	125	8	3	4	2	8	13

Table.3. Performance evaluation for Grid partition experiment with

varying number and types of membership functions

No. of Membership Functions	Membership Type	Training Algorithm	Epochs	Error		
				Training	Testing	Checking
3	Trimf	backpropagation	100	0.065219	0.41708	0.31793
		backpropagation	50	0.066668	0.41544	0.31623
		Hybrid	100	0.0631	0.41426	0.33128
		Hybrid	50	0.0631	0.41426	0.33128
	Gaussmf	backpropagation	100	0.066105	0.4231	0.33059
		backpropagation	50	0.066104	0.4232	0.33058
		Hybrid	100	0.065432	0.41948	0.33416
		Hybrid	50	0.065432	0.41948	0.33416
5	Trimf	Backpropagation	50	0.35024	0.20886	0.236536
	Gaussmf	Backpropagation	50	0.22666	0.27172	0.22958
2	Trimf	backpropagation	50	0.13381	0.33985	0.25283
	Gaussmf	Backpropgation	50	0.11683	0.38484	0.307
2	Gaussmf	Back	30	0.066915	0.41867	0.33276

Table.4. Performance evaluation for Subtractive experiment with varying range of Influence and squash factor

range of influence	squash factor	Training Algorithm	Epochs	No. of MF	Error		
					Training	Testing	Checking
0.5	1.25	backpropagation	50	3	0.65155	0.41884	0.32632
			100		0.64943	0.4184	0.32569
		Hybrid	50		0.64799	0.41497	0.32223
			100		0.64799	0.41497	0.32223
	1	backpropagation	100	4	0.063335	0.41747	0.32351
			50		0.06451	0.41941	0.32778
		Hybrid	100		0.062979	0.41611	0.32213
			50		0.062979	0.41611	0.32213
	1.5	Backpropagation	50	2	0.065478	0.42097	0.32999
		Hybrid			0.064759	0.41587	0.32347
0.2	1.25	backpropagation	50	8	0.0609	0.4109	0.32482
		Hybrid			0.059778	0.40872	0.3214
	1	backpropagation	50	13	0.059828	0.4152	0.32763
		Hybrid			0.059028	0.41003	0.32438
0.8	1.25	backpropagation	50	2	0.64998	0.41506	0.3216
	1				0.65804	0.41966	0.32857

Table.5. Comparison between actual output and output obtained in ANFIS model

Latitude	Longitude	Depth	Predicted Magnitude	Obtained Magnitude
10.53	93.3	112	4.7	4.5
12.41	92.83	45	5.2	5.1
12.67	95.54	10	4.8	4.6
11.08	94.53	71	5.1	4.9
10.67	91.72	30	4.4	4.4
10.82	94.51	20	5	4.8
9.69	90.51	10	5.1	5.1
7.8	94.03	10	5.9	5.8
94.27	94.27	33	5.4	5.2

4. CONCLUSION

In this paper, we have reported predicting earthquake magnitude of Andaman-Nikobar islands using ANFIS. The dataset with 956 earthquake events took place between 1st Oct 2004 and 20th Feb 2016 was selected for training the network model. The present study demonstrated optimum ANFIS architecture by experimenting FIS generation and ANN learning technique. The resulted ANFIS architecture has fuzzy subtractive clustering (range of influence: 0.2, squash factor: 1.25, accept ratio: 0.5, reject ratio: 0.15) with 70 nodes, eight fuzzy rules and hybrid algorithm.

Thus derived neural model efficiently predicts future earthquake's magnitude with very less error. Research concludes that intelligent model can be constructed on the basis of ANFIS for the prediction of earthquake magnitude.

REFERENCES

Bystrov D, Westin J, Practice, Neuro-Fuzzy Logic Systems Matlab Toolbox GUI, Retrieved, 2016

Demuth H, Beale M, Neural Network Toolbox for Use with MATLAB, Retrieved, 2015.

Kalita S, Devi M, Barbara A & Talukdar P, Soft Computing Technique for Recognition of Earthquake Precursor from Low Latitude Total Electron Content (TEC) Profiles, International Journal of Computer Applications, 44 (17), 2012, 11-14.

Kamat R.K and Kamath R.S, Visualization of Earthquake Clusters over Space: K-Means Approach, Journal of Chemical and Pharmaceutical Sciences (JCHPS), 10 (1), 2017, 250-253.

Kamath R.S , Design and Development of Soft Computing Model for Teaching Staff Performance Evaluation, International Journal of Engineering Sciences & Research Technology (IJESRT), 3 (4), 2014, 3088-3094.

Karimi, I, Hallermeier E and Meskouris K, A fuzzy-probabilistic earthquake risk assessment system, Soft Comput, 11 (3), 2006, 229-238.

Mansouri B and Hamednia Y, A Soft Computing Method for Damage Mapping Using VHR Optical Satellite Imagery, IEEE Journal of Selected Topics in Applied Earth Observations And Remote Sensing, 8 (10), 2015, 4935-4941.

Mirrashid M, Earthquake magnitude prediction by adaptive neuro-fuzzy inference system (ANFIS) based on fuzzy C-means algorithm, Natural Hazards, 74 (3), 2014, 1577-1593.

Mittal A, Sharma S and Kanungo D.P, A Comparison of ANFIS and ANN for the prediction of Peak Ground Acceleration in Indian Himalayan Region, Proceedings of the International Conf. on SocProS, AISC, 131, 2011, 457–468.

Natick, MATLAB version R2009b, Massachusetts, The MathWorks Inc., 2011.

Shibli M, A Novel Approach to Predict Earthquakes using Adaptive Neural Fuzzy Inference System and Conservation of Energy-Angular Momentum, International Journal of Computer Information Systems and Industrial Management Applications, 3, 2011, 371-390.

Zamani A, Reza M and Safavi A. A, Application of neural network and ANFIS model for earthquake occurrence in Iran, Earth Science Informatics, 6 (2), 2013.