Scientific Research Publishing

Open Journal of Geology, 2022, 12, 215-233
https://www.scirp.org/journal/ojg
ISSN Online: 2161-7589
ISSN Print: 2161-7570

Feasibility of Simultaneous Application of Fuzzy Neural Network and TOPSIS Integrated Method in Potential Mapping of Lead and Zinc Mineralization in Isfahan-Khomein Metallogeny Zone

Bahareh Hedayat[1], Mohammad Ehsan Ahmadi[2], Hamed Nazerian[3], Aref Shirazi[3], Adel Shirazy[3*]

[1]Faculty of Mining, Petroleum & Geophysics Engineering, Shahrood University of Technology, Shahrood, Iran
[2]Department of Mining Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran
[3]Faculty of Mining Engineering, Amirkabir University of Technology, Tehran, Iran
Email: *adel.shirazy@gmail.com

How to cite this paper: Hedayat, B., Ahmadi, M.E., Nazerian, H., Shirazi, A. and Shirazy, A. (2022) Feasibility of Simultaneous Application of Fuzzy Neural Network and TOPSIS Integrated Method in Potential Mapping of Lead and Zinc Mineralization in Isfahan-Khomein Metallogeny Zone. *Open Journal of Geology*, **12**, 215-233.
https://doi.org/10.4236/ojg.2022.123012

Received: February 7, 2022
Accepted: March 11, 2022
Published: March 14, 2022

Abstract

Iran is located on a silver, lead, and zinc belt and according to the latest studies holds 11 million tons of lead, zinc, and silver stones which constitute 4 percent of global resources. Considering that mineral materials are explored in an uncertain space, exploration investment risk is an inseparable part of these activities. The important fact is to minimize the effect of this undesired factor in exploration. To achieve this, it is required that exploration activities and withdrawals are performed in a certain framework in which risk minimization is considered. Using mineral potential modelling for determining promising zones which should be taken into consideration in more detailed stages could make achieving the purpose possibly. This work is aimed at applying fuzzy neural network and TOPSIS methods simultaneously in order to explore zinc and lead resources. In this article, geological, telemetry, geophysics, and geochemistry data is integrated using fuzzy-neural network (neuro fuzzy) and using TOPSIS method rating for lead and zinc ore deposit potential mapping in Isfahan-Khomein strip which has been introduced as one of zinc and leads mineral scopes in Iran. This area which is composed of several zinc and lead ore deposits has been considered as the target area. Fuzzy integration results of zinc and lead mineralization witness layers confirm the relatively high potential of lead and zinc mineralization in this region having a northwest-southeast trend and involving more than 90 percent of the known indices and ore deposits of the region. In this research, it was shown that the results of TOPSIS-Neuro-Fuzzy integrated model (a combination of neural network and fuzzy logic) have increased the resolution of talented areas from the areas with no mineralization potential in comparison with the fuzzy method individually.

Keywords

Potential Mapping, TOPSIS, Neural-Fuzzy, Zinc and Lead, Isfahan-Khomein

1. Introduction

Goal recognition is a multi-stage activity while exploring mineral materials that start from regional scale (small scale) and continues up to local scale (large scale). In each of the above stages, identification and generation of regions that should be considered as the target region include gathering, analysis, and integration of different exploration data, which is performed in order to extract and infer parts of pattern spatial data and witness mineralization *i.e.* geological, geochemical, or geophysical anomalies along with resources under investigation. Considering that all of the anomalies obtained from each of the exploration approaches do not accompany or introduce mineralization, an effort has been made to use the integration of the results of different methods in order to confirm target areas. A set of processes including various exploration data analysis, extracting mineralization predictive witness patterns, and finally combination and integrating of spatial witnesses in order to identify target areas as well as promising areas in unknown mineralization explorations is called mineral potential modelling [1] [2] [3] [4].

In earth-related sciences, due to the existence of a high level of uncertainty which is resulted from different and sometimes unknown geological activities in a region, using fuzzy model is a good choice in order to justify and model uncertain phenomena and results in an error coefficient reduction. Fuzzy model is a knowledge-based method which in case of integration with data-based methods such as neural network leads to a fuzzy network or fuzzy neural inference system. This model is a very good choice for earth sciences because these sciences are a combination of knowledge and data [5] [6] [7] [8]. Neural networks are appropriate for problems with large data stations and the previous knowledge of the system is not used in network design. This is whilst fuzzy inference systems can use the previous knowledge of the system in the framework of fuzzy regulations. Furthermore, in these systems inexact definition of input and output is possible. If fuzzy logic functions are contributed to neural networks and neural network systems to the fuzzy systems, drawbacks and defects in neural networks and fuzzy systems could be covered [9] [10] [11]. This results in a fuzzy neural network. Fuzzy neural models learn the behavior of the system and extract laws using datasets. In addition, these models are generalizable and cover the key defect of fuzzy systems which is learning and generalization inability. The neural network part automatically creates fuzzy logic laws and membership functions during the learning period. Overall, even after learning is completed, the neural network continues modifying membership functions as well as fuzzy logic laws [12] [13] [14] [15] [16].

Fuzzy neural network method (neuro fuzzy) was applied by Bron, Gruz, and Godeon in mineral potential mapping and earth-related sciences. This method is an integrated method for mineral potential mapping on a continental scale [17] [18] [19] [20]. Popoal, Karanza, and Heel used fuzzy neural model for base metal deposit potential mapping in 2004 [21] [22] [23] [24]. Shabankareh, Fathianpoor, and Tabatabaei using fuzzy neural network prepared the mineral potential maps of the Kashan-Naein metallogeny zone in the GIS environment in 2007 [25] [26] [27] [28]. In addition, Najmi Tabatabaei, and Fathianpoor used this method to identify zones able to mineralize lead and zinc [3] [29] [30] [31] [32].

The word TOPSIS is translated as "a technique for preference arrangements according to their similarities to the ideal solution" into Persian. TOPSIS was developed by Hwang and Yun as a compensative classical method in multi-criteria decision makings for solving priority problems according to the similarities with the ideal positive solutions in 1981 [33] [34]. Malczewski integrated the multi-criteria decision-making method with GIS in 1999 [35]. This method is a better selection for raster data. Models focusing on multi-criteria decision-making models and its different types such as TOPSIS method have been extensively used in previous works. However, they have been rarely used in mining engineering and especially in mine exploration. In this regard, Jafari Rad and Busch's 2011 [36], Pazand, Hezarkhani, and Ataei's in 2012 [37], and Riahi, Tabatabaei and Fathianpoor's study in 2015 [38] could be mentioned in porphyria copper potential mapping and integrated use of TOPSIS method with Shannon entropy by Feizi, Karbalaei-Ramezanali, and Tusi in 2017 [39]. The novelty point of this research is the simultaneous use of relatively up-to-date methods.

2. Raw Data and Methodology

Mineral potential prediction model is indeed a proposed and prescriptive algorithm and model showing the dependence between different geological processes and mineralization controlling processes with places with high resources being investigated by words and symbols.

2.1. Fuzzy Neural Network Method

Fuzzy neural method uses a fuzzy inference system for eigenvector matrix formation (eigenvector space) for neural network input. In this method, components of each vector are indeed the weights of each pattern (class) of different witnesses. These weights are determined using fuzzy mode. Therefore, if there are some predictive X_I maps ($i = 1, \ldots, n$), each of which is composed of m patterns, cs_{ij} will be the worth or rate of X_{ij} ($j = 1, \ldots, m$) for target save search. After the formation of eigenvector space matrix, a subset of it containing known target variables, namely known storage area and areas with no storage are inferred as learning matrix. It is also necessary that verification eigenvector matrix is formed and some storage and non-storage areas are considered as verification. However, after network learning and verification, other vector values (unknown vectors) are estimated and predicted, and finally the obtained values are converted into maps so that mineral potential model is generated. It is noteworthy that Adaptive Neuro-Fuzzy Inference Systems (ANFIS) is the network structure in the integrated fuzzy neural network method [40].

2.2. TOPSIS Method

This model is one of the best multi-criteria decision-making models. In this method, m factors or choices are evaluated by one person or a group of people. This technique is based on the concept that the selected option should be the closest to the positive ideal solution (the best possible case) and the furthest from negative ideal solution (the worst possible case). The ideal solution is the one having the highest profit and the lowest cost. That is whilst; the non-ideal solution is the one having the highest cost and lowest profit. In the TOPSIS method, after forming the data matrix according to m choices and m indices and unscaling it, the weight of each index is determined based on W_j and then the normalized matrix is weighted according to that. These weights show the importance of the criteria provided by the experts, through mental examinations and evaluations, in linguistic terms. The more important indicators have a higher weight. In the next step, the ideal solution and the negative ideal solution are determined and the distance of option i with the ideals is calculated using the Euclidean method to determine the similarity index. The similarity index (CL), which varies between 0 and 1, indicates the relative proximity of each option to the ideal solution. The more similar the ideal is to the chosen option, the closer its similarity index value will be to one. Therefore, the options are ranked based on the value of the similarity index; the option with the highest similarity index is in the first rank and the option with the lowest similarity index is in the last rank [41].

2.3. Geological Setting

The study area is part of the Isfahan-Malayer lead and zinc deposit zone, which is located with a north-west-southeast trend, which is located between longitudes 50˚00' to 52˚00' east and latitudes 32˚30' to 34˚00' north. The length of the study area (Isfahan-Khomein) is about 270 km. Geologically, it is a part of the Sanandaj-Sirjan structural zone, which is located between the folded Zagros belt and the Urmia Dokhtar volcanic zone. From a structural point of view, it can be said that this belt is bounded by a large deep fault, which is a continuation of Daroune fault. Although Cretaceous and post-Cretaceous rocks cover this deep fault, structures in the continuation of this fault are recognizable [42]. Due to the extent of the study area (270 km), there is a great variety of geological formations. Magmatic activity in this area is very intense and important that has taken place in the Paleozoic and Mesozoic periods [43]. Volcanic activity often occurred before Cenozoic. For example, Permian basic and acidic rocks as well as Jurassic tuffs and Cretaceous basic volcanic rocks have been reported from Golpayegan areas [44]. In terms of metamorphic activities, this area has been very active and metamorphic rocks are abundant in the outcrops of Isfahan and Golpayegan. In this belt, the Lower Cretaceous pyroclastic rock sequences, beginning with the base conglomerate, are discontinuously placed on Jurassic-Chilean sandstone units. The conglomerate unit is covered by layers of dolomite and then limestone. Isfahan-Khomein metallurgical zone is part of the Sanandaj-Sirjan structural zone, which is a type of intercontinental formation that magmatic activities and its metamorphic phenomena are effective factors in the formation of mineral deposits.

Lead and zinc deposits in this area are mainly formed during the Cretaceous, in carbonate sequences and along deep faults [45]. Despite the formation of many of these deposits in carbonate host rocks, different deposits have been found and studied [46]. There are different views on the origin of these deposits, all of which are divided into two categories: Mississippi Valley Type (MVT) and Sedex type. Both of these origins seem to have played a role in the generalization of the past; The Sedex type is more prominent in the western part of this belt, but the Mississippi Valley type is more prominent in the eastern part (Isfahan region, etc.) [42]. Based on the studies conducted in this study, in this metallogenic zone of Isfahan-Khomein, about 70 deposits and mineral signs have been identified, which the most definite reserves belong to Emarat and Irankooh mines. Among the lead and zinc deposits and indices in the region, can be found in Irankooh mines including Kolahdarvazeh, Goshfil, Tappeh Sorkh, Godzandan and Khan-e-Gorgi, North basin of Tiran including Surmeh and Anjireh mines and Chakab deposits, Wejin Bala, Vajin Pa'in and Kopeh Motalebi, lead and zinc deposits and indices of Bid-e-Bala, Dar-e-Bid Pa'in, Sadeghabad, Golgahran, Choghasukhteh, Dehq Arabestan, Saleh Prophet, and Laibid and Doshkharat were mentioned.

3. Results and Analysis

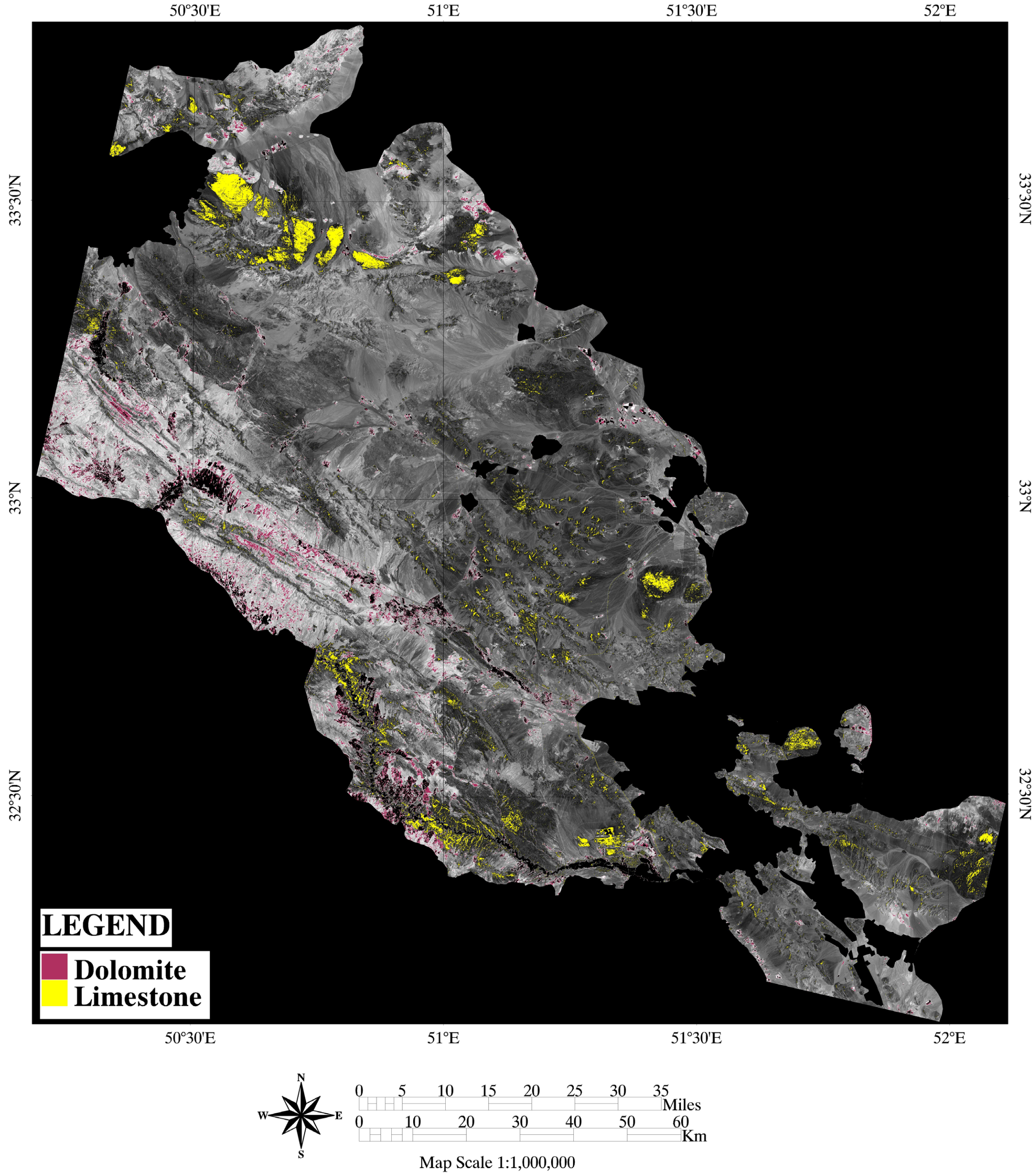
3.1. Preparation of Exploratory Data Layers

Exploration of a mineral reserve requires the simultaneous consideration and validation of several types of spatial data (exploratory surveys using different methods as information layers), such as geology, structural geology, geochemical features, geophysical surveys, satellite images as well as exploratory studies conducted in the past. Raster information layers were used as input data in later steps. All layers were then fuzzy for use in integration.

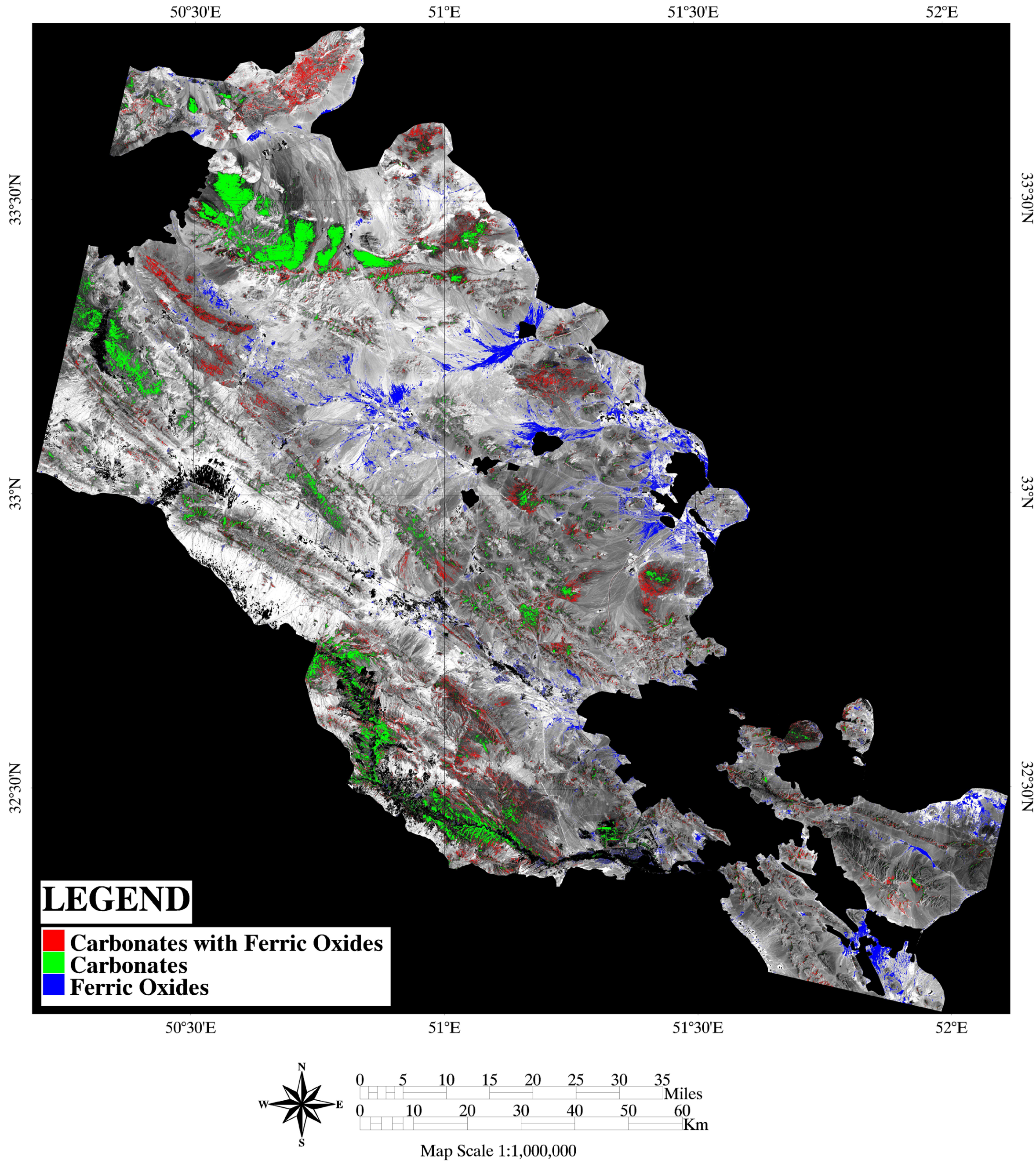
3.1.1. Alteration Information Layer (Remote Sensing)

Controller alterations in sedimentary lead and zinc deposits include iron oxide alteration, silicification, and dolomitization. Due to the abundance of silica in different rock units and the need to identify siliceous zones within the limestone, it is not possible to provide a secondary siliceous alteration layer in carbonate units. In order to prepare the remote sensing information layer and identify the alterations in the study area, OLI sensor data numbered (164-37) related to Landsat 8 satellite and ENVI software were used.

In this study, the ratio +R [R (6, 3)] [R (7, 5)] was used for calcareous areas and the ratio −R [R (6, 3)] [R (7, 5)] was used for dolomitic areas. For the detection of iron oxide, especially carbonates with iron oxide, by two methods of false color combination (FCC) RGB [R (6, 7), R (4, 3), R (5, 6)] and the classification method, spectral angle mapper (SAM) A spectrum is used (**Figure 1**). The alteration



(a)



(b)

Figure 1. (a) Dolomitization alteration factor map in the study area using band ratio +R [R (6, 3), R (7, 5)], (b) Image of iron oxide alteration from SAM processing on satellite data in the region.

exploratory layer is then prepared by combining the dolomitization alteration layer and the carbonates containing iron oxide layer using the sum fuzzy operator.

3.1.2. Geophysical Information Layer

In the Mississippi Valley Type (MVT) lead and zinc deposits, due to the presence of large sulfide masses with high specific gravity, electrical conductivity and high polarization capability and shallow depth of exploration sites, the use of geophysical methods is appropriate. In this research, geophysical information layers have been prepared using airborne magnetometric data and gravimetric data of Isfahan-Golpayegan region.

In the processing of magnetometric data, reduction to the pole (RTP) filter is used. RTP filter calculates magnetic anomalies with the position that the inclination angle of the magnetic field is 90 degrees. In this way, the centers of magnetic anomalies are located right at the main location of the mineralization zones. Therefore, to prepare the geophysical layer map of the magnetic data of the study area, the raw data after IGRF correction is processed in Oasis Montaj software and the final map of the remaining magnetic anomaly is prepared after applying the polarizing filter. In preparing the gravimetric information layer, the necessary corrections were made on the gravimetric data used in this study and the data were processed [21], and the Bouguer anomaly map on Gravimetric data was prepared in the study area. **Figure 2** shows maps of geophysical anomalies.

Finally, by integrating the layers obtained from Booger positive anomaly, gravimetric data and magnetometric anomaly with RTP filter (negative residual anomalies) with the operator, the geophysical information layer is prepared.

3.1.3. Geochemical Information Layer

Using stream sediment data, geochemical halos of lead and zinc anomalies in the area were investigated. Different mobility properties of lead and zinc cations can be used in primary and secondary environments. Extensive halos of zinc, which can be easily detected in secondary environments, indicate the presence of promising areas. In this study, the stream sediments data of three 1:100,000 sheets of Golpayegan, Chadegan and Meymeh were used. Due to insufficient coverage of the area, it was used only for validation and identification of a number of potential areas in the above sheets. Stream sediments were studied to identify anomalies of the elements Pb, Zn, Ba, Cd, Sr, B, Mn and Fe_2O_3. Anomaly maps of the three elements lead, zinc and barium for Golpayegan 1:100,000 sheet are presented as an example in **Figure 3**.

3.1.4. Faults Information Layer

In the exploration of lead and zinc deposits in carbonate rocks, the presence of deep faults through which metallic fluids are directed into carbonate rocks is important. For this reason, an information layer related to the existing structures in the region was prepared as one of the criteria. Fuzzified map of buffers of faults in the area was prepared for integration with other layers. These buffers start in 10 loops with a distance of 2000 meters and increase the distance at an exponential rate to cover the whole area. The map of the existing faults in the study area is shown in **Figure 4**.

3.1.5. Geological Information Layer

One of the main and important layers for exploratory studies is the layer related to geological and petrological formations of the area. This layer was obtained using a 1: 100000 geological map of the study area (**Figure 5**). Formations that are more important for the presence of lead and zinc mineralization, such as dolomitic rocks and limestones, gained higher value, and thus the geological information layer was obtained by fuzzy weighting.

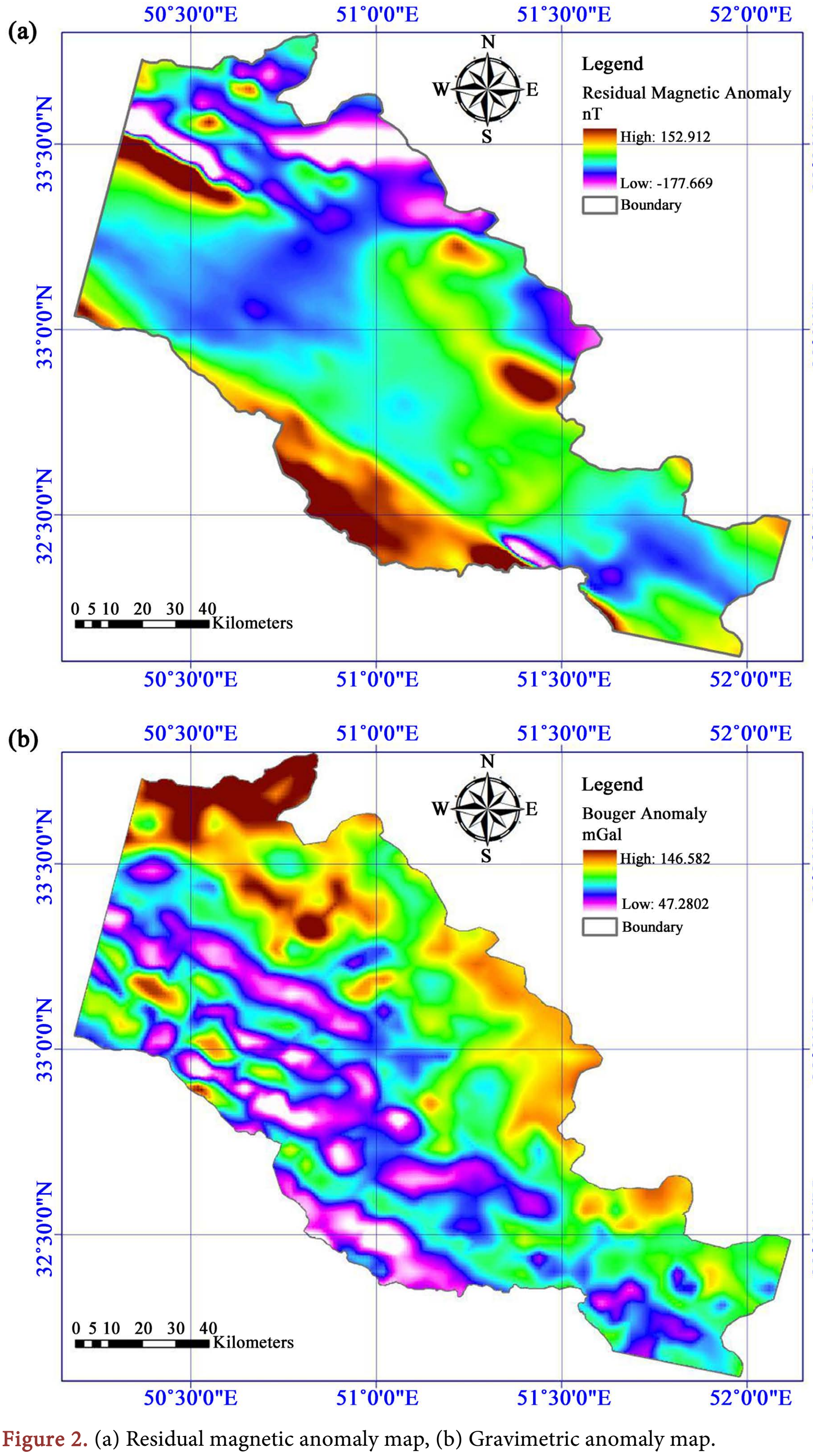
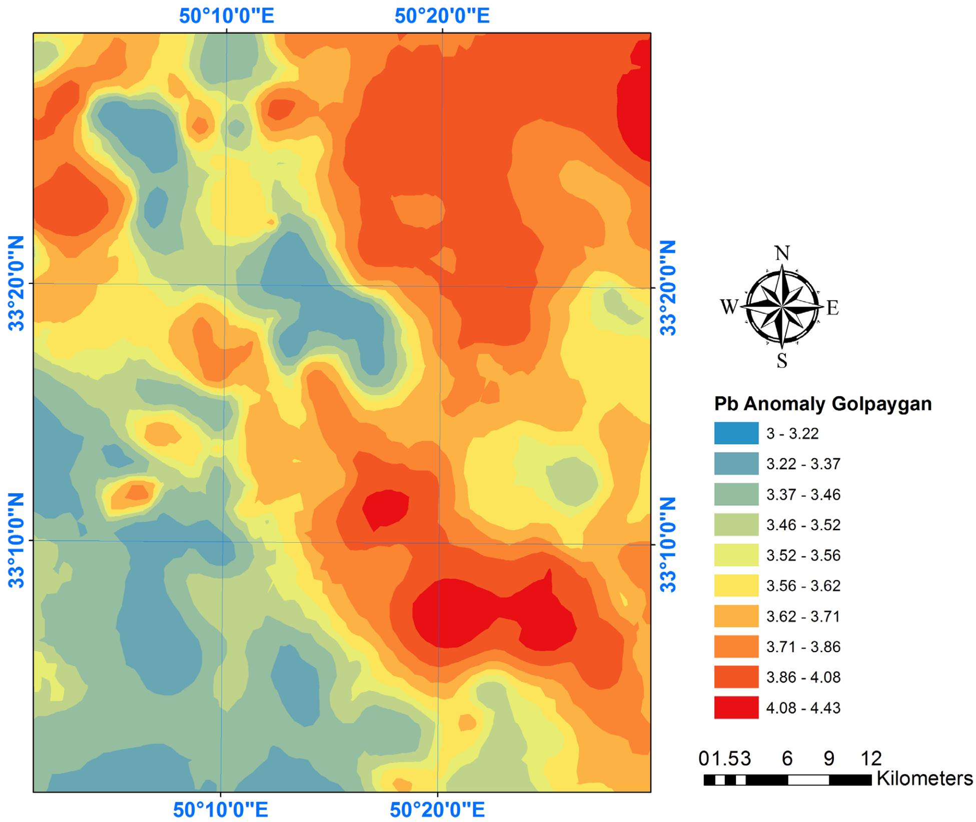
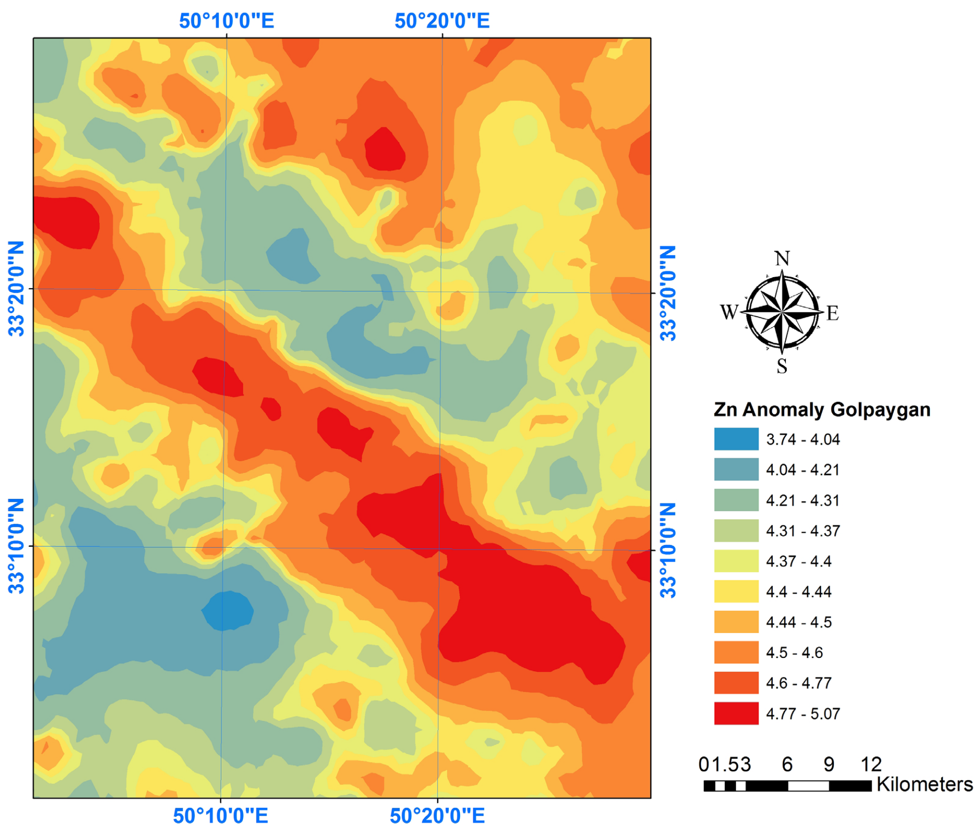


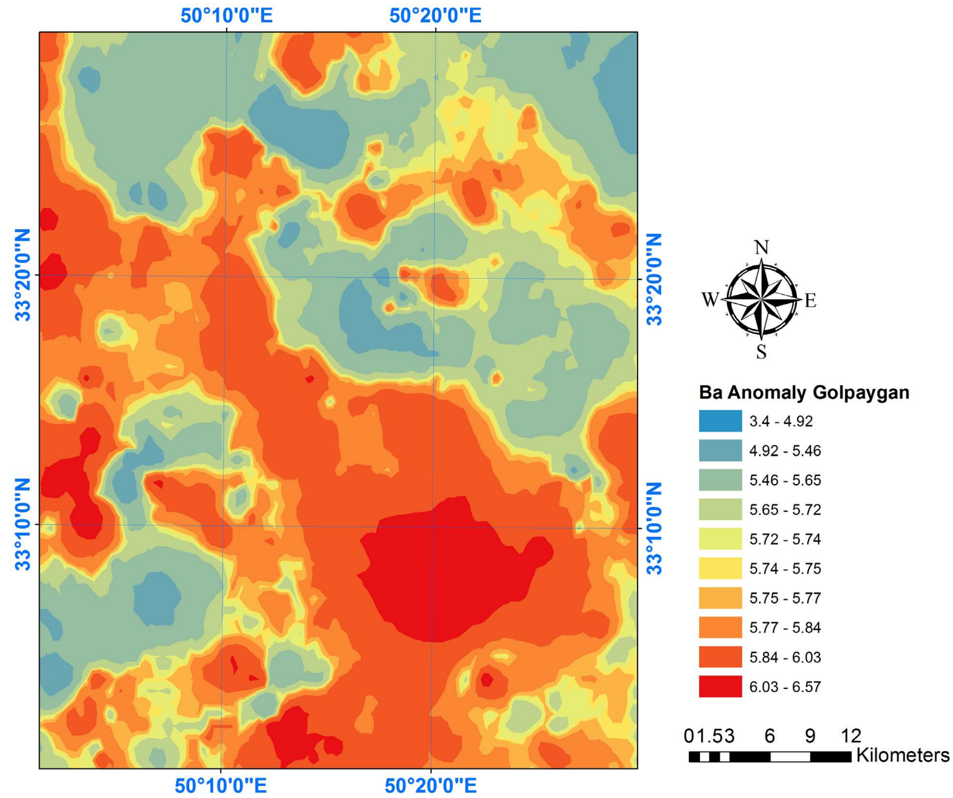
Figure 2. (a) Residual magnetic anomaly map, (b) Gravimetric anomaly map.


50°10'0"E
50°20'0"E
33°20'0"N
33°10'0"N
N
W
E
S
Pb Anomaly Golpaygan
3 - 3.22
3.22 - 3.37
3.37 - 3.46
3.46 - 3.52
3.52 - 3.56
3.56 - 3.62
3.62 - 3.71
3.71 - 3.86
3.86 - 4.08
4.08 - 4.43
01.53 6 9 12
Kilometers

(a)


50°10'0"E
50°20'0"E
33°20'0"N
33°10'0"N
N
W
E
S
Zn Anomaly Golpaygan
3.74 - 4.04
4.04 - 4.21
4.21 - 4.31
4.31 - 4.37
4.37 - 4.4
4.4 - 4.44
4.44 - 4.5
4.5 - 4.6
4.6 - 4.77
4.77 - 5.07
01.53 6 9 12
Kilometers

(b)



(c)

Figure 3. Map of geochemical anomalies resulting from analysis of stream sediment data (Golpayegan 1:100,000 sheet): (a) Pb element, (b) Zn element, (c) Ba element.

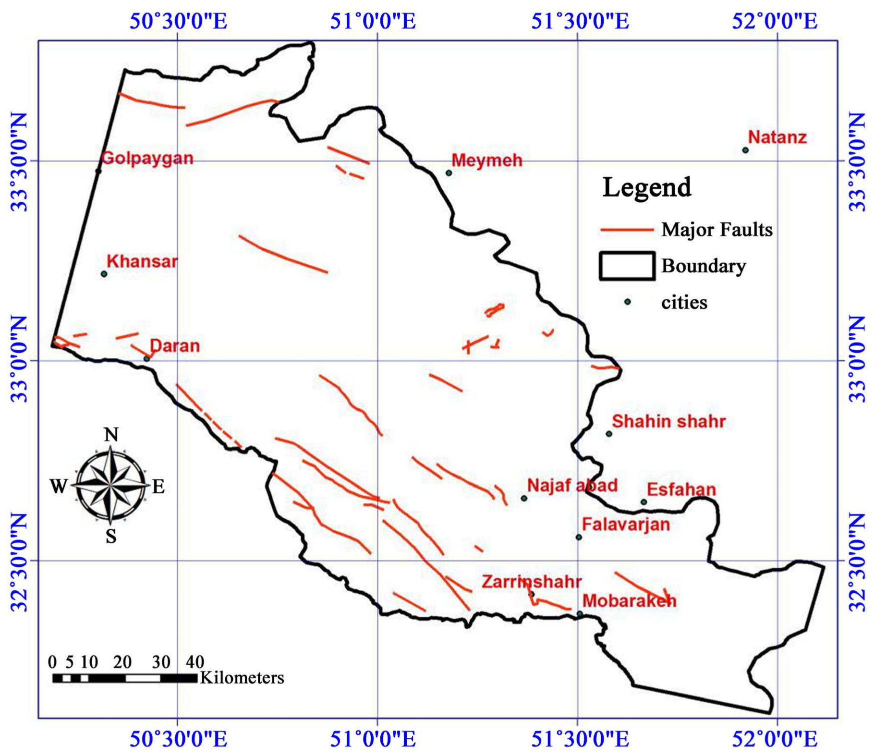


Figure 4. Map of the faults in the study area.

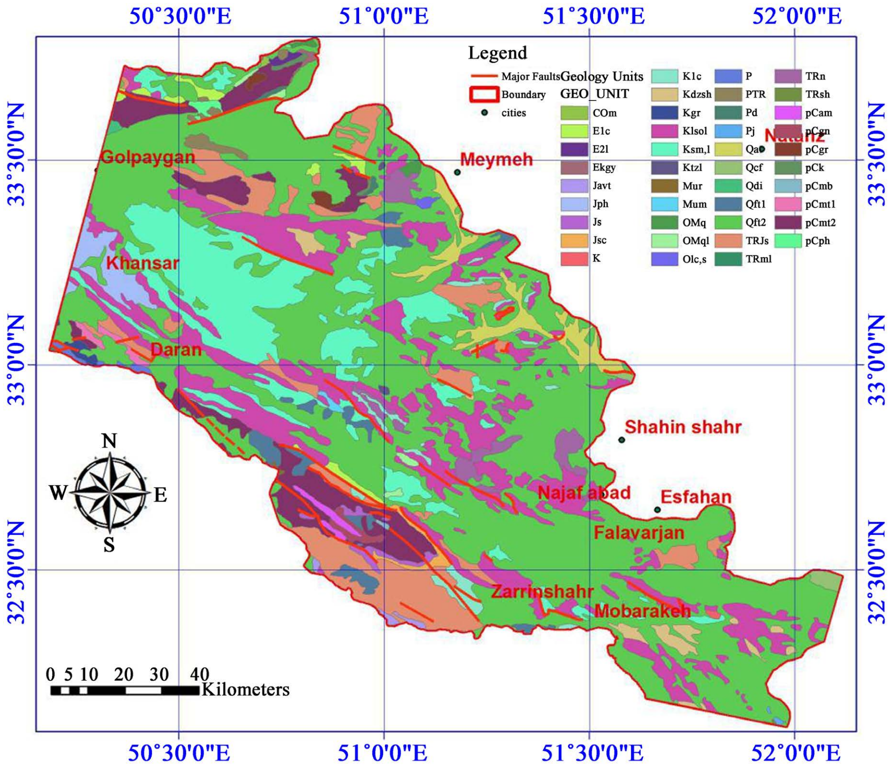


Figure 5. Geological map of the study area.

3.2. Layers Integration and Zoning

In order to identify high potential areas, it is necessary to prepare the layers of exploratory information in GIS software in a specific geographical area and with the same cell resolution. Therefore, the steps of editing and preparing the data and converting them so that they contain all the required information and have a suitable structure for analysis, were performed. In the first stage, the fuzzified layers were integrated to be used as neural network inputs. In the fuzzy overlap method, the maps are combined in pairs or in several stages to obtain the final map. Different fuzzy operators can be used to integrate these maps, combining different operators with different results. The model was optimized by performing it several times and controlling the obtained results. After the model was executed several times by changing the type of operators or its parameters, the final model was obtained. Using the location of known lead and zinc deposits and indices in the study area as well as geochemical anomalies resulting from samples of stream sediments, ideal options for lead and zinc mineralization in the Mississippi Valley type are identified and These ideal options were used to train the fuzzy neural network. Finally, after optimizing the neural-fuzzy network, a prediction model has been prepared for the potential mineralization areas of lead and zinc.

The neural-fuzzy network used in this research is shown in Figure 6, in which the input layers are: longitudinal coordinates of pixels, transverse coordinates of pixels, lithology factor, geophysical factor (fuzzy composition of RTP anomalous field Magnetic residuals and Boger gravimetry anomalies, structures factor (density of faults), alteration factor (fuzzy combination of dolomitization and ferrous carbonates) and the output layer are: known lead and zinc deposits and indices and geochemical anomalies of lead and zinc. In the network structure of the fuzzy nervous system, the Gaussian function is used to fuzzy between inputs and outputs (**Figure 6**, **Figure 7**).

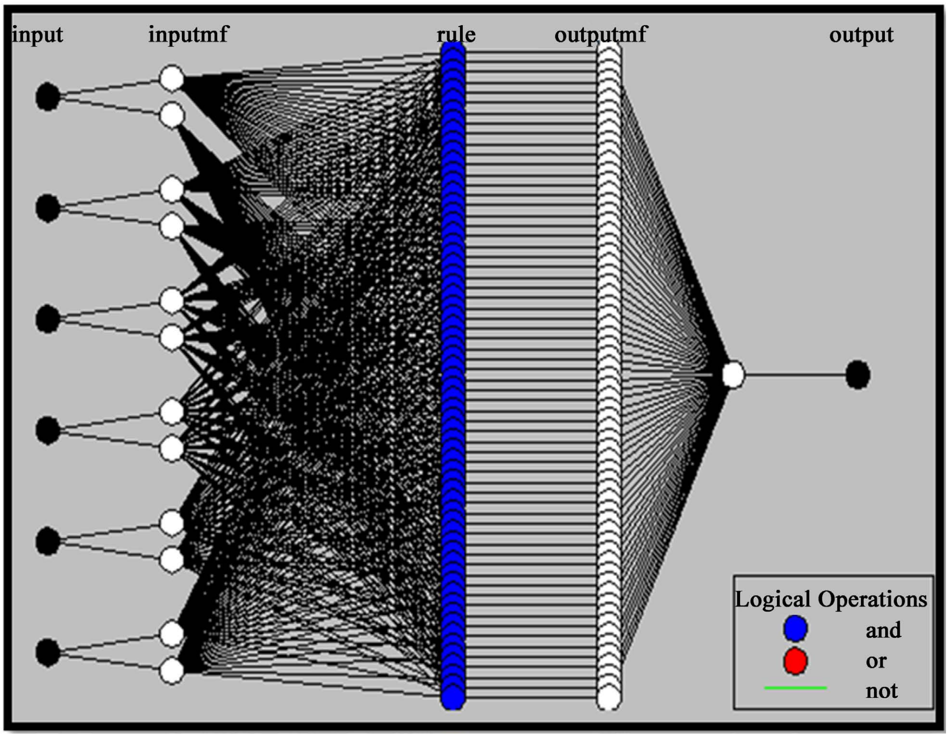


Figure 6. Correlation of Gaussian fuzzy functions of inputs and outputs in the model (ANFIS).

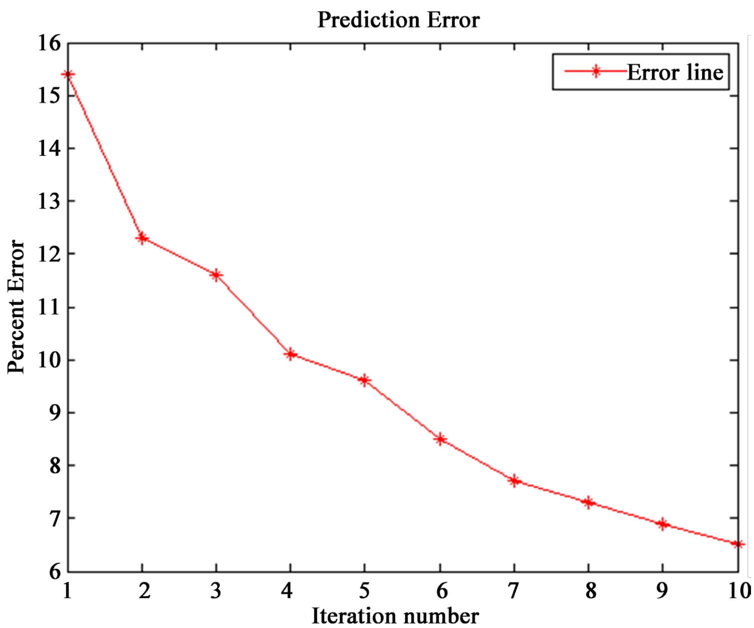


Figure 7. Graph of error rate versus number of repetitions.

4. Discussion and Conclusions

Due to the special ability of ANFIS models in extracting knowledge from existing data, which is the presence or absence of mineralization in the educational stage, as well as the capabilities of TOPSIS in achieving expert diagnosis of ideal options (existence of mineral index properties and avoidance of anti-ideal options (existence of non-mineralization index features), it can be expected that the combination of these two methods will lead to better results. In this regard, the only and most important point is the use of data that covers the entire scope of the phenomenon under study [3]. This point once again shows the special power of ANFIS model in comparison with other conventional models, especially artificial and even fuzzy neural networks alone, which utilize the capabilities of both neural and fuzzy network methods.

Coverage of the study area by very important educational data plays a key role in the generalizability of the model; because smart models do not have a very good ability to extrapolate. The downward trend of the model error with increasing the number of repetitions in **Figure 7** shows the appropriate learning power of the model with increasing the number of repetitions and the appropriate relationship between the selected data as input and the desirability of zones with mineralization potential (**Figure 8**). The average absolute error of the model in the training stage is close to zero and the maximum error in the test stage is less than 0.07, which is considered very desirable. According to **Figure 9**, the final

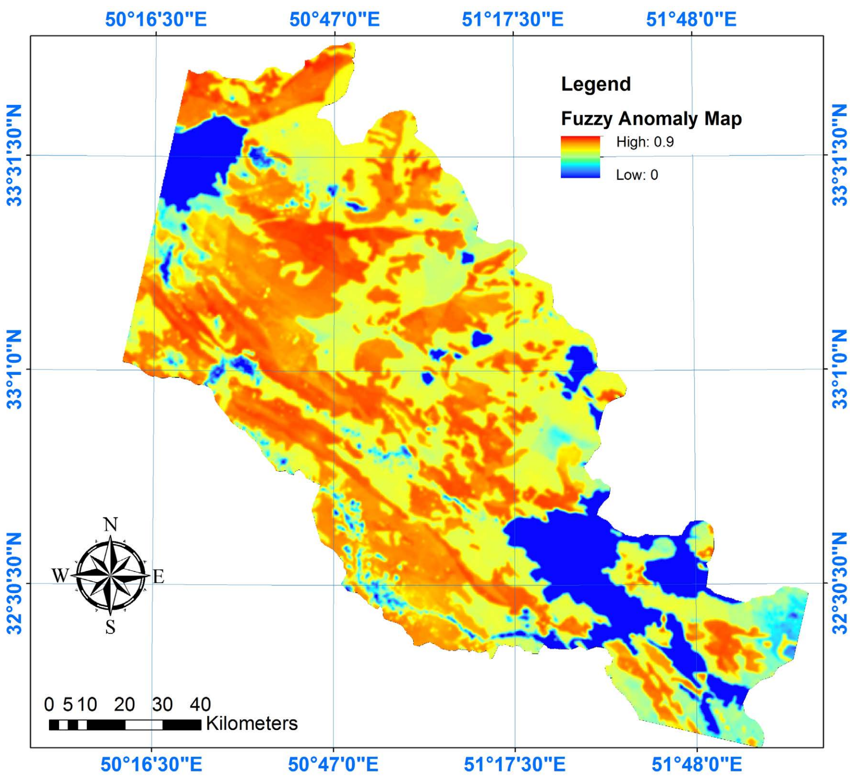


Figure 8. Final map of lead and zinc mineralization potential (Mississippi Valley type) in the study area based on fuzzy logic.

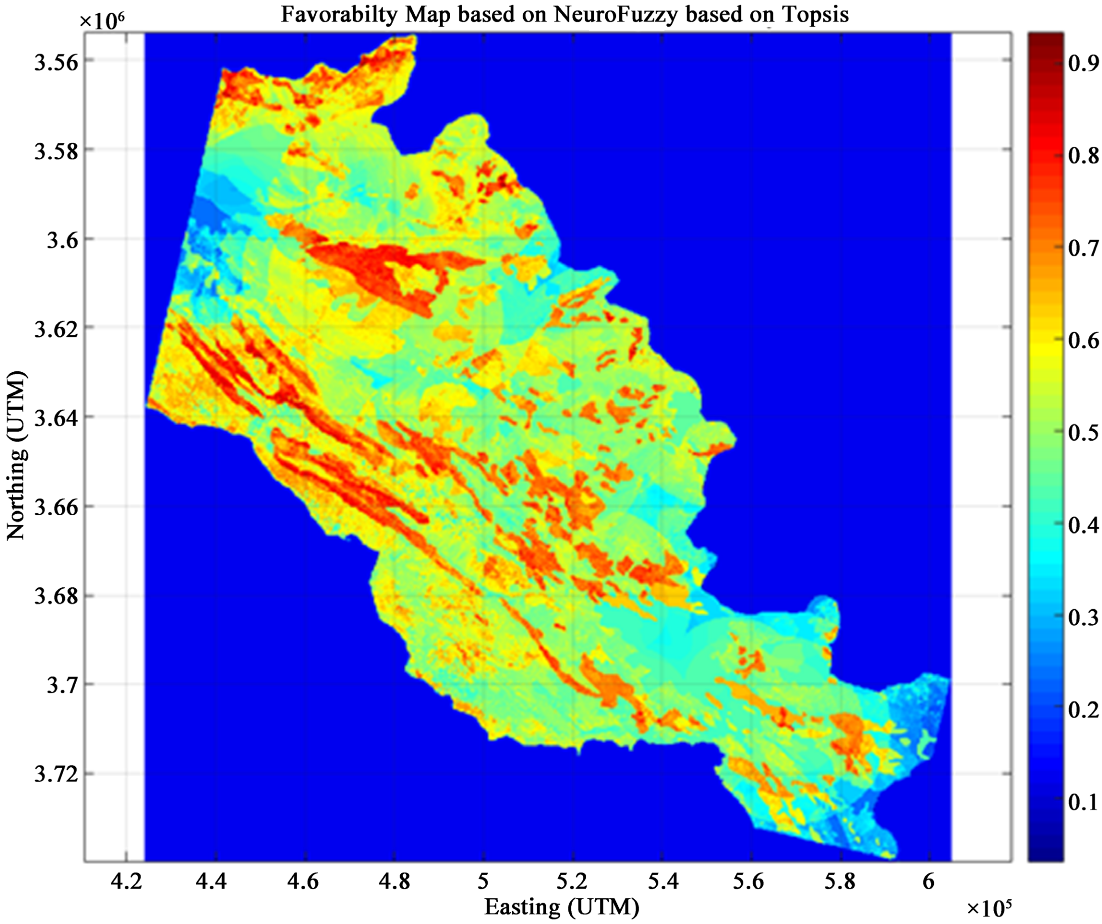


Figure 9. Final map of lead and zinc mineralization potential (Mississippi Valley type) in the study area.

accuracy of the model in predicting the reported points in terms of lead and zinc mineralization above the value of the membership function of 0.5 is estimated at about 85%, which according to the errors presented in the reports of Geological Survey of Iran (GSI) is considered an acceptable result (**Figure 9**).

By analyzing the results obtained from the lead and zinc mineral potential model in Isfahan-Khomein area by integrated TOPSIS-Neuro-Fuzzy method and comparing it with the results of the fuzzy method, a good overlap is observed between the areas with lead and zinc; also in both methods, the northwest-southeast trend of mineralization is visible, but the fuzzy TOPSIS-Neuro-Fuzzy method is limited by using positive and counter-ideal ideal options as fuzzy neural network training data. Mineralization areas, or in other words, increase the resolution of susceptible areas from non-mineralization areas and in fact increase the focus and accuracy of exploration operations to identify target points.

In **Table 1**, the accuracy of the two integrated methods used (Fuzzy, TOPSIS-Neuro-Fuzzy) in the mineral potential of lead and zinc in the study area is calculated. As can be seen, out of 20 known deposits in the study area, 16 deposits in the mineral potential map obtained from the fuzzy integration method correspond to a threshold of 0.5; If by TOPSIS-Neuro-Fuzzy method, this number increases to19 deposits and corresponds to a percentage equal to 95%, which is an acceptable

Table 1. Validation and comparison of integrated methods used in the study area.

Percentage of conformity with the mineral potential model used	Number of known deposits in accordance with the mineral potential model	Number of known deposits in the area	Validation / Integration Method
80 %	16	20	**Fuzzy**
95 %	19	20	TOPSIS-Neuro-Fuzzy

accuracy for modeling mineral potential.

The results of the combined TOPSIS-Neuro-Fuzzy model (a combination of neural network and fuzzy logic) show an increase in the resolution of high potential areas from areas without mineralization potential compared to the fuzzy method alone.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Zhao, P. (1992) Theories, Principles, and Methods for the Statistical Prediction of Mineral Deposits. *Mathematical Geology*, **24**, 589-595. https://doi.org/10.1007/BF00894226

[2] Shirazy, A., Ziaii, M., Hezarkhani, A. and Timkin, T. (2020) Geostatistical and Remote Sensing Studies to Identify High Metallogenic Potential Regions in the Kivi area of Iran. *Minerals*, **10**, Article No. 869. https://doi.org/10.3390/min10100869

[3] Shirazy, A., Ziaii, M. and Hezarkhani, A. (2020) Geochemical Behavior Investigation Based on K-Means and Artificial Neural Network Prediction for Copper, in Kivi Region, Ardabil Province, IRAN. *Iranian Journal of Mining Engineering*, **14**, 96-112.

[4] Shirazy, A., Shirazi, A., Nazerian, H., Khayer, K. and Hezarkhani, A. (2021) Geophysical study: Estimation of Deposit Depth Using Gravimetric Data and Euler Method (Jalalabad Iron Mine, Kerman Province of IRAN). *Open Journal of Geology*, **11**, 340-355. https://doi.org/10.4236/ojg.2021.118018

[5] Saljoughi, B.S. and Hezarkhani, A. (2018) A Comparative Analysis of Artificial Neural Network (ANN), Wavelet Neural Network (WNN), and Support Vector Machine (SVM) Data-Driven Models to Mineral Potential Mapping for Copper Mineralizations in the Shahr-e-Babak Region, Kerman, Iran. *Applied Geomatics*, **10**, 229-256. https://doi.org/10.1007/s12518-018-0229-z

[6] Shirazy, A., *et al.* (2021) Investigation of Geochemical Sections in Exploratory Boreholes of Mesgaran Copper Deposit in Iran. *International Journal for Research in Applied Science and Engineering Technology* (*IJRASET*), **9**, 2364-2368. https://doi.org/10.22214/ijraset.2021.37775

[7] Shirazy, A., Shirazi, A. and Nazerian, H. (2021) Application of Remote Sensing in Earth Sciences—A Review. *International Journal of Science and Engineering Applications*, **10**, 45-51. https://doi.org/10.7753/IJSEA1005.1001

[8] Shirazy, A., Shirazi, A. and Hezarkhani, A. (2018) Predicting Gold Grade in Tarq 1:100000 Geochemical Map Using the Behavior of Gold, Arsenic and Antimony by K-Means Method. *Journal of Mineral Resources Engineering*, **2**, 11-23.

[9] Shirazy, A., Shirazi, A., Heidarlaki, S. and Ziaii, M. (2018) Exploratory Remote Sensing Studies to Determine the Mineralization Zones around the Zarshuran Gold Mine. *International Journal of Science and Engineering Applications*, **7**, 274-279. https://doi.org/10.7753/IJSEA0709.1004

[10] Shirazy, A., Shirazi, A., Ferdossi, M. and Ziaii, M. (2019) Geochemical and Geostatistical Studies for Estimating Gold Grade in Tarq Prospect Area by K-Means Clustering Method. *Open Journal of Geology*, **9**, 306-326. https://doi.org/10.4236/ojg.2019.96021

[11] Shirazy, A., Khayer, k., Shirazi, A., Ansari, A. and Hezarkhani, A. (2020) Cementation Exponent Estimate in Carbonate Reservoirs: A New Method. *Global Journal of Computer Sciences: Theory and Research*, **10**, 66-72. https://doi.org/10.18844/gjcs.v10i2.5894

[12] Kurtulus, B. and Razack, M. (2010) Modeling Daily Discharge Responses of a Large Karstic Aquifer Using Soft Computing Methods: Artificial Neural Network and Neuro-Fuzzy. *Journal of Hydrology*, **381**, 101-111. https://doi.org/10.1016/j.jhydrol.2009.11.029

[13] Shirazy, A., Hezarkhani, A., Timkin, T. and Shirazi, A. (2021) Investigation of Magneto-/Radio-Metric Behavior in Order to Identify an Estimator Model Using K-Means Clustering and Artificial Neural Network (ANN) (Iron Ore Deposit, Yazd, IRAN). *Minerals*, **11**, Article No. 1304. https://doi.org/10.3390/min11121304

[14] Shirazi, A., Shirazy, A., Saki, S. and Hezarkhani, A. (2018) Geostatistics Studies and Geochemical Modeling Based on Core Data, Sheytoor Iron Deposit, Iran. *Journal of Geological Resource and Engineering*, **6**, 124-133. https://doi.org/10.17265/2328-2193/2018.03.004

[15] Shirazi, A., Shirazy, A., Saki, S. and Hezarkhani, A. (2018) Introducing a Software for Innovative Neuro-Fuzzy Clustering Method Named NFCMR. *Global Journal of Computer Sciences: Theory and Research*, **8**, 62-69. https://doi.org/10.18844/gjcs.v8i2.3264

[16] Alalaya, M.M., Al Rawashdeh, H.A. and Alkhateb, A. (2018) Combination Method between Fuzzy Logic and Neural Network Models to Predict Amman Stock Exchange. *Open Journal of Business and Management*, **6**, 632-650. https://doi.org/10.4236/ojbm.2018.63048

[17] Brown, W.M., Gedeon, T.D. and Groves, D.I. (2003) Use of Noise to Augment Training Data: A Neural Network Method of Mineral-Potential Mapping in Regions of Limited Known Deposit Examples. *Natural Resources Research*, **12**, 141-152. https://doi.org/10.1023/A:1024218913435

[18] Shirazi, A., Shirazy, A., Nazerian, H. and Khakmardan, S. (2021) Geochemical and Behavioral Modeling of Phosphorus and Sulfur as Deleterious Elements of Iron Ore to Be Used in Geometallurgical Studies, Sheytoor Iron Ore, Iran. *Open Journal of Geology*, **11**, 596-620. https://doi.org/10.4236/ojg.2021.1111030

[19] Shirazi, A., Shirazy, A. and Karami, J. (2018) Remote Sensing to Identify Copper Alterations and Promising Regions, Sarbishe, South Khorasan, Iran. *International Journal of Geology and Earth Sciences*, **4**, 36-52.

[20] Shirazi, A. and Shirazy, A. (2020) Introducing Geotourism Attractions in Toroud Village, Semnan Province, Iran. *International Journal of Science and Engineering Applications*, **9**, 79-86. https://doi.org/10.7753/IJSEA0906.1002

[21] Porwal, A., Carranza, E. and Hale, M. (2004) A Hybrid Neuro-Fuzzy Model for Mineral Potential Mapping. *Mathematical Geology*, **36**, 803-826. https://doi.org/10.1023/B:MATG.0000041180.34176.65

[22] Shirazi, A., Hezarkhani, A. and Shirazy, A. (2018) Exploration Geochemistry Data-Application for Cu Anomaly Separation Based On Classical and Modern Statistical Methods in South Khorasan, Iran. *International Journal of Science and Engineering Applications* (*IJSEA*), **7**, 39-44. https://doi.org/10.7753/IJSEA0704.1001

[23] Shirazi, A., Hezarkhani, A. and Shirazy, A. (2018) Remote Sensing Studies for Mapping of Iron Oxide Regions, South of Kerman, IRAN. *International Journal of Science and Engineering Applications* (*IJSEA*), **7**, 45-51. https://doi.org/10.7753/IJSEA0704.1002

[24] Nazerian, H., et al. (2021) Predict the Amount of Cu Using the Four Ca, Al, P, S Elements by Multiple Linear Regression Method. *International Journal for Research in Applied Science and Engineering Technology* (*IJRASET*), **9**, 1088-1092. https://doi.org/10.22214/ijraset.2021.38121

[25] Oh, H.-J. and Lee, S. (2010) Application of Artificial Neural Network for Gold-Silver Deposits Potential Mapping: A Case Study of Korea. *Natural Resources Research*, **19**, 103-124. https://doi.org/10.1007/s11053-010-9112-2

[26] Nazerian, H., Shirazy, A., Shirazi, A. and Hezarkhani, A. (2022) Design of an Artificial Neural Network (BPNN) to Predict the Content of Silicon Oxide (SiO2) Based on the Values of the Rock Main Oxides: Glass Factory Feed Case Study. *International Journal of Science and Engineering Applications* (*IJSEA*), **2**, 41-44. https://doi.org/10.7753/IJSEA1102.1001

[27] Khosravi, V., Shirazi, A., Shirazy, A., Hezarkhani, A. and Pour, A.B. (2022) Hybrid Fuzzy-Analytic Hierarchy Process (AHP) Model for Porphyry Copper Prospecting in Simorgh Area, Eastern Lut Block of Iran. *Mining*, **2**, 1-12. https://doi.org/10.3390/mining2010001

[28] Khayer, K., Shirazy, A., Shirazi, A. and Ansari, A. (2021) Determination of Archie's Tortuosity Factor from Stoneley Waves in Carbonate Reservoirs. *International Journal of Science and Engineering Applications* (*IJSEA*), **10**, 107-110. https://doi.org/10.7753/IJSEA1008.1001

[29] Khayer, K., Shirazy, A., Ansari, A. and Hezarkhani, A. (2022) Permeability Estimation from Stoneley Waves in Carbonate Reservoirs. *Geological Bulletin of Turkey*, **65**, 35-42. https://doi.org/10.25288/tjb.974505

[30] Khakmardan, S., Shirazi, A., Shirazy, A. and Hosseingholi, H. (2018) Copper Oxide Ore Leaching Ability and Cementation Behavior, Mesgaran Deposit in Iran. *Open Journal of Geology*, **8**, 841-858. https://doi.org/10.4236/ojg.2018.89049

[31] Khakmardan, S., Doodran, R., Shirazy, A., Shirazi, A. and Mozaffari, E. (2020) Evaluation of Chromite Recovery from Shaking Table Tailings by Magnetic Separation Method. *Open Journal of Geology*, **10**, 1153-1163. https://doi.org/10.4236/ojg.2020.1012055

[32] Noei, S., Sargolzaei, A., Yen, K., Sargolzaei, S. and Wu, N. (2017) Ecopreneur Selection Using Fuzzy Similarity TOPSIS Variants. *American Journal of Industrial and Business Management*, **7**, 864-880. https://doi.org/10.4236/ajibm.2017.77061

[33] Hwang, C. and Yoon, K. (1981) 1981 Multiple Attribute Decision Making: Methods and Applications. Lecture Notes in Economics and Mathematical Systems, Vol. 186, Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-48318-9

[34] Alahgholi, S., Shirazy, A. and Shirazi, A. (2018) Geostatistical Studies and Anomalous Elements Detection, Bardaskan Area, Iran. *Open Journal of Geology*, **8**, 697-710. https://doi.org/10.4236/ojg.2018.87041

[35] Malczewski, J. (1999) GIS and Multicriteria Decision Analysis. John Wiley & Sons, Hoboken.

[36] Rad, A.R.J. and Busch, W. (2011) Porphyry Copper Mineral Prospectivity Mapping Using Interval Valued Fuzzy Sets Topsis Method in Central Iran. *Journal of Geographic Information System*, **3**, 312-317. https://doi.org/10.4236/jgis.2011.34028

[37] Pazand, K., Hezarkhani, A. and Ataei, M. (2012) Using TOPSIS Approaches for Predictive Porphyry Cu Potential Mapping: A Case Study in Ahar-Arasbaran Area (NW, Iran). *Computers & Geosciences*, **49**, 62-71. https://doi.org/10.1016/j.cageo.2012.05.024

[38] Riahi, S., Fathianpour, N. and Tabatabaei, S.H. (2017) Presenting a Mapping Method Based on Fuzzy Logic and TOPSIS Multi Criteria Decision-Making Methods to Detect Promising Porphyry Copper Mineralization Areas in the East of the Sarcheshmeh Copper Metallogenic District. *Journal of Economic Geology*, **9**, 357-374. https://doi.org/10.1007/s11053-017-9338-3

[39] Feizi, F., Karbalaei-Ramezanali, A. and Tusi, H. (2017) Mineral Potential Mapping via TOPSIS with hybrid AHP–Shannon Entropy Weighting of Evidence: A Case Study for Porphyry-Cu, Farmahin Area, Markazi Province, Iran. *Natural Resources Research*, **26**, 553-570.

[40] Jang, J.-S. and Sun, C.-T. (1995) Neuro-Fuzzy Modeling and Control. *Proceedings of the IEEE*, **83**, 378-406. https://doi.org/10.1109/5.364486

[41] Kahraman, C. (2008) Fuzzy Multi-Criteria Decision Making: Theory and Applications with Recent Developments. Vol. 16, Springer, Boston. https://doi.org/10.1007/978-0-387-76813-7

[42] Ghorbani, M. (2013) The Economic Geology of Iran: Mineral Deposits and Natural Resources. Springer, Dordrecht, 1-450. https://doi.org/10.1007/978-94-007-5625-0

[43] Ghorbani, M. (2019) Lithostratigraphy of Iran. Springer, Cham. https://doi.org/10.1007/978-3-030-04963-8

[44] Ghorbani, M. (2013) A Summary of Geology of Iran. In: Ghorbani, M., Ed., *The Economic Geology of Iran*, Springer, Dordrecht, 45-64. https://doi.org/10.1007/978-94-007-5625-0_2

[45] Shahabpour, J. (2007) Island-Arc Affinity of the Central Iranian Volcanic Belt. *Journal of Asian Earth Sciences*, **30**, 652-665. https://doi.org/10.1016/j.jseaes.2007.02.004

[46] Yang, T., Chen, J.L., Liang, M.J., Xin, D., Aghazadeh, M., Hou, Z.Q., *et al.* (2018) Two Plutonic Complexes of the Sanandaj-Sirjan Magmatic-Metamorphic Belt Record Jurassic to Early Cretaceous Subduction of an Old Neotethys Beneath the Iran Microplate. *Gondwana Research*, **62**, 246-268. https://doi.org/10.1016/j.gr.2018.03.016