A Belief Rule Based Expert System to Predict Earthquake under Uncertainty

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Abstract

The impact of earthquake is devastating, which has the capability to stop the socio-economic activities of a region within a short span of time. Therefore, an earlier prediction of earthquake could play an important role to save human lives as well as socio-economic activities. The signs of animal behavior along with environmental and chemical changes in nature could be considered as a way to predict the earthquake. These factors cannot be determined accurately because of the presence of different categories of uncertainties. Therefore, this article presents a belief rule based expert system (BRBES) which has the capability to predict earthquake under uncertainty. Historical data of various earthquakes of the world with specific reference to animal behavior as well as environmental and chemical changes have been considered in validating the BRBES. The reliability of our proposed BRBES's output is measured in comparison with Fuzzy Logic Based Expert System (FLBES) and Artificial Neural Networks (ANN) based system, whereas our BRBES's results are found more reliable than that of FLBES and ANN. Therefore, this BRBES can be considered to predict the occurrence of an earthquake in a region by taking account of the data, related to the animal, environmental and chemical changes.

Keywords: Earthquake, Prediction, Expert system, Uncertainty, Belief rule base.

1 Introduction

People live on earth and their lives can be destroyed by the occurrence of the unprecedented natural calamities. Most of the natural calamities, which bring immense sufferings to the human being, can be noticed before their occurrence. Examples of such calamities are flood, tsunamis, cyclone, tornadoes and many others. However, there are exceptions; for example, earthquake is difficult to notice before its occurrence, although it has the power of annihilating everything [1] [2] [3]. Approximately, a total of 500,000 earthquakes are noticed all over the world each year. Among them, 100,000 are realized while only 100 earthquakes are harmful. As a result of earthquake occurrence, 1,741,127 people died worldwide [4]. In 2016, a severe earthquake occurred in Italy, where 159 people died and 368 people were injured [5]. In Japan, more than 20,000 people were died in 2011 from a catastrophic earthquake, which also severely damaged a nuclear power plant [6]. During earthquake, a severe agitation of landscape can be noticed, mainly causing from the movements within the earth's edge. Usually, an earthquake is occurred when two blocks of earth abruptly slip past one another.

Therefore, the prediction of an earthquake before its occurrences drew significant attention. In [1], certain criteria were suggested to identify the magnitude in Richter scale, place of occurrence, and duration of earthquake. However, the prediction of earthquake is recognized as yet to be solved problem of

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Table 1: Earthquake uncertainty factors

Determinates	Uncertainty Types	Discussion
Vocal response	Incompleteness, vagueness	Animals having the clue of earthquake in a particular area might be less vocal. Hence, it is difficult to get their accurate vocal response.
Leaving normal activity	Inconsistency, vagueness	Abnormal behavior of the animals is observed during earthquake. Intensive reaction may be perceived with increasing earthquake intensity
Sensitivity of mild stimulation	Imprecision	Sensitivity may not contain any fixed pattern.
Change in water level	Imprecision	This forerunner time differs with time
Change in temperature level	Imprecision	This forerunner time differs with time
Radon gas level	Ignorance, inconsistency	Radon gas on the level of air ionization may be changed.

Geo-science, although the identification of earthquake patterns and clusters has been investigated by the researchers of various countries for long time [7][8][9][10][11][12][13][14][15][16].

The classical and knowledge-based models have been widely preferred to predict earthquakes [17]. Seismo-Ionospheric coupling [18][19][20], Formation of Ocean Wave [21], Remote Sensing by Satellite [22], and GPS Dual Frequency System [23] are the examples of classical models. In the classical model, different precursors are used to enable the short term prediction. Since the nature is complex and chaotic, the short term prediction is inappropriate. However, the knowledge-based models used the prior information in predicting earthquake. Neuro-Fuzzy classifiers [24] and Adaptive Neural Networks [25] are the examples of such models. The other categories of this model consist of the approaches, which have been developed by using animal behavior along with information related to the environmental and chemical changes to predict the earthquake [26][27]. The models to predict earthquakes are easy to develop by using the latter approaches when there exist, sufficient amount of historical data. However, the accuracy of the prediction models depends on their capability of addressing various types of uncertainty, those exist with the signs of animal behavior as well as with the environmental and chemical changes as illustrated in Table 1[28][29].

An expert system can be thought of appropriate alternative while there is an absence of algorithmic solution to a problem [30][31]. The earthquake prediction is an example of such a problem due to its complexity, involving multiple factors, often difficult to measure with accuracy. BRBESs (Belief Rule Based Expert Systems) are considered as the appropriate candidates to apply in this category of complex problem [32]. Hence, a BRBES with the capability of predicting earthquake by considering the animal behavior along with the environmental and chemical changes is presented in this article.

The article is organised in the following way. The present section introduces the significance of earthquakes and the possibility to predict such events. The literature review is covered in Section II, while the BRBESs methodology is discussed in Section III. Section IV presents our proposed BRBES to predict earthquakes. Results and discussions are elaborated in Section V, while Section VI concludes the article with an indication of future work.

2 Related work

Earthquake prediction is an important area of research, which is evident from the presence of various types of systems, available in the literature [7][17][18][27][33][34][35][36][37][38][39][40][41][42]. Artificial Intelligence (AI) based methods, including expert systems and data mining techniques are widely used to predict the earthquake with high accuracy [17][33][34]. Different applications of data mining techniques are proposed [17][36][37][40] to predict the earthquake, which include Bayesian belief networks (BBNs), artificial neural networks (ANNs), support vector machines (SVMs), decision trees, as well as logistic models.

Fuzzy logic [30][43] was also used to predict earthquakes. In combination with some modern seismological algorithms, fuzzy expert system was developed in [7]. Another fuzzy expert system was developed by taking account of human reasoning procedures to predict earthquake [33]. In this system, a fuzzy rule base was developed by incorporating the knowledge of human expert. This system used Sugeno type fuzzy inference procedures along with an adaptive network based fuzzy inference procedure to clarify the earthquake parameters. The performance of this system is better than that of human experts. However, when the earthquake magnitude is greater or equal to six, the prediction of the system became inaccurate because of the frequent presence of uncertainty with the earthquake parameters. In addition, Sugeo type inference procedures do not consider the types of uncertainties, which are found with the earthquake parameters, and hence, resulting inaccurate prediction. Rule base expert system was proposed in [34], where earthquakes were predicted by taking account of historical data. Association rule mining technique was employed to discover knowledge [36]. However, association rule itself is a binary approach and hence, uncertainty issues cannot be resolved by this approach [44][45].

In seismically active region, the unusual animal behavior is considered as the important earthquake prediction parameter [27]. The observation of behavior of some animals helps to predict earthquake few seconds to week before its occurrence. The reason for this is that animals have better perceiving power than human. The incorporation of AI methods such as expert systems could produce better prediction result in terms of accuracy.

Thus, from the above it can be argued that all the earthquake parameters as illustrated in Table 1 have not been considered by any of the systems in an integrated framework. Fuzzy logic based approaches are in capable of handling all categories of uncertainty having earthquake elements as illustrated in Table I, especially ignorance, inconsistency and incompleteness both in the process of knowledge representation and inference mechanisms. In addition, the data mining based approaches, which use association rules to discover knowledge, are assertive in nature and hence, the uncertainty issues are not considered. On the contrary, belief rule base expert systems (BRBESs) have the capability to represent the types of uncertainty as illustrated in Table 1 both in the knowledge base as well as in the inference processes [32][46][47][48][49][50] in an integrated framework. Therefore, the next section will introduce the BRBESs methodology.

3 Overview of BRBESs Methodology

The BRBES's methodology represents uncertain knowledge, while it considers a few of steps in the inference procedure [32]. This is elaborated below.

A. A schema to represent uncertain knowledge

Belief rules are used to represent uncertain knowledge, where a belief structure is used in the consequent part of each rule as shown in Eq. (1). Antecedent attributes are associated with the antecedent part with their referential categories as can be seen in Eq. (1). Thus, belief rules can be considered an up-gradation of classical IF-THEN rules. Since belief rules consider referential categories along with degree of beliefs in the belief structure, it allows the capturing of non-linear causal relationship, which is not the case with IF-THEN rules.

$$\begin{aligned}
&R_K: IF\ (X_1\ is\ A_1^k) \cap (X_2\ is\ A_2^k) \cap \ldots \ldots \cap \left(X_{T_k}\ is\ A_{T_k}^k\right)\\
&THEN\ \{(D_1\ is\ \beta_{1k}), (D_2\ is\ \beta_{2k}), \ldots, (D_N\ is\ \beta_{nk})\}\\
&R_K: \beta_{jk} \geq 0,\ \left(\textstyle\sum_{j=1}^{n} \beta_{jk} \leq 1\right)\\
&with\ a\ rule\ weight\ \theta_k\\
&and\ attributes\ weights\ \delta_1, \delta_2, \ldots, \delta_{T_k}, k \in 1, \ldots, L \qquad (1)
\end{aligned}$$

where the Kth rule consists of T_k attributes in the left side of the rule. Each attribute of the left part of the Kth rule is associated with referential category. For example, A_i^K represents the referential category of the X_1 attribute.

The consequent part of the Kth rule consists of only one attribute, but with j referential categories. Each referential category of the consequent attribute of the Kth rule is embedded by a degree of belief. A rule is said to be complete if the summation of all the belief degrees related with each referential category of the consequent attribute of the attribute becomes ”1”. On the contrary, it is considered as incomplete.

A belief rule base comprises L rules. Fig. 1 represents a multilevel BRB framework, developed by taking the context of the earthquake prediction parameters as shown in Table 1. This BRB framework consists of 4 BRBs, namely X7, X8, X9 and X10. The bottom level BRBs are X7, X8 and X9, while the top level BRB is X10. The leaf nodes of X7BRB are the attributes of the antecedent part of the rules considered in this belief rule base, while X7 is the attribute of the consequent part. Eq. (2) can be used to compute the number of rules in X7BRB.

$$L = \prod_{i=1}^{T} J_i \qquad (2)$$

where J_i is the referential categories related with antecedent attribute of a rule, while L denotes the number of rules available in a BRB.

If each leaf node of ’X7BRB contains three referential values, then by using Eq. (2), the value of L will become (3*3*3) = 27.

Eq. (3) illustrates the example of a rule associated with X10BRB.

From Eq. (3), it can be seen that belief degree 60% is embedded with ”High”, 40% with ”Medium” and 0% with ”Low”.

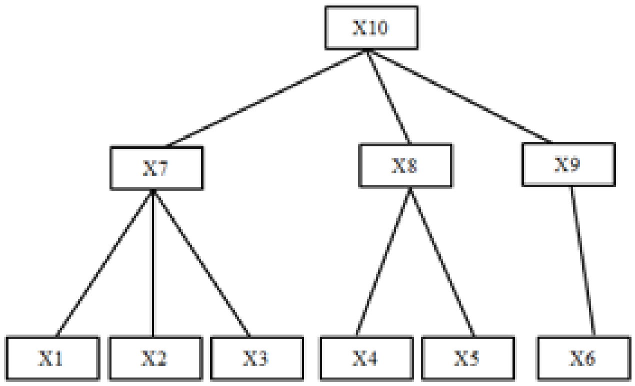
B. BRBES’s Inference Mechanism

The inference mechanism of BRBES is elaborated further.

1. Input Transformation

The value of an antecedent attribute can be transformed by finding its matching degrees to the referential values by using Eqs. (4) and (5) [47].

As ”Vocal response“ (X1) is identified as ”Low“, then this linguistic variable is given a weight of 10% by an expert. Since the utility value for “High” is considered as “100”, for “Medium” as “50” and for “Low” as “0” both in Eqs. (4) and (5), this weighted value 10% will be in the range of 50. Therefore,



X10	Earthquake Prediction
X7	Unusual Animal Behavior
X8	Environment
X9	Chemical
X1	Vocal Response
X2	Leaving Normal Activity
X3	Sensitivity of Mild Stimulation
X4	Change in Temperature Level
X5	Change in Water Level
X6	Radon Gas Level

Figure 1: The BRB framework for predicting earthquake.

$$R_k : \begin{cases} IF\,(\text{Unusual Anmal Behavior is low})\, and\, (\text{Enviromental Changes is high}) \\ (\text{Chemical Changes is medium}) \\ THEN \\ \text{Earthquake Prediction is} \\ \left\{ (High(0.6)), (Medium(0.4)), (Low(0.0)) \right\} \end{cases} \quad (3$$

$$IF\ (H\ value \geq Input\ value \geq M\ value)\ THEN \qquad (4)$$
$$Medium = \frac{H\ value - Input\ value}{H\ value - M\ value},$$
$$High = 1 - Medium,$$
$$Low = 0.0$$

$$IF\ (M\ value \geq Input\ value \geq L\ value)\ THEN \qquad (5)$$
$$Low = \frac{M\ value - Input\ value}{M\ value - L\ value},$$
$$Medium = 1 - Low,$$
$$High = 0.0$$

in this case Eq. (5) will be applied, otherwise Eq. (4). Thus, by applying Eq. (5), the matching degrees for this input data (low) can be obtained for Low as 0.8 (Low = (50 − 10)/(50 − 0)= 0.8) for "Medium" as 0.2 (Medium = 1 − 0.8 = 0.2) and for High as "0", which are illustrated (see Table 2). When the referential categories are assigned with matching degrees then the rule is called packet antecedent and hence, it is considered as active.

2. Rule Activation Weight calculation

The activation weight calculation of a rule comprises calculating the combined matching degree, which is obtained by using Eq. (6) [46] as well as by calculating activation weight, which is obtained by applying

Table 2: Input transformation

Antecedent Name	Antecedent Value	Matching Degree	High	Medium	Low
Vocal Response (X1)	Low	10%	0.0	0.2	0.8

Eq. (7) [32][46][47].

$$\alpha_k = \prod_{i=1}^{T_k} \left(\alpha_i^k\right)^{\delta'_{ki}} \tag{6}$$

where α_k is the combined matching degree.

$$\omega_k = \frac{\theta_k \alpha_k}{\sum_{j=1}^{L} \theta_j \alpha_j} = \frac{\theta_k \prod_{i=1}^{T_k} \left(\alpha_i^k\right)^{\delta'_{ki}}}{\sum_{j=1}^{L} \theta_j \left[\prod_{i=1}^{T_k} \left(\alpha_i^j\right)^{\delta'_{ji}}\right]}, \delta'_{ki} = \frac{\delta_{ki}}{\max_{i=1,\ldots,T_k} \{\delta_{ki}\}} \tag{7}$$

where δ_{ki} is the normalized antecedent attribute weight, obtained by dividing the individual antecedent attribute weight by the summation of all antecedent attribute weights of a rule. Hence, its value should be in between 0 to 1.

From Table 3, it can be observed that rule "6" consists of three antecedent attributes with their individual matching degrees, which need to be combined, by applying Eq. (6). The importance of this rule to calculate the unusual behavior of the animal can be acquired by applying Eq. (7). The implication of this value is that this rule has an important impact in getting the result or it is highly sensitive.

Table 3: Rule activation weight calculation with combined matching degree

Rule Id	Antecedent			Consequent			Combined Matching Degree	Rule Activation Weight
	X1	X2	X3	H	M	L		
6	L (0.1)	M (0.5)	H (0.8)	0.1	0.7	0.2	0.014	1

3. Modified Belief Degree

There could be a situation when input data for all the antecedent attributes of a BRB cannot be available and this phenomenon can be considered as ignorance. In this situation, the degree of belief of the original BRB needs to be modified, which can be obtained by using Eq. (8).

$$\beta_{ik} = \overline{\beta_{ik}} \frac{\sum_{t=1}^{T_k} \left(\tau(t,k) \sum_{j=1}^{J_t} \alpha_{tj}\right)}{\sum_{t=1}^{T_k} \tau(t,k)} \tag{8}$$

where

$$(t,k) = \begin{cases} 1, if\ P_i\ is\ used\ in\ defining\ R_k \left(t = 1,\ldots,T_k\right) \\ 0, otherwise \end{cases}$$

Here, $\bar{\beta}_{ik}$ is the initially assigned degree of belief, while β_{ik} is the modified degree of belief.

From Table 4, it can be observed that the original belief degrees of rule no. 6 have been modified since the input data of ”Vocal response” antecedent attribute is absent. The updated values of the belief degrees are obtained by applying Eq. (8).

Table 4: Belief Degrees Update

Rule ID		High	Medium	Low	Activation Weight
6	Initial	0.1	0.7	0.2	1
	Modified	0.09	0.6	0.34	0.096

4. Rule Aggregation

The rules of BRB need to be aggregated to obtain output data in response to the input data. As an instance, the input data of X7BRB consists of [X1=Low, X2 = Medium, and X3 = High]. The output value, i.e. the value of X7 consequent attribute, needs to be calculated in response to these input data, which can be achieved by aggregating the rules associated with X7BRB. The ER (Evidential Reasoning) inference mechanism is applied to obtain this overall calculative value in terms of fuzzy values. There are two forms of ER, namely, recursive and analytical. The analytical ER is considered to reduce the computational complexity as shown in Eqs. (9) and (10).

$$\beta_j = \frac{\mu \times \left[\prod_{k=1}^{L}\left(\omega_k \beta_{jk} + 1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right) - \prod_{k=1}^{L}\left(1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right)\right]}{1 - \mu \times \left[\prod_{k=1}^{L} 1 - \omega_k\right]} \quad (9)$$

$$\mu = \left[\sum_{j=1}^{N}\prod_{k=1}^{L}\left(\omega_k \beta_{jk} + 1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right) - (N-1) \times \prod_{k=1}^{L}\left(1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right)\right]^{-1} \quad (10)$$

where β_j illustrates the degree of belief related to the attribute of consequent referential category.

By applying Eq. (9) for the input values of X7BRB, the calculated value for the consequent attribute ”X7“, which is obtained, consisting of (H, 0.2), (M, 0.8), (L, 0). By applying Eq. (11) the crisp value can be determined against the fuzzy values.

$$y_m = \sum_{n=1}^{N} D_n * \beta_n(m) \quad (11)$$

where the expected numerical value is referred by y_m, whereas each referential values's utility score is denoted by D_n. By considering the utility score for ”High“ as 10, for ”Medium“ as 5, and for ”Low“ as 0, the fuzzy values of X7 are converted into a numerical value, obtained as (10 * 0.09) + (5 * 0.6) + (0 * 0.34) = 3.9.

4 Belief Rule Based Expert System (BRBES) to Predict Earthquakes

The components of our proposed BRBES are elaborated in the this section.

A. BRBES' Architecture, Design, and Implementation

The BRBES consists of a three-layer architecture, which comprises user interface, inference, and knowledge-base layers as can be seen in Fig. 2.

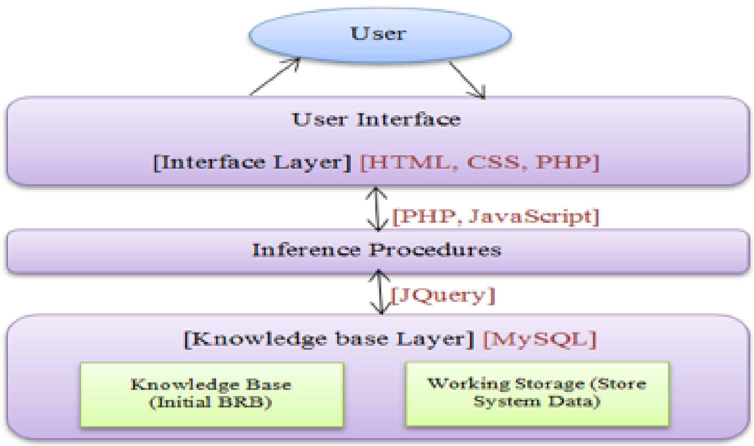


Figure 2: BRBES architecture.

Since the system is web-based, various web programming tools such as PHP, CSS and HTML are considered to build the system interface. The inference layer consists of various inference procedures of BRBES as discussed in the previous section. This layer has been developed by using PHP, JavaScript, and JQuery. For simplicity and shorter development cycles, PHP has been considered. To make the client side behavior dynamic, JavaScript has been used, which maintains the link between the inference and interface layers. On the contrary, JQuery has been considered to maintain the link between the knowledge-base and inference layers. The BRBES's knowledge-base is developed using MySQL because of its flexibility. The initial BRB is also stored in MySQL. In addition, MySQL facilitates quick data access and provides necessary security.

B. Knowledge Base Construction

The multi-level BRB framework is designed in consultation with domain experts. This framework is considered as the starting point to construct the knowledge-base. A BRB can be constructed by applying different approaches consisting of using knowledge of an expert, examining previous data, applying previous rules as well as creating random rules. Here, rules and attributes are assumed to contain uniform weight importance. "X7BRB" is illustrated in Table 5.

C. BRBES Interface

Fig. 3 shows the main interface of the system, although there are other interfaces to input data of the leaf nodes variables of Fig. 1 from the users. From Fig. 3 it can be observed that for the certain input data of three leaf nodes (X1, X2, X3) of "X7BRB", the fuzzy values of the root node X7 i.e. "Unusual Animal Behavior" have been obtained as (High, 72.7%), (Medium, 27.3%) and (Low, 0.00%). Using (11), this fuzzy value of X10 has been transformed into a numerical or crisp value, which is obtained as 6.97 as shown in Fig. 3. Here, one interesting finding is the fuzzy values of the mid-level nodes, which are "X7", "X8" and "X9" can also be converted into crisp values by using (11) and these can be used as the input data to the top level BRB, which is "X10BRB". In this way, a co-relation between the intensity of earthquake and the animal behavior, environment and chemical changes can be established by using

Table 5: Initial BRB for X7BRB

Rule Id	Rule Weight	IF Antecedent	THEN Consequent
		D1∧D2∧D3 is	A11 is
1	1	H ∧ H ∧ H	(H, 1.0), (M, 0.0), (L, 0.0)
2	1	H ∧ H ∧ M	(H, 1.0), (M, 0.0), (L, 0.0)
3	1	H ∧ H ∧ L	(H, 0.9), (M, 0.1), (L, 0.0)
4	1	H ∧ M ∧ H	(H, 0.4), (M, 0.5), (L, 0.1)
5	1	H ∧ M ∧ M	(H, 0.3), (M, 0.4), (L, 0.3)
6	1	H ∧ M ∧ L	(H, 0.0), (M, 0.5), (L, 0.5)
...	...	...	...
27	1	L ∧ L ∧ L	(H, 0.0), (M, 0.0), (L, 1.0)

this BRBES.

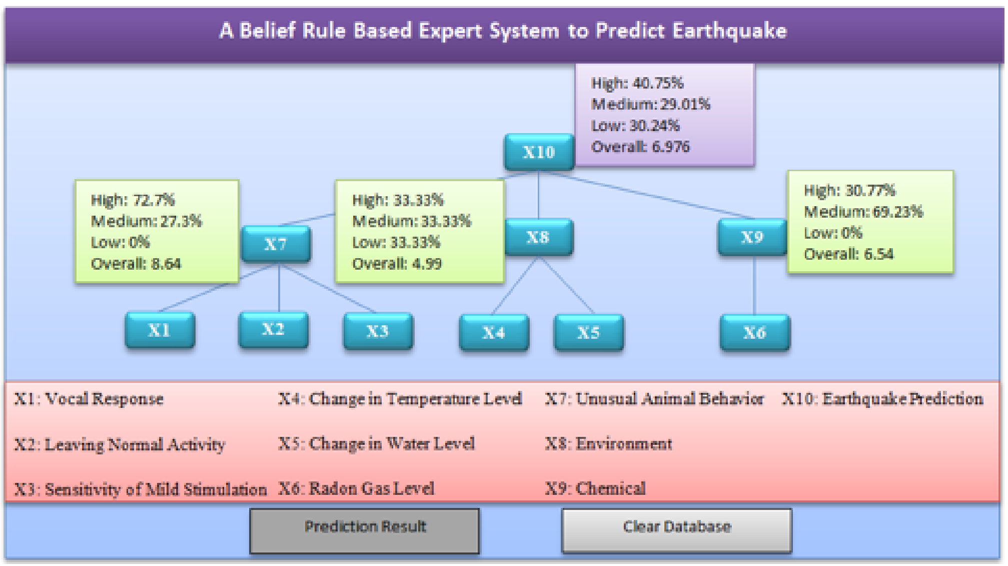


Figure 3: BRB Interface.

5 Results and Discussions

The reliability and the accuracy of the system has been determined by considering 138 historical datasets of different earthquakes around the world. These datasets are associated with the leaf nodes of the system framework as illustrated in Fig. 1. For simplicity, Table 6 illustrates datasets of 10 historical earthquakes, where columns 3–8 show the data of the leaf nodes, while column 9 shows the BRBES generated results in term of crisp value, which is equivalent to the magnitude of earthquake in Richter scale. Column 10 of Table 6 shows the actual magnitude of these historical earthquakes. Fig. 4 illustrates the devastation of earthquake with a magnitude of 8.5, occurred, in Japan in 1896. It is interesting to note that the BRBES generated earthquake result for this earthquake is 8.494, which is very close to the original earthquake's magnitude. BRBES's generated results were also compared with the Fuzzy Logic-based Expert System (FLBES). The output generated by FLBES for the same earthquake is found as 8.11, which is far away from the earthquake original data. In Table 6, column 11 illustrates the FLBES generated results. Finally,

Table 6: Earthquake prediction results generated by BRBES and FLBES along with original results

Earth-quake (1)	Place, Time (2)	X1 (3)	X2 (4)	X3 (5)	X4 (6)	X5 (7)	X6 (8)	BRBES (9)	Original (10)	FLBES (11)	ANN (12)	Benchmark Data (13)
E1	Talcahuano, Chile, 1835	90	90	80	70	75	75	7.8761	8.2	8.09	8.67	1
E2	Tokyo, Japan, 1855	80	80	85	70	70	70	6.9768	7.0	8.08	8.53	1
E3	Sanriku, Japan, 1896	95	90	85	75	75	70	8.494	8.5	8.11	8.29	1
E4	San Francisco, California, 1906	90	85	80	70	75	75	7.7128	7.8	8.09	7.89	1
E5	Kanto, Japan, 1923	90	85	85	75	75	80	8.3501	8.3	8.10	8.37	1
E6	Kita Tango, Japan, 1927	65	80	80	80	80	75	7.3316	7.0	8.10	8.34	1
E7	Sanriku, Japan, 1933	90	90	85	80	85	80	8.442	8.4	8.09	8.29	1
E8	Nankai, Japan, 1946	80	80	85	80	80	80	7.893	8.1	8.08	8.43	1
E9	Uttarkashi, India, 1991	80	85	80	70	75	70	7.0127	6.8	8.08	7.9	0
E10	Shandong, China, 1969	90	85	85	75	75	70	7.2291	7.4	8.09	8.5	1

an ANN based system was also developed. Its results are shown in column 12 of Table 6. The result of the same earthquake by using this system is found as 8.29, which is also far away from the original data.

Table 7: Reliability comparison among four systems

Area Under Curve			
System		Asymptotic 95% Confidence Interval	
		Lower Bound	Upper Bound
Original	0.724	0.586	0.862
BRBES	0.969	0.931	1.000
FLBES	0.789	0.659	0.918
ANN	0.862	0.772	0.952

Receiver Characteristics Curves (ROC) are commonly applied to determine the accuracy of a predictive model. Therefore, this model has been considered to measure the accuracy of the BRBES's outputs. In this model, Area under Curve (AUC) is considered as one of the important metrics. When the value of AUC becomes one then it can be concluded that the accuracy of the prediction is 100% correct. The earthquake magnitude of 6.8 of the original data has been considered as the baseline data. When an earthquake with more than "6.8" is found then the benchmark value is considered as 1, otherwise it is considered as "0". Column 13 of Table 6 shows the benchmark data, which has also been used to generate ROC curves. SPSS 23 has been used to generate the ROC curves.

Fig. 5 illustrates the ROC curves demonstrating a comparison of reliability among the BRBES, FLBES, ANN and the original data, obtained mainly by using the classical models. ROC curve with green line represents BRBES results while with gray line represents FLBES; purple line represents ANN while blue line represents original data. Table 7 illustrates the AUC for BRBES, FLBES, ANN and original data which are 0.969, 0.789, 0.862 and 0.724 respectively. Therefore, it can be argued that the reliability of earthquake prediction of BRBES is better than that of original data because later obtained by using classical models which are not developed by taking account of various categories of uncertainty related with the different variables of earthquake. On the contrary, the FLBESs only considers uncertainties due to ambiguity, vagueness and imprecision in their knowledge representation schema. Therefore, the uncertainties due to ignorance, randomness and incompleteness, which are noticed in Table 1 with the earthquake variables, are not considered in FLBES. On the other hand, the BRBES considers all categories of uncertainties associated with a knowledge representation schema and an inference mechanism which are found in Table 1. Thus, the BRBES's outputs are found reliable in comparison to FLBES as evident from Fig. 5 and Table 7. Here, an interesting observation can be noticed that ANN based sys-

Figure 4: Sanriku Earthquake, Japan, 1896. [Original Result: 8.5, BRBES Result: 8.494]

tems consider only one learning parameter i.e. weight, while BRBESs consisting of learning parameters rule weight, attribute weight and degree of belief [51]. Additionally, ANN represents black-box type of system, which is not concerned with the different categories of uncertainties related with variables of earthquake as illustrated in Table 1. Hence, ANN based system's outputs are not found dependable than from BRBES which can be seen from Fig. 5 and Table 7.

6 Conclusion and Future Work

The design, development as well as the applications of a BRBES to predict earthquake from the animal behavior and from the environmental chemical changed are presented throughout this article. A comparison of the BRBES's results with FLBES, ANN, and original data has been carried out. It can be noticed that BRBES' outputs are found reliable in comparison to FLBES, ANN, and original data. As BRBES considers various categories of uncertainties associated with the variables of animal behavior as well as with the environmental and chemical changes. The BRBES, presented, in this paper is an example of a multilevel BRBES which allows the generation of various scenarios of earthquake predictions. For example, the behavior of animal can be predicted alone before earthquake occurrence. In the same way, both environmental and chemical changes can be analyzed before earthquake occurrence. In this way, the BRBES allows the analysis of possible earthquakes from various perspectives and hence, the decision-makers could take appropriate measures to mitigate the risk of earthquake in a region. Finally, by using the BRBES an aggregated calculative view of earthquake magnitude can be obtained. Such a BRBES can easily be used to predict the earthquake by looking at the behavior of animal by anyone where there is a availability of Internet since the system is web-based. The real time earthquake prediction could be

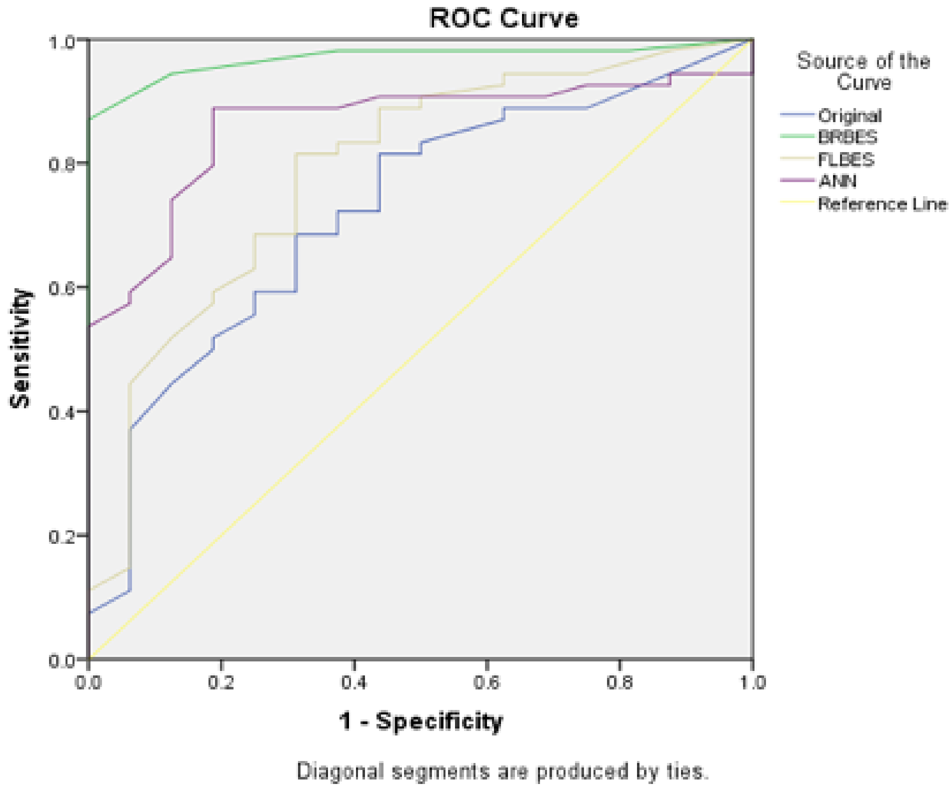


Figure 5: ROC curves comparing reliability among BRBES, FLBES, ANN, and original results

possible if the input data can be acquired by deploying wireless sensor network technologies in a region [52][53][54].

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