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Improving the efficiency of artificial neural networks for ore reserve estimation by employing suitable training methods

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Introduction

Ore reserve estimation is traditionally developed using a model of selected deposit attributes, created by discretizing them into small blocks. Among these attributes, the thickness and the grade are the most critical for the ore reserve estimation. The thickness and the quality characteristics of the deposit are determined by several factors related to the usually complicated geological process which led to the deposit formation. Many of these factors are not well known and cannot be brought easily into a conventional mathematical model. Any attempt to model the geometrical and quality characteristics of a deposit inevitably requires simplifications and assumptions of the spatial variation. The existing methods are mainly based on either geometrical reasoning or statistical techniques and generally assume that the spatial distribution of the modelled parameters is a function of distance.

Artificial Neural Networks (ANNs) have provided a new approach for the estimation of the reserves of a deposit. Since the ANNs are not only trainable nonlinear dynamic systems but also adaptive model-free estimators, no assumption concerning the spatial variation of the deposit attributes need to be made. The basic approach for developing ANN model for the ore reserve estimation is to train the model using an existing borehole data set and appropriate learning methods (Wu and Zhou, 1992; Galetakis, 1999; Kapageridis, 2005; Samanta and Bandopadhyay, 2009; Li et al., 2010).

The way that available data are divided into training, testing, and validation subsets can have a significant influence on the performance of an ANN (Tahmasebi et al., 2011). This study presents methods for dividing borehole data into these subsets considering spatial and quality criteria. These methods are compared with the conventional approach commonly used in the literature, which involves an arbitrary division of the data.

Artificial Neural Networks

Artificial neural networks (ANNs) are nonlinear dynamic systems consisting of a large number of highly interconnected processing units, called artificial neurons or simply neurons, which are organized into a hierarchy (layers of neurons). Their architecture and operation are inspired by our understanding the biological structure of neurons and the operation of the human brain (Galetakis et al., 2002).

Basically, three entities characterize a neural network: the characteristics of individual neuron, the network topology and the learning strategy. Each processing unit (neuron) receives one or more inputs and delivers a single output. The neuron consists of an input function (a summation function) the result of which is fed to activation function which in turn determines the output. The topology of the network is the manner in which neurons are organized and connected. Neurons are combined to form layers which can be connected fully or partially. When the output from every neuron of a particular layer is connected to every neuron in the next layer the network is fully connected otherwise it is partially connected. Associated with each connection between these processing units, there is a weight value defined to represent the connection strength. Each network has an input layer, which accepts the input data to the network, an input layer which delivers the network response and the intermediate layers which represent the hidden features of the problem (Rumelhart et al., 1986).

Feedforward networks are those in which the output from neuron can only feed forward, while feedback networks are those in which the output from a neuron can be directed back as an input to any neuron. Learning methods for neural networks can be classified into supervised and unsupervised. The most commonly used supervised method for feedforward neural networks is the backpropagation.

Ore reserve estimation by ANNs

Estimating the grade and the reserves of a deposit is a particularly critical stage in the planning process of exploitation. The methods used vary depending on the type of the ore, the planned method of exploitation, the required degree of precision and the number and type of the data obtained from the exploration stages. In this study the estimation of the grade and reserves of a copper deposit was conducted by using a feedforward ANN.

The examined cooper deposit is located in the state of Arizona and is described in detail by Hustrulid and Kuchta (2006). It is low-grade porphyry type cooper deposit that has been explored with 40 vertical boreholes of varying depth. In each borehole assays, at an average spacing of 1.5m, were analyzed for the determination of % content of Cu. Borehole assay data were regularized into composites of equal length used then for grade and reserves estimation.

The used feedforward ANN, as shown in Figure 1, had an input layer with 3 neurons, a hidden layer of *m* neurons and an output layer with one neuron. The coordinates of each composite sample were used as inputs, while the content (%) in Cu is used as the output. The optimal number *m* of hidden layer neurons was evaluated during training, while bias

(a_o, b_o) and momentum factor were also used to improve the accuracy of the estimation and to accelerate the training process respectively.

Three different training methods were used. The first training method was the conventional approach which involves the random division of the entire data set into training, testing, and validation subsets. The second training method involves initially the division of the data set into subgroups corresponding to the elevations of the planned benches for the exploitation of the deposit. Subsequently each subgroup was divided into training, testing, and validation subsets using the conventional approach. The third training method include two steps: first the assignment of weights to samples based on their grade (% Cu) and then their division into training, testing and validation randomly. These weights represent samples impact on the training process of the ANN.

To avoid overtraining of neural networks, both the early stopping technique and the control of the number of neurons on the hidden layer were used. A comparative evaluation of these ANN methods and the Kriging was then performed.

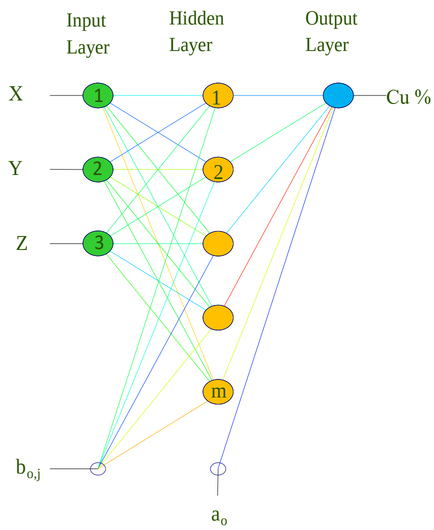

Figure 1. Structure of multiple-layer feedforward network used for ore reserve estimation.

Discussion of results-Conclusions

The obtained results were compared to those of the Kriging method and showed that the ANNs trained either with the first or the second method performed mainly as global estimators. These networks showed the general trend of the variation of the Cu content in the studied area. The large number of samples with low Cu grade have affected the neural network training and led to an underestimation of the Cu content. Neural networks trained with the third method have shown that they can depict both local and global variations in Cu content in the studied area, performing equally to Kriging method.

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