Australian Journal of Basic and Applied Sciences, 4(3): 408-420, 2010
ISSN 1991-8178

Application of Adaptive Neuro-Fuzzy Inference System for Grade Estimation; Case Study, Sarcheshmeh Porphyry Copper Deposit, Kerman, Iran

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Abstract: Knowing the grades of target elements within an explored region is a very important aspect. Such grade value properties and the element correlation is also the most important exploration parameters needed for any one who attempts to decrease the exploration cost and also the exploration risk. These could be achieved by sampling, laboratory analyses and core loggings within the boreholes. Because of the high cost and random mistakes which may happen during the sample preparation, analytical procedures and also the occurrence of other undesired events, one must be aware of getting the non-confidence results. Therefore, applying the methods which could estimate those important parameters based on the poor available information may be useful. In this paper, there is a try to apply the adaptive neuro-fuzzy inference system as a newly applied technique to solve such a problem to evaluate the "copper grade estimation" in Sarcheshmeh porphyry copper system. Based on this modeling, the input data were coordinates of samples (x, y) and the output data was the copper grade for any specific location. Training involves iterative adjustment of parameters of the adaptive neuro-fuzzy inference system using a hybrid learning procedure for mapping each training vector to its output target vector with minimum sum of squared error. The trained adaptive neuro-fuzzy inference system is used to process all feature works. A comparison of different techniques (ANN and Krining) with this new technique (ANFIS) was also carried out. The statistical parameter values of R^2 in these techniques were obtained to be 0.4571 and 0.6889 respectively. After fuzzy logic and neural network combination and making an adaptive neuro-fuzzy inference system, the R^2 value, changed into 0.8987. This method is expected to provide a significant improvement when the testing data come from a mixed or complex distribution.

Key words: Fuzzy logic, neural network, ANFIS, grade estimation, Sarcheshmeh.

INTRODUCTION

The success in a mining activity depends on the accuracy of the total reserves estimation as well as the deposit ore grades. Geostatisticss and Neural Network (NN) are the two prevalent techniques most frequently used today for ore grade estimation (Yama, B.R. and G.T. Lineberry, 1999). Geostatisticsal technique such as ordinary Kriging works under the assumption of stationary condition. Moreover, it is a linear model based on local neighborhood structure. On the other hand, neural network is a non-linear model free estimator, which is robust in noisy and extreme data. Neural network performs better when there is non-linear spatial trends in the data exist, which violates the stationary assumption of ordinary Kriging technique. Each of these techniques has advantages and disadvantages (Cargill, S.M., R.F. Meyer, 1977; David, M., 1977). Several studies reported successful implementations of the neural network technique for the estimates of spatial attributes. For example, Wu and Zhou (1993) applied neural network for copper reserve estimation. Rizzo and Dougherty (1994) used these techniques for characterization of aquifer properties. Koike and Matsuda (2003) investigated neural network for determining the principal metal contents of Hokuroku district in Northern Japan. They also used this technique for estimating content impurities of a limestone mine namely, SiO_2, Fe_2O_3, MnO, and P_2O_5. Also, neural network performance was compared with geostatisticss for grade estimation in a bauxite and a gold deposit (Samanta, B., S. Bandopadhyay, 2004). In the bauxite deposit, neural networks and geostatisticss showed almost equivalent performance, while for the gold deposit the neural network performed better than the geostatisticss (ordinary kriging). The major reason for rapid growth and diverse of neural networks is their

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ability to approximate virtually any function in stable and efficient way. Along these progresses fuzzy logic also could have a great rule in mining especially in grade estimation. The concept of uncertainty resulting from fuzziness has been recognized and applied in various aspects of geology such as "fuzzy" kriging (Bardossy, A., I. Bogardi, 1988), and "fuzzy" variograms (Bardossy, A., I. Bogardi, 1990), carbonate production as a function of depth and distance to platform edge (Broecker, W.A. and T. Takahashi, 1966), permeability as a function of grain size and sorting using fuzzy clustering (Freeze, R.A. and J.A. Cherry, 1979), application of fuzzy set system to prediction the permeability as a function of the size parameters of unconsolidated sand (Krumbein,W.C. and G.D. Monk, 1942). Cheng and Agterberg (Cheng, Q. and F.P. Agterberg, 1999) proposed fuzzy weights of evidence approach that in a hybrid form, allows a complementary utilization of both empirical and conceptual information. In a hybrid fuzzy weights-of-evidence model, knowledge-based fuzzy membership values are combined with data-based conditional probabilities to derive fuzzy posterior probabilities.

The aim of this study is to combine the artificial neural networks (ANNs) and fuzzy logic (FL) to make a powerful tool for grade estimation. It is clear that parameter selection would be one of the most important parts of FL. Therefore, by using input/output dataset and make a fuzzy inference system in which by applying a backpropagation or a method that is based on least squares method, the membership functions would be adjusted. Actually, by combination both fuzzy inference system and neural network it would be possible that the constructed fuzzy system learned form the available data. After determination the ANFIS structure, it would be used to obtain a network for the current purpose, named grade estimation. Also, the results of this investigation shows that fuzzy inference systems are also more valuable when they are combined with the explanatory nature of rules (membership functions) with the power of the neural networks "black box". Based on the pervious studies on this area such as geostatistics (Soltani, S., 2006) and neural network (Tahmasebi, P. and A. Hezarkhani, 2008), the results would be compared with the ANFIS method to evaluate its abilities. The procedure is applied to regional-scale of Sarcheshmeh copper deposit in the center/southwest part of Kerman province (Iran).

Artificial Neural Network (ANNs):

McCulloch and Pitts were the first persons who introduced a model of an elementary computing neuron and six years later, Hebb proposed learning rules. ANNs have seen a rapid growth (after backpropagation) and it has been applied widely in many fields ANN could to extend its applications such as pattern classification, function approximation, identification purpose for linear or nonlinear, multivariable systems. A simple NN has been composed of neurons, links which connects the neurons and weights that assigned to neurons and the bias which assigned to neurons.

The nature of NN is made of mathematical equations which mimic the brain. Since, NN is made up several neuron and different layers; therefore, it would be possible to perform the massive parallel computation (Fig. 1)

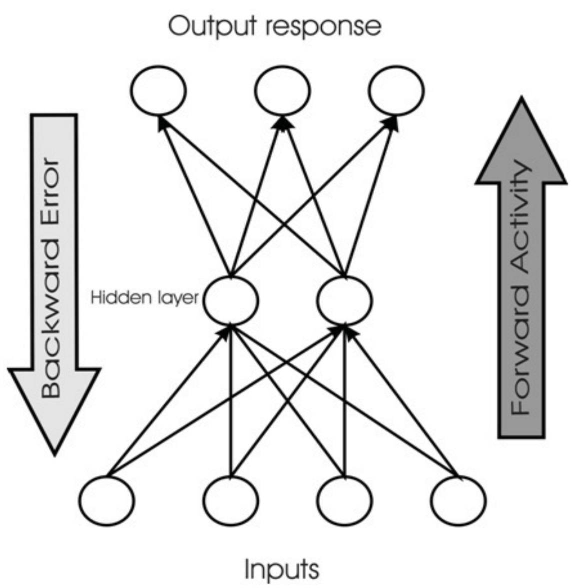

Fig. 1: A Multi-Layer Back-Propagation (BP) Network with One Layer of Hidden Units.

The position and the different neuron connection lead to have several NN and classified in the different groups. These groups could be such as feedforward network (e.g. single layer perceptron, multilayer perceptron and radial basis function), recurrent-feedback networks (competitive networks, Kohonen's SOM, Hopfield network and ART models). All of these structures have their specific applications.

There are several training algorithms which each of them has their specific advantages and disadvantages but backpropagation that is based on error backward and its correction is the most popular one. Actually, this algorithm is based on gradient descent method which according to error surface tries to find the best weight and bias composition in order to minimize the network error (Fig. 1). There are two important processes in BP algorithm: the input passed through the layers and neurons and the error will be calculated then, according to error the input will be backward propagation to adjust weights. However, this method has some disadvantages like slow converges, lack of robustness and inefficiency (Rumelhart, D.E., G.E. Hinton, 1986a). Therefore, several contraptions such as adaptive method and second order method of modification have been proposed to achieve the better training and less error. One of the most successful methods which could to improve the training process is Levenberg-Marquardt (LM) that is a method which is based both Gauss-Newton nonlinear regression and gradient steepest descent method (Rumelhart, D.E., G.E. Hinton, 1986b).

Fuzzy Logic:

The concept of Fuzzy Logic (FL) was conceived by Zadeh (1965) and presented not as a control methodology, but as a way of processing data by allowing partial set membership rather than crisp set membership or non-membership. After Zadeh, several researchers developed the application and the function definitions for the different controller systems that it could be mention to Mamdani (1975) and Takagi (1985), that each of them has their special function. Unlike classical logic which is based on crisp sets of “true and false,” fuzzy logic views problems as a degree of “truth,” or “fuzzy sets of true and false” (Nikravesh, M., 2004). FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information (Young, V.R., 1996). Also, some of the definitions are necessary to know which are described in the following:

Membership Function: is a function which by using of that it would be possible to present the input. The aim of using this function is by using the weights which is with the inputs, the functional overlap between the inputs would be defined and lead to output determination.

Rules: is some instruction which by using them it would be possible for input that by using the membership values and their definitions, give the final output.

FL operators: One of the most popular FL systems is consist of some rules or "*if-then*" rules. Sometimes there are some fuzzy prepositions which describe dependence of one or more variable of output to one or more input variables.

There are two types of fuzzy inference systems that can be implemented in the fuzzy logic applications: Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined (Jang, J.S.R., C.T. Sun, 1997; Mamdani, E.H. and S. Assilian, 1975; Soltani, S., 2006).

One of the most important and difficulty which involved in FL is making decision about its appropriate parameters. For example, the parameters that should be attention and play an important rule in FL ability are membership functions, distributions of MFs, the fuzzy rules composition. Trial and error is one of the methods which by using it the parameter selection would be done. Furthermore, user's experience is one of the parameters that could have an effect on FL modeling. Therefore, all of these problem and lack of knowledge and time lead us to combine both neural networks and fuzzy logic to minimize the error and reach the optimized and better decision about the FL parameters.

Adaptive Neuro-Fuzzy Inference System (ANFIS):

The ANFIS is the abbreviated of *adaptive neuro-fuzzy inference system*. Actually, this method is like a fuzzy inference system with this different that here by using a backpropagation tries to minimize the error. The performance of this method is like both ANN and FL. In both ANN and FL case, the input pass through the input layer (by input membership function) and the output could be seen in output layer (by output membership functions). Since, in this type of advanced fuzzy logic, neural network has been used, therefore, by using a learning algorithm the parameters have been changed until reach the optimal solution. Actually, in this type the FL tries by using the neural network advantages to adjust its parameters. As we know, the different between real and network output in ANN is one of the common method to evaluate its performance. Therefore, ANFIS uses either backpropagation or a combination of least squares estimation and backpropagation for membership function parameter estimation (Jang, J.S.R., C.T. Sun, 1997).

Several fuzzy inference systems have been described by different researchers (Mamdani, E.H., 1974; Sugeno, M. and G.T. Kang, 1988; Sugeno, M. and K. Tanaka, 1991; Takagi, T. and M. Sugeno, 1985; Zadeh, L.A., 1965). The most commonly-used systems are the Mamdani-type and Takagi–Sugeno type, also known as Takagi–Sugeno–Kang type. In the case of a Mamdani-type fuzzy inference system, both premise (if) and consequent (then) parts of a fuzzy if-then rule are fuzzy propositions. In the case of a Takagi–Sugeno-type fuzzy inference system where the premise part of a fuzzy rule is a fuzzy proposition, the consequent part is a mathematical function, usually a zero- or first-degree polynomial function (Mamdani, E.H., 1974; Takagi, T. and M. Sugeno, 1985).

The advantages of FL for grade estimation is clear because it prepare a powerful tool that is flexible and in lack of data with its ability which is if-then rules would able to solve the problems. As discussed, one of the biggest problems in FL application is the shape and location of membership function for each fuzzy variable which solve by trial and error method only. In contrast, numerical computation and learning are the advantages of neural network, however, it is not easy to obtain the optimal structure (number of hidden layer and number of neuron in each hidden layer, momentum rate and size) of constructed neural network and also this kind of artificial intelligent is more based on numerical computation rather that than symbolic computation. Both FL and NN have their advantages, therefore, it is good idea to combine their ability and make an strong tool and also a tool which improve their weak as well as lead to least error. Jang (1992, 1993) combined both FL and NN to produce a powerful processing tool named NFSs which is a powerful tool that have both NN and FL advantages and the most common one is ANFIS.

Assume that the considered FIS has two inputs (x and y) and one output f (Fig. 2). For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if–then rules is as follows Jang (1992):

Rule 1 : If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$ (1)

Rule 2 : If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$ (2)

Figure 2 illustrates the reasoning mechanism for the Sugeno model. The corresponding equivalent ANFIS architecture is shown in Figure 2b. In this diagram, the output of the i^{th} node in layer 1 is denoted as $O_{1,i}$

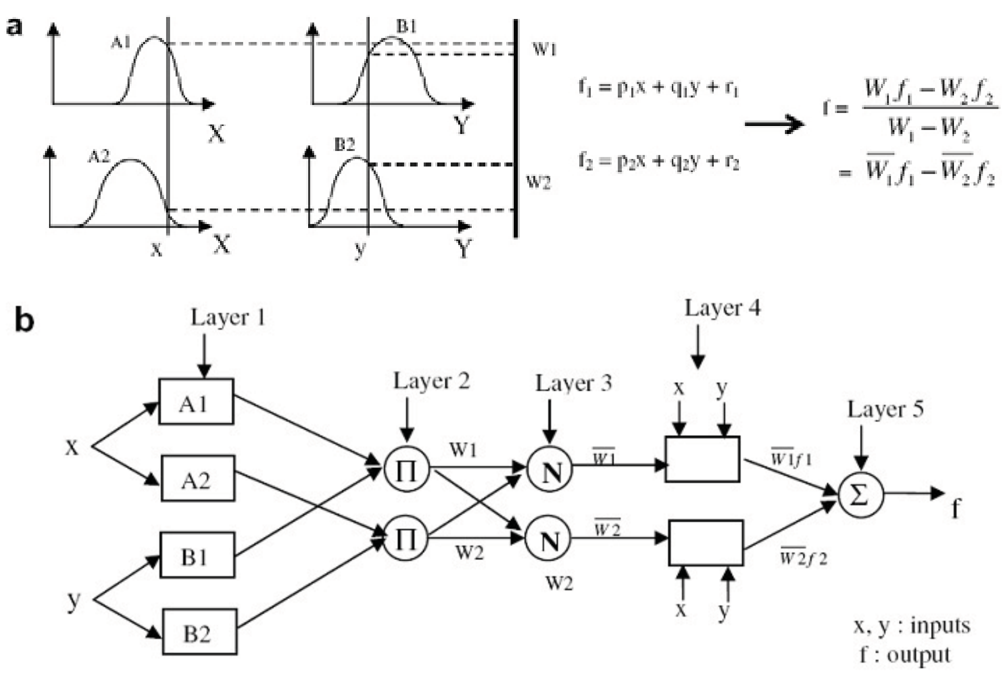

Fig. 2: (a) First-order Sugeno Fuzzy Model. (b) Equivalent ANFIS architecture with two inputs and an output. The output of Fig 2.a is the input into layer 4 of Fig. 2b. The node functions in the same layer are of the same function family as described

Layer 1: Including adaptive nodes.

$$O_{1,i} = \mu_{Ai}(x) \quad \text{for } i = 1,2 \tag{3}$$

$$O_{1,i} = \mu_{Bi-2}(y) \quad \text{for } i = 3,4 \tag{4}$$

- μ_{Ai} (x) and μ_{Bi_2} (y): any appropriate parameterized membership functions.
- $O_{l,i}$: the membership grade of a fuzzy set *A* $(=A_1, A_2, B_1$ *or* $B_2)$ and it specifies the degree to which the given input *x (y)* satisfies the quantifier *A*.

Layer 2: Including fixed nodes labeled Π, whose output is the product of all the incoming inputs:

$$O_{2,i} = \mu_{Ai}(x)^* \mu_{Bi}(y) \quad i = 1,2 \tag{5}$$

Each node output represents the firing strength of a fuzzy control rule.
Layer 3: Including fixed nodes labeled N with function of normalization:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{6}$$

Outputs of this layer are called normalized firing strengths.
Layer 4: Including adaptive nodes.

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{7}$$

Layer 5: Including a single fixed node labeled ∑ with function of summation.

$$\text{Overall output} = O_{5,1} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

Actually, one of the ANFIS advantages is that it uses a hybrid learning procedure for estimation of the premise and consequent parameters Jang (1992). In this process by keeping fixed the premise parameters, it estimates them in a forward pass and then in a backward pass by keeping fixed the consequent parameters the process would be continued. In the first path, the input would be forward and propagated and then by applying the least squared method the error would be calculated where is the third layer. Also, in the second path, the error which happens during the first step would be backward to and the premise parameters are updated by a gradient descent method. The details of the hybrid learning procedure that is used in an ANFIS are given in Jang (1992, 1993).

Application to Sarcheshmeh Porphyry Copper Deposit in Kerman, Iran:
Geology of Region:

The Sarcheshmeh porphyry copper deposit is hosted by a diorite/granodiorite stock (Waterman, G.C. and R.L. Hamilton, 1975), located 65 km southwest of Kerman city, Kerman province, southeastern Iran (Fig. 3).

The stock is a part of the Sahand-Bazmanigneous and metallogenic belt, a deeply eroded Tertiary volcanic field, roughly 100 by 1700 km in extent from Turkey to Baluchistan in southern Iran, consisting mainly of rhyolite, andesite, and numerous felsic intrusions. The volcanics were laid down unconformably over folded and eroded Upper Cretaceous andesitic volcanic and sedimentary rocks (~500 m thick). Subduction and subsequent continental collision during the Paleocene to Oligocene caused extensive alkaline and calc-alkaline volca nic and plutonic igneous activity (Etminan, H., 1977; Shahabpour, J., 1982; Berberian, M. and G.C. King, 1981; Hezarkhani, A., 2006a), including intrusion of a Miocene porphyritic calc-alkaline stock at Sarcheshmeh. Bordering the belt to the southwest is a major zone of complexly folded, faulted, and metamorphosed Tertiary and Paleozoic sedimentary rocks that form the Zagros Mountains.

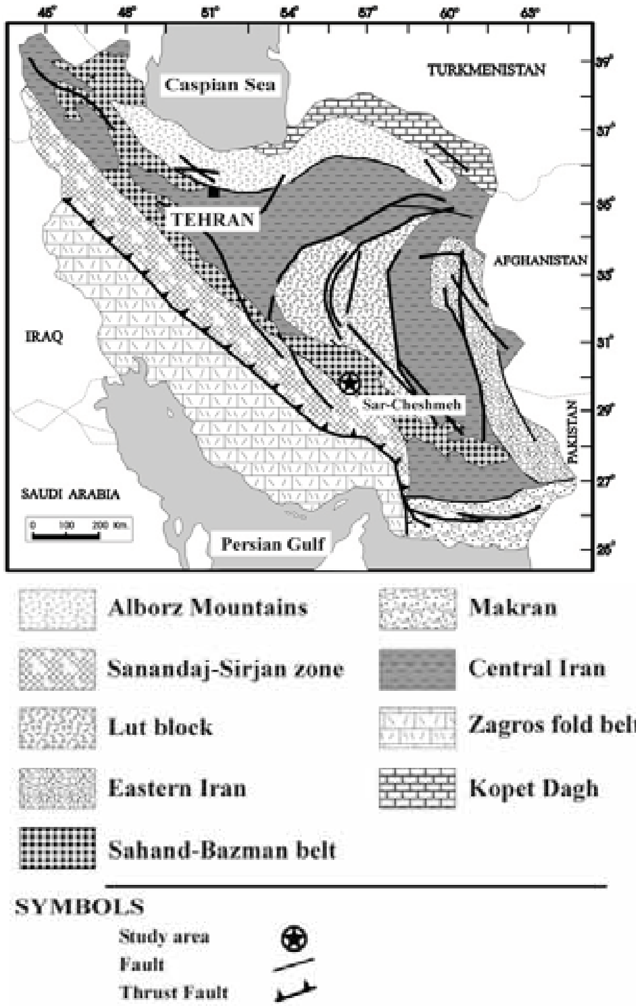

Fig. 3: Simplified Geological Map of the Sarcheshmeh Area (Hezarkhani, A., 2006a).

The Sarcheshmeh stock is a complex intrusive body, which crops out over an area of about 1.1 × 2.2 km. The stock consists of three different igneous phases, listed in order of emplacement (Hezarkhani, A., 2006a; Hezarkhani, A., 2006b): (1) diorite/granodiorite; (2) dacitic and related porphyries; and (3) andesite and related dikes. The diorite/granodiorite is volumetrically the most important and includes most of the central and northern part of the intrusive complex at the current erosional surface. The dacitic porphyries are volumetrically the next most important group of rocks and host part of the mineralization. These two phases are cut by andesitic dikes, which in the northern and western parts of the Sarcheshmeh stock are also locally mineralized. Petrographic studies have shown that mineralized dikes are mainly andesitic, and are related to the diorite/granodiorite intrusive phase. The diorite/ granodiorite and unmineralized andesitic dikes contain some mafic xenoliths, whereas xenoliths are rare in the mineralized dikes (Hezarkhani, A., 2006a).

Mineralization and Copper Distribution:

Hypogene copper mineralization was introduced during phyllic alteration and to a lesser extent during potassic alteration, and occurs as disseminations and veinlets. During potassic alteration, copper was deposited as chalcopyrite and minor bornite; later hypogene copper was deposited mainly as chalcopyrite (Hezarkhani, A., 2004a; Hezarkhani, A., 2004b). Hypogene molybdenite was concentrated mainly in the deep part of the stock, and is associated exclusively with potassic alteration, where it is found in quartz veins accompanied by K-feldspar, anhydrite, sericite, and minor chalcopyrite (Hezarkhani, A., 2004a; Hezarkhani, A., 2004b). The concentration of sulfides and copper mineralization increases outward from the central part of the stock (see

Fig. 4). The ratio of pyrite to chalcopyrite increases from 2:1 in the outer parts of the potassic alteration zone to 10:1 toward the margins of the diorite/granodiorite stock. At the surface of the deposit, rocks are highly altered, and the only mineral that has survived supergene argillization is quartz. Most of the sulfide minerals have been leached, and copper was concentrated in an underlying supergene zone by downward-percolating ground waters. The ore body has dimension of 2000 m by 900 m and is centered on the Sarcheshmeh porphyry stock. Within a 2000×900 m area, and to an overall drilled depth of about 150 m, the ore body contains 450 M tones averaging 1.13% Cu and 0.03% Mo at a cutoff grade of 0.4% Cu (Waterman, G.C. and R.L. Hamilton, 1975).

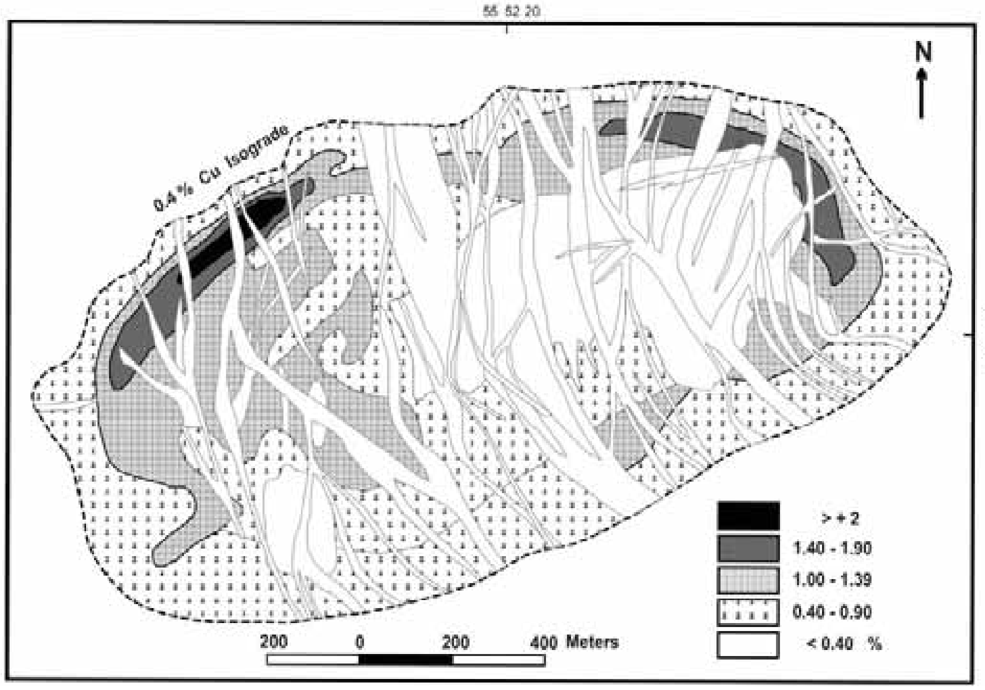

Fig. 4: Copper Mineralization Map within the Sar-Cheshmeh Stock (Hezarkhani, A., 2006a).

Hybrid Neuro-Fuzzy Model:

The hybrid neuro-fuzzy model for grade estimation in the Sarcheshmeh copper deposit was implemented as follows. This new model based on neural network and fuzzy logic was developed using Matlab 7.1 to grade estimation.

Data Collection:

In this study 258 exploratory borehole analyses were applied. The average borehole spacing distances are ~50m along the strike direction. The spacing distance is somewhat lesser in the dip direction.

All 258 available data points were split randomly into three separate individual groups: training, testing, and validation (checking) which their location is shown in Fig. 5. Table 1 shows the ranges of the used dataset for all applying groups. The training set consists of a set of examples which are only used for learning (i.e., to fit the weights of the network). One of the reasons that cause to use a validation data set is that it indicates the network performance after training. Actually, by monitoring the network performance for validation dataset, it is possible to avoid the data memorization. Another dataset which used is the testing dataset. This dataset is consisting of both input and output to investigate the ability of model for its reaction to new data. Actually, by using this dataset the performance of trained model for generalization would be evaluated. Typically 70% of the data is applied for training, 15% for validation purposes and the rest of the data is categorized as testing process (see Fig. 5).

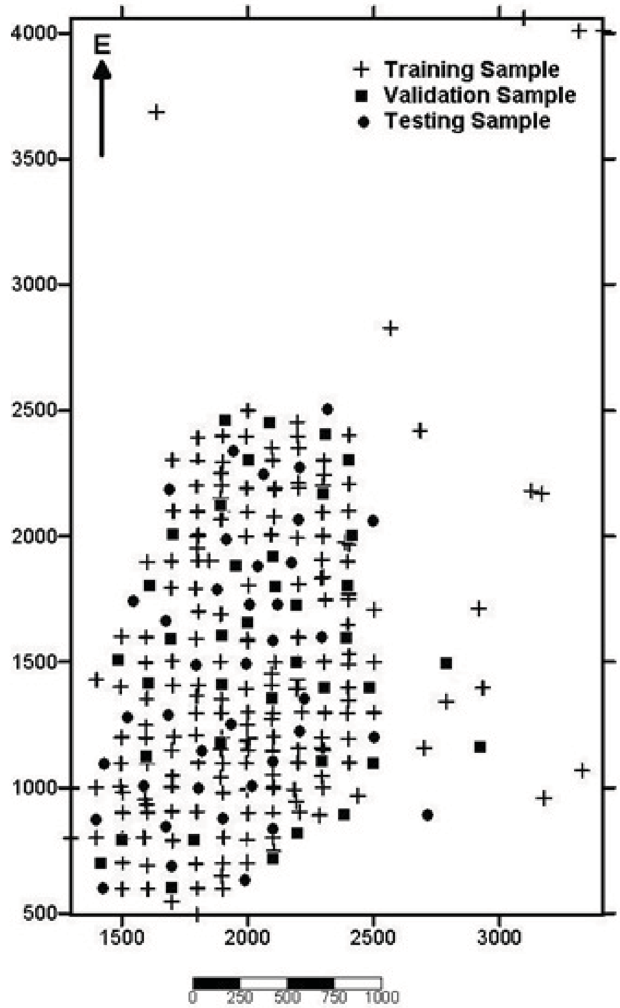

Fig. 5: Distribution of 258 Drillhole Sites of Study Area in Located 65 km Southwest of Kerman city, Kerman Province, Southeastern Iran, and the Locations of Training, Validation and Testing Data Used in This Study.

Table 1: Summary Statistics of the Used Data Set.

Statistical parameters	Mean	Variance	Maximum	Minimum
Value	0.797	0.875	9.86	0.01

Simulation:

Targets are the output that by using ANFIS the input should be tried to map. In the case of grade estimation, there are two-dimensional input (*x, y*), which represents the sample location. We used a set of mentioned data for this simulation. Each of the features was normalized into range of [0 1] by using the following formula:

$$X_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

Where x is the data which should be normalized, the x_{max} and x_{min} are maximum and minimum of the original data respectively and X_{norm} is the normalized data which transformed.

Training of Adaptive Neuro-Fuzzy Inference System:

Trining of neuro-fuzzy have several steps. At the first step of training, the initial fuzzy sets should be determined. Actually the fuzzy sets define the number of sets for each input variable and their shapes. The not that should be attention is that large number of sets may produce better fitness in training process but a poor validation Therefore, to avoid from these problems, after several experiments, we selected 5 sets for each input variable. During training, all of the training dataset would be present to network and it tries by learning the spatial relationship between the data to minimize the error. Sometime lower error could not guaranty the better performance of network and it may because of network overtraining.

There is need to monitor how well the network is learning. It is important to mention that when the input pass through the network, the aim of the ANN is to by parameters adjusting lead the network to the smallest error "as much as possible". Therefore, by error monitoring of training dataset, it would be possible to supervise on network training. The objective function which has been used here is MES (Mean Square Error). Definitely, the aim of using this network or the entire models is to reach the smallest error and also it is true here. Another way to an accurate solution is to set a criterion to stop the training phase that the goal of the stop criterion is to maximize the network's generalization.

Currently, the training is based on 50 epochs which is using the hybrid learning algorithm. According to Fig. 6, it is obvious that the total sum of squared error for validation vectors converged to a minimum of 0.106 at the end of 20 training epochs. Therefore, 20 epochs was selected for grade estimation process. The trained Takagi–Sugeno type fuzzy inference system was used for estimate the grade of all the 258 available data.

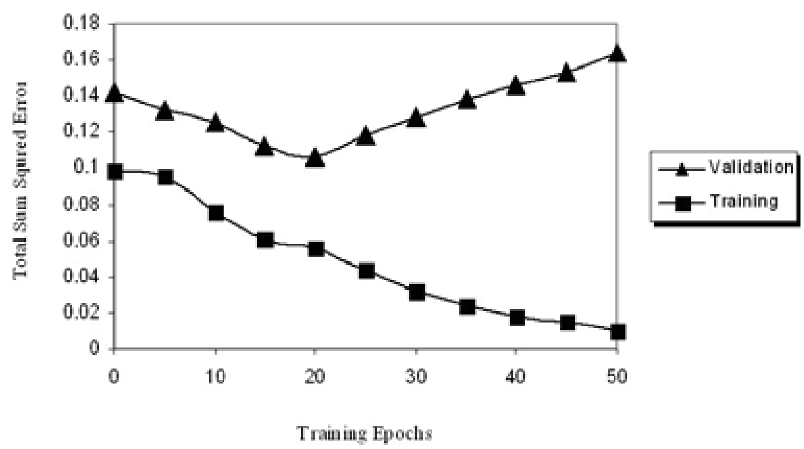

Fig. 6: Number of Training Epochs versus Total Sum of Squared Error for Training Vectors and Validation Vectors.

Validation of Grade Estimation:

According to the strategy based on the rank of their SSE (Sum Square Error), several networks were investigated to obtain the desired structure that was done according to our based.

As mentioned earlier, five bell-typed fuzzy membership functions were selected to describe the input and output variables. This is translated in 5^2=25 rules (regarding the two inputs with five fuzzy sets each) as shown in Fig. 7. In the structure of Fig. 7, each neuron in the first layer is coordinates (x and y) and the second layer is an adaptive with a parametric activation function. Its output is the grade of membership to which the given input satisfies the bell type membership function (as selected). The membership function is stated through a parametric expression, based whose change affects the shape of the membership function. The third layer output is the firing strength of the *ith* rule which all of its nodes are fixed. The process which happens in the third layer is that they calculate the ratio of the *ith* rule's firing strength relative to the sum of all rule's firing strength resulting in a normalized firing strength. In the fourth layer, each of the 25 nodes contains the adaptive node (Eq. (7)). The single node in fourth layer synthesizes information transmitted by Layer 3 and returns the overall output using the Eq. (8).

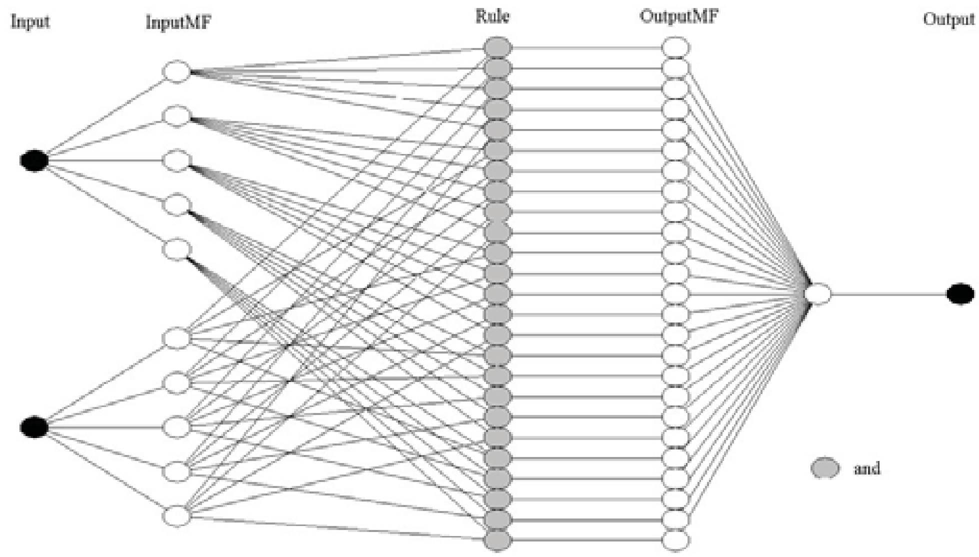

Fig. 7: Adaptive Neuro-Fuzzy Structure for Grade Estimation.

RESULTS AND DISCUSSION

One of the most important steps in hybrid neuro-fuzzy modeling is the fuzzy membership values definition. As mentioned earlier, the generalized bell membership functions specified by five parameters were used in the present model. There are two membership function, Gaussian and Bell membership functions. The bell membership function has some advantages such as being a little more flexible that the Gaussian membership functions. Therefore the parameters of network would be more adjusted by using the bell membership function. Also, both membership functions have advantages such as being smooth and nonzero at all points (MATLAB, 2007).

In order to test the performance of *ANFIS* after training, the test data point was presented to the network. Each predicted value was compared against the actual observed value to measure the network performance. For this purpose, another group of 39 random input–output data points (15% of all data) were used. The coefficient of determination R^2 gives information about the training of network, having a value in the between [0, 1]. If the coefficient of determination is close to (1), it shows how much the learning is successful. MSE is used to determine how much the network has reached the desired output values. In addition, the result of final model predictions compared to the actual results and the obtained results for testing dataset are shown in Fig. 8. On the other hand, Fig. 8 shows the real and simulated results values that were compared only for unseen data set (test data set) that shows an acceptable coefficient (coefficient of determination is 0.8987) between the predicted and experimental data can be achieved.

The proposed methodology was also compared with other prediction methods like artificial neural network (ANN) and geostatisticss. The aim of this comparison is to show the performance and the advantages of the applied method results compared to the other ones.

According to Table 2 that show the pervious studies on this region (Soltani, S., 2006; Tahmasebi, P. and A. Hezarkhani, 2008)s, application of ANFIS shows an overall improvement compared to the other estimation methods (FL, ANNs, Kriging). While Kriging shows lesser coefficient of determination than that of the ANFIS for the testing data set (R^2 = 0.6889, Table 2). It shows a considerable improvement during prediction of the unseen (test) dataset. Also, according to Table 2, the performance of ANN (R^2 = 0.4573) is lesser than Kriging. Since, because of the complex condition of the case study region and noisy data, the intelligent methods (ANN) could not to have a better prediction for grade (Tahmasebi, P. and A. Hezarkhani, 2008). But, by applying the geostatistics method, it shows the better performance for grade estimation which it show the ability of this method to finding the relationship between the variables (Soltani, S., 2006). But, because of the noisy and complex structure of available data, ANN could not find any spatial relationship between the variables which is because of more sensitivity of ANN to noisy and inadequate data.

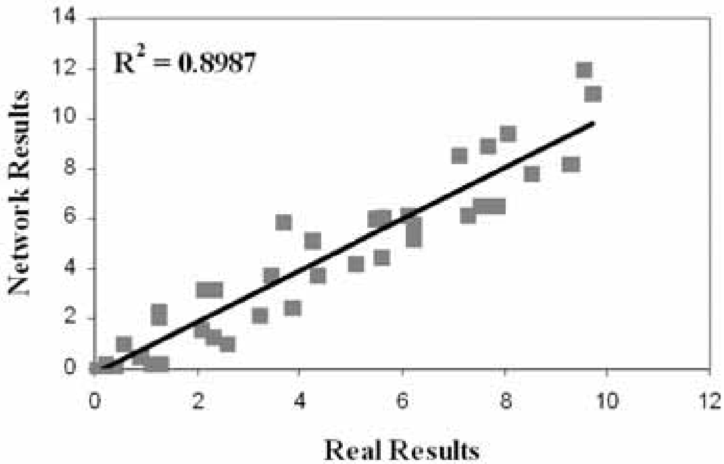

Fig. 8: Real Results vs. Network Predictions for Testing Dataset.

Table 2: Comparison the Results of Different Methods for Grade Estimation.

Method	ANN	Geostatistics (Kriging)	ANFIS
R^2	0.4573	0.6889	0.8987

The better performance of ANFIS than the other intelligent methods is because of FL and ANN combination. The path which a input would covered is like that the input fuzzy inference system convey coordinates of sample to input membership functions then it pass through the membership function and changes, after that its results go to the rules which according to available rules, its categiriy would be determined and it would have a value, next, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output. Both mentioned membership functions (Bell and Gaussian) have been tested and also it is important to mention that the used rules generally are based on the model and variables which are depended on user experience and trial and error methods. Furthermore, the shape of membership functions depends on parameters, and changing these parameters will change the shape of the membership function. These problems are also seen in neural network application. Most of neural network selected by trial and error method and most of them are depended on to user's experience (Tahmasebi, P. and A. Hezarkhani, 2008) that cause to weak performance of ANN application. The entire artificial intelligent have their advantages and disadvantages. In FL applications, the quality of the problem (by ruels) is more interesting and it would be pay more attention than the other aspect of the problem. Hence the quality aspect of problem would be ignored. In contrast, the most advantages of neural network are their ability in learning and its power for high numerical computation. According to earlier discussions, it is obvious there are some problems such as determining the shape and location of membership functions (MFs) for each fuzzy variable involved with FL and the efficiency of the FL depends on the estimated parameters of premise and consequent parts. Also, the problems like number of hidden layer, number of each neuron in each hidden layer, learning rate, momentum coefficient and etc. are also involved with ANN modeling. Most of the mentioned problems generally could be solved by trial and error method only.

All of these problems lead us to use the FL and ANN together. Actually, one of the advantages of this method is that it use parallel both neural network and fuzzy logic. Because, by using this method it would be possible to select the best membership functions in order to have best output "as well as possible". This aim would be done by applying ANN, because it helps FL to learn through its learning algorithm.

The results also demonstrate the ability of an adaptive neuro-fuzzy inference system to predict the grade in such a way that the contribution of such grade distribution is maximized and predict the grade with high accuracy.

Conclusion:

The current research has been carried out for developing powerful tool grade estimation could be applied in grade estimation extensively. By using a fuzzy inference system in the framework of an adaptive neural network, it provide a tool which make the grade estimation more acuurate because by usinf both neural network and fuzzy logic, it would be possible to estimate the fuzzy inference system parameters. This method could be applied extensively to solve the mining problems in which most of them are in some specify fuzzy conditions. The performance of the model with respect to the predictions made on the test data set would able the network to perform more accurate that both the other methods. It was also illustrated that applying this methodology to solve the geological aspects would be able to predict the more accurate grade. In Iran, all known porphyry copper mineralization occurs in the Cenozoic Sahand–Bazman Orogenic Belt (Hezarkhani, A., 2006b). As far as the exploration of porphyry copper deposit concerned, this belt has a great. The Bahreasman, Takht, Kuhe Panj, Darrehzar, Sarcheshmeh, Meiduk, Gowde kolvary, Darre Zereshg, South of Ardestan, Sharif Abad and Songun are the important copper deposits in this area that most of the geological setting are similar (Dimitrijevic, M.D., 1973; Dimitrijevic, M.D., I. Djokovic, 1973). Based on this research, it is also concluded the ANFIS technique could be used as a very accurate, reliable and fast method for grade estimation for porphyry copper deposits such as these types of deposits in the Central Iranian Volcanic Belt. One reason may because of the combination the abilities of both quantities and qualities of neural network and fuzzy logic to improve the estimation rather than the other methods. By attention to the complicated structural geology and the numerous evolved variables in Sarcheshmeh, grade estimation has not been evaluated correctly for many years. Applying this method enabled us to find a very accurate grade. Based on this method, the hybrid neuro-fuzzy model predicted grade estimation with high accuracy "with the R^2 of 0.8987" which is representing a very acceptable correlation compare to the other methods such as ANN and Kriging with determination coefficient of 0.4571 and 0.6889 respectively. This adaptive technique is not limited to only solving the grade estimation aspects, but it also could be used in other geological and mining areas. This is particularly useful when it is desirable to incorporate interpretive knowledge based on a more complex understanding of the data.

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