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Prediction of Copper Mineralization by the Artificial Neural Network (GRNN & BPNN) in Mesgaran Exploration Area, Eastern Iran

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Abstract: Mesgaran exploration area is located in South Khorasan province, 26 km south of Sarbisheh city. The mineral potential of coppersmiths is copper mineralization. According to 75 surface samples taken, the analysis results are examined using the method of radial artificial neural network and error propagation. Also, after training to see the networks, the results can be used for other places. The strength of this study is that it does not require costly analyses to predict copper levels in other parts of the range, and simple analyses can estimate copper levels with an acceptable probability percentage and use the results to advance operations. In this area, the neural method was identified with higher accuracy.

Keywords: Artificial Neural Network, ANN, BPNN, Radial Neural Network, South Khorasan, Copper.

1. INTRODUCTION

In mineral exploration, methods and studies have been very extensive [1-15]. An artificial neural network is an information processing idea inspired by the biological nervous system and processes information like the brain. The critical element of this idea is the new structure of the information processing system. The system comprises a large number of highly interconnected processing elements called neurons that work together to solve a problem. ANNs, like humans, learn by example. An ANN is set up to perform specific tasks, such as identifying patterns (predicting) and categorizing information, during a learning process. Learning is accompanied by adjustments to the synaptic connections between nerves in biological systems [16-18].

With their remarkable ability to infer meanings from complex or ambiguous data, neural networks can be used to extract patterns and identify methods that are very complex and difficult for humans and other computer techniques to be aware of. A trained neural network can be used as an expert in the information given to it for analysis. It can estimate new desired situations and answer "what if" questions [19-21].

Another advantage of these networks is adaptive learning, which is the ability to learn how to perform tasks based on the information given for practice and introductory experiences. The second is self-organization, in which an ANN can create or present itself for the information it gains during the learning period. The third is the timely performance of ANN calculations that can be performed in parallel and special hardware designed and built to take advantage of this feature .

Fourth is the error tolerance without interruption in the coding of information; the small failure leads to the corresponding performance degradation. However, several network capabilities may remain even with significant damage [22-24].

To create chaotic neural networks, a chaotic neuron has been introduced. The ability to act on information in return networks is more significant than in conventional networks due to feedback loops. In-network training, the error propagation algorithm is used for modeling. Compared to other neural networks, the number of hidden layer neurons in chaotic networks is more petite, and their ability to generalize is higher .

There is a neural network in which processor units are process-focused on a particular situation. This focus is modeled through radial functions or RBF for short. In terms of the overall structure, they often have a faster learning and preparation process. Because neurons focus on a specific operating range, it will be easier to adjust them.

Another type is the error propagation network, a collection of neurons arranged in different layers. After multiplying the weights in the weights in the passages between the layers, the input values reach the next neuron and accumulate there. After passing through the relevant network function, form the output of the neurons. The obtained output is compared with the desired output, and the obtained error is used to correct the network weights.

2. GEOLOGY & GEOLOCATION

Mesgaran mining area is located 29 km south of Sarbisheh city. It has an area of 10 square kilometers and is rectangular. The geographical location of the range in the UTM system is between latitudes 0770500 to 0773000 east and latitudes 3577500 to 3581500 north (Figure 1) [25-27].

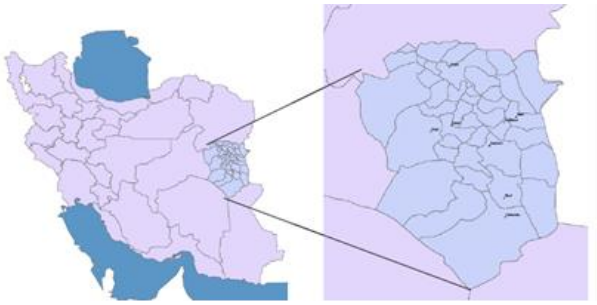

Figure 1: Location of the study area in South Khorasan Province, Sarbisheh

Access to this area is possible through the main road Sarbisheh-Nehbandan.

There are no rough heights in this area, mainly in the form of hills and plains. Roads are available in most places and can be easily accessed anywhere [28].

Due to the presence of mafic and ultramafic rock assemblages (ophiolite sequences) and erosion performance on these units, the area's topography is gentle and calm hills. Sedimentary parts of the region, especially areas with limestone, have a harsher topography than the mineral boundary.

The study area is a small part of the structural zone of eastern Iran in terms of structural-sedimentary divisions of the country. It is metallurgically located in the northern part of the Ahangaran-Bandan gold zone [29].

Lithologically, the exploration ranges include ultrabasic units, diabase dikes, pillow basalts, calcareous outcrops, phyllite, and schist lenses. One of the newest lithological units is the travertine unit. This complex is exposed as porous travertine around the travertine springs. The rock units exposed in the area of Mesgar show a complete ophiolite sequence. However, due to the compressive stresses in the region, the boundaries of these units are mainly faults, and the protrusion of super-basic rocks, basics, and ocean sediments does not follow any order.

3. DISCUSSION AND METHODOLOGY

This review is programmed in MATLAB and SPSS software, and its codes can be downloaded at the end of the article [8, 21, 30, 31].

First, the data, which included the analysis of samples in 44 elements, were randomly divided into two categories: educational and experimental. It is worth mentioning that educational and experimental data were separated by 70% and 30%. According to Table 1, the correlation between calcium, aluminum, phosphorus, and sulfur was high, and these elements were selected in the network training [32].

Then two methods of the artificial neural network after propagation of error and radial artificial neural network were applied to these data, and the results were presented.

This correlation was performed by the Spearman method due to non-normal data.

Table 1: Spearman's element correlation matrix

	Al	Ca	P	S
Al	1.000	.033	-.368**	-.558**
Ca	.033	1.000	-.116	-.040
P	-.368**	-.116	1.000	.732**
S	-.558**	-.040	.732**	1.000

3.1 GENERAL REGRESSION NEURAL NETWORK (GRNN)

In this method, according to experience, the value of the grid radius was considered 0.02. This is a numerical radius between 0 and 1, which must be obtained by changing the optimal value [33].

This method has a good speed so that the radius can be changed quickly, and the results can be seen. It is worth mentioning that this method can also use linear regression and compare the results if it answers and is acceptable to confirm the results.

The results can be seen in Figures 2 to 4.

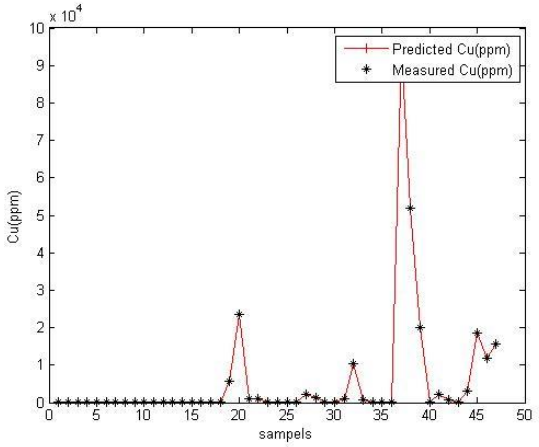

Figure 2: Estimated amount of copper in educational data

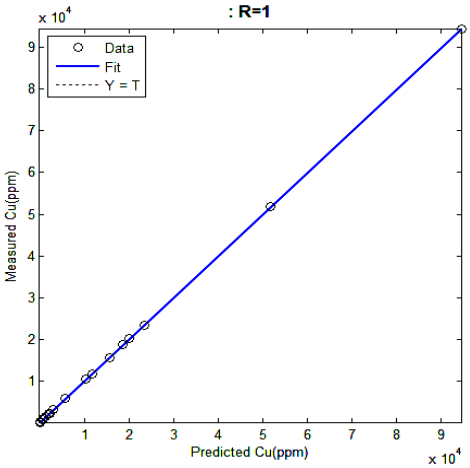

Figure 3: Regression of estimated and real data on educational data

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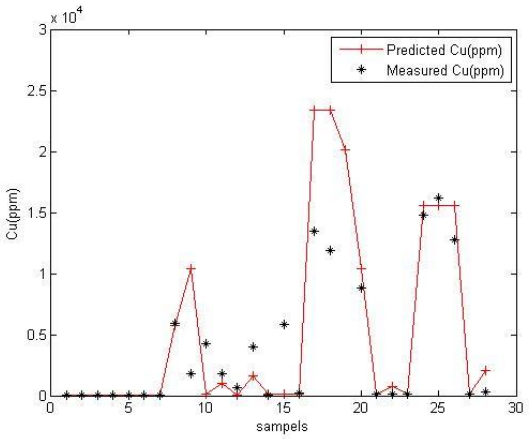

Figure 4: Estimated amount of copper in experimental data

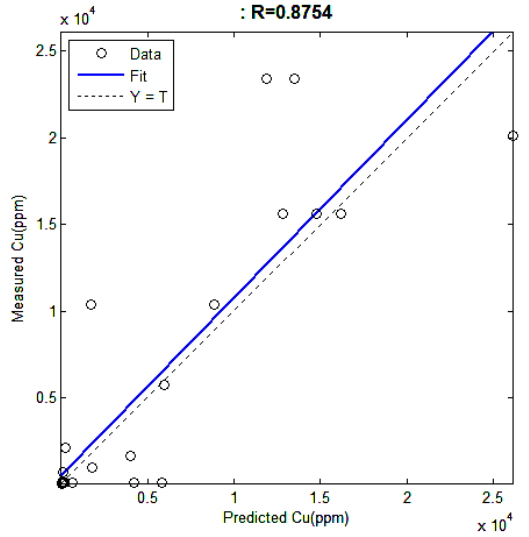

Figure: Regression of estimated and actual data on experimental data

According to the result of this method, the data can be estimated with 87% accuracy, which is acceptable.

3.2 BACK-PROPAGATION NEURAL NETWORK (BPNN)

In this method, according to the experience, the number of network neurons was ten, and the segmental input function was also considered normalized [27, 29].

In this type of network, experimental data should be divided into two categories so that no more fitting is done. For this purpose, experimental data were randomly divided into two categories and used in the method.

The results can be seen in Figures 5 to 8.

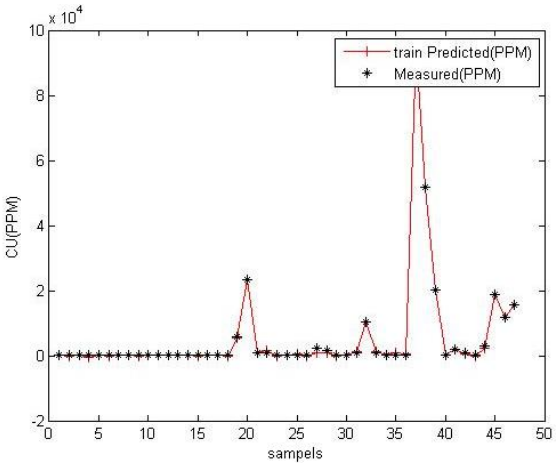

Figure 5: Estimated amount of copper in educational data

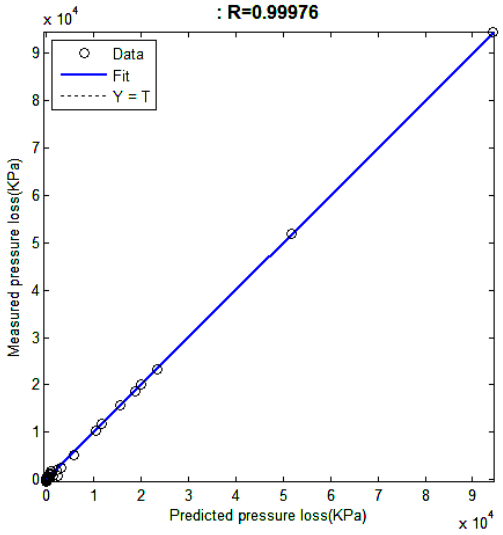

Figure 6: Regression of estimated and real data on educational data

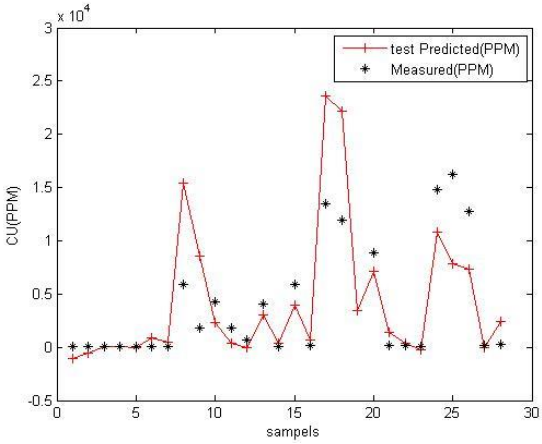

Figure 7: Estimated amount of copper in experimental data

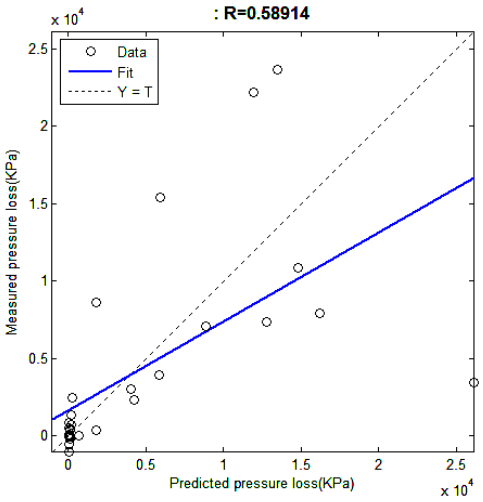

Figure 8: Regression of estimated and actual data on experimental data

According to the result of this method, the data can be estimated with 59% accuracy, which is somewhat acceptable [34].

4. CONCLUSION

Mesgaran exploration area is located in South Khorasan province, 26 km south of Sarbisheh city. The mineral potential of coppersmiths is copper mineralization. According to 75 surface samples taken, the analysis results are examined using the method of radial artificial neural network and error propagation. Also, after training to see the networks, the results can be used for other places. The strength of this study is that it does not require costly analyses to predict copper levels in other parts of the range, and simple analyses can estimate copper levels with an acceptable probability percentage and use the results to advance operations. The radial neural method with 88% accuracy and the error propagation with 59% accuracy for the experimental data estimated the amount of copper in this range. Due to the significant percentage of the radial neural network, this method can be considered superior in this area. Also, according to the presented graphs, the results can be calculated for other points. The codes used in this study were presented for further research and use elsewhere.

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