# Correlation between IP and Rs and grade data in modeling and evaluation of a copper deposit, case study: the Sarbisheh copper deposit, Iran

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## Abstract

This paper addresses the application of integrated chargeability and resistivity method and grade data in modeling and evaluation of copper deposits. We argue that the relationship between IP, Rs and grade data may be used for modeling and reserve estimation and tested this argument for Sarbisheh copper deposit that is located in eastern Iran. Geology and mineralization situation of Sarbisheh deposit was reviewed. Then geophysical survey design was carried out based on the borehole exploration data and other parameters such as geological and topographical factors. Five profiles were designed and surveyed using dipole-dipole array. The obtained data was processed and 2D sections of IP and Rs were prepared for each profile by inverting the data using the Res2dinv software. Based on the geostatistical methods, a 3D block model for IP and Rs data was constructed using Datamine Studio software and this model was evaluated by some exploratory boreholes in the study area. The relationship between IP and Rs and copper grade has been calculated based on statistical and neural network methods. In the cases that borehole data was unavailable, Cu grade was estimated using regression and multivariate regression analysis. Moreover, Cu grade was predicted by neural network at unrecognized points. Then Cu grade was calculated for each block identified by IP 3D model. Finally, a 3D block model of this copper deposit was constructed. According to the drilling tests, there is a good correlation between 3D block model and real Cu grade modeling.

**Keywords:** IP and Rs; Grade Estimation; 3D Modelling; Deposit Evaluation; Statistical Methods; Artificial Neural Network.

## 1- Introduction

Mineral exploration is a complex endeavor carried out by combining different methods and disciplines. Construction of a 3D model of a deposit is the most prominent and challenging goal of mineral exploration. The main issue is to obtain more information in less time and by lower costs so new techniques and methods are inevitable. Application of geophysical exploration methods has recently been increasing due to their optimizations in cost and time. Integrated geophysical methods are commonly used in mineral exploration to obtain qualified results (Mostafaie and Ramazi, 2015). All geophysical techniques are based on detection the contrasts in different physical properties of materials (Telford *et al*., 1990). Geophysical tools, including different techniques such as induced polarization (IP) and resistivity (Rs), are important techniques in exploration for ores located in basement rocks (Sultan, Mansour, Santos, and Helaly, 2009). Resistivity and induced polarization (IP) methods are among the most applicable geophysical methods used in subsurface studies. These methods are used for selection of the best drilling points for exploration purposes (Ferdows and Ramazi, 2015.). Due to its low cost and time saving and its limited environmental damages, a combination of induced polarization (IP) and Electrical resistivity (Rs) methods have been widely used in various mineral exploration studies such as polymetal in China (Yang 2008), porphyry copper in Mexico (Flores *et al*., 2009), Manganese in Iran (Ramazi and Mostafaie, 2013), lenses of water-saturated unfrozen rocks (taliks) (Kozhevnikov *et al*., 2014), sulfate in Iran (Mostafaie and Ramazi, 2015), and gold-silver deposit (Gurin *et al*., 2015). IP and Rs surveys are predominantly used for identification of possible mineralization and suggesting drilling points for their testing. In this paper, however, we tested the possible relationship between IP and Rs data and real metal grade in an attempt to extent the applicability of these surveys. For this purpose, we used regression, multivariate regression and the neural network methods. Then by integration of IP, Rs and grade data, a 3D model of deposit was constructed that can be used for deposit evaluation and ore reserve estimation.

## 2- Methodology

At first, Resistivity (Rs) and induced polarization (IP) methods was used. Then geophysical inversion and modeling, statistical analysis and artificial neural network were conducted. These methods are extensively used in data processing (Uddameri, 2007; Celik *et al*., 2009).

### 2.1- Regression

Regression analysis is a statistical process used for estimating the relationships among variables and includes many techniques for modeling and analyzing several variables on the relationship between a dependent variable and one or more independent variables (Howarth, 2001). Regression analysis is widely used for prediction and forecasting, with substantial overlap with the field of machine learning. Regression analysis is also used to understand which among the independent variables are related to the dependent variable, and to explore the forms of these relationships (Scott, 2012). There are several type of regression such as linear, logistic, polynomial, ridge and etc. (Howarth, 2001, Faul, 2009) and their usage depends on data and research goal. Regression analyze has been used in various researches (e.g. Zou, 1995; Moskovskaya, 2007; Lin *et al*., 2012).

### 2.2- Multivariate Linear Regression Analysis (MLRA)

Over the past few years, multivariate regression analysis was widely used in earth science disciplines for prediction of various objectives (e.g., Khanlari *et al*., 2012; Granian *et al*., 2015). Multivariate regression analysis is a method with one dependent and many independent variables. In this method, assuming that a dependent variable (Y) is expressed as the function of independent variable (Xi):

$$Y=f\,(Xi)$$

If Y is a linear function of Xi, the regression is called linear, and if the defined function is non-linear it would be the non-linear regression (Granian *et al*., 2015).

Multivariate Linear regression has been useful modelling tool for various surface and subsurface earth science. Therefore, in this paper, multivariate linear regression has been used. The general form of the model is as follows:

$Y=a_0x_0+a_1x_1+a_2x_2+a_3x_3+\ldots+a_nx_n+\varepsilon$

Where y is dependent variable, $x_1$, $x_2$... $x_n$ are independent variables, $a_0$, $a_1$, $a_2 \ldots a_n$ are regression coefficients in the model. In linear regression analysis, the regression coefficients are calculated by the least square method. In linear regression analysis, the most important criteria is required so that the fitness of the function would be acceptable is the high value of the correlation coefficients ($R^2$ ), that can be obtained from the following equation:

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{Y}-Yi)2}{\sum_{i=1}^{n}(Yi-\bar{Y})2} = 1-\frac{\sum_{i=1}^{n}(Yi-\hat{Y})2}{\sum_{i=1}^{n}(Yi-\bar{Y})2}$$

Where $\hat{Y}i$ is the calculated value of the i*th* sample of the dependent variable, $\bar{Y}$ is the mean of the dependent variable and Yi is the value of i*th* sample of the dependent variable. If the model is well fitted for the data, $R^2$ is close to 1; meanwhile, in the absence of a linear relation between the dependent variable and the independent variables, $R^2$ will be almost zero.

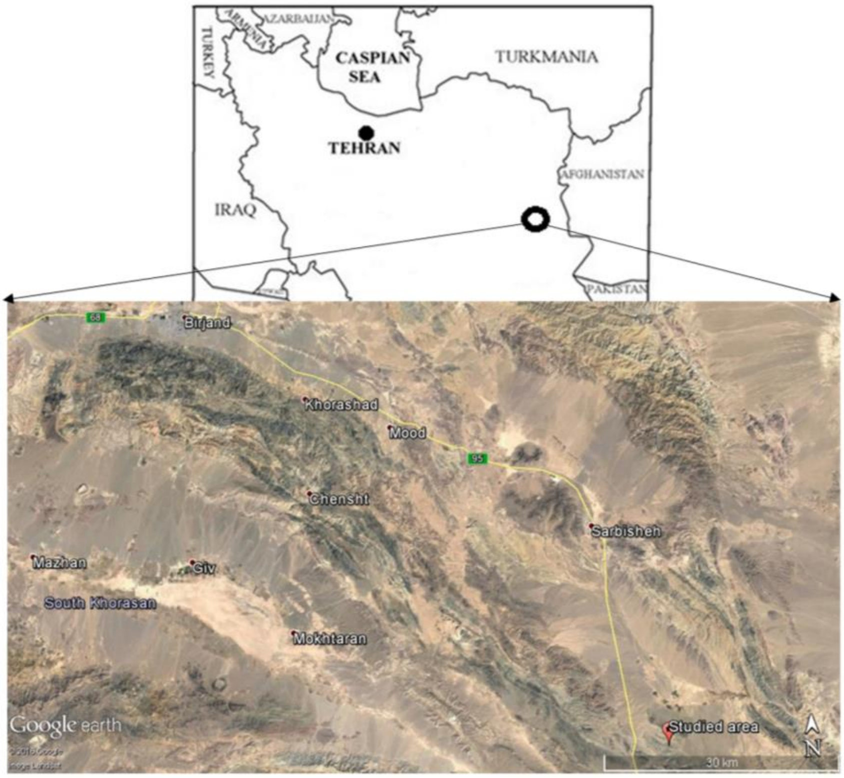


*Figure 1) Location of the study area in Iran and Birjand.*

**2.3- Artificial neural network**

Neural network is a mathematical algorithm that can be trained for solving a problem that normally require human intervention. (Park and *et al*., 2010). ANN is massively parallel-distributed processor that stores experimental knowledge and makes it available for use. It is similar to the human brain in two ways: (i) knowledge is acquired by means of learning process by a network, and (ii) the inter-neuron connection strengths known as synaptic weights are used to store the knowledge (Haykin, 1994). Each Artificial neural network consist of three layers including input, hidden and output layers. The input layer consists of neurons, each neuron of which receives one of the input variables. The intermediate or hidden layer consists of neurons each of which computes a non-linear transformation and the third or output layer consists of neurons, each of which computes a desired output variable. The output value of neurons depends on the weighted sum of an input and a weight (Singh *et al*., 2013). ANN is the more wide and various techniques with much extended theory which its explanations is not the scope of this paper. For complete information, please refer to researches by

Calderon-Macias *et al*. (2000); El-Qady and Ushijima (2001); Singh *et al*. (2006, 2010) and Singh *et al*. (2013).

**3- Study area**

The Sarbisheh copper deposit was located in the Birjand district, southern Khorasan Province, east of Iran. The location map and access roads were presented in (Fig. 1). From a geological point of view, Sarbisheh copper deposit is located within the Eastern flysch zone of Iran that is extensively tectonized and has been divided into three main groups including (i) lithology group of ophiolite series, (ii) flysch sediments and (iii) volcanic rocks, volcanic-sedimentary and igneous rocks. In the study area, there are various types of lithology which are as follows (Fig. 2). Ultrabasic rocks such as dunite, pyroxenite, serpantinite; flysch sediments such as sandstone, limestone, diabase and diabase tuffs (cretaceous to quaternary). Alteration zones include iron oxide zone, solidification zone, calcite- silica veins, and serpentine and epidotic zones. According to the topography and geological setting of the study area, dipole-dipole array was selected for this investigation. Therefore, resistivity and time domain-induced polarization data have been surveyed by dipole–dipole array. Based on the boreholes plan, the profile locations are selected, so that in each profile there is at least one exploratory borehole. Five profiles have been surveyed by dipole- dipole array in parallel with spacing of 30 m between the profiles (Fig. 2). The electrode spacing of this survey was 20 meter, and n increases from 1 to 10. Profile direction was N-S.

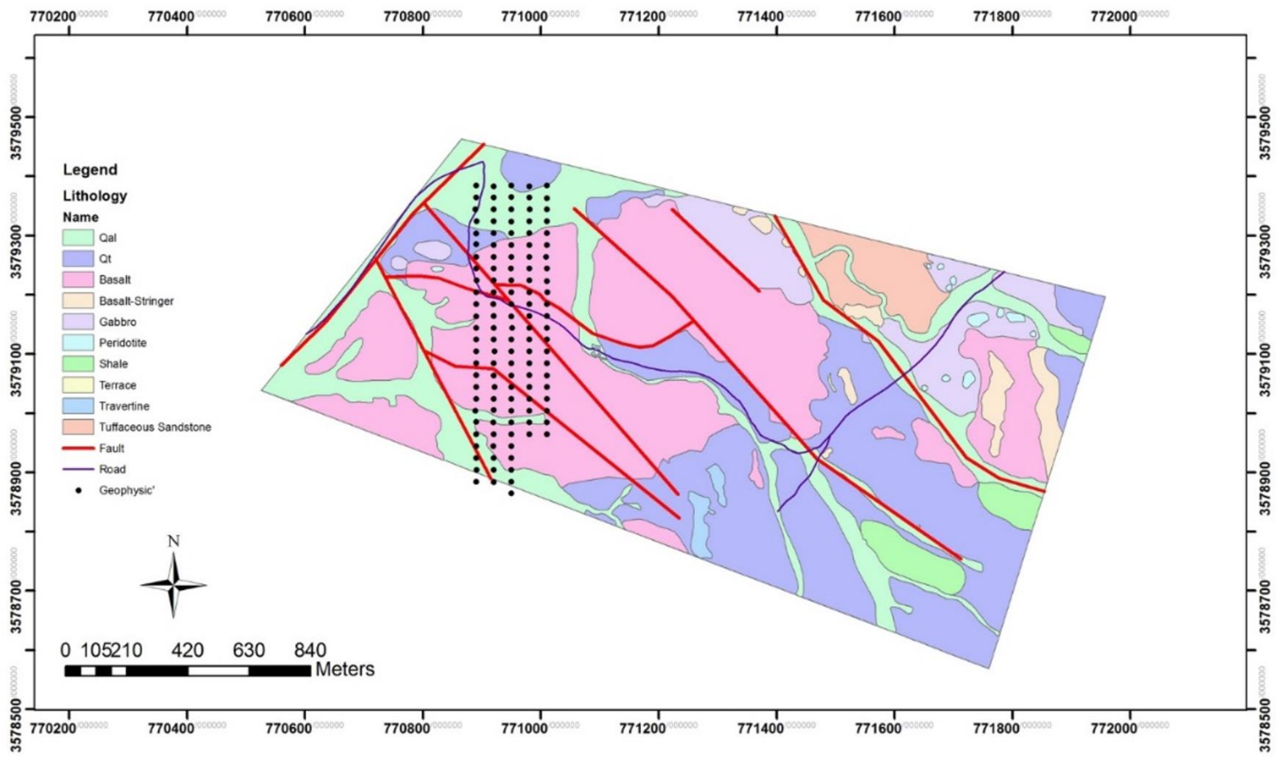

*Figure 2) Lithology map of the Sarbisheh cooper deposit and location of the geophysical surveys.*

**4- Results and discussions**

Field surveying and data acquisition was done successfully. The obtained data was revised, the data accuracy was checked, and then data processing was carried out. In the first stage, geophysical data was inverted using Res2dinv software and 2D sections have been prepared. Then the 3D model of IP and Rs data was prepared based on the geostatistical methods. As mentioned before, there are exploratory boreholes in the some locations of study area. In the next stage, the relationship between IP and

Rs and Cu grade in the testing borehole locations was investigated and calculated using statistical and artificial neural network. Based on the obtained relationship and the integration of IP and Rs and drilling results, 3D model of Cu grade constructed and presented and was checked by geostatistical methods and test boreholes.

## 4.1- Inversion results

As mentioned earlier, inversion of the IP and Rs data was done in the first stage, and then 2D electrical resistivity and IP imaging was carried out. The resistivity and IP data sets were inverted using the RES2DINV software (Loke and Barker, 1996) to create 2D sections. The resistivity and IP datasets were inversed by the Newton and Gauss–Newton methods, from the RES2DINV software package (Loke and Dahlin, 2002). Since the inversion results are not the main subject of this research, compiled sections are presented briefly. The results shows a positive relationship between induced polarization and resistivity in this deposit, meaning that the anomaly is a body with a high value of IP and Rs. In this area, IP is between 0 to 100 msec and Rs is between 0 to 2200 Ωm. Anomalies of this section show that mineralization is in the form of veins and zones with East-West direction in this deposit (Fig. 3).

## 4.2- 3D model of IP and Rs

At first, variography was done using SGeMS software (Bohling, 2007). Variogram for various parameters such as different azimuth and dip were calculated. The appropriate theoretical models based on the least square differences were fitted to the variogram. The related and required parameters for modelling were calculated. Based on the obtained characteristics of the variograms, 3D modelling of IP and Rs data was carried out using Datamine Studio software. Data of two-dimensional modeling obtained from Res2Dinv software was used as input. Two models of induced polarization (IP) and resistivity (Rs) are presented in Figure 4.

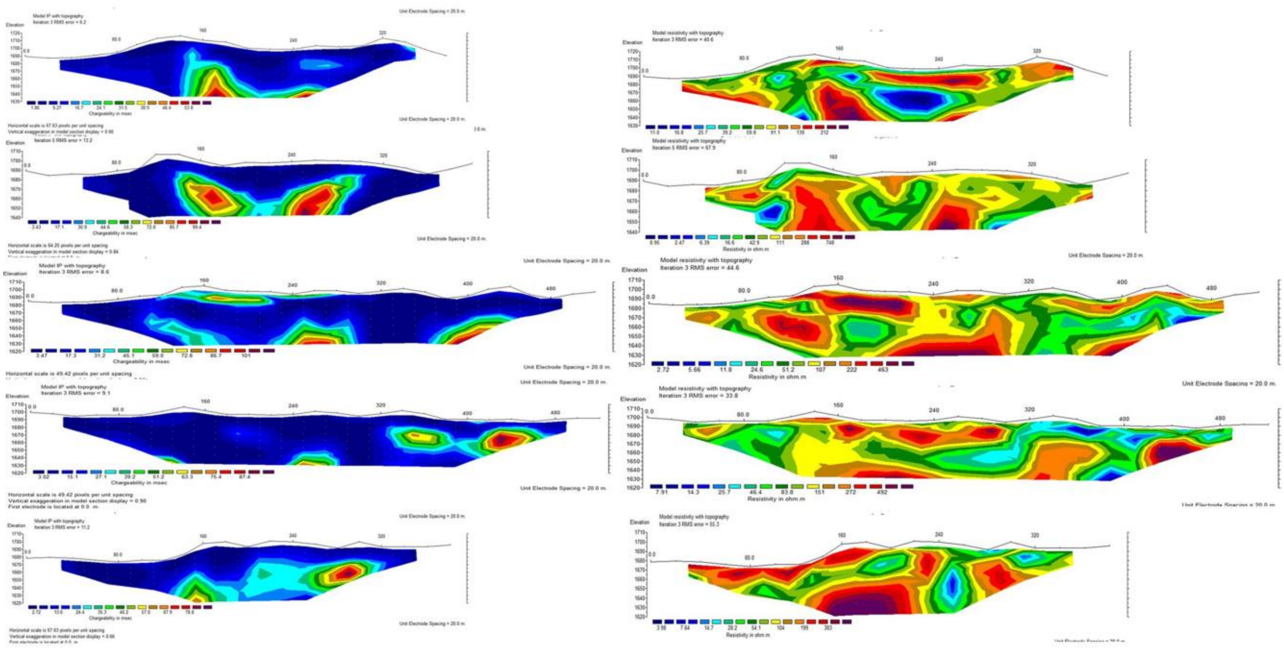

*Figure 3) The inversion results of profile1 to profile 5 in the Sarbisheh Copper deposit.*

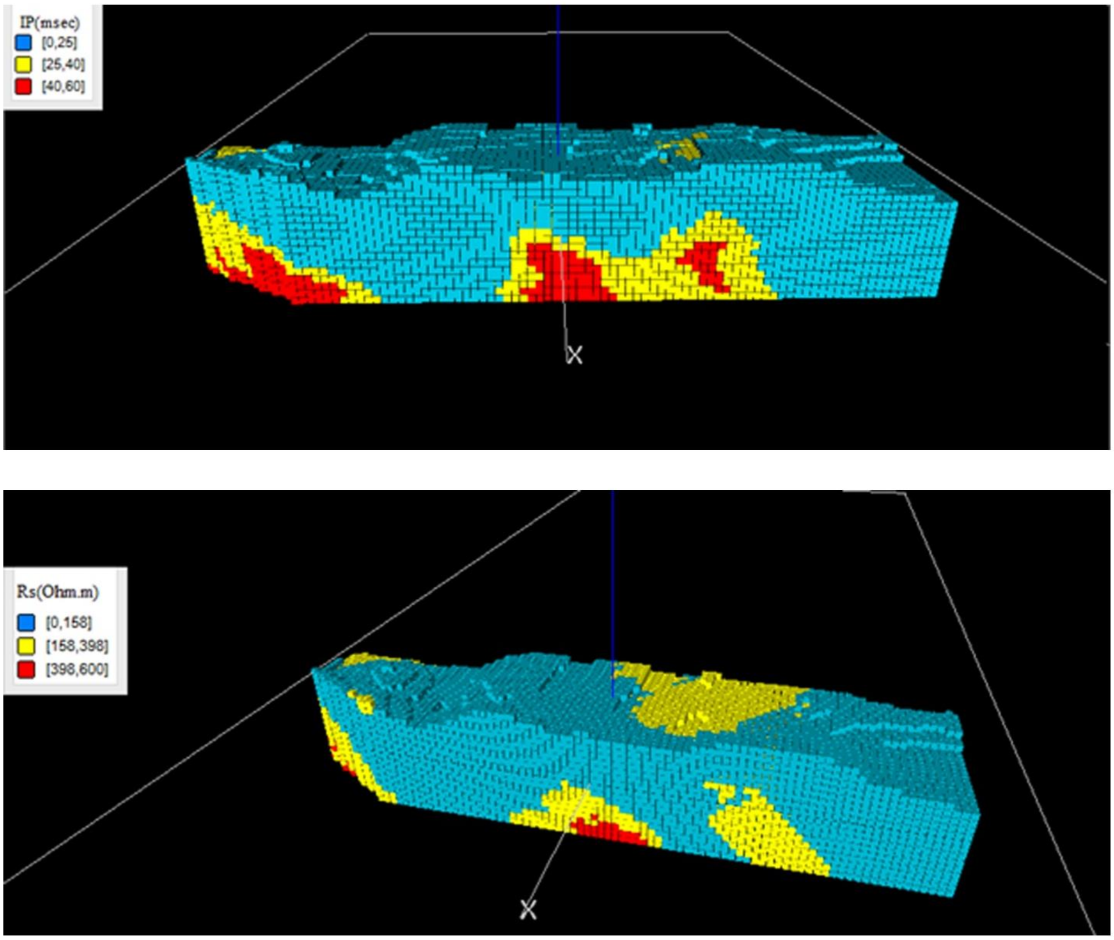


*Figure 4) The 3D modeling constructed for IP (Top) Rs (Lower).*

Fractal method was used for threshold determination and on this basis, three classes were separated. Class I includes the value of 0 to 25 msec shown by the blue color (Fig. 4), as classified in the background. Class I in the Rs model and background value include the value of 0 to 158Ωm. In Class II, the anomaly value is shown by the yellow color in the models. Anomaly value of IP include the value between 25 to 40 msec, and in the Rs model they include values between 158 to 398 Ωm. Class III includes powerful anomaly shown by the red color in the models. Powerful anomaly is determined by a value of more than 40 msec in the IP model and by values of over 398 Ωm in the Rs model. According to these models, there are some anomalies in the study area. There is a mineralization body in the middle of the study area with E-W strike. This body starts from a depth of 40 m to 60m, and according to 3D model, it is a continuous mineralization body. In the southern part of the area, there is a good anomaly with a high value of IP and Rs. This anomaly is smaller than one mentioned earlier. Generally, these two bodies are important mineralization zones that are worth exploring. In other locations, there are small and much less important anomalies. These results were confirmed by drilling results.

### 4.3- Regression results

In the first stage, correlation between IP and Cu grade checked out. IP assumed as independent variable and Cu as dependent variable. In the other words in Y = f(X) function, X = IP and Y = Cu. For this purpose, regression analyze was used. As mentioned previously, there are several type of regression and the best type was selected after testing these regression types. Because of high $R^2$, the polynomial regression type is selected (Fig. 5) and based on the analyze, the following equation was obtained;

$y = 2.1233X^2 + 8.0965X - 151.28$ with $R^2 = 0.8944$

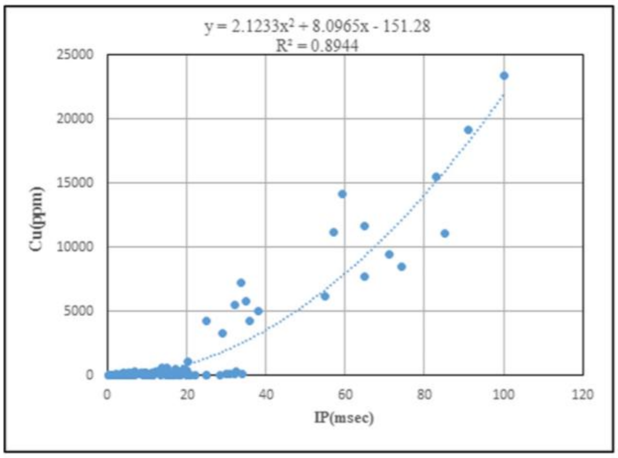


*Figure 5) The diagram of IP value against Cu value and the fitted chart.*

### 4.4- Multivariate Linear Regression Analysis

In this stage, we want to check out the correlation between IP, Rs and Cu grade simultaneously. MLRA is method with one dependent and many independent variables. In this analyze we assumed Cu grade as dependent variable and IP and Rs as independent variables. The histogram and the boxplot of variables is obtained then the following equation was calculated. The r-squared of this equation is 54%.

$Cu (\%) = 35 - 4.99 IP + 0.162 Rs + 0.0446 IP^2 - 0.000087 Rs^2 + 70.7 LN IP - 36.0 LN Rs.$

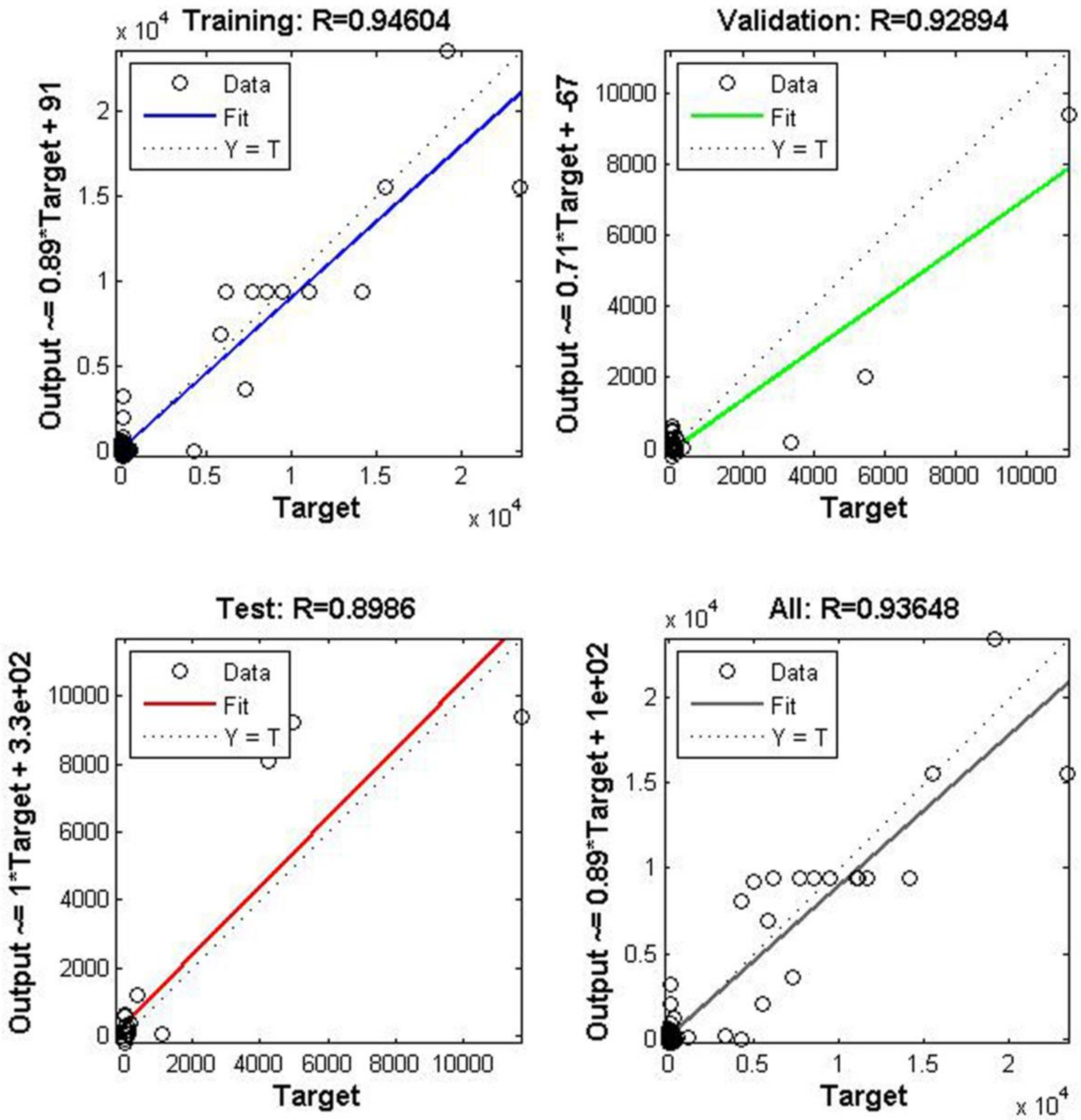


*Figure 6) The results of the ANN analyze.*

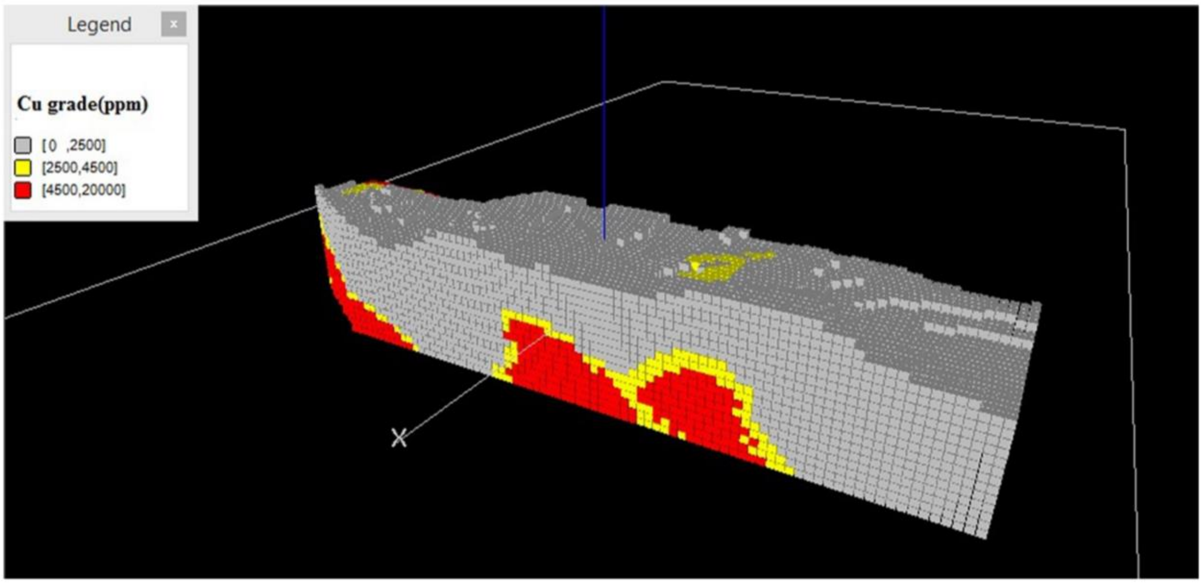


*Figure 7) The constructed 3D model of Cu Grade based on the relation between IP and Rs and grade.*

### 4.5- Artificial Neural Network

Since R Sq. is about 54% and cannot express relationship between IP, Rs and Cu grade well, we can conclude that the multivariate regression results are not very accurate. So we used the ANN methods to check out the relation between IP, Rs and Cu grade simultaneously. For this purpose IP and Rs data selected as input; Cu grade selected as output and processing started. After many tests, the best model with least error was chosen. The hidden neuron is 8 in the selected model. The result of ANN analyze with its parameters presented in Fig. 6.

After mentioned analyzed and obtained relationship between IP, Rs and Cu grade, these results was generalized to the study deposit. The copper grade of this deposit estimated, especially in the location that there is not any boreholes, according to the result of three methods that presented earlier. Then 3D model of Cu grade was prepared. The error of provided models are checked out by comparing with real Cu grade and the best model was selected and presented in Fig. 7.

## 5- Conclusions

Combination of IP and Rs methods resulted in the identification of mineralization zone, and preparation of 3D model of IP and Rs using geostatistical methods that outlined anomaly distribution as well. Then, correlation between IP, Rs and Cu grade has been checked out in the locations using exploratory boreholes. Relation between IP and Cu grade was checked out using regression analyze. The polynomial regression has achieved the best fit with R Sq. of about 0.9 so IP has a high correlation with Cu grade and on this basis, Cu grades were estimated in all parts of the deposit. To obtain the relation IP, Rs and Cu grade, we used multivariate regression method which resulted in an equation with R Sq. of about 55% that expresses this relation. Cu grades were estimated and modelling was done based on this equation in the Sarbisheh deposit. For more accurate of Cu estimation, ANN has been used and the relation of IP, Rs and Cu grade was checked out and based on these results, a 3D model of Cu grade was constructed and compared with real model of Cu grade. The 3D model based on polynomial regression is the most closest to the real model. However, other two models are acceptable.

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