

Assessment of Ore Grade Estimation Methods for Structurally Controlled Vein Deposits - A Review*

¹C. A. Abuntori, ¹S. Al-Hassan and ¹D. Mireku-Gyimah
¹University of Mines and Technology, Box 237, Tarkwa, Ghana

Abuntori, C. A., Al-Hassan, S. and Mireku-Gyimah, D. (2021), "Assessment of Ore Grade Estimation Methods for Structurally Controlled Vein Deposits – A Review", *Ghana Mining Journal*, Vol. 21, No. 1, pp. 31-44.

Abstract

Resource estimation techniques have upgraded over the past couple of years, thereby improving resource estimates. The classical method of estimation is less used in ore grade estimation than geostatistics (kriging) which proved to provide more accurate estimates by its ability to account for the geology of the deposit and assess error. Geostatistics has therefore been said to be superior over the classical methods of estimation. However, due to the complexity of using geostatistics in resource estimation, its time-consuming nature, the susceptibility to errors due to human interference, the difficulty in applying it to deposits with few data points and the difficulty in using it to estimate complicated deposits paved the way for the application of Artificial Intelligence (AI) techniques to be applied in ore grade estimation. AI techniques have been employed in diverse ore deposit types for the past two decades and have proven to provide comparable or better results than those estimated with kriging. This research aimed to review and compare the most commonly used kriging methods and AI techniques in ore grade estimation of complex structurally controlled vein deposits. The review showed that AI techniques outperformed kriging methods in ore grade estimation of vein deposits.

Keywords: Artificial Intelligence, Neural Networks, Geostatistics, Kriging, Mineral Resource, Grade

1 Introduction

Mineral resource estimates are the basis for undertaking a mining project; so, it is necessary to get the estimates of a deposit accurate enough to prevent erroneous financial expectations. Geostatistics is the most popular technique for resource estimation. Its efficiency and supremacy have been demonstrated in several studies (Samanta *et al.*, 2005a). However, in recent times, due to Neural Network (NN) advancements, it has emerged as an alternative ore grade estimation method. The principle of operation of these NN techniques is quite different. Geostatistical techniques, such as kriging, operate under the assumption of stationarity (Pan *et al.*, 1993; Yamamoto, 2000; Chatterjee *et al.*, 2010) and produce linear models based on local neighbourhood structures (Tahmasebi and Hezarkhani, 2010a). On the other hand, NN is a nonlinear estimator, making it robust with noisy data as in the case of vein deposits. The presence of multiple lithological types and the nature of the formation can cause kriging to underperform in predicting the distribution of ore grade (Chatterjee *et al.*, 2006). In the past decade, the efforts to minimise the effects of assumptions using geostatistics resulted in various researchers (Rizzo and Dougherty, 1994; Samanta *et al.*, 2005b; Samanta *et al.*, 2004a; 2004b; Dowd and Saraq, 1994; Koike *et al.*, 2001; 2002; Matías *et al.*, 2004; Chatterjee *et al.*, 2006) developing different approaches in geostatistics and NNs for ore grade estimation. The popularity of NNs in ore grade estimation stems from its flexibility and ability to include nonlinear relationships between input and output data (Bishop, 1995; Chatterjee *et al.*, 2006). This paper aimed to review the most commonly used

kriging methods and AI techniques used to estimate ore grade in vein deposits, compare the results, and highlight the better estimation technique.

1.1 Overview of Vein Deposits

Vein deposits, also known as 'lodes' or 'reefs', can be defined as fractures or fissures filled with solidified minerals and are mostly known as tabular domains dipping at an angle from the horizontal (Dominy *et al.*, 1999b). These type of deposits are known to be about 3 m wide (Dominy *et al.*, 1999a; 1999b). Most narrow auriferous veins possess visible gold erratically disseminated within the orebody which can easily be extracted by gravity separation. According to Dominy *et al.* (1999b), faults or shear zones are known to host veins occurring in structures/fractures (either single or multiple structures). Since the structure of vein deposits is highly related to geometry, the geometrical properties such as dip, strike, and width continuously vary throughout the deposit's entire length, leading to its complex nature (Dominy *et al.*, 1999b). Narrow vein deposits generally exhibit the deposition of both high-grade and low-grade values disseminated within the deposit. Due to this, the grade distribution typically display a positively skewed distribution characterised by many low-grade values and randomly distributed few high-grade values (Dominy *et al.*, 1999b; Roy, 2000). Also, the mineralised zone may not be distributed throughout the entire vein but can be restricted to a particular structure which sometimes exhibits multi-stage deposition.

1.2 Classical and Distance Weighting Methods

The classical and distance weighting techniques are methods used in ore grade estimation. The classical methods include the polygonal, triangular and cross-sectional estimation methods while the types of distance weighting techniques include the Inverse Distance Weighting (IDW) method (Sinclair and Blackwell, 2004). Resource geologists employ these techniques to estimate grade values which are then assigned to blocks within the deposit, resulting in possible in erroneous estimates.

The classical methods of grade estimation were mostly used before the age of computers, and are still used to quickly estimate resources regardless of their shortcoming.

The polygonal method of estimation uses drill hole data where the average grade of the surrounding drill holes is assigned to the polygon's entire area. This method of estimation is also mostly applied to simple-to-moderate geometry orebodies with minimal grade variability.

The triangular estimation method builds each triangle from three adjacent drill holes with the triangular area, receiving three average grades. The mineral reserves are determined by each triangle's area, together with its weighted thickness and grade. The mean grade for each triangle, G_T , is given by Equation (1) (Sinclair and Blackwell, 2004):

$$G_T = \frac{\sum(G_i \times VT_i)}{\sum(VT_i)} \quad (1)$$

where: G_i = grade of each vertex; and VT_i = Vertical thickness at each sample location forming the triangular block. The main problems associated with this estimation method are that: anisotropies are not often considered using the same corner point grade and thickness for more than one-grade calculation eventually influences the grade estimates.

The cross-sectional method of grade estimation is executed by delineating ore zones, through drawing perimeters based on cut-off grade, in sections which are either regularly or irregularly spaced along the entire orebody. The influence areas are assigned grades by expanding the drill hole samples halfway to adjacent drill holes and sections (Kapageridis, 1999; Sinclair and Blackwell, 2004). This estimation method can be applied to deposits with sharp and relatively smooth contacts such as tabular deposits. As a result, the cross-sectional technique is known to depict strong geological controls. However, it is affected by the irregularity of ore-waste contact; hence, the unknown quantity of waste

included can cause overestimation of grade. In estimating the resources using the cross-sectional method, the mean grade of each section is computed by weighting the sample grades by their lengths. With this, the global mean grade is achieved as the weighted mean grade of the sections by volume or tonnage, as shown in Equations (2) and (3) (Ilham and Matrani, 2020). The global tonnage can also be calculated using Equation (3).

$$G_G = \frac{\sum(G_{si} \times T_{si})}{\sum(T_{si})} \quad (2)$$

$$T_g = \sum(T_{si}) \quad (3)$$

where: T_G = Global tonnage; G_G = Global mean grade; T_{si} = Tonnage of section, si ; and G_{si} = Mean grade of material in section, s_i .

Thus, the classical methods are known to estimate the resources in wider and uniform deposits as inferred from the previous sections. Hence, due to the narrow nature of vein deposits and random grade distribution, applying classical methods in the grade estimation process produce biased estimates resulting in overestimation or underestimation.

Resource estimation conducted using the IDW method is achieved by assigning a linear combination of grades of the surrounding samples to a block or a point. With this method, samples' properties are assumed to be more identical once they are taken closer to each other than when they are taken farther apart. The general, IDW, is given by Equation (4) (Rossi and Deutsch, 2014):

$$Z_B = \frac{\sum\left(Z_i \times \frac{1}{d_i^n}\right)}{\sum\left(\frac{1}{d_i^n}\right)} \quad (4)$$

where Z_B is the estimated variable of the block (of grade, thickness or accumulation); Z_i is the value of the sample at location i ; d_i is the separation distance from point i to the point of reference; and n is the power index (a positive integer). The value of "n" is chosen arbitrarily, but is often based on the type of deposit being dealt with. Hence, the power index is directly related to the degree of continuity of the grade variation. A continuous grade variation indicates that two close samples tend to give more identical information about the deposits' characteristics than two samples taken farther apart. Therefore, a high power index is used to minimise the influence of distant samples. The power index, n , can take values from 0 to infinity; but the commonest value is 2. According to Kapageridis (1999), the IDW is mostly applied to deposits with

reasonable geometry with low to high-grade variability.

The distance weighting technique is an improvement of the classical methods. This method is best applied in uniform orebodies. However, when used in estimating the resources in vein deposits, the results obtained are not optimum due to the complex grade distribution. On the contrary, estimates obtained are less biased as compared to the classical methods. Also, to improve estimates, errors must be accounted for, assessed and minimised by making adjustments in the estimation of grade. Hence, once the resource is estimated using IDW or a classical method, the errors are evaluated to check the accuracy of the estimates.

1.3 Geostatistics

Geostatistics began in the early 1960s by Matheron and Krige for mineral resource estimation. The concept of geostatistics is a combination of various sciences such as geology, statistics, and probability theory (Kapageridis, 1999). This concept works best when the samples within an orebody are spatially correlated. The various sciences that makeup geostatistics make the estimation process extremely complicated in its application to resource estimation for any given amount of data. Also, the theory of regionalised variables forms the basis of geostatistical methodology. According to Journel and Huijbregts (1978), the spatial distribution of several measurable quantities can be characterised for every mineralised zone. In a geostatistical analysis, the orebody's geological nature is first of all modelled after which the structures characterising the spatial variability of ore grades using variograms are examined (Kapageridis, 1999; Dominy *et al.*, 2002; Dutta *et al.*, 2010). This semi-variogram is computed using Equation (5) (Bohling, 2005).

$$\gamma(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [Z(u_{\alpha} + h) - Z(u_{\alpha})]^2 \quad (5)$$

where u is the vector of coordinates; $z(u)$ is the variable under consideration as a function of spatial location; h is the vector between the two; $N(h)$ is the number of pairs found at distance h apart; and $Z(u + h)$ is the value of a second variable at location h units from u .

Once the semi-variogram is modelled, grade interpolation and estimation are done using kriging, a geostatistical method (Kapageridis, 1999; Sinclair and Deraisme, 1974). Kriging is applied based on grade continuity as depicted in the variograms and the sample positions. By this, it calculates the optimal weights by assessing the minimum estimation variance obtained from the generated

variograms. Therefore, Kriging is a step-up of the IDW method since it is based not only on distance but also on spatial variability and possible anisotropy.

From the analysis made, the clear definition of an orebody's geological controls allows for more representative grade estimation. However, variogram analysis can easily be done for massive and uniform orebodies compared to structurally controlled deposits due to multiple structures at the boundaries of the mineralised zone. In estimating the resources in a vein deposit, the significant errors that have the greatest impact occurs during the definition of the orebody's geometry (Deutsh, 1989; Dominy *et al.*, 1999a), which is paramount in resource estimation (Roy, 2000).

Although geostatistics is claimed to be the best in resource estimation (Rossi and Deutsch, 2014), it has a limitation since it is unable to effectively tackle the clear definition of geological controls of structurally controlled deposits (Sinclair and Deraisme, 1974; Dominy *et al.*, 1997; Roy, 2000; Dominy *et al.*, 2004). Due to this, in the research of Dominy *et al.* (1999a), the authors stated that in estimating the resources in narrow veins, classical or geostatistical methods could be used; however, classical techniques are often used due to the difficulty in applying geostatistical methods (Roy, 2000). In applying the non-geostatistical methods in resource estimation of narrow veins, outlier values can cause overestimation of the resources whereas outlier values in geostatistics can result in distorted variograms due to high nugget effect, which renders the variograms useless for onward estimation (Roy, 2000; Dominy *et al.*, 1999a). The outlier values encountered are 'cut' to a specific value (Deutsh, 1989; Dominy *et al.*, 1999a; Fytas *et al.*, 1990) which is often determined through the experience of the resource estimator (Dominy *et al.*, 1999a; Fytas *et al.*, 1990; Roy, 2000). Some ways of cutting the values are highlighted by Roy (2000). The main aim of cutting the high-grade values is to alter the samples' distribution to prevent overestimating the mean grade values. On the contrary, these manipulations can result in estimation errors, leading to underestimating grades and overestimating material quantity (Fytas *et al.*, 1990).

Ordinary Kriging (OK), the fundamental kriging method, faces the same challenges of overestimating skewed distributions as in non-geostatistical resource estimation methods. Due to this challenge, several kriging methods have been developed over the years to fix this problem; but this has resulted in more time consuming, complicated and overly expensive resource estimation processes than OK (Roy, 2000). These kriging methods include indicator kriging (Fytas *et al.*, 1990; Journel, 1983;

Journel, 1984; Kwa and Mousset-Jones, 1986; Roditis, 1986), disjunctive kriging (Yates *et al.*, 1986; Ortiz *et al.*, 2005), multigaussian kriging (Verly, 1983), probability kriging (Journel, 1985; Verly and Sullivan, 1985), lognormal kriging (Armstrong and Boufassa, 1988), outlier restricted kriging (Arik, 1992) and cokriging (Pan *et al.*, 1993)

In summary, geostatistics applies a local neighbourhood search to develop a local fitting model. The values obtained at nearby sample points are used to predict the value at an unknown point using a linear combination of weights (Samanta *et al.*, 2004a). The weight assigned to a sample point depends on the spatial correlation structure of the deposit obtained by the variogram model of the data; and as such is not ideal in estimating the resources in vein deposits due to the heterogeneous grade distribution.

1.3.1 Structural Analysis

Structural analysis is the most crucial step as the parameters obtained from the variogram analysis determine if geostatistics can estimate the mineral of interest. In conducting structural analysis, a semi-variogram must be modelled using the sample data to check the orebody's continuity and structure under consideration. The results obtained from the semi-variogram model serve as a quantitative summary of all available structural information for resource estimation. The data obtained represent the regionalised variables distributed throughout a given space (Journel and Huijbregts, 1978; Roy, 2000). These variables possess two main characteristics: local randomness (indicating random variation) and the structural pattern characterised by a function (Roy, 2000). However, under strict stationarity, the geospatial structure must remain the same under translation (Journel and Huijbregts, 1978; Roy, 2000). Hence, according to Roy (2000), the expected mean should remain constant in all directions; however, quasi-stationarity is perceived to exist in practice where the spatial structure is presumed to be unchanging for a given distance.

The sample data obtained from structurally controlled deposits usually contain multiple outlier values. Therefore structural analysis in geostatistics, which generally results in distorted variograms due to nugget effect renders the variograms useless (Roy, 2000; Dominy *et al.*, 1999a) for onward estimation.

1.3.2 Grade Estimation

The information required for the estimation process itself is embodied in the semi-variogram model. This variogram is used to analyse the variability of

the grade throughout a given space. Kriging is employed for the grade estimation process using the variogram parameters. In kriging, each sample is assigned a weight which is then linearly combined to minimise the estimated variance. Doing so minimises the anticipated error between the estimated grade and the actual grade (Roy, 2000). The estimation variance obtained is essential in reviewing the accuracy of the estimates.

In vein deposits, the actual grade estimation becomes problematic as the variogram values required to undertake the grade estimation activity are rendered confusing. This is where the resource estimator relies on experience by making assumptions about the variogram parameters to estimate the grade values.

1.3.3 Geostatistics for Vein Deposit Estimation

Daya (2012) estimated the resources in the Iran Choghart north hydrothermal iron ore deposit made up of veinlets. The statistical analysis of the data showed a gaussian distribution which was transformed into a gaussian anamorphosis transformation. The empirical variograms generated for structural analysis indicated that at multiple directions, no geometric anisotropy occurred since the same range of sills were obtained. This deposit was estimated using OK to estimate the grade of iron in the deposit. OK was again applied by Daya (2015) to estimate the resources of a vein-type copper deposit in Iran that virtually had the same structural properties as the iron ore deposit.

Roy (2000) estimated the Poura deposit, which consists of steeply dipping gold-silver mineralised quartz veins with an average thickness of 2 m. Semi-variograms and OK were used for estimating grade and thickness. The researcher, however, developed a computer block kriging program called Krige2D for his kriging calculations. There was no correlation between grade and vein thickness, grade and depth, or grade and distance along strike in the statistical analysis. The grade and vein thickness indicated lognormality with the histogram of the thickness showing spikes. The variograms generated demonstrated a pure nugget effect. The researcher explained that OK mostly overestimates the grade of deposits when the distribution is skewed. However, according to Dominy *et al.* (1997), Dominy *et al.* (1999a) and Fytas *et al.* (1990), once the coefficient of variation is less than one, OK works well. Despite this condition, the researcher went ahead to use OK even though the grade distribution was skewed, and the coefficient of variation of the grade was 1.1. Krige2D estimated the resources quite well since the undiluted resources decreased by 21%; the mean value of confidence increased with the average grade decreasing by 9%.

Dominy *et al.* (1997; 1999a; 1999b) assessed the challenges in resource estimation of vein deposits leading to the poor applicability of geostatistics in ore grade estimation.

Sinclair and Deraysme (1974) applied OK in estimating the mineral resource of the Eagle Copper Vein deposit in British Columbia. The deposit was a sulphide mineralised quartz vein with an average thickness of 1.2 m, consisting mainly of chalcopyrite, some amounts of pyrite and covellite. The main parameters estimated were accumulation and vein thickness which gave lognormal distributions signifying skewed distributions. The data obtained were from three parallel drifts, which resulted in the inability to check for anisotropy, thereby causing the authors to assume the deposit to be isotropic. Hence, the variograms generated for the horizontal direction that appeared to be sinuous were assumed to be similar to the other directions. Therefore, there was a kriging problem in the remaining two dimensions that the authors resolved by calculating the actual distances between paired samples throughout the vein's vertical and horizontal positions to obtain an “unfolded” or “flattened” vein deposit. Two main structures were identified for vein thickness and accumulation. Therefore, the variograms quantified the geometric form of the deposit. The local grade estimation results obtained using OK were not good (relative standard deviation for the grade was 21.9%) but at the time of the research, it was the best possible result based on the available data.

1.4 Artificial Intelligence

John McCarthy was the first to propose the concept of Artificial Intelligence (AI) in 1956 at the Dartmouth Conference (McCarthy *et al.*, 2006). However, the ability to make machines think and learn just like humans was introduced by Alan Turing (Muggleton, 2014). Artificial Neural Network (ANN) is a branch of AI. ANN is a combination of processing systems modelled after the brain's neural structure using artificial systems to form a computational structure (Dutta *et al.*, 2010; Diepen *et al.*, 2017). These scientists, therefore, laid the foundation for AI to become what it is today. AI can, thus, be explained as the branch of computer science that creates intelligent machines to operate as humans. AI aims at developing intelligent machines by programming computers to possess traits such as knowledge, learning, reasoning, perception, problem-solving and the ability to manipulate and move objects.

The recent developments in computing have paved the way for AI techniques like Machine Learning Algorithms (MLA) that operate non-linearly in

estimating resources (Li *et al.*, 2010; Dutta *et al.*, 2010). These AI techniques can learn the causal functional relationship existing between available data samples (Dutta *et al.*, 2010). The input data is trained to give the AI technique the ability to learn relationships between input and output patterns for adequate prediction of values such as grade values unsampled areas (Dutta *et al.*, 2010).

Before data is analysed in an ANN, it is vital to adequately divide the data for analysis and prediction, unlike geostatistics, that does not require data segmentation. The data obtained is usually divided into training, testing and validation datasets. The training data sets are used to train the network resulting in its ability to learn.

The basic ANN structure (Fig. 1) has three layers which is made up of the input, hidden and the output; however, multiple hidden layers are accepted in the ANN structure. External input parameters are received into the network through the input layer at each input neuron $X_j = (X_1, X_2, X_3, \dots, X_m)^T$ which are assigned specific weights w_{kj} and a bias b_i . The input values are then transformed into weighted inputs and are transferred to the hidden layer. A mathematical nonlinear activation function in the hidden layer is then used to decide if the data in the input neuron should be activated or not after which the transformed data is given out through the output neuron. The input of the output layer is obtained from the output of the hidden layer. An activation function is used to transform the input of the hidden layer to the output layer which produces the final network output y_k .

Each connection is given its corresponding weight, and each signal moving along the linkage is multiplied by a connection weight (Mahmoudabadi *et al.*, 2008). Within the ANN structure, there are mathematical algorithms that ensure the processing and predictability of the network. Some of these parameters and algorithms are the weights, biases and activation functions.

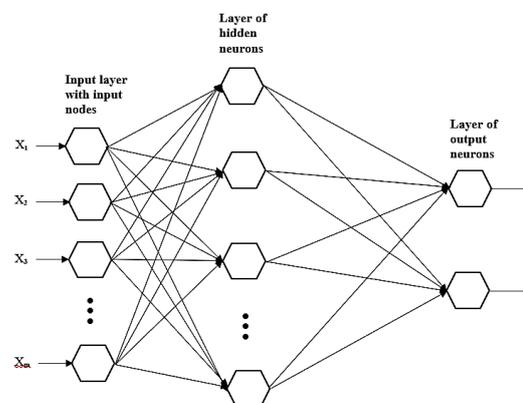


Fig. 1 Basic Structure of a Layered ANN

The artificial neuron is the basic unit of a typical ANN that serves as the ANN structure's processing element. Fig. 2 shows the artificial representation of the mammalian neuron (cell body, axon, synapses, and dendrites). The artificial neuron simply calculates the weighted sum of input, adds a bias and decides if it should be “fired” or not.

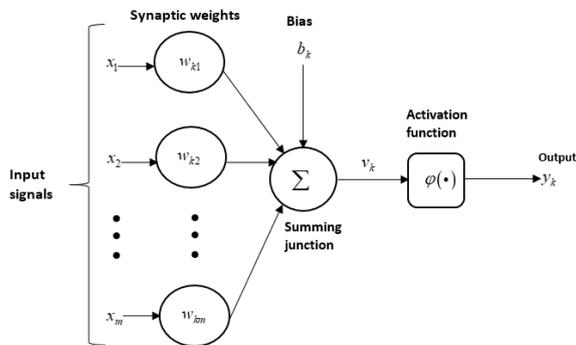


Fig. 2 Basic Structure of an Artificial Neuron

The summing junction represents the cell body with a bias, b_k for increasing or decreasing the output, activation function indicates the axon, the synaptic weights (w_{kj}) for the synapses, and the input signals (x_i) signifies the dendrites. Input signals (x_i) are sent from the user or software to the synaptic weights (w_{kj}) to be multiplied where k encompasses a set of synapses recognised by weight w . After the weighted input signals have been multiplied, they are summed up at the summing junction by a linear combiner, expressed in Equation (6) (Kapageridis, 1999).

$$u_k = \sum_{j=1}^m w_{kj} x_j \quad (6)$$

The bias b_k is then applied to the u_k to give input (v_k) to the activation function $\varphi(\cdot)$. The activation function then limits the amplitude range of the neuron's output to a finite value (Kapageridis, 1999), expressed mathematically in Equation (7).

$$y_k = \varphi(v_k) \quad (7)$$

AI techniques have been applied in estimating resources due to their computational advancements, learning capability, and ability to make no assumptions and user-friendliness. Some AI techniques have effectively been employed in ore grade estimation using few sample data points (Wu and Zhou, 1993; Li *et al.*, 2010; Al-Alawi and Tawo, 1998; Kapageridis and Denby, 1998a; Kapageridis and Denby, 1998b; Kapageridis, 2002; Samanta *et al.*, 2005b; Mahmoudabadi *et al.*, 2008; Tahmasebi and Hezarkhani, 2010b; Zhang *et al.*, 2013). Others on the other hand encountered some estimation problems at the structural control areas of

heterogeneous and complicated deposits (Al-Alawi and Tawo, 1998).

1.4.1 Artificial Intelligence for Resource Estimation

AI techniques have been applied in ore grade estimation by several researchers (Dowd and Saraq, 1994; Singer and Kouda, 1996; Kapageridis and Denby, 1998b; Koike *et al.*, 2001; Koike and Matsuda, 2003; Samanta *et al.*, 2005a; Samanta *et al.*, 2004a) due to their ability to handle nonlinear data trends. A summary of the AI techniques employed in resource estimation is presented in Table 1. Most of the AI techniques used in ore grade estimation are ANNs as observed in Table 1.

1.5 Merged ANN and Geostatistics for Resource Estimation

In some cases, ANN has been merged with geostatistics in mineral resource estimation. Jalloh *et al.* (2016) developed a technique called the artificial neural network model with geostatistics (ANNMG) for 3D geological block modelling in a mineral sand deposit. They trained, tested and validated the BPNN from exploratory drill holes. The validated model was used to generalise the mineral grades at known and unknown locations. This was then combined with geostatistics to develop the 3D model. The model performed well as the regression analysis showed that the actual and predicted grade values were quite close. Also, Dimitrakopoulos (1990;1993) researched AI techniques that deal with qualitative information and the expert knowledge of geostatisticians, resulting in his proposition of artificially intelligent geostatistics. The AI model allowed the geostatistician to assess, discover and combine pieces of relevant rational knowledge and information in a given region of analysis. For the variogram calculations, the expert system had three major parts. The first part of the system was the knowledge-based and inference engine (feedforward AI network). The second was the intelligent interface to the user. While the third part was the geostatistical estimation process, which included the variogram modelling and grade estimation using kriging. The expert model was applied in uncertainty estimation of acid deposition and porosity characterisation in a 3D petroleum reservoir. The results obtained from the expert system and conventional geostatistical methods produced comparable results.

Table 1 Summary AI Techniques Applied in Mineral Resource Estimation

Author(s)	Deposit	Technique
Wu and Zhou (1993)	Gold deposit	Multilayer Feedforward Neural Network (MLFNN)
Al-Alawi and Tawo (1998)	Bauxite deposit	Backpropagation Neural Network (BPNN)
Kapageridis (1999), Kapageridis <i>et al.</i> (1999a; 1999b; 2000)	Iron ore	Modular neural Network (Radial Basis Function (RBF) with Stuttgart Neural Network Simulator (SNNS) and Multilayer Perceptron (MLP)) integrated into VULCAN software
Kapageridis and Denby (1998a; 1998b)	Iron ore	Modular neural network made of Radial Basis Function (RBF) and Multilayer Perceptron (MLP)
Matías <i>et al.</i> (2004)	Slate	MLP, Regularisation Networks (RN) and RBFNN
Samanta <i>et al.</i> (2004b; 2005b)	Gold	Kohonen Neural Network (KNN), MLFNN and Single Layer Feedforward Neural Network (SLFN) with the Adaboost algorithm, BPNN
Chatterjee <i>et al.</i> (2006; 2010)	Limestone, Lead-Zinc	ANN, SVM with k-means clustering NN ensemble and GA
Samanta <i>et al.</i> (2005a)	Bauxite	MLFNN-Genetic Algorithm (GA)
Mahmoudabadi <i>et al.</i> (2008)	Iron ore	BPNN-GA
Samanta and Bandopadhyay (2009)	Gold	RBFNN with cooperative evolutionary algorithm
Badel <i>et al.</i> (2010)	Iron ore	MLFNN with k-means clustering and conjugate gradient descent
Li <i>et al.</i> 2010	Copper	Wavelet Neural Network (WNN)
Guo (2010)	Iron ore	MLFNN with X-Ray Diffraction (XRD)
Dutta <i>et al.</i> (2006; 2010)	Alumina and Silica, Gold	ANN-GA, Support Vector Regression (SVR) and BPNN
Tahmasebi and Hezarkhani (2010a; 2011)	Iron ore	ANN- Fuzzy Logic (ANN-FL) and ANN-GA, MLFNN
Tahmasebi and Hezarkhani (2010b; 2012)	Porphyry copper	Adaptive Neuro-Fuzzy Inference System (ANFIS), GA-ANFIS and GA-Coactive ANFIS (CANFIS)
Gholamnejad <i>et al.</i> (2012), Maleki <i>et al.</i> (2014) and Nezamolhossein <i>et al.</i> (2017)	Iron ore	BPNN and Support Vector Machine (SVM), MLFNN
Granek (2016)	Copper-gold deposit	SVM and Convolutional Neural Network (CNN)
Zhang <i>et al.</i> (2013)	Sulphide deposit	Weighted Least Square Support Vector Regression (WLS-SVR)
Li <i>et al.</i> (2013)	Copper deposit	Self-adaptive Learning Particle Swarm Optimisation-SVR (SLPSO-SVR)
Jafrasteh and Fathianpour (2017)	Phosphate deposit	BPNN, Local Linear Radial Basis Function with Skewed activation function (LLRBF-SG), Simultaneous Perturbation Artificial Bee Colony algorithm (SPABC)
Jafrasteh <i>et al.</i> (2018)	Porphyry copper	MLP, Random Forest (RF) and Gaussian Process (GP)
Singh <i>et al.</i> (2018)	Iron ore	Recurrent Neural Network (RNN)
Jahangiri <i>et al.</i> (2018)	Porphyry copper	MLFNN with Gustafson-Kessel (GK) clustering algorithm
Manna <i>et al.</i> (2018)	Copper ore	MLFNN with ADAM optimiser

2 Resources and Methods Used

2.1 Resources Used

About 76 papers spanning 40 years from 1974 to 2018, were used in this review. These resources were obtained mainly from Google/Google Scholar search engine. Keywords like ore grade estimation using AI techniques, mineral resource estimation using AI techniques, ore grade estimation of vein deposits, mineral resource estimation of vein deposits, ore grade estimation of vein deposits using geostatistics, mineral resource estimation of vein deposits using geostatistics, ore grade estimation of vein deposits using kriging, mineral resource estimation of vein deposits using kriging, mineral resource estimation of vein deposits using classical methods of estimation, mineral resource estimation of vein deposits using IDW method, ore grade estimation of vein deposits using IDW, ore grade estimation of vein deposits using AI techniques and mineral resource estimation of vein deposits using AI techniques were used. Over 30 journals and conference proceedings provided papers regarding this research. Some of these journals include Elsevier, Springer, International Journal of Mining Science and Technology, CIM Bulletin, Mathematical Geology, Neurocomputing and Exploration and Mining Geology.

Based on the resources used in this study, Zhang *et al.* (2013) clearly indicated the structural and veinlike nature of the sulphide deposit employed in their study. The other researchers (Table 1) on the other hand did not clearly indicate the vein like nature of the deposit. However, some studies showed that their AI techniques were applied in heterogeneous data sets (Samanta *et al.*, 2004a; Jafrasteh *et al.*, 2018; Gholamnejad *et al.*, 2012; Tahmasebi and Hezarkhani, 2011; Badel *et al.*, 2010; Tahmasebi and Hezarkhani, 2010b; Mahmoudabadi *et al.*, 2008; Singh *et al.*, 2018; Samanta *et al.*, 2005b; Kapageridis, 2002; Wu and Zhou, 1993; Li *et al.*, 2010; Kapageridis and Denby, 1998a; Al-Alawi and Tawo, 1998) which are common in vein deposits.

2.2 Methods Used

To determine the performance of AI techniques in ore grade estimation, the AI techniques were assessed by a thorough review of the papers obtained during this study. As such, six categories of the performance of AI techniques were obtained to capture the studies that fell under those categories. The categories used were: AI outperforming kriging and other techniques, kriging outperforming AI, Kriging and AI performing equally, AI performing well without being compared with other techniques, AI not performing well without being compared

with other techniques, and merged AI and geostatistics. The Percentage Performance (PP) of AI techniques under each category is expressed in Equation (8).

$$PP = \frac{\text{Sum of Papers under each Category}}{\text{Total No. of Papers used in Review}} \times 100\% \quad (8)$$

3 Results and Discussion

For the application of AI techniques for ore grade estimation, 47 papers were reviewed to determine AI's performance, which is summarised in Tables 2 and 3.

Table 2 Summary of the Performance of AI in Ore Grade Estimation

AI Outperforming Kriging or other Techniques	AI Performing Well without Comparing with other Techniques	AI and Kriging Performing Equally Well
Chatterjee <i>et al.</i> (2010)	Tahmasebi and Hezarkhani (2010a)	Dutta <i>et al.</i> (2006)
Samanta <i>et al.</i> (2004a)	Gholamnejad <i>et al.</i> (2012)	Samanta <i>et al.</i> (2005a)
Jafrasteh <i>et al.</i> (2018)	Jafrasteh and Fathianpour (2017)	Samanta <i>et al.</i> (2004b)
Tahmasebi and Hezarkhani (2011)	Manna <i>et al.</i> (2018)	Kapageridis and Denby (1998a)
Kapageridis and Denby (1998b)	Li <i>et al.</i> (2010)	Kapageridis <i>et al.</i> (2000)
Wu and Zhou (1993)	Kapageridis <i>et al.</i> (1999a)	Nezamolhossein <i>et al.</i> (2017)
Kapageridis (2002)	Guo (2010)	
Mahmoudabadi <i>et al.</i> (2008)	Kapageridis <i>et al.</i> (1999b)	
Chatterjee <i>et al.</i> (2006)	Tahmasebi and Hezarkhani (2012)	
Al-Alawi and Tawo (1998)	Singer and Kouda (1996)	
Dutta <i>et al.</i> (2010)		
Tahmasebi and Hezarkhani (2010b)		
Zhang <i>et al.</i> (2013)		
Li <i>et al.</i> (2013)		
Koike and Matsuda (2003)		
Koike <i>et al.</i> (2002)		
Samanta and Bandopadhyay (2009)		

Table 3 Summary of the Performance of AI in Ore Grade Estimation

Merged AI and geostatistics	Kriging outperforming AI	AI not performing well without comparing with other techniques
Jalloh <i>et al.</i> (2016)	Singh <i>et al.</i> (2018)	Samanta <i>et al.</i> (2005b)
Dimitrakopoulos (1993)	Badel <i>et al.</i> (2010)	Maleki <i>et al.</i> (2014)
Dimitrakopoulos (1990)	Matías <i>et al.</i> (2004)	Granek (2016)
Koike <i>et al.</i> (2001)		Jahangiri <i>et al.</i> (2018)
Rizzo and Dougherty (1994)		
Dowd and Saraq (1994)		

Table 2 summarises the various researches where AI outperformed kriging and other techniques, AI performing well without comparison with other methods and AI and kriging performing equally well. Kriging outperforming AI, AI not performing well and merged AI and geostatistical techniques for ore grade estimation are summarised in Table 3.

In determining the PP of the AI techniques of each category, Equation (8) was employed. Hence, 36% of the data indicated that AI outperformed kriging and other methods. AI performed well 21% of the time without being compared with other techniques. AI and kriging performed equally well 15% of the time. 13% of the research merged AI with geostatistics ore grade estimation. Kriging outperformed AI 6% of the time. A performance chart of the review is shown in Fig. 3.

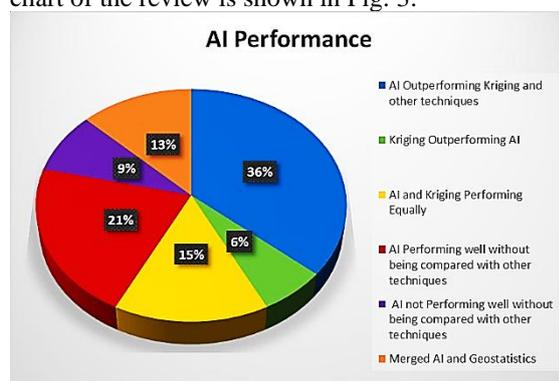


Fig. 3 Performance of AI for Ore Grade Estimation

Based on the study, AI techniques go beyond algorithmic programming and works exceptionally well for nonlinear input-output mapping (Samanta *et al.*, 2004a). In ore grade estimation, NN uses the

spatial coordinates as input parameters that incorporate the spatial relationships with the output, grade. In some cases, the lithology is used as an input (Chatterjee *et al.*, 2010). The interrelationships within the input and output variables are obtained by neurons which are a group of processing units (Gholamnejad *et al.*, 2012). The interconnected spatial relationship of the inputs and output is obtained through a series of weighting functions. The weights are then altered during the training process to guarantee that the outputs are close to the actual grade value. During the training process, the network learns, which gives it the ability to produce good results from the rest of the data that was not used during the training process (Samanta *et al.*, 2004a).

4 Conclusions and Recommendation

4.1 Conclusions

The process of applying geostatistics in ore grade estimation involves data preprocessing, structural analysis and grade prediction. This makes the application of geostatistics in resource estimation lengthy and time-consuming. Nonetheless, geostatistics and ANNs (Table 1) are currently the two dominant techniques used for reserve estimation as observed in Tables 2 and 3. One technique's superiority over the other for ore grade estimation has not been fully established, as revealed by various researchers (Samanta *et al.*, 2004a; Samanta *et al.*, 2005a; Dutta *et al.*, 2006; Kapageridis *et al.*, 2000). Nevertheless, the mode of operation of these two techniques works under different frameworks. Geostatistical methods are linear models based on a local neighbourhood structure and work under the assumption of stationarity work. AI techniques on the other hand, are nonlinear estimators, robust for noisy and extreme data values which should therefore perform better in vein deposits due to the presence of multiple outliers. Therefore, AI techniques naturally perform better when there is a nonlinear spatial trend in the data values, which violates stationarity's assumption in the kriging technique.

It is quite problematic using geostatistics to estimate the resources of structurally controlled deposits since the variograms obtained are complicated and sometimes rendered useless. This causes the resource estimator to rely on experience and assumptions to get the variogram parameters used for the grade estimation itself. The effects of assumptions, the complex nature of deposits and the attempt to improve OK to satisfy conditions of non-stationarity, has resulted in more complicated kriging techniques that are time-consuming (Tahmasebi and Hezarkhani, 2012; Li *et al.*, 2010). Hence, applying geostatistical methods for resource

estimation becomes problematic when stationarity conditions are not satisfied (Nezamolhosseini *et al.*, 2017). AI techniques handle both stationary and non-stationary data points. They perform exceptionally better in non-stationary conditions, making it a viable alternative in resource estimation while reducing processing time. AI also has the ability to learn patterns to give optimum results.

4.2 Recommendation

Due to the complex nature of structurally controlled vein deposits, it is vital that AI techniques be applied in estimating the resources in such deposits. AI techniques such as ANN are designed to handle non-stationary values and handle sample data with a high nugget effect. These techniques make little to no assumptions, can learn patterns and are less time-consuming. They also give comparable results with kriging with far less data and mostly outperform kriging in resource estimation.

Acknowledgement

This research was funded and supported by the Ghana National Petroleum Corporation through the GNPC Professorial Chair of the Mining Engineering Department in the University of Mines and Technology.

References

- Al-Alawi, S. M. and Tawo, E. E. (1998), "Application of Artificial Neural Networks in Mineral Resource Evaluation", *Journal of King Saud University-Engineering Sciences*, Vol.10, No.1, pp. 127-138.
- Arik, A. (1992), "Outlier Restricted Kriging: A new Kriging Algorithm for Handling of Outlier High Grade Data in Ore Reserve Estimation", *In Proceedings of the 23rd International Symposium on the Application of Computers and Operations Research in the Minerals Industry*, Society of Mining Engineers, Littleton, Colorado pp. 181–187.
- Armstrong, M. and Boufassa, A. (1988), "Comparing the Robustness of Ordinary Kriging and Lognormal Kriging: Outlier Resistance", *Mathematical Geology*, Vol. 20, No. 4, pp. 447–457.
- Badel, M., Angorani, S. and Shariat, M. (2010), "The Application of Median Indicator Kriging and Neural Network in Modeling Mixed Population in an Iron Ore Deposit", *Computers and Geosciences*, Vol. 37, No. 4, pp. 530-540.
- Bishop, C. M. (1995), *Artificial Neural Networks for Pattern Recognition*, Clarendon Press, Birmingham, UK, 498 pp.
- Bohling, G. (2005), "Introduction to Geostatistics and Variogram Analysis", *Kansas Geological Survey*, Vol. 1, pp.1-20.
- Chatterjee, S., Bhattacharjee, B. S. and Pal, S. K. (2006), "Ore Grade Estimation of a Limestone Deposit in India using an Artificial Neural Network", *Applied GIS*, Vol. 2, No. 1, pp. 1–20.
- Chatterjee, S., Bandopadhyay, S. and Machuca, D. (2010), "Ore Grade Prediction using a Genetic Algorithm and Clustering Based Ensemble Neural Network Model", *Mathematical Geosciences*, Vol. 42, No. 3, pp. 309–326.
- Daya, A. A. (2015), "Ordinary kriging for the Estimation of Vein Type Copper Deposit: A case study of the Chelkureh, Iran", *Journal of Mining and Metallurgy A: Mining*, Vol. 51, No.1, pp. 1–14.
- Daya, A. A. (2012), "Reserve Estimation of Central Part of Choghart North Anomaly Iron Ore Deposit through Ordinary Kriging Method", *International Journal of Mining Science and Technology*, Vol. 22, No. 4, pp. 573–577.
- Deutsh, C. (1989), "Mineral Inventory Estimation in Vein Type Gold Deposits: Case Study on Eastmain Deposit", *CIM Bulletin*, Vol. 82, No. 930, pp. 62–67.
- Diepen, G., Sloot tot Everlo, T. and Bouazzaoui, H. (2017), "Part 2: Artificial Intelligence Techniques Explained", <https://www2-deloitte.com>, Accessed: January 8, 2020.
- Dimitrakopoulos, R. (1990), "Towards Intelligent Systems for Geostatistical Ore Reserve Estimation", *International Journal of Surface Mining and Reclamation and Environment*, Vol. 4, No. 1, pp. 37–41.
- Dimitrakopoulos, R. (1993), "Artificially Intelligent Geostatistics: A framework Accommodating Qualitative Knowledge-Information", *Mathematical Geology*, Vol. 25, No.3, pp. 261-279.
- Dominy, S. C., Annels, A. E., Camm, G. S., Wheeler, P. and Barr, S. P. (1999a), "Geology in the Resource and Reserve Estimation of Narrow Vein Deposits", *Exploration and Mining Geology*, Vol. 6, No. 4, pp. 317-333.
- Dominy, S. C., Annels, A. E., Camm, G. S., Cuffley, B. W. and Hodkinson, I. P. (1999b), "Resource Evaluation of Narrow Gold-Bearing Veins: Problems and Methods of Grade Estimation", *Transactions of the Institution of Mining and Metallurgy (Section A)*, 108, pp. A52-A69.
- Dominy, S. C., Camm, G. S. and Phelps, R. F. G. (1997), "Narrow vein mining-A challenge to the Operator", *Mine Planning and Equipment Selection*, Vol. 97, pp. 125-132.
- Dominy, S. C., Noppé, M. A. and Annels, A. E. (2004), "Errors and Uncertainty in Mineral Resource and Ore Reserve Estimation: The Importance of Getting it Right", *Exploration and Mining Geology*, Vol. 11, No. 1-4., pp. 77–98.
- Dominy, S. C., Stephenson, P. R. and Annels, A. E. (2002), "Classification and Reporting of Mineral Resources for High-Nugget Effect Gold Vein

- Deposits", *Exploration and Mining Geology*, Vol. 10, No. 3, pp. 215–233.
- Dowd, P. A. I. and Saraq, C. I. (1994), "A Neural Network Approach to Geostatistical Simulation", *Mathematical Geology*, Vol. 26, No. 4, pp. 491–503.
- Dutta, S., Misra, D., Ganguli, B., Samanta, B. and Bandopadhyay, S. (2006), "A Hybrid Ensemble Model of Kriging and Neural Network for Ore Grade Estimation", *International Journal of Mining, Reclamation and Environment*, Vol. 20, No. 1, pp. 33–45.
- Dutta, S., Bandopadhyay, S., Ganguli, R. and Misra, D. (2010), "Machine Learning Algorithms and Their Application to Ore Reserve Estimation of Sparse and Imprecise Data", *Journal of Intelligent Learning Systems and Applications*, Vol. 2, No. 2, pp. 86–96.
- Fytas, K., Chaouai, N. E. and Lavigne, M. (1990), "Gold Deposits Estimation Using Indicator Kriging", *CIM Bulletin*, Vol. 83, No. 934, pp. 77–83.
- Gholamnejad, J., Kasmaee, S., Kohsary, A. and Nezamolhosseini A. (2012), "Grade Estimation of Ore Stockpiles by using Artificial Neural Networks : Case Study on Choghart Iron Mine in Iran", *International Journal of Mining and Mineral Engineering*, Vol. 4, No. 1, pp. 17-25.
- Goldberg, D. E. (1989), *Genetic Algorithms in Search, Optimisation and Learning*. Addison-Wesley Publishing Company, Canada, 432 pp.
- Granek, J. (2016), "Application of Machine Learning Algorithms to Mineral Prospectivity Mapping", *Published Doctoral Dissertation*, University of British Columbia, Vancouver, 105 pp.
- Guo, W. W. (2010), "A Novel Application of Neural Networks for Instant Iron-Ore Grade Estimation", *Expert Systems with Applications*, Vol. 37, No. 12, pp. 8729–8735.
- Ilham, M. and Matrani, B. F. A. (2020), "Quantitative mapping of limestone reserves using cross-section method in Mangkung Village, Western Praya, West Nusa Tenggara", *IOP Conference Series: Earth and Environmental Science*, Vol. 413, No. 1, 1-6 pp.
- Jafrasteh, B. and Fathianpour, N. (2017), "A Hybrid Simultaneous Perturbation Artificial Bee Colony and Back-Propagation Algorithm for Training a Local Linear Radial Basis Neural Network on Ore Grade Estimation", *Neurocomputing*, Vol. 235, pp. 217–227.
- Jafrasteh, B., Fathianpour, N. and Suárez, A. (2018), "Comparison of Machine Learning Methods for Copper Ore Grade Estimation", *Computational Geosciences*, Vol. 22, No. 5, pp. 1371–1388.
- Jahangiri, M., Ghavami Riabi, S. and Tokhmechi, B. (2018), "Estimation of Geochemical Elements using a Hybrid Neural Network-Gustafson-Kessel Algorithm", *Journal of Mining and Environment*, Vol. 9, No. 2, pp. 499–511.
- Jalloh, A. B., Kyuro, S., Jalloh, Y. and Barrie, A. K. (2016), "Integrating Artificial Neural Networks and Geostatistics for optimum 3D Geological Block Modeling in Mineral Reserve Estimation: A Case Study", *International Journal of Mining Science and Technology*, Vol. 26, No. 4, pp. 581–585.
- Journal, A. G. (1983), "Nonparametric Estimation of Spatial Distributions", *Journal of the International Association for Mathematical Geology*, Vol. 15, No. 3, pp. 445–468.
- Journal, A. G. (1984), "The Place of Non-Parametric Geostatistics", *In Geostatistics for Natural Resources Characterisation*, Springer, Dordrecht pp. 307–335.
- Journal, A. G. (1985), "Recoverable Reserves Estimation- The Geostatistical Approach", *Mining Engineering*, Vol. 37, No. 6, pp. 563–568.
- Journal, A. G. and Huijbregts, C. J. (1978), *Mining Geostatistics*, Academic Press, London, 610 pp.
- Kapageridis, I. and Denby, B. (1998a), "Ore Grade Estimation with Modular Neural Network Systems. A Case Study", *Information Technology in the Mineral Industry*, A. A. Balkema, Rotterdam, 9 pp.
- Kapageridis, I. K. and Denby, B. (1998b), "Neural network Modelling of Ore Grade Spatial Variability", *In International Conference on Artificial Neural Networks*, Springer, London, pp. 209–214.
- Kapageridis, I., Denby, B. and Hunter, G. (1999a), "Integration of a Neural Ore Grade Estimation Tool in a 3D Resource Modelling Package", *In Proceedings International Joint Conference on Neural Networks*, Washington, Vol. 6, pp. 3908-3912.
- Kapageridis, I., Denby, B. and Hunter, G. (1999b), "GEMNET II – A Neural Ore Grade Estimation System", *In 29th International Symposium on the Application of Computers and Operations Research in the Minerals Industries*, Tuscon, 10 pp.
- Kapageridis, I. K. (1999), *Application of Artificial Neural Network Systems To Grade Estimation*, Published Doctoral Dissertation, University of Nottingham, England, UK, 267 pp.
- Kapageridis, I. K. (2002), "Artificial Neural Network Technology in Mining and Environmental Applications", *Mine planning and Equipment selection*, pp. 172–179.
- Kapageridis, I. K., Denby, B. and Schofield, D. (2000), "GEMNET II – An Alternative Method for Grade Estimation", *Mine Planning and Equipment Selection*, pp. 1–8.
- Koike, K., Matsuda, S., Suzuki, T. and Ohmi, M. (2002), "Neural Network-Based Estimation of Principal Metal Contents in the Hokuroku District, Northern Japan, for Exploring Kuroko-

- type Deposits", *Natural Resources Research*, Vol. 11, No. 2, pp. 135–156.
- Koike, K. and Matsuda, S. (2003), "Characterising Content Distributions of Impurities in a Limestone Mine using a Feedforward Neural Network", *Natural Resources Research*, Vol. 12, No. 3, pp. 209–222.
- Koike, K., Matsuda, S. and Gu, B. (2001), "Evaluation of Interpolation Accuracy of Neural Kriging with Application To Temperature-Distribution Analysis", *Mathematical Geology*, Vol. 33, No. 4, pp. 421–448.
- Kwa, B. L. and Mousset-Jones, P. F. (1986), "Indicator Kriging Applied to a Gold Deposit in Nevada, USA", *In Proceedings of the 17th APCOM Symposium*, pp. 185–194.
- Li, X. L., Xie, Y. L., Guo, Q. J. and Li, L. H. (2010), "Adaptive Ore Grade Estimation Method for the Mineral Deposit Evaluation", *Mathematical and Computer Modelling*, Vol. 52, No. 11–12, pp. 1947–1956.
- Li, X. L., Li, L. H., Zhang, B. L. and Guo, Q. J. (2013), "Hybrid Self-Adaptive Learning Based Particle Swarm Optimization and Support Vector Regression Model for Grade Estimation", *Neurocomputing*, Vol. 118, pp. 179–190.
- Mahmoudabadi, H., Izadi, M. and Menhaj, M. B. (2008), "A Hybrid Method for Grade Estimation using Genetic Algorithm and Neural Networks", *Computational Geosciences*, Vol. 13, No. 1, pp. 91–101.
- Maleki, S., Ramazia, H. R. and Moradi, S. (2014), "Estimation of Iron Concentration by using a Support Vector Machine and an Artificial Neural Network-The Case Study of the Choghart Deposit Southeast of Yazd, Yazd, Iran", *Geopersia*, Vol. 4, No. 2, pp. 201–212.
- Manna, B., Samanta, B., Chakravarty, D., Dutta, D., Chowdhury, A., Santra, A. and Banerjee, A. (2018), "Hyperspectral Signature Analysis using Neural Network for Grade Estimation of Copper Ore", *In IOP Conference Series: Earth and Environmental Science*, Vol. 169, No. 1, pp. 1–12.
- Matías, J. M., Vaamonde, A., Taboada, J. and Gonzalez-Manteiga, W. (2004), "Comparison of Kriging and Neural Networks with Application to the Exploitation of a Slate Mine", *Mathematical Geology*, Vol. 36, No. 4, pp. 463–486.
- McCarthy, J., Minsky, M. L., Rochester, N. and Shannon, C. E. (2006), "A proposal for the Dartmouth summer research project on artificial intelligence", *AI Magazine*, Vol. 27, No. 4, 12–14pp.
- Muggleton, S. (2014), Alan Turing and the development of artificial intelligence, *AI Communications*, Vol. 27, No. 1, 3–10pp.
- Nezamolhosseini, S. A., Mojtahedzadeh, S. H. and Gholamnejad, J. (2017), "The Application of Artificial Neural Networks to Ore Reserve Estimation at Choghart Iron Ore Deposit", Vol. 6, pp. 73–83.
- Ortiz, J. M., Oz, B. and Deutsch, C. V. (2005), "A Step by Step Guide to Bi-Gaussian Disjunctive Kriging", *In Geostatistics Banff 2004*, Springer, Dordrecht, pp. 1097–1102.
- Pan, G., Gaard, D., Moss, K. and Heiner, T. (1993), "A Comparison between Cokriging and Ordinary Kriging: Case Study with a Polymetallic Deposit", *Mathematical Geology*, Vol. 25, No. 3, pp. 377–398.
- Rizzo, D. M. and Dougherty, D. E. (1994), "Characterisation of Aquifer Properties using Artificial Neural Networks: Neural Kriging", *Water Resources Research*, Vol. 30, No. 2, pp. 483–497.
- Roditis, I. S. (1986), "A Performance Evaluation of the Indicator Kriging Method on a Gold Deposit : A Comparison with the Ordinary Kriging Method", *Published MSc Thesis*, The University of Arizona, USA, 138 pp.
- Roy, W. D. (2000), "Using Geostatistics to Estimate the Resources of a Narrow Vein Gold Deposit", *Published Doctoral Dissertation*, Dalhousie University, Halifax, Nova Scotia, Canada, 61 pp.
- Samanta, B., Bandyopadhyay, S. and Ganguli, R. (2004a), "Data Segmentation and Genetic Algorithms for Sparse Data Division in Nome Placer Gold Grade Estimation Using Neural Network and Geostatistics", *Exploration and Mining Geology*, Vol. 11, pp. 69–76.
- Samanta, B., Bandyopadhyay, R., Ganguli, R. and Dutta, S. (2004b), "Sparse Data Division Using Data Segmentation and Kohonen Network for Neural Network and Geostatistical Ore Grade Modeling in Nome Offshore Placer Deposit", *International Association of Mathematical Geology*, Vol. 13, No. 3, pp. 189–200.
- Samanta, B., Ganguli, R. and Bandyopadhyay, S. (2005a), "Comparing the Predictive Performance of Neural Networks with Ordinary Kriging in a Bauxite Deposit", *Mining Technology. Transactions of the Institutions of Mining and Metallurgy: Section A*, Vol. 114, pp. A129–A139.
- Samanta, B., Bandyopadhyay, R., Ganguli, R. and Dutta, S. (2005b), "A Comparative Study of the Performance of Single Neural Network vs Adaboost Algorithm Based Combination of Multiple Neural Networks for Mineral Resource Estimation", *Southern African Institute of Mining and Metallurgy*, Vol. 105, No. 4, pp. 237–246.
- Samanta, B. and Bandyopadhyay, S. (2009), "Construction of a Radial Basis Function Network using an Evolutionary Algorithm for Grade Estimation in a Placer Gold Deposit", *Computers and Geosciences*, Vol. 35, No. 8, pp. 1592–1602.

- Sinclair, A. J. and Deraysme, J. (1974), "A Geostatistical Study of the Eagle Copper Vein, Northern British Columbia", *CIM Bulletin*, Vol. 746, pp. 131–142.
- Singer, D. A. and Kouda, R. (1996), "Application of a Feedforward Neural Network in the Search for Kuroko Deposits in the Hokuroku District, Japan", *Mathematical Geology*, Vol. 28, No. 8, pp. 1017–1023.
- Singh, R. K., Ray, D. and Sarkar, B. C. (2018) "Recurrent Neural Network Approach to Mineral Deposit Modelling", *In 4th International Conference on Recent Advances in Information Technology*, pp. 1–5.
- Tahmasebi, P. and Hezarkhani, A. (2010a), "Comparison of Optimised Neural Network with Fuzzy Logic for Ore Grade Estimation", *Australian Journal of Basic and Applied Sciences*, Vol. 4, No. 5, pp. 764–772.
- Tahmasebi, P. and Hezarkhani, A. (2010b) "Application of Adaptive Neuro-Fuzzy Inference System for Grade Estimation; Case Study, Sarcheshmeh Porphyry Copper Deposit, Kerman, Iran", *Australian Journal of Basic and Applied Sciences*, Vol. 4, No. 3, pp. 408–420.
- Tahmasebi, P. and Hezarkhani, A. (2011), "Application of a Modular Feedforward Neural Network for Grade Estimation", *International Association for Mathematical Geology*, pp. 1–8.
- Tahmasebi, P. and Hezarkhani, A. (2012), "A Hybrid Neural Networks-Fuzzy Logic-Genetic Algorithm for Grade Estimation", *Computers and Geosciences*, Vol. 42, pp. 18–27.
- Verly, G. (1983), "The Multigaussian Approach and its Applications to the Estimation of Local Reserves", *Journal of the International Association for Mathematical Geology*, Vol. 15, No. 2, pp. 259–286.
- Verly, G. and Sullivan, J. (1985), "Multigaussian and Probability Krigings- Application to the Jerritt Canyon Deposit", *Mining Engineering*, Vol. 37, No. 6, pp. 568–574.
- Wu, X. and Zhou, Y. (1993), "Reserve Estimation using Neural Network Techniques", *Computers and Geosciences*, Vol. 19, No. 4, pp. 567–575.
- Yamamoto, J. K. (2000), "An Alternative Measure of the Reliability of Ordinary Kriging Estimates", *Mathematical Geology*, Vol. 32, No. 4, pp. 489–509.
- Yates, S. R., Warrick, A. W. and Myers, D. E. (1986), "Disjunctive Kriging: 1 Overview of Estimation and Conditional Probability", *Water Resources Research*, Vol. 22, No. 5, pp. 623–630.
- Zhang, X., Song, S., Li, J. and Wu, C. (2013), "Robust LS-SVM Regression for Ore Grade Estimation in a Seafloor Hydrothermal Sulphide Deposit", *Acta Oceanologica Sinica*, Vol. 32, No. 8, pp. 16–25.

Authors



C. A. Abuntori is Postgraduate Assistant at the Department of Mining Engineering of the University of Mines and Technology (UMaT), Tarkwa. She holds a BSc (Hons.) degree in Mining Engineering and is currently a Doctoral candidate in Mining Engineering at UMaT. Her research interests include Artificial Intelligence, Mineral Resource Estimation, Mineral Economics and Mine Planning and Design.



S. Al-Hassan is an Associate Professor in the Mining Engineering Department at the University of Mines and Technology, Tarkwa. He obtained his BSc (Hons.) and Postgraduate Diploma in Mining Engineering from the University of Mines and Technology in 1982 and 1983 respectively. He obtained his PhD from the University of Wales, Cardiff, UK in 1994. He is a Member of Ghana Institution of Engineers (MGhIE), Ghana Institution of Geoscientists (MGhIG) and Australian Institution of Mining and Metallurgy (MAusIMM). His research areas include Mineral Reserve Estimation, Mine Planning and Design, Mineral Economics and Small-Scale Mining.



D. Mireku-Gyimah is a Professor of Mining Engineering and a Consulting Engineer currently working at the University of Mines and Technology, Tarkwa, Ghana. He holds the degrees of MSc from the Moscow Mining Institute, Moscow, Russia, and PhD and DIC from the Imperial College of Science, Technology and Medicine, London, UK. He is a member of the Institute of Materials, Minerals and Mining of UK and also a fellow of Ghana Institution of Engineers and the Ghana Academy of Arts and Science. His research and consultancy works cover Mineral Resource Estimation, Mine Design and Planning, Mine.