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Artificial Neural Networks Technique for Seismic Hazard Prediction Using Seismic Bumps

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***Abstract*—**Natural disasters have occurred and will continue to cause human and material damage. Therefore, the idea of "preventing" natural disasters will never be possible. However, their prediction is possible with the advancement of technology. Even if natural disasters are effectively inevitable, their consequences may be partly controlled. The rapid growth and progress of artificial intelligence (AI) had a major impact on the prediction of natural disasters and risk assessment which are necessary for effective disaster reduction. Earthquake prediction to prevent the loss of human lives and even property damage is an important factor; that, is why it is crucial to develop techniques for predicting this natural disaster. This study aims to analyze the ability of artificial neural networks (ANNs) to predict earthquakes that occur in a given area. The used data describe the problem of high energy (higher than 10^4 J) seismic bumps forecasting in a coal mine using two long walls as an example. For this purpose, seismic bumps data obtained from mines have been analyzed. The results obtained show that the ANN is able to predict earthquake parameters with high accuracy; the classification accuracy through neural networks is more than 94%, and the models developed are efficient and robust and depend only weakly on the initial database.

***Keywords*—**Earthquake prediction, artificial intelligence, AI, Artificial Neural Network, ANN, seismic bumps.

I. Introduction

A seism or earthquake is one of the most dangerous natural disasters, it tops the list of deadliest disasters in recent decades. Unlike a hurricane or a volcanic eruption, an earthquake strikes in a few seconds giving no chance to flee. We cannot avoid an earthquake but the main objective of many research tasks is to provide the location where the future earthquake will occur. More than a million earthquakes rattle the world each year. Of course, this telluric activity is not, in most cases, perceptible to humans.

The seism or earthquake, shake or shake succession of soil may be more or less violent. This could be the result of the sudden release of stress in the crust of the earth, which causes a shift of two compartments along a fault and an elastic rebound. These shocks can be imperceptible or very destructive. Early warning for these natural hazards is an important phase to prevent losses in life and to reduce resulting catastrophic consequences.

The various aspects of protection against the earthquake effects have been the subject of many research works, on the area of assessment and the decrease of seismic risks. Earthquake prediction has been a major subject for the community of scientists. The importance of earthquake prediction is a challenging problem. It is believed that several indicators are associated with earthquake upcoming events. The well-known factors in earthquake existence are sometimes hard or impossible to measure; as well, the relationships between these factors are not simple and need broad investigation and analysis. Many researchers attempted to predict earthquakes in many regions of the world, among those research works, Zhang et al. [1] suggested a multi-scale wavelet analysis for single-component recordings. Moreover, the wavelet method and the average energy value for the detection of seismic wave arrival time in three-component stations were used by Colak et al. [2]. Dehbozorgi and Farokhi [3] tried the neuro-fuzzy system in their study using seismometer data. Xu et al. [4] carried out an analysis on data obtained from DEMETER satellite and feedback neural network was used; seismic band information electron density in this study, electron temperature, ion temperature and a series of physical quantities measured by DEMETER satellite, including oxygen ion density were employed to create sample sets for back propagation neural network. Moustra et al. [5] attempted to evaluate the performance of this technique in predicting earthquakes in Greece. They considered two cases of studies; the first case concerns the prediction of the next day's magnitude earthquake and the second concerns the prediction of the magnitude of the impending seismic event after the occurrence of seismic electric signals. In their study, the time series magnitude is employed as input data for the first part and the output is the magnitude of the following day. In the second part, the seismic electric signals were incorporated as data input and the intended output is the magnitude of upcoming seismic events. Radial basis function neural networks model to estimate large earthquake occurrence is analyzed by Alexandridis et al. [6]. Reyes et al. [7] used the ANNs in the aim to predict earthquakes in Chile, one of the countries with high telluric activity. The input data are dependent on b-value, the Bath's law, and the Omori-Utsu's law parameters that are strongly correlated with seismic activity.

An intelligent system for prediction of earthquakes analyzing seismic data bumps using support vector machine as

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classification algorithm is suggested by Celik et al. [8]. Some studies were carried out using seismic bumps such as Bilen et al. [9], who established an earthquake prediction system analyzing seismic bumps data using k nearest neighbor classification algorithm.

ANNs are widely used and have been applied in many areas. Sukran et al. [10] created a valuation map in geographical information systems (GIS) through ANN methodology. Turgut [11] applied a back propagation ANN for gravity field modeling. ANNs are becoming a powerful tool for prediction classification, estimation, segmentation and prediction. The back propagation is the most used as a learning algorithm for the training process of ANN.

The approach used in this study is the multilayer perceptron type ANN, applied on seismic bumps data used for earthquake prediction which are obtained from a Polish coal mine.

II. Material and Methods

A. Data

The data used in this study are downloaded from seismic-bumps Data Set, [12]; these data describe the problem of high energy (higher than 104 J) seismic bumps forecasting in a coal mine [13]. Data come from two of long walls located in a Polish coal mine. In the data set, each row contains information about the seismic activity in the rock mass during an estimated 8-hour shift. It contains 19 attributes and 2584 instances.

If a decision attribute has the value 0, this means that no high energy seismic bumps occurred in the next shift; else if it has 1, then in the next shift any seismic bump with an energy higher than 104 J was registered.

TABLE I
DATA DESCRIPTION

Name	seismic-bumps
Data types	Multivariate
Data task	Classification
Attribute types	Real
Instances	2584
Attributes	19
Year	2013
Area	Other
Description	The data describe the problem of high energy (higher than 104 J) seismic bumps forecasting in a coal mine.

B. Artificial Neural Networks

ANNs [14] are derived from biological models and are composed of interconnected elementary computing units (neurons).

C. Multilayer Perceptron

Multilayer perceptron (MLP) is one of the most used neural networks for approximation problems [15], [16], classification [17], [18] and prediction [19], [20]. It consists of three groups or layers of units. An input layer is connected to a layer of intermediate units called hidden layer, which is in turn connected to an output layer. Starting from the input layer to the output layer and passing through the hidden layers, all the neurons of a layer are the inputs of each neuron of the next layer.

TABLE II
ATTRIBUTES INFORMATION [12]

N°	Attribute	Description
1	seismic	result of shift seismic hazard assessment in the mine working obtained by the seismic method (a - lack of hazard, b - low hazard, c - high hazard, d - danger state)
2	seism acoustic	result of shift seismic hazard assessment in the mine working obtained by the seism acoustic method
3	shift	information about type of a shift (W - coal-getting, N - preparation shift);
4	genergy:	seismic energy recorded within previous shift by the most active geophone (GMax) out of geophones monitoring the long wall
5	gpuls	a number of pulses recorded within previous shift by GMax
6	gdenergy	a deviation of energy recorded within previous shift by GMax from average energy recorded during eight previous shifts
7	gdpuls	a deviation of a number of pulses recorded within previous shift by GMax from average number of pulses recorded during eight previous shifts
8	ghazard	result of shift seismic hazard assessment in the mine working obtained by the seism acoustic method based on registration coming from GMax only
9	nbumps	the number of seismic bumps recorded within previous shift
10	nbumps2	the number of seismic bumps (in energy range [102,103]) registered within previous shift
11	nbumps3	the number of seismic bumps (in energy range [103,104]) registered within previous shift
12	nbumps4	the number of seismic bumps (in energy range [104,105]) registered within previous shift
13	nbumps5	the number of seismic bumps (in energy range [105,106]) registered within the last shift
14	nbumps6	the number of seismic bumps (in energy range [106,107)) registered within previous shift
15	nbumps7	the number of seismic bumps (in energy range [107,108]) registered within previous shift
16	nbumps89	the number of seismic bumps (in energy range [108,1010]) registered within previous shift
17	energy	total energy of seismic bumps registered within previous shift
18	Max energy	the maximum energy of the seismic bumps registered within previous shift
19	class	the decision attribute - '1' means that high energy seismic bump occurred in the next shift ('hazardous state'), '0' means that no high energy seismic bumps occurred in the next shift ('non-hazardous state')

The activation functions used in a MLPs are mainly threshold or sigmoid functions. It can solve non-linearly separable problems and more complicated logical problems. In this study a MLP with three-layer is used.

- The input layer: In this layer, the input unit receives and inputs the values of attributes: $x_1, x_2, \ldots, x_p$ of the network where no calculation is performed.
- The hidden layer: It is a layer between the input layer and output layer; a MLP can contain one or more hidden layers.
- The output layer: It is the last layer that holds the result.

The output of the neurons considered for the development of a MLP is a differentiable function of real variables, it is the sigmoid function defined by:

$$\sigma(y) = \frac{e^y}{e^y+1} = \frac{1}{1+e^{-y}} \qquad (1)$$

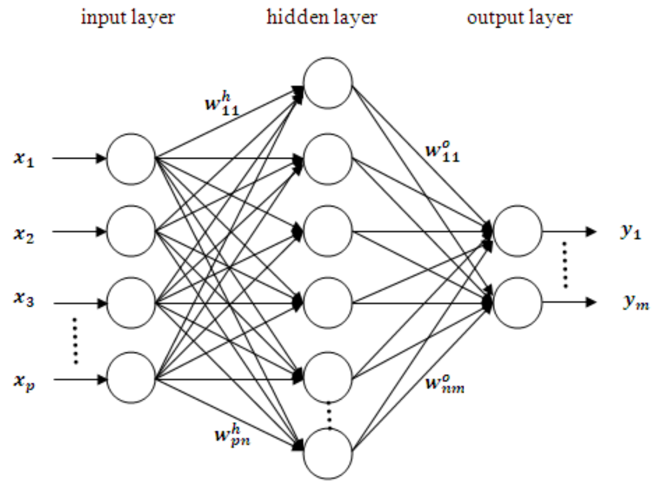

Fig. 1 An MLP with one hidden layer

The derivative of the sigmoid function σ is:

$$\dot{\sigma}(y) = \frac{e^y}{(1+e^y)^z} = \sigma(y)\big(1-\sigma(y)\big) \quad (2)$$

The derivative will be used in the update rule of weight by the back-propagation algorithm [21].

The MLP considered in this paper is defined by real entries $\vec{x} = (x_1, \dots, x_p)$, real synaptic weights $\vec{w} = (w_1, \dots, w_p)$, and the output y is calculated according to (3):

$$y(\vec{x}) = \frac{1}{1+e^{-y}} \text{ where } y = \vec{x}\vec{w} = \sum_{i=1}^{p} w_i x_i \quad (3)$$

D.Learning by Backpropagation Algorithm

The principle of the algorithm is to minimize the error function E between the desired output and calculated output. So, this algorithm determines a vector $\vec{w}$ that minimizes $E(\vec{w})$. The error is defined as:

$$E = E_{(\vec{x},\vec{y})}(\vec{w}) = \frac{1}{2}\sum_{j=1}^{m}\left(y_j^d - y_j\right)^2 \quad (4)$$

The back-propagation algorithm:

Input: a sample Ω^{ANN} of $R^p * R^m$

A MLP with an initial structure: input layer C_0, q-1 hidden layers $C_1, \dots, C_{q-1}$, and an output layer C_q,

Random initialization of weights in the interval [0,1] for each connection.

Set the value of ε.

Repeat

Take an example $(\vec{x}, \vec{y^d})$ in Ω^{ANN}

Calculate the output $\vec{y}$ of MLP for input $\vec{x}$ by (3)

---Calculation of $\delta_j$back-propagation---

For all output cells j, calculate,

$$\delta_j = y_j(1-y_j)(y_j^d - y_j) \quad (5)$$

End For

For each layer from q-1 to 1

For each cell j of the current layer

∀ i ∈ Succ(j), Succ(j) is the set of neurons which take as input the output of the neuron j, calculate

$$\delta_j = y_j(1-y_j)\sum_i(\delta_j * w_{ij}) \quad (6)$$

End For

End For

--- Update weights ---

For all weights

$$w_{ji} = w_{ji} + \varepsilon\delta_j x_{ji} \quad (7)$$

End For

End Repeat

Output: an MLP defined by the initial structure, output y and weights w_{ji}, with minimum error.

III. Results and Discussions

In this section, to show the contribution of the earthquake prediction by MLP, a model is developed that is able to predict the seismic hazard using seismic bumps data.

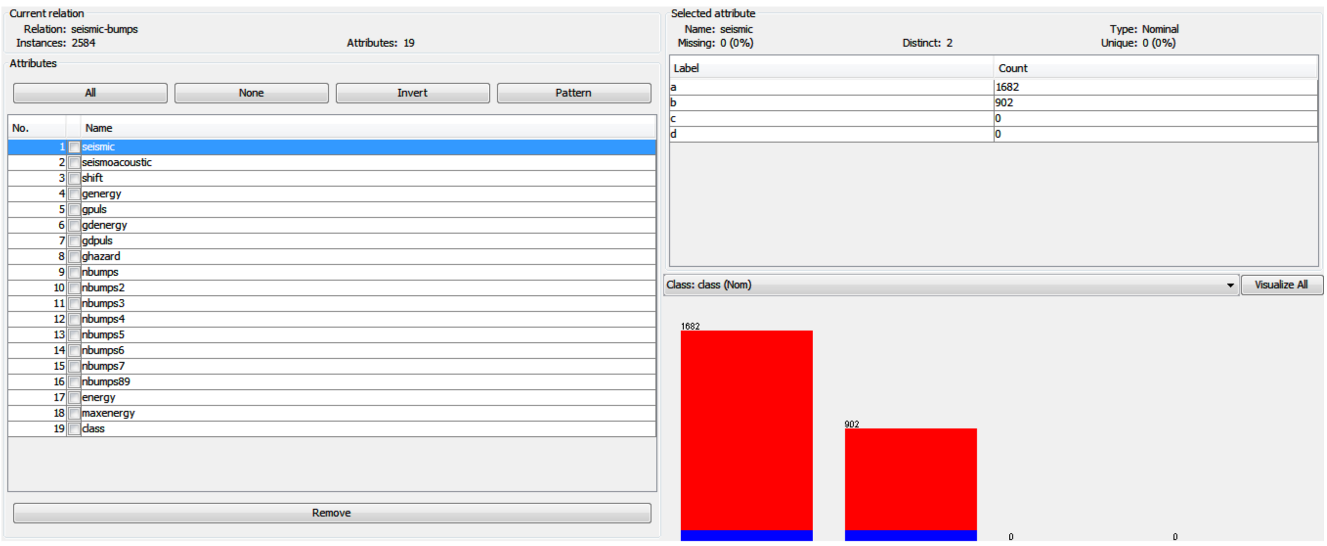

Fig. 2 Charged data

```
=== Run information ===

Scheme:       igss.classifiers.functions.MultilayerPerceptron -L 0.3 -M 0.2 -N 500 -V 0 -S 0 -E 20 -H a
Relation:     seismic-bumps
Instances:    2584
Attributes:   19
              seismic
              seismoacoustic
              shift
              genergy
              gpuls
              gdenergy
              gdpuls
              ghazard
              nbumps
              nbumps2
              nbumps3
              nbumps4
              nbumps5
              nbumps6
              nbumps7
              nbumps89
              energy
              maxenergy
              class
Test mode:    evaluate on training data
```

Fig. 3 Data information

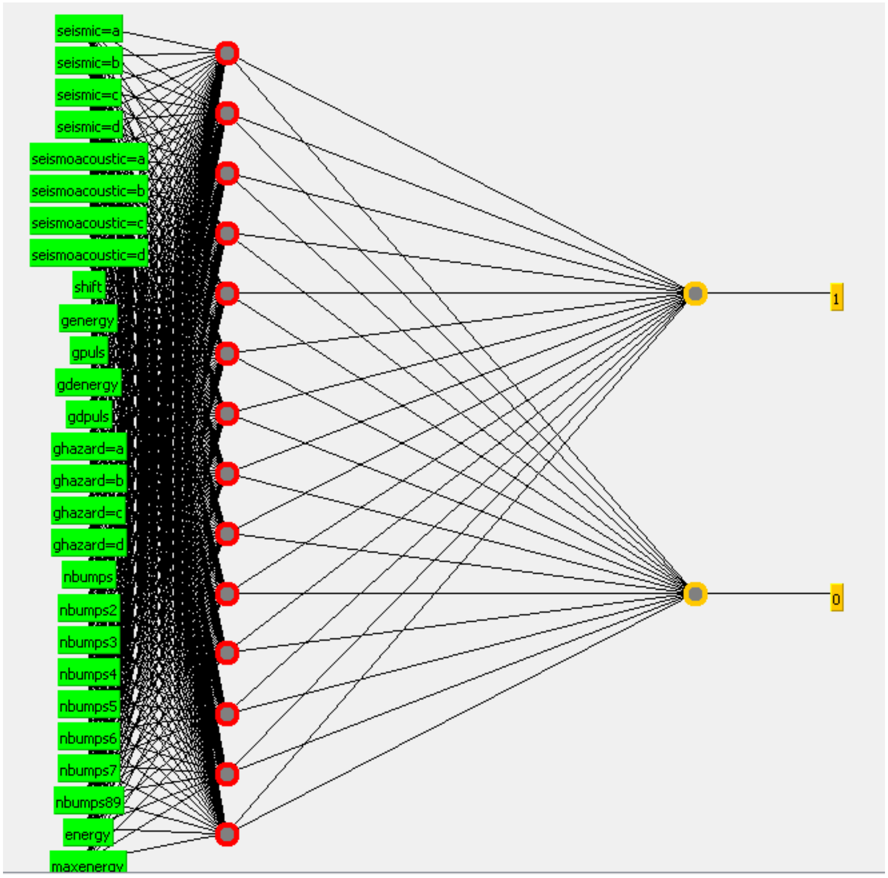

Fig. 4 MLP architecture

To be able to use multi-layer networks in learning, one thing is essential: a method indicating how to choose network architecture to solve a given problem. That is to say, be able to respond to the following questions: how many hidden layers? How many neurons per hidden layers?

The number of hidden layers and the nodes are usually determined by trying different networks topologies and selecting the one with the least error.

There are some rules to estimate the number of hidden nodes. The criteria to select optimal number of hidden layer neurons in the used MLP are calculated by dividing the number of input-output pairs in the training set by two.

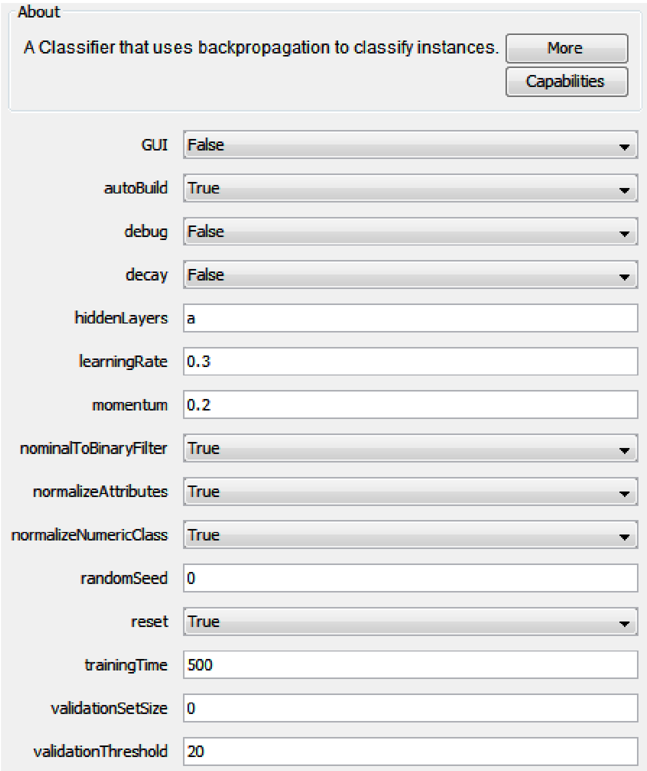

Fig. 5 MLP parameters

The values of MLP parameters used in this research are:

- Number of input layer units = 27
- Number of hidden layers = 1
- Number of hidden layer units = 14
- Number of output layer units = 2
- Learning rate = 0.3
- Learning cycle = 500

```
=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances        2433               94.1563 %
Incorrectly Classified Instances       151                5.8437 %
Kappa statistic                          0.2194
Mean absolute error                      0.0781
Root mean squared error                  0.2234
Relative absolute error                 63.3787 %
Root relative squared error             90.0936 %
Total Number of Instances             2584

=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
  0.135     0.002      0.852     0.135     0.234      ?         1
  0.998     0.865      0.943     0.998     0.97       ?         0

=== Confusion Matrix ===

    a    b   <-- classified as
   23  147 |    a = 1
    4 2410 |    b = 0
```

Fig. 6 Prediction results

An ANN model was developed to predict earthquakes that occur in a given area taken from a Polish coal mine. In this regard, an MLP model was constructed using 27 inputs and two outputs as shown in Fig. 4, and after undertaking the MLP parameters study as shown in Fig. 5, an MLP model with one hidden layer and 14 neurons in the hidden layer was selected.

Fig. 6 shows predicted Seismic Bumps for the training data using MLP, the accuracy rate reached is 94.16%. The model is used successfully for predicting of any seismic bump with a high energy seismic bump (higher than 10^4 J) occurred in the next shift or no high energy seismic bumps occurred in the next shift, with error of 5.84%. According to these results, artificial intelligent techniques can predict seismic hazard with high level of accuracy.

IV. Conclusion

In this study, a non-classical, ANN-based approach was developed to predict earthquake using seismic bump data. An accuracy rate of 94.16% was achieved. The obtained results showed that the effectiveness of the presented approach is able to predict seismic hazard more accurately than methods commonly used.

The main advantage of using ANNs over other statistical and numerical techniques is their ability to capture the non-linear relationship among the variables involved and optimization can be performed very quickly, without the need to use a mathematical form of the relationship between input and output data. Their ability to learn by examples makes them very flexible and powerful. The only disadvantage of ANN is that it is a black box learning approach, we cannot interpret results and relationship between inputs and outputs.

In our future work, it is recommended to optimize the ANN by other techniques such as evolutionary algorithms and metaheuristics.

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