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A Liquefaction Study Using ENN, CA, and Biogeography Optimized-Based ANFIS Technique

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ABSTRACT

In any construction projects, assessment of liquefaction potential induced due to seismic excitation during earthquake is a critical concern. The objective of present model development is to classify and assess liquefaction potential of soil. This paper addresses emotional neural network (ENN), cultural algorithm (CA), and biogeography optimized (BBO)-based adaptive neuro-fuzzy inference system (ANFIS) for liquefaction study. The performance of neural emotional network and cultural algorithm has also been discussed. BBO-ANFIS combines the biogeography features to optimize the ANFIS parameters to achieve higher prediction accuracy. The model is trained with case history of liquefaction databases. Two parameters are used as inputs: the cyclic stress ratio and standard penetration test (SPT) value. The performance of these models was assessed using different indexes, for example, sensitivity, specificity, FNR, FPR, and accuracy rate. The performance of all models is compared. Among the models, the BBO-ANFIS model has been outperformed and can be adopted as a new reliable technique for liquefaction study.

KEYWORDS

ANFIS, Biogeography-Based Optimization (BBO), Cultural Algorithm, Earthquake, ENN, Soil-Liquefaction

I. INTRODUCTION

When the ground is shaken strongly during an earthquake, some types of soils liquefy, often subjected to ground failures. Liquefaction is recognized as one of the main causes of earthquake-related ground failure. Different soil behaves differently in response to the earthquake. In case of saturated sandy soils, liquefaction occurs instantly. This phenomenon is very common in sandy soil. Liquefaction of soil is a major concern for any geostructure. Therefore, the determination of the potential for seismic liquefaction of soil is an important job in the geotechnical project. Several methods have been proposed to decide liquefaction capability of soil deposits. The stress-based procedure (Seed & Idriss, 1971; Seed et al., 1983, Liao et al., 1988) is the most general method practiced by engineers for liquefaction assessment. Idriss & Boulanger (2004, 2006) recommended revised semi- empirical strategies for getting to the liquefaction capability of soil. Juang et al.(2008) and Jha & Suzuki, (2009) carried out reliability study for liquefaction potential of soils utilizing SPT-test data. Samui & Sitharam (2011),

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A.Shahri (2016), Kumar & Rawat (2017) assessed and predicted the liquefaction potential using different artificial neural network models. Umar et al.(2018) have been employed the deterministic and probabilistic study of liquefaction for many areas in Bihar. The objective of this paper is to propose some model for soil-liquefaction potential classification. In latest years, many alternative techniques for computer-assisted pattern recognition have developed as a result of advances in computational software. The primary concept behind pattern identification systems such as neural networks, fuzzy logic or genetic programming is to learn from experience in an adaptive manner and to extract different distinctions. Artificial neural networks (ANN) are the most commonly used methods of pattern recognition used to determine the incidence of liquefaction based on SPT field data. ((e.g., (Hanna, Ural, & Saygili, 2007); (Juang and Chen 1999)). However, the major drawback of the ANNs approach is the network structure's large complexity. We are developing intelligent machines with successful applications. However, in order to improve machine learning, it is promising to imitate definite artificial emotions. This article introduces a neural emotional network based on the algorithm of emotional back propagation. Here the efficiency of an emotional neural network investigated. For the potential of soil liquefaction, the emotional neural network will be implemented. Experimental findings indicate that artificial feelings can be effectively modeled and applied to enhance the learning of neural networks and generalization. In scientific terms, a person's feeling at a specified time is called 'emotion'. Researchers have studied the function of emotions in artificial intelligence from a multitude of perspectives. Human emotions have more than just a logical, reasonable element; they are closely associated with behavior and feelings. For the same reasons people will need emotions for future machines (Yoon, Sangjoo Park, & Anyoung Kim, 2004). Machines will need a type of emotion — machine emotion — when they have to operate continually without people's assistance. In human decision-making process, emotions play an important role. Abu and Zitar (2007) suggested and enacted an emotional agent design that resembles certain human behaviors. They noted that artificial emotions could be used to influence decision-making in different ways. While machine learning and making decisions on machines, we have always ignored the emotional variables ; however, it is quite conceivable to artificially model certain feelings in the learning algorithm of machine learning (EBP) (Khashman, 2008). An emotional neural network (ENN) is based on the emotional back propagation learning algorithm, which is an improved version of the conventional learning algorithm for back propagation. There are two simulated feelings in the emotional neural network that help the procedures of network learning and classification.

Further, a combination of neural networks and fuzzy systems known as adaptive neuro-fuzzy inference system (ANFIS) has been applied in this study. ANFIS is a network based on a Takagi-Sugeno fuzzy inference system. ANFIS model takes advantages of both neural networks and fuzzy systems. Neuro-fuzzy networks are latest geotechnical techniques and have recently been implemented in many geotechnical fields((Ni, Lu, & Juang, 1996); (Romo & García, 2003); (Shahin, Maier, & Jaksa, 2003); (Shahin & Jaksa, 2005)). It has been effectively implemented for a broad range of classification issues in learning fuzzy rules ((Jyh Shing Roger Jang, 1993); (Lin & Lee., 1996); (Rahman & Wang, 2002); (Wang & Lee, 2002)). Seif El-Nasr et al. (2000) suggested a fuzzy logic adaptive model of emotions (FLAME) as a structure for generation of emotions in agents. FLAME utilizes previous experience to evaluate emotions. Kort et al. (2001) suggested a model for conceptualizing the effect of emotions on learning. For emotion learning, Poel et al. (2002) adopted modular neural hybrid network architecture, called SHAME. An integral fuzzy neural network model known as the Adaptive Neuro-Fuzzy Inference System (ANFIS) is developed in this research to evaluate the potential for liquefaction of soil. Experimental findings showed that the hybrid neuro-fuzzy network has excellent efficiency in classification compared to some other typical neuro-fuzzy networks. Kaya (2016) and Kayadelen (2011) used Neural Network and Neuro-Fuzzy techniques for predicting soil liquefaction. Xue & Yang (2013) and Kumar et al. (2014) suggested a neuro-fuzzy method to predict the seismic potential of soil liquefaction.

Further, a new design method proposed here using a biogeography-based optimization (BBO) algorithm and Cultural Algorithm (CA). Cultural algorithm is a class of computational models obtained from the observation in nature of cultural evolution and is used to solve complicated calculations. It is used to overcome difficult calculations of the new universal search algorithms for optimization and have many other applications ((Ali, Awad, Suganthan, & Reynolds, 2016); (Haldar & Chakraborty, 2015); (Wu, Zhang, Huang, & Sun, 2014);(Xuesong; Yan, Hu, Yao, Liang, & Fan, 2013); (Zadeh & Kobti, 2015); (Zhang Y 2008)). Zhang (2011) studied concerning the natural explanation about CA and introduces its basic theory. Yan et al. (2017) introduced an enhanced cultural algorithm and its use in image matching techniques.

A new biogeography-based optimization algorithm (BBO) is created to optimize the parameters of both the main networks and the sub network. BBO is a population-based evolutionary algorithm (EA) that is based on the mathematics of biogeography. Zheng et al. (2015) placed forward an earthquake population classification hybrid neurofuzzy network based on differential biogeography-based optimization. Zhang (2008), Simon et al. (2009), Hadidi (2015) and Yan et al. (2017) successfully applied cultural algorithm and its appliance in various field. Bui et al. (2018) proposed new ANFIS hybrids with multiple optimization algorithms. The work described in this article is aimed at classifying liquefaction potential of some region in Bihar state.

II. THEORETICAL BACKGROUND OF MODELS

Emotional Neural Network (ENN)

Some researchers have effectively implemented neural networks with an emotional learning algorithm in various AI-based application, such as prediction and classification, intelligent control and pattern recognition (Lotfi and Akbarzadeh, 2014). This section describes the learning algorithm for the emotional neural network that is based on the learning algorithm for emotional back propagation (BP). Khashman (2008, 2009) discussed the flow of data within the emotional neural network in detail. In general, emotional Neural network (ENN) models have many parameters capable of interacting with input, output and statistical weights than conventional ANN models. In this study, the implementation of the ENN network in prediction soil liquefaction potential based on the EmBP model is evaluated. BP has been most commonly used ever due to its easy implementation, and very fast training. It comprises of three layers: input layer with (i) neurons, hidden layer with (h) neurons, and output layer with (j) neurons. In many other applications, the Emotional Neural Network can be used effectively with good output to be predicted. Examples of research works have been carried out that have attempted to include emotions in machines in one way or another ((Levine, 2007); (Taylor & Fragopanagos, 2006); (Miranda & Aldea, 2005); (Ushida, Hirayama, & Nakajima, 1998); (El-Nasr et al., 2000); (Gratch, 2000); (Poel et al., 2002); (Taylor & Fragopanagos, 2005)). Here the algorithm of the emotional neural network (ENN) is described. The ENN has emotional weights and two emotional parameters; anxiety and confidence.

Fig.1 refers to emotional neural network configuration- input layer with (i) neurons, hidden layer with (h) neurons, and output layer with (j) neurons. Here, XH_i and YH_i denotes input and output values of i neurons respectively. The output of the hidden layer neuron is calculated from the input of the hidden layer neuron. Therefore, the output of the each hidden layer neuron is defined as:

$$YH_h = \left(\frac{1}{1 + \exp(-XH_h)} \right) \tag{1}$$

Where, XH_h and YH_h are input and output of neuron h in hidden layer, respectively.

The output of each output layer neuron is calculated from the input value of output neuron, therefore the output of each output layer neuron is defined as:

$$\mathrm{YJ}_{\mathrm{j}} = \left(\frac{1}{1 + \exp(-\mathrm{XJ}_{\mathrm{j}})} \right) \tag{2}$$

Where, XJ_j and YJ_j are input and output values of neuron j in output layer, respectively.

Due to its performance simplicity and effectiveness, Usually ENN was used as a supervised learning algorithm for the neural network. This article aims at reviewing and developing emotional based neural networks and describes the techniques by which investigators have successfully implemented them in multiple artificial intelligence-based applications, such as intelligent control, recognition of patterns, prediction and classification problem.

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS model is developed by Jang(1993). An ANFIS has the ability to learn from data, such as that possessed by an artificial neural network. Kumar and Rawat (2017) proposed soil liquefaction and its evaluation based on SPT by soft-computing techniques. ANN &ANFIS techniques have been adapted to the development of soft computing models. For the projections of output for a specified input, it utilizes neural network and fuzzy. The inputs are mapped using the Membership Function (MF). The first-order model Sugeno fuzzy ((Takagi and Sugeno (1985)) was used in this paper.

An adaptive neuro-fuzzy inference system combines both neural networks and fuzzy systems and united the advantages of both neural networks and fuzzy systems in a corresponding means to conquer their drawbacks. The combination of a neural network and fuzzy logic into neuro-fuzzy models applies low-level learning and the advantages of high-level of fuzzy systems. Thus, ANFIS models (Sadoghi Yazdi, Kalantary, & Sadoghi Yazdi, 2011) combined the adaptive capacity of the neural network and the fuzzy qualitative approach of the logic. A Fuzzy inference system (FIS) has a fuzzification interface that converts crisp input information into a fuzzy value, a rule base that contains a range of fuzzy if – then rules. The Fuzzy inference systems have three main parts (Fig. 2):

-Fuzzification stage,
- Inference engine,
- Defuzzification

A simple ANFIS is shown in Fig. 3, where a circle shows a fixed node, whereas a square shows an adaptive node, it illustrates in Fig. 3 (Padmini, Ilamparuthi, & Sudheer, 2008). There is input and output nodes in this framework and nodes function as membership functions (MFs) and guidance in hidden layers. For simplicity, we suppose there are two inputs and one output from the examined FIS. The Sugeno type Fuzzy Inference System (FIS) has been used in this study. A Sugeno FIS composed of two input variables x and y, one output variable f (Fig.4) will result in two fuzzy laws:

Rule 1: If x is A_1, y is B_1 then $f_1 = p_1 x + q_1 y + r_1$ (3)

Rule 2: If x is A_2, y is B_2 then $f_2 = p_2 x + q_2 y + r_2$ (4)

Where the two crisp inputs are x and y, and where A1 and B1 are the associated node function linguistic labels. The corresponding parameters of i^{th} rule are p_i, q_i, and r_i. It consists of the following five layers. The performance of each layer is described as shown in Fig. 3.

- Layer 1(Input nodes)
- Layer 2 (Rule nodes)
- Layer 3 (Average nodes)
- Layer 4 (Consequent nodes)
- Layer 5 (Output nodes)

Layer 1: Every node is represented by i in this layer. Parameters are referred in to this layer as basis parameters. It is an adaptive node with node function.

$$O_i^1 = \mu A_i(x) \text{ for } i = 1, 2 \tag{5}$$

Where x is the contribution to node i, and where A_i is the linguistic label associated with the function of this node.

Layer 2: This layer is the first layer that has been hidden. Each node in this layer is marked as fixed node II, the output of which is the result of all incoming signals.

$$O_i^2 = w_i = \mu\, A_i(x)\, \mu\, B_i(y) \text{ for } i = 1, 2 \tag{6}$$

Layer 3: Each node in this layer is marked as N, the normalized firing strengths are calculated as

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \text{ for } i = 1, 2 \tag{7}$$

Layer 4: Each node i, is an adaptive node with a node feature in this layer

$$O_i^4 = \overline{w}_i f_1 = \overline{w}_i(p_i x + q_i y + r_i) \tag{8}$$

Layer 5: The single node in this level analyzes the overall ANFIS output as

$$O_i^5 = \sum \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

ANFIS model will be developed on the basis of the data set of coaching and testing. The aim of the training data set is to evolve the ANFIS model. The testing data set will be used to verify ANFIS. The data normalization ranges from 0 to 1. With the help of MATLAB, the ANFIS model will be created. An ANFIS's attractive characteristics include: simple to implement, quickly and precise learning, powerful generalization skills, great explaining equipment through fuzzy rules, and simple to integrate both linguistic and numerical knowledge to solve problems ((Jyh Shing Roger Jang & Sun, 1995); (J.S.R. Jang, Sun, & Mizutani, 1997)).

IV. CULTURAL ALGORITHM (CA)

This research introduces the latest model for the optimization of hybrid artificial intelligence — namely, adaptive neuro-fuzzy inference framework with cultural (ANFIS-CA) algorithm for liquefaction classification issues. The ANFIS model has better performance, but it has some limitations due to this optimization of soft computing techniques used.

Cultural algorithm is an algorithm proposed by Reynolds (Robert G. Reynolds, 1994). CA is expressing an ideal framework (see Fig.5). CA is a computational model of cultural evolution in solving problems of optimization that require a vast quantity of domain knowledge to guide individuals ‘ collective decisions in the population. CA has been applied to problems in a large distributed social network by extensive data, numerous domain limitations, many objectives, and multiple agents. CA uses various information sources to compound evolutionary systems and agents for the evolution process. There are two main components of cultural algorithms: demographic space and the atmosphere of belief (Reynolds, 1999, Soza et al., 2011). These two spaces are linked via a communication protocol explaining how individuals who think in their own experiences can connect both spaces with the rules.

The population space can include any population-based computational models, like genetic algorithms and evolutionary programming (Robert G. Reynolds, Ali, & Jayyousi, 2008). The belief space supports the information reservoir which every one of their experiences is for other individuals to learn them indirectly. A flowchart of the Cultural Algorithm is represented in Fig. 6.

V. BIOGEOGRAPHY-BASED OPTIMIZATION (BBO)

The optimization algorithm based on biogeography has been suggested based on biogeography theory. BBO was originally introduced by Simon 2008. BBO has emerged as a new evolutionary algorithm inspired by the science of biogeography. The BBO algorithm is a strong and novel approach to optimization. In BBO, an individual solution to the problem is similar to a habitat. BBO is usually used to optimize multidimensional functions, but it does not use the function gradient, which means that the function does not need to be distinguishable as required by the conventional optimization method. BBO can therefore be used on discontinuous functions. In the BBO scheme, an index is allocated to the geographic zones named as a habitat suitability index (HSI). Habitability of the habitats and areas is specified by a variable called suitability index variable (SIV).

For example, in a linear model of class (see Fig. 7), if the population of solutions are sorted in decreasing order of fitness, the pth solution's immigration rate λp and emigration rate μp are calculated as

$$\lambda = I\frac{p}{P} \tag{10}$$

$$\mu = E(1-\frac{p}{P}) \tag{11}$$

where, P is the size of population, and I = maximum possible immigration rate, E = emigration rate.

According to Fig.7, when there is no population in it, the highest immigration rate to the habitat happens. As the population amount in the habitat rises, the immigration rate reduces. The basis algorithm of BBO is represented below-

Algorithm 1 The Basic BBO Algorithm.

1 Randomly initializes a population of *P* solutions (habitats);
2 **while** stop condition is not met **do**
3 Sorting the habitats in decreasing order of fitness;
4 Calculate the migration and mutation rates of the habitats;
5 **for** $p = 1$ **to** P **do**
6 **for** $i = 1$ **to** n **do**
7 **if** *rand*() < λp **then** *//migration*
8 Select a habitat *Hq* with probability μ μq ;
9 *Hp,i* ¬ *Hq,i* ;
10 **for** $p = 1$ **to** P **do**
11 **for** $i = 1$ **to** n **do**
12 **if** *rand*() < πp **then** *//mutation*
13 *Hp,i* ¬ *li* + *rand*() × (*ui* − *li*);
14 Evaluate the fitness values of the habitats;
15 Update the best known solution;
16 **return** the best known solution.

VI. RESULTS AND DISCUSSIONS

The database used in this research involves 238 field observations based on SPT data. The data was separated into two sets when the formulation was performed: such as

(a) A training dataset: This is requisite to create the model. In this study, 167 data out of the 238 are regarded for training dataset.
(b) A testing dataset: This is necessary for estimating the efficiency of the model. The remaining 71 data are regarded as a test dataset in this study.

The implementation of any model consists of training and testing. In this work, a total of 238data were used. For training the neural networks, 167data were used. The remaining 71 data were used for testing purposes only. They were preprocessed using Eq. (12) before the datasets were used to train the BP model. Each parameter is normalized with 0 to 1,

$$y = \frac{x - x_{Min.}}{x_{Max} - x_{Min}} \tag{12}$$

where y is a normalized input parameter, x is the original input parameter; x_{max} and x_{min} are the maximum and minimum parameters, respectively. To develop the models, initial SPT field data acquired from Chi-Chi, Taiwan earthquake used, where liquefaction and no liquefaction state has been observed. Here, out of total 288 datasets, 164 data are for the sites those liquefied and 124 are for non-liquefied sites after earthquake. Tables 1 and 2 (Hwang & Yang, 2001) represent the performance of the model using training and testing dataset respectively.

Table 1. Performance of training dataset for model

site	(N1)60	CSR	Actual Class
MingjianShiang	8.47	0.451	-1
Taiping City	3.58	0.378	-1
Wufengshinag	6.38	0.714	-1
Wufengshinag	8.71	0.514	-1
Yuanlin Jen	4.05	0.417	-1
Taichung Harbour	10.19	0.132	-1
Taichung Harbour	8.82	0.139	-1
Taichung Harbour	10.71	0.148	-1
Taichung Harbour	7.25	0.145	-1
Taichung Harbour	6.72	0.142	-1
Tautuen Jen	3.02	0.271	-1
Taichung Harbour	8.89	0.15	-1
Taichung Harbour	5.7	0.134	-1
Taichung Harbour	12.63	0.153	-1
Taichung Harbour	9.93	0.151	-1
Taichung Harbour	6.96	0.163	-1
Taichung Harbour No.3	6.16	0.148	-1
Taichung Harbour No.3	6.05	0.145	-1
Taichung Harbour No.3	5.32	0.145	-1
Taichung Harbour No.3	8.79	0.152	-1
Taichung Harbour No.3	5.58	0.14	-1
Taichung Harbour No.3	4.31	0.136	-1
Taichung Harbour No.3	4.99	0.144	-1
Taichung Harbour No.3	4.96	0.144	-1
Chiuanshing	5.04	0.217	-1
Chiuanshing	13.4	0.214	-1
Chiuanshing	13.11	0.174	-1
Chiuanshing	11.88	0.209	-1
MingjianShiang	14	0.663	-1
MingjianShiang	8.61	0.391	-1
MingjianShiang	7.39	0.633	-1
MingjianShiang	13.43	0.699	-1
MingjianShiang	19.25	0.67	-1
Chanbing Industrial Park	5	0.12	-1
Chanbing Industrial Park	8.22	0.119	-1
Chanbing Industrial Park	3.26	0.118	-1
Chanbing Industrial Park	2.93	0.127	-1
Chanbing Industrial Park	5.73	0.124	-1
Chanbing Industrial Park	3.28	0.118	-1
Chanbing Industrial Park	2.39	0.13	-1

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Table 1. Continued

site	(N1)60	CSR	Actual Class
Nantou City	9.4	0.296	-1
Nantou City	6.55	0.283	-1
Nantou City	11.62	0.386	-1
Yuanlin Jen	10.81	0.228	-1
Nantou City	10.62	0.458	-1
Nantou City	9.75	0.306	-1
Nantou City	12.14	0.384	-1
Nantou City	4.35	0.36	-1
Nangang Industrial Park	15.78	0.362	-1
Nangang Industrial Park	14.34	0.356	-1
Maolo River	7.53	0.289	-1
Tsautuenjen	7.03	0.325	-1
Yuanlin Jen	8.14	0.247	-1
Yuanlin Jen	6.94	0.235	-1
Yuanlin Jen	9.58	0.195	-1
Yuanlin Jen	8.33	0.222	-1
Yuanlin Jen	9.76	0.238	-1
Yuanlin Jen	6.29	0.232	-1
Yuanlin Jen	7.69	0.234	-1
Yuanlin Jen	6.34	0.228	-1

During an earthquake, the liquefaction sensitivity of a soil mass depends on both seismic and soil parameters. The input parameters in this study are used as SPT value $(N_1)_{60}$ and cyclic shear stress ratio (CSR). To use these data for classification purposes, the liquefied sites are assigned a value of 0 while the non-liquefied sites are assigned a value of 1 in order to make this a problem of binary classification. So, the output of the model is either 1 or 0. According to the results of network training, the network has effectively achieved the relationship between the input parameters and output. The verification of ENN model is to be done by the testing dataset. Data normalization ranges from 0 to 1. The ENN model will be developed with the help of MATLAB. For comparison from actual data a confusion matrix is developed.

To develop the ANFIS models 238 datasets were taken and incorporated for the development of fuzzy neural network models. The dataset is obtained from the paper of Umar et al. (2018). This work is based on the datasets of SPT and bore. Initially, two basic factors of input for the development of fuzzy neural network models, i.e. *CSR* and *SPT-N* were used to predict the potential for liquefaction. In this model, the same training dataset, testing dataset, and normalization technique have been used similar to previous model. The verification of ANFIS model is to be done by the testing dataset. The data normalization ranges from 0 to 1.The ANFIS model will be developed with the help of MATLAB. For comparison from actual data a confusion matrix is developed.

Table 2. Performance of testing dataset for Model

site	(N1)60	CSR	Actual Class
Maolo River	27.8	0.354	1
Nangan Bridge	3.67	0.379	-1
Taichung Harbour	8.48	0.136	-1
Taichung Harbour	11.57	0.128	-1
Taichung Harbour	5.7	0.143	-1
Taichung Harbour	7.04	0.148	-1
Taichung Harbour No.3	5.52	0.105	-1
Taichung Harbour No.3	8.44	0.146	-1
Taichung Harbour No.3	6.86	0.152	-1
Taichung Harbour No.3	4.96	0.148	-1
Chiuanshing	5.31	0.193	-1
MingjianShing	14.48	0.606	-1
MingjianShing	8.61	0.673	-1
Chanbing Industrial Park	11.86	0.127	-1
Chanbing Industrial Park	7.27	0.126	-1
Chanbing Industrial Park	11.8	0.121	-1
Nantou City	16.59	0.41	-1
Nantou City	6.71	0.3	-1
Nantou City	12.04	0.433	-1
Maolo River	35.34	0.384	1
Yuanlin Jen	8.14	0.248	-1
Yuanlin Jen	8.14	0.222	-1
Yuanlin Jen	9.85	0.226	-1
Yuanlin Jen	9.76	0.196	-1
Yuanlin Jen	5.61	0.221	-1
Yuanlin Jen	6.03	0.217	-1
Yuanlin Jen	7.22	0.228	-1
Yuanlin Jen	3.31	0.182	-1
Yuanlin Jen	11.49	0.203	-1
Yuanlin Jen	3.86	0.199	-1
Yuanlin Jen	5.31	0.208	-1
Yuanlin Jen	6.53	0.197	-1
Yuanlin Jen	11.32	0.199	-1
Yuanlin Jen	12.54	0.201	-1
Yuanlin Jen	10.65	0.165	-1
Maolo River	27.92	0.364	1
Yuanlin Jen	9.41	0.194	-1
Maolo River	10.86	0.294	-1
Maolo River	33.43	0.275	1
Maolo River	35.09	0.339	1

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Table 2. Continued

site	(N1)60	CSR	Actual Class
Maolo River	7.53	0.304	-1
Maolo River	18.66	0.42	-1
Maolo River	7.11	0.411	-1
Maolo River	4.58	0.412	-1
Maolo River	20.51	0.352	-1

Table 3. CA and BBO tuning parameter

	CA-tuning parameters	BBO-tuning parameters
Maximum Number of Iterations	500	1000
Number of population	20	50
Alpha	0.3;	0.9
Beta	0.5	0.5
Parameter of Mutation	0.1	0.1
Sigma	0.02*((Decision Variables Upper Bound)-(Decision Variables Upper Bound))	0.02*((Decision Variables Upper Bound)-(Decision Variables Upper Bound))

The tuning parameter of BBO and CA is shown in the Table 3.

Initially trial and error method has been adopted to train the models considering different optimization. Table 3 shows the optimization parameters (maximum iteration, number of population, alpha, beta, percentage of mutation and sigma) of the hybrid models. Additionally, confusion matrixes were plotted for comparative study. Comparison analysis clearly indicates that the BBO models implement better than the other models for classification of liquefaction.

Model Performance Assessment

- ***Confusion Matrix***

Two measures were used to evaluate the classification algorithms: accuracy and confusion matrix. Results are presented with regard to the accuracy and confusion matrix. A confusion matrix is also known as an error matrix in machine learning, particularly in the problem of statistical classification. The confusion matrix (Kohavi & John, 2014) includes information about the true and predicted classifications on a classification system. Table 4 demonstrates the confusion matrix used in this study for a binary classifier and Table 7 shows various parameter of confusion matrix. Confusion Matrix is given as;

I. *Sensitivity or True Positive Rate (TPR)*

The fraction of properly detected is indicated by the TPR or true positive rate. TPR is a main parameter for assessing network performance in this study. Sensitivity value of 1.0 is best whereas 0.0 is the worst.

$$TPR = Sensitivity = \frac{TP}{TP + FN} \tag{13}$$

II. *Specificity or True Negative Rate (TNR)*

A true negative is a result where the negative class is properly predicted by the model.

$$TNR = Specificity = \frac{TN}{TN + FP} \tag{14}$$

III. *Miss Rate or False Negative Rate (FNR)*

A false negative is a result where the negative class is wrongly predicted by the model.

$$FNR = \frac{TN}{TN + FP} = 1 - TPR \tag{15}$$

IV. *Fall-out or False Positive Rate (FPR)*

A false positive is a result in which the model predicts the positive class wrongly.

$$FPR = \frac{FP}{FP + TN} = 1 - TNR \tag{16}$$

V. *Accuracy (ACC)*

It is the rate of correctly predicting each sample data into the correct group. Predictions of model accuracy were evaluated using estimates of error for both training and testing data sets using Eq.15.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{17}$$

Figs.(8 and 9)) represent various parameter of CA model training (MSE=0.0730, RMSE=0.275, Error St.D.=0.2704) and testing (MSE=0.1132, RMSE=0.336, Error St.D.=0.2997). Figs.(11 and 12)) represent various parameter of BBO model training (MSE=0.05704,RMSE=0.268,Error St.D.=0.239)

Table 4. Confusion matrix

	+1	−1
+1(Actual, No Liquefaction)	TP	FN
-1(Actual, Liquefaction)	FP	TN

TP = number of right projection that an instance is positive;
FP= number of incorrect projection that an instance is positive;
TN= number of right predictions of a negative case (or zero);
FN= number of inaccurate projections of a negative instance (or zero).

Table 5. Confusion matrix based on training of dataset

Confusion Matrix	Chi-Chi earthquake data	CA- ANFIS	BBO-ANFIS
	$\begin{bmatrix} 113 & 23 \\ 6 & 60 \end{bmatrix}$	$\begin{bmatrix} 112 & 12 \\ 4 & 74 \end{bmatrix}$	$\begin{bmatrix} 108 & 7 \\ 8 & 79 \end{bmatrix}$

Table 6. Confusion matrix based on testing of dataset

Confusion Matrix	Chi-Chi earthquake data	CA- ANFIS	BBO-ANFIS
	$\begin{bmatrix} 40 & 16 \\ 6 & 24 \end{bmatrix}$	$\begin{bmatrix} 46 & 13 \\ 3 & 24 \end{bmatrix}$	$\begin{bmatrix} 47 & 7 \\ 2 & 30 \end{bmatrix}$

Table 7. Various parameter of confusion matrix

	Chi-chi earthquake data training	Chi-chi earthquake data testing	ENN Model	CA-ANFIS-training	CA-ANFIS testing	BBO training	BBO-testing
TPR	0.8309	0.7143	0.762195	0.9032	0.7796	0.9391	0.8703
TNR	0.9091	0.8000	0.958904	0.9487	0.8888	0.9080	0.9375
FNR	0.1691	0.2857	0.237805	0.0967	0.2203	0.0608	0.1296
FPR	0.0909	0.2000	0.041096	0.0512	0.1111	0.0919	0.0625
ACC	0.8564	0.7442	0.727612	0.9207	0.8139	0.9257	0.8953

Table 8. Binary classification values of the models

Observed Value	ENN model	BBO model	CA model
0	0	0	0
0	0	0	0
0	0	0	0
1	0	1	1
1	0	1	1
1	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
1	1	1	1
1	0	1	1
0	0	0	0
0	0	0	0
1	0	0	0
0	0	0	0
1	0	1	1
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
1	0	1	1
1	1	1	0
0	1	0	0
0	0	0	0
1	0	1	1
0	0	0	0
1	0	1	1
0	0	0	0
0	0	0	0
1	0	1	1
0	0	0	0
1	0	1	1
1	0	1	1
1	0	1	1
0	0	0	0
0	0	0	0

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Table 8. Continued

Observed Value	ENN model	BBO model	CA model
0	0	0	0
1	0	1	1
0	0	0	0
1	0	1	1
1	0	1	1
1	0	1	1
0	0	0	0
0	0	0	0
1	0	1	1
0	0	0	0
1	0	0	0
1	0	0	0
1	0	1	1
1	0	1	1
1	0	1	1
0	0	0	0
1	0	1	0
0	0	0	0
0	0	0	0
0	0	0	0
1	0	1	1
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
1	0	1	1
1	0	1	1
1	0	1	1
1	0	1	1
1	0	1	1
1	0	1	1
0	0	0	0
1	0	1	1
1	0	1	1
0	0	0	0
0	0	1	1
0	0	0	0
0	0	0	0
0	0	0	0

continued on next page

Table 8. Continued

Observed Value	ENN model	BBO model	CA model
0	0	0	0
1	0	1	1
0	0	1	0
0	1	0	0
1	0	1	1
0	0	0	0
0	0	0	0
0	1	0	0
0	0	0	0
1	0	1	1
1	0	1	1
0	0	1	1
1	0	1	1
1	0	1	0
0	0	0	0
0	0	0	0
1	0	1	1
0	0	0	0
0	0	0	0
1	0	1	1
0	0	0	0
1	0	1	1
0	0	0	0
1	0	1	1
1	0	1	1
1	0	1	1
1	0	1	1
1	0	1	1
0	0	0	0
1	0	1	1
0	0	0	0
1	0	1	1
0	0	0	0
1	0	1	0
1	0	1	0
1	0	1	1
0	0	0	0
0	1	0	0
0	1	0	0
1	1	1	1
0	1	0	0

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Table 8. Continued

Observed Value	ENN model	BBO model	CA model
1	1	1	1
0	1	0	0
0	1	0	0
0	1	0	0
1	1	1	1
0	1	0	0
0	1	0	0
1	1	0	0
0	1	0	0
1	1	1	1
1	1	1	1
1	1	0	0
0	1	0	0
0	1	0	0
0	1	0	0
1	1	1	1
1	1	1	1
0	0	0	0
0	1	0	0
0	1	0	0
0	1	0	0
1	1	1	1
0	1	0	0
0	1	0	0
0	1	0	0
1	1	1	1
0	1	0	0
0	1	0	0
0	1	0	0
0	1	0	0
0	1	0	0
1	1	1	1
0	1	0	0
0	1	0	0
1	1	1	1
0	1	0	0
0	1	0	0
1	1	1	1
0	1	0	0
1	1	1	1
0	0	1	1

continued on next page

Table 8. Continued

Observed Value	ENN model	BBO model	CA model
0	0	0	0
0	1	0	0
0	0	0	0
1	0	1	1
0	1	0	0
1	1	1	1
0	0	0	0
0	1	0	0
1	0	1	1
0	0	1	0
0	0	0	0
1	0	1	1
1	0	1	1
0	1	0	0
0	1	0	0
1	0	0	0
0	0	1	0
0	0	0	0
1	0	1	1
0	0	1	1
1	0	1	1
0	0	0	0
0	0	1	0
1	0	1	1
1	0	1	1
1	1	1	1
0	1	0	0
0	1	0	0
1	1	1	1
1	1	1	1
0	1	0	0
0	1	0	0
1	1	1	1
0	1	0	0
0	1	0	0
1	1	1	1
1	0	1	1
1	1	1	1
0	1	0	0

and testing(MSE=0.08957, RMSE=0.2998, Error St.D.=0.2997). Figs.(10 and 13)) show epoch of CA and BBO model. An epoch is a complete display of the whole data set during the training process. It presents the error of the first50 learning epochs for CA model and error of the first100 learning epochs for BBO model. The results affirmed that the BBO model with low error values of root mean square error (RMSE) equal to 0.2998 is more accurate than ENN model (RMSE =0.721) and CA model (RMSE =0.336). It is found that the BBO model has the lowest RMSE compared to all models. Table 8 illustrates binary classification values of all models, where '0' values indicate liquefaction case and value '1' represent non-liquefied case. It shows the comparison of all models.

VI. CONCLUSION

In this paper, the functionality of three different soft computing methods were analyzed and validated. The scope of this study is to implement the above models for prediction of soil liquefaction in Bihar state. This study provided the implementation of an algorithm for studying an emotional neural network (ENN), BBO and CA model based on ANFIS for prediction of soil liquefaction. The input variables of all models are $(N_1)_{60}$and *CSR*. The analysis of results depicted that all the models are quite good to accomplish binary classification. The performance of these models was assessed using different indexes i.e. sensitivity, specificity, FNR, FPR and accuracy rate. ENN uses the emotional back propagation learning algorithm. Among the models, the BBO-ANFIS model has been outperformed and can be adopted as a new reliable technique for this study. The study found that the suggested models in this research improve classification precision and are viable techniques for anticipating classification of soil liquefaction. The adopted new BBO-ANFIS model can be viable techniques to study the problem the liquefaction and can be used in the field of geotechnical engineering to solve the field related problems. The developed models should be used with practical knowledge.

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