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| **RESEARCH ARTICLE**

Estimation of Shadan gold grade using borehole coordinate data by machine learning technique

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| ABSTRACT
Grade estimation is one of the key stages in technical and economical evaluation of a mine. The grade values have significant effect on planning, designing and managing mine. Therefore, it seems necessary to apply methods that estimate these values with high accuracy and correctness. One of the best and accurate methods to obtain a grade in a deposit is to dig exploratory boreholes which is not possible due to high costs. So we used artificial neural network to reduce the costs. Artificial neural network, back propagation error algorithm has the ability to estimate the gold grade using borehole coordinate exploration data. This plan is also consonant with operational and real requirements. Because in all wells, logs are taken and in a small number of wells, coring is done or we may not have a core in some parts of the well or it has been destroyed. Therefore, having a well-trained network, it is possible to simulate the gold grade of the well or the parts without a core. As a result, in each well, an estimate of the gold grade is obtained, which can be used to provide a better and more reliable model for the deposit for simulation. The results of test and validation data indicate the remarkable ability of the machine learning techniques system in estimating the gold grade in the data. Grade estimation using two criteria called squared normalized, and squares mean of network performance error (for train, average is 0.057), (for test, average is 0.094) , (for validation, average is 0.088) and also The regression between the predicted and the real values of Train, Test and Validation are obtained respectively, as 0.90, 0.75 and 0.80. The results show that the neural network gives a reasonable estimation for gold grade.

| KEYWORDS

grade estimation, shadan gold deposit, wells coordinate data, machine learning

| ARTICLE INFORMATION

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1. Introduction

Iran is located in the central part of the Tethyan orogenic and metallogenic belt, and its diversity in magmatism, geodynamics and mineralization is a consequence of the subduction of various generations of Tethyan Ocean and the accretion of Gondwana-derived micro-continents to the southern margin of Eurasia (Stocklin, 1968; Berberian & King, 1981; Richards & Sholeh,2016). Numerous mineral deposits are known to be associated with the Neotethyan Ocean evolution (Richards, 2015). This subduction and subsequent collision have produced three main magmatic belts: (i) the Eastern Iranian Magmatic Belt (EIMB), (ii) Urumieh-Dokhtar Magmatic Belt (UDMB), and (iii) the Alborz-Azerbaijan Magmatic Belt (AAMB) (Berberian & King, 1981; Verdel et al., 2011; Pang et al., 2013; Omidianfar et al., 2020).
The Sistan suture zone is a branch of the Neotethyan Ocean with a complex tectonic history (Camp & Griffis, 1982; Tirrul et al., 1983; Pang et al., 2013). Magmatic activity in Sistan suture zone and generally in east of Iran was occurred during a period mostly from Middle Eocene to the Late Oligocene (Pang et al., 2013). Subduction between the Lut Block and the Afghan Block is a controversial issue and various tectono- magmatic theories have been proposed. Verdel et al. (2011) ascribed the mineralization

in the Eastern Iran to an extensional rift basin but most researchers believe that the subduction is an undeniable subject. Saccani et al. (2010) by studying the ophiolitic complex of Nehbandan, suggested that subduction has played a key role in closure of the Sistan Ocean and the associated mineralization, resulted from the eastward intra-oceanic subduction of the Sistan Ocean beneath the Afghan Block. In addition, Camp & Griffis (1982) and Tirrul et al. (1983) proposed that magmatic activity in East of Iran resulted from eastward subduction of the Sistan Ocean beneath the Afghan Block. On the other hand, Berberian & King (1981), Zarrinkoub et al. (2012) and Pang et al. (2013) proposed that subduction of the Sistan ocean was westward beneath the Lut Block. Meanwhile, two-sided asymmetric subduction is another theory in closure of the Sistan Ocean (Arjmandzadeh et al.,2011). Omidianfar et al. (2020) studied the Koudakan intrusive in EIMB, and proposed a delamination of thickened lithosphere after collision between the Lut Block and Afghan Block.

The Tertiary plutonic and volcanic rocks are widely distributed in southwest of Birjand and

Recently, significant deposits have been reported in this area including Maherabad, Khopik, Khunic and Hired. Mahdavi et al. (2020) stated that the Shadan area is a porphyry deposit. Richards (2012) determined the age of the Shadan gold (+copper) deposit as 37.26 ± 0.26 Ma. Malekzadeh & Karimpour (2011) reported the U-Pb zircon ages of the 39 ± 0.8 Ma from monzonite rocks of the Maherabad Cu-Au deposit. Malekzadeh et al. (2014) attributed the formation of the Khopic porphyry copper deposit to Middle Eocene magmatism in eastern Iran. The Khunic area has been studied by Samiee et al. (2019) who believed that the hydrothermal breccia in the central part of the area is the main mineralization phase. As reported by Karimpour et al. (2007), the Hired gold-tin prospecting area is associated with S-type granites.

Due to the ambiguities about the petrogenesis of magmatic systems in Shadan area, the purpose of this study is to discuss and present the geochemical data to decipher the petrogenesis and petrology of the Shadan intrusive and subvolcanic rocks in the East of Iran in the context of geodynamics and metallogenic evolution of the system (Fig. 1).

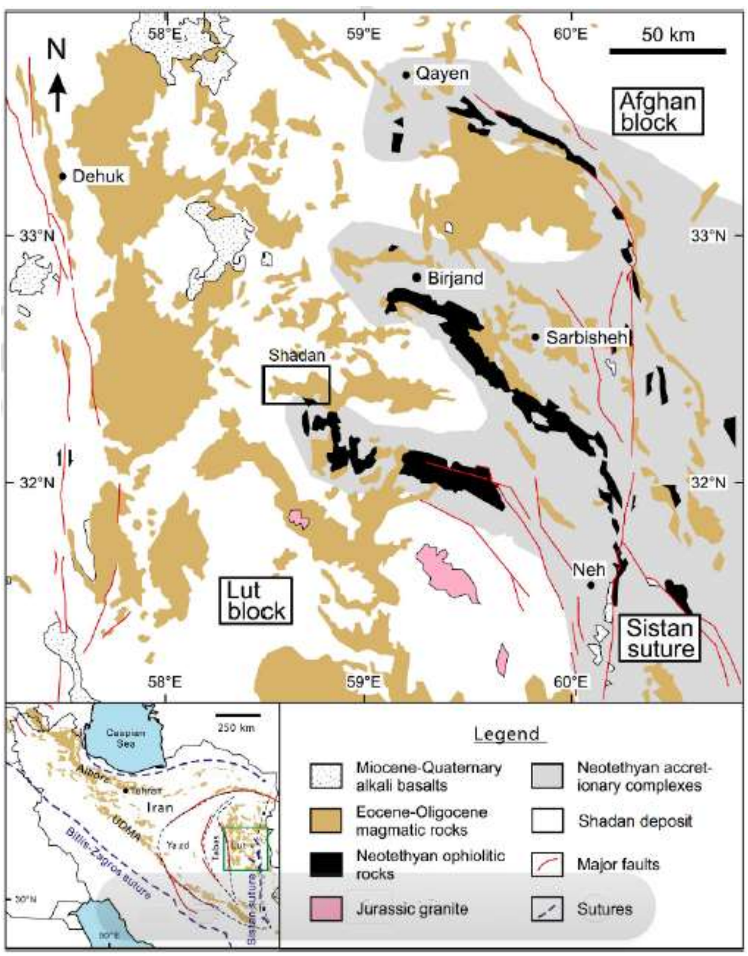


Figure 1. Geological map of Lut-Sistan region, east of Iran and location of the Shadan deposit in the Lut Block (Modified from Pang et al., 2013 and Modabberi et al., 2019)

2. Geology of studied area

Shadan area is located in 60 km southwest of Birjand, near the Khousf town, in the Lut Block, (32˚23′ 42″-32˚20′ 56″ N and 58˚ 56′ 96″- 58˚59′ 57″ E) in the South Khorasan province, Iran.The Lut Block with a length of 900 km is one of the structural units of the Central Iran microcontinent, which is bounded to the west by the Nayband Fault, to the east by the Nehbandan fault and Sistan suture zone, to the north by the Dorouneh fault and to the south by the Jazmourian depression (Berberian & King, 1981). The Lut Block is composed of a pre-Jurassic metamorphic basement, Jurassic sedimentary rocks and various generation of Late Mesozoic and Cenozoic volcanic-intrusive rocks (Camp & Griffis, 1982; Tirrul et al., 1983). The magmatic activity in the Lut Block initiated in the middle Jurassic (165-162 Ma) and its peak was in the Tertiary (Karimpour et al., 2011). In terms of geological situation, Shadan gold (+copper) deposit is located in the 1:250000 Birjand geological map (Vahdati-Daneshmand & Eftekhar-Nejad, 1991) and in the northeast corner of the 1:100000 geological map of Sarchehe- Shoor (Vassigh & Soheyli, 1975).

Based on the 1:100000 sheet of Sarcheh-e-Shoor, study area consists of dacite, altered andesite, tuff breccia and a number of subvolcanic to intrusive rocks. However, field evidence and petrographic studies indicated that most of the volcanic rocks in the Sarcheh-e-Shoor geological map, are subvolcanic and intrusive rocks. According to the 1:1000 Shadan geological map (Karand Sadr-e-Jahan Co. 2022) and field studies (Fig. 2), Mineralization in Shadan region befall in two separate areas, respectively in oxide and sulfide regions. The main metallic minerals in these regions including pyrite, chalcopyrite, chalcocite, bornite, magnetite, pyrrhotite, hematite, colitis, malachite, iron hydroxides. Lithological units can be divided into three units:

1) Eocene volcanic-pyroclastic rocks with intermediate to mafic composition, which have undergone quartz-carbonate, argillic and propylitic alteration,

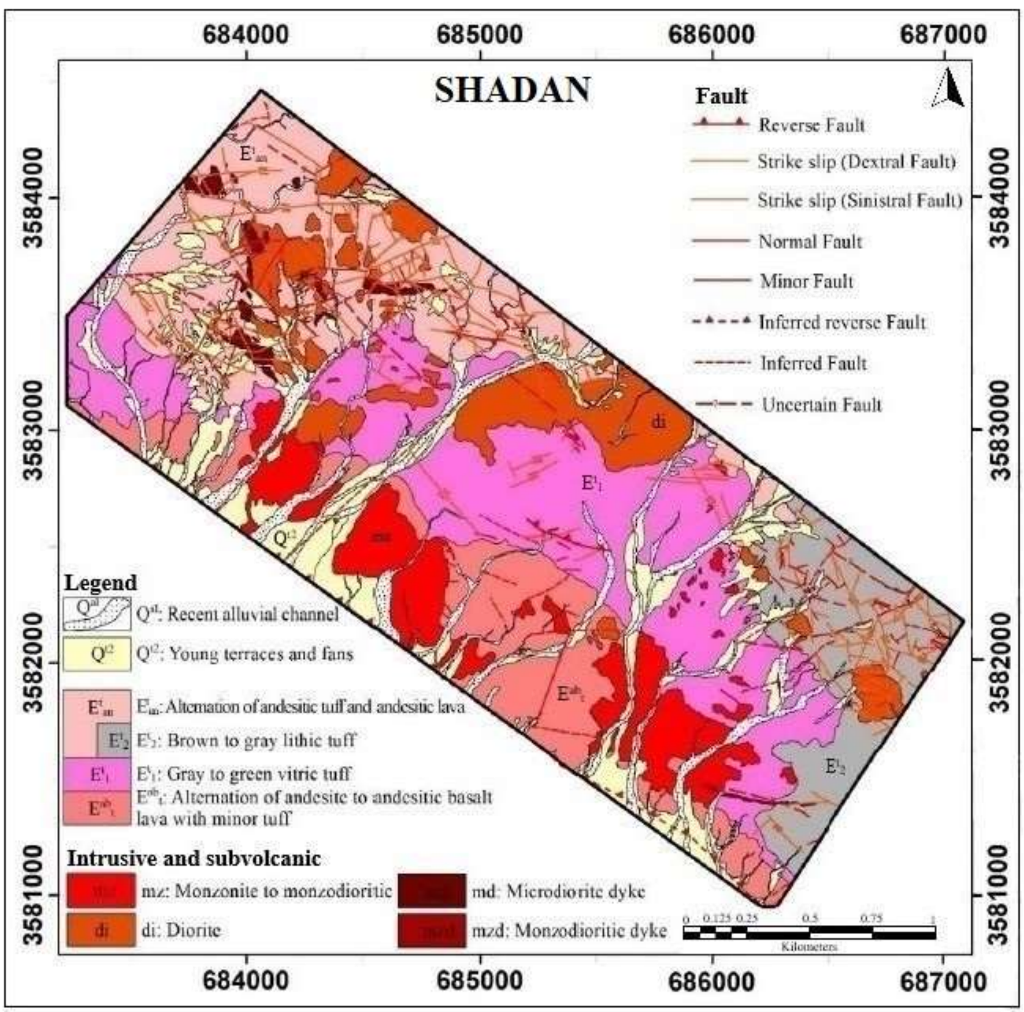


Figure 2. Simplified geological map of the Shadan area (Karand Sadr-e-Jahan Co. 2022)

2) Eocene-Oligocene subvolcanic and intrusive rocks with northwest-southeast trend and intermediate to felsic composition, which intruded into the volcanic-pyroclastic rocks. These rocks consist of granodiorite to gabbro-diorite with potassic, sericitic, argillic, quartz-carbonate and propylitic alteration,

3) Quaternary unit, consisting of young and old terraces, recent alluvium and debris. Based on the tectonic studies, faults especially strike-slip faults are major structures in the Shadan area. Approximately, faults have been formed in all directions in the study area;

3. Materials and methods

The estimation of grade is one of the most key and complicated aspects in the valuation of a deposit. The complication arises from scientific uncertainty. In recent years, due to the increasing dependence of mining projects on the most accurate determination of grade, different methods have been developed for the estimation of grade, including geometric rules, distance-based methods, and geostatistics. However, each of these methods has limitations and weaknesses that affect the accuracy of the estimates.

The application of advanced methods in grade estimation plays an important role in reducing errors and overcoming limitations in estimation. These reductions in errors and limitations can lead to improved reservoir estimation, which in turn can result in better design and economic planning for the mine. Regarding the errors encountered in the field when using conventional methods for grade estimation in gold mines, this research explores the efficiency of intelligent estimators, such as artificial intelligence, for the grade estimation of the Shadan gold deposit. This research includes an economic method for estimating the gold grade using borehole coordinate data, and fortunately, the results are acceptable

The most important property of neural networks, non-linearity and ability is removing noise. Neural networks doesn't need to the clear instructions and specific mathematical models and for solve problems that their formulas are unknown and or ambiguities it's not seen there, it's applicable. As where in mineral complicate data and non-linearity. Therefore, artificial neural networks, it can be effective technique to solve this problem.one of the usage of neural networks in earth science issues, it's estimation of grade. In the issues of estimation of gold grade by neural networks, network input is wells coordinates data and gold grade at those coordinates (network output) network training by this data. Then for each coordinate provided to learned neural network, the corresponding output in those coordinates is estimated grade, by network.

4. Preparation of used data

For every research which faced by artificial intelligence neural network we need the data. In this research we use, term of exploratory data of the well coordinates (X, Y, Z) and the nature gold grade exist of this wells in Shadan gold deposit. Now Wells are drilled vertically so these coordinates it's available to use. and not important to made new coordinates (x, y). Alone part of gold grade data also normalized by SPSS program so that to be understandable for MAT lab program, input and output data defined like a Matrix.

5. Statistical data studies

The statistical studies conducted in this research include the calculation and analysis of fundamental statistical parameters, such as the mean, standard deviation, and variance of the grade dataset along with its composite coordinates. In this study, **SPSS** software was used for statistical analysis. The table below presents the values of the statistical parameters.

Table (1) shows the values of statistical parameters measured on composite data by Spss software

Statistics					
		X	Y	Z	Au(ppm)
N	Valid	789	789	789	789
	Missing	0	0	0	0
Mean		685976.637	3581749.980	1592.711	.3583
Std. Error of Mean		14.5140	11.2454	1.1308	.01200
Median		686134.267	3581653.513	1588.908	.2662
Mode		686130.0[b]	3581556.5	1589.4	.17
Std. Deviation		407.6855	315.8741	31.7643	.33704
Variance		166207.458	99776.472	1008.972	.114
Skewness		-1.454	2.145	3.346	5.776
Std. Error of Skewness		.087	.087	.087	.087
Kurtosis		1.213	5.282	13.653	48.532
Std. Error of Kurtosis		.174	.174	.174	.174

Range	1557.3	1551.5	206.0	4.16
Minimum	684818.4	3581449.0	1546.9	.14
Maximum	686375.7	3583000.5	1752.9	4.30

Table (2) values of the statistical parameters measured on the grade composite data

the amount of	Statistical parameters
Number of data	789
Average	0.2976
Standard error of the mean	0.00639
Middle	0.2000
fashion	0.20
standard deviation	0.17941
Variance	0.032
crookedness	1.599
Standard error of the deviation	0.087
stretch	3.437
Standard error of elongation	0.174
The range of changes	1.20
Minimum data	0.10
Maximum data	1.30

The results of statistical studies on these composites indicate that the dataset undergoes gradual changes in depth and across different dimensions. The mean of these data is approximately 0.30, the variance is 0.032, and the standard deviation is approximately 0.18. The variance and standard deviation values indicate the degree of dispersion of the data relative to the mean. Skewness measures the asymmetry of a distribution, while kurtosis describes the degree of peakedness or flatness.

The sharper the peak and the wider the tail of the probability function, the higher the kurtosis index. The kurtosis coefficient varies within the range of (-2 to +∞). If the absolute value of the skewness coefficient is less than 0.1, the data distribution is closer to the standard normal distribution. However, if the absolute value of the kurtosis coefficient is greater than 0.5, the given distribution significantly deviates from the standard normal distribution (Davis JC, 2007). In this study, the kurtosis coefficient was calculated to be 3.4, indicating that the data distribution is not normal.

The following diagrams illustrate the relationship between the box plots of two input variables and the actual values. Data points outside the box are considered outliers, which are categorized into two types:

1. A circle represents scattered data points located near the box.
2. An asterisk represents highly scattered data points that are far from the box.

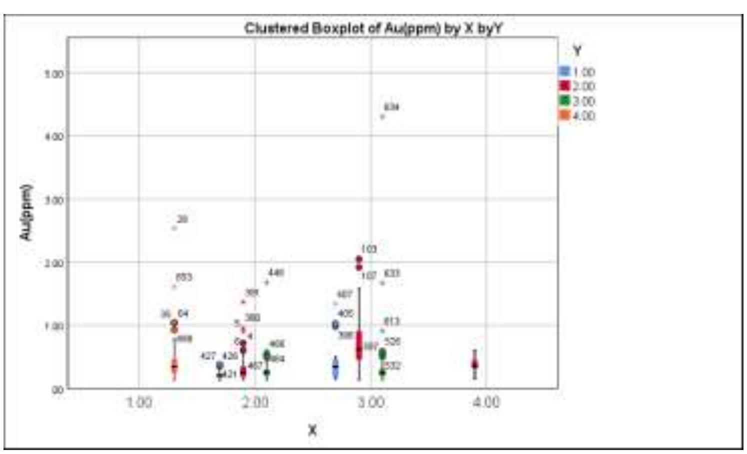


Diagram (1) box diagram of geographic longitude and latitude with borehole grade and their statistical relationship.

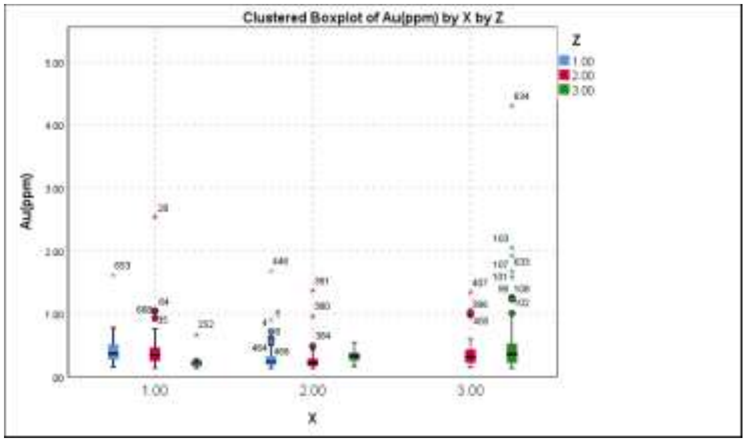


Diagram (2) Box chart of elevation level and geographical latitude with grade in each sample and their statistical relationship.

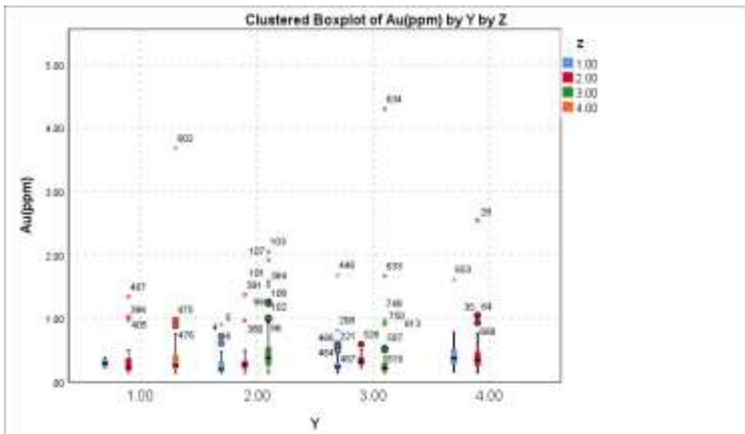


Diagram (3) box diagram of elevation level and geographic longitude grade in each borehole and their statistical relationship.

As can be seen in the diagrams above, traditional statistics can only find the relationship between The input and output are presupposed assumptions that may not be true for the data. So, traditional statistics method has a very weak capability in estimating the grade, especially when that the number of data and the type of data are different.

These data, which are selected for neural network training, cannot be used directly. Because this makes the training process more difficult and reduces the efficiency of the network, and on the other hand, since the degree of the network parameters is not the same, it means that slight changes in the weight with a higher degree cause significant changes in the weights with a lower degree. It gets wet. Therefore, a series of normalization is performed on the data. In normalization, it is tried to distribute the data in an interval close to zero (for example, between 1 and -1) and a standard deviation close to one (Duboisa et al., 2007). In this study, the data have been normalized in the range (0-1)

6. Back propagation network (BPN)

An Artificial Neural Network (ANN) is a simplified simulation of biological neural networks in human brains. ANN is capable of “learning”; that is, it can be trained to improve its performance by either supervised or unsupervised learning. The back-propagation network (BPN) and the supervised learning, i.e., learned by samples, are chosen in this study. After learning (or training), the trained weight can be used for future prediction of debris flow occurrence. The BPN is an ANN using back-propagation algorithm and is one of the popular ANNs, which has been widely applied to many scientific and commercial fields for non-linear analysis and prediction. The structure of BPN contains three layers: input, hidden, and output layers as shown in Fig. 3. Each layer contains *I*, *J*, and *K* nodes denoted respectively by circles. The node is also called neuron or unit. The circles are connected by links, denoted by arrows in Fig. 1, each of which represents a numerical weight. The *wij* is denoted as numerical weights between input and hidden layers and so is *wjk* between hidden and output layers as also shown in Fig. 3. The processing or the computation is performed in each node in the hidden and output layers. The back propagation learning algorithm is composed of two procedures: (a) feed-forward and (b) back propagation weight training.

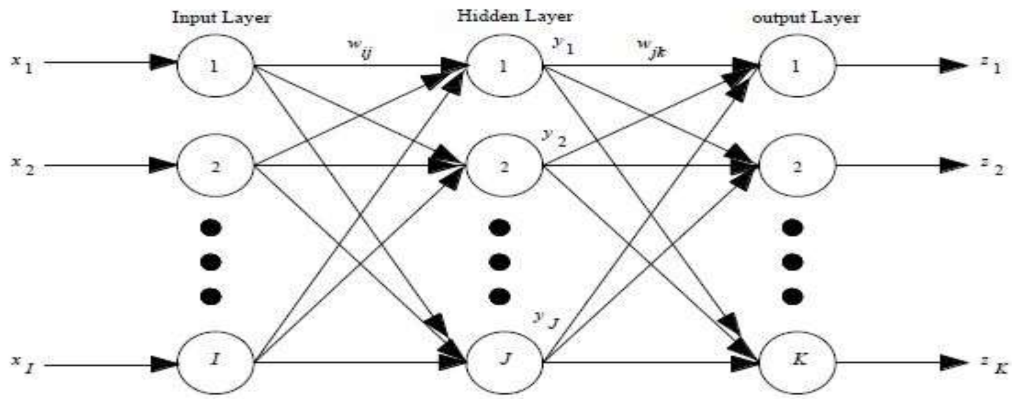


Figure 3. Neural network structure back propagation (baolong zhu, 2011)

6.1. ***Training samples and results***

Total of 15 records used for training were selected from Shadan Gold deposit. This study utilized these records to feed into the ANN model for training. The learning rate and momentum term were 0.01 and 0.87, respectively. The stop criterion of error function was set to 0.001 and the maximum number of iteration was 3000. The initial weights were random numbers generated by the computer. After 290 times trained, a single study sample error of less than 7%, which shows convergence of network.

The learning process is done in such a way that first an initial guess is made for the weights and bias values of the network. Then, using a learning rule, these values are corrected and repeated until the weights and biases are fixed or their difference in times is minimized. In this network that I have arranged, the answer is obtained in less than 300 repetitions (in many cases even less than 100 repetitions). Otherwise, the result will be displayed at the end of each step when the number of repetitions in the learning process reaches 3000.

The selected performance function is (MSE), (Mean Square Error), which expresses the mean square errors for the training data. The network has two intermediate layers, respectively 33 and 39, whose transformation function is Tansig and Logsig and has an output layer of a neuron with linear transformation function or Purelin. The LM training function has been used to train the network because the error of the LM algorithm decreases faster than other algorithms.

The studied area, where the percentage of gold grade was different in each sample, after the preparation and normalization of the composite data, was tested for a point-by-point grade- estimate, after running the MAT lab program and comparing the real gold grade with the estimated gold grade by network, the results obtained are as follows:

The training regression value is 0.90, the test regression value is 0.75 and the validation regression value is 0.80. The error of the training data for the said network is 0.003%, which can be seen in the form of the cycle (Epoch) traveled until reaching the desired network. In the following figures, we are looking at the regression and a comparison between the real non-zero values and the equivalent estimated values in the point by point training, test and validation, in those coordinate is stable and reliable for estimated gold grade.

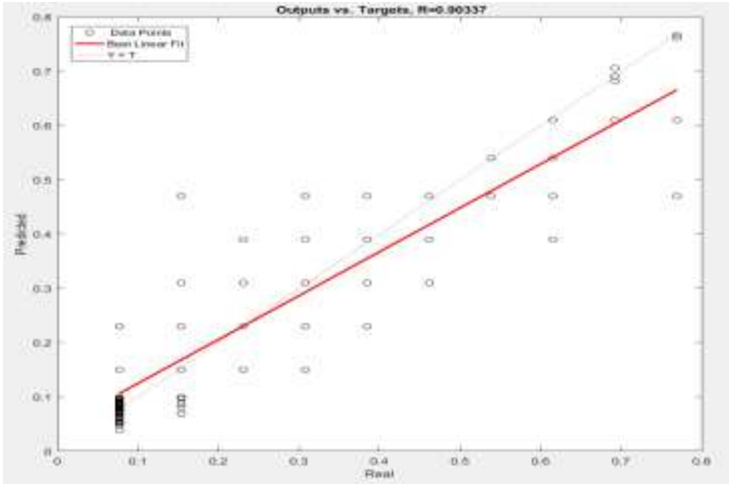
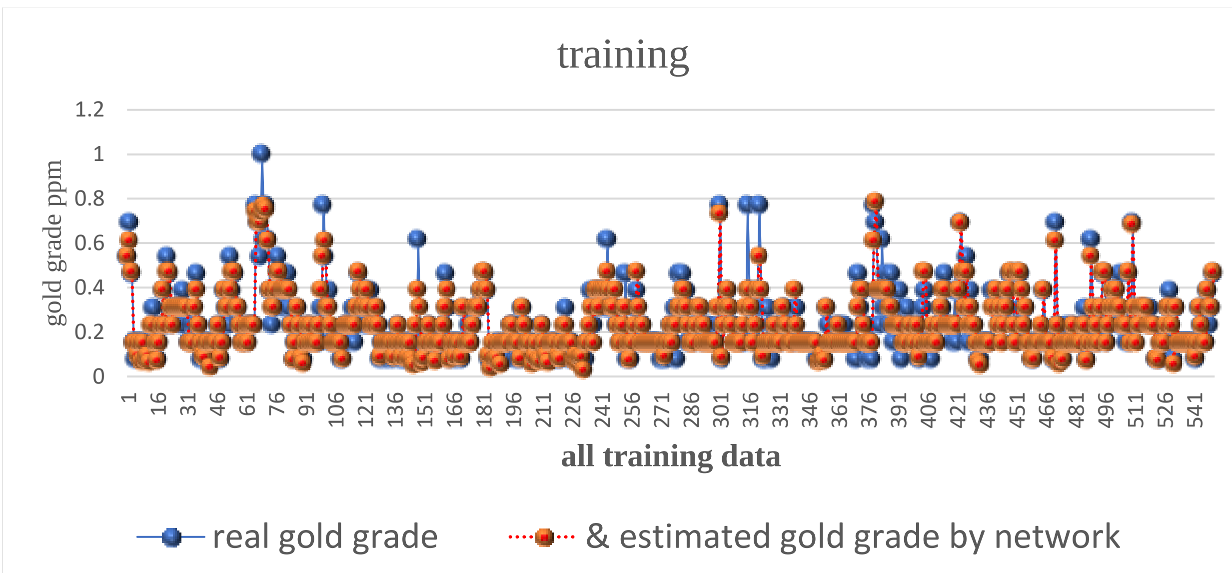


figure 4. the regression coefficient (R) train, it shows the between network outputs and the real output



Graph 1. Comparison of training data, real gold grade & estimated gold grade by network.

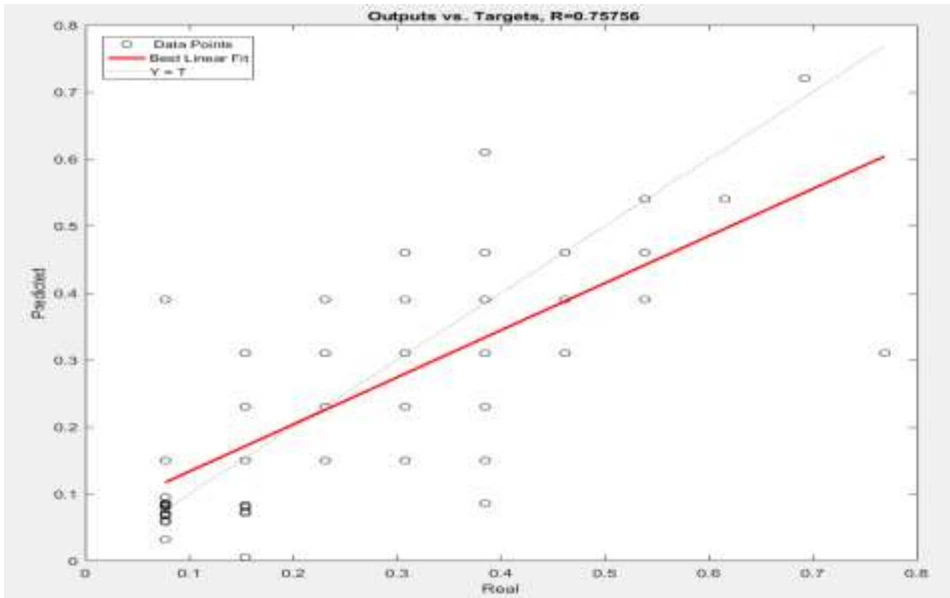
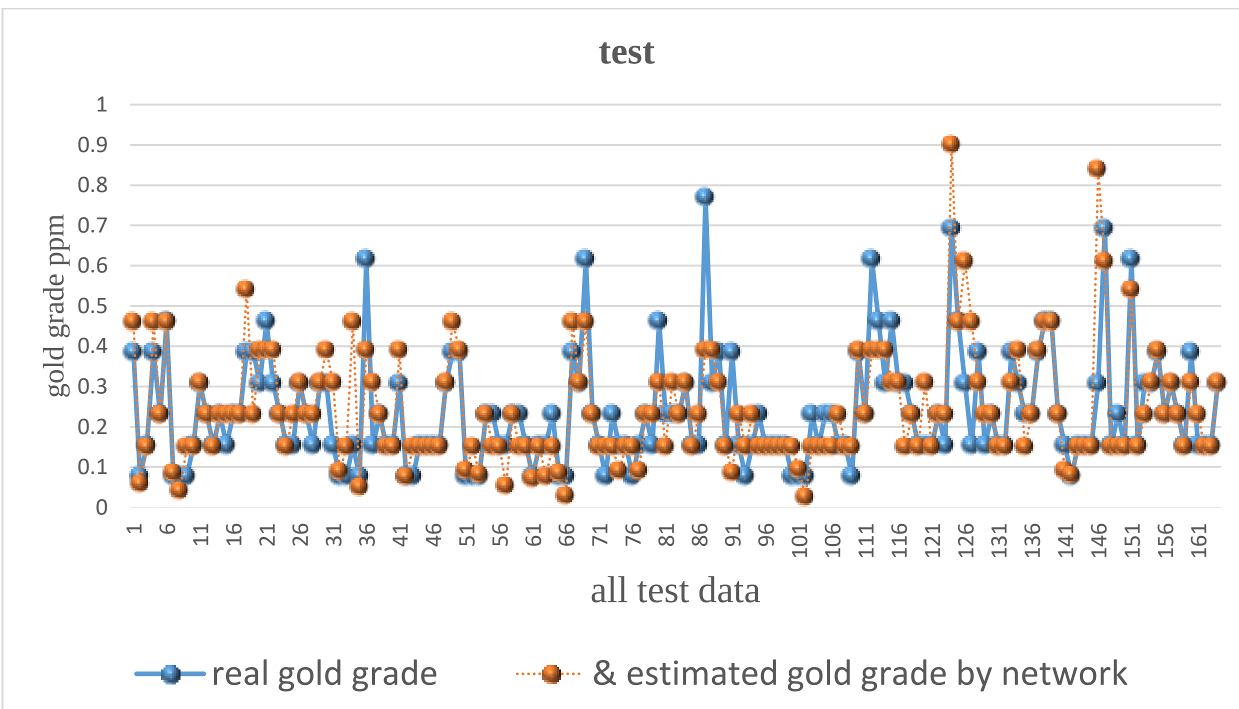


Figure 5. the regression coefficient (R) test, it shows the between network outputs and the real output



Graph 2. Comparison of test data, real gold grade & estimated gold grade by network.

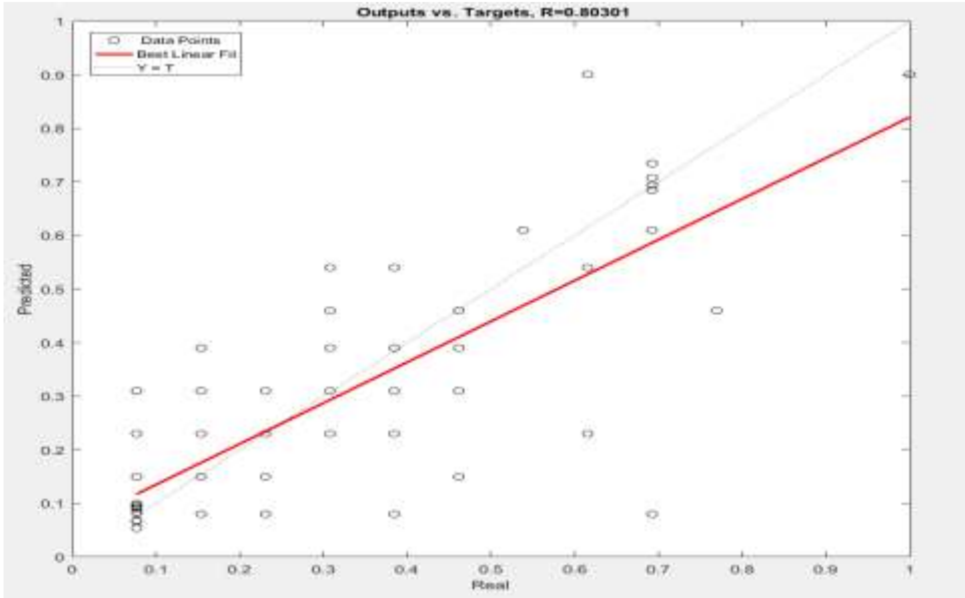
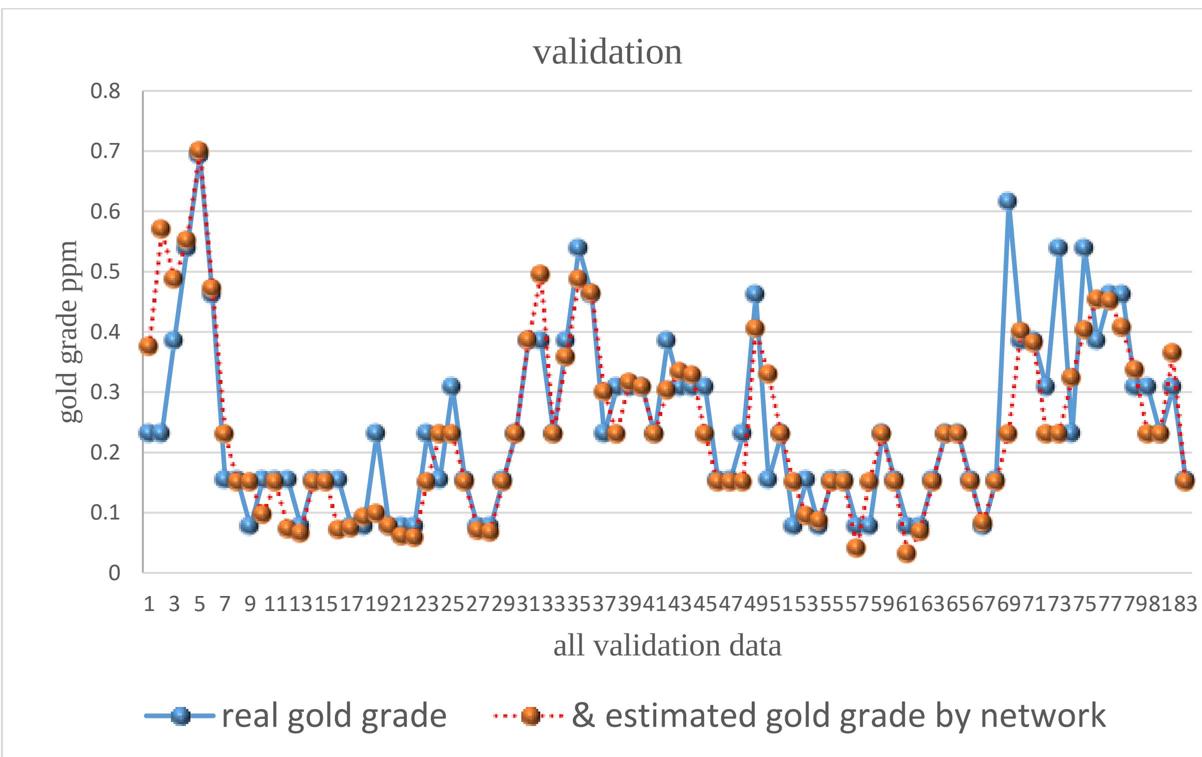


Figure 6. the regression coefficient (R) validation, it shows the between network outputs and the real output.



Graph 3. Comparison of validation data, real gold grade & estimated gold grade by network

Then to ensure efficiency and stability of network selected fifteen iteration and run the MAT lab program, the root mean square errors for training is 0.0576 for test 0.0948 and for validation 0.0887, this results are for every fifteen iterations. the mean square error of training, test and validation of network shows that, the network has excellent stability for gold grade estimation, and regressions obtained from this implementation was for training 0.90, for test 0.75 and for validation 0.80 which shows that the network is stable and reliable.

8. Conclusion

In this study, a machine learning method based on the backpropagation neural network was used to estimate the gold grade of the Shadan gold mine. The results indicated that this method is capable of providing accurate and stable gold grade estimations with high precision. After running the MATLAB R2016a program and comparing the network's predicted outputs with real data, the output match rates were obtained as 90% for the training phase, 75% for testing, and 80% for validation. Additionally, the RMSE values were recorded as 0.0576 for training, 0.0948 for testing, and 0.0887 for validation.

The findings of this study demonstrated that:

- The proposed machine learning-based method has the capability to solve complex problems.
- Before using any neural network, data quality control and normalization should be performed.
- The backpropagation neural network can estimate the gold grade using exploratory borehole coordinate data.
- This method is compatible with operational and real-world needs, as it can provide accurate gold grade estimations in areas where core sampling has not been conducted or has been lost.

These results suggest that the applied method can serve as an effective tool for modeling and estimating mineral reserves, thereby enhancing the accuracy of mine planning and design.

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