Expert System for Earthquake Prediction

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Earthquake is one of the most hazardous natural calamity. Many algorithms have been proposed for earthquake prediction using expert systems (ES). We aim to identify and compare methods, models, frameworks, and tools used to forecast earthquakes using different parameters. The analysis shows that most of the proposed models have attempted long term predictions about time, intensity, and location of future earthquakes. An investigation on different variants of rule-based, fuzzy, and machine learning based expert systems for earthquake prediction has been presented. Moreover, the discussion covers regional and global seismic data sets used, tools employed, to predict earth quake for different geographical regions. Bibliometric and meta-information based analysis has been performed by classifying the articles according to research type, empirical type, approach, target area, and system specific parameters.

Keywords: Fuzzy Expert System ; Machine Learning ; Neural Network

1. Fuzzy Expert System (FES)

The concepts of fuzzy set and fuzzy logic were introduced in 1965 by[1]. Fuzzy expert system accepts input as crisp variables and converts it into fuzzy variables. Fuzzy inference engine applies the rules suggested by an expert to formulate the knowledge base. Fuzzy variables combined with linguistic variables to generate membership functions. Techniques based on Fuzzy logic have the benefits over multiple procedures due to their ability to combine with linguistic variables. These fuzzy variables would be converted back into the crisp variable to generate output through the process called defuzzification. Fuzzy logic is more suitable in the situations where a greater number of uncertainties have been involved, such as, earthquake prediction and in the scenarios where an approximate but quick solution is required. Fuzzy logic is not a logic that is fuzzy itself, but a logic that can be used to demonstrate fuzziness[2]. The vagueness of fuzzy logic has been highlighted in[3] by examining the events that cannot be recorded statistically such as crack in the undergroundfault, etc. A new attenuation relationship has been proposed in[4] using three fuzzy input sets including epicentral distance, earthquake magnitude and intensity using earthquake data set of Taiwan and United states of America (USA). A normalized fuzzy ground motion model has been demonstrated using a rational design tool through a combination of natural language with seismic data statistics to quantify response frequency. The earthquake pattern in the Zagros range has been examined in[5] using fuzzy rule-based ES model for some earthquakes. The proposed model has been evaluated using the Molchan statistical procedure by comparing complicated reasoning procedure of the forecasting model with knowledge simulation provided by human experts using the datasets of Iran. A rock burst forecasting model has been presented in[6] by studying the seismic features of coal mining in China. In this study, Gaussian shaped membership function has been combined with the exponential distribution function using reliability theory. The comprehensive forecasting result was obtained by integrating the maximum membership degree principle (MMDP) and the variable fuzzy pattern recognition (VFPR) method. The performance of the proposed model has been evaluated using seismic data collected over the period of four months. The proposed model has been able to forecast the rock burst incident in the coal mine of China. Multiple algorithms have been combined for development of the hybrid prediction model[7][8]. Ionospheric disturbance has been examined in [26]and a fuzzy logic-based gradient descent method has been proposed to forecast the ionospheric change parameters. The gradient descent estimated values were used to tune the membership function. The satisfactory performance has been observed during evaluated of the proposed model using data collected from two geomagnetic storms on the low latitude.[9] has claimedearthquake prediction on the bases of the classification of seismicsignals.

2. Rule Based Expert System (RBES)

In RBES domain knowledge is represented by a set of rules and the current situation is presented with the set of facts stored in the database. An inference engine is responsible to match the rule with the fact. The fired rule may change the set of facts and add new facts. Many researchers have used rule based expert system for earthquake prediction. A belief rule based expert system has been presented in[10] to predict the earthquake under uncertainty. Specific animal behavior in response to environmental and chemical changes has been examined for earthquake prediction.[1] developed rules from historical earthquake data using predicate logic. These rules have been mathematically validated on real time data. Prediction is performed through RBES that takes current earthquake attributes for prediction of future earthquake.

3. Neuro Fuzzy Expert System (NFES)

Fuzzy logic is combined with neural networks to develop expert systems. Fuzzy logic provided a high level reasoning procedure by including domain information from the domain expert and neural network has been used to develop low level computational structures. The Neuro fuzzy expert system has been used in many articles to analyze multiple aspects of data for earthquake predictions.[11] combined grid partition, subtractive clustering and fuzzy C-means (FCM) for the development of models using NFES structure.[12] applied NFES to compute land sliding susceptibility using statistical index (WI).[13] collected geographical information to pass through six different membership functions for measuring land sliding susceptibility using NFES. Many researchers have analysed combination of artificial neural network and fuzzy inference system[14][15][16][17]. Earthquake attribute such as magnitude, depth, longitude and latitude has been studied in[18] to provide input to NFES for computation of the future earthquake.

4. Machine Learning (Ml)

Machine Learning has been widely used for making earthquake predictions due to their ability to improve over time. With the huge amount of earthquake instrumental data, machine learning approaches are capable enough to improve efficiency and accuracy in earthquake prediction. Multiple machine learning methods including, Artificial Neural Network (ANN), Support Vector machine (SVM), K-nearest neighbour (KNN), Native Bayes (NB) and random forest algorithms have been exercised for earthquake prediction. [19] applied Artificial Neural Networks, Support Vector Machines and Random Forests to perform temporal investigations on earthquake catalogue of Cyprus region and calculated sixty seismic indictors for making short term earthquake prediction.[20] applied different machine learning algorithms namely support vector machine (SVM), K-nearest neighbor (KNN), random forest (RF), and Naïve Bayes (NB) algorithms in R programming language for earthquake prediction using seismic dataset of India. [21] studied the thermal anomalies that happened before the earthquake occurred in Imphal, India, in 2016 and investigated multiple seismic facts through satellite data using machine learning algorithms for an earthquake.[22] collected records of aftershocks of the Kermanshah (Iran) Earthquake and applied different machine learning (ML) algorithms, including Naive Bayes, k-nearest neighbors, a support vector machine, and random forests to predict future earthquakes by observing aftershock patterns.[23] exercised neural networks for earthquake signal detection. [24] listed the detailed description of the monitoring techniques used for earthquake prediction.[25][26] presented a comprehensive review of machine learning methods used for earthquake prediction.[27] made seismic hazards forecasts by using two different machine learning based methods for both spatial and space-time prediction of strong earthquakes.[28] determined the significance of shallow land slide triggers in making earthquake forecasts using machine learning methods.[29] improved the conventional waveform correlation method and presented a new method for detection of seismic signals for monitoring the false alarms using machine learning. [30] identified, classified and reviewed the prominent machine/deep learning models used in energy systems. [31] discussed multiple artificial intelligent models utilized for hydrologic model prediction in past decade. [32] highlighted the opportunities and challenges presented by big data for informed decision-making.[33] developed a food forecast model using multiple optimization methods.

References

1. Aqdas Ikram; Usman Qamar; A rule-based expert system for earthquake prediction. *Journal of Intelligent Information Systems* **2014**, *43*, 205-230, 10.1007/s10844-014-0316-5.
2. Saeed Ghorbani; Morteza Barari; Mojtaba Hoseini; Presenting a new method to improve the detection of micro-seismic events. *Environmental Monitoring and Assessment* **2018**, *190*, 464, 10.1007/s10661-018-6837-6.
3. Manuel Jesús Fernández-Gómez; G. Asencio-Cortés; A. Troncoso; Francisco Martínez-Álvarez; Large Earthquake Magnitude Prediction in Chile with Imbalanced Classifiers and Ensemble Learning. *Applied Sciences* **2017**, *7*, 625, 10.3390/app7060625.
4. Abraham Ahumada; Abdusselam Altunkaynak; Ashraf Ayoub; Fuzzy logic-based attenuation relationships of strong motion earthquake records. *Expert Systems with Applications* **2015**, *42*, 1287-1297, 10.1016/j.eswa.2014.09.035.
5. Sedigheh Farahi Ghasre Aboonasr; Ahmad Zamani; Fatemeh Razavipour; Reza Boostani; Earthquake hazard assessment in the Zagros Orogenic Belt of Iran using a fuzzy rule-based model. *Acta Geophysica* **2017**, *65*, 589-605, 1

0.1007/s11600-017-0055-4.

6. Wu Cai; Linming Dou; Min Zhang; Wenzhuo Cao; Ji-Quan Shi; Longfei Feng; A fuzzy comprehensive evaluation methodology for rock burst forecasting using microseismic monitoring. *Tunnelling and Underground Space Technology* **2018**, *80*, 232-245, 10.1016/j.tust.2018.06.029.
7. Tahernia, N. Fuzzy-Logic Tree Approach for Seismic Hazard Analysis. Int. J. Eng. Technol. 2014, 6, 182–185.
8. Wang, S.; Liu, H.; Wang, S.; Tong, S.; Wang, R. Pseudo-acoustic inversion method and its application. In Proceedings of the 2010 Seventh International Conference on Fuzzy Systems and Knowledge Discovery, Yantai, China, 10–12 August 2010; Volume 2, pp. 598–601.
9. El Hassan Ait Laasri; Es-Saïd Akhouayri; Dris Agliz; Daniele Zonta; Abderrahman Atmani; A fuzzy expert system for automatic seismic signal classification. *Expert Systems with Applications* **2015**, *42*, 1013-1027, 10.1016/j.eswa.2014.08.023.
10. Hossain, M.S.; Al Hasan, A.; Guha, S.; Andersson, K.; A Belief Rule Based Expert System to Predict Earthquake under Uncertainty. *J. Wirel. Mob. Netw. Ubiquitous Comput. Dependable Appl.* **2018**, *9*, 26–41, .
11. Masoomeh Mirrashid; Earthquake magnitude prediction by adaptive neuro-fuzzy inference system (ANFIS) based on fuzzy C-means algorithm. *Natural Hazards* **2014**, *74*, 1577-1593, 10.1007/s11069-014-1264-7.
12. Iman Nasiri Aghdam; Mohammad Hossein Morshed Varzandeh; Biswajeet Pradhan; Landslide susceptibility mapping using an ensemble statistical index (Wi) and adaptive neuro-fuzzy inference system (ANFIS) model at Alborz Mountains (Iran). *Environmental Earth Sciences* **2016**, *75*, 1-20, 10.1007/s12665-015-5233-6.
13. Omid Ghorbanzadeh; Hashem Rostamzadeh; Thomas Blaschke; Khalil Gholaminia; Jagannath Aryal; A new GIS-based data mining technique using an adaptive neuro-fuzzy inference system (ANFIS) and k-fold cross-validation approach for land subsidence susceptibility mapping. *Natural Hazards* **2018**, *94*, 497-517, 10.1007/s11069-018-3449-y.
14. Abayon, R.C.; Apilado, J.R.; Pacis, D.B.; Chua, M.G.; Aguilar, A.V.; Calim, J.; Padilla, S.M.A.; Puno, J.C.S.; Apsay, M.R.B.; Bustamante, R. A Weather Prediction and Earthquake Monitoring System. In Proceedings of the 2018 IEEE Conference on Systems, Process and Control (ICSPC), Malacca, Malaysia, 14–15 December 2018; pp. 203–208.
15. Shibli, M. A novel approach to predict earthquakes using adaptive neural fuzzy inference system and conservation of energy-angular momentum. Int. J. Comp. Inf. Syst. Ind. Manag. Appl. 2011, 2150, 371–390.
16. Torres, V.M.; Castillo, O. A Type-2 Fuzzy Neural Network Ensemble to Predict Chaotic Time Series. In Studies in Computational Intelligence; Springer: Berlin/Heidelberg, Germany, 2015; Volume 601, pp. 185–195.
17. Tosunoğlu, N.G.; Apaydin, A. A New Spatial Algorithm Based on Adaptive Fuzzy Neural Network for Prediction of Crustal Motion Velocities in Earthquake Research. Int. J. Fuzzy Syst. 2018, 20, 1656–1670.
18. Kamath, R.S.; Kamat, R.K.; Earthquake Magnitude Prediction for Andaman-Nicobar Islands: Adaptive Neuro Fuzzy Modeling with Fuzzy Subtractive Clustering Approach. *J. Chem. Pharm. Sci.* **2017**, *10*, 1228–1233, .
19. Khawaja M. Asim; Sayed S.R. Moustafa; Iftikhar Azim Niaz; Eslam Elawadi; Talat Iqbal; F. Martínez-Álvarez; Seismicity analysis and machine learning models for short-term low magnitude seismic activity predictions in Cyprus. *Soil Dynamics and Earthquake Engineering* **2020**, *130*, 105932, 10.1016/j.soildyn.2019.105932.
20. Vasti, M.; Dev, A. Classification and Analysis of Real-World Earthquake Data Using Various Machine Learning Algorithms. In Lecture Notes in Electrical Engineering; Springer: Singapore, 2019; pp. 1–14
21. Mukhopadhyay, U.K.; Sharma, R.N.K.; Anwar, S.; Dutta, A.D. Correlating Thermal Anomaly with Earthquake Occurrences Using Remote Sensing; Springer: Berlin/Heidelberg, Germany, 2019; pp. 863–875.
22. Sadra Karimzadeh; Masashi Matsuoka; Jianming Kuang; Linlin Ge; Spatial Prediction of Aftershocks Triggered by a Major Earthquake: A Binary Machine Learning Perspective. *ISPRS International Journal of Geo-Information* **2019**, *8*, 462, 10.3390/ijgi8100462.
23. Zheng Zhou; Youzuo Lin; Zhongping Zhang; Yue Wu; Paul Johnson; Earthquake Detection in 1D Time-Series Data with Feature Selection and Dictionary Learning. *Seismological Research Letters* **2019**, *90*, 563-572, 10.1785/0220180315.
24. Fabio Corbi; L. Sandri; Jonathan Bedford; Francesca Funiciello; S. Brizzi; Matthias Rosenau; S. Lallemand; Machine Learning Can Predict the Timing and Size of Analog Earthquakes. *Geophysical Research Letters* **2019**, *46*, 1303-1311, 10.1029/2018gl081251.
25. Kong, Q.; Trugman, D.T.; Ross, Z.E.; Bianco, M.; Meade, B.J.; Gerstoft, P. Machine Learning in Seismology: Turning Data into Insights. Seism. Res. Lett. 2018, 90, 3–14.
26. Galkina, A.; Grafeeva, N. Machine Learning Methods for Earthquake Prediction: A Survey. In Proceedings of the Fourth Conference on Software Engineering and Information Management (SEIM-2019), Saint Petersburg, Russia, 13 April 2019; full papers. p. 25.

27. Valeri G. Gitis; Alexander B. Derendyaev; Machine Learning Methods for Seismic Hazards Forecast. *Geosciences* **2019**, *9*, 308, 10.3390/geosciences9070308.
28. Al-Najjar, H.A.H.; Kalantar, B.; Pradhan, B.; Saeidi, V. Conditioning factor determination for mapping and prediction of landslide susceptibility using machine learning algorithms. In Earth Resources and Environmental Remote Sensing/GIS Applications X; International Society for Optics and Photonics: California, CA, USA, 2019; Volume 11156, p. 111560K.
29. Tyler Ganter; Amy Sundermier; Sanford Ballard; Alternate Null Hypothesis Correlation: A New Approach to Automatic Seismic Event Detection. *Bulletin of the Seismological Society of America* **2018**, *108*, 3528-3547, 10.1785/0120180074.
30. Amir Mosavi; Mohsen Salimi; Sina Faizollahzadeh Ardabili; Timon Rabczuk; Shahaboddin Shamshirband; Annamaria R. Varkonyi-Koczy; State of the Art of Machine Learning Models in Energy Systems, a Systematic Review. *Energies* **2019**, *12*, 1301, 10.3390/en12071301.
31. Amir Mosavi; Pinar Ozturk; Kwok-Wing Chau; Flood Prediction Using Machine Learning Models: Literature Review. *Water* **2018**, *10*, 1536, 10.3390/w10111536.
32. Adrienn Dineva; Amir Mosavi; Sina Faizollahzadeh Ardabili; Istvan Vajda; Shahaboddin Shamshirband; Timon Rabczuk; M.H. Ahmadi; Review of Soft Computing Models in Design and Control of Rotating Electrical Machines. *Energies* **2019**, *12*, 1049, 10.3390/en12061049.
33. Saeed Nosratabadi; Amirhosein Mosavi; Shahaboddin Shamshirband; Edmundas Kazimieras Zavadskas; Andry Rakotonirainy; Kwok-Wing Chau; Sustainable Business Models: A Review. *Sustainability* **2019**, *11*, 1663, 10.20944/preprints201810.0378.v3.

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