

# Ventilation system reliability evaluation based on PNN neural network

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**Keywords:** Ventilation system reliability, Probabilistic neural network (PNN), Evaluation method.

**Abstract.** In order to accurately and quickly identify the level of ventilation system reliability of coal mines, a new evaluation method based on Probabilistic neural network (PNN) was proposed in this paper. The design of structure of network, the rationale of evaluation algorithm and the performance of proposed method were discussed in detail. The case analysis indicated that the application of proposed method is feasible and reasonable and this evaluation method is easier and more practical. The research of this evaluation method could provide a new way of thinking for reliability judgment of the mine ventilation system.

## Introduction

Mining is one of the most hazardous industries and the most fearful disaster to impact the safety states during the coal mining in the world. Underground mining of coal presents the most dangerous work environment and conditions. Hence, coal mines safety evaluation system plays a very important role in coal mines safety and mine ventilation system, a main auxiliary system of the mine production system, has a fatal effect on the safety of the mine. The ventilation system reliability is one of the fundamental guarantees for the safe production in coal mines. Therefore, the evaluation technique of ventilation system reliability in coalmines has been become a research hotspot in many countries.

The ventilation system reliability is affected by multiple factors, and the degree of influence of various factors on ventilation system is different. Ventilation system reliability is a comprehensive result of the interaction of these factors. The ventilation system reliability evaluation technique has very strong engineering background, has the important practical value, and has very deep theories as the foundation. The latest techniques on analytic hierarchy process (AHP) method [1], grey theory method [2], fuzzy comprehensive evaluation [3], BP neural network [4] and rough sets method [5] etc. all have the extensive application in ventilation system reliability. But there is somewhat deficiency and disadvantage in each method. For example, the AHP-based methods and the fuzzy comprehensive evaluation methods require human expertise which used to determine the weights of each index and the fuzzy rules, respectively, so these methods cannot avoid the influence from human factor. Moreover, there are some difficulties in acquiring knowledge and in maintaining the database. BP-neural-network -based methods can directly acquire experience from the training data, and overcome some of the shortcomings of subjectivity. However, certain issues, such as local convergence and determination of the structure of network are not easy to handle. Hence, it is necessary to bring forward a directive idea, which can overcome the current shortcomings and limitations. So, in this study, a new ventilation system reliability evaluation method based on Probabilistic neural network (PNN) was investigated.

This paper is organized as follows: Section 2 presents the outline of PNN. A concrete application of the proposed method is given in Section 3 and the model building and evaluation process are discussed in detail in this section. Finally, the last section concludes this paper.

## Outline of PNN

Probabilistic neural network (PNN) is a common network model, which is based on Bayesian classifier and probabilistic function [6]. PNN has a wide range of applications in model identification,

time series prediction, signal processing, as well as fault diagnosis and other fields [7–10]. The PNN is a pattern classifier that combines the widely used Bayes decision strategy with the Parzen nonparametric estimator for estimation of probability density functions of different classes. Unlike other neural network architectures, PNN is easy to implement and the network is easily interpretable [11].

Generally, the probabilistic density function is the normal probabilistic density function as follows.

$$f_A(X) = \frac{1}{(2\pi)^{\frac{m}{2}} \sigma^m} \left(\frac{1}{n_A}\right) \sum_{p=1}^{n_A} \exp\left(-\frac{(X - X_{Ap})'(X - X_{Ap})}{2\sigma^2}\right)$$

where  $f_A(X)$  represents the value of probabilistic density function of Category A at point X;  $m$  represents the number of input variables;  $\sigma$  represents smooth parameter;  $n_A$  represents the number of training vectors in Category A;  $X$  represents the testing data vectors;  $X_{Ap}$  represents the p-th training data in Category A.

Because

$$\frac{1}{(2\pi)^{\frac{m}{2}} \sigma^m} \left(\frac{1}{n_A}\right) = \text{constant} = h$$

$$(\mathbf{X} - \mathbf{X}_{Ap})'(\mathbf{X} - \mathbf{X}_{Ap}) = \sum_{i=1}^m (x_i - x_i^{Ap})^2$$

the probabilistic density function can be simplified as follows

$$f_A(X) = h \sum_{p=1}^{n_A} f_{Ap}$$

where

$$f_{Ap} = \exp\left(-\frac{\sum_{i=1}^m (x_i - x_i^{Ap})^2}{2\sigma^2}\right)$$

where  $x_i$  represents the value of i-th input variable in the testing sample;  $x_i^{Ap}$  represents the i-th input variable of the p-th sample of Category A in the sample base.

The PNN network is simply a parallel 4-layer structure: input, pattern, summation, and decision layers (Fig. 1). The input layer receives and normalizes input vector; each unit in pattern layer represents a training vector with response function  $\exp[(\mathbf{X}'\mathbf{X}_{Ap} - 1)/\sigma^2]$ . Summation layer computes the summation of each pattern and multiplies the loss factor. Decision layer selects the largest one in summation layer as the classification result.

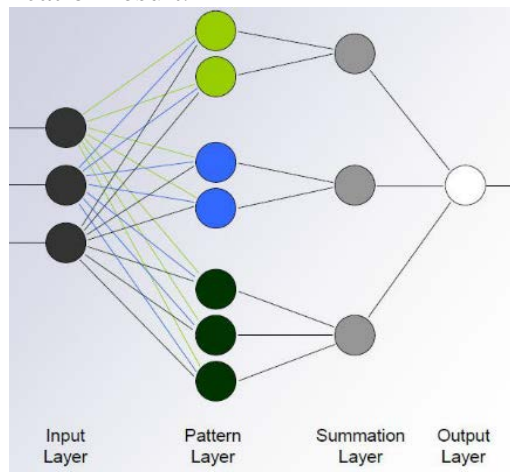


Fig. 1 The structure of PNN

## **PNN Use of a PNN to evaluate the reliability of mine ventilation system**

**Model building.** To prove the efficiency and validity of the proposed PNN-based evaluation method, a real-world engineering application about the reliability evaluation of mine ventilation system is given in the following.

According to the degree of influence of the various factors upon the ventilation system reliability of coal mines and in agreement with past studies [4, 12], the following 12 main factors were chosen as the features for the evaluation of ventilation system reliability. These features of input patterns would be most useful for recognition. These features included: 1. ventilation network complexity, 2. the rationality of mine wind pressure, 3. running stability of mine main fan, 4. comprehensive efficiency of mine main fan, 5. qualification rate of mine ventilation equipment's, 6. supply-requirement ratio of mine air quantity, 7. qualification rate of air quantity of using wind place, 8. qualification rate of the air quality of using wind place, 9. qualification rate of the temperature of using wind place, 10. Qualification rate of disaster prevention facilities, 11. The flexibility of reversed ventilation system in mine and 12. Electricity fee per ton coal. So the feature vector of ventilation system reliability status contains 12 feature values. According to the engineering practice, past studies [4] and the opinion of relevant experts, the ventilation system reliability status is classified into 3 level patterns, i.e. pattern 1: safe; pattern 2: moderately safe and pattern 3: unsafe. Based on above discussion, the structure of PNN for application of mine ventilation system reliability evaluation comprised 4 layers and the number of input neuron nodes and output neuron nodes was 12 and 3, respectively.

**Working process.** The detailed PNN-based evaluation algorithm can be described as following:

Step 1. Read exemplar vectors and class numbers.

Step 2. Sort these into 3 sets where each set contains one class of vectors.

Step 3. For each  $k, (k = 1, 2, 3)$ , define a Gaussian function centered on each exemplar vector in set  $k$  and define the summed Gaussian output function.

Once the PNN is defined, then we feed vectors into it and classify them as follows:

Step 1. Read input vector and feed it to each Gaussian function in each class.

Step 2. For each group of hidden nodes, compute all Gaussian functional values at the hidden nodes.

Step 3. For each group of hidden nodes, feed all its Gaussian functional values to the single output node for that group.

Step 4. At each class output node, sum all of the inputs and multiply by constant.

Step 5. Find maximum value of all summed functional values at the output nodes.

**Results.** The historical data sets come from literature [4]. The training data set contained 15 instances (shown in Table 1) and the testing data set contained 3 instances (shown in Table 2).

We use training data set to train the PNN and use test data set to verify the trained PNN. The simulation results are shown in Fig. 2 and Fig.3. It can be seen from the Fig.2 that there no error sample when we input the training samples into the trained PNN. Hence, the PNN has a good learning performance. From the Fig.3, we can find that the PNN recognized correctly other 3 samples as a test group, which proved that the PNN-based recognition method has strong generalization ability. In fact, the trained PNN could be used to evaluate additional unknown samples and the results are basically consistent with the engineering practice.

## **Conclusion**

(1) A novel evaluation method based on the PNN for mine ventilation system reliability is proposed in this paper. The structure design of network and the evaluation algorithm are presented in detail. Compared with other traditional ANN-based methods, PNN is easy to implement and the network is easily interpretable

(2) This paper is the first application of ENN on coal mines safety status pattern recognition. The tested results indicate that this method is feasible and reasonable and this evaluation method is easier and more practical in engineering application.

Table 1 Training data

No	Evaluation index of ventilation system reliability												Reliability level
	1	2	3	4	5	6	7	8	9	10	11	12	
1	2.10 3	0.51 2	0.43 4	0.71 6	0.93 5	1.05 4	0.94 3	0.88 6	0.97 6	0.91 3	0.92 4	0.51 2	1
2	0.78 5	0.91 8	0.77 4	0.52 5	0.98 1	1.19 8	0.90 1	0.98 6	0.92 4	0.95 2	0.91 7	0.87 3	1
3	3.53 1	0.75 3	0.89 6	0.67 4	0.91 3	1.31 3	0.95 1	0.86 7	0.94 8	0.90 3	0.98 2	0.93 6	1
4	1.56 4	0.48 1	0.56 2	0.88 5	0.94 2	0.02 4	0.92 6	0.87 5	0.97 2	0.93 8	0.93 9	0.64 8	1
5	2.36 7	0.28	0.55 1	0.69 6	0.93 5	1.16 4	0.93 7	0.93 5	0.91 8	0.97 6	0.90 4	0.29 5	1
6	3.74 5	1.22 6	0.37 3	0.51 5	0.84 6	1.23 5	0.98 6	0.87 5	0.81 5	0.80 2	0.85 6	1.18 3	2
7	4.90 1	1.15 4	0.24 6	0.57 8	0.75 9	1.46 2	0.81 5	0.70 2	0.85 2	0.83 9	0.87 5	1.92 4	2
8	3.07 1	1.47 3	0.47 5	0.62 4	0.82 5	1.37 2	0.90 1	0.75 8	0.87 4	0.87 6	0.96 4	1.62 8	2
9	4.34 8	1.35 1	0.27 9	0.75 2	0.86 4	1.31 7	0.83 5	0.87 6	0.86 3	0.82 9	0.85 2	1.02 8	2
10	3.74 6	1.08 4	0.38 6	0.64 1	0.85 7	1.27 3	0.98 6	0.84 5	0.83 6	0.83 8	0.91 4	1.28 9	2
11	4.56 2	1.72 5	0.11 2	0.02 1	0.18 7	0.9	0.21 3	0.21 7	0.69 3	0.67 4	0.53 6	2.29 4	3
12	7.84 1	1.66 3	0.04 3	0.54 1	0.70 9	1.63 4	0.72 4	0.68 3	0.72 5	0.75 7	0.27 4	1.93 7	3
13	5.34 2	2.17 6	0.91 7	0.12 5	0.30 3	0.39 5	0.55 3	0.54 8	0.56 2	0.59 2	0.88 4	6.04 5	3
14	6.92 3	1.92 4	0.28 3	0.26 3	0.53 2	2.06 5	0.86 4	0.47 5	0.46 3	0.48 9	0.73 7	4.29 1	3
15	9.14 3	1.88 6	0.19 5	0.33 6	0.61 4	2.63 1	0.15 7	0.20 3	0.12 5	0.11 7	0.56 3	3.98 2	3

Table 2 Test data

No	Evaluation index of ventilation system reliability												Reliability level
	1	2	3	4	5	6	7	8	9	10	11	12	
1	1.59 4	0.35 1	0.66 3	0.83 5	0.84 1	0.12 4	0.82 3	0.96 5	0.87 2	0.84 8	0.92 1	0.73 5	1
2	4.07 2	2.37 3	1.57 5	0.52 4	0.72 5	1.67 2	0.80 1	0.85 8	0.77 4	0.67 6	0.95 4	1.32 8	2
3	6.74 1	2.36 3	0.32 1	0.64 1	0.80 9	1.76 5	0.89 2	0.54 8	0.65 2	0.55 7	0.17 4	1.83 7	3

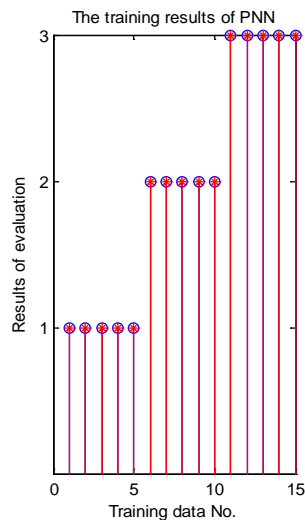


Fig. 2 The results of training

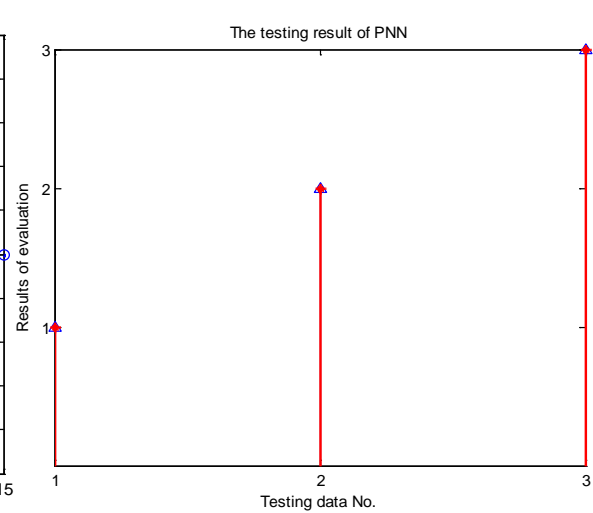
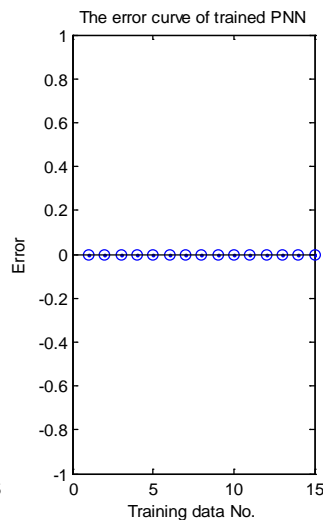


Fig. 3 The results of test

## Acknowledgement

The authors are grateful for the anonymous reviewers who made constructive comments.

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