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PNN-based Rock burst Prediction Model and Its Applications

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ABSTRACT

Rock burst is one of main engineering geological problems greatly threatening the safety of construction. Prediction of rock burst is always an important issue concerning the safety of workers and equipments in tunnels. In this paper, a novel PNN-based rock burst prediction model is proposed to determine whether rock burst will happen in the underground rock projects and how much the intensity of rock burst is. The probabilistic neural network (PNN) is developed based on Bayesian criteria of multivariate pattern classification. Because PNN has the advantages of low training complexity, high stability, quick convergence, and simple construction, it can be well applied in the prediction of rock burst. Some main control factors, such as rocks' maximum tangential stress , rocks' uniaxial compressive strength , rocks' uniaxial tensile strength and elastic energy index of rock are chosen as the characteristic vector of PNN. PNN model is obtained through training data sets of rock burst samples which come from underground rock project in domestic and abroad. Other samples are tested with the model. The testing results agree with the practical records. At the same time, two real-world applications are used to verify the proposed method. The results of prediction are same as the results of existing methods, just same as what happened in the scene, which verifies the effectiveness and applicability of our proposed work.

Keywords: Probabilistic neural network (PNN); Rock burst; Prediction

Modelo de predicción de fractura de rocas basado en una red neuronal probabilística y sus aplicaciones

RESUMEN

El fracturamiento o explosión de rocas es uno de los principales problemas en ingeniería geológica que amenaza significativamente la seguridad de una construcción. La predicción del fracturamiento de rocas es importante para la seguridad de los trabajadores y el equipamiento en túneles. En este artículo se propone un nuevo modelo de predicción de fracturamiento de rocas basado en una red neuronal probabilística (PNN por sus siglas en inglés) para determinar la posible ocurrencia e intensidad de uno de estos eventos en proyectos subterráneos. La PNN se desarrolló con base en un criterio Bayesiano para la clasificación multivariada de patrones. Debido a que la PNN tiene las ventajas de una menor complejidad de adiestramiento, estabilidad, rápida convergencia y simplicidad en su construcción, se puede adecuar en la predicción del fracturamiento de rocas. Algunos factores principales de control, como la fuerza máxima tangencial de rocas, la resistencia de compresión uniaxial, la fuerza de tensión uniaxial, y el índice de energía elástica de las rocas fueron escogidos como los vectores característicos de la PNN. El modelo se obtuvo a través del adiestramiento de datos sobre fracturamiento de rocas en proyectos subterráneos en diferentes localidades. Otras datos también se analizaron con el modelo. Los resultados de la evaluación se ajustan a los registros observados. Simultáneamente, se utilizaron dos aplicaciones prácticas para verificar el método propuesto. Los resultados de la predicción son similares a los de métodos existentes, un factor que además se presentó en las pruebas de campo, lo que demuestra la efectividad y la aplicabilidad de la metodología propuesta.

Palabras clave: Red Neuronal Probabilística; fracturamiento de rocas; predicción.

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1. Introduction

A rock burst is a sudden and violent expulsion of rock from the surrounding rock mass. Rock burst is considered a dynamic instability phenomenon of surrounding rock mass of un-derground space in high geostatic stress and caused by the violent release of strain energy stored in the rock mass. Rock burst occurs during excavating underground space in the form of a stripe of rock slices or rock fall or throwing of rock fragments, sometimes accompanied by crack sound. Rock bursts are related to the fracture of rock in place and require two conditions for their occurrence: stress in the rock mass sufficiently high to exceed its strength, and physical characteristics of the rock which enable it to store energy up to the threshold value for sudden rupture. Rocks which yield gradually in plastic strain under load usually do not generate rock bursts. The likelihood of rock bursts occurring increases as the depth of the mine increases. Rock bursts are also affected by the size of excavation, becoming more likely if the excavation size is around 180m and above. Induced seismicity such as faulty methods of mining can trigger rock bursts. Other causes of rock bursts are the presence of faults, dikes, or joints (Dong et al., 2013).

Because rock burst occurs suddenly and intensely, it usually causes injury including death to workers, damage to equipment, and even substantial disruption and economic loss of under-ground space excavation. Therefore, there is a need for the development of suitable computa-tional methods for the prediction and control of rock bursts particularly for a safe and economic underground excavation for construction or mining in the burst-prone ground. For this case, numerous related research works, concerning about the mechanism, characteristics or type, the cause of formation, the critical conditions and preventive methods of rock burst have been con-ducted by many researchers. Many researchers have suggested various theories, many predic-tion methods, and empirical correlation, such as fuzzy-base evaluation method (Wang et al., 1998; Amoussou et al., 2013), distance discriminant analysis (Wang et al., 2009; Wang et al., 2017), support vector machine (SVM) (Zhao, 2005; Zhou et al., 2012, extension-theory-based method (Xiong et al., 2007), rough-set-based method (Yang, 2010), unascertained measurement method(Shi et al., 2010), numerical simulation (Zhen & Gao, 2017; Zhu et al., 2010) and case study (Mansurov, 2001).

These studies offered new ideas and approaches for rock burst prediction. However, each method discussed above has its advantages and disadvantages, and understanding, predicting and controlling the rock bursts still pose a considerable challenge for underground engineering.

As an important means, the ANN-based method for prediction of rock burst has been adopted by many researchers gradually in recent years (Bai et al., 2002; Zhang et al., 2012). Ar-tificial neural network technique is considered the most effective and reliable artificial intelli-gence methods for solving classification, prediction and recognition problems.

Currently, back propagation (BP) and radial basis function (RBF) networks are used in the field of prediction of robust classification. However, for network training, they are all easily trapped in local minimum values. Probabilistic neural network (PNN), on the other hand, is a feedforward neural network. It is derived from the Bayesian network and a statistical algorithm called kernel Fisher discriminant analysis. It was introduced by Specht and Donald(1990). Be-cause PNN has the advantages of low training complexity, high stability, quick convergence, and simple construction, it has a wide range of application in model classification, identification, prediction, as well as fault diagnosis and other fields(Adeli and Panakkat, 2009; Song et al., 2007; Ataa et al., 2017; Rutkowski, 2004). In this work, according to the practice of complicat-ed problems of the rock burst prediction, the PNN is applied to predicting rock burst classifica-tion.

2. Material and Methods

2.1. Criteria and indexes of rock burst and rock burst classification

2.1.1. Criteria considering stress in surrounding rock

The criteria listed in Table 1 were proposed early, and only considered the stress level in surrounding rock. Furthermore, different scholars chose different parameters as an evaluation index of criterion for rock burst, and the classification of rock burst intensity also differed from each other. So it is difficult to use these criteria in the construction of underground engineering.

Table 1. Criteria only considering stress in surrounding rock.

Scholar	Criteria of rock burst	Source
RUSENSES	$\sigma_\theta / \sigma_c < 0.20$ (No rock burst activity)	(Rusenses, 1974)
	$0.20 \le \sigma_\theta / \sigma_c < 0.30$ (light rock burst activity)	
	$0.30 \le \sigma_\theta / \sigma_c < 0.55$ (Moderate rock burst activity)	
	$\sigma_\theta / \sigma_c \ge 0.55$ (Strong rock burst activity)	
TANG	$\sigma_c / \sigma_1 > 0.33$ (light rock burst activity)	(Tang, 2000)
	$0.16 < \sigma_c / \sigma_1 < 0.25$ (Moderate rock burst activity)	
	$\sigma_c / \sigma_1 < 0.16$ (Strong rock burst activity)	
WANG et al	$\sigma_\theta / \sigma_c < 0.30$ (No rock burst activity)	(Wang et al., 1998)
	$0.30 \le \sigma_\theta / \sigma_c < 0.50$ (light rock burst activity)	
	$0.50 \le \sigma_\theta / \sigma_c \le 0.70$ (Moderate rock burst activity)	
	$\sigma_\theta / \sigma_c > 0.70$ (Strong rock burst activity)	
HOKE and BROWN	$\sigma_\theta / \sigma_c = 0.34$ (Light stripping)	(Hoek and Brown, 1997)
	$\sigma_\theta / \sigma_c = 0.42$ (Strong stripping)	
	$\sigma_\theta / \sigma_c = 0.56$ (More lining)	
	$\sigma_\theta / \sigma_c = 0.70$ (Strong rock burst)	
Tao	$\sigma_c / \sigma_1 > 14.5$ (No rock burst activity)	(Tao, 1988)
	$5.5 < \sigma_c / \sigma_1 \le 14.5$ (light rock burst , with light sound)	
	$2.5 \le \sigma_c / \sigma_1 < 5.5$ (Moderate rock burst, with crack sound)	
	$\sigma_c / \sigma < 2.5$ (Strong rock burst, with strong crack sound)	
TURCHANINOV	$(\sigma_\theta + \sigma_L) / \sigma_c < 0.30$ (No rock burst activity)	(Turchaninov et al., 1972)
	$0.30 < (\sigma_\theta + \sigma_L) / \sigma_c \le 0.50$ (Rock burst probably)	
	$0.50 < (\sigma_\theta + \sigma_L) / \sigma_c \le 0.80$ (Rock burst surely)	
	$(\sigma_\theta + \sigma_L) / \sigma_c > 0.8$ (Strong rock burst activity)	

Note: σ_θ is the maximum tangential stress of surrounding rock, MPa; σ_c is the axial stress of surrounding rock, MPa; σ_L is the maximum in si-tu stress of engineering area, MPa; σ_1 is the uniaxial compressive strength of rock, MPa;

2.1.2. Comprehension criteria considering stress, properties of surround-ing rock and energy

1) The following criterion is presented with rock burst tendency index and energy condition of surrounding rock (Dong et al, 2013).

$$W_{qx} \ge 1.5 \tag{1}$$

$$\sigma_1 \ge \sigma_c / \sqrt{\alpha W_{qx}} \tag{2}$$

$$\alpha = 1 + \zeta^2 - 2\mu\zeta \tag{3}$$

$$\zeta = \sigma_2 / \sigma_1 \tag{4}$$

where W_{qx} is the rock burst tendency index; σ_1 and σ_2 are the major and middle principal stress in surrounding rock, respectively; μ is the Poisson ratio.

2) It is stipulated that rock burst could occur if $\sigma_\theta / \sigma_c \le K_s$ in which the value of K_s related to σ_t / σ_c criterion.

3) Kidybinski (1981) proposed an elastic energy index W_{et}. No rock burst activity, moderate rock burst activity and strong rock burst activity, meet the conditions W_{et} <2.0, 2.0≤ W_{et} ≤5.0, and W_{et} >5.0, respectively.

2.1.3 Input characteristic vector for PNN

The indexes of criterion should reflect the main factors of rock burst - the properties and stress of surrounding rock. At the same time, they should be obtained easily and can be compared with each other for different cases. In this work, the compressive rock strength σ_c, tensile strength σ_t, elastic energy index W_{et} and the maximum tangential stress σ_o are chosen as the indexes of criterion. Compressive rock strength σ_c, tensile strength σ_t, and elastic energy index W_{et} can indicate the properties of surrounding rock, and the tangential stress σ_o can reflect the virgin geostatic stress condition and the influence of the shape and dimension of the underground space on rock burst. In this work, σ_o, σ_c, σ_t and W_{et} are selected as the input index for PNN model to predict the degree of rock burst activity. Hence, the input characteristic vector for PNN is $[\sigma_o, \sigma_c, \sigma_t, W_{et}]$.

2.1.4 Classification for intensities of rock burst

According to the extent and intensity of the characteristics of the rock burst phenomenon in the underground openings, the grade of rock burst is divided into four degrees, namely none rock burst, light rock burst, moderate rock burst, strong rock burst, respectively. So the PNN model output is rock burst degree, output = [none rock burst, light rock burst, moderate rock burst, strong rock burst]. Also, the division of rock burst degree can be described in Table 2 (Wang et al., 1998; Zhou et al., 2012; Zhang et al., 2004)

Table 2. Standard of classification for intensities of rock burst.

Rock burst classification	Failure characteristics
Strong Rock burst	The surrounding rock is burst severely, and suddenly thrown out or ejected into the tunnel, accompanied by a strong burst and the roaring sound, air spray, storms phenomena with continuity, and rapidly expand to the deep surrounding rock.
Moderate Rock burst	The surrounding rock is deformed and fractured, there is a considerable number of rock chip ejection, loose and sudden destruction, accompanied by crisp crackling, and often presented in the local cavern of surrounding rock.
Light Rock burst	The surrounding rock is deformed, cracked or rib spilled, there is a weak sound and no ejection phenomenon.
None Rock burst	No sound of rock burst and rock burst activities.

2.2. PNN-based Rock burst Prediction Model

2.2.1 Outline of PNN

Probability neural networks are a tool for handling uncertainty for improving learning per-formance. Probability uncertainty and fuzziness uncertainty processing play a key role in boost-ing classification systems including extreme learning machines and decision trees (Wang et al., 2015; Lu et al., 2015). PNN is essentially a classifier that places the Bayes estimate in a feed-forward neural network. The central concept of Bayes criterion classification is the minimal "predictable risk" of the Bayes decision. The Bayes decision is based on the non-parametric estimation of the probability density function; accordingly, it obtains the classification results. Based on its advantages, such as rapid training time, a stable and simple neural structure, and good convergence, it is suitable for use in defect recognition.

For a multi-class problem with σ_1, σ_2, , σ_q, σ_s, we apply to the above issues two types of classification problems in Bayes decision classification. For p-dimensional vector $X = \{x_1, x_2, , x_p\}$ based on the Bayes decision rule, we determine the status of $\theta\epsilon\theta_q$ with its measurement set,

$$d(x) \in \theta_q [h_q l_q f_q(x) > h_k l_k f_k(x), k \neq q] \tag{5}$$

In the Equation (5), h_q represents the priori probability of $\theta = \theta_q$, $d(x)$ as the Bayes decision of test vector X , h_k is the priori probability of $\theta = \theta_k$, and l_q and l_k are incorrectly classified into other categories of losses. The latter should belong to θ_q and θ_k. Besides, $f_q\ (x)$ and $f_q\ (x)$ are probability density function of θ_q and θ_k, respectively.

$$f_q(x) = \frac{1}{(2\pi)^{p/2}\sigma^p m^p} \sum_{j=1}^{m_q} \exp[-\frac{(x - x_{qj})^T (x - x_{qj})}{2\sigma^2}] \tag{6}$$

where X is a sample of the input vector to be classified, p is the dimension of sample vectors, x_{qj} is the j-th sample of the category θ_q, and m^q is the sample number of category θ_q. Additionally, σ is the smoothing parameter.

Figure 1 depicts a schematic diagram of the multi-class classification PNN. X is a vector to be classified as the neurons in the input layer. It is passed to the corresponding neurons in the hidden layer with no change. The hidden layer then transmits each neuron in the accumulated layers. At this point, the output obtained by the accumulation layer is the estimation of the probability density function of each pattern for the test vectors. Accordingly, the category of the occurrence of the maximum probability of the current test vector is the one that corresponds to the largest probability density function. This function is the output of the accumulation layer. The neuron output with the probability density maximum is 1; the corresponding category is the one to which h belongs.

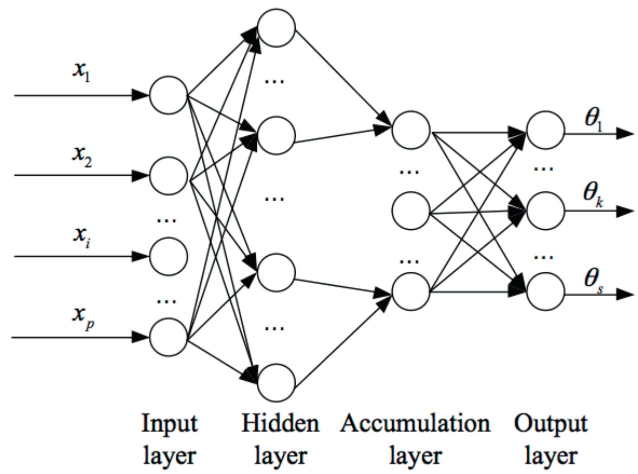

Figure 1. Schematic diagram of the multi-class classification PNN.

2.2.2 PNN modeling for prediction of rock burst

The number of input layer neurons of PNN is the same as the dimensionality of the input characteristic vector. Based on discussed above, σ_o, σ_c, σ_t, and W_{et} are selected as the input characteristic vector for PNN model and the input vector of PNN = $[\sigma_o, \sigma_c, \sigma_t, W_{et}]$. Hence, the number of input layer neurons of PNN is 4.

The number of output neurons of PNN is the same as the number of classification of rock burst activity. According to the section 2.4, the grade of rock burst is divided into four degrees, and the PNN model output is rock burst degree and the output vector = [none rock burst, light rock burst, moderate rock burst, strong rock burst]. So the number of output layer neurons is 4.

The number of hidden layer neurons is determined by the training data set. The number of hidden layer neurons is equal to the sum of the number of each category of training sample

The number of accumulation layer neurons is the same as the number of classification of rock burst activity. Here, the number of accumulation layer neurons is 4.

The design of PNN modeling for prediction of rock burst includes the following aspects: a collection of data sets, data preprocessing, build a PNN, network model, training PNN, testing PNN etc. The design process is shown in Figure 2.

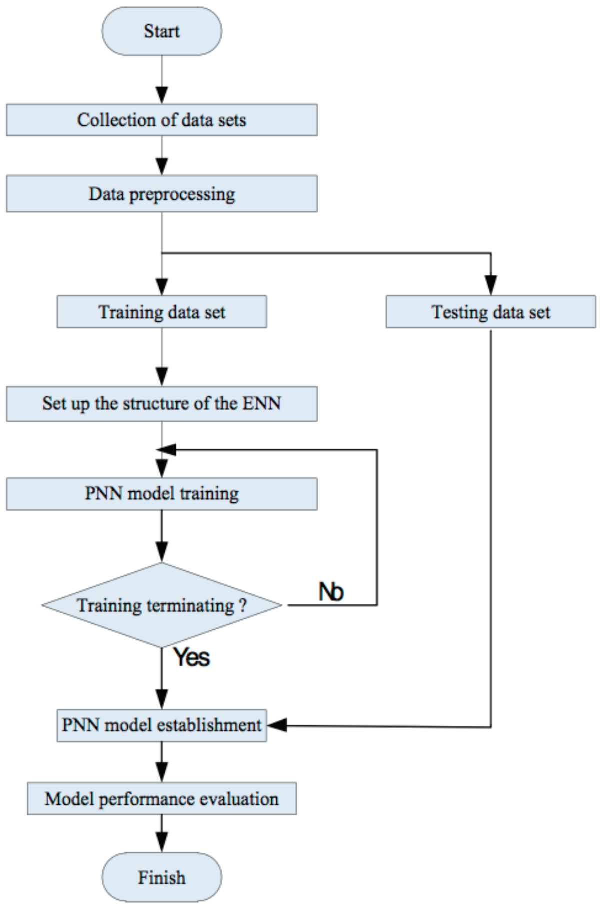

Figure 2. The design process of PNN modeling for prediction of rock burst.

3. Results

Rock burst samples which come from underground rock projects in domestic and abroad are collected as training data set (Show in Table 3) and testing data set (Show in Table 4) to verify the rationality of our posed method.

The relationship among the indexes of criteria, the occurrence of rock burst and its intensity is very complicated. For the sake of the capability of PNN for pattern recognition, we attempt to predict the rock burst activity by using PNN.

Four degrees of rock burst activity, including none rock burst, light rock burst, moderate rock burst and strong rock burst are indicated by 1, 2, 3 and 4, respectively.

PNN model and criterion are obtained through training data sets of rock burst samples which come from underground rock projects in domestic and abroad. The training effect and the training error are shown in Figure 3. It is noted from Figure 3 that the misjudgment ratios of training samples using PNN model is 0, which prove that the PNN has a good learning performance. Figure 4 is the perdition results of testing samples. From the Figure 4, we can find that the prediction accuracy of PNN model is 100%. The results show that the prediction results agree well with the practical records, which prove the PNN-based rock burst model is useful and available and can be applied to the prediction for the possibility and classification of rock burst in underground engineering.

Table 3. Collected samples of rock burst.

No.	σ_θ(MPa)	σ_c(MPa)	σ_t(MPa)	W_{et}	Actual conditions	Source
1	18.8	178	5.7	7.4	1	(Wang et al., 1998)
2	11	115	5	5.7	1	(Wang et al., 1998)
3	12.3	237.1	17.66	6.9	1	(Du et al.,2006)
4	21.8	160	5.2	2.22	1	(Wu and Yang, 2005)
5	20.9	160	5.2	2.22	1	(Wu and Yang, 2005)
6	12.1	160	5.2	2.22	1	(Wu and Yang, 2005)
7	30.9	82.56	6.5	3.2	2	(Du et al.,2006)
8	61	171.5	22.6	7.5	2	(Wang et al., 1998)
9	34.15	54.2	12.1	3.17	2	(Cai et al., 2005)
10	69.8	198	22.4	4.68	2	(Cai et al., 2005)
11	25.49	54.2	2.49	3.17	2	(Zhang 2005)
12	48.75	180	8.3	5	3	(Wang et al, 2009)
13	62.5	175	7.25	5	3	(Wang et al, 2009)
14	75	180	8.3	5	3	(Wang et al, 2009)
15	57	180	8.3	5	3	(Wang et al, 2009)
16	89	236	8.3	5	3	(Wang et al, 2009)
17	50	130	6	5	3	(Wang et al, 2009)
18	55.4	176	7.3	9.3	3	(Wang et al, 2009)
19	48	120	1.5	5.8	3	(Zhao 2005)
20	63	115	1.5	5.7	3	(Zhao 2005)
21	49.5	110	1.5	5.7	3	(Zhao 2005)
22	55.6	256.5	18.9	9.1	3	(Du et al.,2006)
23	72.07	147.09	10.98	6.53	3	(Zhang 2005)
24	89.56	190.3	17.13	3.97	3	(Li and Wang, 2009)
25	89.56	170.28	12.07	5.76	3	(Li and Wang, 2009)
26	89.56	187.17	19.17	7.27	3	(Li and Wang, 2009)
27	54.2	133.99	9.09	7.08	3	(Li and Wang, 2009)
28	108	140	8	5.5	4	(Wang et al, 2009)
29	89	128.6	13.2	4.9	4	(Du et al.,2006)
30	91.3	225.6	17.2	7.3	4	(Du et al.,2006)
31	108.4	138.4	7.7	1.9	4	(Cai et al., 2005)
32	105	171.3	22.6	7.27	4	(Cai et al., 2005)
33	105	237.16	17.66	6.38	4	(Cai et al., 2005)
34	105	304.21	20.9	10.57	4	(Cai et al., 2005)

Table 4. Testing samples.

No.	σ_θ(MPa)	σ_c(MPa)	σ_t(MPa)	W_{et}	Actual conditions	Source
1	75	170	11.30	9	3	(Hou et al., 1992)
2	43.40	123	6	5	3	(Hou et al., 1992)
3	62.60	165	9.40	9	3	(Hou et al., 1992)
4	105	128.61	13	5.76	4	(Cai et al., 2005)
5	105	306.58	13.90	6.38	4	(Cai et al., 2005)
6	7.50	52	3.70	1.30	1	(Yang and Li, 2000)
7	24.93	99.70	4.80	3.80	1	(Yang and Li, 2000)
8	14.96	99.70	4.80	3.80	1	(Yang and Li, 2000)
9	34.15	54.20	12.10	3.17	2	(Cai et al., 2005)
10	54.20	134	9.10	7.10	3	(Cai et al., 2005)

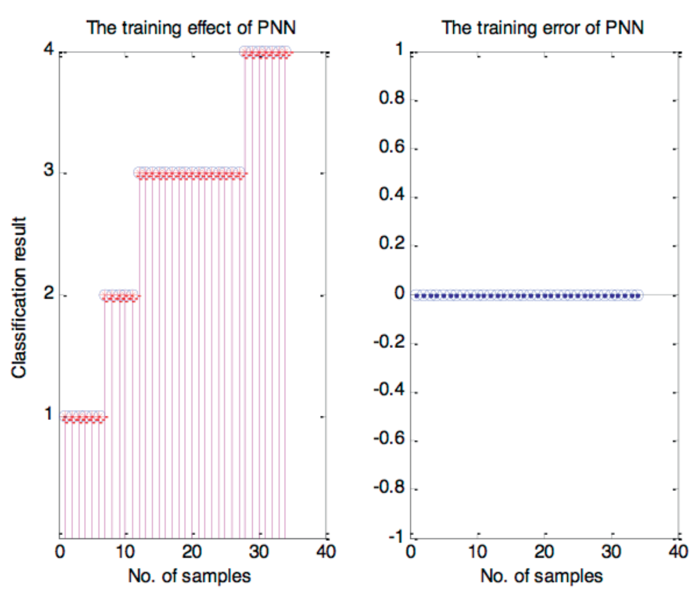

Figure 3. The training of PNN.

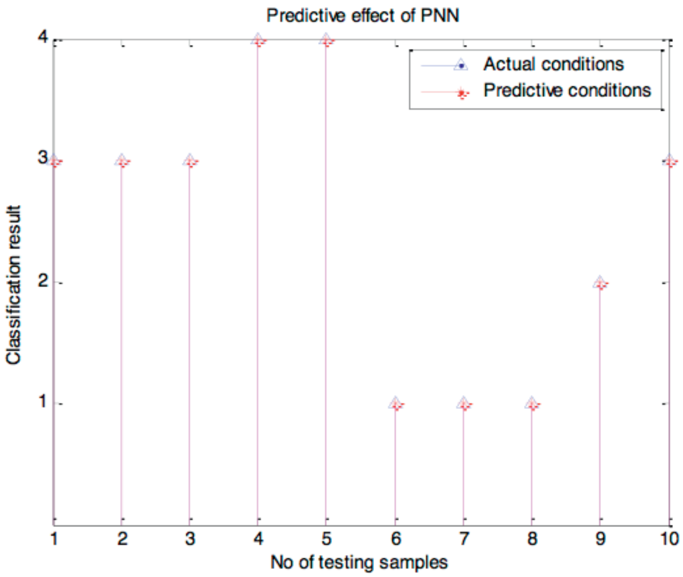

Figure 4. The perdition results of testing samples.

The results of the PNN-based method are compared with that SVM-based method, BP-based method, and LVQ-based method. The calculated results of PNN, SVM, BP and LVQ are listed in Table 3. From Table 3, we can find that the misjudgment ratios of tested samples using SVM, BP, LVQ, and PNN are 10%, 20%, 20% and 0, respectively. The compared predicted results show that it is feasible and appropriate to use PNN model for rock burst prediction.

Table 5. Comparison of calculation results by different methods.

No.	Actual conditions	SVM	BP	LVQ	PNN
1	3	3	3	3	3
2	3	3	3	3	3
3	3	3	3	3	3
4	4	4	4	4	4
5	4	4	3	3	4
6	1	2	1	1	1
7	1	1	2	1	1
8	1	1	1	1	1
9	2	2	2	3	2
10	3	3	3	3	3

To study the effectiveness and feasibility in engineering practice applications, two real-world examples are analyzed by using our posed PNN-based rock burst prediction method.

Case 1: Tongyu tunnel engineering

Tongyu Tunnel is currently one of the most deep-lying and longest tunnels in Chongqing, China. Its geological conditions are incredibly complex. The measured data of rock burst in depth 900m at a cross section of K21+680 of Tongyu tunnel are listed in Table 6 (He et al., 2008). Applying our proposed prediction model to rock burst prediction of this engineering, the result of prediction is light rock burst activity. The results agree well with the practical records.

Table 6. Prediction of rock burst in depth of 900 m at the cross section of K21+680 of Tangyu tunnel.

σ_θ(MPa)	σ_c(MPa)	σ_t(MPa)	W_{et}	Prediction result	Actual conditions
47.56	58.5	3.5	5	light	light

Case 2: Qinnling tunnel engineering

The QingLing tunnel is the longest railway tunnel in China and takes the third place in the world at present. Reference (Thaldiri et al., 2017; Li and Wang, 2009) provides rock burst measured data for of QingLing tunnel engineering. Some measured data listed in Table 7. Table 7 compared the performance of the proposed method with existing BP-based method (Bai et al., 2002) and unascertained measurement method(Shi et al., 2010). From the Table 7, the result of prediction is same as the results of existing BP-based method and unascertained measurement method, just same as what happened in the scene. This case further confirms that the PNN-based method is effective and practical in the application of prediction of rock burst. On the other hand, PNN-based method has the advantages of low training complexity, high stability, quick convergence, and simple construction.

Table 7. A case of Qinling tunnel is analyzed by using our proposed method.

Location	σ_θ(MPa)	σ_c(MPa)	σ_t(MPa)	W_{et}	PNN	BP	UMM	Actual condition
Qinling Tunnel of Xikang Railway Dyk77+176	56.1	131.99	9.44	7.44	Moderate	Moderate	Moderate	Moderate
Qinling Tunnel of Xikang Railway T2	70.3	128.3	8.7	6.4	Moderate	Moderate	Moderate	Moderate

4. Discussion

In this paper, a novel PNN-based rock burst prediction model is proposed to determine whether rock burst will happen in the underground rock projects and how much the intensity of rock burst is. PNN model is obtained through training data sets of rock burst samples which come from underground rock project in domestic and abroad. Other samples are tested with the model. The testing results agree with the practical records. At the same time, two real-world applications are used to verify the proposed method. The results of prediction are same as the results of existing methods, just same as what happened in the scene, which verifies the effectiveness and applicability of our proposed work.

5. Conclusions

Because PNN has the advantages of low training complexity, high stability, quick convergence, and simple construction, it can be well applied in the prediction of rock burst. In this work, a PNN-based prediction model of rock burst is presented. According to the mechanism of rock burst, rocks' maximum tangential stress σ_θ, rocks' uniaxial compressive strength σ_c, rocks' uniaxial tensile strength σ_t and elastic energy index W_{et} are defined as the criterion indices for rock burst prediction in the proposed PNN-model. Some collected rock burst samples which come from underground rock projects in domestic and abroad and two real-world engineering in China are used to verify the new model. The prediction results demonstrated that the developed PNN-based prediction model is effective and efficient approach to predict rock burst potential grade.

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