ARTIFICIAL NEURAL NETWORK TECHNOLOGY IN MINING AND ENVIRONMENTAL APPLICATIONS

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ABSTRACT: A number of mining and environmental related problems have been approached using ANN technology. These problems commonly relate to pattern classification, prediction and optimisation. ANNs have been successfully applied to these areas and are therefore suitable for similar mining and environmental problems. The general trend in the mining industry for automation to the greatest degree calls for technologies such as the ANNs that can utilise large amounts of data for the development of models which otherwise are very difficult or sometimes even impossible to identify. The examples presented in this paper support the choice of ANNs as the basis for developing solutions to mining and environmental problems were conventional techniques fail in one way or another.

1 INTRODUCTION

Artificial intelligence (AI) tools have been in use for years in a number of mining related applications. Expert and knowledge based systems, probably the most popular AI tools, have found their way into a number of computer-based applications supporting everyday mining operations as well as production of mining equipment. In recent years, AI has provided tools for optimising operations and equipment selection, problems involving large amounts of information that humans cannot easily cope with in the process of decision-making. These AI systems together with an ever-increasing number of sophisticated purpose-built computer software packages have created a very favourable environment for the introduction of yet another powerful AI tool, the Artificial Neural Networks.

In the '90s the mining industry has been introduced to a number of ANN based systems, some of them finding their way to a fully commercialised product, as will be illustrated by some examples in this paper. It should be noted however that these examples are very few considering the total number of applications at the research level, and the overall research effort carried out at universities and research institutes around the world.

2 THEORETICAL BACKGROUND

A brief introduction to the artificial neural network structure and operation is given below.

2.1 Artificial Neural Network Structure

The model of the artificial neuron or processing element (PE) (Figure 1) forms the basis of the artificial neural network (ANN) structure. ANNs consist of layers of interconnected PEs as shown in Figure 2. This layered structure is the most common in ANNs and is usually called the fully connected feedforward or acyclic network. However, there are ANNs that do not adopt this structure.

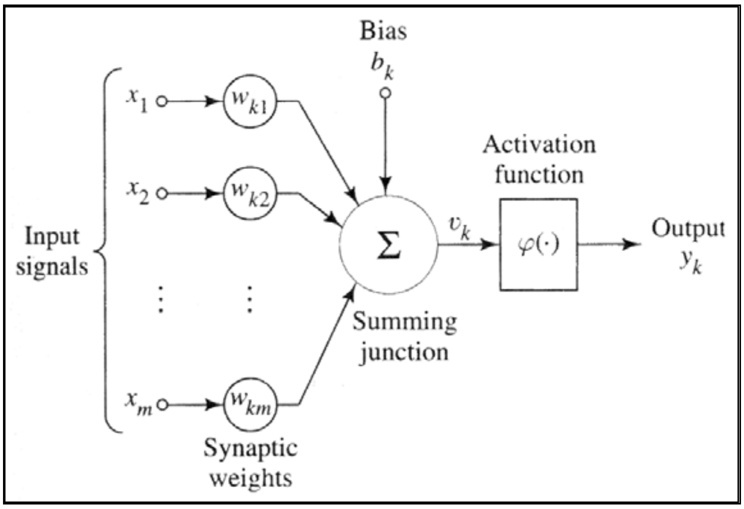

Figure 1. Artificial neuron structure or processing element (PE) (Haykin, 1999).

The starting point of the ANN structure is a layer of input units that allows the entering of information into the network. The input units cannot be considered as PEs mainly because there is no processing of information taking place at them with the exception of normalisation (when required). Normalisation is the process of equalising the signal range (commonly to a range between 0.1 and 0.9) of different inputs. Normalisation ensures that changes in the signals of different inputs have the same effect on the network's behaviour regardless of their magnitude.

Following the input layer is one ore more internal or hidden layers. The use of the word hidden is mainly due to the fact that they are not accessible from outside the ANN. The first hidden layer is fully interconnected with the units of the input layer. In other words, all PEs of the hidden layer receive the signal from each input unit. The signals are multiplied by a weight which is different for every connection. In the case of more than one hidden layers, there will be full interconnection between subsequent layers as in the case of the input and first hidden layer.

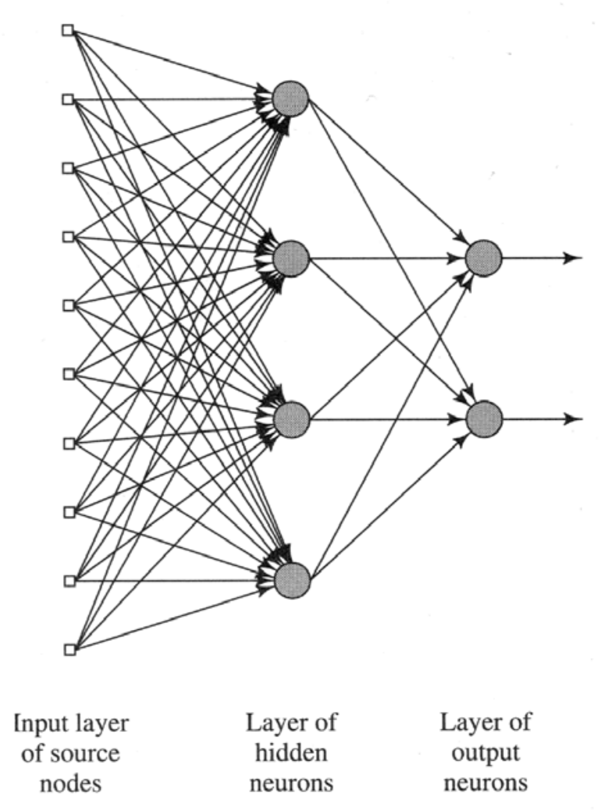

Figure 2. Artificial neural network structure.

The final part of the ANN structure is the output layer. The units of this layer are also PEs, which receive the signals from the last hidden layer and perform similar processing to that of the hidden PEs. If normalisation is used in the input layer, then the outputs of the output PEs have to be transformed back to the range of the original data to get sensible results. This is required normally when the ANN is used for function approximation.

2.2 Learning

Learning from examples is the main operation of any ANN. Learning in this case means the ability of an ANN to improve its performance through an interactive process of adjusting its free parameters. The adjustment of an ANN's free parameters is stimulated by a set of examples presented to the network during the application of a set of well-defined rules for improving its performance called a learning algorithm. There are many different learning algorithms for ANNs, each with a different way of adjusting the synaptic weights of PEs and different way of formalising the measurement of the ANN's performance.

2.3 Application

After the ANN reaches the required performance by learning examples, it can be used for computing output values for input that can be known to the network or not. It simply behaves as a series of functions that produce an output for a particular input.

3 MINING AND ENVIRONMENTAL APPLICATIONS

In this section a number of examples of mining and environmental ANN applications is presented. There are a lot more examples that cannot possibly fit in a single paper and the selection of the those presented is not based on their significance.

3.1 Exploration and Reserve Estimation

Exploration and reserve estimation commonly involves the prediction of various parameters characterizing a mineral deposit or a reservoir. The input data usually come in the form of samples with known positions in 3D space. The majority of the ANN systems developed for these predictive tasks are based on the relationship between modelled parameter and sample locations. The most common practice when developing the training patterns set for an ANN, is to generate input-output pairs with the input being the sample location and the desired output being the value of the modelled parameter at that location. In other words, most of the ANN systems treat the modelling of the unknown parameters as a problem of function approximation in the sample co-ordinates space.

Some other systems go a step further to exploit information hidden in the relationship between neighbouring samples. The estimation of a parameter at a specific location in 3D space is, in this case, depending on information from samples around that location.

An example of an ANN system for ore grade/reserve estimation was developed by Wu and Zhou (1993). The network architecture, as shown in Figure 3, is a Multi-Layered Perceptron with four layers: an input layer, two hidden layers, and one output layer. The network receives two inputs, the Easting and Northing of samples. The two hidden layers are identical and have 28 units each. It is a relatively large network considering the dimension of the input space (2D).

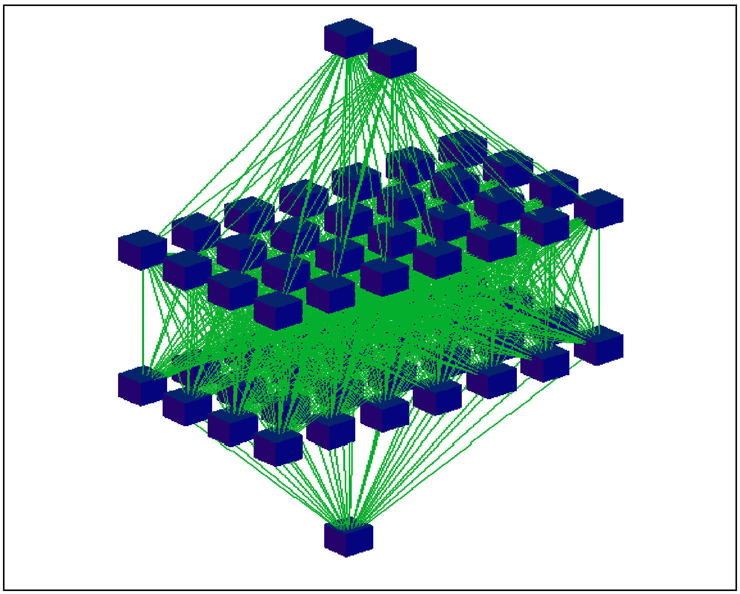

Figure 3. ANN for ore grade/reserve estimation (Wu and Zhou 1993).

One of the very few examples of ANN system being developed to a fully commercial product, is Neural Technologies' Prospect Explorer (Neural Mining Solutions 1996). It is a complete system offering data analysis, visualization, and detection of anomalies as well as analysis of the relationships between them.

The system is based on a neural structure called AMAN (Advanced Modular Adaptive Network), shown in Figure 4. AMAN is not a type of neural network. It is a complex system consisting of different types of networks, which are trained, in both supervised and unsupervised mode. The user has a choice of networks and learning strategies depending on the problem at hand.

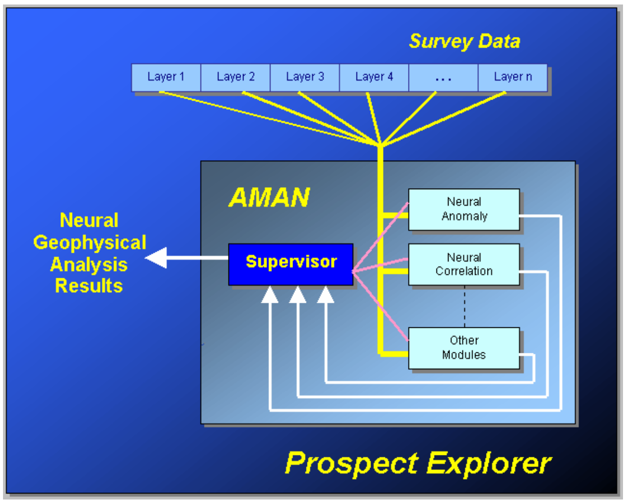

Figure 4. Structure of AMAN – core of Prospect Explorer.

AMAN as part of the Prospect Explorer can help to automate the detection of anomalies from large quantities of survey data. Prospect Explorer has been used with success in a reasonably complex exploration task that took place at the Girliambone region in New South Wales, Australia. This case study involved several layers of data from a copper mine area of 110 square kilometers. The system has successfully identified the already known deposits in the area as well as some unknown.

The GEMNet system developed by Burnett (1995) is a very good example of a modular neural network system for grade/reserve estimation. Figure 5 illustrates the principle of GEMNet's operation. The deposit is divided into overlapping zones. The selection of zones was arbitrary, which is a point where improvement could be made. In each zone, a different network was trained and the final estimate for every point was taken as the average of the networks trained in the specific area. As zones were overlapping, there was almost always more than one network giving estimates. Having more than one estimates led to the introduction of a reliability measure based on the variance of the individual estimates – an indicator that can be used as a guide for the reliability of the final estimate.

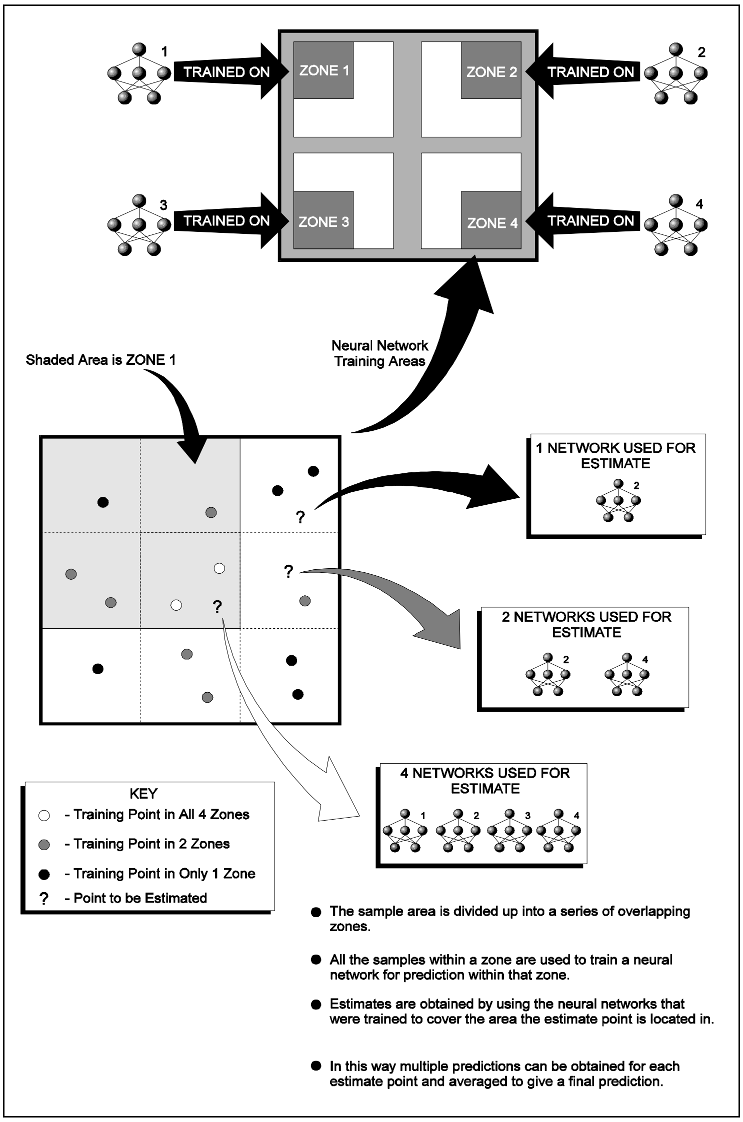

Figure 5. Grade Estimation Modular neural NETwork (GEMNet) (Burnett 1995).

3.2 Geophysics

Geophysics is a relatively new area for ANN systems. However, in the last few years ANNs have become a very popular tool in the interpretation of seismic and geophysical data from various sources.

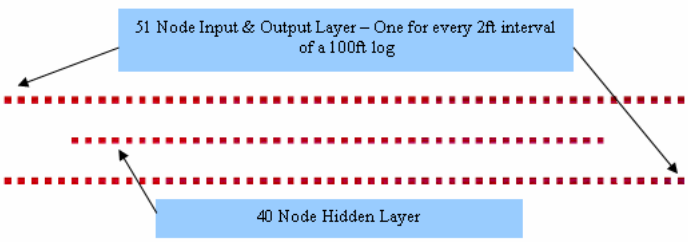

Figure 6. Back-propagation network used for lateral log inversion (Garcia and Whitman 1992). Connections between layers are not shown.

Garcia et al. have used a MLP trained using back-propagation for the inversion of lateral electrode well logs

(Garcia and Whitman 1992). Inversion represents the process of constructing an earth model from the log data. The data used for training the network were derived from a finite difference method that simulated the lateral log. The trained network was tested using real data and the results were compared with those from an automated inversion model. The study has shown promising results and has presented the advantages of the use of ANN for the specific problem.

In a similar fashion, Rogers et al. used a MLP network for the prediction of lithology from well logs (Rogers, Fang, Karr, and Stanley 1992). Malki and Baldwin (1996) compared the results produced by neural networks trained using well logs from different service companies. More specifically, networks were trained using data from one service company and tested on data from another, and the study was repeated using training data from both companies and tested on data from each one individually. The results have shown that better performance is obtained when using data from both service companies.

Wanstedt et al. applied neural networks to the interpretation of geophysical logs for orebody delineation (Wanstedt, Huang, and Malmstrom 1998). The data used for the development and testing of their approach were taken from the Zinkgruvan mine in Sweden. The network used was quite small – three layers with 3 inputs, 7 hidden units, and 1 output. The inputs were the gamma-ray, density, and susceptibility, and the output was the ore grade (Zn, Pb, or Ag). The study reports good results in estimating the grades and consequently interpreting the lithology. Unfortunately no numerical measurement of the network's performance is provided.

Murat et al. used a MLP for the identification of the first arrival on a seismogram (Murat and Rudman 1992). Roessler (1992) used NETS, a neural network simulator written at NASA/Johnson Space Center to develop a neural network for analysing wave arrivals from seismic waves transmitted from one borehole and received from another. The network was trained on a binary pixel image of the seismic trace data. The input layer consisted of a large array (97 x 41 = 3977) of input nodes, the hidden layer had 50 units, and the output layer had two units. The network was trained to produce a binary pattern in its outputs, i.e. the outputs were either 1 or 0. The different combinations of outputs were indicative of the relative position of the first arrival to the current positive lobe. Once again, no numerical measurement of the networks performance during training and testing was provided in the study.

Barhen and Reister (1999) developed DeepNet, a system based on the MLP that predicts well pseudo logs from seismic data across an oil field. DeepNet combines a very fast learning algorithm, systematic incorporation of uncertainties in the learning process, and a global optimisation algorithm that addresses the optimality of the learning process. The system has been successfully applied in the Pompano field in the Gulf of Mexico.

3.3 Rock Engineering

King et al. have developed an unsupervised neural network for the discovering of patterns in roof bolter drill data. The network successfully classified 617 drill patterns to just 9 or 16 unique features representing major geologic features of a mine roof. The patterns consisted of the penetration rate, thrust, drill speed, and torque. A system consisting of this network and an expert system was developed for the evaluation of coal mine roof supports (King, Hicks, and Signer 1992, 1993).

Millar et al. used self organising networks to model the complex behaviour of rock masses by classifying input variables related to the rock stability into two groups: failure or stability (Millar and Hudson 1993).

Walter (1999) used *Kohonen* networks for the classification of mine roof strata into one of 32 strength classes. The developed system can provide an estimate of strength within two seconds giving the drill operator a warning almost in real time when a potentially dangerous layer is reached.

3.4 Mineral Processing

Neural networks have been successfully applied to a number of pattern classification problems. Particle shape and size analysis seems to be a natural field of application for ANNs and specially for unsupervised techniques.

Maxwell et al. developed an ANN based system for particle size analysis based on video images. The system analyses images from material on a conveyor and predicts the particle size distribution (Maxwell, Denby, and Pitts 1995).

Oja and Nyström (1997) applied *self-organising maps* (SOM) for particle shape quantification. Image analysis is performed to mineral slurry particles by use of a SOM which extracts the features affecting the behaviour of powders and slurries. The training data set consisted of 3000 binary images of 500 particles. The produced map size was 12 x 10. The developed SOM was tested on 360 particle images with success. The test showed that the SOM was capable of clustering differently minerals that did not have strong shape features.

Deventer et al. used again the SOM for on-line visualisation of flotation performance (van Deventer, Bezuidenhout and Moolman 1997). The structure of the froth is quantified by the neighbouring grey level dependence matrix. The SOM had a map size of 20 x 20 and there were three classifications of Zn grade peaks as being positive (Class_+1), zero (Class_0), or negative (Class_-1) for each of the image features. The classification was based on a number of image features. The developed SOM was to be used as part of an automated computer vision system for the control of flotation circuits.

Petersen and Lorenzen (1997) applied the SOM to the modelling of gold liberation from diagnostic leaching data. The data came from seven different gold mines in South Africa. The ores from the mines were fed to mills and the ore samples were screened into three size intervals. One of the fractions was further screened into six size fractions giving a total of eight fractions. Representative samples were then fed to a ball mill, and the product was screened into the same six size fractions. On each of the fractions, diagnostic leaching was performed for each of the ore types. The percentage of gold deportment and percentage of gangue, the percentage of free gold in each fraction, the head grade, and the mass distribution were projected to a 10 x 10 map. The clustering produced was well defined for the different sample sources (gold mines) except for one of them.

3.5 Remote Sensing

Probably one of the most popular areas of neural network application, remote sensing presents problems which are ideal for architectures such as the SOM, the LVQ, or even the standard MLP. The examples given here, even though not directly linked to mining activities, demonstrate the potential of ANNs in this field.

Bischof et al. used a MLP for the multispectral classification of Landsat images (Bischof, Schneider and Pinz 1992). These images came from a Landsat Thematic Mapper (TM) and were 512 x 512 pixels in size. They were also analysed into 7 spectral channels (bands) which were used as the inputs to the network (13 units for each band representing different intervals from 0 to 255). The network then had to learn to classify the 7 band values to one of four types of land (built-up land, forest, water, and agricultural land), each represented by an output of the network. Even though this architecture gave good results, the developers extended the network to include a 7 x 7 pixel map of texture from band 5. Naturally the number of hidden units was increased from 5 to 8 units. The results from this extended architecture were better than the non-extended one in all types of land.

Gopal and Woodcock (1996) used a MLP for the detection of forest change from Landsat TM images between 1988 and 1991. A 10-input vector of 10 TM bands (5 from 1998 and 5 from 1991) is used with the single output being the absolute or the relative change. The results obtained with the developed MLP were better than those obtained with the conventional method for this task.

Poulton and Zaverton (1992) give a comparative study between different neural network architectures used for classification of TM images. The architectures compare were the back-propagation network, LVQ, counter-propagation network, functional link, probabilistic network, and the SOM. From the tests performed, they concluded that the LVQ architecture was the most flexible and robust one. They also suggested the use of ANNs for the analysis of geochemical and geophysical data, location of favorable prospects using GIS data, lithologic mapping from remote sensing data, and estimation of parameters in a similar way with kriging.

Krasnopolsky (1999) used a MLP for the retrieval of multiple geophysical parameters from satellite data. These parameters were the surface wind speed, columnar water vapor, columnar liquid water, and sea surface temperature (the four outputs of the MLP). The MLP had five inputs taken from five Special Sensor Microwave Imager brightness temperatures. The hidden layer had 12 units. The simultaneous retrieval of multiple parameters improved the retrieval of each one individually allowing physically coherent and consistent geophysical fields to be produced.

Xiao and Chandrasekar (1997) used a MLP for rainfall estimation from radar observations. More specifically, two networks have been developed, one using reflectivity as the only input, and the other using both reflectivity and differential reflectivity as the inputs. The networks were trained on data obtained from a multi-parameter radar and raingages from the Kennedy Space Center. The trained networks were then used to estimate rainfall for four days during the summer of 1991. The trainning patterns consisted of a square grid (3 x 3km) of reflectivity values as well as distances from the grid nodes to the point of estimation. The raingage values were used as the target outputs. The trained network estimates and raingage values have shown good agreement at all sites.

3.6 Process Control-Optimisation and Equipment Selection

Process control and optimisation tends to be a tedious task involving large amounts of data from very different sources. ANNs are ideal for handling such tasks and this is why many researchers in the field of process control turned to them for developing solutions. Process control and optimisation of mineral processing plants as well as the mining process itself are a special case of these tasks and can therefore be approached by neural networks.

Van der Walt et al. used the MLP for the simulation of Resin-in-pulp process for gold recovery (Van der Walt, van Deventer, Barnard and Oosthuizen 1992). Flament et al. (1993) used the MLP for the identification of the dynamics of a mineral grinding circuit and the development of a control strategy. Bradford (1994) used neural networks in a number of studies modelling the behaviour of different parts of a mineral processing plant.

Ryman-Tubb and Bolt of Neural Mining Solutions Pty Ltd (1996) describe the use of the AMAN architecture (described before) for integrated process system modelling and optimisation. The suggested areas of application include froth flotation, carbon-in-pulp (CIP), milling, and others. Their case study presented a real-life example based on a multi-stage copper extraction process. The trained networks (MLPs) were used for the following:

- Prediction of stripped copper cathode from electrowinning
- Prediction of raw material usage
- Identification of key plant parameters
- Analysis of the effect of plant input parameters
- Economic optimisation to determine cost-effective control settings

The developers claimed the following benefits from the ANN approach:

- Decreased raw material costs
- Increased copper production
- Optimised planning of new and existing heap operations
- Ability to implement “Just-in-time” purchasing policy
- Planning of new heaps
- Reduce reliance on individual and human operation

Finally, Schofield (1992) investigated the use of neural networks as well as other AI tools for the selection of surface mining equipment.

4 CONCLUSIONS

Quite clearly, the spectrum of neural network applications in mining and environmental engineering is very wide. This is demonstrated by a number of exciting and very promising studies by a number of people from different scientific fields. The examples presented in this paper support the choice of ANNs as the basis for developing solutions to mining problems were conventional techniques fail in one way or another. Mining is always about time and money and so far neural networks have shown that they can be very good in both terms. The systems described in the above examples were fast, reliable and most of the times provided a very stable theoretical background on which the validity of the proposed solution is based.

The general trend in the mining and environmental industry for automation to the greatest degree calls for technologies such as the ANNs that can utilise large amounts of data for the development of models which otherwise are very difficult or sometimes even impossible to identify. The speed of ANNs – at least in application mode – also allows the development of real- or almost real-time systems which can quickly recognize potential problems or even danger during a certain process.

Another advantage of ANNs is in the minimisation of the necessary assumptions for a given problem. Specially in the case of grade estimation, this attribute proves very valuable. The examples of ANN application to grade estimation given earlier in this paper supported this and other advantages of neural networks.

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