Scenario of Environmental Research and Development
ISBN: 978-93-5346-498-1 Page No. 1-11
Peer-Reviewed Edited Volume Publication Date: 31/12/2018

A Critical Review on Artificial Intelligence on Earthquake Probability Assessment

Ratiranjan Jena, *Biswajeet Pradhan

Centre for Advanced Modelling & Geospatial Information System,

School of Information, Systems and Modelling,

University of Technology Sydney, Australia

*Corresponding Author E-Mail Id: biswajeet24@gmail.com

Abstract: *The application of neural network and hybrid methods of GIS with artificial intelligence is growing exponentially in a huge scale worldwide. To execute a detail description among all the different approaches of artificial intelligence, we need a map of the completely emerging architecture of the principles and applications. In this review, we have critically analysed and discussed various artificial intelligence models to understand their significance in earthquake probability assessment. The review characterised by two important aspects of the AI approaches. Firstly, we have discussed several artificial intelligence models and secondly, analysed their importance in the field of seismology. The review provide a better understanding about the various artificial intelligence techniques that will help the researchers and scientist to apply in a proper scientific way.*

Key Words: *Earthquake; Artificial intelligence; probability assessment; critical review.*

I. INTRODUCTION:

Seismic waves propagation beneath the earth surface generally produce earthquakes. Waves released from the earthquake focus are divided into body and surface waves. The surface waves vertical motion are generally recorded by the installed seismometers in different spatial locations in the world to measure the earthquake properties (Douilly et al., 2013). Seven large tectonic plates are taking parts in the earth tectonic movement. However, around 20 sub-plates are also within the large plates that are continuously moving and creating deformation condition. Ground motions are several types that may occur (Klein 2003). According to the plate tectonics theory, divergence, convergence and transform motion occur along the plate boundaries. When two plates move away from each other, produce divergent plate boundaries (Holtzman and Kendall, 2010). In the convergence phenomena, variable densities of plates move towards each other; and the high-density plate subduct beneath the low-density plate and thereby produced mountains (Tang et al., 2011). Transform plate boundaries develop when the two plates slide past each other (Ekström 2012). The earthquakes that are resulted along these boundaries of divergence, convergence and transformation are characterised by faults (Holtzman and Kendall, 2010). Faults are characterised by stress. Therefore, when the stress release, large energy patterns results that are called as seismic waves or we can say formally seismic activity occurred. Other than faults, there are several other reasons that may cause earthquake such as volcanic activity, mine blasts, nuclear tests etc. The focus point of an earthquake is the point where seismic waves generated and we simply say that earthquake hypocentre (Gershenzon et al., 1993). Earthquake study is a complex scenario because geophysical layers involvement makes more complicated. The actual deformations and alteration of minerals or structure with respect to different period can be analysed through geophysical seismic study. Different earthquake measuring units such as body wave magnitude (Mb), Local Magnitude (ML), Surface wave magnitude (MS), Energy Magnitude (Me), Moment Magnitude (Mw), Duration Magnitude (MD) and Felt Area Magnitude (Fa) are used(Gutenberg and Richter 1956). Different monitoring stations are settled to measure the earthquake parameters. By using geophysical and geological information, the earthquake analysis can be conducted (Plataniotis et al., 1998). Felt magnitude is almost similar to Mb magnitude, as it is computed and checked for any earthquake. There are some unknown computational techniques beside these known units, and the recordings cannot be used for further analysis. These techniques are called as Unknown magnitude (UK) (Bajc et al., 2013; Fry and Grettenberger, 2011; Weldeab 2012; Di Giacomo et al., 2010; Nassir et al., 2012). However, several artificial intelligence techniques are growing in the field of natural hazard analysis and development. Some artificial intelligence techniques are used for the seismic hazard, vulnerability and risk assessment. Therefore, AI is extremely popular for the seismic probability assessment.

Researchers and scientists from all over the world have been adopted different new and hybrid algorithms on the basis of artificial intelligence techniques from the last decade. They have been used to predict the earthquake challenges such as depth, location, magnitude and time. These algorithms and techniques can be include the traditional methods or may produce new algorithm by a hybrid technique along with nature-inspired algorithms. Therefore, in this review we have discussed some well-developed artificial intelligence techniques for the earthquake probability measurement. The reviews are organised as follows; abstract, in section 1introduction and section 2provides review on artificial intelligence for earthquake prediction and finally section 3ended with the conclusions.

II. REVIEW OF ARTIFICIAL INTELLIGENCE FOR EARTHQUAKE PROBABILITY ASSESSMENT

2.1 Feed Forward Neural Network

Feed forward networks are also popularly known as deep feed forward neural networks, or multilayer perceptions (MLPs) (Reyes et al., 2013).The main aim of feed forward neural network is to approximate some function to execute a better scientific analysis and to provide an effective result.

For a classifier, y = f(x;)

Where input is X

and category is Y

For mapping $\mathbf{y} = f(x\mathbf{;}\ \theta)$ and here θas the parameter value that makes the best function approximation. It uses mostly the sigmoid functions such as; logistic functions and generalised logistic functions. It is called as feed forward because the network performs in a forward way from the input of X towards the output of Y. In addition, feed forward neural networks are extended to a broad network that includes feedback connections; recurrent neural networks developed (https://towardsdatascience.com).The network mostly used on Seismic Electric signals, predicts the magnitude probability and future seismic events and provides 80.55% accuracy (Moustra et al., 2011). The details about this neural network can be understood from (Zamani et al., 2012;Mardiyono et al., 2012).

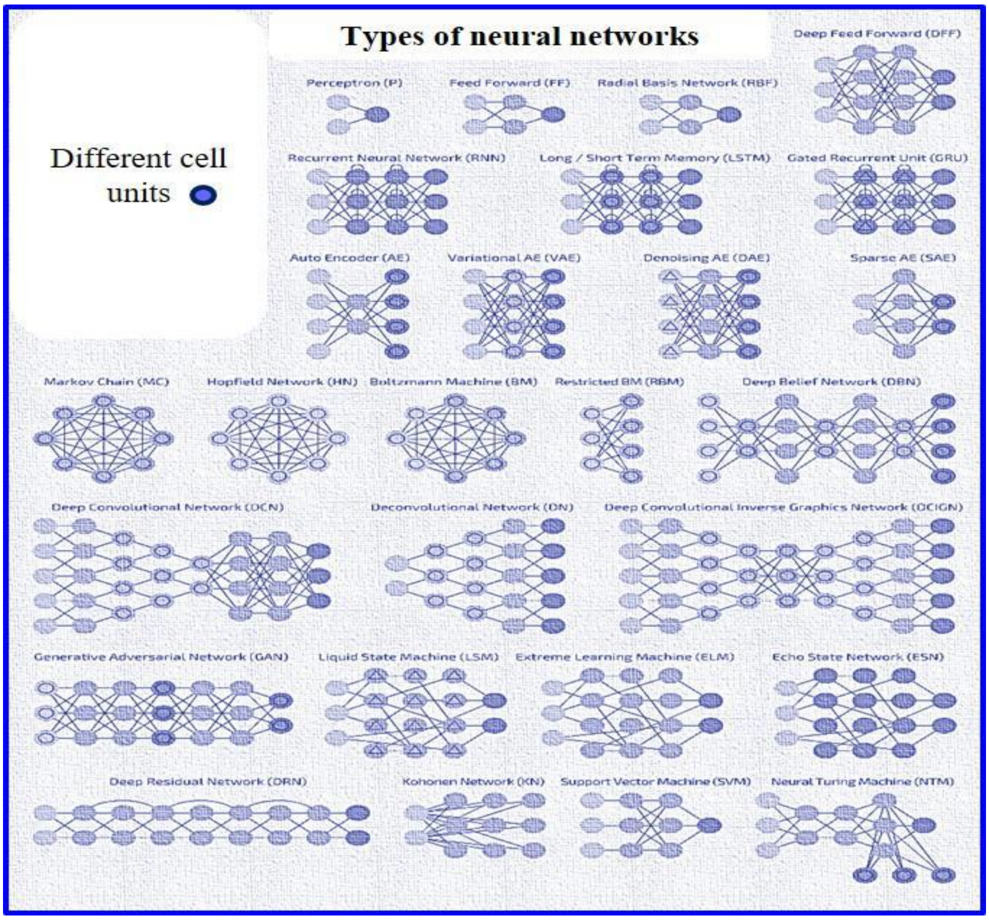

Fig. 1 Different types of neural networks. *Source:* (**https://towardsdatascience.com).**

2.2 Back propagation Neural Network

The back propagation neural network used several equations that provide a way of gradient of the cost function computation process. Back propagate neural network performs in a backward direction from the output side towards the input direction. The algorithm that is behind this network are;

Input x**:** Activation a1setup for the input layer.

Feed forward: For each $L=2,3,\ldots,Ll=2,3,\ldots,L$ compute$z^l=w^l a^l-1+b^l z^l=w^l a^l-1+b^l$ and $a^l=\sigma(z^l)a^l=\sigma(z^l)$ (1)

Output error δL**:** The vector computation $\delta L=\nabla aC\odot\sigma'(zL)\delta L=\nabla aC\odot\sigma'(zL)$ (2)

Back propagate the error: For
each $L=L-1,L-2,\ldots,2l=L-1,L-2,\ldots,2$compute $\delta l=((wl+1)T\delta l+1)\odot\sigma'(zl)\delta l=((wl+1)T\delta l+1)\odot\sigma'(zl)$ (3)

Output: The cost function gradient.

It can be described in different way such as; Back propagation with a single modified neuron and Back propagation with linear neurons**.** Output Error of prediction is propagated with constant ratio in a backward direction to inner

ISBN: 978-93-5346-498-1 Page No. 1-11
Peer-Reviewed Edited Volume Publication Date: 31/12/2018

layers. It provides prediction accuracy up to 71% or little more. The details of this network can be understood clearly from (https://towardsdatascience.com).

2.3 Artificial Bee Colony Algorithm

Several optimization problems that comes in various fields of engineering, GIS, mapping, modelling etc. Effective algorithms of optimization are always required to tackle efficiently the real-world complex problems. In the past years, intelligence algorithms developed based on the behaviours of birds, insects and fishes that were proposed to solve optimization issues. The different types of algorithm are particle swarm optimization (PSO) (Douilly et al., 2013), artificial bee colony (ABC) (Holtzman and Kendall, 2010), ant colony optimization (ACO) (Klein 2003), and firefly algorithm (FA) (Tang et al., 2011). Many recent studies was performed and has shown that ABC provides better result or as much comparable to some other intelligence algorithms significantly. Hybrid strategy can be developed using ABC. This is effective to predict Tsunami intensity. It provides lower mean square error. This algorithm is a part of Swarm Intelligence algorithms is well established with strong root. The details of this can be found in (Li et al., 2013).

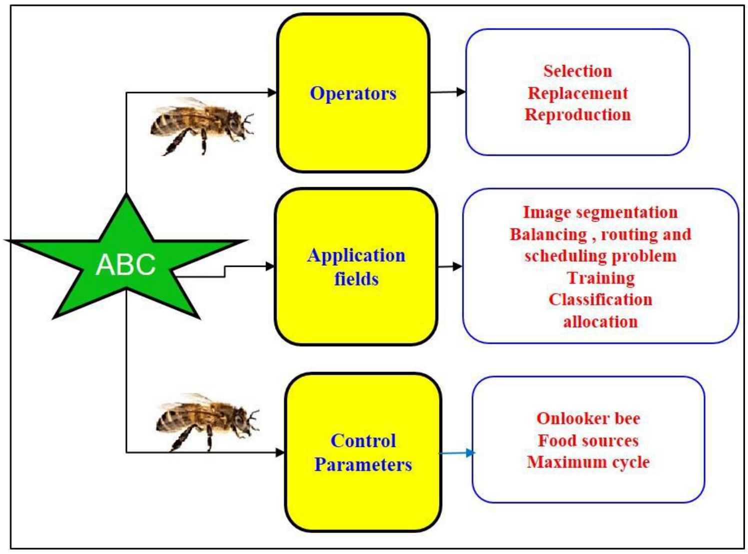

Fig. 2 Represents artificial bee colony algorithm approach. *Source* (Rajan et al., 2015)

2.4 Genetic Algorithm

A genetic algorithm is developed based on the theory of Charles Darwin's natural evolution. Natural selection processes are reflected in the algorithm in which fittest individuals are selected for offspring reproduction of the next generation(Goldberg 1998). The algorithm divided into five different parts that was explained below. Structural formation can be study using genetic algorithm (Nicknam et al., 2010).

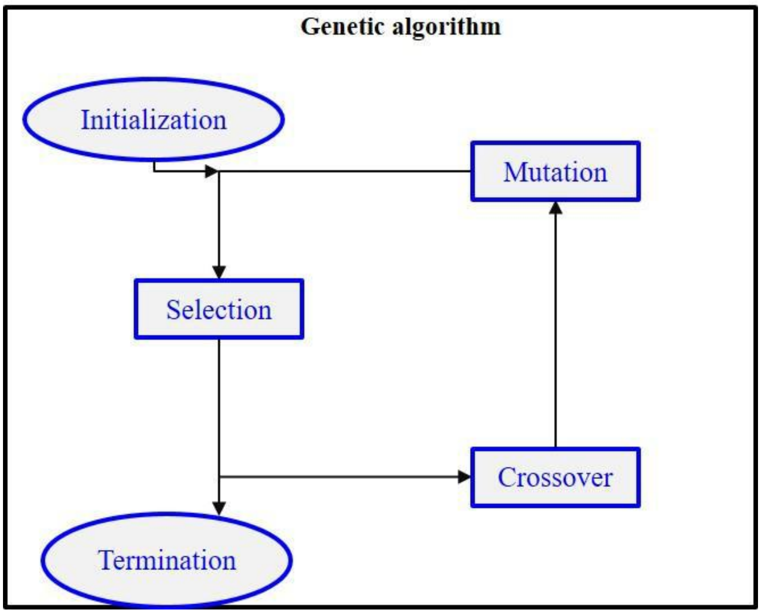

Fig. 3 Genetic algorithm processing steps. Source: (http://www.pohlheim.com).

Lower the uncertainty and mostly used for forecasting after main shocks. This algorithm is specifically used combining together with support vector machines for earthquake for a better analysis. It can be applied to incomplete seismic data. The algorithm is highly efficient in earthquake prediction. Most significantly used in research with different alterations. The detail information about initial population, fitness function, selection, crossover and mutation processes can be found in (Goldberg 1998).

Initial population

The process starts with a Population characterised by set of individuals. Each individual is a solution to the each issue. An individual is characterized by variables called as Genes. However, genes are joined into a line to create Chromosome, which is called as solution. In the genetic algorithm, the set of genes are represented through a string, with different alphabet. Generally, binary values such as one and zeros are used.

Fitness function

The fitness function projects the fitness of an individual to compete with anonymously. It provides a fitness score to every individual for the solution of any problem. The probability of individual selection for reproduction is anonymously based on its fitness score.

Selection

In the phase of selection, it is a necessity to select the individuals those are fittest and passing off their genes to the next generation. Two pairs of individuals should be selected according to the fitness scores. However, high fitness individuals are more effective to be selected for reproduction.

Crossover

Crossover is the phase, which is significantly important in the genetic algorithm. Therefore, each pair parents need to mate and a crossover point randomly chosen within the genes.

Mutation

In some new offspring genes are subjected to a mutation characterise by randomly low probability. The termination of algorithm occurs with the converged population. The genetic algorithm has significantly proposed and produced a set of solutions to each problem.

2.5 Hidden Markov model

Hidden Markov models (HMMs) are the root for preparing sequence labelling probabilistic models of linear problems. These models give a conceptual flowchart for making the complex models of intuitive picture. A diverse range of programs operated by HMMs, including gene finding, multiple sequence alignment, profile searches and regulatory site identification etc.(Chambers et al., 2012)HMMs are characterised by the computational sequence analysis. HMM is applicable to classification of seismic zones (Beyreuther et al., 2012).This model can be applied to identify future changes in a region. HMM is specifically applied to seismic stress patterns for identifying key features, which are difficult to observe in a normal condition. Variations modelling in specific classes can be applied when changes occurs.HMM can also be called as statistical inspired model. This can be applied for time series analysis along with the applications of speech synthesis and recognition (Votsi et al., 2013).

2.6 Fuzzy Logic

Zadeh (1965) that uses one toolkit to execute analysis for the complex problems first proposed the fuzzy logic method. Fuzzy logic is the technique that considers the spatial objects within a map as the members of a set. Classically, in the set theory, an object as a set member that has a membership value of one, or is not a member with a membership value of zero. This method generally applied to seismic data to find out the parameters of earthquakes (Aydin et al., 2009). It is mostly used for the detection of degradation and to prepare maps. It produces results more desirable than Multiple Regression Model (Li et al., 2010). Fuzzy logic is an effective method for various types of hazard assessments. It is capable of dealing with analysing uncertain and incomplete seismic data. Fuzzy logic works on the quantified laws principles that associated with seismic features and the relationships in between (Sen 2011).

2.7 Hybrid Methods

2.7.1 Adaptive Neuro Fuzzy Inference System (ANFIS)

Due to some weak points, GIS analysts try to develop very effective, sophisticated and hybrid methods to sort out the drawbacks of previous methods. For example, ANFIS is one hybrid method which is a composite of artificial neural network (ANN) and fuzzy logic(Schumann et al., 2007)and it is found to be optimal (Tien et al., 2012b). This method needs extremely minimum input as stated by in ANFIS from various experts and provides robust performance, thus appears better and suitable for the seismic studies. From the last two to three decades, progress on various model free techniques such as fuzzy logic and ANNs has been considerably changed. An interesting alternative method produced by these two modelling tools.

2.7.1 Genetic Algorithm-Based Artificial Neural Network (ANN-GA)

GA is one of the biological application that characterised with computational algorithm. This approach was developed to implement for optimum solutions (Goldberg & Kuo, 1987). A genetic algorithm holds the searching capability and it may not provide the best possible solution. It gives a better solution due to the hybrid integration of algorithms that take advantages of both algorithms. Therefore, ANN-GA is a hybrid approach of ANN and genetic algorithm (GA) (Wan & Lei, 2009). The GA sub model characterised by the objective function that is used for weights initialization and biases as explained by(Chau et al., 2005b):

$$min J(W,\theta) = \sum_{i=1}^{p} \left| Y_i - \int (X_i, W, Q) \right| \qquad (4)$$

Where,

W=weight; θ =bias or threshold value; $i =$ data sequence; $p =$ training data pairs; $X_i = i$th input data; $Y_i = i$th measured data; and $\int(X_i, W, \theta)$is simulated output. The main aim of the GA sub model is to minimise the accumulative errors between the simulated and the measured data. This approach is extremely useful for the earthquake prediction and modelling.

2.7.3. Ensemble statistical algorithm

Ensemble technique is a combination of statistics with multiple classifiers that provides better outputs than any single method. Ensemble classification is extremely popular which provides more accurate and reliable results than any individual models applied to any particular field. Such models are extremely powerful to improve the reliability of the prediction results of seismic analysis(Rokach, 2010), however, these methods have not been used in Groundwater domain. The present study proposes few simple and novel ensemble techniques that integrate some types of classifiers. With this integration, it is aimed to enhance the productivity and reliability of previous approaches, to improve their performance, and reduce their weak points. Ensemble statistical algorithm is efficient and cost effective for the earthquake prediction.

2.7.4. Integrated artificial intelligence using RS and GIS

Various studies that has proved the probability of seismic assessment of earthquake prediction by the combination of remote sensing (RS) modeling in GIS environment. In the literature, several approaches with some improvement in methodology have been reported using these techniques such as Pradhan (2010b), Pradhan et al., (2009), Stephens et al., (2012) etc. Although these are able to produce acceptable results with good accuracy, however, contain some weak points that should be improved in future (Matgen et al., 2007).This combined approach of RS and GIS can be applied as a valuable and cost effective technique for the earthquake probability assessment. Therefore, this approach is highly recommendable.

III. CONCLUSION

Artificial Intelligent gains popularity in many fields including remote sensing and GIS based modeling. One of the main reasons of this rise is because of big data and computing performance becomes more powerful than other techniques. New applications may be developed such as remote sensing based visual questioning systems, where questions in natural languages could be asked associated with an image, or a GIS database, and the system can automatically answer the question by using the information in the image, seismic study using spatial analysis, that needs robust methods. This review explained the details of the description of various artificial intelligence models to apply in seismic analysis and provides idea to design a monitoring system for future. It explains the hybrid method for vulnerability and risk modelling of earthquakes within a new framework. The outcome from this review clearly indicates that the development of risk assessment modelling based on probability and uncertainty is possible. In general, this research used remotely sensed data and GIS to analyze natural hazards in terms of detection, modeling and optimization of conditioning factors. This goal can be achieved by having proper analysis to be able to take the proper actions in the case of hazard occurrence to mitigate the damages. This research proposed an easy, accurate and provides understandable earthquake detection method, which recognized the earthquake locations within short period with small budget. In natural hazard and environmental studies, common AI methods such as SVM, ANN, and DT have been widely used; however, new AI methods such as neural networks or ensemble of these models are rarely applied. AI methods aim to improve the accuracy of susceptibility, hazard and risk maps and predictions of future scenarios. The seismic modelling can be done using machine learning and artificial intelligence methods, which indicated the relationship between historical events of particular natural hazard and their contributing factors.

In conclusion, this study proved that AI, statistical and GIS based model could be successfully applied in seismic hazard and risk assessment. This study gives a description of several artificial intelligence techniques that can help in development and future environmental planning. The methods described in this review can provide rapid, accurate and cost-effective results.

IV. ACKNOWLEDGEMENT

Authors would like to acknowledge the University of Technology Sydney for the technical support and special thanks to UTS library for providing the supporting materials to complete this review.

V. REFERENCES

1. Douilly R., Haase J. S., Ellsworth W. L., Bouin M. P., Calais E., Symithe S. J., Armbruster J. G., DeLépinay B. M., Deschamps A. and Mildor S. L. (2013). Crustal Structure and Fault Geometry of the 2010 Haiti Earthquake from Temporary Seismometer Deployments, *Bulletin of the Seismological Society of America,103(4),*2305-2325.
2. Klein E. M. (2003). Geochemistry of the Igneous Oceanic Crust. *Treatise on Geochemistry, 3,* 433-463.
3. Holtzman B. K. and Kendall J. (2010). *Organized melt, seismic anisotropy, and plate boundary lubrication, Geochemistry, Geophysics, Geosystems,11(12),* 1-29.
4. Tang C.-C., Zhu L., Chen C.-H. and Teng T.-L. (2011). Significant crustal structural variation across the Chaochou Fault, southern Taiwan: New tectonic implications for convergent plate boundary, *Journal of Asian Earth Sciences,41(6),* 564-570.
5. Ekström L. R. S. G. (2012). Earthquakes along Eltanin transform system, SE Pacific Ocean: fault segments characterized by strong and poor seismic coupling and implications for long-term earthquake prediction, *Academic Commons, Columbia University,*188.
6. Gershenzon N. I., Gokhberg M. B. andYunga S. ((1993). On the electromagnetic field of an earthquake focus. *Physics of the earth and planetary interiors,*77(1), 13-19.
7. Plataniotis K. N., Katsikas S. K., Lainiotis D. G. and Venetsanopoulos A. N. (1998). Optimal seismic deconvolution: Distributed algorithms,Geoscience and Remote Sensing. *IEEE Transactions, 36(3),* 779-792.
8. Gutenberg B. and Richter C. F. (1956). Magnitude and energy of earthquakes. *Annals of Geophysics,9(1),* 1-15.
9. Fry B. and Gerstenberger M. (2011).Large apparent stresses from the Canterbury earthquakes of 2010 and 2011. *Seismological Research Letters,82(6),* 833-838.
10. Bajc J., Zaplotnik Ž., Živčić M. and Čarman M. (2013). Local magnitude scale in Slovenia. Advances *in Geosciences, 34(34)*, 23-28.
11. Weldeab S. (2012). Timing and magnitude of equatorial Atlantic surface warming during the last glacial bipolar oscillation. *Climate of the Past,8(5),* 1705-1716.
12. Di Giacomo D., Parolai S., Bormann P., Grosser H., Saul J., Wang R. and Zschau J. (2010). Suitability of rapid energy magnitude determinations for emergency response purposes. *Geophysical Journal International,180(1*), 361-374.
13. Nassir S. A. Saad A.-H. and Aref L. (2012). Duration magnitude calibration of Kuwait national seismic network. *Scientific Research and Essays, 7(4),* 453-459.

14. Reyes J., Morales-Esteban A. and Martínez-Álvarez F. (2013). Neural networks to predict earthquakes in Chile. *Applied Soft Computing, 13(2)*, 1314-1328.
15. Moustra M., Avraamides M. and Christodoulou C. (2011). Artificial neural networks for earthquake prediction using time series magnitude data or Seismic Electric Signals. *Expert systems with applications,38(12)*, 15032-15039.
16. Zamani A. S. (2012). Response Prediction of Earthquake motion using Artificial Neural Networks. *International Journal of Applied Research in Computer Science and Information Technology,1(2),* 50-57.
17. Mardiyono M., Suryanita R. and Adnan A. (2012). Intelligent monitoring system on prediction of building damage index using artificial neural network. *TELKOMNIKA Indonesian Journal of Electrical Engineering,10(1)*,155-164.
18. Li H., Li J. and Kang F. (2013). Application of the artificial bee colony algorithm-based projection pursuit method in statistical rock mass stability estimation. *Environmental Earth Sciences,68(8)*,2337-2345.
19. Guo X.-D., Tian J., Wang W., WangZ.-T. and Ma D.-H. (2011). Method for Building Settlements Prediction Due to Earthquake Liquefaction Based on GA-SVR [J]. *Journal of Beijing University of Technology,6*, 005.
20. Goldberg D. E. and Holland J. H. (1988). Genetic algorithms and machine learning. *Machine learning,3*(2), 95-99.
21. Nicknam A., Abbasnia R., Bozorgnasab M. and Eslamian Y. (2010). Synthesizing strong motion using empirical Green's function and genetic algorithm approach. *Journal of Earthquake Engineering,14(4)*, 512-526.
22. Chambers D. W., Baglivo J. A., Ebel J. E. and Kafka A. L. (2012). Earthquake forecasting using hidden Markov models. *Pure and applied geophysics, 169*(4), 625-639.
23. Beyreuther M., Hammer C., Wassermann J., Ohrnberger M. and Megies T. (2012). Constructing a Hidden Markov Model based earthquake detector: application to induced seismicity. *Geophysical Journal International,189(1),* 602-610.
24. Votsi I., Limnios N., Tsaklidis G. and Papadimitriou E. (2013). Hidden Markov models revealing the stress field underlying the earthquake generation. *Physica A: Statistical Mechanics and its Applications,392(13)*,2868-2885.
25. Aydin I. K., M.; Akin, E. (2009). The Prediction Algorithm Based on Fuzzy Logic Using Time Series Data Mining Method. *World Academy of Science: Engineering & Technolog,51*, 91.
26. Li X E. M., Lim Bs, Zhou Jh, Gan Op, Rutkowski L. (2010). Fuzzy regression modeling for tool performance prediction and degradation detection. *Int J Neural Syst,5*, 405-424.
27. Şen Z. (2011). Supervised fuzzy logic modeling for building earthquake hazard assessment, *Expert systems with applications, 38(12)*, 14564-14573.

28. Schumann, G, Matgen, P, Hoffmann, L, Hostache, R, Pappenberger, F, &Pfister, L. (2007). Deriving distributed roughness values from satellite radar data for Groundwater inundation modelling. *Journal of Hydrology, 344(1)*, 96-111.
29. Tien Bui, Dieu, Pradhan, Biswajeet, Lofman, Owe, &Revhaug, Inge. (2012). Landslide susceptibility assessment in vietnam using support vector machines, decision tree, and Naive Bayes Models. *Math. Probl. Eng.* doi: http://dx.doi.org/10.1155/2012/974638
30. Goldberg, David E, &Kuo, Chie Hsiung. (1987). Genetic algorithms in pipeline optimization. *Journal of Computing in Civil Engineering, 1(2)*, 128-141
31. Chau, KW, Wu, CL, & Li, YS. (2005). Comparison of several Groundwater forecasting models in Yangtze River. *J HydraulEng, 10(6)*, 485-491.
32. Rokach, Lior. (2010). Ensemble-based classifiers. *Artificial Intelligence Review, 33*(1-2), 1-39.
33. Pradhan, B, Shafiee, M, &Pirasteh, S. (2009). Maximum Groundwater prone area mapping using RADARSAT images and GIS: Kelantan river basin. *Int. J. Geoinformatics., 5*, 11.
34. Pradhan, Biswajeet. (2010). Groundwater susceptible mapping and risk area delineation using logistic regression, GIS and remote sensing. *J. Spatial. Hydrol*., 9.
35. Stephens, E M, Bates, P D , Freer, J E, & Mason, D C. (2012). The impact of uncertainty in satellite data on the assessment of Groundwater inundation models. *J. Hydrol., 414*, 162-173.
36. Matgen, Patrick, Schumann, G, Henry, J B, Hoffmann, Lucien, &Pfister, Laurent. (2007). Integration of SAR-derived river inundation areas, high-precision topographic data and a river flow model toward near real-time Groundwater management. *Int. J. Appl. Earth Obs. Geoinf., 9*, 247-263.
37. https://towardsdatascience.com, retrieved 28th Sep, 2018.