Shahrood University of Technology
Iranian Society of Mining Engineering (IRSME)
Journal of Mining and Environment (JME)
journal homepage: www.jme.shahroodut.ac.ir
THOMSON REUTERS
Vol. 11, No. 3, 2020, 865-879.
DOI: 10.22044/jme.2020.9939.1923

Integrating Geophysical Attributes with New Cuckoo Search Machine-Learning Algorithm to Estimate Silver Grade Values–Case Study: Zarshouran Gold Mine

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Received 1 August 2020; received in revised form 25 August 2020; accepted 26 August 2020

Keywords

IP/RS attributes

Cuckoo search

Machine-learning

Zarshouran deposit

Numerical methods

Abstract
The exploration methods are divided into the direct and indirect categories. Among these, the indirect geophysical methods are more time- and cost-effective compared with the direct methods. The target of the geophysical investigations is to obtain an accurate image from the underground features. The Induced polarization (IP) is one of the common methods used for metal sulfide ore detection. Since metal ores are scattered in the host rock in the Zarshouran mine area, IP is considered as a major exploration method. Parallel to IP, the resistivity data gathering and processing are done to get a more accurate interpretation. In this work, we try to integrate the IP/RS geophysical attributes with borehole grade analyses and geological information using the cuckoo search machine-learning algorithm in order to estimate the silver grade values. The results obtained show that it is possible to estimate the grade values from the geophysical data accurately, especially in the areas without drilling data. This reduces the costs and time of the exploration and ore reserves estimation. Comparing the results of the intelligent inversion with the numerical methods, as the major tools to invert the geophysical data to the ore model, demonstrate a superior correlation between the results.

1. Introduction

The geophysical methods are widely used in underground deposit explorations. These methods provide time- and cost-effective valuable information from the underground layers without drilling (Selley et al., 2005). Among the different geophysical methods, the induced polarization and resistivity methods are the best for exploration of the Carlin sulfide gold deposits (Yuval, 1995; Hasani Pak & Shoja-at, 2000). Douglas has used the induced polarization and resistivity data to identify the depth of the mineralization (Douglas et al., 1999).

On the other hand, the non-linearity and noise reduction are the most significant characteristics of the artificial neural networks (ANNs). One of the usages of these networks, especially when they are supervised (as machine-learning tools), is ore grade estimation in geology and mining engineering. In order to do this, ANN is trained to find the pattern between the input (coordinate and geophysical attributes) and the output (grade) data. Different parameters influence the grade distribution, some of which are not considered in the mathematical models. Almost in all the grade estimation methods, the most considerable item is the distance to the known grade; hence, many other factors such as geology, rock mechanics, and ore shape and type should be considered. These parameters can be regarded as the geophysical, geochemical, and other data formats. Knowing the best places for exploration boreholes, which can be concluded from an accurate grade model, leads us to reduce the costs of drilling and predict the shape and the status of the ore body. In order to find this model,

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it is necessary to integrate the different above-mentioned data formats. Without integrating and processing the data, it is impossible to find the optimum places for drilling (Porwal, 2006). The machine-learning algorithms are powerful tools to integrate different data and extract the pattern between the input and output values (Bishop, 1995).
Singer and Kouda have used ANNs to estimate the distance from ore veins (Singer & Kouda, 1997). They have also utilized the probability artificial neural networks for the ore vein classification. In 1999, they made a comparison between the potential maps produced from ANNs and the weight of evidence methods (Singer & Kouda, 1999). The results obtained showed fewer error values for the test data in the ANN model (2%) compared to the 23% error in the weight of the evidence method. Brown et al. (2000 & 2003) have integrated GIS and ANN to produce the 1:100,000 ore potential map. They applied multi-layer perceptron (MLP) artificial neural networks with a 68% accuracy in map production. The most important weak point of MLPs is the influence of the small numbers of the input data on the accuracy of the model, which can be seen in this work. Hosseinali and Alesheikh have used MLPs to weigh different data layers and produce the copper potential map (Hosseinali & Alesheikh, 2008). The most significant part of their work was to use ANNs in order to find the shape of the ore body. Harris and Pan have employed the probability and regression ANNs to detect the ore veins (Harris & Pan, 1999). The results of their work demonstrated a better accuracy in the vein location prediction using the probability networks. Some scientists have used the integration of ANNs and other methods for a potential map production such as the integration of ANNs and remote sensing (Sanchez et al., 2003). Others have integrated ANNs with the probability rules (Skabar, 2005).
Many studies have been done to integrate the geophysical data using the artificial neural networks such as processing the ground-penetrating radar (GPR) data (Poulton & El-Fouly, 1991). Polton and Steinburg have integrated the electromagnetic data using ANNs (Poulton et al., 1992). Spichak and Popoa have made progress on the magnetotelluric data via optimizing the ANN algorithm (Spichak & Popova, 2000). Some research works have been done to gain data on inversion resistivity using ANNs (El-Qady & Ushijima, 2001; Calderón-Macías et al., 2001; Singh et al., 2005). Alimoradi et al. have used a probability supervised neural network to integrate the magnetic geophysical data in order to estimate the depth of dikes (Alimoradi et al., 2011). In this work, the geophysical data obtained from 17 profiles in the Zarshouran gold mine was integrated using the new supervised Levenberg-Marquardt-based backpropagation algorithm trained with the cuckoo search (Nazri et al., 2013) to estimate the values of silver grade in the areas without drilling data. We considered 75 data points obtained from six boreholes that were on the geophysical profiles. The input data were the X, Y, and Z coordinates and the IP and RS values. The output data was the silver grade values from logs. Finally, the grade distribution from the machine-learning algorithm was modeled and compared with the geophysical models of the profiles using the Res2Dinv software.

2. Methodology

2.1. Site Geology

The Zarshouran gold deposit is located in the north-western region of Iran. Figure 1 shows the geographical location of this deposit. The gold mineralization in the Zarshouran area is similar to the disseminated epithermal deposits in sedimentary rocks, especially carbonates (Carlin-type), and can be seen in two different shapes:

- Very fine-grained particles, which have been disseminated in the deposit with high values of arsenic and sulfide;
- Forming an organic gold-carbon complex with the organic carbon in the Zarshouran unit, showing a high grade of gold.

Mineralization can be seen as veins in the silicified zones in Zarshouran carbonaceous limestone with regular veinlets or massive in the middle part of Zarshouran. The minerals associated with gold in the Zarshouran deposit are orpiment, realgar, stibnite, sphalerite, galena, cinnabar, and copper. Gang minerals are also quartz, fluorine, barite, and calcite.

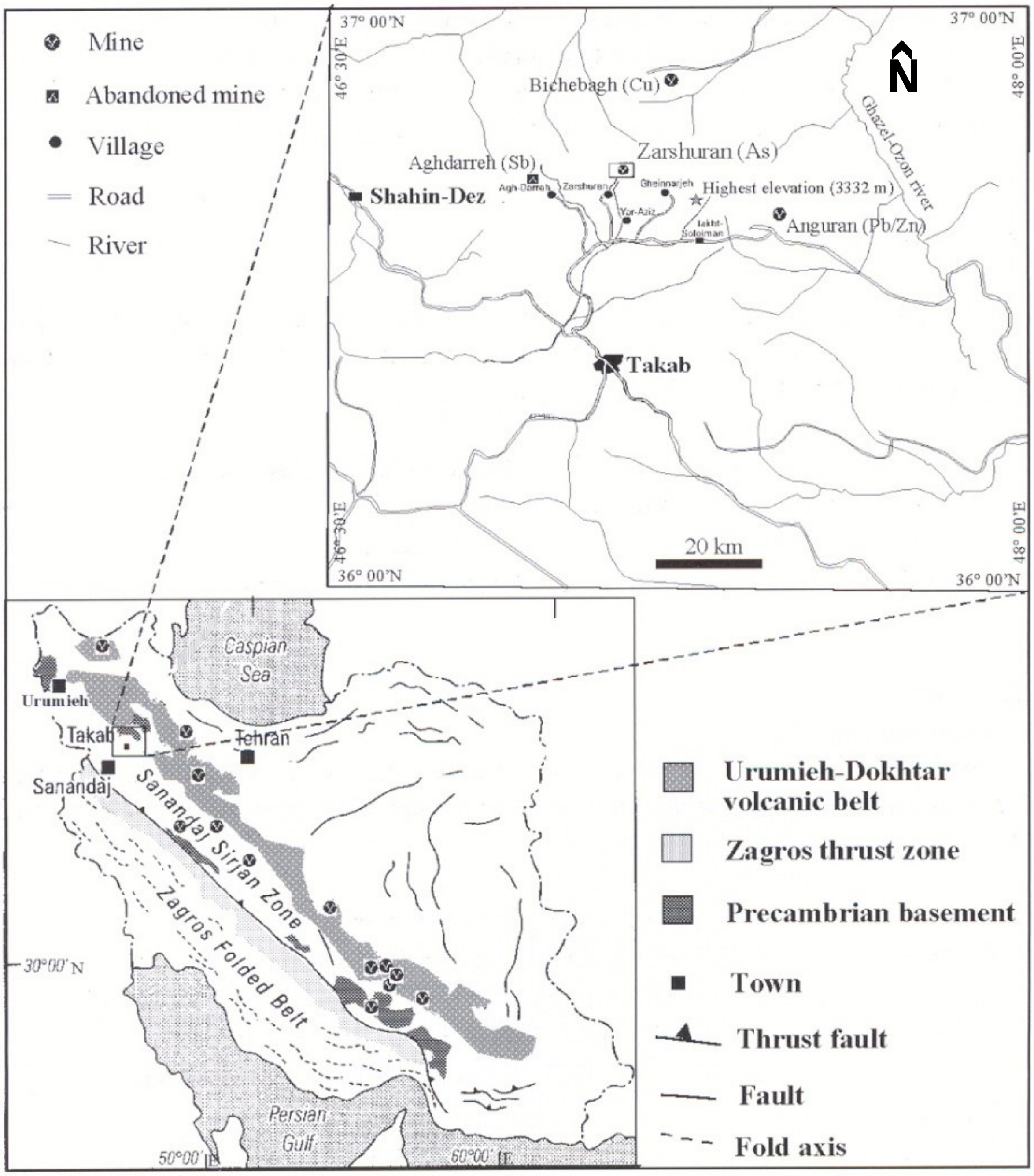

Figure 1. Geographical location of Zarshouran deposit.

2.2. Data Acquisition and Preparation

The geophysical surveys (IP/RS) were carried out in the Yeganli area in the south-western region of the main open-pit of the Zarshouran gold deposit to find new deposits in the studied area. Figure 2 presents the location of the Yeganli area with the geophysical profiles on it. Since the mineralization trend in this area is north west-south east, the profiles are designed perpendicular to this trend. In order to cover the Yeganli area, a rectangle with a dimension of 1650 m*760 m was considered. All profiles were performed in this rectangle. Seventeen profiles with a distance of about 100 m and the survey point spacing of 30 m on each profile were carried out. Figure 3 illustrates the name and the number of geophysical profiles. The IP/RS array used in this work was pole-dipole with 222 surveyed points on each profile.

Figure 2. Location of the Yeganli area with the geophysical profiles on it.

Figure 3 shows the coordination of all profiles. There are four electrodes in the pole-dipole array. The current will be transmitted into the earth via A and B electrodes, and the potential differences will be received by M and N. M and N, which are close to each other, are the potential dipoles, and A and B, which are in the physical extreme, are the current dipoles.

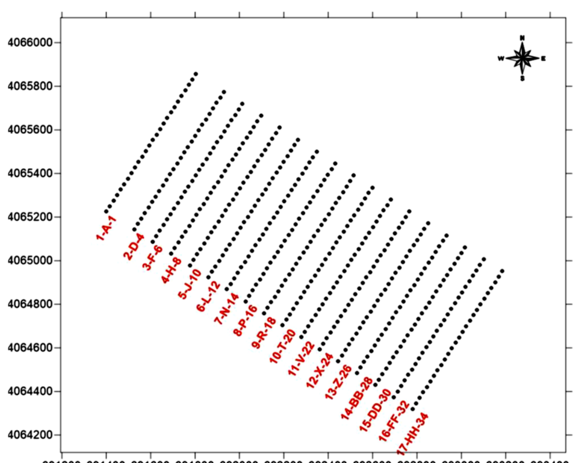

Figure 3. Coordination of all profiles.

3. Levenberg-Marquardt Cuckoo Search (CSLM) Machine-Learning Algorithm

Yang and Deb have introduced a metaheuristic algorithm based on the cuckoo search in 2010 (Yang and Deb, 2010). This algorithm simulates the parasitic behavior of a kind of bird called cuckoo. The cuckoo lays its eggs in other bird's nests. Most of the time, the host bird cannot recognize the cuckoo's eggs from its eggs; however, if the parasite egg can be recognized, the host bird will throw it away or leave the nest to build another one. Some cuckoos are so professional that they find a nest with eggs exactly similar to theirs. This reduces the probability of their eggs being thrown away or the nest being abandoned and also increases the probability of their chicks staying alive. The CS algorithm follows three basic rules. These rules are as follow (Nazri *et al*., 2013):

- Each cuckoo lays an egg and leaves it randomly in a nest.
- The best nest with the best eggs introduces the next generation.
- The number of host nests is fixed and the cuckoo's egg can be recognized by the host bird with the probability of Pa [0.1].

If the cuckoo's egg is detected by the host bird, it will be thrown away or the host bird will leave the nest. This situation can be approximated by the partial probability of Pa from n nests. Reducing this probability to zero means a 100% success of the cuckoo in saving its eggs and requires the true selection of the nests.

A flow diagram of CSLM is illustrated in Figure 4. The cuckoo search is a metaheuristic algorithm initiated by an initial random population. In this algorithm, the weights are selected by the first part of the diagram, and the network is trained by these weights through the second part. The strength of this algorithm is its capability in reducing errors and increasing the accuracy and speed of the network compared to other backpropagation training algorithms.

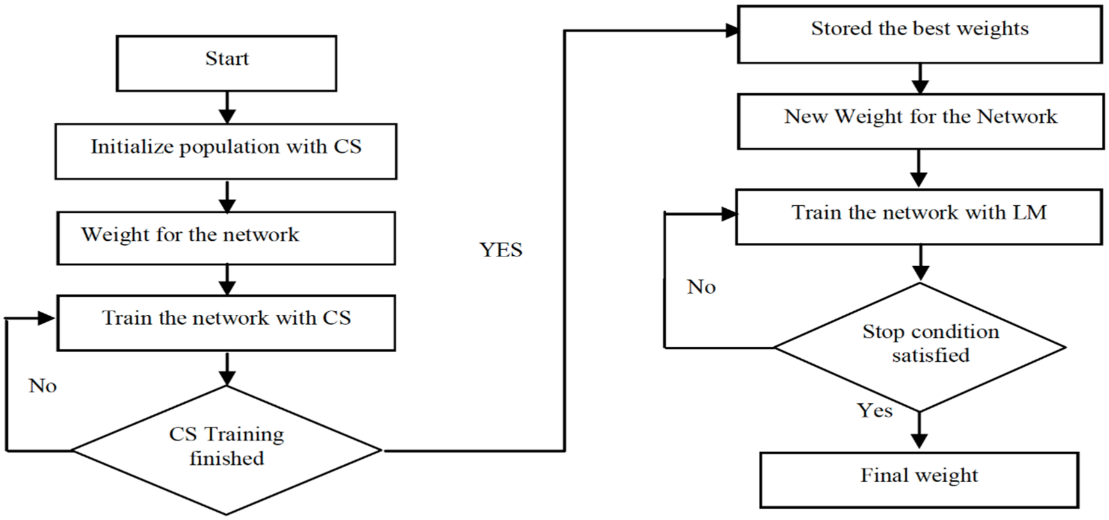

Figure 4. CSLM algorithm (Nazri et al., 2013).

Two different sets of data are necessary to prepare the network, i.e. input and output. The input data is the X, Y, and Z coordinates and the values of IP and RS, which can be obtained from the geophysical surveys as explained before. The output data is the grades of the silver in boreholes located on the geophysical profiles. The total number of data is 75 data points from the boreholes and geophysical surveys. The architecture of the network is shown in Figure 5.

Since the main objective of this work was grade estimation, the machine-learning (ML) method was selected based on the following reasons (Alimoradi, 2008):

- Machine-learning tools are very powerful in pattern recognition.
- They are suitable in cases with input-output data.

MLs are computational models based on the human understanding of the cortical structure of the brain and cognition. Algorithmically, MLs are parallel adaptive systems; therefore, they require training. Back-propagation is a powerful method of supervised learning developed after the seminal work by Paul Werbos and David E. Rumelhart in the 1970s and 80s (Demuth & Beale, 2002). The details of various methods of ML design and training are beyond the scope of this paper and are explained elsewhere (e.g. see Hagan *et al.*, 1996).

In this work, we successfully developed and implemented a network with three hidden layers of 14, 12, and 8 nodes, respectively. The network architecture is shown in Figure 6.

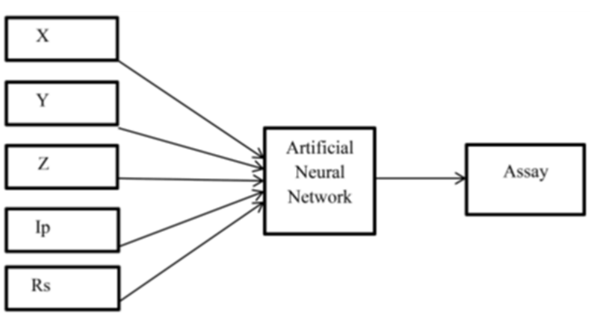

Figure 5. Architecture of neural network.

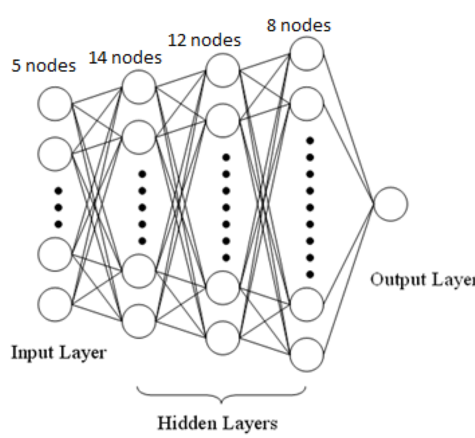

Figure 6. Our proposed network with three hidden layers. The input layer has five nodes, the next three hidden layers (intermediate layers) have 14, 12, and 8 nodes, respectively. The output layer is a single node.

4. Results and Discussion

We checked the CSLM results with 11 different traditional algorithms for training the input data in multi-layer perceptron artificial neural networks. All these algorithms were used in this work to determine the best-suited one. The results of each algorithm are presented in Table 1 as the average of 100 different random iterations for the best-evaluated structure.

Table 1. Results for different training algorithms.

No	Algorithm	Neurons in each hidden layer	RMS_{train}	RMS_{test}
1	Traincslm	14 12 8	0.048	0.077
2	Trainlm	14 12 8	0.073	0.092
3	Traingdx	7 8 9	0.090	0.100
4	Trainrp	21 22	0.986	0.215
5	Traincgf	7 8 9	0.133	0.168
6	Traincgp	10 11 12	0.108	0.117
7	Traincgb	12 15	0.096	0.240
8	Trainscg	12 14 16	0.078	0.080
9	Trainbfg	20 21 22	0.098	0.223
10	Trainoss	8 10	0.145	0.134
11	Traingd	8 8	0.350	0.380
12	Traingdm	12 13 14	0.123	0.173

Columns 4 and 5 in Table 1 are the average values of root mean square (RMS) error for the train and test data in each training algorithm. According to the values of the RMS error, the best-fitted algorithm is the Cuckoo Search Levenberg-Marquardt (TrainCSLM) with the minimum values of RMS for the train and test data. The reduction in the network error increases the reliability of the network predictions. CS, as an optimization engine for the BP algorithms, searches for a hybrid model to find the best learning parameters. Since the results of the machine-learning methods were not unique, the best model was run in 20 iterations to check the stability of the model. The RMS results presented in Table 1 are the average values for 20 iterations.

The other training algorithms such as the one-step secant and Fletcher-Powell conjugate gradient were also used; however, they were discarded due to their high tolerance for the test errors and low reliability in our application (Demuth & Beale, 2002; Alimoradi, 2006). With a network of only one or two hidden layers, over-training was often observed. Over-training happens when the network is highly trained but its predictions appear erroneous for the test data. This can be the consequence of the complexity of the problem investigated here and modeled in our neural network. Table 2 illustrates the minimum and maximum error values for the Traincslm algorithm. The absolute training error E_{train} is calculated as follows:

$$E_1 = |r_1 - p_1|,\ E_2 = |r_2 - p_2|, \dots, E_n = |r_n - p_n| \quad (1)$$

and:

$$E_{train} = \frac{\sum_{i=1}^{n} E_i}{n} \quad (2)$$

In Equation 1, r is the real grade value, p is the predicted grade value from the network, and n is the number of training data. E_{test} is the same as E_{train}; however, it is calculated from the test data. RMS_{train} is the mean square error of the training data and is obtained from Equation 3:

$$RMS_{train} = \frac{\sqrt{E_1^2 + E_2^2 + \cdots + E_n^2}}{\sqrt{n}} \quad (3)$$

RMS_{test} is calculated as RMS_{train} for the test data.

Table 2. Minimum and maximum error values for Traincslm algorithm.

E_{train}	E_{test}	RMS_{train}	RMS_{test}
0.0285	0.0409	0.04	0.077
0.0408	0.0968	0.0866	0.170

As it can be seen in Table 2, RMS of the error in training is less than 10%. For the test results, RMS of the error varied between 7% and 17% for the 100 iterations performed. The reduction in the network error increases the reliability of the network predictions and requires the availability of additional training data. Finally, the parameters of the network are shown in Table 3. The results of the training are presented in Figure 7.

In Figure 7, R is the correlation coefficient between the real and predicted silver grade values. The correlation coefficient is close to 1.0, implying a good network performance. Our data in the Zarshouran (Yeganli) site has only silver grade values. We used the above-mentioned neural network to classify the test data. The results obtained are shown in Figure 8.

Table 3. Parameters of the best network.

Parameter	Value
Network	Backpropagation
Training algorithm	Traincslm
Number of hidden layers	3
Input layer neurons	5
Output layer neurons	1
First hidden layer neurons	14
Second hidden layer neurons	12
Third hidden layer neurons	8
Trainparam.Goal	0.008
Trainparam.Epochs	1000
Trainparam.Show	100
Learning rate	0.9

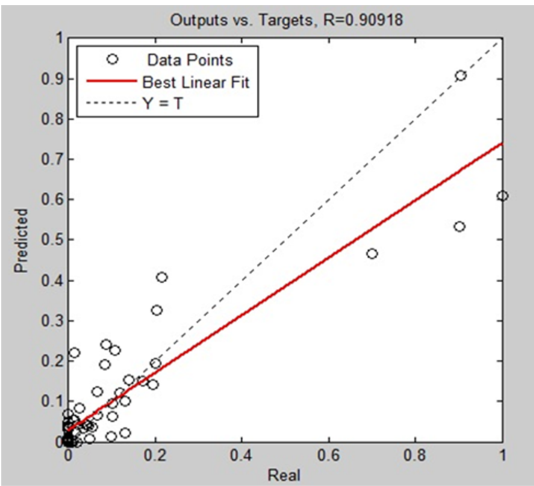

Figure 7. Correlation coefficient for the train data.

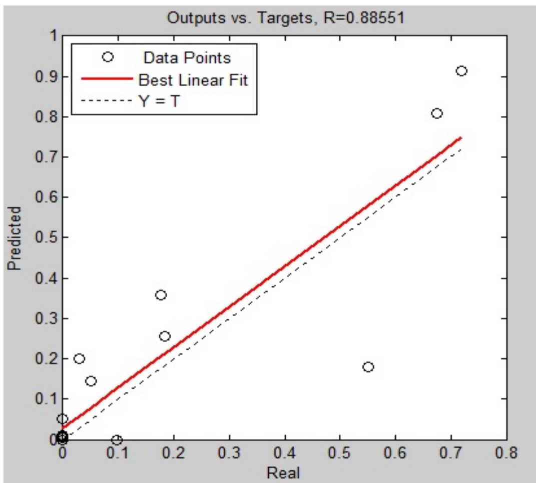

Figure 8. Correlation coefficient for the test data.

During testing, a correlation coefficient greater than 0.85 was generally obtained (as exhibited in Figure 8). This shows that the silver grade values in the test data are practically well-correlated with the network predictions; therefore, it deemed appropriate to be exceedingly meticulous with the reliability of the computational tool that was developed as a part of this work to perform the task of classification. This is evident in Figure 9, remarkably demonstrating the performance of the trained network.

The real values of silver grade shown by plus mark in Figure 9 could be easily predicted by the back-propagation neural network by multiply mark. Although there are many points with zero values, the network can still predict the higher values accurately.

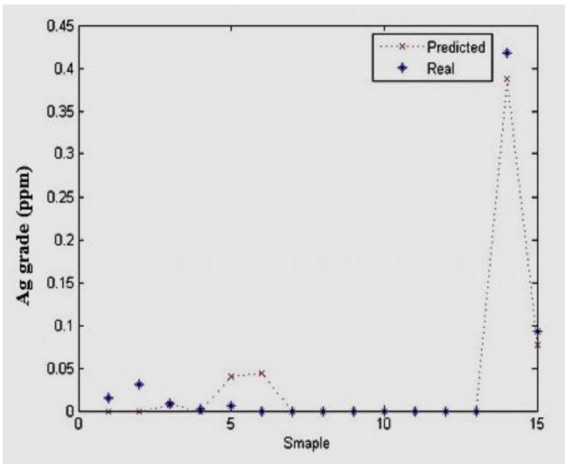

Figure 9. Predicted results for the test data.

5. Evaluating Machine-Learning Method Compared with Geophysical Models

Since our dataset was limited to 75 data, many of which had data a silver grade of zero, it was necessary to validate the ML results with the geophysical profiles. To do this, the silver grades estimated using ML were modeled for each profile (as shown in Figure 10).

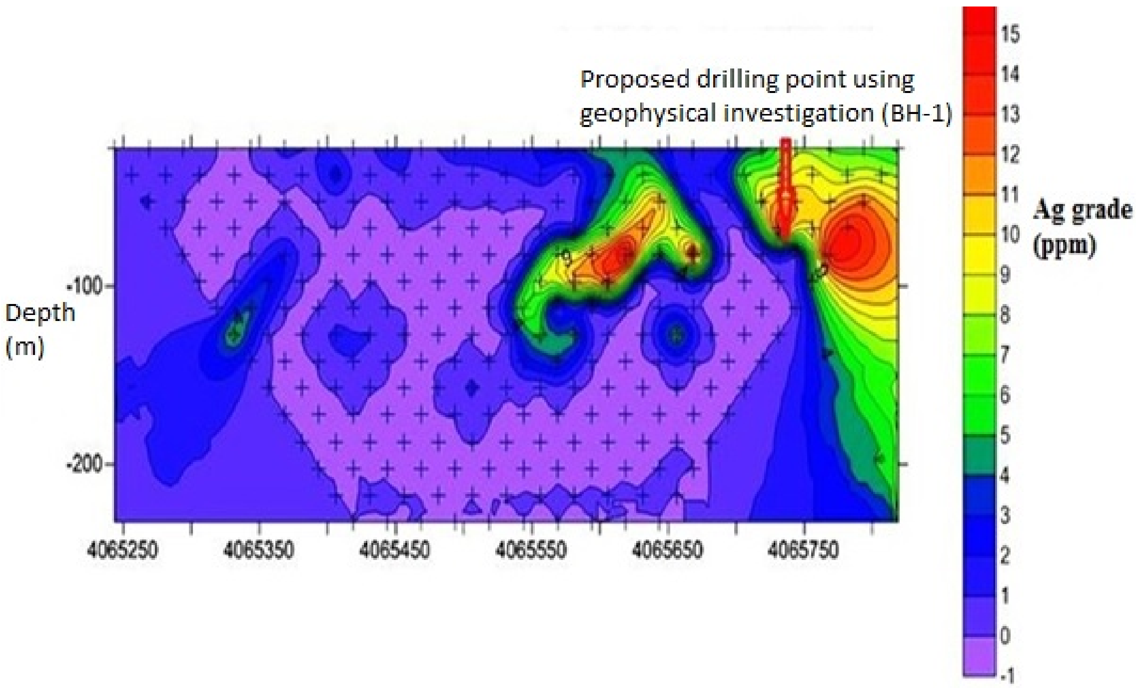

Figure 10. Silver grade model from ML for profile 1.

5.1. Profile 1

This geophysical profile is the northernmost profile of the area with a 720 m length. The distance between the survey points is 30 m, and the depth of the investigation is about 230 m. The Res2Dinv software was used to make the inversion on the surveyed geophysical data in this profile. Figure 11 shows the inverted model of profile 1. The upper part illustrates the model of chargeability, and the lower part is the resistivity model.

Generally, there are two potential zones in this section according to the chargeability profile (two zones with high chargeability values as red zones). According to the geological pieces of evidence, the geophysicists of the project assumed the right part of this section as the priority of the next exploration activities and introduced a borehole to this part (BH-1 in the chargeability section). The position of the introduced BH-1 is specified by the red arrow in the ML section (Figure 10). The exact position of the anomalous zone is in the right hand of this arrow. ML could predict both potential zones accurately with a difference of 50 m to the center of the right-hand anomaly. This difference can be due to the lack of enough test data (core analysis) in this part of the section to correlate them with the predicted values by ML. The depth of both anomalies is about 100 m, and the distance between the anomalous zones is also about 200 m, which can be estimated and modeled accurately by the ML method.

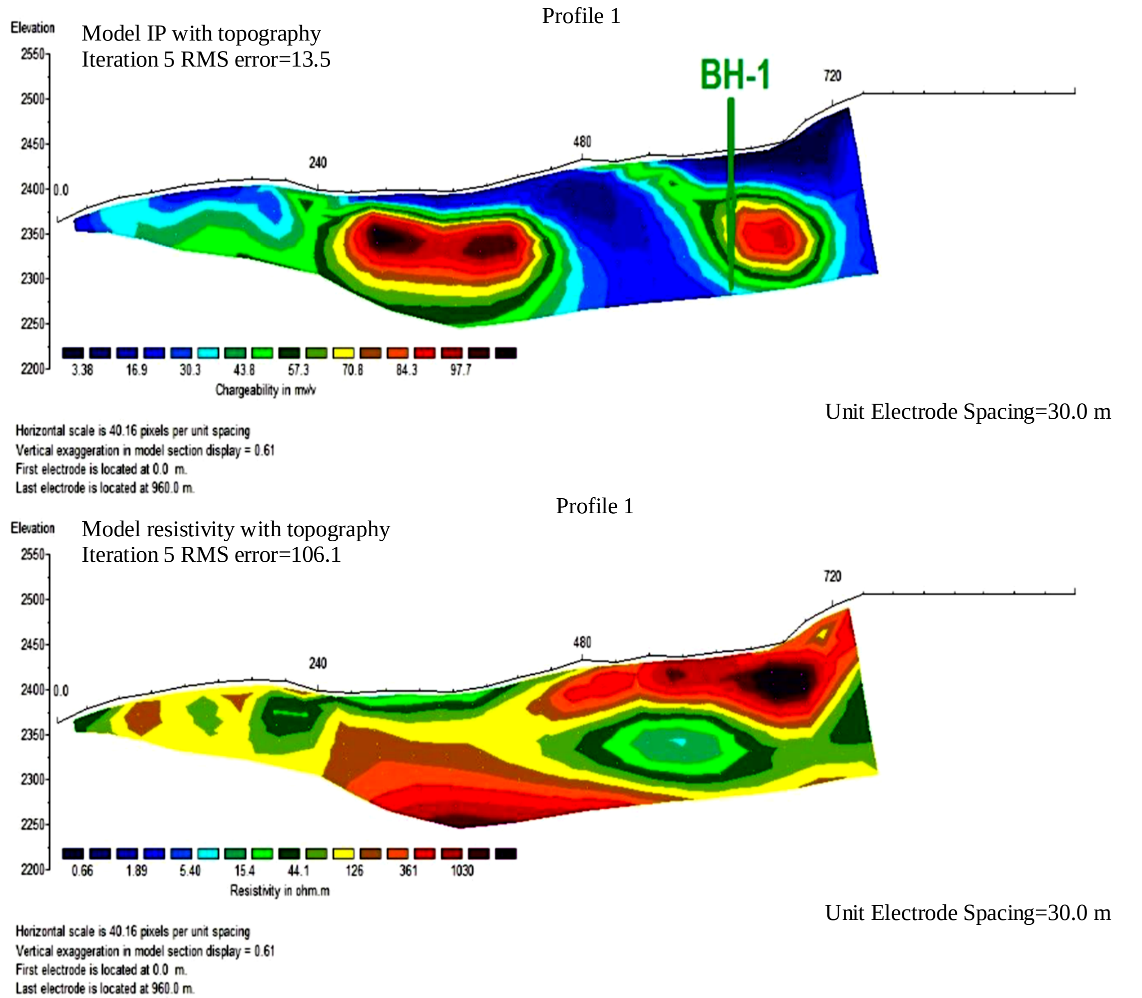

Figure 11. Inverted values of geophysical data using the Res2DInv software for profile 1.

5.2. Profile 4

The length of this profile is 720 m with a 30-m distance between the survey points, and the depth of the investigation is about 190. Figures 13 and 14 illustrate the inverted geophysical sections of chargeability and resistivity and the estimated silver grade section using the new machine-learning tool.

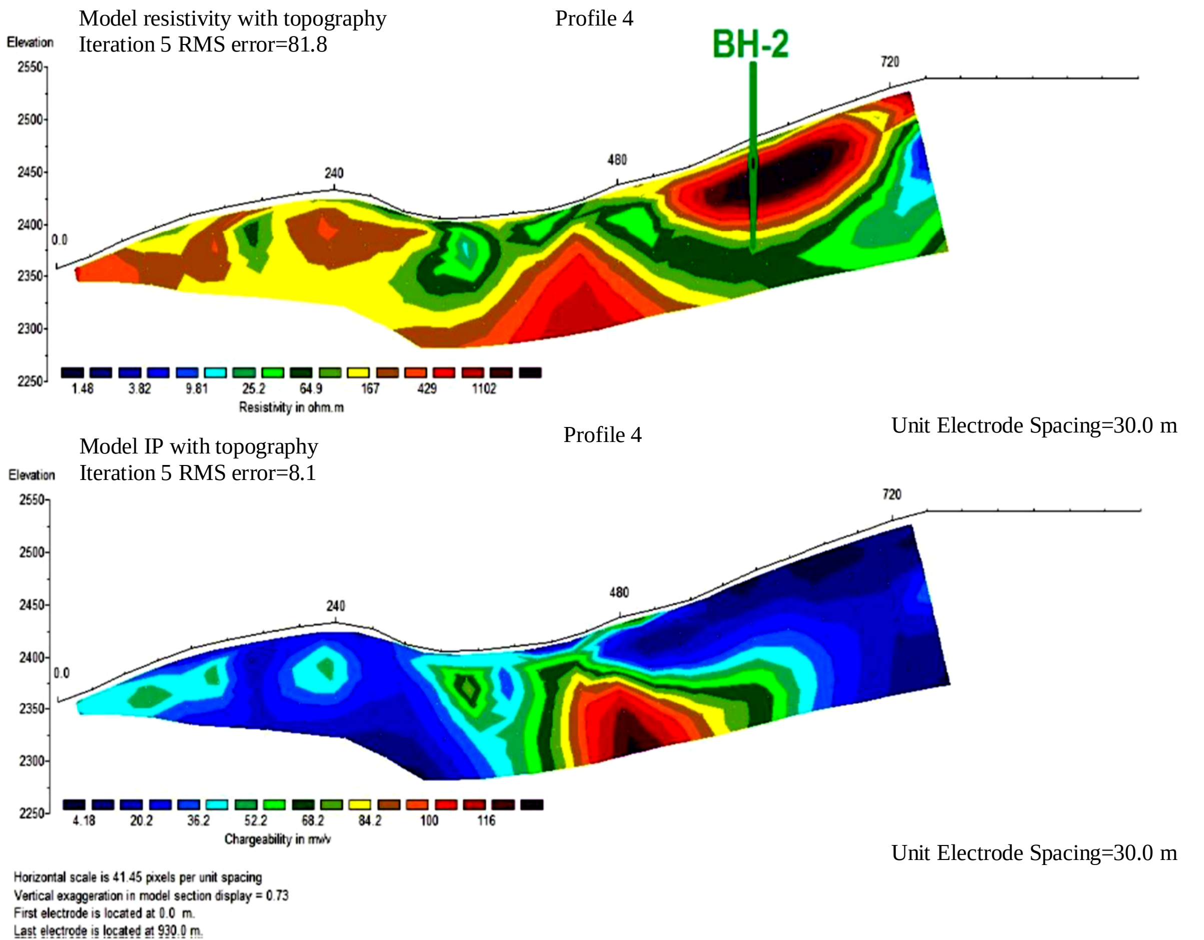

Figure 12. Inverted values of the geophysical data using Res2DInv software for profile 4.

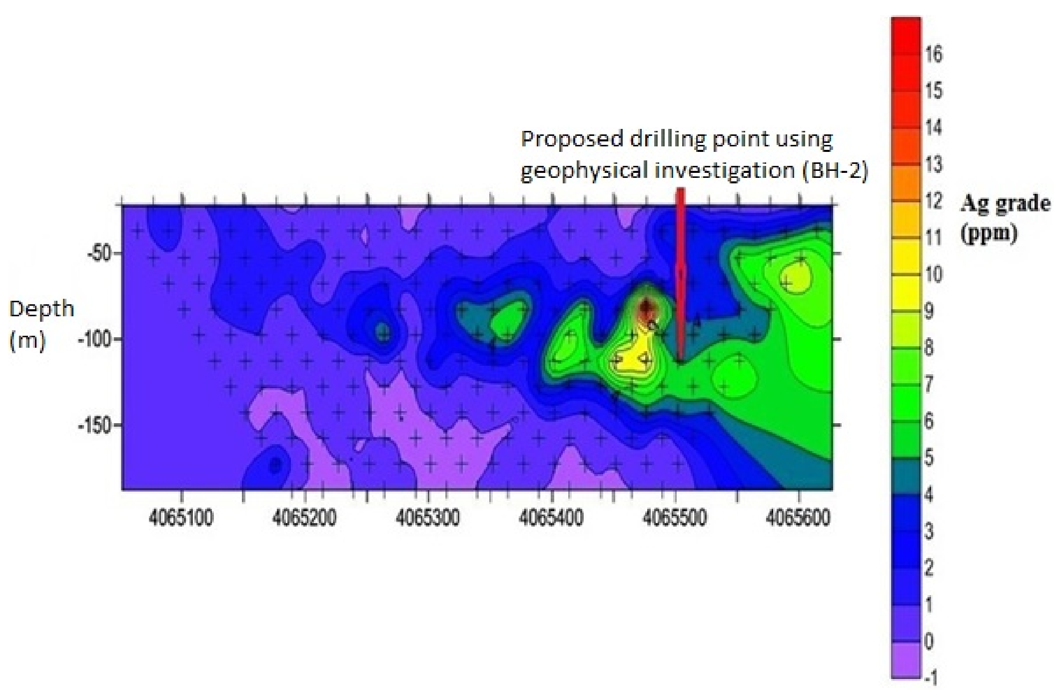

Figure 13. Silver grade model from ANN and surfer for profile 4.

It can be concluded from the geophysical sections (Figure 12) that there is a major anomaly in the right-hand part of the profile. This anomaly is about 120 m far from the end of the profile and has a depth of 50 m. Figure 13 shows that ML is able to predict the horizontal location of the anomaly very accurately; however, the predicted depth is about 25 m deeper than the actual depth. This also can be due to the lower resolution of ML according to the quality and lack of the core analysis data.

5.3. Profile 9

The length of this profile is 720 m with a 30-m distance between the survey points, and the depth of the investigation is about 190. Figures 15 and 16 illustrate inverted the geophysical sections of chargeability and resistivity and the estimated silver grade section using machine-learning. Figure 14 shows that the main anomaly of this section is located in the middle part of the profile with a depth of about 150 m. Borehole 3 was proposed in the middle of the anomaly according to the Res2Dinv model. Although ML has predicted the location of the maximum grade (more than 13.5 ppm) correctly, according to Figure 15, the shape of the anomaly is extended into the end of the profile. The chargeability section also shows the extension of the anomaly to the end of the profile by increasing the depth. Moreover, the resistivity section confirms the existence of the anomaly in the right-hand part of the section according to the lower values of the resistivity in this part.

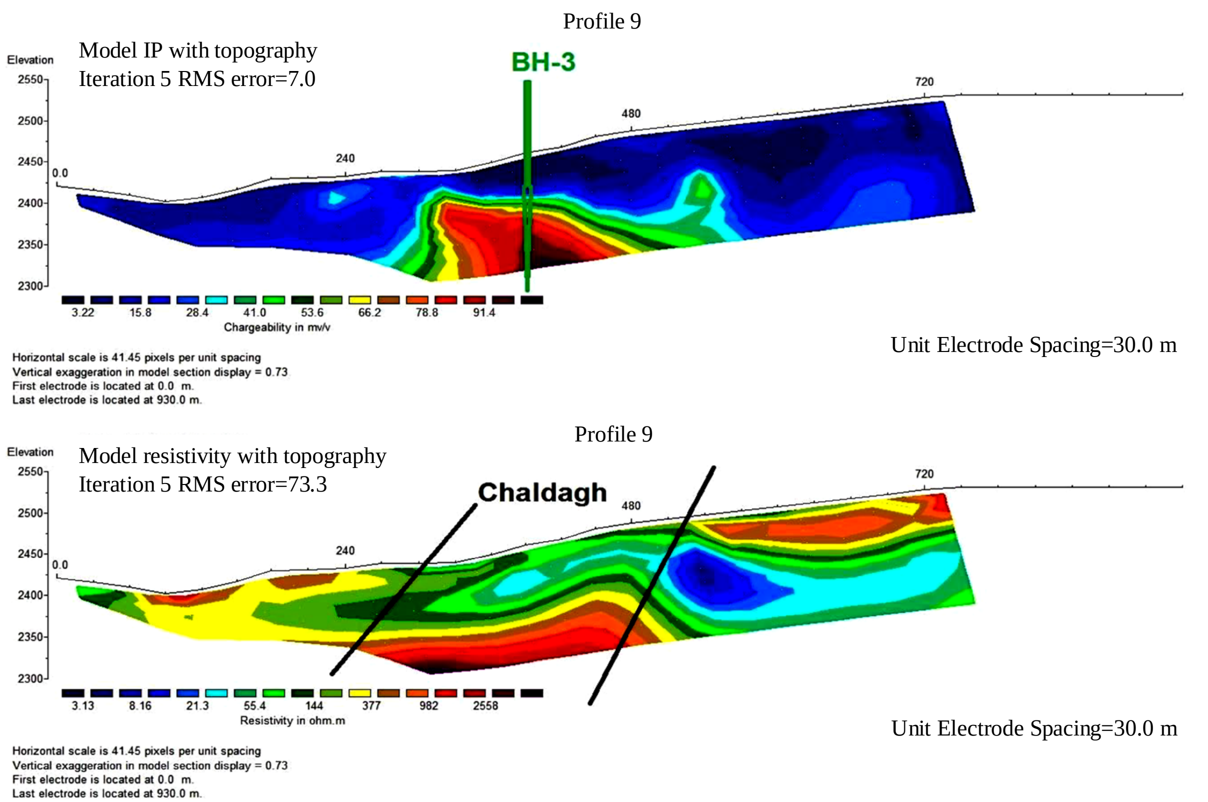

Figure 14. Inverted values of the geophysical data using the Res2DInv software for profile 9.

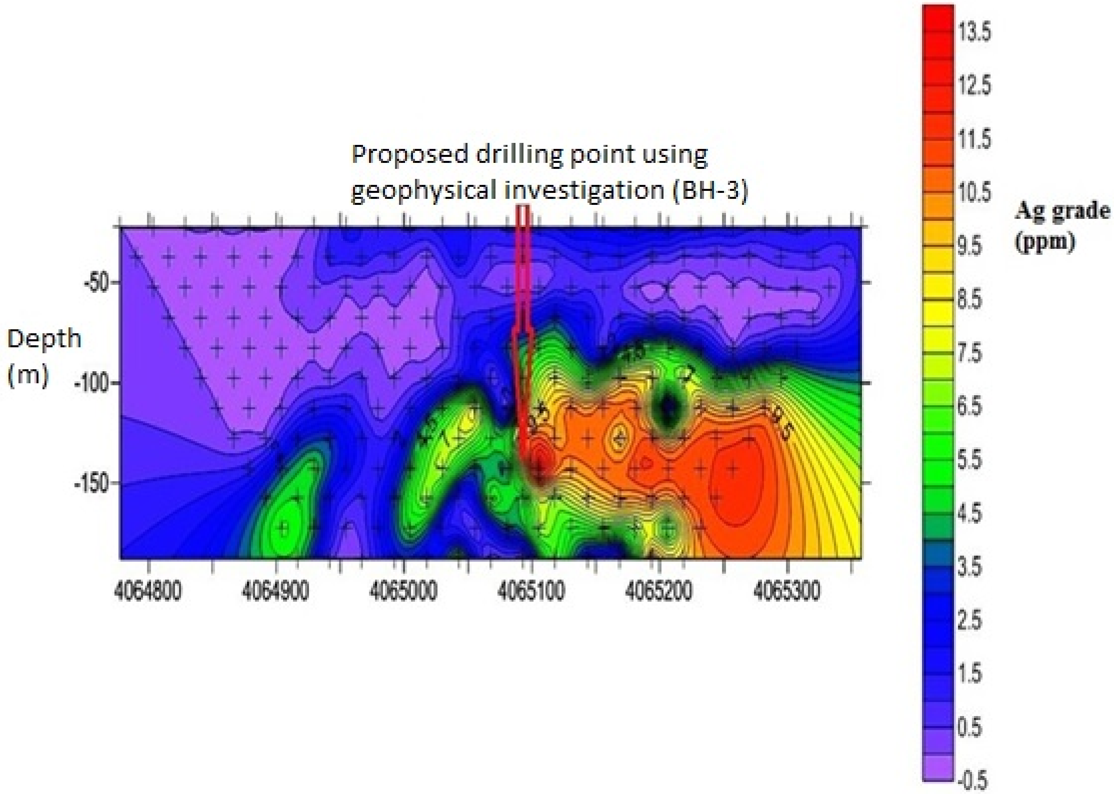

Figure 15. Silver grade model from ANN and surfer for profile 9.

6. Conclusions

The measurement noise and the non-linear relationship between the geophysical attributes and ore grade quantities exert difficulties in performing geophysical interpretation reliably. The IP/RS method, as a geophysical-based nondestructive method, is common in problems of predicting potential zones in sulfide ores. Consequently, other viable methods of prediction such as the one proposed in this paper may be deemed necessary in real cases. We successfully implemented and tested an artificially intelligent computational agent (a new cuckoo search-based machine-learning tool) to consider the unknown non-linear relationships between the system variables in our prediction problem (foreseeing the ore grade). Our approach uses the X, Y, and Z coordinates and the IP and RS values as the input system variables. The network seeks the relationship between these input variables adaptively and strives to a desirable output, which is, in our case, the real ore grade values obtained from the direct sampling and analyzing after borehole drilling.

We considered a real site to test our methodology. The Yeganli area in the Zarshouran gold mine case showed that the network could train itself very well with the practically complete correlation between the real ore grade values and the predicted ones (a correlation coefficient R close to one). As a double-check, we compared the results of the machine-learning technique with the numerical modeling of the geophysical data performed by Res2DInv. The Res2DInv numerical inversion illustrates the best location for further drillings as the targets of mineral deposits. The network also exhibited a remarkable capability in estimating the unknown zones by comparing the results of ML prediction with the numerical models in three geophysical profiles. The results obtained showed that the network did predict these profiles reliably. There were some disparities in some places between the results of ML and Res2DInv numerical models. We speculate the followings as the possible reasons for this peculiarity:

- The locations of the drilled holes were not exactly on the geophysical profiles.
- The data scattering of the outputs was limited, and there was a specific skewness in data.
- The number of training data (80% of 75 data points) is not sufficient for the network to consider all the different possibilities of various conditions.
- The nature of the machine-learning tools is soft computing, and numerical methods are hard.

- Earth heterogeneity leads us to use the soft computing tools to recognize the hidden pattern better.

The remedy would be obtaining more drilling samples from the profiles and finding the real ore grade values, then augmenting the training of the neural network with the new data and ore grade values. It is also recommended to use the output data with a suitable distribution of all ranges (if possible) in other cases, specifically in disseminated sulfide deposits, in which it has been proven that there is a proper relationship between IP/RS and the mineral grade values. We speculate this would enhance the accuracy of the network predictions considerably.

Acknowledgments
The many constructive comments and pieces of advice received during this work from Mr. Mohammad Ebrahim Sabaei, working at the Zarshouran gold mines and Mineral Industries Development Company, are appreciated. Furthermore, we sincerely appreciate the comments received from and the enlightening discussions with our anonymous reviewers that improved the paper.

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تلفیق نشانگرهای ژئوفیزیکی با کمک الگوریتم یادگیری ماشین جستجوی Cuckoo به منظور تخمین مقادیر عیار نقره – مطالعه موردی: معدن طلای زرشوران

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ارسال 2020/08/01، پذیرش 2020/08/26

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چکیده:

روش‌های اکتشافی به دو دسته‌ی مستقیم و غیر مستقیم تقسیم می‌شوند.از بین آنها، روش‌های غیر مستقیم ژئوفیزیکی جزء روش‌های کم هزینه تر و مقرون به صرفه‌تر از لحاظ زمانی در قیاس با روش‌های مستقیم هستند. هدف بررسی‌های ژئوفیزیکی، به دست آوردن یک تصویر صحیح از زیر زمین است. روش پلاریزاسیون القایی، یک روش مرسوم در تشخیص کانه‌های سولفیدی فلزی است. از آنجایی که کانه‌های فلزی در محدوده‌ی معدنی زرشوران به صورت پارکنده در سنگ بستر قرار دارند، لذا روش پلاریزاسیون القایی به عنوان روش اصلی اکتشافات ژئوفیزیک در این محدوده مورد نظر قرار گرفت. به موازات برداشت‌های پلاریزاسیون القایی، برداشت داده‌های مقاومت مخصوص الکتریکی نیز به منظور ایجاد تفسیری دقیقتر صورت گرفت. در این تحقیق سعی بر تلفیق داده‌های ژئوفیزیک مقاومت مخصوص الکتریکی و پلاریزاسیون القایی به همراه مقادیر عیاری گمانه‌ها و اطلاعات زمین شناسی به کمک الگوریتم یادگیری ماشین جستجوی Cuckoo و به منظور تخمین مقادیر عیار نقره شده است. نتایج نشانگر قابلیت بالای روش در تخمین مقادیر عیار، علی الخصوص در مناطق فاقد داده‌های حفاری است. این امر کمک به کاهش هزینه‌ها و زمان عملیات اکتشاف و تخمین ذخیره خواهد کرد. مقایسه نتایج مدل‌سازی معکوس هوش مصنوعی و روش مدل‌سازی عددی، به عنوان روش اصلی در معکوس سازی داده‌های ژئوفیزیک، نشانگر انطباق بسیار خوب نتایج روش هوش مصنوعی با مدل عددی بوده است.

کلمات کلیدی: نشانگرهای ژئوفیزیک، جستجوی Cuckoo، یادگیری ماشین، ذخیره زرشوران، روش‌های عددی.