Journal of Geochemical Exploration 100 (2009) 25–36

Contents lists available at ScienceDirect

Journal of Geochemical Exploration

journal homepage: www.elsevier.com/locate/jgeoexp

Neuro-fuzzy modelling in mining geochemistry: Identification of geochemical anomalies

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ARTICLE INFO

Article history:
Received 15 September 2007
Accepted 19 March 2008
Available online 11 April 2008

Keywords:
Mining geochemistry
Neural networks modelling
Zone dispersed mineralization (ZDM)
Blind mineralization (BM)
Identification of geochemical anomalies (IGA)
Zonality method

ABSTRACT

Local and mine scale exploration models for anomaly recognition within known ore fields are discussed. Traditional geochemical exploration methods are based on multivariate statistical analysis, metallometry, vertical geochemical zonality and criteria of natural field geochemical associations, which suffer several shortcomings, including lack of a geostatistical generalised approach for separating anomalies from background. These shortcomings make the interpretation process time consuming and costly. Fuzzy set theory, fuzzy logic and neural network techniques seem very well suited for typical mining geochemistry applications. The results, obtained from applying the proposed technique to a real scenario, reveals significant improvements, comparing the results obtained from applying multivariate statistical analysis. Computationally, the introduced technique makes possible, without exploration drilling, the distinction between blind mineralisation and zone of dispersed ore mineralisation. The methodology developed in this research study has been verified by testing it on various real-world mining geochemical projects.

1. Introduction

Research on geochemical methods for exploration of ore deposits (Cu, Pb, Zn, Au, W, etc.) dates back to 1930 when the first survey of this kind was carried out by Fersman (1939). Since then, this technique has been greatly modified and improved (Beus and Grigorian, 1977). Solovov (1987, 1990) and Baranov (1987) have considered the factors leading to the technique's acceptance or rejection. Recent work on the theory and application of soil and rock geochemical analysis in exploration have identified some problems, particularly in the area of multivariate anomaly recognition.

For geochemical anomaly separation, various statistical methods have been used (Cheng et al., 1994, 1996) including probability graphs, univariate and multivariate analysis (Govett et al., 1975; Beus and Grigorian, 1977; Solovov and Matveev, 1985; Solovov, 1987, 1990; Grigorian and Ziaii, 1997). The multifractal IDW (Inverse Distance Weighted) and fractal concentration–area (C–A) method (Cheng, 1999; Cheng et al., 2000; Lima et al., 2003) and the element concentration–distance (C–D) (Li et al., 2003) approach were introduced which can be used to assist exploration geologists and geochemists in geochemical data analysis and anomaly separation. It has been applied to the stream sediment geochemical data set (regional exploration). The C–D model and Cheng et al.'s C–A method may complement each other. In the C–D procedure, original element concentration data can be treated directly, and therefore it is unnecessary to process the data with pretreatment of any smoothing procedure, thus enhancing recognition of a geochemical anomaly from background.

Exploration geologists often need to separate anomalies associated with mineralization from background reflecting local and mine scale geological processes. Mining geochemistry is part of Applied Geochemistry, and is based on the utilization of geochemical techniques to increase ore reserves of known mines by assessing the ore potential of deep horizons. Recent experience in the application of mining geochemistry techniques, illustrates their efficiency in discovering blind and weakly eroded ore bodies within areas of active and old mines (including ancient ones). This trend in geochemical exploration is without any doubt very important, because it increases ore reserves and mine revenue (Grigorian, 1992).

Many mining geochemical problems are characterized by being complex, uncertain and ill-defined. Complexity arises due to various reasons such as lack of data, insufficient knowledge, and inherent uncertainty in the system. For example, recognition between blind and false anomalous patterns is a typical scenario of a complex mining system. Several models have been developed in the past to predict geochemical anomalies at mine scale. Most of the models are concerned solely with the identification of geochemical anomalies (IGA). The multivariate anomaly recognition in geochemical

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doi:10.1016/j.gexplo.2008.03.004

exploration is defined here as blind mineralization, outcropping and zone dispersed mineralisation (ZDM).

Geochemical anomalies based on ZDM model might well be similar in intensity to that associated with blind mineralisation. Grigorian (1985, 1992) presented a zonality model to identify blind mineralisation from ZDM. In the active mines, vertical geochemical zonality is the most important peculiarity of primary halos. This pattern is represented by supra-ore geochemical haloes of blind ore bodies. So that, the Zonality method is very important and effective in the search for most promising anomalies.

Lithogeochemical methods are suggested by Solovov (1987), who postulates that this approach, or metallometry, is relatively easy when used, not only for IGA, but also for the quantitative evaluation of ore reserves. An important point that should be considered in the interpretation of secondary geochemical haloes is the erosion level of a mineral deposit since it affects the size and extent of anomalies in soil. This point has been conceptualised by different examples known as model of (a) blind economic mineralization, (b) outcropping economic mineralisation and (c) zone of dispersed mineralisation (Beus and Grigorian, 1977; Ovchinnikov and Grigorian, 1978; Levinson, 1980; Solovov, 1987). Soil anomalies associated with outcropping economic mineralisation would be normally stronger than those associated with blind mineralisation, and they may be erroneously assumed to be more promising than others, unless the erosion levels are taken into account. Soil anomalies based on the ZDM model may well be similar in intensity to those associated with the blind mineralisation. But if they are not properly interpreted, fruitless exploration may be the result. Root zones (ZDM) of some types of ore deposits, typically have a different metal association from the ore zone and leakage (upper) zones, and these associations may be helpful in identifying the relationship of a soil anomaly to mineralisation. Characterizing horizons of erosional surfaces of a steeply dipping ore body and its primary halo in host rocks is a problem with no direct and known solution. To date there are only two generally reliable ways of acquiring knowledge on IGA. These are laboratory measurements, and vertical zonality coefficient interpretation. Laboratory measurement on the cores obtained from the field or sample archives provides precise (assuming adequate equipment) vertical zonality coefficient of values (Beus and Grigorian, 1977; Levinson, 1980). These are used in geochemical simulation studies, as well as any other design and development studies in the field. The other method for IGA determination is a geochemical model of mineralisation in bedrock and soils (Grigorian, 1985).

In this research, a new method for IGA determination was introduced. The proposed methodology, which is based on an artificial neural network, is quite inexpensive compared with the traditional exploration methods. Furthermore, it does not require interruption of production, and provides vertical zonality coefficient values. These values are comparable to those obtained by laboratory measurements on core samples. A feasibility study, based on the proposed method for

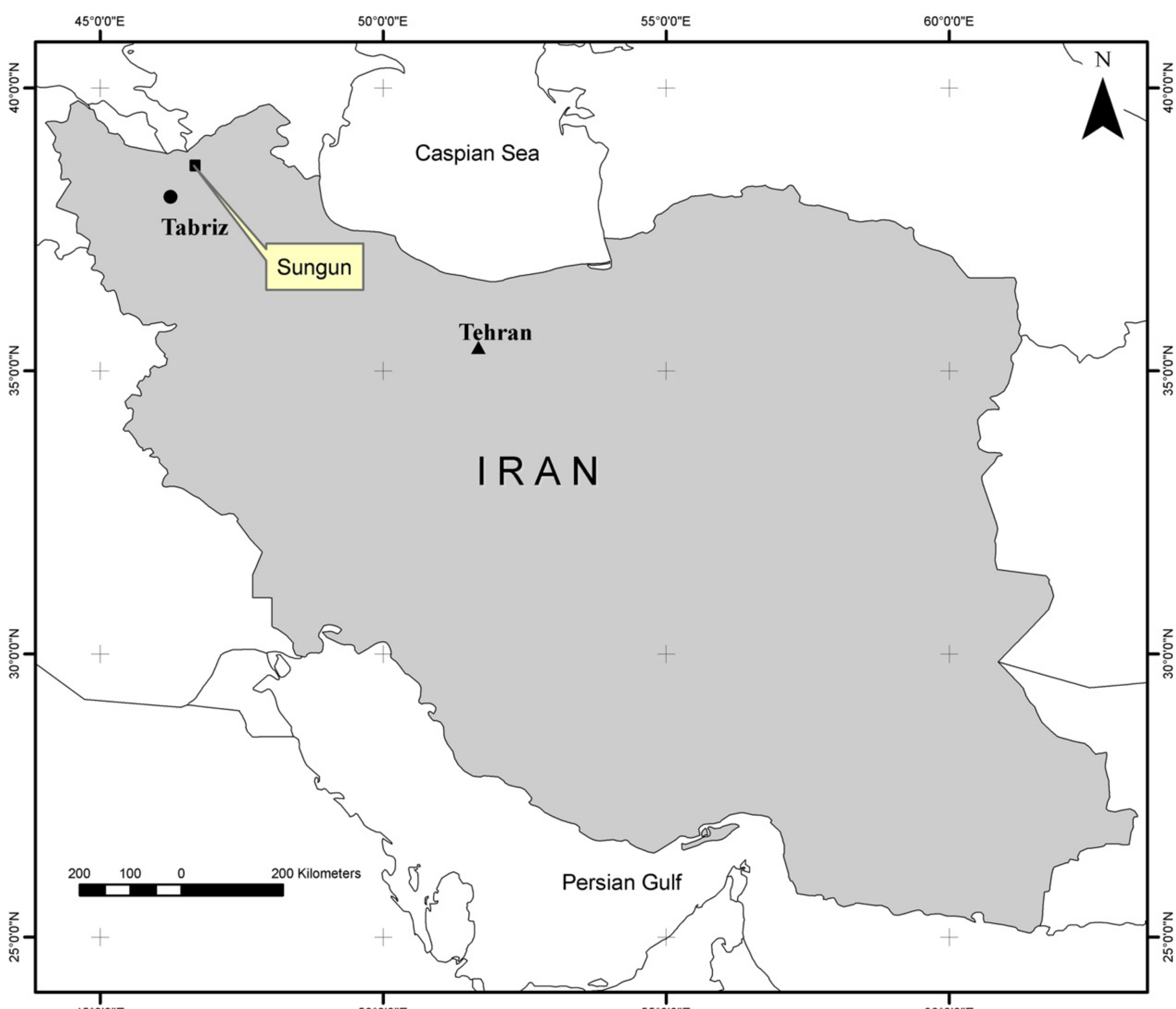

Fig. 1. Location of Sungun–Astamal mineral field in NW Iran.

IGA estimation, shows effective and useful results. It has been demonstrated that in porphyry copper mineralisation, an application of a carefully designed and elaborated neuro-fuzzy model can provide acceptable results.

Traditional Zonality method has played an important role to multivariate anomaly recognition in mining geochemistry. The problem with these methods is demonstrated by the assessment of primary and secondary geochemical data from porphyry copper in NW Iran (Grigorian, 1994; Ziaii, 1996; Ziaii and Ziaei, 2006). This paper, presents the results of the application of the Back Propagation Artificial Neural Network (BP-ANN) with fuzzy c-means (FCM) using the same data. BP-ANN is one of the most popular versions of ANN, and is widely used in geosciences such as remote sensing and geochemical exploration for hydrocarbons (Zhang and Bai, 2002) and hydrology (Dixon, 2005).

This paper is organized in the following sections: first, a general overview of the traditional modeling method adopted in this study is presented; next, the neuro-fuzzy modeling approach is applied to real-world cases within the framework of mining geochemistry and finally, conclusions are given and further research directions are pointed out.

2. Geological setting of study area and previous work

The study area is situated in north-west Iran and 75 km north-west of Ahar (Sungun and Astamal village) (Figs. 1 and 2). Sungun is the largest open-cast copper mine in Iran. It is in the primary stages of extraction. The exploration from 1979 to 1993 confirmed that Sungun reservoir is about 995 million tons with copper grade 0.661% and molybdenum grade 240 ppm. The probable reservoir is about 1700 million tons (Technical report the Iranian Copper Company; Grigorian, 1994; Ziaii, 1996). The Sungun porphyries are of Oligo-Miocene age, and were intruded, as a sub-volcanic complex into Upper Cretaceous carbonate rocks, a series of Eocene arenaceous–argillaceous rocks, and a series of Oligocene dacitic breccias, tuffs and trachy-andesitic lavas. The Sungun porphyry copper deposit is one of two major copper deposits associated with calc-alkaline intrusive rocks in the Caenozoic Sahand–Bazman volcanic belt. It is emplaced at a paleodepth of 2000 m, at temperatures ranging between 670 and 780 °C, and comprising early monzonite/quartz-monzonite and a later diorite/granodiorite phase. The formation of the Astamal porphyry is due to the intrusion of the Astamal pluton, of Oligocene age into Cretaceous limestone. The average composition of this pluton is granodiorite (Bazin and Hubner, 1969; Hezarkhani and Williams-Jones, 1998; Hezarkhani, in press).

Fig. 2 shows Sungun porphyry copper zone, including Sungun 1, Sungun 2, Sungun 3, Astamal area and other copper mineralization. As shown in Fig. 2, the geochemical landscape types in Sungun–Astamal area comprise of two distinct sub-areas. The Northern sub-area is mountainous humid zone, and the Southern area is mountainous humid–semiarid zone. These areas both have cold and snowy winters.

Based on previous studies (Hezarkhani and Williams-Jones, 1998; Hezarkhani, in press), there was no information for Sungun 2 area, Figs. 3 and 4. In 1992, Sungun 2 has been selected for waste deposit. However, the studies based on traditional Zonality method in 1994 recognised Sungun 2 as blind mineralisation. Eventually, by exploring blind anomalies in Sungun 1 and Sungun 2 the whole area became a large deposit. We will explain this matter in more detail in Section 3.2.

3. Proposed approach

In this section, the traditional methods used for IGA estimation are explained first. Then the proposed approach for quantitatively recognition between blind anomalies and false anomalous' patterns

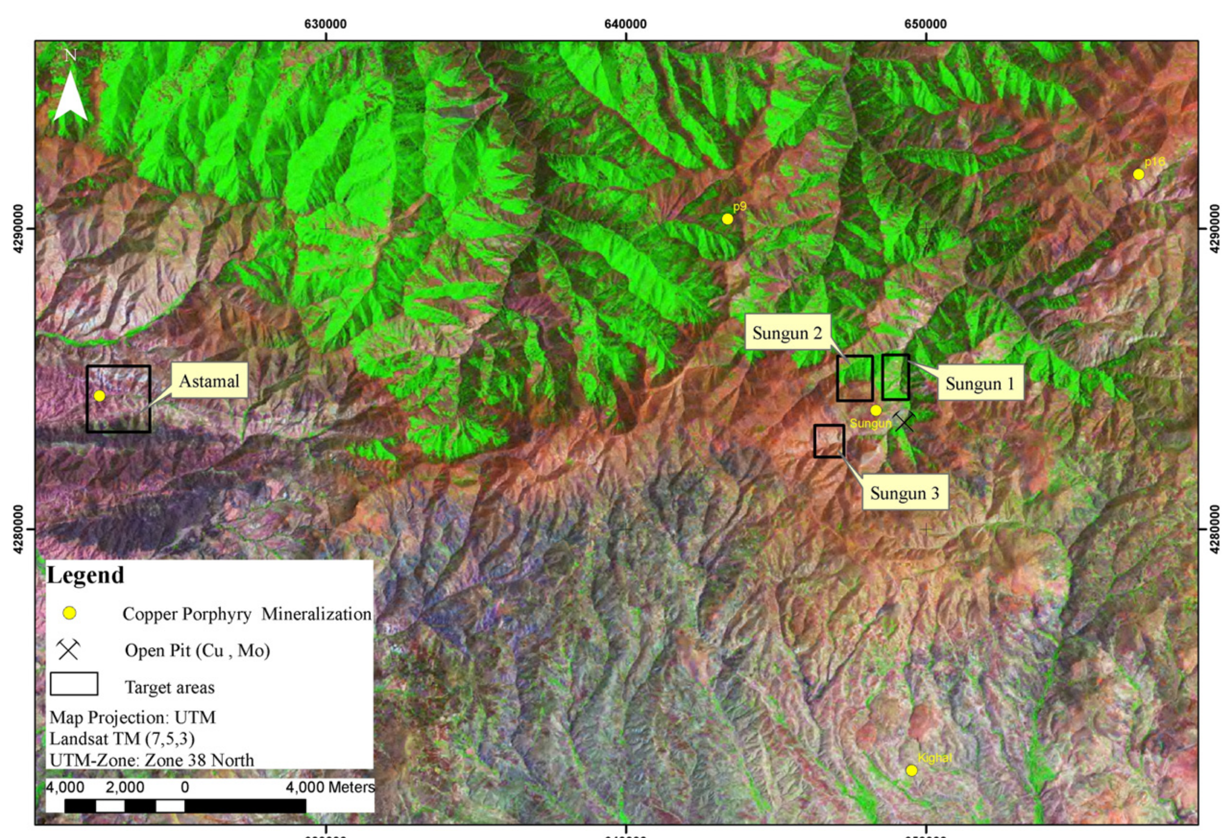

Fig. 2. Geomorphological landscapes of Sungun–Astamal area.

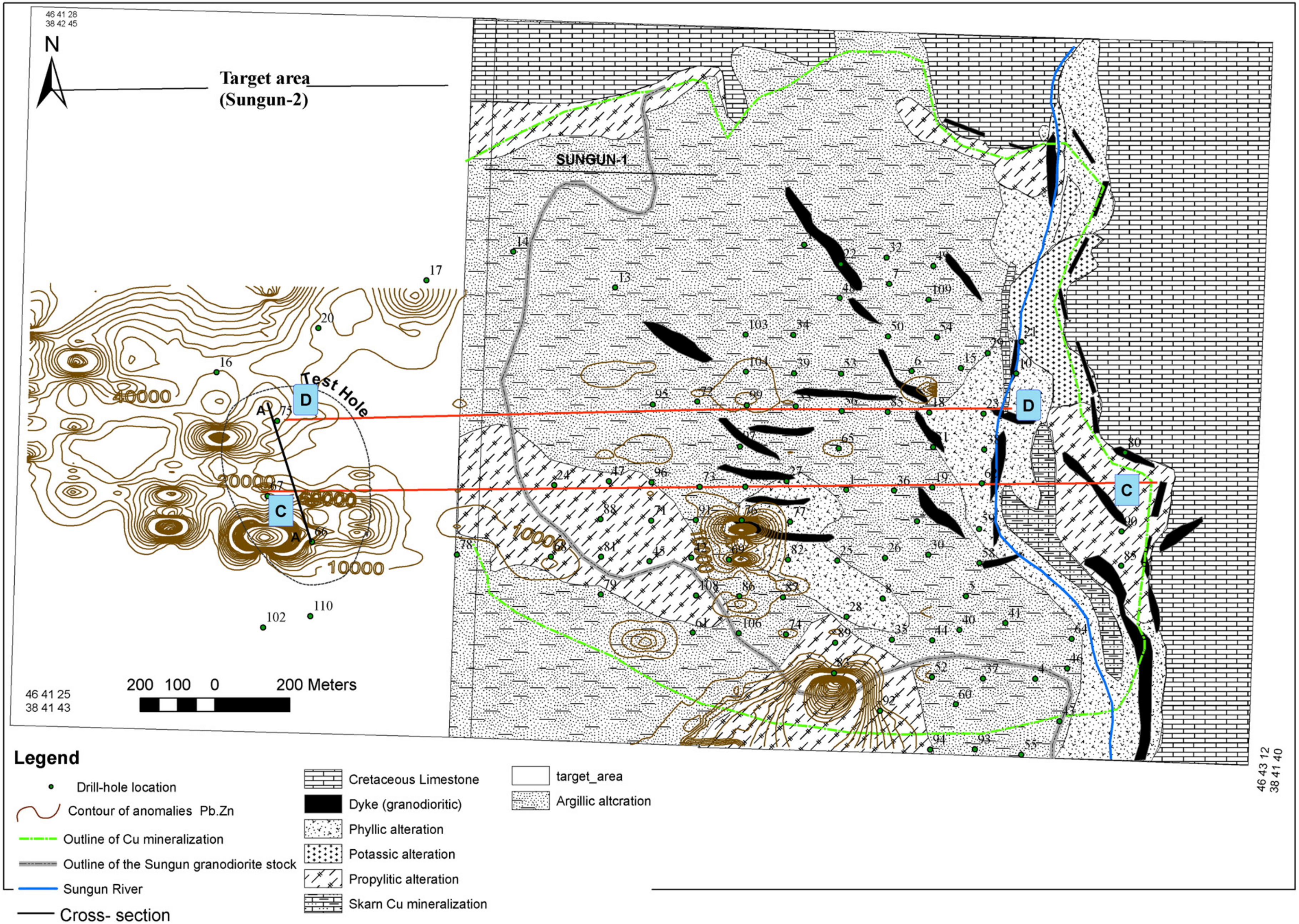

Fig. 3. Geological map of the Sungun prospect showing section C–C and section D–D.

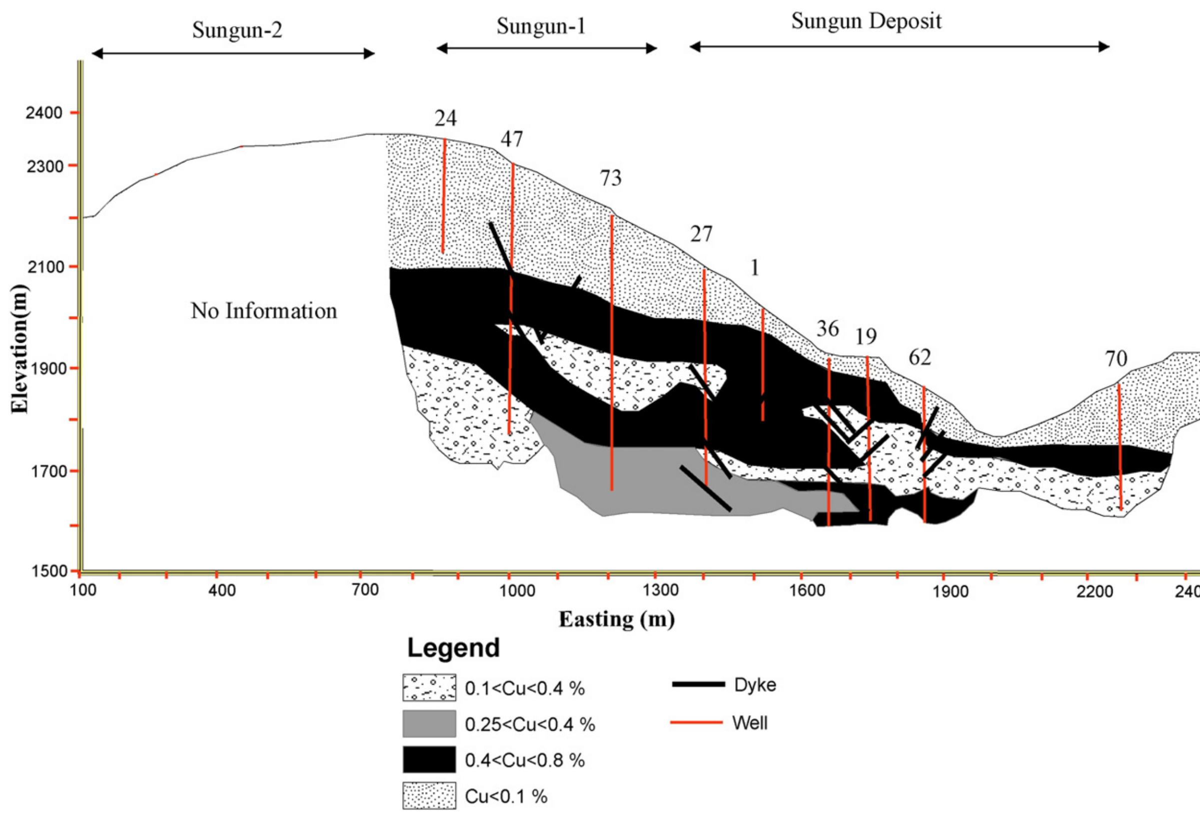

Fig. 4. Cross section of C–C in Sungun area (after Hezarkhani, in press).

(ZDM), using Back Propagation Artificial Neural Networks with fuzzy c-means cluster analysis, are discussed.

3.1. Properties of geochemical data and geochemical anomalies

Secondary and primary geochemical dispersion haloes are sampled and analysed by geologists and geochemists to detect geochemical patterns reflecting the underlying geological structures. The detailed description of the sampling methods and basic statistics of the raw data are explained in Table 1 (Grigorian and Ziaii, 1997).

At the stage, where detailed evaluations of target areas are needed, high-density sampling, especially of bedrock and soil is required. Geometrical characteristics of anomalies such as shape, orientation and spatial variability can be essential in geochemical anomaly recognition. The geological structures corresponding to geochemical characteristics usually show distinct geometric properties. The discrimination of multivariate anomaly recognition in mining geochemistry should take the following aspects of geochemical values into account: (i) soil and rock survey geochemical data, (ii) the frequency distribution of indicator-element contents, (iii) element contents and spatial location of samples, (iv) the geometrical characteristics of anomalous areas (values, location and distances between samples), (v) geochemical landscape conditions of area, and (vi) type of mineralisation and metallogenic zone. The primary data layer of soil was manipulated in a multiplicative zonality map (MZM) to generate secondary data layers of (i) soil indicator-element contents, and (ii) geochemical and mineralogical types. These secondary data layers were used in the neuro-fuzzy models as inputs. Core archive data and locations of the wells were used to validate the model predictions, and not as model inputs.

Table 1
Results of the geochemical dataset in Sungun and Astamal area

Element	Cu (ppm)	Mo (ppm)	Pb (ppm)	Zn (ppm)	Geothermal parameters	Sample size	Area sampling (Km^2km^2)
Sungun area	36	1.48	23.2	65	Background values	2900	5
	42	2.3	31	74	Threshold values		
	6500	500	9100	3900	C_{max}		
Astamal area	39	2.2	19	64	Background values	920	1
	71	4.9	31	94	Threshold values		
	1460	49	1220	3950	C_{max}		
	26	1.2	15	56	Clark Beus and Grigorian, (1977)		

3.2. Traditional Zonality method

The geochemical indices for evaluation of the newly found anomalies are derived through studies of the primary geochemical haloes of typical standard ore deposits. Residual secondary soil haloes in most cases are well correlated in composition and structure with the ore bodies and primary haloes which have generated them. Their successful use is related to the landscape-geochemical conditions in the ore regions.

With reference to traditional models of geochemical anomalies, and features of partially overlapping haloes of hydrothermal ore mineralisation, a universal model for exploring blind mineralisation and determining the degree of denudation of a deposit with the help of models of geochemical anomalies and overlapped haloes, has been summarised. It is based on three criteria: counter zoning (Grigorian, 1985, 1992), natural field of geochemical associations (Baranov, 1987) and metallometry (Solovov, 1987, 1990). Calculating the vertical zonality coefficient from primary geochemical halos has been applied, since the results of the drilling stage of exploration became available. These calculations assume a linear relationship between vertical zonality coefficients and depth of mineralisation responses. It should be mentioned that the linear model was used to emphasise that in

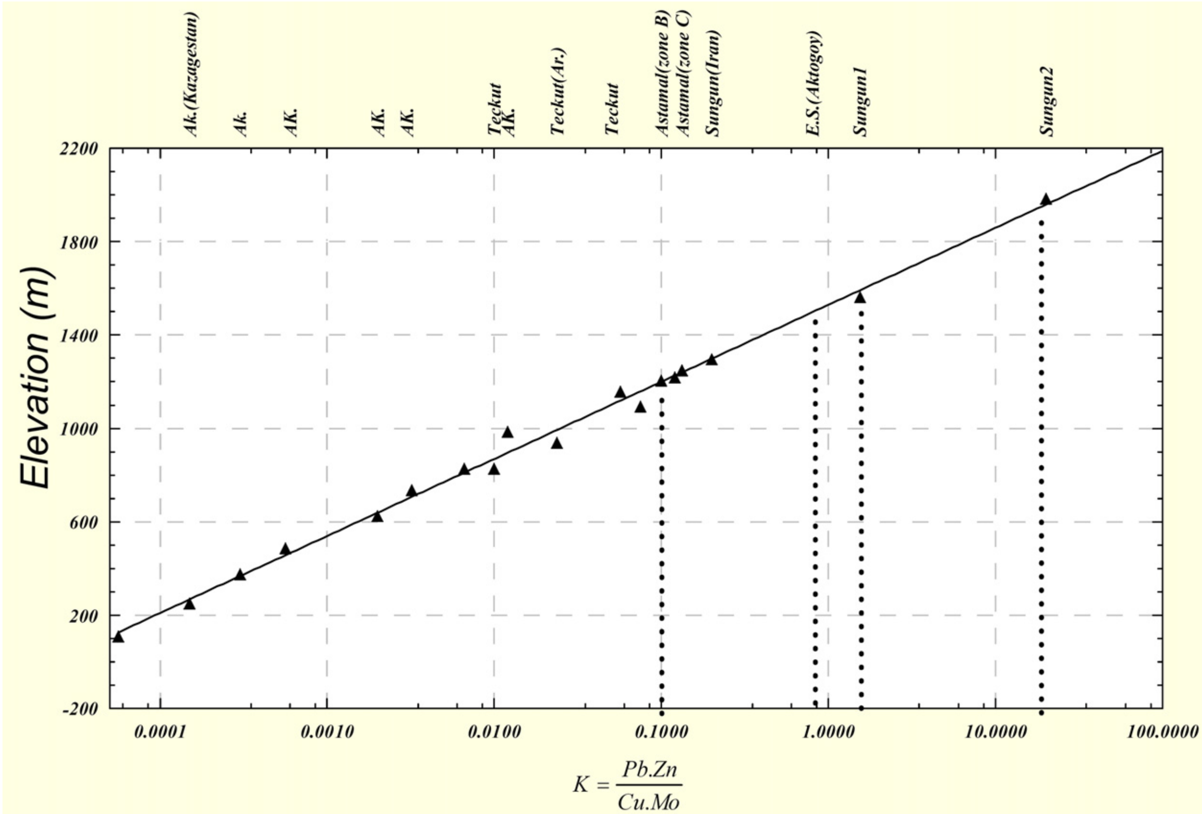

Fig. 5. Geochemical model for porphyry copper deposit.

these calculations it is assumed that a known function (linear or non-linear) is sufficient to model the relationship between these geochemical haloes of parameters and the aforementioned depth mineralisation responses (Grigorian, 1992).

The primary method for IGA determination is a geochemical model of porphyry copper mineralisation in bedrock and soil in the Sungun deposits. Fig. 5, shows a graph of multiplicative vertical geochemical elements distribution pattern in ores and primary halos (geochemical modelling) from three porphyrycopper deposits, where the mineral observation points fall on a straight line. The model shown in Fig. 5 has been constructed for the Aktogy (Kazakhstan), Asarel (Bulgaria) and Tekhut (Armenia) porphyry copper deposits. Despite the considerable differences in their geological setting, the points that are strictly on the straight line, suggest the existence of a quantitatively uniform vertical geochemical zonality in the structure of primary haloes of the deposits (Grigorian, 1994; Ziaii et al., 2006).

It can be deduced from Fig. 5 that such a zonality implies the same levels (upward and downward) of mineral deposits and haloes of a given ore formation. Such haloes of a given ore formation are characterised by strictly defined vertical geochemical zonality coefficient values (Ziaii et al., 2006; Ziaii and Ziaei, 2006). The practical significance of this quantitative uniform geochemical zonality will be evident, if it is considered that it makes possible the evaluation of the level of erosion crosscut by any geochemical anomaly in a given formational type; such as a porphyry copper deposit in this particular case. A gradient characterising the vertical zonality coefficient allows the reliable differentiating among various types of mineralization and their primary haloes: supra-ore, upper-ore, ore, lower-ore, and under-ore (Solovov, 1987, 1990; Grigorian, 1992). The above-described quantitative uniform geochemical zonality of porphyry copper mineralisation based on the results of detailed geochemical modelling of only three deposits, was used in interpretation of geochemical sampling results in the Sungun ore district.

Using the Zonality method resolves the known problems of exploration for blind mineralisation and identification of zones of dispersed ore mineralisation in the field of geochemical exploration. For example, at the Sungun porphyry Cu–Mo ore field the Zonality method of geochemical exploration discovered two types of blind mineralisation (see Figs. 3, 5 and 6, Sungun-2 and Sungun-1) and two ZDM (see Figs. 5 and 8). Two of the anomalies, which were considered, promising for blind mineralisation on the basis of Fig. 5, have been tested. The 66 and 67 drillings (Fig. 7) of both anomalies support the results obtained using traditional Zonality method.

The Zonality method within the south and north Astamal areas (Fig. 8) revealed geochemical anomalies with low grades of Cu and Mo. To assess the possibilities for the occurrence of blind mineralisation, associated with these anomalies, the vertical geochemical zonality multiplicative coefficient values were calculated. Based on calculations on lithogeochemical data and Zonality method (Fig. 5), three ZDM anomalies (A, B, and C in Fig. 8) have been recognised in Astamal area. Two of the ZDM anomalies in north and south Astamal (anomalies B and C, Fig. 8) were tested by drilling two drill-holes on each anomaly.

Based on calculations on lithogeochemical data and Zonality method (Fig. 5), a blind mineralisation anomaly (Fig. 9) has been recognised in Sungun 3 area. Multivariate blind anomaly recognised using Zonality method, based on lithogeochemical data has been shown in Fig. 9.

An anomalous zone related to a single source, may be composed of a series of smaller anomalies (supra-ore and sup-ore anomalies). Discontinuity in Figs. 6, 8 and 9 can be caused by such factors as high ground noise, background noise, analytical errors, less optimum survey grid layout, and uneven geological condition. Before the interpretation of the anomalous patterns, their component anomalies should be reassembled. These components must meet the following criteria:

a) Coexistence of two local maxima for supra-ore and sup-ore. This coexistence implies blind mineralisation.

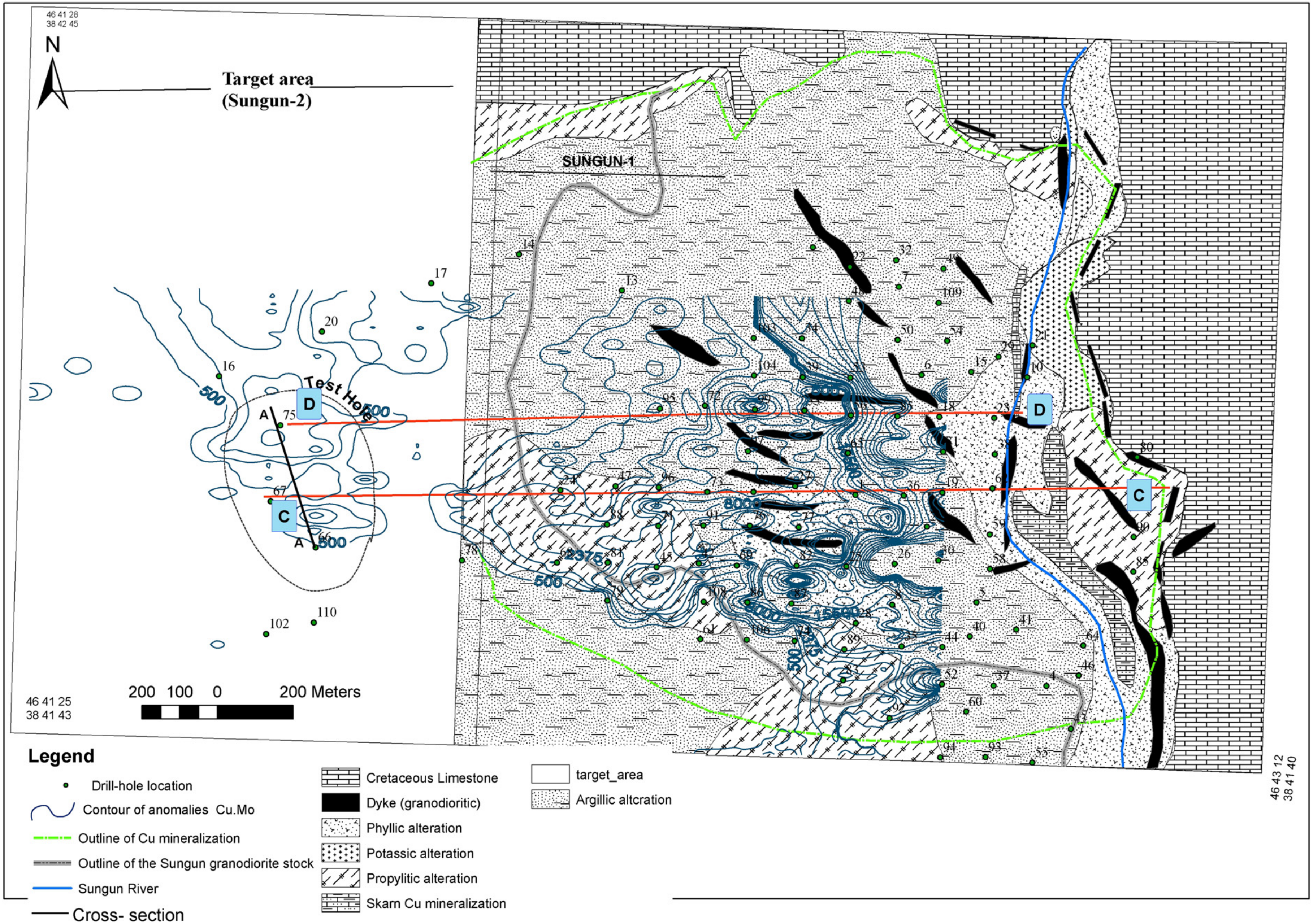

Fig. 6. Multivariate blind anomaly recognised using Zonality method, based on lithogeochemical data in Sungun-1 and Sungun-2 in NW Iran.

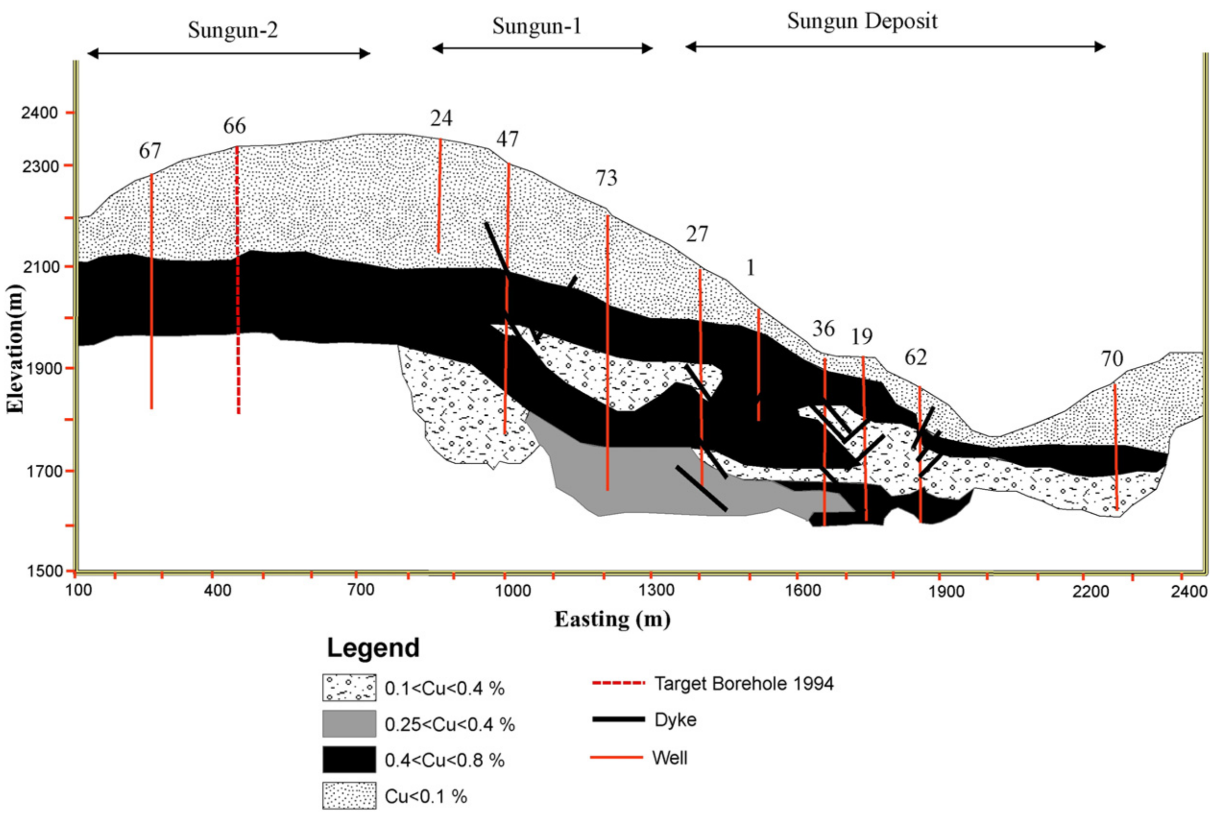

Fig. 7. Cross section of C–C in the Sungun area (see in Fig. 3), bore hole test.

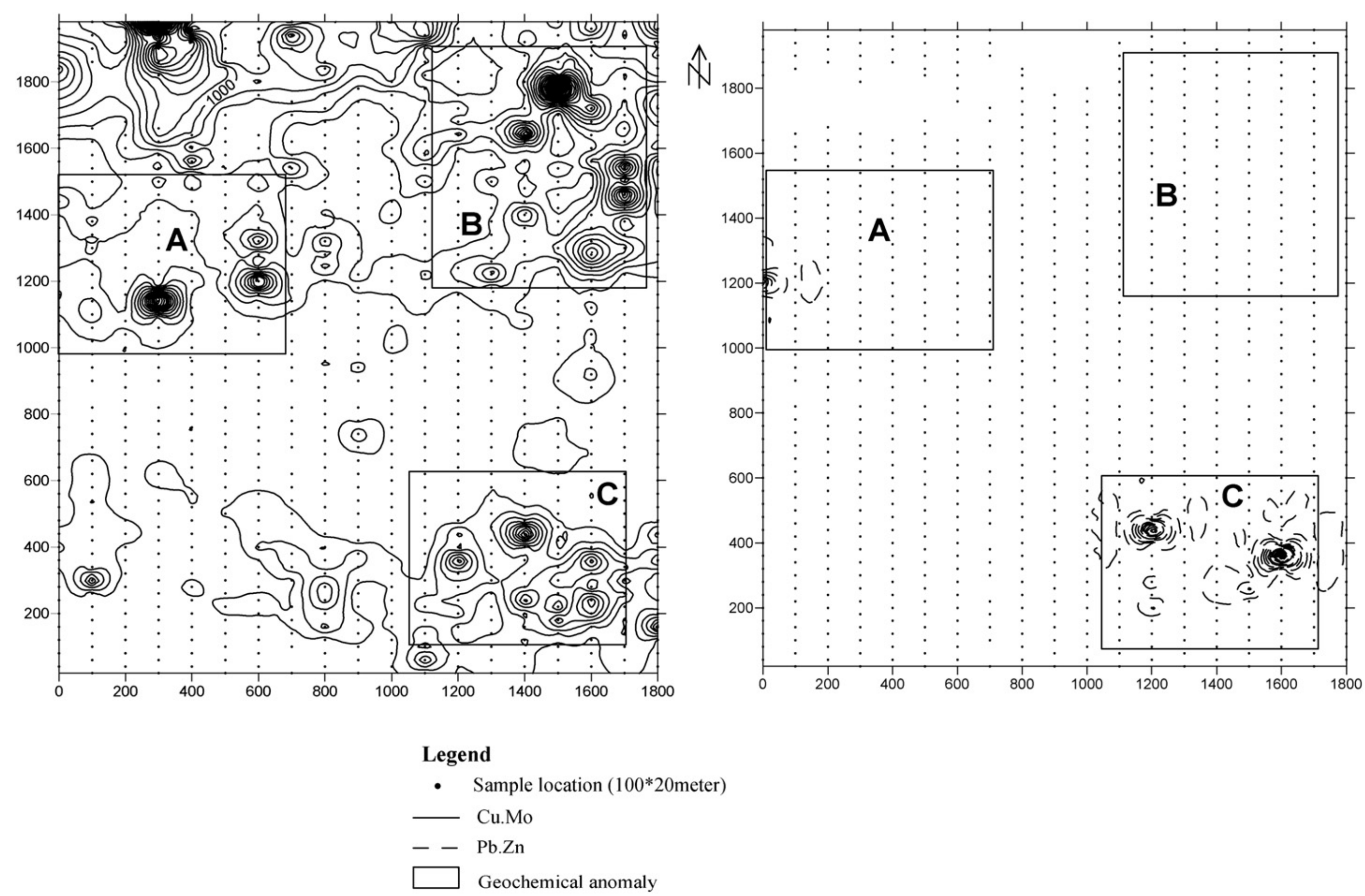

Fig. 8. Multivariate ZDM anomaly recognised using Zonality method, based on lithogeochemical data (100×20 m) in north and south Astamal, NW Iran.

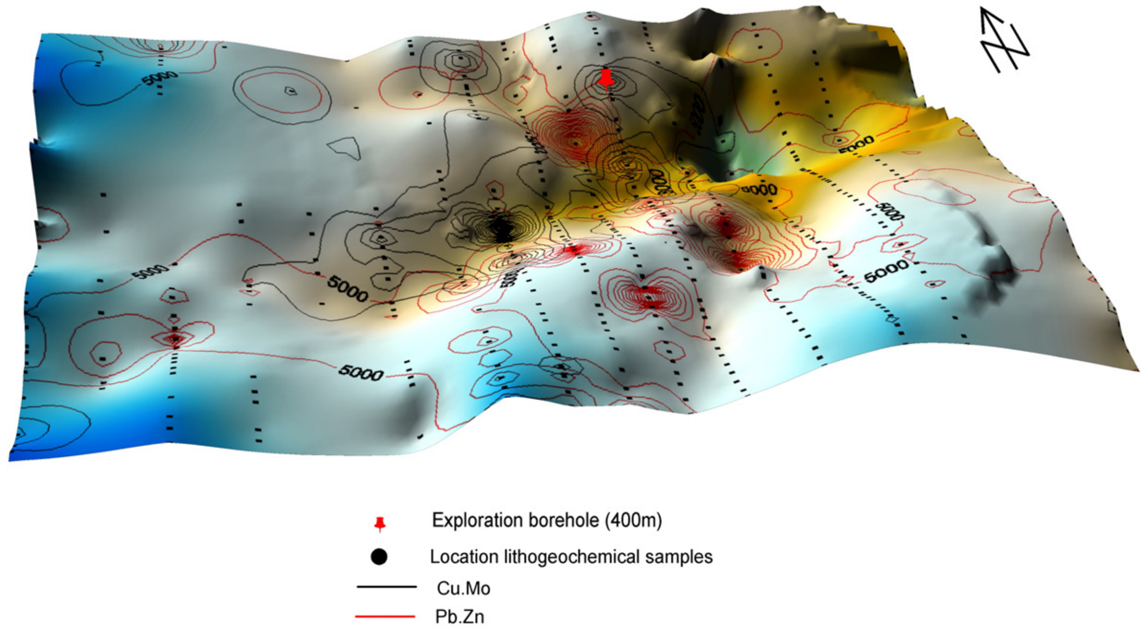

Fig. 9. Multivariate blind anomaly recognised using Zonality method, based on lithogeochemical data (100×20 m) in the Sungun-3, NW Iran.

b) Existence of a single component implies ZDM.
c) Using mean value geochemical indicator elements, outside geochemical anomalies, for eliminating background noise in data interpretation
d) The multiplicative geochemical anomalies and their spatial associations with particular geological features are critical aspects of mineral distribution for exploration and understanding ore geometry.

This combination of anomalies was conducted for the ZDM anomalies. The results are shown in Figs. 6, 8 and 9. The blind mineralisation and ZDM anomalies recognised with Zonality method are more coincident than those with alteration methods (Figs. 4 and 7). This finding demonstrates that traditional zonality method is more powerful than alteration methods.

However, traditional methods of multivariate statistical analyses, used to recognise anomalous mineralisation in mining geochemistry, have several shortcomings: (1) it is difficult to isolate anomalies where the data are not normally distributed; (2) it is hard to separate distinct anomaly populations corresponding to well defined formation mechanisms, while separating anomalies from background; (3) it is not fitting to present illustrations of multivariate anomalies on contour maps and (4) the presentation of polydimensional results obtained from analyses in the form of coefficients of zoning, generalised quantities-multiplicative geochemical indicator ratios for the type of mineralisation, intensity, etc (Simeon, 1981).

3.3. The proposed neuro-fuzzy model

Neuro-fuzzy techniques can be considered as a hybrid discipline between neural networks and fuzzy logic. They not only bring out the best of both techniques, but they also facilitate a comprehensive sensitivity analysis, common with neural network without going into elaborate sensitivity analysis associated with fuzzy logic. Neuro-fuzzy modelling is an approach where the fusion of neural networks and fuzzy logic find their strengths, since these two techniques complement each other. The neuro-fuzzy approaches employ heuristic learning strategies, derived from the domain of neural network theory to support the development of a fuzzy system. It is possible to completely map neural network knowledge to fuzzy logic (Bezdek, 1981; Bezdek et al., 1984). A combination of network and fuzzy logic

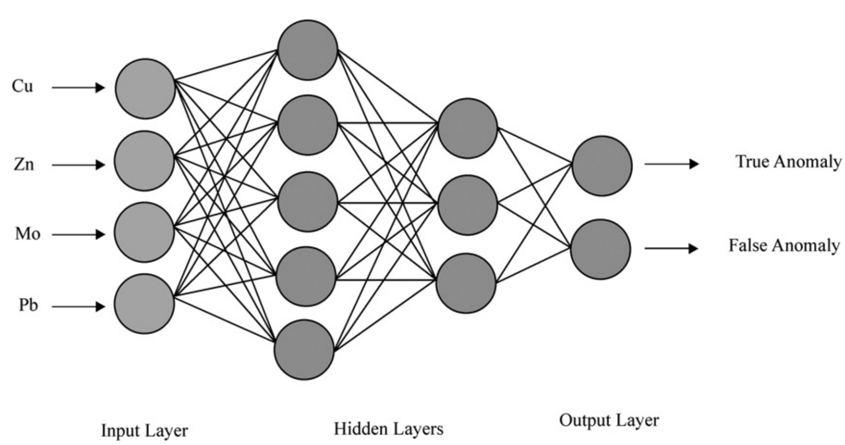

Fig. 10. The proposed neuro-fuzzy network architecture.

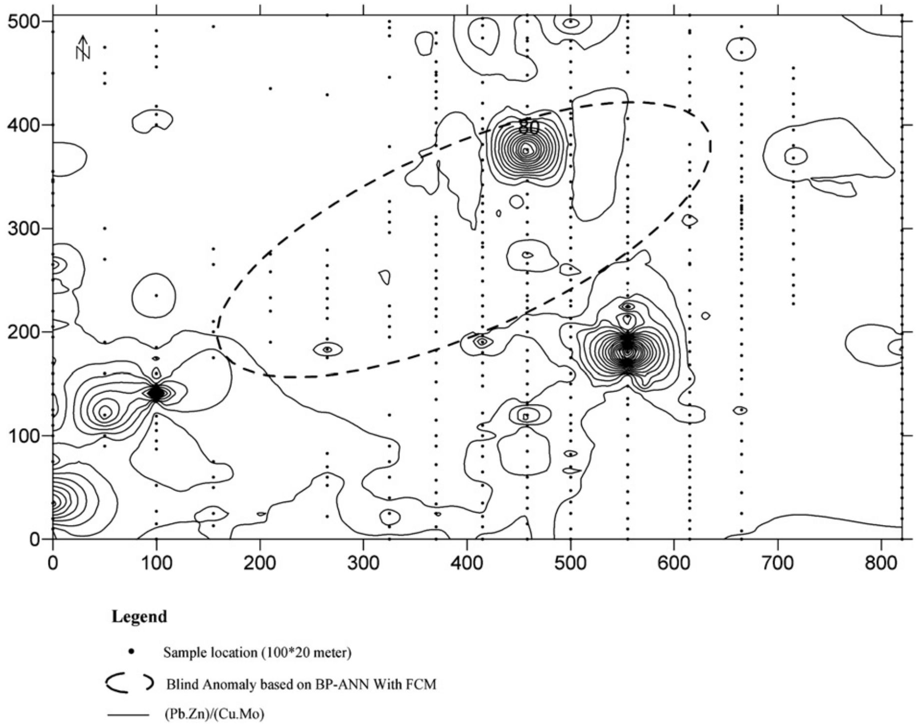

Fig. 11. Multivariate BM anomaly recognised using BM-ANN, based on FCM in Sungun-3 NW Iran.

techniques should help overcome the shortcomings of both techniques (Dixon, 2005). Neuro-fuzzy techniques can learn a system behaviour from a sufficiently large data set, and automatically generate fuzzy rules and fuzzy sets to a pre-specified accuracy level. Also, they are capable of generalisation, thus overcoming the key disadvantages of the fuzzy logic-based approaches, viz., self-learning, inability to meet pre-specified accuracy, and lack of generalisation capability (Bezdek, 1981; Bezdek et al., 1984).

The fuzzy c-means (FCM) algorithm partitions a data set into a predefined c-number of clusters. It is a data clustering technique,

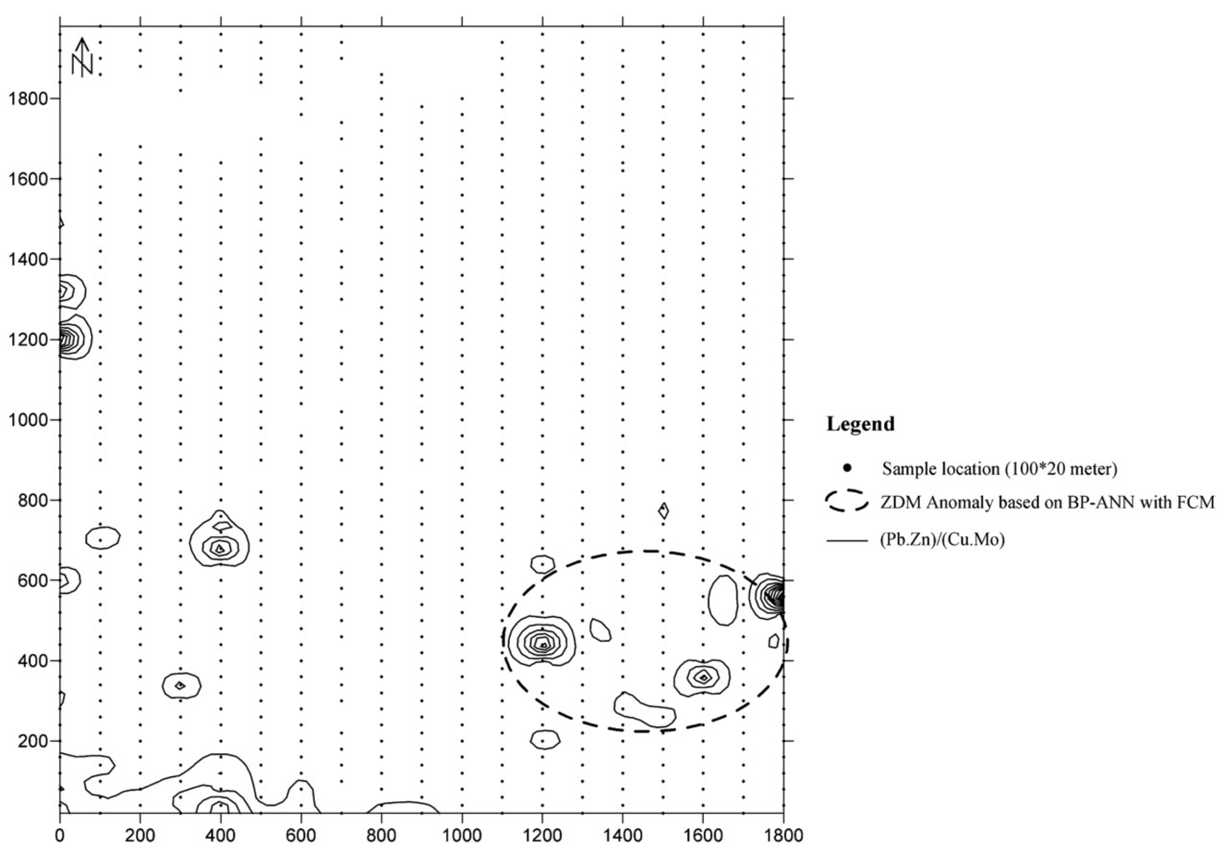

Fig. 12. Multivariate ZDM anomaly recognised using BM-ANN, based on FCM in South Astamal NW Iran.

where each data point belongs to a cluster to some degree that is specified by a membership grade. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. Clustering is a mathematical tool that attempts to discover structures or certain patterns in a data set, where the objects inside each cluster show a certain degree of similarity. A more detailed discussion of FCM with examples is given by Bezdek (1981) and Bezdek et al. (1984). Combined use of FCM and non-linear mapping furnishes a powerful method to find meaningful data grouping within a dataset (Vriend et al., 1988). In this study FCM cluster analysis, and non-linear mapping, are considered as suitable for discerning structures in geochemical datasets.

In this study, a four-layer neuro-fuzzy network has been considered (Fig. 10), where the nodes of the first layer represent the inputs. The activation functions of the second layer nodes and the third layer act as a hide node, so that the input layer provides the fuzzy rule (FCM) base. The output of this layer determines the activation level at the output memberships. As ordinary neural nets, the neuro-fuzzy one learns from a training data set, Tansing functions and rules, by means of a Back Propagation Artificial Neural Network (BP-ANN) algorithm. Tansing is a neural transfer function. Transfer functions calculate a layer's output from its net input.

Use of neuro-fuzzy model requires similar steps as neural networks. Development of a neuro-fuzzy model is comprised of three steps: (a) learning, (b) validation, and (c) application and the entire data sets were divided accordingly. During the learning step the neuro-fuzzy networks were provided with various combinations of data for pattern recognition purposes and the neuro-fuzzy network modified its internal representation by changing the values of its weights to improve the mapping of input to output relationships. During the validation step, the network was given a set of data as new input, and the net mapped the inputs to output relationships based on previously learned patterns without their weights. Once the learning and validation steps were completed, the application data, which were much larger than the learning and validation data sets, were used to generate geochemical exploration blind mineralisation from ZDM.

This approach was established on the basis of geochemical characteristics and origin of the various populations in geochemical data, such as background, blind anomalies and ZDM anomalies (false anomalies).

The topology of the BP-ANN with FCM was optimised using the outputs of the BP-ANN and the correct rate. As shown in Fig. 6, the output of the BP-ANN is in the form of two distinct types of false anomalies (False) and blind mineralisation (True). The application of this method does not need any information related to the statistical distribution of input data. The proposed approach is the quantitative recognition between anomalies of economic and non-economic patterns, using BP-ANN with FCM analysis.

4. Case study

This section explains the lithogeochemical data that have been provided by NICICO (National Iranian Copper Industries Company) from Sungun and Astamal area. The samples have been analysed by emission spectrometry, atomic absorption and other methods for elements Cu, Mo, Pb, Zn, Ag, As and Sb (Table 1). For data from NW Iran (Sungun and Astamal area), the BP-ANN has four nodes in the input layer and has two nodes in the output layer, (Fig. 10). The input consists of Cu, Mo, Pb and Zn.

The background noise has been eliminated by using FCM. This has been shown in Figs. 11 and 12 as the areas inside the broken-line elliptic shapes. The obtained data then will be checked by the trained BP-ANN for discrimination of BM from ZDM. After applying the proposed method (combination of FCM and BP-ANN), Sungun-3 has been recognised BM (Fig. 11), and South Astamal anomaly has been recognised ZDM (Fig. 12). Our findings revealed that the combination method applied in this research is more powerful than the traditional Zonality method.

5. Conclusion

Multivariate anomaly recognition for mining geochemistry has suffered from major problems in recognition and illustration of anomalies on contour maps. Previous work focused only on the separation of anomalies from the background. However, there actually exist at least two distinct anomaly populations in mining geochemistry. Therefore, the traditional Zonality methods cannot correctly separate anomalies from background as the two distinct populations are treated as one single population. As the prospecting methods are different for different anomalous populations, the two distinct anomaly population have to be separated first, which has not been recognised previously. Conventional statistical analysis, which has been used as a traditional Zonality method in geochemical exploration, is time consuming and costly. This is because it lacks geostatistical generalised mechanisms for separating anomalies from background. Therefore, the traditional Zonality methods, on the basis of the previous concept, cannot accomplish the separation.

This study demonstrates that BP-ANN, with FCM, can be applied to multivariate recognition of lithogeochemical anomalies and separation of the two type anomalies (ZDM or false anomaly and BM), even when normality in the data is not met. The FCM cluster analysis produces the training set for BP-ANN and separated background from lithogeochemical anomalies. It has been shown that the resultant output has been significantly improved, compared with the traditional method. The results, obtained by applying the proposed technique to a real scenario, reveals significant improvements, when comparing the results obtained from applying multivariate statistical analysis. Computationally, the introduced technique makes it possible, without exploration drilling, to distinguish between zones of dispersed ore mineralisation (false anomaly) and blind mineralization.

Acknowledgements

The research was funded by the School of Mining, Petroleum and Geophysics at the Shahrood University of Technology. The authors are grateful to S. Grigorian (RAS) for his useful suggestions which helped to improve the Zonality method and the anonymous reviewers for their very constructive and helpful comments on the final manuscript.

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