Integration of a Neural Ore Grade Estimation Tool in a 3D Resource Modeling Package

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Abstract

Ore grade estimation is a key aspect in the evaluation of a mineral deposit. In this paper an alternative approach to currently applied methods of ore grade estimation is presented. This alternative approach involves a modular neural network system integrated in a state of the art 3D resource modelling package. The need for a new method of ore grade estimation comes from the difficulties in applying conventional methods such as geostatistics. These methods require a lot of assumptions, knowledge, skills and time to be effectively applied while their results are not always easy to justify. The aim of the proposed system, called GEMNet II is to provide fast and reliable ore grade estimation, with minimum assumptions and minimum requirements for modelling skills. GEMNet II has been tested on a number of real deposits. The results obtained so far have shown that it can provide with a very fast and robust alternative to the existing time-consuming methodologies for ore grade estimation.

Introduction

Artificial neural networks find their way to an increasing number of industrial applications. The mining industry is no exception to this fact. Neural network methodologies have been developed and applied to various aspects of mining and mining related problems.

Ore grade/reserve estimation is one of these problems and has always been the subject of extensive research [1, 2, 3, and 4]. Geostatistics is the main approach to ore grade estimation. It is the result of at least three decades of research carried out by people from various fields like geology, mathematics and engineering. In spite of the extensive development and wide support, geostatistics prove to be very difficult to learn and apply efficiently and also very time-consuming.

The special characteristics of artificial neural networks make them a natural choice for the problem of ore grade estimation. GEMNet II is trying to utilise these characteristics to provide with a technique that is easy to learn and understand user friendly, and reliable. GEMNet II is interfaced with VULCAN, a suite of 3D modelling programmes for the earth resources industry, which allows the visual validation of the results and their direct use in the process of reserves estimation.

Development of the neural networks for GEMNet II is carried out using the Stuttgart Neural Network Simulator (SNNS). SNNS provides with the learning algorithms, neural network topologies, and a number of tools for batch training of the networks and conversion of trained networks into C code. The use of SNNS aided the development of prototype networks and allowed for their integration with the complete system.

Radial Basis Function Networks in GEMNet II

Radial basis function networks (RBF) have certain characteristics that make them ideal for the problem of ore grade estimation [5]. RBF networks have been successfully applied for function approximation [6,7,8,9,10,11]. GEMNet II is treating ore grade estimation as a problem of function approximation with the functions being the ore grade spatial variability and spatial distribution. The RBF networks used in GEMNet II share the same non-linear basis function, the Thin Plate Spline. During the initialisation of the networks, the centre vectors are positioned in the input space using Kohonen training. All input patterns are normalised to represent vectors with length 1 as required for Kohonen training. Training is carried out by Batchman, which is one of the tools available with SNNS for batch training of networks [12]. Batchman is called using a number of training scripts part of the GEMNet II system. During training, the networks are synthesising an approximation of ore grade spatial variability in different directions in 3D-space and ore grade spatial distribution. In other words, the networks learn the input-output mapping from the exploration data samples presented to them.

GEMNet II system architecture

As already mentioned, GEMNet II is a very modularised system (Figure 1). There are three modules of RBF networks each responsible for a different aspect of ore grade estimation. These modules receive input from a data control module which is accepting two types of input files from VULCAN, containing drillhole samples and block model centroid co-ordinates, as well as specification files, containing additional information to customise the estimation procedure to the user's needs.

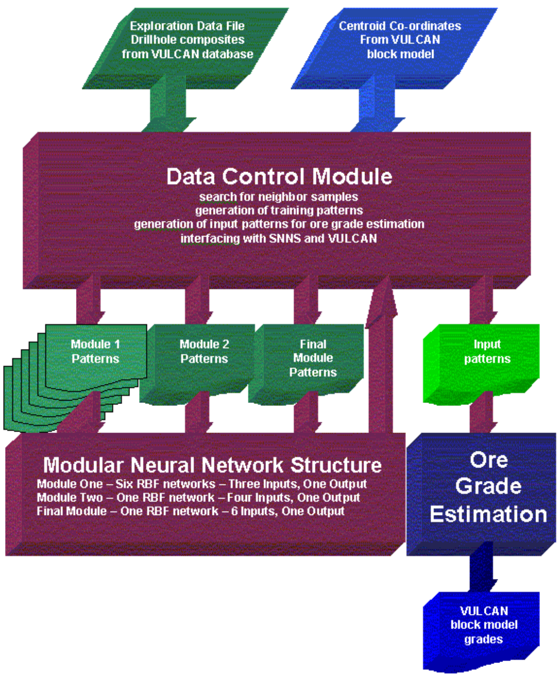

Figure 1: GEMNet II modular architecture.

The drillhole samples file contains records consisting of sample co-ordinates, ore grade analysis, and sample length, and is used for the construction of training patterns and input patterns for the estimation process. The block model centroids file contains records consisting of block centroid co-ordinates and is used for the construction of the input patterns for the estimation process.

The essence of GEMNet II operation is in the way of constructing the training patterns. There are three different types of patterns formed, targeted to the three different neural network modules of the system. Searching the area around each sample for neighbour samples forms the first (Stage 1) type of patterns. The sampling space is divided in six subspaces (north, south, east, west, upper, and lower) originating from the training sample's co-ordinates as shown in Figure 2. The exploration data processing module is searching for samples in these subspaces and forms patterns consisting of the ore grade, distance and length of the neighbour sample as inputs, and ore grade of the training sample as output. There are a number of patterns formed for each training sample providing enough information for modelling the effects of neighbour sample's grade, distance, and length to the training sample's grade.

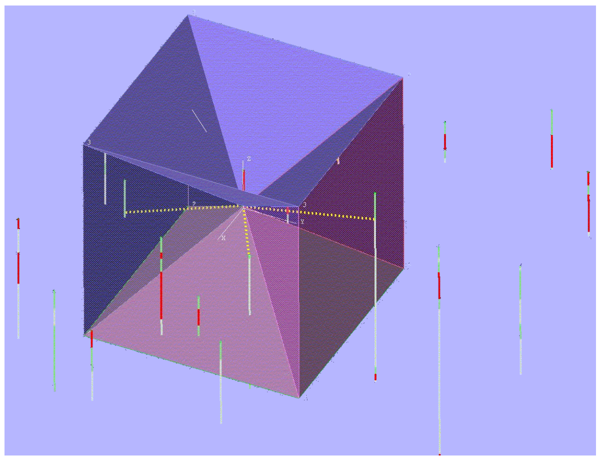

Figure 2: Neighbour sample search method used in GEMNet II.

The training patterns formed at this stage are used for training the Stage 1 module consisting of six RBF networks each responsible for one of the six subspaces. In real deposits with real sampling schemes there are always samples usually at the edges of the sampling area that have no neighbour samples in some of these subspaces. GEMNet II will still create patterns for those that do have neighbours. The missing estimate from the RBF network responsible for an empty subspace is provided from the Stage 2 RBF network.

The Stage 2 module consists of a single RBF network with four inputs - the training sample co-ordinates and sample length - and one output, the ore grade of the sample. This network learns the relationship between co-ordinates in 3D-space and ore grade and therefore requires no information on neighbour samples and can be used when these are missing.

The Final stage module consists of a single RBF network with six inputs - the outputs/estimates of Stage 1&2 modules - and one output, the training sample's ore grade. Training patterns for Final stage module are formed after training of Stage 1 and Stage 2 is finished.

The exploration data control module is also forming input patterns to be used during ore grade estimation on the basis of a block model of the deposit. The drillhole data file is searched using exactly the same procedure only this time the place of the training samples is taken by the block centroids. The other difference of course is the lack of output vectors in the patterns. These input patterns are presented to the trained networks and the output of the Final stage network is directed to the block model in VULCAN for further processing and visualisation.

Integration of GEMNet II with SNNS and VULCAN

As mentioned before, training of networks is achieved using Batchman in SNNS. GEMNet II comes with standard SNNS templates for untrained networks, which are used as the starting point for Batchman. GEMNet II also creates pattern files fully compatible with SNNS and provides the training scripts for calling Batchman. The output of Batchman is the fully trained SNNS network topology files, which are then passed to the C code extraction tool in SNNS, the SNNS2C. SNNS2C creates standard ANSI-C code. Once converted to C code, the neural networks are compiled and used for the ore grade estimation process, which is the final stage of the operation of GEMNet II.

The interface with VULCAN consists of commands and options already existing in the package and options that were added specifically for GEMNet II. VULCAN provides options for construction of drillhole composite files, which GEMNet II can read directly and use for the development of the training patterns. VULCAN also includes options for exporting the centroid co-ordinates of the blocks from the block model of a deposit. The user can specify various criteria for the selection of blocks to be included, e.g. blocks inside an orebody or a part of the mine design. The same criteria can be applied to the drillhole samples included in the composite samples file. This way it is possible to limit grade estimation in GEMNet II to a specific part of the deposit using a specific part of the available data, which are relevant with it. Figure 3 shows a general picture of GEMNet II operation.

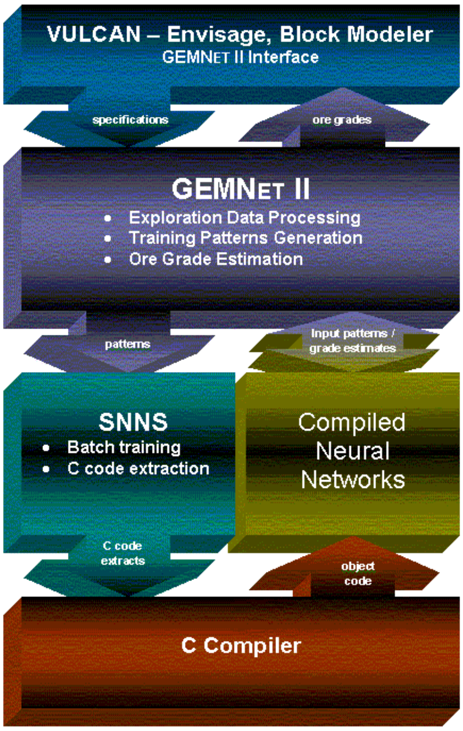

Figure 3: GEMNet II system operation.

There are several options that were build into VULCAN specifically for GEMNet II that can be accessed through the GEMNet menu in VULCAN - Envisage. Choosing one of these options calls one of the scripts coming with GEMNet II, which are written in Perl language. These scripts are called Lava scripts in VULCAN. They usually lead to a panel that the user can fill with the specifications for the estimation or changes in the default architectures of the neural networks.

The *Run* option calls GEMNet II to start, using the specifications as given in the two specification panels. GEMNet II runs in a separate console window were several messages from GEMNet II and the SNNS tools are printed. At the end of the run the user can save these messages in a text file for future reference.

The output of GEMNet II is a file containing block records that consists of block centroid co-ordinates, ore grade estimate, estimate reliability indicator, and stage number. The reliability indicator is just a general way of checking the validity of an estimate by calculating the variance of the individual RBF networks estimates for the specific block. High variance means low reliability and vice versa. The stage number indicates whether the estimate is provided by the combination of Stage 1, 2 and Final or solely by Stage 2 as in the case of a block far from the sampling area. The user can actually specify the maximum number of empty subspaces for Stage 1 that can be tolerated before the estimate is completely assigned to Stage 2, bypassing the Final stage.

The output file is imported back to the block model. The user has to add variables to the block model so that it can accept the neural estimates and the two parameters mentioned, before importing of the output file. It is then possible to see on screen the block model of the deposit coloured by the reliability indicator and identify areas where the estimation process fails to provide reliable results (Figure 4).

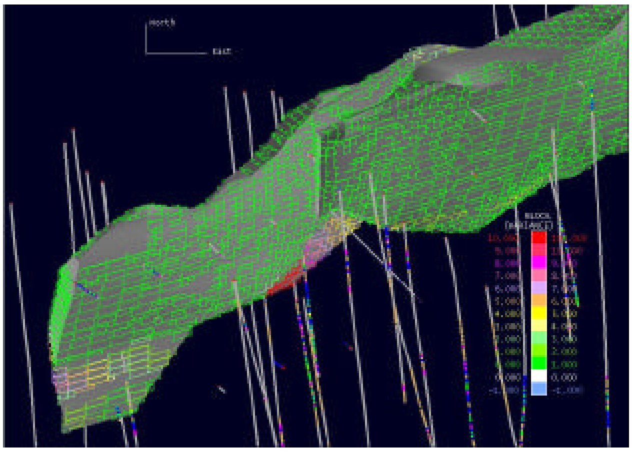

Figure 4: Block model in VULCAN coloured by GEMNet II estimate reliability indicator.

These areas can be isolated from the rest of the orebody and re-estimated using different specifications. The block model can also be coloured by the stage number showing the part of GEMNet II responsible for the estimate. The combination of the two visual representations of the estimation process can guide the modifications of the network and estimation specifications towards a better result.

Application of GEMNet II

GEMNet II has been applied to a number of case studies using exploration data from real deposits [5,13]. The data were obtained directly from the actual exploration programme and not using a simulation process. At the same time a complete geostatistical analysis has been carried out using exactly the same data. Cross-validation has been used in both approaches to examine the performance of the estimation process. In the case of GEMNet II, a percentage of the original drillhole data has been kept out of the training process to use it as a testing basis (usually around 15% of the data). The reason for not running cross-validation on the entire drillhole data set as normally happening in geostatistics is to ensure that the neural networks have not been trained with the samples used in this process and to allow for a more objective way of comparing the two approaches. The same data were used to cross-validate kriging (the geostatistical estimation process). The results of cross-validation have shown that GEMNet II can provide equally good and sometimes even better results with geostatistics. In all cases the difference in absolute error between the two approaches has been up to a maximum of 5%. The difference in the development and application time of the two estimation processes has been, in all cases, significant.

GEMNet II, in the worst case, required a couple of hours to adjust the estimation process to the data at hand (by training the networks) and provide estimates for the block model. A complete geostatistical analysis and a kriging run are usually measured in days of work. Geostatistics also require a larger knowledge base from the user to be able to apply them efficiently. In comparison the knowledge requirements of GEMNet II are very low since the system is extracting a great part of this knowledge from the data presented to it. There are many points during the geostatistical approach that the users have to use their own judgement and make decisions that will affect significantly the results obtained. In GEMNet II the interaction with the user is kept to a minimum not allowing for the introduction of user errors or misjudgements in the estimation process. Therefore GEMNet II provides estimates that depend completely on the data at hand.

Conclusions

This paper has shown how GEMNet II, a highly modularised system utilising neural network technology, has been developed and applied to mineral ore grade estimation. The main components of the system as well as the system's operation were analysed. The aims of the system were explained and a brief comparison with the already established approach was given. The benefits of the GEMNet II approach were discussed in depth. Research work currently carried out at the AIMS Research Unit includes a series of case studies. These case studies will enable the identification of the types of deposits that the system can be applied to as well as the assumptions inherited by the system as a consequence of it being based on function approximation.

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