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A REVIEW OF OPERATIONAL EARTHQUAKE FORECASTING METHODOLOGIES USING LINGUISTIC FUZZY RULE-BASED MODELS FROM IMPRECISE DATA WITH WEIGHTED REGRESSION APPROACH

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Abstract: It is, by now, well recognized that earthquake disaster analysis always yields some amount of "impreciseness" or "vagueness" or "fuzziness" due to heterogeneity in the underlying phenomenon, and/or explanatory variables, and/or response variable. Therefore, for a more realistic modelling, there is a need to incorporate this aspect in traditional models like weighted linear regression models. The present paper analytically examines some of the modern seismological earthquake algorithms used for analyzing seismo-electro-telluric-geodetic data used across the globe. The main techniques discussed are probabilistic models, precursor models, neural networks, active fault models, bayesian belief network and decision trees which provide primary solutions to the problems inherent in the prediction of earthquakes. In the study for earthquake occurence as we encounter multiple variables processes having mutual contact and mutual attributes we have devised a procedure for finding quantitative relationship estimated by missing values and coarsely discretized data value and the total error of the sample data between these variables through weighted regression.The objective of the study is interpreting the spatio-temporal properties of geographical objects with the help of regression equations and fuzzy rules for finding interconnectedness among the attributes for underlying physical phenomena of seismic behavior. We would conclude with a summary and some thoughts on future research in the area.

KEYWORDS: Earthquakes, precursors, soft computing, prediction, algorithms, fuzzy analysis, regression, best-fit, rule induction.

Introduction

Earthquake prediction is one of the most important unresolved problems in geosciences. Several researchers of the world, including Indian researchers have been actively involved in earthquake precursors and prediction studies using multi-disciplinary tools and techniques without a common consensus on any of sound methodologies that can predict the earthquake (Gupta, 1992; Mishra, 2012). Many researchers across the world especially of U.S.A [Shimazaki and Stuart, 1985; Dmowska,1997], Japan [Asada, 1982], Italy [Dragoniand Boschi 1992], Turkey [Vogel and Itsikara, 1982], China [Shih-jung, 1993], Netherlands [Kisslinger, 1986], India [Guha and Patwardhan, 1985] have long been monitoring earthquake patterns and clusters. Over the past decade, earthquake prediction research [Kellis Borok and Soloviev, 2003] has been revitalized and predictability experiments are currently active worldwide. Periodic variations in the earth's variations of electrical and magnetic fields at the Earth's surface. Operational earthquake forecasting techniques has been rejuvinated with the advent of new seismic monitoring resources and instrumentation. The recent decade has been rife with optimistic outcomes or even marred by total disappointments [Geller, 1997].

Some of the researchers have also established earthquake occurrence to be completely unpredictable by nature [Geller *et al.,* 1997] with the deterministic localization of a future event in a narrow time window as highly improbable. However, to validate the relevance of earthquake algorithms, there is a need to establish the trustworthiness of the space-time forecasting scale of prediction algorithms. Gupta (1988) and Gupta and Singh (1989) successfully identified earthquake precursors based on earthquake quiscence, swarm and cluster analyses in the Northeast India, which happened in the given window of time, depth and magnitude (Gupta, 1988), however, the technique was confined to the area under NE India. Studies made by Gupta (2001; 2007) indicated that reservoir induced earthquake forecast may appear feasible at Koyna, India, through rigorous monitoring of reservoir induced seismicity and its rupture nucleation, which is considered as the milestone in the field of earthquake precursor versus prediction study for the region. These studies by Gupta (1988, 2001, 2007) clearly suggested the quality of seismological data and sound algorithm for data analyses along with comprehensive interpretational skill can play important role in identifying the plausible operational earthquake forecasting methodology for different tectonic zones. The strategic [Molchan, 1990] system of earthquake prediction algorithm design and implementation need certain computational evaluator framework model as [Mohsin and Azam, 2011] based on Fuzzy systems can be designed by learning from examples used in seismic prediction and pre-warning of time series of the earth quakes of maximum magnitude that provides expert knowledge/hypotheses about the geodynamic regional models validation of space and temporal data analysis. Excellent progress has also been made in understanding the shorter-term, smaller-scale processes that control earthquake nucleation and rupture dynamics.

The physics of earthquakes significant to prediction [Main, 1995, 1996, 1999] covers a broad range of topics characteristic of the genesis mechanism, structure of lithosphere and local tectonic regimes. There is a need for time-dependent hazard [Reiter, 1991] assessment relative to seismogenesis mechanism. Researchers can study the relation between the time of occurrence of the earthquake and the precursor. Earthquake prediction might be approached by a step by step prediction technique involving analysis of the multi-scale interaction and increase of seismic activity before the main rupture. Statistical distributions of earthquake sizes, earthquake temporal interactions, spatial patterns and focal mechanisms are largely universal. The paper is organized as follows: first, various earthquake algorithms are discussed; second, the method for classifying techniques based on computational approaches is elaborated; third, regression analysis method based on fuzzy extension of belief function theory to analyze this data is demonstrated and finally, the conclusion of the study are discussed.

General Scheme of Prediction in Earthquake Algorithm

The dynamics of the lithosphere from the point of decision making involves a relevant field in a certain area prior to time of occurrence of event based on spatio-temporal patterns of seismicity [Dutta *et al.*,2012]. The first is to find a deterministic signal, or pattern of signals, in $I(t)$ that can predict future earthquakes; i.e., to identify a diagnostic precursor that ensures with high probability that a target event will occur in a specific sub-domain. The second approach is to cast deterministic predictions based on probabilistic forecasts. If the probability of a target event during a fixed forecasting interval is $P(t)$, the decision rule might be to cast a regional alarm for the subsequent interval whenever this time-dependent probability exceeds some threshold value $P0$. If the probability model is accurate, the consequence of choosing a higher or lower threshold can be evaluated in terms of the anticipated false-alarm and failure-to-predict error rates. However, if $P(t)$ is low at all times, which is typical in forecasting large earthquakes over short periods, at least one of the prediction error rates will always be high, regardless of the decision rule. Such predictions always contain less information than the forecasts from which they were derived.

Consequently, for most decision-making purposes, probabilistic forecasting provides a more complete description of prospective earthquake information than deterministic prediction. Fuzzy membership functions in this method of analysis plays a significant role as we can establish intrinsic feature of a system model, but it will vary with the information that conditions the state of the system. On the other hand, it is found that premonitory increase of the earthquakes' correlation range; these chains are the dense, long, and rapidly formed sequences of small and medium earthquakes. The components of soft computing include neural networks, fuzzy systems, evolutionary computation and swarm intelligence. Many of these soft computing methods are used for earthquake prediction (Figure 1). In this paper we have designed using catalog of functions fm is finite, because there is also a finite number of sets Am and Bm for classical regression problem based on a real data set, the scalar input *x* represents the time (in milliseconds) after a simulated impact of a earthquake as a space time hazard. The response variable *y* is the magnitude of earthquake occurrence due to sub surface strain change.

The purpose of this study is to improve the state of knowledge, through a parametric search of earthquake algorithms for the purpose of aiding decision makers in reducing seismic hazards. Evaluation of strong clustering through spatial and time series analysis, corresponding to foreshocks, aftershocks and occasionally large-earthquake pairs. They determine that fault system geometry acts as the primary control of earthquake recurrence statistics. The system also involves the computational fault system earthquake simulators [Rundle *et al.,* 2000] to define the empirical probability

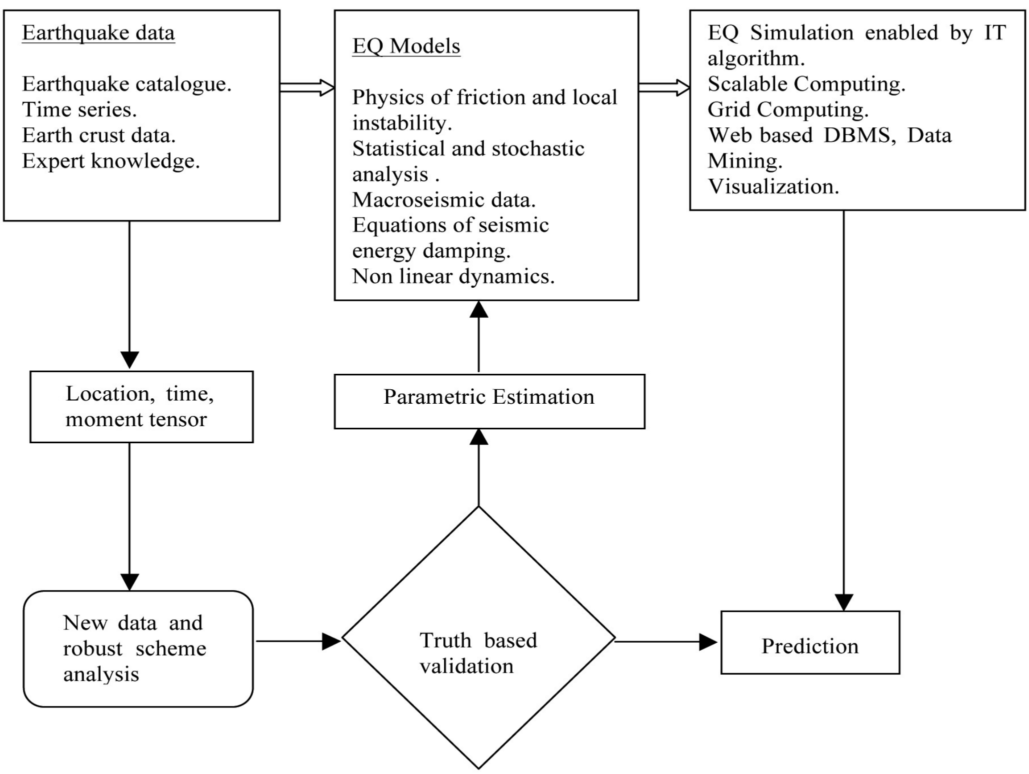

Figure 1: General Scheme of Prediction by Extraction of Dynamics of Observable Behavior of Earthquake System.

density distributions for regional assessments of earthquake probabilities.

Discussion of Algorithms

Prediction studies vary from purely theoretical geophysics to statistical parameters, mathematical and computational modeling including neural networks, genetic programming and data mining of earthquake parameter data recorded in historical catalogs of seismic regions. Most of the algorithm information have been collected and compiled from various internet resources and have then been analyzed. All the algorithms have been studied and analyzed for their robustness and also significant limitations for analysis. A comparative estimation is later presented based on the algorithmic study.

Every Earthquake a Precursor According to Scale (EEPAS) model uses the previous minor earthquakes in a catalog to forecast the major ones. It is based on the precursory scale increase and is a causal phenomenon, which involves an increase in the magnitude and rate of occurrence of minor earthquakes close to the source region of a major event. The model is found to show no errors with time variance. EEPAS could be used in lieu of a time-invariant baseline model for independent seismicity in conjunction with an epidemic-type short-term forecasting model to improve daily forecasts of earthquake probabilities thus useful for long range predictions. There are two models to estimate the probabilities of future earthquakes in California. The first model estimates time-independent, long-term (5-year) probabilities of magnitudes $m \geq 4.95$ in California. The second model estimates short-term (one-day) probabilities of future $m \geq 3.95$ earthquakes within the same region. Both models are extended and/or modified versions of those developed by [Helmstetter *et al*. 2006, 2007]. The model lags behind as it treats every earthquake as a precursor hence longer monitoring and computation. The framework has to be supported by a separate expert system to monitor between long-term and short term forecast of seismic environments.

A Testable Five-Year Forecast of Moderate and Large Earthquakes Based on Smoothed Seismicity by [Kagan *et al.,* 2007] involves the forecast uses earthquake data only, with no inherent use of tectonic, geologic, or geodetic information. The forecast is based on observed regularity of earthquake occurrence rather than on any physical model. The estimated rate density depends linearly on the magnitude of past earthquakes and inversely as epicentral distance. Forecasting algorithm predicts not only the rate, size distribution, and location of future earthquakes, as almost all other forecast programs do, but also focal mechanisms of these events with an indication of forecast uncertainty. Significant drawbacks of the technique involves cases where earthquake data is not numerous as researchers often estimate the spatial distribution of large earthquakes based on the observed distribution of smaller earthquakes. Smoothed seismicity forecasts also operate under the condition of stationarity that is difficult to be tested independent of the forecasting problem.

Formal evaluation of the Reverse Tracing of anomalies in an earthquake prediction algorithm (RTA) is a pattern recognition algorithm that uses earthquake catalog data to declare alarms for moderate to large earthquake expected in the subsequent months based on the spatial extent of the alarms which is highly variable and each alarm typically lasts nine months, although alarms may be extended in time and space. RTA comprises two distinct steps for short-term chain recognition and intermediate-term chain confirmation of spatial occurrence of earthquakes. The first step consists of grouping all events in a de-clustered regional catalog into chains comprised of neighbors. Two events are neighbors if one follows the other by less than t0 days and has an epicenter within r km of the first event. The second step of RTA seeks to confirm the short-term precursor by searching for intermediate-term precursors within each chain's spatial domain. The system identifies four types of precursory behavior that involves increase in seismic activity, increase of clustering, increase of correlation length, and transformation of the gutenberg-richter relation.RTA have been mostly explored in a more theoretical context by researchers in the statistical physics community, particularly with respect to critical behavior in complex systems [Blanter & Shnirman 1997, Sornette 2000]

Testing alarm-based earthquake predictions through Regional Earthquake Likelihood Models developed by the Southern California Earthquake Center (SCEC) and U. S. Geological Survey (USGS) has recently established a facility for prospective testing of scientific earthquake predictions in California and a number of experiments are now underway. This method of testing alarm based prediction depends on the Molchan diagram [Molchan,2003]—a plot of miss rate and fraction of space-time occupied by alarm—and is applicable to a wide class of predictions, including probabilistic earthquake forecasts varying in space, time, and magnitude. Method can be applied to more complex forecasts, including time-varying, magnitude-varying, and fault-based alarm functions. Essential drawback of this method is that it needs more spatial resolution.

M8 uses traditional description of a dynamical system adding to a common phase space of rate (N) and rate differential (L) dimensionless concentration (Z) and a characteristic measure of clustering (B) to determine middle-range predictions for a certain area U. M8 algorithm considers the earthquake records of high magnitude. For this purpose it draws the diameter from the source to measure the wave's propagation recording of earthquake records. It then predicts the earthquake for the next five years by generating the alarm.

CN algorithm involves selection of the objects for recognition with a fixed time step with discretization and coding of functions. The algorithm predicts the time of increased probability for the occurrence of a strong earthquake. M8 and CN are routinely globally tested using information on past seismicity to predict new strong earthquakes. M8 and CN give statistically significant results at global scale. Complexities do arise as time window defined for M8 and CN is very large. Complex interaction for the dynamics of the lithosphere due to stress strain interactions is also missing from M8 & CN.

The Mendocino Scenario or MSc algorithm was designed to find the seismic prediction of the earthquakes with 7.2 or above magnitude developed prior to the Eureka earthquake 1980 in California can be applied as a second approximation of M8. It is used to identify cluster of earthquakes with specified percentile and others of quiet boxes and then project such windows for statistical analysis It allows us to reduce significantly the area of alarm (by a factor from 5 to 20).

Next Strong Earthquake (NSE) algorithm is applied to predict a strong aftershock or a next main-shock in a sequence assuming that a strong earthquake of magnitude M1 has occurred at origin time t. The proposed algorithm has to predict whether the next strong can occur with magnitude M>=M1-a within time interval (t+s,t+T)and circle of radius R(M1) centered at the epicenter of the one that occurred. Algorithm scores with its hamming pattern recognition procedure that defines the threshold to separate small, medium and large values. Major drawback of the method is that in subduction zones like in circum-pacific where occurrence of the NSE does not depend on the rate of events in the aftershock sequence. Secondly the threshold Mo is chosen so that the values greater than Mo-3 are reasonably complete in the catalog. However it has been found that Mo is subject to alteration everywhere.

Comparative testing of clustered seismicity models on prominent aftershock sequences: Performance of a total of 9 models from different classes for the Short-Term Earthquake Probability (STEP) model and STEP model elements, a suite of Epidemic Type Aftershock Sequence (ETAS) [Ogata *et al.*,1993] models with parameter dependence on time and space and various spatial triggering kernels, and a suite of models deriving seismicity rates based on the rate and state theory following stress changes due to large and moderate earthquakes in the aftershock sequence. So advantage of the process lies in robustness of the model although it is not evaluated on aftershocks from a range of tectonic settings.

Artificial Neural Network Application in Earthquake prediction involves neural network classifiers used to solve the purpose of finding parameters and effects under consideration along other geophysical phenomena. The study integrates physical precursors in the neural network in order to narrow the forecasting windows. ANN's are software emulators that make a robust classifier framework for earthquake forecasting because of their mathematical universality, their fault-tolerance, and their ability to deal with semi-quantitative data. The consistency and reliability with which these assessments can be further improved because of parallel computing and features like high learning capability, robustness, generalization and easy simulation and interpretation of patterns. A major limitation of the system is that it takes time to train the model before applying for a certain region. The consistency and reliability with which these assessments are to be made are not fully tested.

The Map of Expected Earthquakes (MEE) deal with failure process of rocks and geological medium as a self-similar and self-organizing system of blocks of different scales. This is based on the kinetic conception of strength of solid materials image of anomaly behavior of different seismological parameters before strong ($M^{3}5.5$) earthquakes. MEE algorithm uses the principle of space-time scanning of the earthquake catalog within the limits of the studied seismo-active region.The system involves use of bayesian approach maps of conditional probability distribution of strong earthquake. These maps were named as Maps of Expected Earthquakes (MEE). MEE algorithm have been tested on regional earthquake catalogs of Caucasus, Kamchatka, Kuril and Greece and Western Turkey. MEE algorithm is open for inclusion in it physically and statistically formulation although the algorithm fails to detect in which area of the increased probability there will be a next strong earthquake.

VAN method involves a research on electrotelluric precursors (Varotsos *et al.,* 1982) has shown that materials under stress emit characteristic electrical signals which are recorded prior to earthquakes by measuring anomalous electrical activity in the ground. Varotsos maintains that predicting the location, time, and magnitude of a number of earthquakes require huge stresses or extreme sensitivity and a remarkable conductivity structure for electric signals not valid for other structures. However there are a number of critics to this method who question the very principle of this method saying that further modification network sensors and data processing is required to make the system fully functional.

On the Properties of Predominant-Period Estimators for Earthquake Early Warning (Presis) studies predominant period for the rupture duration of earthquake using the first few seconds of P waves for a nonlinear function of spectral amplitude and period that gives greater weight to higher amplitudes and higher frequencies in the spectrum that approximate estimate of magnitude that can be used for earthquake early warning system. Local site effects likely contribute significantly to the variability in predominant period estimates of magnitude, resulting in non-ideal properties of the estimator may be another limiting factor that adds noise to the results.

Status of Seismic Hazard Analysis (SHA) proposes a framework where any arbitrarily complex (e.g., physics based) SHA component can "plug in" for end-to-end SHA calculations having open source object oriented, platform, web/GUI enabled, distributed (potentially), Java (or wrapped code) validated network. This involves hazard and shake-map calculator. Components can be geographically distributed (using web-services and distributed object technologies) for grid computing for full hazard maps. Intensity measure relationship involves list of supported intensity-measure types through adjustable parameters. SHA remains limited as it needs more physical data approaches often influenced by noise or lack of proper acquisition techniques. Lack of consensus among parties means have multiple options to the study of the forecast.

Earthquake prediction using active-block analysis on dynamic prediction approaches of the crustal block has been proposed in an "active crustal block" [Wang *et al.,* 2002] to describe mechanism of the present day plate tectonic movement. The study was made in southwestern sichuan region through integrative multidisciplinary studies of fault systems. Relationship between dynamic crustal system and strong earthquakes studied with GPS observational data. iSTEP program involves identifying geomagnetic, seismological ,geodetic and ionospheric precursors and statistical testing of precursors. The remote sensing techniques characterize feasible mechanism behind identified precursory phenomena, correlating identified precursory phenomena with earthquake.

Accelerating seismicity before large earthquakes and the stress accumulation model shows that large earthquakes can be preceded by a period of accelerating seismic activity of moderate-sized earthquakes but this phenomenon has yet to be clearly understood. The stress accumulation model based on the concept of elastic rebound, simulates accelerating seismicity from theoretical stress changes during an idealized seismic cycle. In this view, accelerating seismicity is simply the consequence of the decrease, due to loading, of the size of a stress shadow due to a previous earthquake. First, it is shown that a power-law time-to-failure equation can be expressed as a function of the loading rate on the fault that is going to rupture. Second, a new methodology to extract accelerating seismicity from background seismicity and new statistics to test the robustness of the extracted accelerating patterns is implemented. The model always monitors the background seismicity. This gives an opportunity to understand the random earthquakes that can occur on fault or shear zones. It is not understood when the stress accumulation can result in fault breakage and produce a tremor.

Earthquake precursors in monitoring of geophysical and biological parameters: Anomalous changes in various geo-electrical and geodetic parameters has been observed by many researchers across the globe. The possibility of ionospheric disturbances, radon fluctuation provide a significant evaluator and parametric approaches in a data driven model. The approach presents varying outcomes in validating the analysis of short-term variations in different parameters prior to the considered earthquake confirm the existing ideas on heterogeneity of spatial manifestation of earthquakes' precursors. The advantage of this technique lies in the regular anomalies prior to the earthquake occurrence although a significant mathematical or statistical hypotheses is yet to be explored in the definition of precursory relationships with earthquake generation mechanisms.

Computing earthquake forecast probabilities using numerical simulations of the physics of realistic fault systems involves automated methods, including the use of numerical simulations of interacting earthquake fault system. It is called "Virtual California as it was used to simulate earthquakes on the San Andreas fault and its associated fault system. The Virtual California model includes elastic interactions among the faults in the model consisting of topologically realistic system-level approaches to the modeling of earthquake faults, driving at the correct plate tectonic rates, and frictional physics on the faults using the physics obtained from laboratory models with parameters consistent with the occurrence of historic earthquakes. A synthetic earthquake catalog utilizing Virtual California that use paleo-seismic data to identify intervals within the artificial data which most closely resemble the current seismic state of California; simulations to compute probability of future large earthquakes in space and time where large data tests can be implemented.

Determination of earthquake source mechanism using spectral and waveform analysis by studying fault plane solutions and source parameters are regularly done for deciphering the nature of earthquakes occuring in the indian sub-continent. Waveform and spectral analysis of body waves are processed on a regular basis for interpreting characteristics of displacement spectrum in terms of seismic moment, fault length and stress drop. This can be calculated for local earthquakes. Advantage of the mechanism lies in the fact that parametric analysis of a local earthquake can be done for analyzing the source mechanism based on stress drop for a fault length but the analysis is yet provide circumstantial evidence why the earthquake behavior over the time scale can be different or stress drop behavior for a future earthquake can vary for a different fault length. A lot of research has been put in by Indian scientists to study precursors. India's first Multi-Parameter Geophysical Observatory (MPGO) has been established at Ghuttu, Central Himalaya. Precursory signals resulting from stress-induced changes in density, magnetization, resistivity, seismic wave velocity, fracture propagation, crustal deformation, electromagnetic and radon gas emission as well as fluctuations in hydrological parameters have been monitored. Beside this, Aggarwal *et al.,* 1975, Bhattacharya *et al.,* 2007, Dutta *et al.,* 2007, have done significant work for introducing new scenarios for earthquake analysis.

Discussion in Formulating a Data Driven Approach Fuzzy Rule Base Analysis For Earthquake Prediction Technique

Prediction studies for earthquake is dependent on the proper analysis and extraction of information from purely theoretical geophysics using statistical, mathematical, and computational modeling approaches involving neural networks, genetic programming and data mining of earthquake parameter data recorded or processed using operational techniques for time-dependent seismic hazards. It is observed that earthquake genesis is a complex phenomenon that involves innumerable parameters of which many of those are still not known to us. Several parameters related to crustal heterogeneities as diagnostic to earthquake precursors are estimated using latest state of seismological modeling in different tectonic environ, such as crack density, saturation rate, porosity parameters in addition to seismic velocity and Poisson's ratio by several authors (Mishra and Zhao, 2003; Mishra *et al.,* 2003; Mishra *et al.,* 2010; Singh *et al.,* 2011; Singh *et al.,* 2012a, b) in order to understand the earthquake generating processes. These studies however provided several limitations on quality of data with respect to data resolution, precise arrival time estimates, determination of precise magnitudes and hypocenter locations (Mishra *et al.,* 2007a, b; Mishra *et al.,* 2008; Mishra *et al.,* 2011), which constrain in the development of operational earthquake forecasting methodologies. Review of the magnitude and depth of earthquakes has been found which are used to identify the distance from the origin. The probability in a particular sub-domain is a number P that ranges between 0 (no chance of a target event) and 1 (certainty of a target event). A time-independent forecast is one in which the sub-domain probabilities depend only on the long-term rates of target events; the events are assumed to be randomly distributed in time, and the probabilities of future events are thus independent of earthquake history or any other time-dependent information. In a time-dependent forecast, the probabilities P(t) depend on the information I(t) available at time t when the forecast is made. The historical data are collected which has follow the time series methodology, combine the data mining for preprocessing and finally apply the fuzzy logic rules to predict the impact of earthquake. Time series values are transformed to phase space by using a nonlinear method and then apply the fuzzy logic to predict optimum value as in Figure 2.

Studies dealing with Fuzzy linear regression (FLR) model can be broadly classified into two approaches, viz. (i) Linear programming (LP)-based methods, and (ii) Fuzzy least squares (FLS)

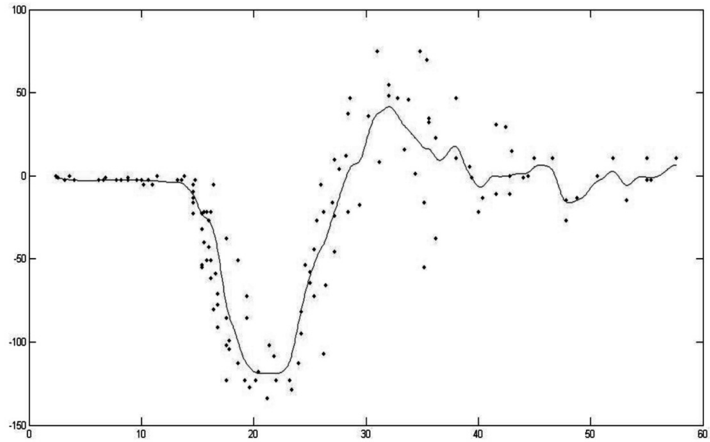

Figure 2: Data Points and Predictions.

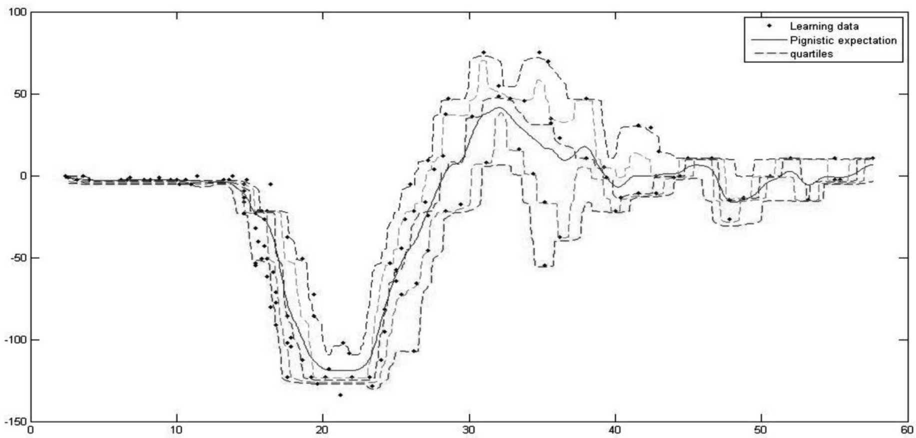

Figure 3: Computation of Predictions for Test Examples of Quartiles for Output Pignistic Distribution.

methods. In the former approach, proposed by Tanaka *et al*., (1982), parameters of FLR model:

$$Y = A_0 + A_1 X_1 + \ldots + A_p X_p$$
$$\text{where } A_i = (a_{ic}, a_{iw}),\ Y = (y_c, y_w)$$

are estimated by minimizing vagueness of model- data combination, subject to constraints that each data point must lie within estimated value of response variable. This can be visualized as a LP problem and solved by using "Simplex procedure" with Figure 3. It was shown that widths of prediction intervals in respect of Fuzzy linear regression model were much less than those for Multiple linear regression model. As number of data points increases, the number of constraints in LP increases proportionally, thereby resulting in computational difficulties. The second approach based on Fuzzy least squares (FLS) method, was pioneered by Diamond (1988), which as its name suggests, is a fuzzy extension of Least squares method based on a new defined distance on the space of fuzzy numbers.

The graphical output of the prediction is given in Figure 4 as the Fuzzy surf diagram. The impacts of earthquakes are described in this diagram. The levels are changed from low to high. If M magnitude is low and Dt depth is shallow the impact of earthquake is medium. Likewise if M is high and Dt is shallow then the impact of the earthquake is also high. If M is low and Dt is shallow, then the impact of the earthquake is medium. The maximum impact of the earthquake is shown in surf diagram. Therefore the fuzzy logic could predict the maximum number of occurrence. The rules are generated with the assumption that Magnitude (M), Depth (Dt) and Impact (I) dependent on latitude and longitude are linguistic variables. The possible values for linguistic variables are as follows: Magnitude (M) - Low, Medium and High\Depth (Dt) – Shallow (S) and Deep (D)\ Impact (I) – Low (L), Medium (M) and High (H)\Fuzzy rules:\ In this paper, fuzzy knowledge bases comprise M fuzzy if—then rules of the following type:

Rule m : If M is A_{m1} and Dt is A_{mn} then I is Bm with weight wm; where x = ðx1; x2; . . .; xn and y are, respectively, the input and the output values. Am1,...,Amn are linguistic labels or ‘‘or’’ combinations of labels, whose corresponding fuzzy sets are arranged in a prespecified fuzzy grid (that will not change during the learning). The consequents Bm can be either singletons or fuzzy numbers. For example:

Rule 1 : If M is LOW or MEDIUM or HIGH and Dt is SHALLOW OR DEEP then I is LOW or MEDIUM with weight 0:8;

The rule base is interpreted according to the First Inference Then Aggregation (FITA) principle (Cornelis and Kerre 2003) as best way of preprocessing a dataset with a high degree of imprecision in the input.

The shallow earthquakes depths are identified using available methods. The obvious understanding of earthquake and precursors of earthquakes are used to create a new method for predicting earthquake. This will help to find the accurate impact of earthquake and distance from the origin point. Regression analysis plays a very important role in identifying earthquake sequences that show clustering in space and time which trigger the earthquakes. Guberman and Rotwain, 1986 solved incomplete information (incomplete data, absence of mathematical model) by using classifications for a natural control set involving increase of tectonicity. Estimates of earthquake sizes can be characterized by g representing a spatial domain of identification of fault characteristics (including length, depth, and segmentation) and t forecasts (months to years in advance) and short-term predictions (hours or days in advance). Using these approach the problem of modeling r (t, g, M) is equivalent to constructing

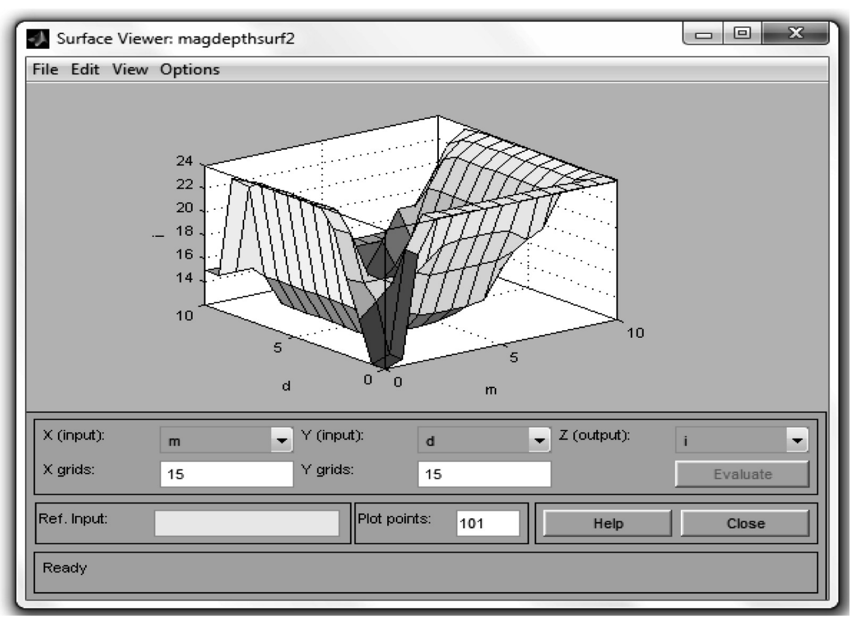

Figure 4: Fuzzy Rule for Impact of Earthquake.

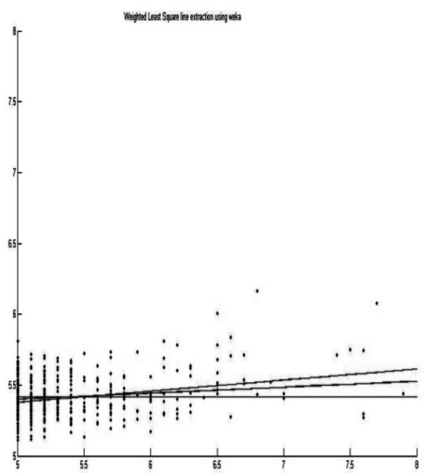

Figure 5a): Weighted Line Fit using Weka.

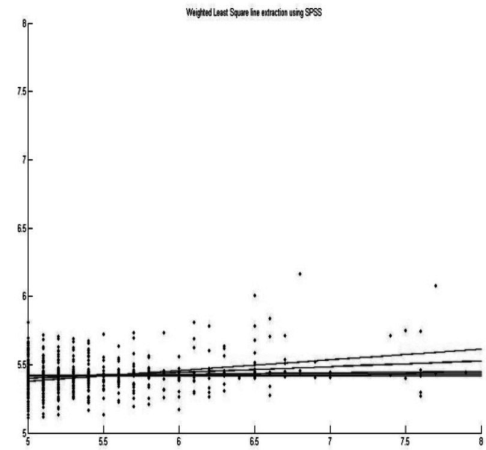

Figure 5b): Weighted Line Fit using SPSS.

a model of the seismic process in the phase space (t, g, M) in terms of conditional rate where M is the maximal magnitude of the earthquake expected to occur in the bin dg× dt with some probability P (dg, dt). Successful occurrences of earthquake records can be predicted using statistically significant algorithms [Boschi, 2007] and applying data mining methodologies to an existent database ranking score for each attribute showing the relevance (predicting power).

The algorithm efficiency depends parametrically on the quality of the correlation and factor analysis of the attributes. Analyze the data with regression analysis method based on fuzzy extension of belief function theory. An example of the inferred relationship between the maximal magnitude of expected earthquake *M*max and geological has been given using weka and spss [Dutta *et al.,* 2011]. In this study, the magnitude taken as dependent attribute , statistical and logical inference of the relationships between the latitude, longitude and focal depth was found to be an independent function. In [Dutta *et al.,* 2011] the earthquake size estimates in South Asia coming from various sources and consisting of different magnitude types and intensity data was plotted against unified magnitude Mr. Data association and their relationships between attributes yields a significant order based on weka and spss tools. It was found that Magnitude (Mr) = -0.0349 * latitude + -0.0145 * longitude + 0.0029 * focal depth + 7.5245. Trend and deviation analysis using regression techniques spatial resolutions characteristic of the earthquake parameters, all of the ongoing seismicity both before and after the largest events accumulates to a global structure consisting of a few separate clusters in the feature space.

Figure 5a and 5b are the line extractions based on weighted least square method. The error residuals are minimized with the square of the distances of all data points to a function. Weighted least squares regression actually increases the influence of an outlier, the results of the analysis may be far inferior to an un-weighted least squares analysis. Evaluating this probabilistic mode of study for check of the algorithm efficiency based on fiinding the relation between the attributes logical inference can be drawn among the attributes. Earthquake cycle is not periodic, and time between successive earthquakes can be highly irregular whereby fuzzy rule base definition and weighted regression analysis plays a very important role for time stamp definition of earthquake occurence based on relationship between magnitude, focal depth and impact based on origin location of the earthquake.

Conclusion

In contrast to fuzzy linear models, very little research work so far has been done dealing with "Fuzzy nonlinear models (FNMs)". Buckley and Feuring (2000) proposed "Evolutionary algorithm solutions" for fitting some particular parametric FNMs. Specifically, for given fuzzy data, the algorithm searches from the "Library" of fuzzy functions (which includes linear, polynomial, exponential, and logarithmic) that function which best fits the data. Evidently, this is not at all satisfactory for fitting parametric FNMs to data and so is an engrossing area for future research. Strong Motion Instrumentation Network and Site Characterization of Its Stations (Chopra, 2008) is being checked to set up an Early warning infrastructure in Indian sub-continent. Lot of research work is being put in by Indian scientists to develop indigenous solutions for earthquake forecasting and response in India. The authors have taken several extracts from different literature reviews in pursuit of a comprehensive bibliography and classification framework in identifying the limitations and challenges to earthquake prediction algorithms. Future work in the area could focus on multiple research directions by deploying an appropriate infrastructure to utilize low probability forecasting for operational purposes. Implementation must be orchestrated in a way that reduces the vulnerability of society and improves community resilience, while the responsible scientific research on earthquake predictability can develop operational forecasting capabilities based on preciseness of data and robust algorithm.

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