The Application of Artificial Neural Networks to Ore Reserve Estimation at Choghart Iron Ore Deposit

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Abstract

Geo-statistical methods for reserve estimation are difficult to use when stationary conditions are not satisfied. Artificial Neural Networks (ANNs) provide an alternative to geo-statistical techniques while considerably reducing the processing time required for development and application. In this paper the ANNs was applied to the Choghart iron ore deposit in Yazd province of Iran. Initially, an optimum Multi Layer Perceptron (MLP) was constructed to estimate the Fe grade within orebody using the whole ore data of the deposit. Sensitivity analysis was applied for a number of hidden layers and neurons, different types of activation functions and learning rules. Optimal architectures for iron grade estimation were 3-20-10-1. In order to improve the network performance, the deposit was divided into four homogenous zones. Subsequently, all sensitivity analyses were carried out on each zone. Finally, a different optimum network was trained and Fe was estimated separately for each zone. Comparison of correlation coefficient (R) and least mean squared error (MSE) showed that the ANNs performed on four homogenous zones were far better than the nets applied to the overall ore body. Therefore, these optimized neural networks were used to estimate the distribution of iron grades and the iron resource in Choghart deposit. As a result of applying ANNs, the tonnage of ore for Choghart deposit is approximately estimated at 135.8 million tones with average grade of Fe at 56.14 percent. Results of reserve estimation using ANNs showed a good agreement with the geo-statistical methods applied to this ore body in another work.

1. INTRODUCTION

Artificial Neural Networks (ANNs) have shown to be promising computational alternatives to the ore reserve estimation. A neural network is a computational model that is based on the neuron cell structures of the biological nervous system. Given a training set of data, the neural network can learn the data pattern with a learning algorithm. The ability of learning in ANNs provides an interesting alternative to the conventional geo-statistical ore reserve estimation, especially where the second order stationary assumption about the spatial distribution of ore grade, within ore body, is not satisfied. Also, in Kriging the nearby sample points are used to estimate the grade of a specified location using a linear weighting (local fitting model), while in ANNs the grade of spatial variability is captured through the nonlinear input-output mapping via a set of connection weights (global fitting model). However, in ANNs method there is no need to calculate experimental variograms [1]. Geo-statistical calculation requires large amount of samples, therefore with a small number of input data, the calculation of variograms become increasingly uncertain, even impossible [2]. Geo-statistical calculations also require suitable computer programs and a considerable mathematical background [3]. The objective of present work is to examine the applicability of ANNs method to estimate the Fe grade at the Choghart iron ore deposit, in Yazd province of Iran.

2. ARTIFICIAL NEURAL NETWORKS AND ORE RESERVE ESTIMATION

For grade estimation using neural network, some data in the form of samples with known positions in 3D space are used as input data and grade attribute is used as an output for the respective data sets. The complex spatial structure between input and output patterns is captured through a network via a set of connection weights, which are adjusted during training of the networks. The network captures an input–output relationship through training and acquires certain prediction capability so that for a given input (northing, easting and elevation coordinates) the network produces output (grade/grades). The network architecture that was used in the current analyses was a Multi Layer Perceptron (MLP) feed forward neural network. The advantage of using the MLP architecture is that this type of network is able to employ different activation functions in hidden and output layers. As a result, complex nonlinear input–output pattern is captured by a combination of multiple hidden units with different activation functions.

Several researchers have applied neural networks for grade estimation in the past. Wu and Zhou investigated the ANNs approach for copper reserve estimation [4]. Rizzo and Dougherty used ANNs to characterize aquifer properties [5] and Singer and Kouda searched for a mineral deposit [6]. Yama and Lineberry explored ANNs in ore grade estimation [7]. Ke used an ANNs for ore grade estimation in a placer gold deposit in Alaska [8]. Koike et al. applied an ANNs to determine the principal metal contents of the Hokuroku district in northern Japan [9]. Koike and Matsuda also used this technique for estimating content impurities of a limestone mine such as SiO_2, Fe_2O_3, MnO and P_2O_5 [10]. Samanta et al. [11] and Dutta et al. [12] applied an ANNs to study a bauxite deposit. Dutta also used an ANNs to study a placer gold deposit and Greenscreek polymetallic lode deposit [13].

In usual grade estimation by ANNs, coordinates were applied as input parameters. Although in some cases additional parameters such as dependent grade attributes were also used. Misra et al. introduced one more Au input variable with the coordinate variables [1]. Also, Dutta et al. applied Au, Pb, Zn and Cu variables with the X and Y coordinates as input parameters to estimate As grade [12]. For grade estimation and mapping, the grade of all internal unknown points between known points should be estimated. While, the only distinct attributes of these points are coordinates. As a result, the use of additional parameters such as another dependent grade attribute may not be applicable in all cases.

An introduction to MLP with back-propagation learning algorithm that has been used in this study, is presented in the following paragraphs.

3. MULTILAYER FEED FORWARD NEURAL NETWORK (MFNN)

In this work the model considered in the MFNN included three inputs and one output variables. This topology is shown in Figure 1. Input variables were northing (Y), easting (X) and elevation (Z) coordinates and the output is the Fe grade, i.e. $G = f(X,Y,Z)$. For example, a network having one hidden layer (with a log-sigmoid activation function) and one output layer (linear function) is depicted.

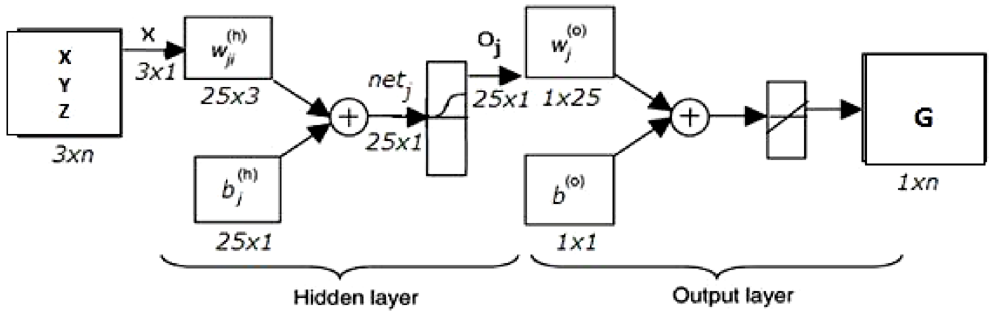

Figure 1. Schematic diagram of MFNN with (3-25-1)-MLP topology (after Omid et al.) [14].

We name this network, a (3-25-1)-MLP topology, that is n=3 and m=25. In general, the value at the output unit is always the same for a certain set of input values. Therefore the output $\hat{g}$ (predicted Fe grade) can be seen as a function of the input values, X, Y and Z. The bias parameters, $b_j^{(h)}$ and $b^{(o)}$, may be viewed as weights from an extra input having a fixed value of one. The general expression for Fe operation can compactly be cast into:

$$\hat{g} = \sum_{j=1}^{m} w_j^{(o)} f\left(\sum_{i=1}^{n} w_{ji}^{(h)} O_i + b_j^{(h)} \right) + b^{(o)}, \quad (1)$$

Where $\hat{g}$ is the predicted value of the Fe grade in the network, i=1, 2, …, n, j=1, 2, …, m and:

$$O_j = f(net_j) = \frac{1}{1 + e^{-net_j}} \quad (2)$$

Notice that the log-sigmoid and linear activation function are employed to the hidden and output layers, respectively. Similar expressions, as in (2) and (3), and diagrams, as in Figure 1, can be given for more complex networks.

The first step in developing MFNN deals with the definition of the network architecture, which is defined by the basic Processing Elements (PEs) i.e. neurons and their interconnections (layers). MLP are normally trained with error Back Propagation (BP) algorithm [15]. MLP learns the distribution of grades over the complete training set and is used for estimating grades at points inside the ore body. The knowledge obtained during training phase is not stored as equations or in a knowledge base, but is distributed throughout the network in the form of connection weights between neurons [16]. It is a general iterative solution method for weights and biases. BP algorithm uses a Gradient Descent (GD) technique which is very stable but has slow convergence properties. Several methods for speeding up BP algorithm have been used including adding a momentum term or using a variable learning rate. The Levenberg-Marquardt (LM) algorithm that is used in this study is a modification of the Newton's method for non-linear optimization. The LM and Newton methods use the gradient and other numerical quantities such as the Hessian matrix of the error surface, which consist of the 2nd order derivative of the error function. These methods are also based on the concept of quadratic approximation of the error function in a local region. If the error function is truly quadratic in nature, the Newton's method finds the minimum solution in a single iteration. Therefore, the success of this technique depends upon how closely the error function resembles the quadratic function. Even the LM algorithm will diverge if the quadratic approximation is not appropriate. Searching for an optimal solution using this method requires the calculation of the inverse of the Hessian matrix, which should be positive definite. Newton's method does not always guarantee the positive definiteness of Hessian matrix. The LM algorithm introduces a regularization term into the Hessian matrix so that positive definiteness of the Hessian matrix is guaranteed [13].

The performance of the trained networks was measured by Mean Square Error (MSE) and coefficient of determination (R^2) on another set of data (testing set), not seen by the network during training and cross-validation, between the predicted values of the network and the target (or experimental) values as follows [17]:

$$MSE = \frac{\sum_{j=1}^{N} (\hat{g}_j - g_j)^2}{N} \quad (3)$$

$$R^2 = 1 - \frac{\sum_{j=1}^{N} (\hat{g}_j - g_j)^2}{\sum_{j=1}^{N} (g_j - \bar{g})^2} \quad (4)$$

Where $\hat{g}_j$ is the network (predicted) output from observation j, g_j is the experimental output from observation j, $\bar{g}$ is the average value of experimental output, and N is the total number of data observation.

In this research work, NeuroSolutions software Version 5.0 [18] was used for the design and testing of MFNN models. To develop a statistically sound model, the networks were trained several times (three) and the average values were recorded for each parameter. To avoid 'overfitting', the MSE of the validating sets was calculated after adjusting of the weights and biases. The training process continued until the minimum MSE of the validating sets was reached early-stopping scheme.

4- CHOGHART IRON ORE DEPOSIT

For this study, Choghart iron ore deposit was selected. Choghart iron mine is located at 12km north-eastern of Bafq city and 125km south-eastern of Yazd city, Iran (Figure 2). Conventional open pit mining method is used to extract 134 million tones of ore reserve at an annual rate of 3 million tones. The initial open pit mine was developed at an elevation of 1286m above mean sea level (150 meter from surrounding regions) in 1971 and will be continued down to the elevation of 812.5m. There are about 137 drill holes in the whole region.

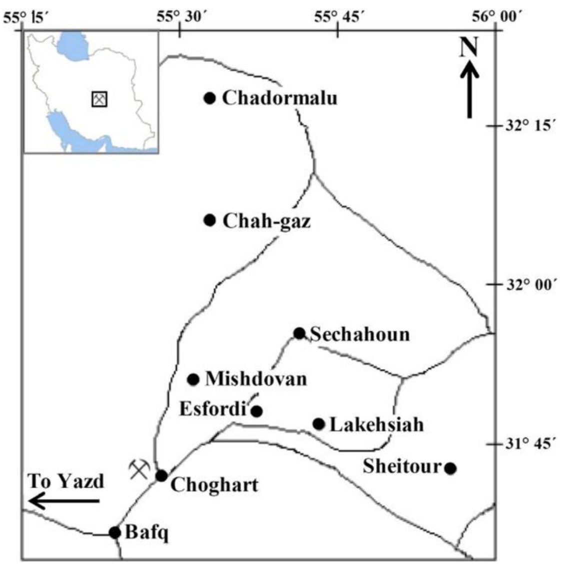

Figure 2. The location of the Choghart iron ore deposit [22].

Figure 3 shows the 3D displaying of the spatial location of boreholes in Choghart deposit. Iron is the main constituent of the deposit. Due to the extent and richness of the Choghart deposit, the area was studied extensively, and geological, geophysical and geochemical characteristics of deposit are well documented in the published literatures [19-21].

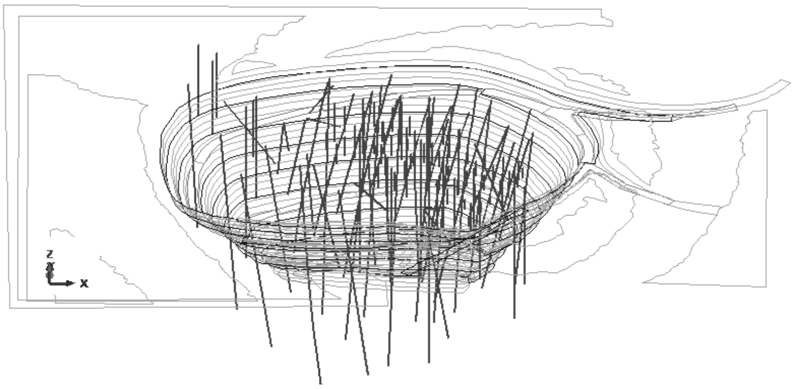

Figure 3. A schematic 3D presentation of the spatial location of the boreholes in Choghart deposit.

5- DATA PREPARATION

In order to use neural network method for estimation of ore reserve, several data preparation steps need to be performed:

5-1 Preparation of composite data

Using raw data for training neural network has following problems; 1- network will be unable to be trained due to intense spatial grade variability 2- trained network will have weak validation results because of overtraining problem. As the core sample lengths are not equal, to overcome this problem the data samples are composited in equal length. Thus, the raw data obtained from 137 drill holes are composited in 3.3m (equal to the average length of cores in one drilling run) using a moving average method to make ore grade changes in a smoother manner (Figure 4).

5-2- Separation of the ore from waste

Using the ore and waste composites data in the grade estimation procedure will cause an overestimation in tonnage and underestimation in average grade. Thus, data were separated in two groups of ore and waste composites and only composites inside the ore body were used in ore grade estimation. Finally, these data were collected in terms of easting (X), northing (Y) and elevation (Z) coordinates, and Fe grade.

5-3-Determination of outlier data

Outliers are the data that have a meaningful difference with the others or with the mean. These differences may be due to experimental errors, which sometimes occur during sampling, preparation or analysis. These data should be removed from inputs. In this study the Box-plot chart method was used for this purpose. However, no outlier was found.

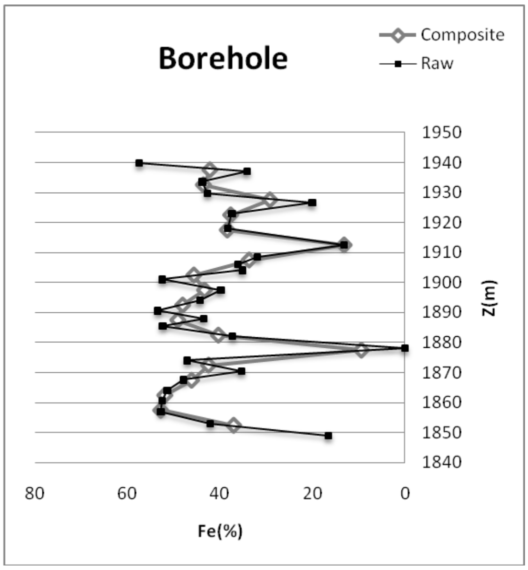

Figure 4. Raw data vs. composited Fe grades in an example borehole.

5-4- Data normalization

As the final step of data preparation, the data were normalized into [-1, 1]. In general, an artificial neural network has no natural tendency to be trained on very high or very low values. The major aim of normalization is to increase network training ability on these values.

5-5- Preparation of subdatasets

For ANNs analysis, three datasets are needed: a training set, a validation set and a test set. For valid results, these three sets of data should be statistically similar. Normally, the training set should comprise a major chunk of the dataset so that the network learns the input/output patterns properly. The validation set is basically used as an independent observer and the test dataset is used for model validation. It is a general practice to divide the entire dataset into three subsets, where members of each subset are chosen randomly. However, Bowden et al. cited several problems with random data division and cautioned to use this approach blindly [23]. In this regard, Samanta et al. [11, 24] have reported successful applications of a Genetic Algorithm (GA) to generate statistically similar datasets. But due to very large data set and low nugget effect, random data division was used to divide the data in the problem studied here. Hence, 1952 samples have been chosen as training set, 450 samples as validation set and the remaining 601 data, selected as testing.

6- DESIGNING OF ESTIMATION SPACE

Initially, before designing network, estimation space should be determined. Estimation space is a space that should be girded using blocks. The block model characteristics for the calculation of Fe grade are shown in Table 1. Also, a sub blocking factor for better edge detection and prevention of overall tonnage overestimation, was considered.

Table 1. The block model characteristics in Choghart deposit.

Sub blocking	block size	Maximum coordinates	Minimum coordinates	coordinates
6.25	25	8800	7590	Y
6.25	25	5200	4500	X
3.125	12.5	1100	800	Z

Based on information in Table 1, a 3D block model of ore body and surrounding waste material was built, using SURPAC 6 software [25].

This block model was then constrained by geological boundaries. These boundaries obtained from geological mapping of boreholes, blast holes and outcrops. The advantage of using this boundary was that, it helped us to exclude the waste materials, thus, we could prevent tonnage overestimation. Figure 5 shows the ore body 3D block model in the Choghart deposit.

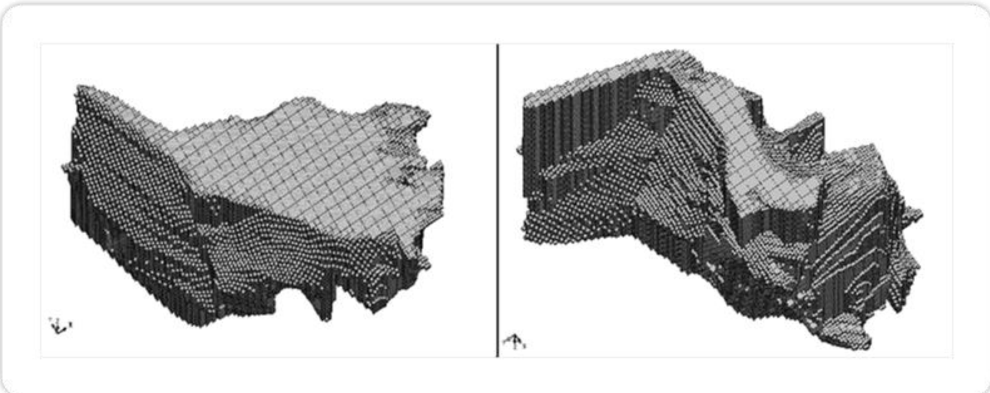

Figure 5. A schematic view of ore body 3D block model of Choghart deposit, confined by geologic boundary.

Because the mixture of samples from different ore zones resulted in forming multiple population, it is usually suggest to separate data to homogenous different zones. Therefore, the next step is to define domains in order to identify more than one possible population within the input data. Geological 3D fault model that shows the spatial relationship between the geologic faults and the ore body, identified four populations (homogenous zones) within Choghart ore body. Figure 6 depicts the identified four populations in Choghart deposit. Therefore, input data were classified into 4 groups, each of them coincides with each population. Then grade estimation was done within each domain separately. In the next section the effects of population separation on the estimated grades will be investigated.

7- OPTIMUM NETWORK DESIGN

7-1- Designing of optimum network using the whole data set

In this section, the whole input data set were used in the grade estimation process. During network training and learning, network parameters should be adapted through a continuing process of stimulation by the environment in which the network is embedded. The accuracy of learning is determined by the manner that parameters are optimized [8]. These parameters are optimized using sensitivity analysis and will be discussed in detail in the following section.

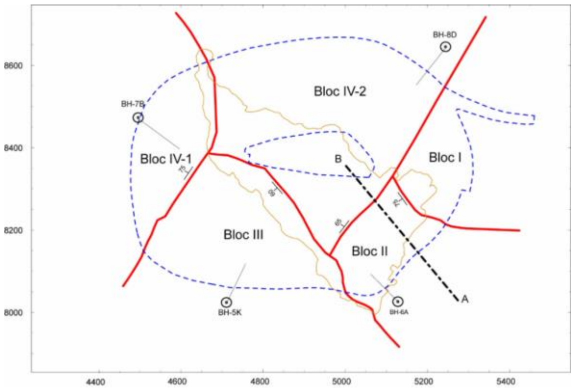

Figure 6. Four populations within the Choghart ore deposit (solid lines represent the major faults and the block boundaries (homogenous zone), dashed lines indicates the mine pit boundary) [21].

In MLPs, these parameters are: number of hidden layers, number of hidden units, learning algorithms and activation functions. Sensitivity analysis are carried out to choose the number of layers, the number of neurons of middle layers and activation functions, respectively.

7-1-1- Sensitivity analysis of hidden layers

In most situations, there is no easy way to determine the best number of hidden layers without training several networks and estimating the generalization error. Several "rules of thumb" for choosing the hidden layer Processing Elements (PEs) have been suggested in the published literatures [26-29]. These rules of thumb cannot be generalized, because they are not always valid for all training cases. The optimum number of hidden layers (and also hidden units in each layer) depend on the complexity of network architecture, the number of input and output units, the number of training samples, the degree of the noise in the sample data set, the training algorithm and the training criteria [8]. Hence, the parameters of hidden layers are commonly defined by performance measurements using trial and error procedure.

As described in previous section, the sample data obtained from 137 drill holes. Three inputs and one output were used. In this work for sensitivity analysis to choose optimum number of hidden layers, the MFNN architecture was used for training, with the following characteristics: LM training algorithm, LogSig transfer function for hidden layers and MSE increase training stop criteria. The results of this analysis are presented in Table 2.

Table 2. Results of sensitivity analysis of hidden layers (in whole set of Choghart data)

MSE	R value	Training time	Hidden layers
80.0	0.41	00:00:50	0
54.3	0.66	00:25:47	1
47.6	0.71	01:10:36	2
48.8	0.70	04:19:12	3

Table 2 indicates that, with zero-hidden layer, convergence is obtained in a short time. The performance, however, is poor with a low R value of 0.41 and a high MSE value of 80. On the other hand, with one-hidden-layer, values of R and MSE are not good enough yet. But with two-hidden-layers or three-hidden-layers, the results are better. With regard to the training time, R value and MSE, two-hidden-layers architecture is chosen as an optimum one.

7-1-2- Sensitivity analysis of neurons in hidden layers

Selecting the number of hidden units does greatly influence the performance of training a network. As in the case of number of hidden layers, the best number of hidden units is difficult to determine. Several factors, such as the network architecture, the degree of noise, the number of hidden layers and the complexity of the function have to be taken into account in selecting the number of hidden units.

As discussed above, the number of hidden units depends on several factors. For the statistical analysis, many networks with different number of hidden units were examined to estimate the training and the generalization errors for each case. Then, the network with minimum estimated generalization error was selected. Based on the results of Table 2, the network with two hidden layer was selected. Therefore, two separate analyses need to be carried on layers.

For the first analysis, the number of second hidden-layer-neurons fixed on 4, and analysis carried on first hidden layer. Results of these analyses are shown in Figure 7. It can be seen that the number of 20 neurons with the minimum cross validation error, is the best for the first hidden layer. The same analysis carried on second hidden layer, while the first hidden units were fixed on 20 (Figure 8). It can be seen that, the number of 10 neurons for the second hidden layer is the best and has the minimum validation MSE.

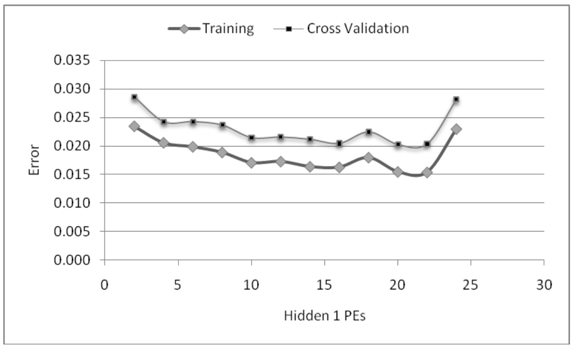

Figure 7. Average of MSE vs. the number of first hidden layer neurons.

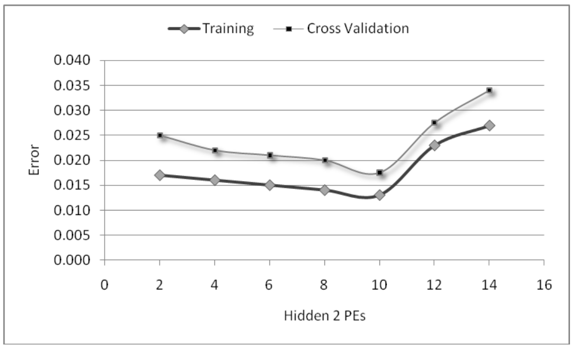

Figure 8. Average of MSE vs. the number of second hidden layer neurons.

7-1-3- Sensitivity analysis of activation functions

As noted by Suykens et al. [30], transfer functions in neural networks could be selected based on the type of application. Also, Ke et al. have tested the influence of various activation functions on ANNs in a gold deposit [31]. In line with that, this section explores the effect of the various transfer functions in Choghart ore modeling exercise.

7-1-3-1- Influence of transfer functions on hidden layers

In order to analyze the influence of transfer functions on hidden layers, several transfer functions including logistic, Tanh, Linear and Gaussian were tested. Then in order to determine model performance the predicted Fe values for each transfer function was compared to the known true value. As mentioned above this comparison was carried out by obtaining R and MSE values. Figures 9 and 10 show the R and MSE values for various types of transfer functions on the hidden layers.

As can be seen, the logistic sigmoid transfer function performs better than the other functions. Also, the Tanh function is the second best one for using as hidden layer transfer function.

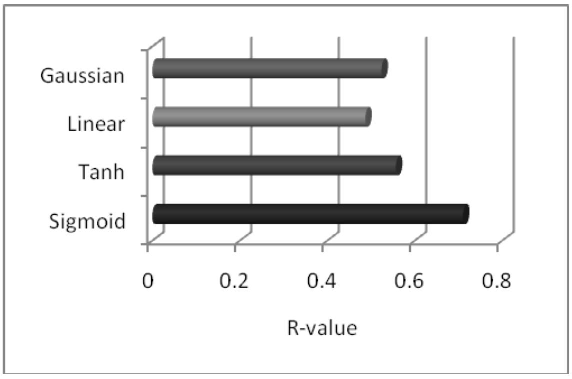

Figure 9. R value for various transfer functions on hidden layer.

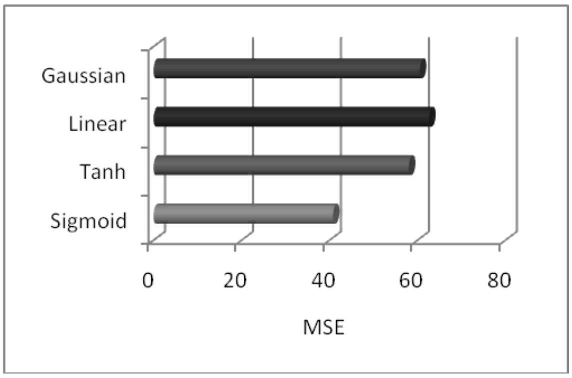

Figure 10. MSE value for various transfer functions on hidden layer.

7-1-3-2- Influence of transfer functions on output layer

Although usually linear transfer is the selected function for the output layer, but due to the nature of this case, the sensitivity analysis was used to select the function. To analyze the influence of transfer functions on output layer, several transfer functions were used. Figures 11 and 12 show the R and MSE values for various types of transfer functions. As it is clear from these figures, linear transfer function is the best choice for output layer.

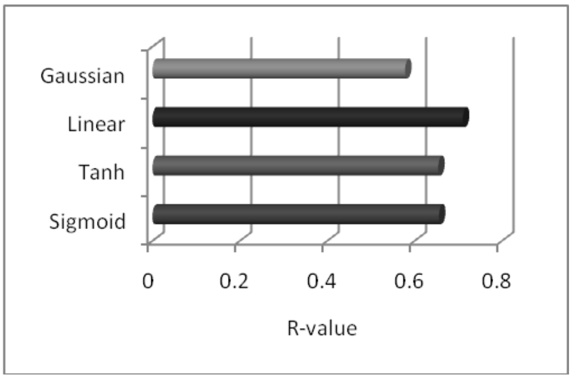

Figure 11. R value for various transfer functions on output layer.

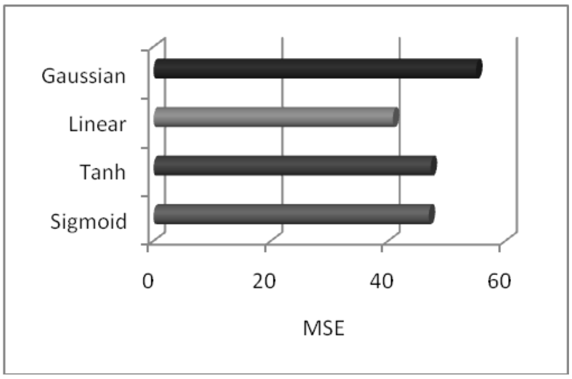

Figure 12. MSE value for various transfer functions on output layer.

7-1- 4- Comparison between predicted values and actual values

To investigate the accuracy of neural network modeling, the overall performance was also confirmed by the comparison between predicted values and actual values (Figure 13). As it can be seen, there is good agreement between two values.

7-2- Designing optimum networks within each domain

As discussed before, in order to increase network capability for grade estimation purpose, data were classified into four populations. Subsequently, all sensitivity analyses like those described previously, were carried out on each domain. Thus, in each domain, analyses such as network selection, number of hidden layers, number of hidden neurons, learning rules and activation functions, were carried out and the optimum network was selected according to the obtained sensitivity analyses results. Finally, four optimal networks were selected for each group of data. Table 3 shows these optimal networks.

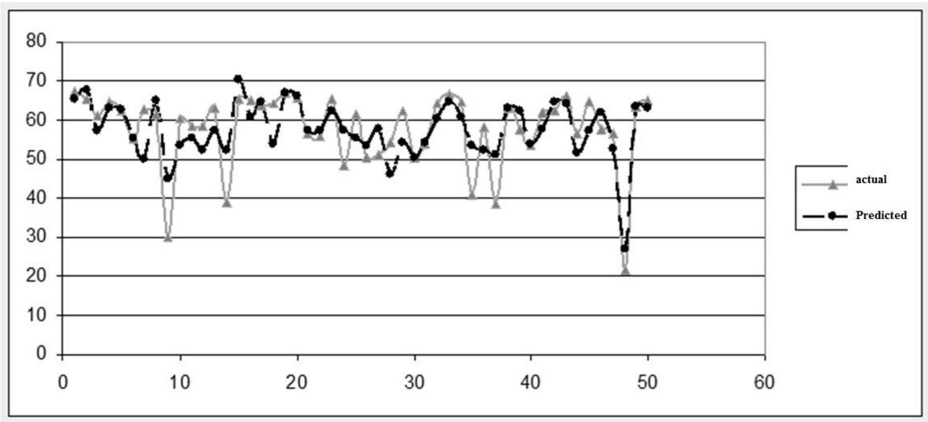

Figure 13. Predicted values (obtained from designed neural network) vs. actual values.

Table 3. Optimum networks characteristics and their testing results, in different populations.

R-value	MSE	Learning rule	Activation function	No. of Hidden layers	Population No.
0.70	25.4	Mom	Tanh	3	1
0.73	23.2	LM	LogSig	1	2
0.74	23.5	Mom	LogSig	4	3
0.77	20.3	LM	LogSig	1	4

8- RESULTS AND DISCUSSION

To estimate the reserve of Choghart iron ore deposit, first, estimation was carried out within the ore body. Then, the orebody was split into blocks whose dimensions are determined according to the deposit extent and open pit design parameters such as mining bench height.

After that, the grade was estimated for each block using ANNs. Designing optimal neural network was carried out by various sensitivity analyses including; network type, number of hidden layers, number of hidden units, learning rule and activation functions. In these work, the networks capability was measured using networks efficiency in grade estimation, for test data series, by means of R and MSE values.

The optimal network characteristics are shown in Table 4. It can be seen that the optimal network is a MLP with two hidden layers and 3-20-10-1 architecture. The generalization capability of this network was tested and the results are presented in Table 5.

Table 4. Optimum network characteristics

Attribute	Comments
Network type	Multi-layer perceptron
Architecture	3-20-10-1
Hidden-layers activation function	Logistic sigmoid
Output-layer activation function	Linear
Learning rule	Levenberg-Marquardt

Table 5. Optimum network testing results

Performance	Fe
MSE	47.62
NMSE	0.50
MAE	4.57
Min Abs Error	0.0027
Max Abs Error	38.86
R	0.71

As mentioned before, for more investigation and to decrease the grade estimation error, it was decided to subdivide the estimation space into smaller and more homogenous zones. Therefore, the deposit was divided into four sub-zones that fitted into four main tectonic zones. Subsequently, the designing of neural network was conducted within each zone, separately. To achieve this aim, all sensitivity analyses similar to those described above, were performed within each zone and the optimum networks were selected. The characteristics of four optimal networks in four different zones and also that of in the whole deposit are shown in Table 6.

Table 6. Comparison among the network characteristics of four homogenous zones to the whole deposit in Choghart

Domain	MSE	R-value
1	25.4	0.70
2	23.2	0.73
3	23.5	0.74
4	20.3	0.77
Whole deposit	47.6	0.71

Table 6 presents the testing results of networks on different domains. Correlation coefficients of all networks are more than 0.7 and less than 0.77. Accordingly, there is no significant improvement in R-value. However, R-value in domain 4 has a meaningful prominence with respect to whole deposit domain. But MSE values show that optimal networks in domains 1 to 4 have a noticeable superiority in comparison with the optimum network without population separation. Thus dividing deposit into four sub-zones was successful in networks capability improvement.

Ore grade distribution in different altitudinal levels were estimated by the final neural network. An example of this type of estimation, at 1000 elevation of Choghart deposit, is shown in Figure 14.

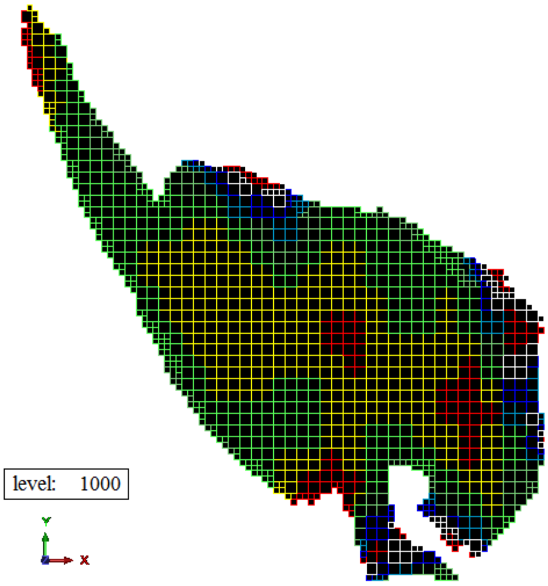

Figure 14. A schematic plan of ore distribution at the 1000 meter elevation, estimated by Artificial Neural Network.

The results of this work was compared to the results of the reserve estimation of Choghart deposit using geostatistical method [21]. The ore reserve estimation results of both ANNs and geostatistics in every bench are presented in Figure 15.

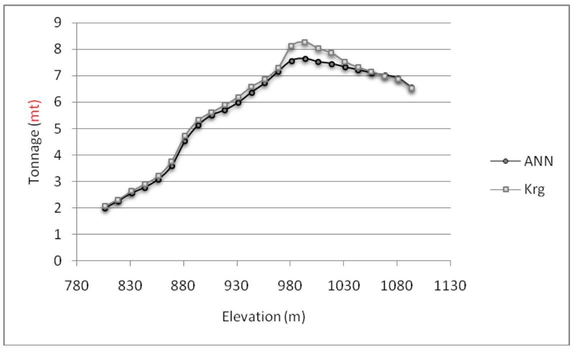

Figure 15. Comparison between ANNs and Kriging reserve estimation results.

As it can be seen from Figure 14, there is a good agreement between the results of ANNs and geostatistics.

9- CONCLUSION

This study is focused on the neural network modeling for the estimation of Choghart iron ore reserve. Due to the spatial variability, multiple dimensional inputs and very noisy drill hole sample data from the selected region, it required that the neural network be organized in multiple-layers to handle the non-linearity. Various neural network architectures were investigated and the back propagation was selected for modeling the ore reserve estimation. Sensitivity analysis was performed for the following parameters: number of hidden layers and hidden neurons, type of activation functions, learning rules. The influences of these parameters on the predicted output were analyzed in details and optimal parameters were determined. To investigate the accuracy and promise of neural network modeling as a tool for ore reserve estimation, the overall performance was also validated by the analysis of correlation coefficient (R), mean squared error (MSE), and the comparison between predicted values and actual values. Finally optimal architecture for iron grade estimation was 3-20-10-1. Values of R and MSE for iron grade estimation were 0.71 and 47.6, respectively. For more investigation and to increase the network capability for grade estimation purpose, data were classified into four populations. Subsequently, all sensitivity analyses were carried out on each domain. Afterwards, the optimum network was selected according to analyses results. Finally four optimal networks were selected for four distinct domains. These networks were tested and the obtained results were compared with overall optimum net results. The results of this comparison showed that these nets perform far better than the overall one. As the final part of this study, the optimized neural networks were used to estimate the distribution of iron grades and the volume of iron resource in Choghart deposit. As a result of ANNs, the tonnage estimation of ore between 800m-1100m elevations for Choghart deposit was approximately 135.8 million tones with average grade of 56.14 percent Fe.

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