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Neuro-Fuzzy and Neural Networks Models to Estimate Radon Exhalation Rate in Uranium Ore-Rock Mine

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Abstract:

Radon gas concentration and its daughter products in underground uranium ore-rock mines are often controlled using system for mechanical ventilation. In those mines the calculation of exhalation rate is potentially based on ventilation system parameters. Neural Networks and Fuzzy logic as influential computational models for categorization and estimation, are used in many application fields. These two techniques are fairly complementary to each other in a way that what one is missing of the other can provide. Normally talking all kind of systems that include these two techniques can be called Neuro-Fuzzy systems. The present work has set a Neuro- Fuzzy and artificial neural network (ANN) model for predicting radon exhalation rate using experimental data of uranium ore-rock in China throughout mine ventilation. The effects of different ranges of training sample sets on forecasting performance of ANN and Neuro- Fuzzy are represented. Results show that Neuro-Fuzzy model used to predict radon exhalation rate of uranium ore-rock for the duration of mine ventilation, relatively give more accurate results than ANN methods. Furthermore, it is found that the models are more successful in terms of cost and time.

Key words: Neuro-Fuzzy; Uranium Mine; Ventilation; Radon Exhalation Rate; Artificial Neural Network.

1. INTRODUCTION

Fuzzy systems and Artificial Neural Networks (ANNs) are two important techniques of artificial intelligence, which have many applications in various fields such as supervision, production, diagnostic, control systems, etc. The combination of ANNs and Fuzzy Systems which is called Neuro-Fuzzy begins to be important as it utilize the advantages of both techniques. Those advantages are concerned in revealing the functionality stored in the model at the same time having generalization capabilities and learning. Neuro-Fuzzy Systems are able to learn and tune their parameters based on input-output patterns represented in the learning phase, as well they work like a fuzzy logic system in the execution phase. Neuro-Fuzzy systems have the ability to solve technical diagnostic assignments and complex problems due to the combined features they have [1].

A famous natural radioactive gases is radon (alpha-particles emitter) which cannotbe tasted, seen or smelt, but can only be detected with special equipment. It is formed from the radioactive decay of radium (R_a-226 $\rightarrow$ R_n-222), which is resulted from the radioactive decay of uranium (U-238). The amount of uranium which is found in small quantities in all soils and rocks, varies from place to place. Radon decays to form radioactive daughters particles that can enter the body by inhalation. The risk of developing cancers of the respiratory tract especially of the lungs increases due to the inhalation of the short-lived decay products of radon. Smoking is the main cause of lung cancer deaths. However each year, about 15,000 lung cancer deaths are recorded in the United States and 1100 in the UK from breathing radon in the indoor air of homes [2].

Radon levels in outdoor air, indoor air, soil air, and ground water can be extremely different. Radon discharged from rocks and soils is quickly diluted in the atmosphere. Concentrations in the out-of-doors are commonly terribly low and doubtless don't present a hazard. Radon that emanated in poorly ventilated buildings, caves, mines, and tunnels can reach high concentrations in some circumstances. The construction method and also the degree of ventilation will influence radon levels in buildings. A person's exposure to radon can additionally vary consistent with how explicit buildings and areas are used [2-3].

It is known that as a result of inhalation of ^{222}Rn, a daughter product of decay chain of ^{238}U, and its daughter products, the equivalent dose to the entire lung is 20% and 45% higher than the equivalent dose in other tissues [1].

Several studies have been undertaken to evaluate the radon exhalation rate from building materials. The Austrian Standard ONORMS 5200 has proposed that a type of building material is considered acceptable if the annual effective dose does not exceed 2.5 mSv [3-4].

In this study the prediction model set is applied to forecast the equivalent radon exhalation rate of uranium ore-rock throughout mine ventilation in China for a uranium mine gallery 317 [5]. The results of Neuro-Fuzzy and ANN model have been presented and discussed in this paper. The paper contains four sections. After the introduction, the methodology of the Neuro-Fuzzy and ANN is discussed in the second section. The last two sections include results and discussion and conclusions. The present study is important to identify any harmful radiation which can be used as reference information to evaluate any changes in the radioactive background level.

2. METHODOLOGY

2.1 Artificial Neural Networks

The human brain consists of neurons which are artificially done in a simplified way using artificial neural networks. They can be used in an abstract way to model linear and non linear systems. The performance of the training algorithms, their parameters do not include information that can be directly understood by the human operator or that can be related to the physical properties of the system to be modeled and the quality of the signals used for training determine the ability of the artificial neural networks. One of the types of ANN is fuzzy neural network (FNN) in which feedforword is the only connection allowed between neurons (i.e. there are no lateral or feedback connections) [6-7].

2.1.1 Feed Forward Neural Network

A FNN is a layered structure, which can include non-linearity. The basic element of a FNN is the neuron that is shown in Fig. 1[6-11].

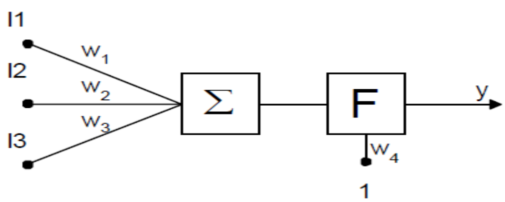

Fig.1 Neural Structure.

The neuron implements the general equation:

$$y=F(\sum_{i=1}^{n} li.wi)$$

Where usual functions for F are sigmoidal, linear and hard limit. A FNN is composed of an input layer, one or more hidden layers with one or more neurons and an output layer where frequently the neurons are linear. The Multi Input Single Output FNN in Fig. 2 implements the following general equation:

$$y=F_1(\sum_{j=1}^{nj} w'_{j1} f_j(\sum_{l=1}^{nl} w_{lj} l_l))$$

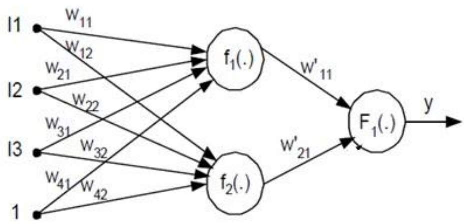

Fig.2 Feedforward Neural Network Structure.

2.1.2 Learning Algorithms of FNN

Many algorithms have been developed to use with FNN like the well known Backpropagation or the most effective Levenberg-Marquardt. The algorithms developed or adapted for the use with FNN are based on minimizing a criterion (which is most frequently based in the error between the desired and the obtained output). Most of them are based on derivative calculations of the error as a mean to minimize it. The Levenberg-Marquardt algorithm was chosen because of the robustness and fastest convergence [6-11].

2.2 Neuro-Fuzzy Systems

A Fuzzy inference system (FIS) can use human knowledge by storing its fundamentals components in a rule base, and perform fuzzy reasoning to infer the overall output value. The derivation of if-then rules and corresponding membership functions depends, a lot on the a priori knowledge about the system. However there is no systematic way to transform experiences and knowledge of human experts to the knowledge base of a FIS. There is also a need for adaptability or some learning algorithms to produce outputs within the required error rate. On the other hand, FNN learning mechanism does not rely on human expertise. Due to the homogenous structure of FNN, it is difficult to extract structured knowledge from either the weights or the configuration of the FNN. FIS and FNN are equivalent which make the form of the NFS that take advantage of the capability that FIS have to store human expertise knowledge and the capacity of learning of the FNN. A common way to apply a learning algorithm to a FIS is to represent it in a special FNN like architecture, which is what we have in ANFIS. In this work, ANFIS was the NFS solution selected because of the strength and highest convergence [6, 12-15].

2.2.1 ANFIS Architecture

The ANFIS architecture [15] is illustrated inFig.3.

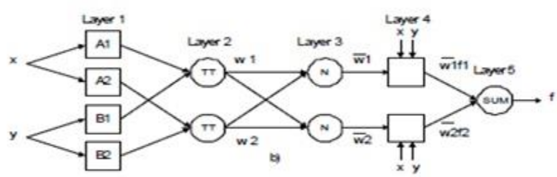

Fig.3 ANFIS Architecture.

Assume that the fuzzy inference system under consideration has two inputs x and y and one output z, for example. For the first order Sugeno fuzzy model a common rule set with two fuzzy if-then rules is the following:

Rule1: If x is A1 and y is B1, then
f1=p1x+q1y+r1;
Rule2: If x is A2 and y is B2, then
f2=p2x+q2y+r2.

The ANFIS architecture is shown in Fig. 3, where nodes of the same layer have similar functions.The output f in Fig. 3, can be written as:

$$f = \frac{w1}{w1+w2}\,f1 + \frac{w2}{w1+w2}\,f2$$

$$= \overline{w1}(p1x+q1+r1)+\overline{w2}(p2x+q2+r2)$$

$$= (\overline{w1}x)p1+(\overline{w1}y)q1+(\overline{w1})r1+(\overline{w2}x)p2+(\overline{w2}y)q2+(\overline{w2})r2$$

This way an adaptive network that is functionally corresponding to a first order Sugeno fuzzy model is constructed. From the ANFIS architecture shown in Fig. 3, it can be seen that when the values of the principle parameters (layer 1) are fixed, the overall output can be expressed as a linear combination of the resulting parameters (layer 4) [6, 12-16].

2.2.2 Learning Algorithms of ANFIS

There are two phases in the learning algorithms which are the forward pass and the backward pass. In the forward pass of the hybrid learning algorithm, node outputs values go forward until layer 4 and the resulting parameters are known by the least squares method. In the backward pass, the output errors are propagated backward and the principle parameters are updated by gradient descent method. A wide range of values are experienced to search for the best solution for first and second order system models as there is no rule to set up the perfect number of neurons in the hidden layer of the FNN structure. Three neurons are used for the direct model and four ones for the hidden layer to get the most excellent solutions in the first order approach models. While three neurons are used for the direct model and six ones for the inverse model (hidden layer) to obtain the best solutions in the second order approach models. The models have one output neuron with linear activation function [6,12-17].

3. RESULTS AND DISCUSSION

The work done is mainly focused on computational time reduction and for this reason two different artificial intelligence methods are used in turn to forecast. However, it is used in order to estimate the performance and design of an efficient artificial intelligence method to predict the equivalent radon exhalation rate for a uranium mine gallery 317 in China. The effects of different ranges of training sample sets on forecasting performance of ANN and ANFIS are investigated. Three training sample set sizes 50%, 65% and 70% of total available experimental data are used. The ventilation rate and wind pressure are taken as the input vector to the neural networks and the equivalent radon exhalation rate as the output vector.

The available experiments data are divided into two sets to develop a neural network or Neuro-Fuzzy system, one set for training purposes, and the other for test set. The range of the training sample set is an important concern for neural network applications. In this research, data are considered for both ANN and ANFIS. Therefore, three ANN and ANFIS architectures are designed for forecasting. The sample data come from the total 14 groups of measurements data of radon exhalation rate of china uranium mine gallery 317 [5], shown in Table 1.

Table 1: The input data and the output experimental data for equivalent radon exhalation rate results of a uranium mine gallery 317.

Serial Number	Ventilation Rate(m^3/s)	Wind Pressure (mmHg)	Equivalent Radon Exhalation Rate ($10^{-8}Ci/(s \cdot m^2)$)
1	1.9730	0.2800	0.1771
2	2.7930	0.4050	0.1888
3	3.1030	0.1800	0.4391
4	2.7040	0.1000	0.3483
5	2.9990	0.1800	0.4402
6	1.0030	0.2050	0.1398
7	0.9590	0.1800	0.0739
8	1.6450	0.0800	0.2241
9	0.7880	0.4500	0.0639
10	1.4080	0.0550	0.1725
11	1.3700	0.4050	0.1374
12	1.3200	0.7430	0.0836
13	1.0580	0.4800	0.0936
14	1.3580	0.1680	0.1936

The selected sample data for input which represent radon exhalation rate are 7, 9 and 10 groups corresponding to 50%, 65% and 70% respectively taken in the two models for training them. The later 3 groups measured data are test data. Table 2 indicates forecasting of equivalent radon exhalation rate using ANN model for different training inputs.

Table 2: Forecasting of Equivalent Radon Exhalation rate using ANN model for different training inputs

Serial Number	Experimental Data (10^{-8}Ci/s.m^2)	Forecasting Using Different Numbers of Training Data					
		50% of Training Data		65% of Training Data		70% of Training Data	
		Forecasting Value (10^{-8}Ci/s.m^2)	Percentage Error (%)	Forecasting Value (10^{-8}Ci/s.m^2)	Percentage Error (%)	Forecasting Value (10^{-8}Ci/s.m^2)	Percentage Error (%)
1	0.1771	0.2093	18.1810	0.0814	54.0370	0.1891	6.7750
2	0.1888	0.1912	1.2710	0.2174	15.1480	0.1875	0.6880
3	0.4391	0.4314	1.7530	0.4322	1.5710	0.4345	1.0470
4	0.3483	0.3597	3.2730	0.3322	4.6220	0.3445	1.0910
5	0.4402	0.4243	3.6110	0.4167	5.3380	0.4393	0.2040
6	0.1398	0.1177	15.8080	0.1107	20.8150	0.1076	23.0320
7	0.0739	0.1213	64.1400	0.1127	52.5030	0.1072	45.0600
8	0.2241	0.2518	12.3600	0.2857	27.4870	0.1828	18.4290
9	0.0639	0.0356	44.2870	0.0659	3.1290	0.0525	17.8400
10	0.1725	0.2572	49.1010	0.2561	48.4630	0.1716	0.5210
11	0.1374	0.0924	32.7510	0.0971	29.3300	0.0388	71.7610
12	0.0836	0.0414	50.4780	0.1614	93.0620	0.0844	0.9560
13	0.0936	0.0124	87.7520	0.1099	17.4140	0.0043	95.4050
14	0.1936	0.1269	34.4520	0.1296	33.0570	0.1309	32.3860

Table 3 shows Forecasting of equivalent radon Exhalation rate using ANFIS model for the same three training groups. Results from the three groups of training 50%, 65% and 70% for the two models show that ANFIS gives better results than ANN.

Table 3: Forecasting of Equivalent Radon Exhalation rate using ANFIS model for different training inputs

Serial Number	Experimental Data (10^{-8}Ci/s.m^2)	Forecasting Using Different Numbers of Training Data					
		50% of Training Data		65% of Training Data		70% of Training Data	
		Forecasting Value (10^{-8}Ci/s.m^2)	Percentage Error (%)	Forecasting Value (10^{-8}Ci/s.m^2)	Percentage Error (%)	Forecasting Value (10^{-8}Ci/s.m^2)	Percentage Error (%)
1	0.1771	0.1771	0.0000	0.1771	0.0000	0.1771	0.0000
2	0.1888	0.1888	0.0000	0.1888	0.0000	0.1888	0.0000
3	0.4391	0.4391	0.0000	0.4391	0.0000	0.4392	0.0220
4	0.3483	0.3483	0.0000	0.3483	0.0000	0.3483	0.0000
5	0.4402	0.4402	0.0000	0.4401	0.0122	0.4401	0.0220
6	0.1398	0.1398	0.0000	0.1398	0.0000	0.1398	0.0000
7	0.0739	0.0739	0.0000	0.0739	0.0000	0.0739	0.0000
8	0.2241	0.1290	42.4360	0.2241	0.0000	0.2241	0.0000
9	0.0639	0.1356	112.2060	0.0639	0.0000	0.0639	0.0000
10	0.1725	0.1102	36.1150	0.1591	7.7680	0.1725	0.0000
11	0.1374	0.1566	13.9730	0.1461	6.3310	0.1451	5.6040
12	0.0836	0.1600	91.3870	0.0872	4.3060	0.0816	2.3920
13	0.0936	0.1461	56.0890	0.0968	3.4180	0.0947	1.1750
14	0.1936	0.1058	45.3510	0.1758	9.1940	0.1587	18.0260

Figures 4, 5 and 6 illustrate the comparison between experimental data for equivalent radon exhalation rate and output values that are predicted by ANN and ANFIS based on the 50% 65% and 70% sample sizes, respectively. These figures show that the performance of ANFIS in forecasting equivalent radon exhalation rate results is better than ANN both in training and testing sets.

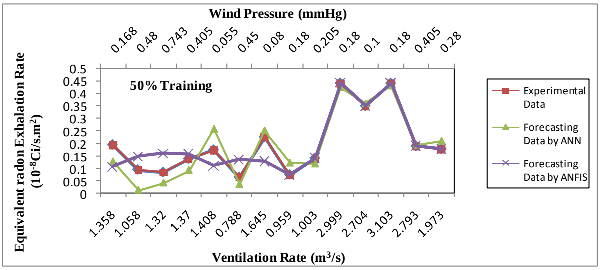

Fig.4 Comparison between equivalent radon exhalation rate experimental data and predicted values by ANN and ANFIS based on the 50% training data.

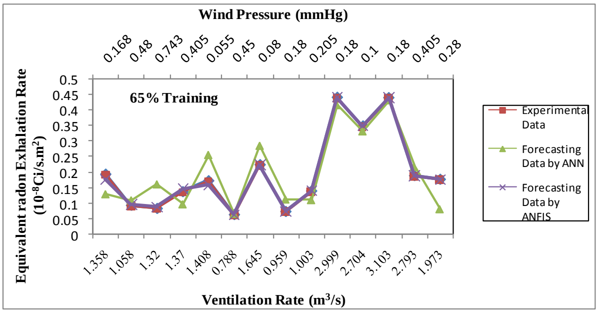

Fig.5 Comparison of equivalent radon exhalation rate experimental data and predicted values by ANN and ANFIS based on the 65 % training data.

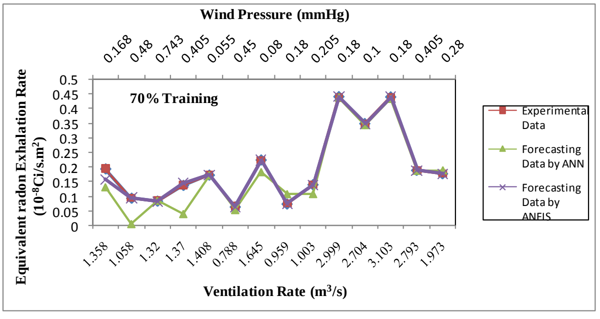

Fig.6 Comparison between equivalent radon exhalation rate experimental data and predicted values by ANN and ANFIS based on the 70% training data.

In this study a number of evaluation methods are used to measure the performance and the forecasting accuracy of ANN and ANFIS methods. The next four statistical indicators used are Mean Average Percentage Error (MAPE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Deviation (MAD) [16-18].

Table 4 shows the difference between ANN and ANFIS in each evaluation criteria for three training sample set sizes 50%, 65% and 70 % of the total available data. As it can be observed, in all training sample set sizes, MAPE, MSE, RMSE and MAD of ANFIS structure are lower than ANN structure. Therefore, the overall performance of ANFIS is better than ANN, and the results demonstrated that the ANFIS model gives higher accuracy of forecasting than the ANN model does.

Table 4: Comparison of training and testing sets using ANFIS and ANN.

Method Used in Prediction	Percentage of Training Data	MAPE	MSE	RMSE	MAD
ANFIS	50%	28.39700	0.00270	0.05170	0.03321
	65%	2.21700	0.00004	0.00680	0.00430
	70%	1.94590	0.00009	0.00990	0.00510
ANN	50%	29.87300	0.00290	0.05380	0.03670
	65%	28.99800	0.00280	0.05260	0.02490
	70%	22.51400	0.00200	0.04450	0.02700

The effects of different sizes of training sample sets 50%, 65%, 70% on forecasting performance of ANFIS are examined by comparison of evaluation criteria .The results show that for 70% of training data is preferred over the other training data in terms of the four evaluation criteria. This means that, 70% adapts itself well to the training data set, so that using more data for training of the network not only impair more accurate forecasting for radon exhalation rate,but it may also have adverse effects on accuracy of the network for both models.

5. CONCLUSIONS

The paper introduced a Neuro-Fuzzy (ANFIS) and artificial neural network (ANN) model for predicting equivalent radon exhalation rate of uranium ore-rock throughout mine ventilation. Equivalent radon exhalation rates vary with ventilation rate, wind pressure and other technical factors. In this work the wind pressure and the ventilation rate are taken as the input vector, and the equivalent radon exhalation rate as the output vector.

The two models ANFIS and ANN used for radon exhalation rate prediction show their high potential in forecasting. These models are successful because of their nature that reveals essential interdependence between the parameters of the modeled system. The idea of ANN and ANFIS systems are reviewed as computational models and stimulated the creation of Neuro-Fuzzy Systems. In the modeling of radon exhalation rate, the training and test sets errors achieved are better in ANFIS than in ANN structure.

Different evaluation criteria using statistical calculation are used to identify the performance measurement of these two models. Also, for more accurate forecasting of ANN and ANFIS, the effects of different ratio for training data are examined. The results show that these artificial intelligence methods were capable of predicting the rate of radon exhalation. In all training data ratios, ANFIS results are more accurate than ANN results in terms of all evaluation criteria. In addition, the ANFIS results using 70% of the training data is more precise than other cases when using 50% and 65% of the training sample sets.

Finally, the study of this work is to become aware of any harmful radiation in the surrounding environment, which, can be used as reference information to review any changes in the radioactive background level.

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