GEMNET II – A Neural Ore Grade Estimation System

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Abstract

This paper describes a neural ore grade estimation system developed at the AIMS Research Unit of the University of Nottingham. GEMNET II is a modular neural network system designed to receive drillhole information from an orebody and perform ore grade estimation on a block model basis. The aims of the system are to provide a valid alternative to conventional grade estimation techniques while reducing considerably the time and knowledge required for development and application. GEMNET II is fully integrated inside VULCAN, one of the leading software packages for resource modelling, allowing for advanced visual validation of the grade estimation process. The system uses parts of the SNNS v4.1 neural network simulator for the development and training of the neural network modules. A number of case studies have been carried out using GEMNET II. The results obtained and the overall functionality of the system prove that neural networks can offer a fast and robust grade estimation technique and a valid alternative to well established methodologies in this area.

Introduction

Artificial Neural Networks (ANN) become increasingly popular within the mineral resources industry. ANN technology provides solutions to problems characterised by shortage or bad quality of input data. Estimation of ore grades within an orebody is one of these problems where ANNs can be applied successfully, as it was demonstrated by a number of examples in the past. Such examples include the work of Wu and Zhou (1993), Clarici et al (1993), Denby and Burnett (1995), Kapageridis and Denby (1998a) and Cortez et al (1998). Most of this research work has been constrained to two-dimensional data organised on regular grids or data from simulated deposits. The authors of this paper have been developing a complete neural ore grade estimation tool consisting of modules of ANNs in the past two years. Early results (Kapageridis and Denby, 1998b) from a real 3D copper/gold deposit have shown the potential of the approach which was also proven by a series of case studies with data from other real deposits. The development of the GEMNET II system described in this paper was based on the integration of this modular neural network architecture with VULCAN, one of the world's leading 3D software packages for earth resources modelling.

Modular Neural Network Architecture

The heart of GEMNET II is a Modular Neural Network structure (MNN). The building unit of this structure is a special type of ANN, the *Radial Basis Function network* (RBF). The RBF network model is motivated by work on function approximation (Powel, 1987) as well as the characteristics found in many part of biologic nervous systems. The RBF network is a feedforward, single hidden layer, fully interconnected network. All hidden units receive the input vectors *x*. Hidden units consist of a non-linear basis function *h* centred around the hidden unit weight vector *t* which is considered as the centre of the basis function. The weight vector has an adaptable range of influence or *receptive field*. Another parameter in the basis function is the bias *p* of the hidden unit The RBF networks in GEMNET II use the same basis function, the *Thin-Plate Spline*:

$$
\begin{aligned}
h(r^2, p) = h(q, p) &= p^2 q \ln(p\sqrt{q}) \\
&= (pr)^2 \ln(pr)
\end{aligned}
$$

where

$$
\begin{aligned}
q &= |\vec{x} - \vec{t}\,|^2 \\
r &= |\vec{x} - \vec{t}\,|
\end{aligned}
$$

The development of the RBF networks begins with their initialisation, which involves centring of the weight vectors in the input space using a special training algorithm known as *Kohonen learning*. The result of initialisation using Kohonen learning is that the centre vectors are homogeneously spread over the space of input vectors. A precondition of this type of learning used during the initialisation stage is that all input patterns have to be normalised, i.e. represent vectors with length between zero and one. Following the initialisation stage is the training of the RBF networks. During training, the free parameters of the networks are adjusted. These parameters are the centre vectors, the receptive field of the weight vectors, and the bias of each hidden unit. In GEMNET II, the RBF networks are trained in *batch mode* meaning that any changes to the free parameters take place after all training patterns have been presented once.

GEMNET II uses parts of the Stuttgart Neural Network Simulator (SNNS). SNNS provides the necessary tools for batch training of networks and their conversion into ANSI-C code. The compiled C code extracts from the trained networks are then used to provide the estimates. The integration of the SNNS tools with GEMNET II is achieved by a number of training scripts written in the scripting language of SNNS, the *Batchman*. GEMNET II also provides the templates of the untrained RBF networks and makes direct calls to the SNNS C code extraction tool, the *SNNS2C.*

The RBF networks in GEMNET II are arranged in three modules each responsible for a different aspect of the ore grade estimation process. The first module includes six RBF networks which model the ore grade's spatial variability in a different direction in space. The space around each training sample is divided into six sectors (Figure 1). Training patterns are formed for each of the six networks by forming pairs of samples using the training sample and one of the neighbour samples inside the specific sector. The number of training patterns formed varies from sector to sector and therefore from network to network. These training patterns consist of the grade of the neighbour sample, its distance from the training sample, and the neighbour sample length as inputs and the training sample grade as output.

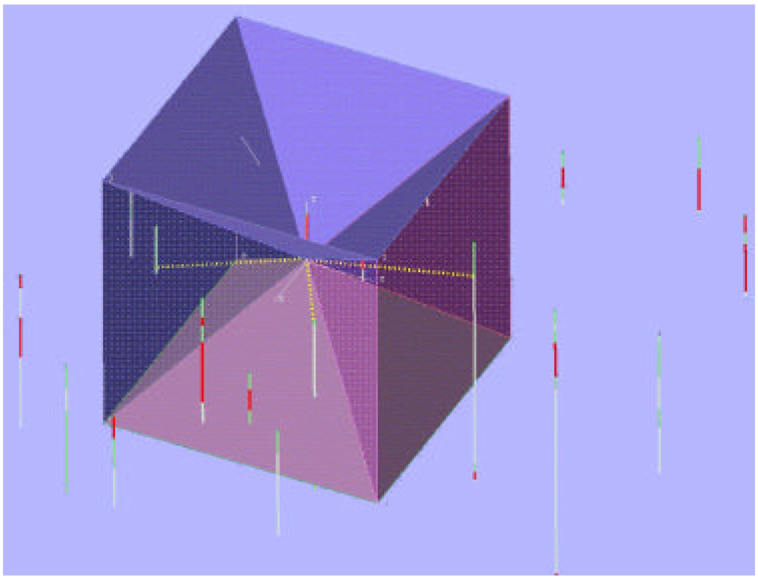


Figure 1: 3D space partitioning for training patterns formation in GEMNET II. Space around each training sample is divided into six sectors: upper, lower, north, south, east, and west.

The second module consists of a single RBF network, which is trained using the X-Y-Z co-ordinates and length of the training samples as inputs and their grade as output. This network "learns" in essence the relationship between location in space and ore grade. The training patterns are derived directly from the exploration data after they have been normalised. GEMNET II relies on this module to give estimates at such locations in the deposit area where there are no neighbour samples in some directions to provide the necessary inputs to the first module's networks. In most cases this is necessary at the edges of the sampling area.

The third and final module of the MNN system consists of a single RBF network which is trained using the outputs of the first and second module as inputs and the ore grade of the training sample as output. This network performs a final weighting of the individual estimates in order to provide with a single estimate for each estimation point.

This modular neural network structure interacts with a data control module, which is responsible for the normalisation of exploration data, training patterns generation, interfacing with the neural network simulator (SNNS), and also interfacing with VULCAN. The overall structure of GEMNET II is illustrated in Figure 2. The data control module receives the block model centroids from VULCAN and creates input patterns to be presented to the trained ANNs during the estimation stage. These input patterns are formed in a similar manner with the training patterns by searching the drillhole database for neighbouring samples. The difference is that input patterns do not include the required output (actual ore grade of the blocks). Another very important task for the data control module is the collection of the individual estimates from the first and second neural modules and the generation of the final module's training patterns. After the completion of the ore grade estimation process, the results are transformed back to their original form, i.e. the effect of normalisation is reversed, to enable their proper importing back to VULCAN's block model.

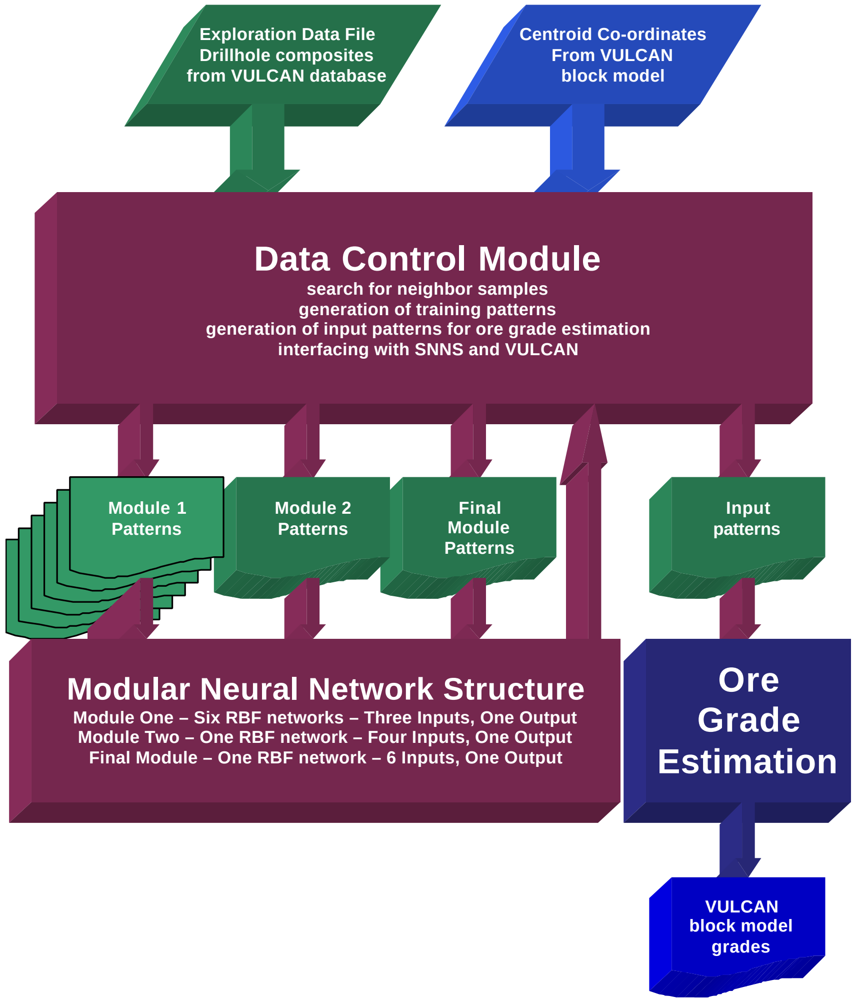


Figure 2: Block diagram of GEMNET II system structure. Some intermediate file structures are also shown.

The following block diagram (Figure 3) also illustrates how GEMNET II interacts with VULCAN, SNNS and the C Compiler.

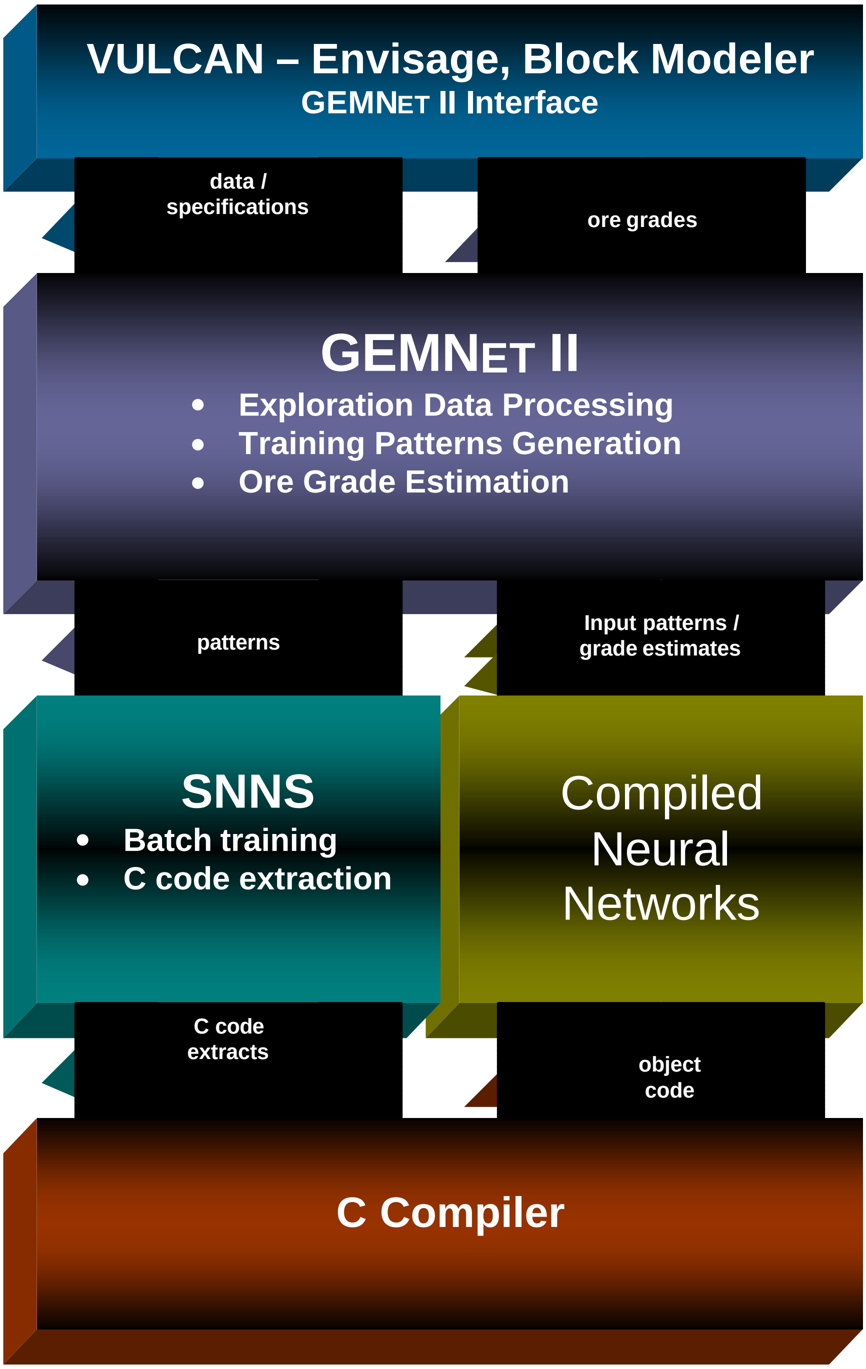


Figure 3: Integration of the GEMNET II ore grade estimation system with VULCAN and SNNS.

Integration With VULCAN

The VULCAN suite of 3D modelling software provides all the necessary tools for interfacing GEMNET II as an external system for ore grade estimation. The integration of GEMNET II with VULCAN involves both the block modelling module (Block Modeller) and the graphics editor (ENVISAGE). GEMNET II provides several scripts written in VULCAN's own scripting language Lava, which is an extension to the standard Perl language. These scripts allow the user to control the operation of GEMNET II from inside ENVISAGE by changing the MNN training and validating specifications, choosing composite and block model export files, running GEMNET II, and importing the results back to the Block Modeller.

VULCAN provides a complete range of geostatistical tools, which can be used to compare the results from GEMNET II, inverse distance, and kriging. GEMNET II can be called as a standalone program provided that the specification files exist and have the required settings. This proves useful when the number of samples and number of blocks is large and the hardware cannot cope with the memory requirements. However, even in the case of standalone use, the results from GEMNET II will still need to be imported into the block model in VULCAN.

The output of GEMNET II is a file containing block records that consist of block centroid real-world co-ordinates, ore grade estimate, and two more parameters used for validating the estimates: the *reliability indicator* and the *stage* or *module number.* The reliability indicator is calculated as the variance of the six neural modules individual estimates that lead to the final estimate in the file. It can be used as a guide to areas where the estimation process is problematic. High variance of the individual estimates means that the final estimate is less reliable. The module number indicates the module responsible for the estimate. The user has the option to override the final module and use only the second module (trained with the X-Y-Z co-ordinates) in cases where there are more than a certain number of sectors in 3D space containing no neighbour samples. After importing the output file to VULCAN, the user can view the block model coloured according to the reliability indicator and the module number in order to validate the results and find ways of improving the overall performance of the system.

Using GEMNET II – A Real Deposit Case Study

Using GEMNET II is very straightforward. The user has to create a composites file using the options available in VULCAN. The compositing method for GEMNET II is normally a direct transformation of samples to composites, i.e. from each sample a separate composite is derived. This means that composites have varying length, which is one of the inputs required by the networks of the MNN structure. Figure 4 shows one of the deposits used as a case study for the development of GEMNET II. The drillhole database contains 1362 samples, 227 of them inside the orebody shown. The data control module used these samples to create training patterns for the first module's RBF networks. The number of patterns for each of the networks varied as follows:

North: 1502, South: 1017, West: 1473, East: 517, Upper: 2526, Lower: 578

These numbers and the ratios between them change depending on the sampling scheme, i.e. the drilling pattern and the inclination of the drillholes.

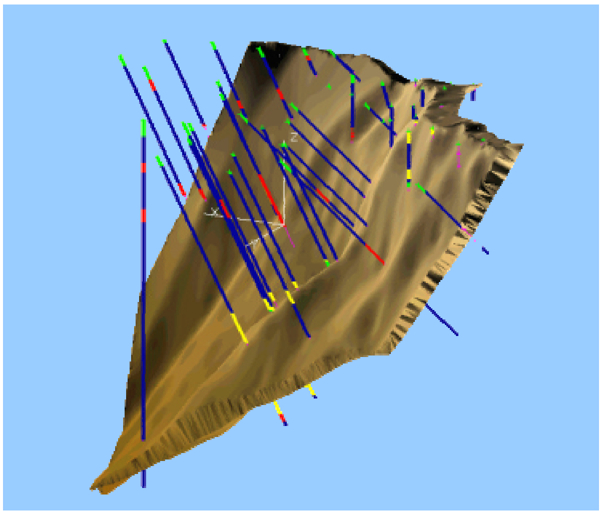


Figure 5: Copper/gold deposit and drillholes as visualised in ENVISAGE, VULCAN's graphical editor. This is one of several real deposits used for the development of GEMNET II.

The block model contained over 190,000 blocks but only a small percentage of them (less than 10%) was inside the orebody. GEMNET II was constrained in estimating blocks inside the orebody only. Of the 227 samples inside the orebody, 53 were excluded from training the networks and were used for testing the system's accuracy during grade estimation. After training, validation and grade estimation the results were imported back to the block model. Figure 6 shows a vertical section of the block model coloured by GEMNET II gold grade estimates.

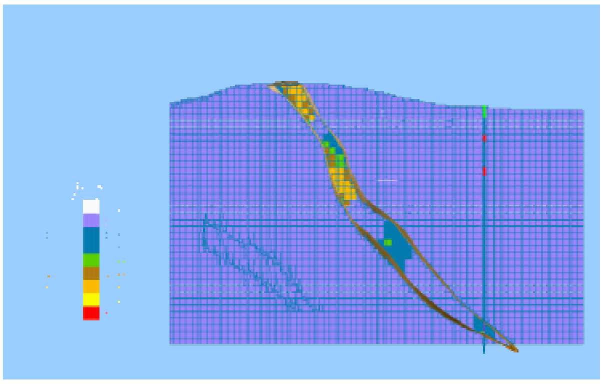
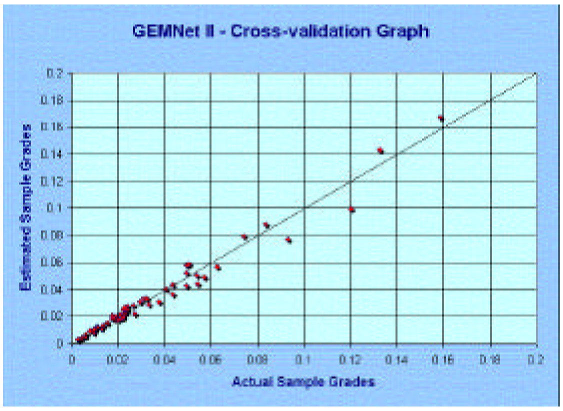
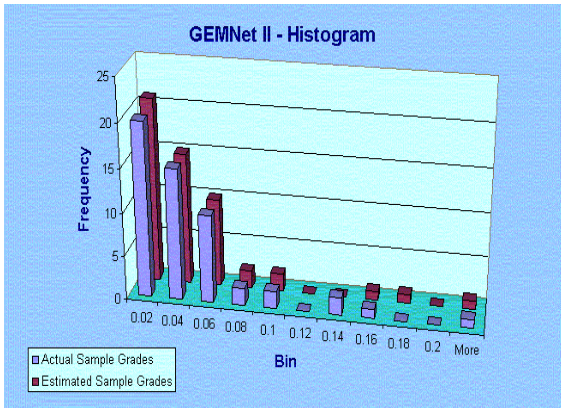


Figure 6: Cross-section through the block model showing GEMNET II gold grade estimates.

The average absolute error on the 53 testing samples was 10.03% which is more than acceptable considering the time required by GEMNET II to complete its operation. Specifically, GEMNET II required less than one hour to build the training patterns and train the networks, and about ten minutes to estimate the block grades. The following figures (Figure 7a, b) show how close were the estimates to the actual drillhole samples.





a) **b)**

Figure 7: a) Data fit graph of GEMNET II estimates, and ***b)*** histograms of actual and estimated gold grades.

Conclusions

This paper has shown how GEMNET II, a modular neural network system has been developed and applied to ore grade estimation. The structure of the system and its integration with a complete earth resources modelling package were analysed. The benefits of the GEMNET II approach were demonstrated through a case study using real data from a real deposit. Current research work at the AIMS Research Unit includes a series of case studies which will prove further more the validity of the approach and a series of modifications to the Modular Neural Network Structure and the interface with VULCAN which will make the system more user-independent and user-friendly.

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