NEURAL NETWORK ASSESSMENT OF ROCKBURST RISKS FOR DEEP GOLD MINES IN SOUTH AFRICA①

Feng Xiating
College of Resources and Civil Engineering,
Northeastern University, Shenyang 110006, P. R. China
S. Webber
CSIR Mining Technology, Johannesburg, South Africa
M. U. Ozbay
Department of Mining Engineering,
University of the Witwatersrand, Johannesburg, South Africa

ABSTRACT A neural network modeling to assess rockburst risks for deep gold mines in South Africa has been described. About 200 cases of rockbursts from a database were used to train the neural network. The results from the test cases of VCR and Carbon Leader mining, for both stopes and tunnels, were presented. It was shown that, although it has the potential to assess rockburst risks, the proposed empirical approach is still highly dependent on the accuracy of the case records collected and the way the database is structured. Within the confines of the database used, various quantitative and qualitative features affecting rockbursts were identified and their integration of an expert system and neural networks was proposed.

Key words neural network rockburst risk South Africa

1 INTRODUCTION

The problem of mining-induced seismic events (rockbursts) has been a common feature of deep gold mines in South Africa[1]. This problem has been critical at greater depths, particularly when the mining ore body is associated with faults, dykes and pegmatites. Many a time area rockbursts have caused fatalities and extensive damage to the surface and underground mine structures. The area rockburst is generally influenced directly by tectonic stresses, geological discontinuities and indirectly by mining activities. Though many efforts have been made by researchers to understand the causes, and to predict the occurrence of these area rockbursts, the success achieved has been limited. This is partly due to the complex nature of rock mass and the complex physical process of rockbursts. Uncertainties exist in geological data and in properties of rock masses, some geological data may be missing, the rock mass properties must be estimated from theoretical procedures or large field tests, therefore, a perfect set of input data for prediction was seldom given to the modelers. In such circumstances, the experience of similar mining in similar geological conditions and the expertise of experienced geomechanical engineers have invaluable values for drawing the best predictions from insufficient and uncertain data. Current methods focusing on looking for exact mathematical descriptions or only on local magnitude often result in unsatisfying results. In such cases the ability of artificial neural network of coping with incomplete information further encourages us to explore the extrapolating ability of rockburst risk assessment for deep gold mines in South Africa[2-4].

The artificial neural network is a new branch of intelligence science and has developed

① Project 59604001 supported by the National Natural Science Foundation of China and project 96014513 supported by the PhD Science Foundation of National Education Committee of China Received Dec. 20, 1996; accepted Mar. 25, 1998

rapidly since the 1980s[5-8]. The artificial neural network is an information processing system emulating the structure and functions of human brain. It consists of numerous simple processing elements connected together (see Fig. 1) according to certain rules and is able to response dynamically to an outside stimulus and process information. As for the human brain, the structure and processing sequence of the artificial network are parallel. The artificial neural network has a very strong learning ability and can adapt itself to the outside environment by learning. In an artificial neural network, knowledge is not stored in some specific memories but distributed in the whole system. In order to store knowledge there must be numerous connections. The artificial neural network can learn from incomplete and inaccurate data, even with considerable noise, and has a very robust of error-tolerance. The artificial neural network, if properly trained, can give an approximately optimal solution from limited and distorted information.

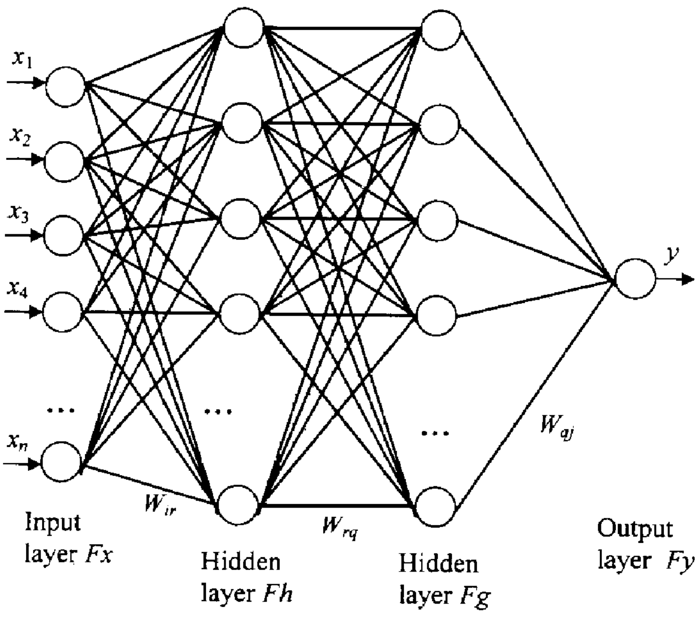

Fig. 1 Structure of network for rockburst assessment

In this paper a neural network modeling on rockburst risk assessment is proposed. Assessment of rockburst risks in stope faces with Carbon Leader reef mining and VCR reef mining as well as in tunnels in general were modeled respectively. Several historical cases were used to test the model and system. The results obtained are interesting.

2 ESTABLISHMENT OF NONLINEAR MODEL FOR ROCKBURST RISK ASSESSMENT

Suppose a data set of history case $(x_p, y_p)(p = 1, 2, \cdots, N)$ for rockbursts as

$$x_p = (x_{p1}, x_{p2}, \cdots, x_{pn})$$

$$y_p = (y_{p1}, y_{p2}, \cdots, y_{pm})$$

where x_{pi} is the ith factor causing rockbursts, $i = 1, 2, \cdots, n$; y_{pj} is the jth index indicating rockburst risk assessment, $j = 1, 2, \cdots, m$.

According to engineering experience, the factors affecting rockbursts in South African gold mines can be considered depending on different reefs (Carbon Leader reef, VCR reef, Vaal reef, Main reef, Basal reef, Kloof reef, Composite reef, etc.) and engineering types (stope face, gully, tunnel). For example, for stope face with Carbon Leader reef mining or VCR reef mining the factors such as depth below surface, dip, structure type, mining method, stope width, strike span, permanent support, region support and temporary support were determined by statistical analysis of rockburst cases. Rockburst risks may be assessed by percentage.

Modeling on rockburst risk assessment is to establish a relationship between y_p and x_p as

$$G: R^n \rightarrow R^m$$

$$y_p = G(x_p) \quad (p = 1, 2, \cdots, N) \qquad (1)$$

Generally, the relationship G is nonlinear. Instead of mathematical equation, a parallel distribution representation was used for the relationship G. In this new representation, let $y_p = (y_{p1}, y_{p2}, \cdots, y_{pm})$ be represented by the output nodes and $x_p = (x_{p1}, x_{p2}, \cdots, x_{pn})$ be represented by the input nodes to construct a multilayer feedforward neural network shown in Figure 1. There may be one or more hidden layer(s) between the input layer and the output layer in order to represent a complex nonlinear mapping of rockburst risks. According to Hertz *et al*[8], the network with two hidden layers is enough to represent nonlinear relationship of problems. The prediction errors of the networks with different numbers of hidden layers (from 1 to 7 hidden layers) were also compared in experiment of rockburst risk assessment. The results also indicate that the network with two hidden layers is the best for the study in this paper. The node threshold function is sigmoidal, as

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The nonlinear rockburst risk assessment represented by Eqn. (1) is recognized by using machine learning performed on neural network. A training sample data set is used to train the multilayer feedforward neural network to obtain a nonlinear model, which is very approximated to the actual G. Thus, the nonlinear rockburst model can be represented by

$$\hat{y}_{pj} = f(\sum_q W_{qj} \cdot f(\sum_r W_{rq} \cdot f(\sum_{i=1}^{n} W_{ir} x_{pi} + \theta_r) + \theta_q) + \theta_j) \tag{3}$$

where $\hat{y}_{pj}$ is computing output for the ith variable of the pth learning sample, x_{pi} is data of the ith input parameters of the pth sample. If x_{pi} is descripted qualitatively, it needs to be transformed into numerical value by using the constructed different rules.

The connection weights W_{ri}, W_{rq}, W_{qj} and thresholds θ_r, θ_q, θ_j are determined automatically by using machine learning. Thus, the nonlinear representation of Eqn. (1) will be obtained. An extrapolating estimation algorithm[9-11] is used to perform this learning.

3 ASSESSING ROCKBURST RISKS BY USING HISTORICAL CASES

3.1 Assessing rockburst risks in stope faces with Carbon Leader reef mining

Rockburst risks at stope face with Carbon Leader reef mining were assessed firstly. A history case data set for rockburst events occurred was collected from a rockburst database that was established by CSIR Mining Technology (see Fig. 2). In each column in Fig. 2, an "x" is used to mark the presence of a particular feature of the case record. If a feature is absent a "." is used as appropriate. There are 32 features for each record that is derived from the descriptions used in the rockburst database. Each pattern is presented as a vector in a 32-dimensional space consisting of 1s and 0s in which "x" corresponds to 1, "." corresponds to 0. It is not required that each node contains only 1s or 0s - the node may contain any number among 1 and 0. Each node represents one feature shown in Fig. 2.

The 72 patterns (the first 72 cases shown in Fig. 2) were random selected for model recognition and other 7 patterns (the last 7 cases shown in Fig. 2) were used to test the accuracy of the learned model. A multilayer feedforward neural network was trained to obtain nonlinear model for rockburst risk assessment. Many of network configurations were tested for this nonlinear estimation. The number of nodes in the 1st and 2nd hidden layer was estimated from 1 to 100 respectively. The best topology of the network was 32 → 65 → 1, this is, 32 nodes for the input layer, 65 nodes for hidden layer and 1 nodes for the output layer (See Fig. 1).

During the model learning, the different learning parameters η and α were taken from 0.1 to 0.95 at 0.05 interval respectively. The best parameters were $\eta = 0.1$, $\alpha = 0.1$ for the given training sample set and the network. The determined network needs 2001 learning iterations to obtain the best extrapolating outputs of rockburst risk assessment. Rockburst risks of 7 new cases were assessed as 0.0%, 0.0%, 98.6%, 0.1%, 0.0%, 0.0%, 0.0% respectively. In fact, only the case 75 shown in Fig. 2 did occur rockburst.

Another experiment was carried out to test the capability of the system to find main features of rockbursts. In this experiment, the features of the case 78 are used as the cues. However, instead of the actual cues of permanent support "backfill" with "backfill + hydraulic props", "hydraulic props" or "packs" respectively, and instead of the cues of region support "backfill + stabilizing pillar" with "stabilizing pillar", "backfill" or "none" respectively, rockburst risks are all assessed with 0.0%. If the cue of permanent support "backfill" is replaced by "packs", and the cue of region support "backfill + stabilizing pillar" is replaced by "none", the cue of temporary support "hydraulic props" is replaced by "none", respectively, rockburst risk is

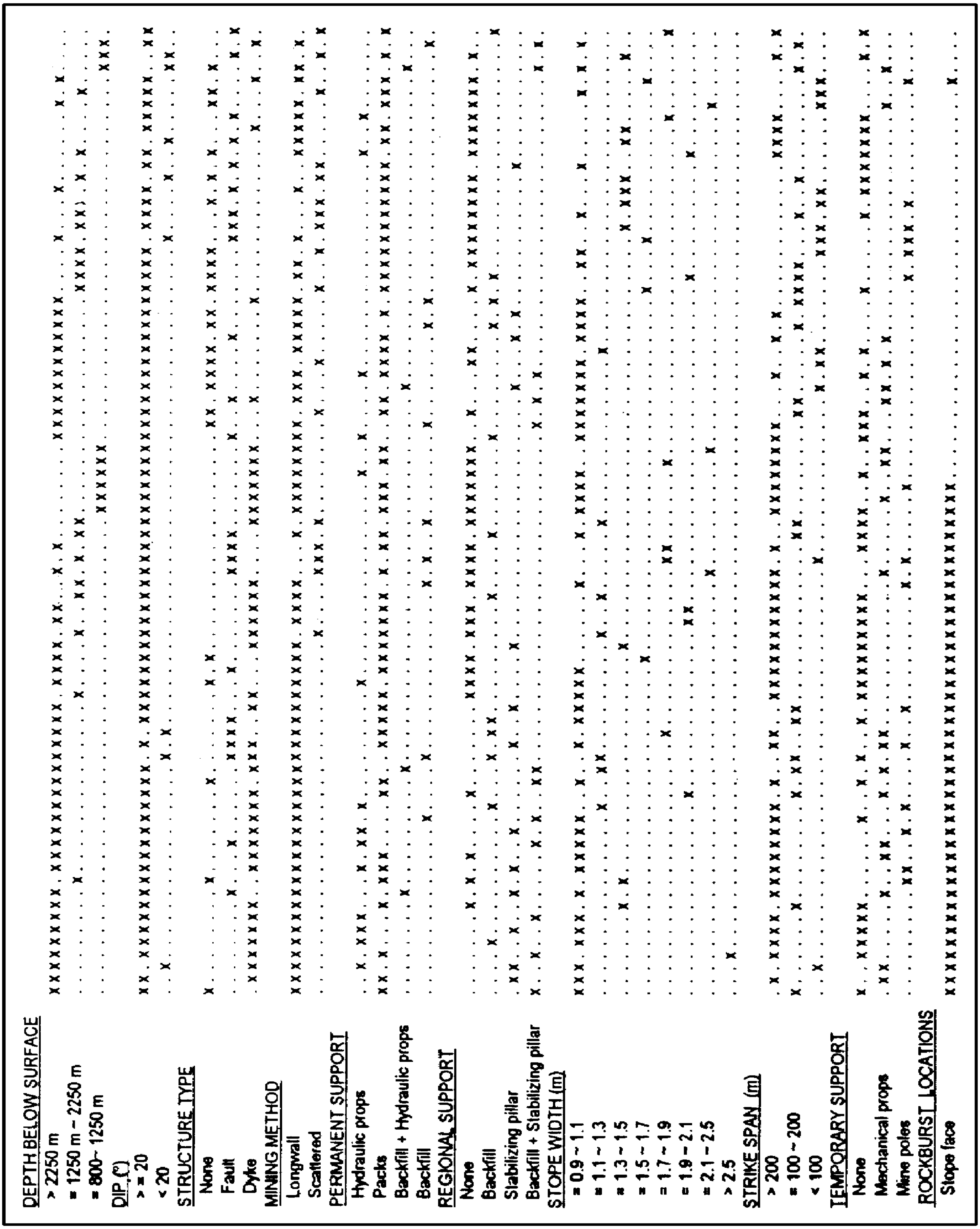

Fig. 2 Rockburst case records of stope faces used as learning and testing patterns (Reef: Carbon Leader)

then assessed with 24.2%. If the cue of permanent support "backfill" is replaced by "packs", the cue of region support "backfill+ stabilizing pillar" is replaced by "none", the cue of temporary support "hydraulic props" is replaced by "none", and the cue of strike span "100~ 200 m" is replaced by "> 200 m", respectively, rockburst risk is thus increased to 96.7%. If the cue of temporary support "hydraulic props" is kept, even though the cue of strike span is taken as "> 200 m", "100~ 200 m" or "< 100 m" respectively, it would be no rockburst risk for the case 78.

3.2 Assessing rockburst risks in stope faces with VCR reef mining

A history case data set for rockburst events occurred at stopes with VCR reef mining was collected from a rockburst database that was established by CSIR Mining Technology. The 100 samples were randomly selected for model recognition and another 4 samples were used to test the accuracy of the learned model.

As for the previous experiment, many neural network architectures were tested and the best topology was 32 → 65 → 1. The learning parameters were both taken as 0.1. According to the minimum-error principle of extrapolated assessments, the model output for the best assessment of rockburst risks of the 4 new cases were 3.9%, 88.8%, 97.6%, 100.0% respectively. In fact, the cases 102, 103 and 104 did occur rockbursts.

3.3 Assessing rockburst risks in tunnels for gold mines in general

The 60 history cases of rockburst events occurred at tunnels for gold mines in general were collected from a rockburst database that was established by CSIR Mining Technology. The 56 samples were random selected for model recognition and other 4 samples were used to test the accuracy of the learned model.

Once again, many neural network architectures were tested and the best topology of the network was 20 → 30 → 1. Input nodes were represented by factors, such as depth below surface, structure, excavation width, excavation height and permanent support, with various ranges. The learning parameters were taken as $\eta = 0.05$, $\alpha = 0.1$. The model was obtained by training the network at 100 iterations of learning. Rockburst risks of the 4 new cases were assessed as 99.7%, 0.0%, 98.5%, 0.0% respectively. In fact, rockburst did occur at the 57th and the 59th cases.

In order to test the capability of the system to find main features of rockbursts another experiment was also done. In this experiment, the features of the case 57 are used as the cues. However, instead of the actual cues of depth below surface "= 1 225~ 2 250 m" and structure type "dyke", the depth below surface "> 2 250 m" and the structure type "none" were used. Then the risk of rockburst was assessed as "33.1%". If the depth below surface "> 2250 m" was kept, and the structure type "fault" was used, the risk of rockburst rises to "99.9%". Instead of the actual cues of depth below surface "= 1 225~ 2 250 m", and the depth below surface "= 800~ 1 250 m" was used, then the risk of rockburst was assessed only "62.2%". Instead of the actual cues of depth below surface "= 1 225~ 2 250 m," the depth below surface "< 800 m" was used, then the risk of rockburst reduces to "0.0%". Instead of the actual cues of depth below surface "= 1 225~ 2 250 m" and structure type "dyke" the depth below surface "= 800~ 1 250 m", the structure type "none" or "fault" were used, then the risk of rockburst were assessed as "0.2%," and "59.5%", respectively.

4 CASE STUDIES

4.1 Case 1

In Western Deep Levels West Mine, Carbon Leader reef were mined with longwall method. Stope width was 0.9 m, strike span was 24 m. The geological structure is dyke and joints parallel to dyke. Dip was 20° and dip span was 270 m. The field stress was 72 MPa. Hangingwall rock was dyke with the UCS of greater than 300 MPa, footwall rock was dyke with UCS greater than 300 MPa. Permanent support was "packs", regional support was "backfill+

stabilizing pillar", no temporary support was adopted.

The neural network model assessed rockburst risk in this mining area was 99.9%. On the another way, the developed expert system by authors gave its assessment that rockburst would be "high". In fact, a big rockburst did occur in this mining area (Hypocenter *X*: 28 726, Hypocenter *Y*: − 38 619, Hypocenter *Z*: 3 180) at 9:33 PM, February 11, 1994. The width of fall was 2.4 m, height of fall was 0.8 m and lengths of fall was 0.8 m. The local magnitude was 1.72

4.2 Case 2

Composite reef mining was carried out with Longwall method in Er pm G. M. K#. Stope width was 0.9 m, strike span was 200 m, geological structure was dyke, dip was 19° and dip span was 240 m. Hangingwall rock was Quartzite with UCS 180 MPa, footwall rock was Maraisburg formation with UCS 235 MPa. Field stress was 141 MPa. Permanent support was 1.1 m by 1.1 m solid timber packs+ pipesticks, stabilizing pillar was used as regional support, 3 rows of hydraulic props with 1 m of spacing were used as temporary support.

The neural network model assessed rockburst risk in this mining area was 96.6%. The developed expert system assessed that rockburst would be "severe". In fact, a severe rockburst did occur in this mining area at September 23, 1993 12:40 PM. The width of fall was 10 m, height of fall was 0.7 m and length of fall was 50 m.

5 CONCLUSIONS

In light of discussion above the following conclusions can be drawn:

(1) It is sometimes complicated for traditional analysis methods to assess rockburst risks. Generally, it needs experiential data to determine calculation parameters. The proposed self-learning based and adaptive modeling method in this paper can overcome some of these problems. In which, the final nonlinear assessment model for rockburst risks is recognized by the artificial neural network itself from learning the history cases of rockburst and expressed in the parallel distribution of information in the nodes of the artificial neural network. So long as history records of rockburst data are available, neural network model can grasp knowledge of assessing rockburst risks by learning and then gives good extrapolated estimation.

(2) An improved back propagation algorithm was proposed in order to improve the ability of neural network to extrapolate assessment of rockburst. The minimum square error sum of rockburst risk assessment for new samples that are not used to train the network were used to judge whether the model recognition procedure ends or not. Therefore, some problems such as the local minimum and excessive training that the traditional methods have can be overcome.

(3) Stope faces with Carbon Leader reef mining and VCR reef mining were modeled. The 79 Carbon Leader reef mining cases and 104 VCR reef mining cases have been collected. Some cases were used to train the network to obtain nonlinear model of rockburst risk assessment. Within the confines of the database used, various quantitative and qualitative features affecting rockbursts were identified. These features are depth below surface, dip, structure type, mining method, stope width, strike span, permanent support, regional support and temporary support.

(4) Also, tunnels (airway, roadway, and haulage) for gold mines in general were modeled. 60 cases have been collected from a rockburst database. The affecting factors such as depth below surface, structure, excavation width, excavation height and permanent support were also identified within the confines of the database used.

(5) Besides affecting factors mentioned above, energy release rate (ERR), excess shear stress (ESS), structure number, distance from structure, face angle with structure, support resistance, stope close rate and virgin stress ratio and rock strength have contributed to rockbursts. So, in this case, an expert system was constructed to assess the possibility of rockbursts. The expert system included about 950

rules, some important parameters, such as ERR, ESS, etc, were included in rules. The expert system and neural network models were integrated into an intelligent assessment system to make extrapolating assessment of rockburst risks. It is shown from the results of rockburst risk assessment of some new cases that accuracy of models is high.

ACKNOWLEDGMENT

The authors would like to thank CSIR Miningtek for her financial support and The University of Witwatersrand, Johannesburg for her favorable research environment. The authors also like to thank CSIR Miningtek for the providing of a rockburst database and many staff members in the Department of Mining Engineering, particularly Prof. Huw Phillips, Ms Dee Mckee, Mr. Geoff Clatworthy for their kindly helps.

REFERENCES

1 Chamber of Mines Research Organization. An Industry Guide to Methods of Ameliorating the Hazards of Rockfalls and Rockbursts, 1988 edition. South Africa.

2 Feng Xiating, Wang Yongjia and Yao Jianguo. International Journal of Rock Mechanics and Mining Sciences, 1996, 33(6): 647- 653.

3 Feng Xiating. International Journal of Surface Mining, Environment and Reclamation, 1995, 9: 57- 62.

4 Feng Xiating and Lin Yunmei. Expert Systems in Rock Mechanics. Shenyang: Liaoning Science and Technology Press, 1993.

5 Rumelhart D E and McClelland J L eds. Parallel Distributed Processing. Cambridge: MIT Press, 1986, 200- 400.

6 Grossber S. Neural Network, 1991, 1: 17- 61.

7 Hechit-Nielsen R. Neuron Computing. Reading Massachusetts: Addison Wesley, 1990: 120- 230.

8 Hertz J, Krogh A and Palmer R G. Introduction to Theory of Neural Computation. Reading Massachusetts: Addison Wesley. 1989: 134- 198.

9 Feng Xiating and Wang Yongjia. International Journal of Rock Mechanics and Mining Sciences, 1997, 34(1): 135- 141.

10 Feng Xiating and Katsuyama K. Geophysical Journal International, 1997, 128: 547- 556.

11 Feng Xiating, Webber S and Ozbay M U. In: Proc of 1st Southern African Symposium on Rock Engineering, 1997.

(Edited by He Xuefeng)