

Forecasting Coalbed Methane Resources by Artificial Neural Network*

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Abstract

The accuracy of counting coalbed gas resources directly influences the economic benefit of coalbed gas exploitation. Some common computing methods are usually linear and difficult to resolve coalbed gas resources prediction of complex geological condition areas. Nevertheless, the artificial neural network figures out this problem finely. In this work, we use the method to forecast coalbed gas resources of central and southern of Qinshui basin. On basis of the study of coalbed gas resources influencing factors and control mechanism, we extract four main impact factors that can be quantified as input parameters, which are coal distribution area, thickness, density and gas content. We train the samples of the Shanxi Formation and Taiyuan Formation in nine zones hundreds of thousands of times and establish the prediction model of the studied region's coalbed gas resources amount using artificial neural network, with a global error of 2.21×10^{-4} . We also use this model to conduct prediction of other zones in the studied region, and the result show that there are tremendous coalbed gas resources in Yangcheng-Changzi, Qinshui, Anze-Qinyuan and Tunliu-Xiangyuan of central and southern Qinshui basin. There also exists the potential for available resources. In addition, we conduct statistics to the total coalbed gas resources of the area of 6,239.2 km² in Qinyang basin, which are 9685.63×10^8 m³, and the result has few differences with the result of coalbed gas resources survey results by Zhang Jiancheng et al. of Zhongyuan Oilfield. This confirms that artificial neural network could be used to the prediction of coalbed gas resources amount, and show the superiority of the method.

Introduction

The magnitude and distribution of coalbed methane resources are the import content of the geological estimation of coalbed methane and is the mainstay of the economic budge before exploiting coalbed methane at the same time. The accuracy of calculating coalbed methane resources directly influences the economic benefit of coalbed methane exploitation. Some common used computing methods are usually linear and difficult to resolve the coalbed methane resources prediction of the complex geological condition areas. Nevertheless, the artificial neural network figures out this problem finely.

In this work, we mainly use the error back propagation neural network of the artificial neural network to forecast coalbed methane resources of central and southern of Qinshui basin. In the practical application, we need input training samples when studying. Each input of all the training samples is called one training cycle. When having entered all the samples in one training cycle, we need calculating the global error and modify the weight along the back direction of inputting. Studying need proceed one cycle by one cycle until the objective function reaching minimum value or less than one set value. A whole error back propagation neural network model include the frame and the link of the frame, in other words, which are the network structure the learning algorithm of the network.

Discussion

The error back propagation neural network structure includes the network layer numbers and the neural number of each layer. This text uses error the back propagation neural network with three layers, which are the input layer, the hidden layer and the output layer. The neurons of the input layer are the known index numbers of the samples, and the neurons of the output layer are the predictive indexes, while the neurons of the hidden layer are determined by many ways. In this text, the neural numbers of the hidden layer are calculated like that two times of the neuron numbers of the input layer and the output layer subtracts one.

The network structure is as above. Then how do the neurons connect in the network? They are rationally connected by the learning algorithm. The error back propagation neural network has two kinds of sign circulating. It is supposed that the unit j of the output layer is $y_j(n)$ in Iteration n , and then the error of the neuron is as below.

$$e_j = d_j(n) - y_j(n) \quad (1)$$

Defining the square error of the neuron is $\frac{1}{2}e_j^2(n)$, the total square error of the output in the moment is as below:

$$E(n) = \frac{1}{2} \sum_{j \in c} e_j^2(n) \quad (2)$$

The aim of the study is making $E(n)$ reaching the minimum. The process of the unit j receiving the sign of the front layer and then generating the error sign as seen in [Figure 1](#).

Recording $v_j(n) = \sum_{i=0}^p w_{ji}(n)y_i(n)$, then p is the number before inputting the unit j , and $y_j = \varphi(v_j(n))$, figuring out the gradient of $E(n)$ to w_{ji} as below:

$$\frac{\partial E(n)}{\partial w_{ji}} = \frac{\partial E(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)} \frac{\partial v_j(n)}{\partial w_{ji}(n)} \quad (3)$$

Owing to $\frac{\partial E(n)}{\partial e_j(n)} = e_j(n)$, $\frac{\partial e_j(n)}{\partial y_j(n)} = -1$, $\frac{\partial y_j(n)}{\partial v_j(n)} = \varphi'(v_j(n))$, $\frac{\partial v_j(n)}{\partial w_{ji}(n)} = y_i(n)$, getting:

$$\frac{\partial E(n)}{\partial w_{ji}(n)} = -e_j(n)\varphi'(v_j(n))y_i(n) \quad (4)$$

The correction of the weight is as below:

$$\Delta w_{ji}(n) = -\eta \frac{\partial E(n)}{\partial w_{ji}(n)} = \eta \delta_j(n) y_i(n) \quad (5)$$

In the above equation, the negative sign shows that the correction is consistent with the gradient descent direction.

$\delta_j(n) = -\frac{\partial E(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)} = e_j(n)\varphi'(v_j(n))$, as the local gradient, there are two cases discussed as below:

1. e unit j is an output unit, and $\delta_j(n)$ is the product of $\varphi'(v_j(n))$ and $e_j(n)$.

$$\delta_j(n) = (d(n) - y_j(n))\varphi'(v_j(n)) \quad (6)$$

2. the unit j is the hidden unit, and $\delta_j(n)$ is the product of $\varphi'(v_j(n))$ and the weighted sum of the latter layer as seen in [Figure 2](#).

$$\delta_j(n) = -\frac{\partial E(n)}{\partial y_j(n)} \varphi'(v_j(n)) \quad (7)$$

Supposing k is the output unit, so

$$E(n) = \frac{1}{2} \sum_{k \in \epsilon} e_k^2(n) \quad (8)$$

Taking the derivation of the above equation to $y_j(n)$, getting

$$\frac{\partial E(n)}{\partial y_j(n)} = \sum_k e_k(n) \frac{\partial e_k(n)}{\partial y_j(n)} = \sum_k e_k(n) \frac{\partial e_k(n)}{\partial v_k(n)} \frac{\partial v_k(n)}{\partial y_j(n)} \quad (9)$$

Owing to $e_k(n) = d_k(n) - y_k(n) = d_k(n) - \varphi(v_k(n))$, so

$$\frac{\partial e_k(n)}{\partial v_k(n)} = -\varphi'(v_k(n)) \quad (10)$$

While $v_k(n) = \sum_{j=0}^q \omega_{kj}(n) y_j(n)$, in the equation, q is the output numbers of the unit k . Taking the derivation of the equation to $y_j(n)$, getting

$$\frac{\partial v_k(n)}{\partial y_j(n)} = \omega_{kj}(n) \quad (11)$$

Substituting the equation (11) and (12) to the equation (2-10), getting

$$\frac{\partial E(n)}{\partial y_j(n)} = -\sum_k e_k(n) \varphi'(v_k(n)) \omega_{kj}(n) = -\sum_k \delta_k(n) \omega_{kj}(n) \quad (12)$$

So $\delta_j(n) = \varphi'(v_j(n)) \sum_k \delta_k(n) \omega_{kj}(n)$. The above can be summed up as:

$$\left[\begin{array}{c} \text{the weight correction} \\ \square \omega_{ji} \end{array} \right] = \left[\begin{array}{c} \text{the study step} \\ \eta \end{array} \right] \times \left[\begin{array}{c} \text{the local gradient} \\ \delta_j(n) \end{array} \right] \times \left[\begin{array}{c} \text{the input sign of the unit} \\ y_i(n) \end{array} \right]$$

Coalbed methane resources are influenced by many factors, such as the areal distribution of coal, the thickness characteristics of coal, the volume weight of coal, the methane content, the pore structure feature, the coal quality, the metamorphic grade and so on. However, most of

the above effect factors are used to estimate the coalbed methane only through qualitative analysis. Based on the deep study of coalbed methane resources influencing factors and control mechanism, we extract four main impact factors that can be quantified as input parameters, which are the distribution area, thickness, volume weight and methane content of the coal.

Summary

We train the samples of the Shanxi Formation and Taiyuan Formation in nine zones hundreds of thousands times, and establish the prediction model of the studied region's coalbed methane resources using the artificial neural network, with a global error of 2.21×10^{-4} . We also use this model to conduct prediction of other zones in the study region, and the results show that there are tremendous coalbed methane resources in Yangcheng-Changzi, Qinshui, Anze-Qinyuan and Tunliu-Xiangyuan of central and southern of Qinshui basin. There also exists the potential for recoverable resources. In addition, we conduct statistics to the total coalbed methane resources of the area of $6,239.2 \text{ km}^2$ in Qinshui basin, which is 9.68563×10^{11} cubic metres, and the result has little differences with that of coalbed methane resources survey results by Zhang Jianchen et al. of the Zhongyuan Oilfield. This confirms that the artificial neural network could be used in predicting coalbed methane resources and the result shows the superiority of the method.

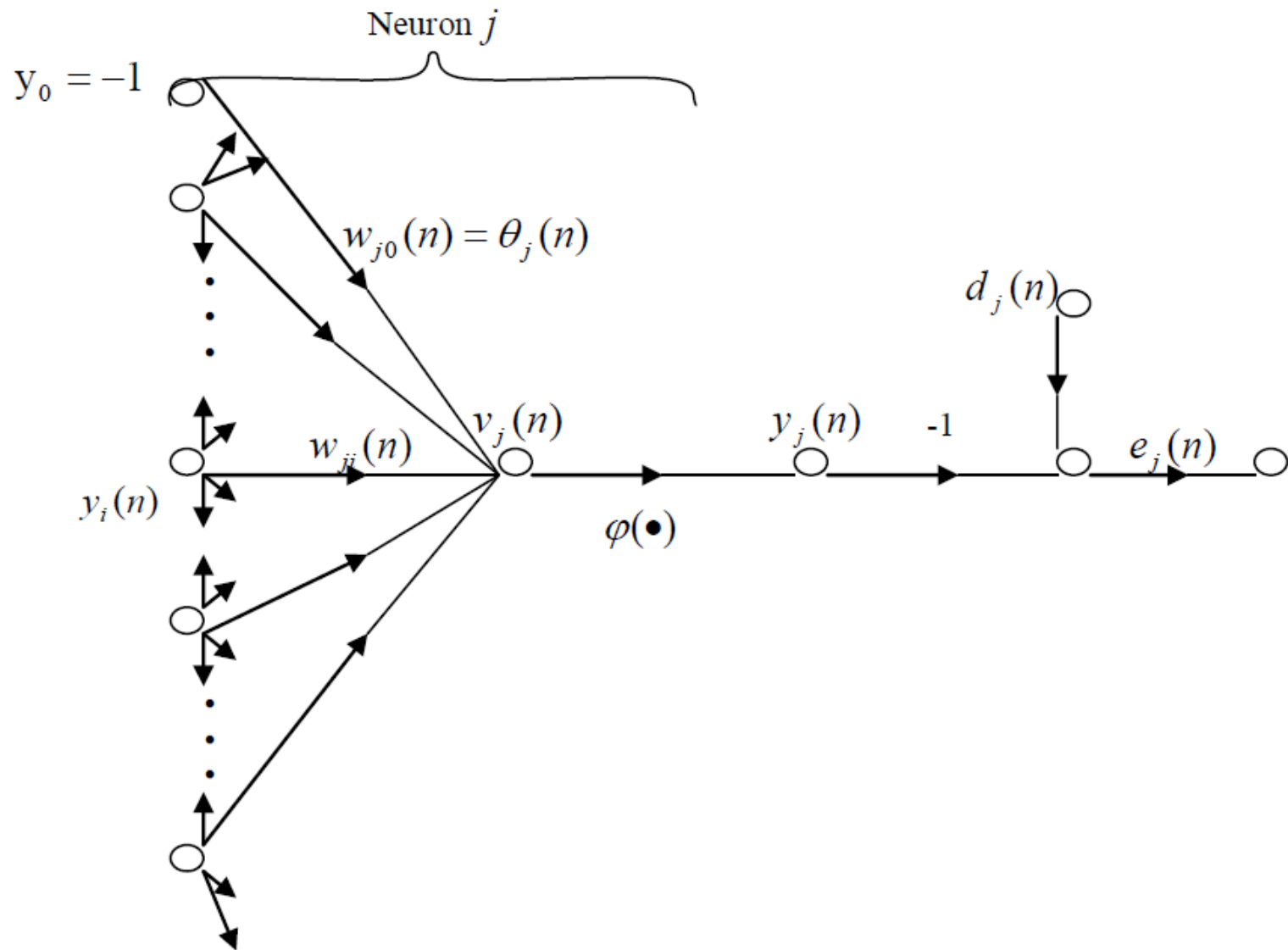


Figure 1. Circulation of the unit j .

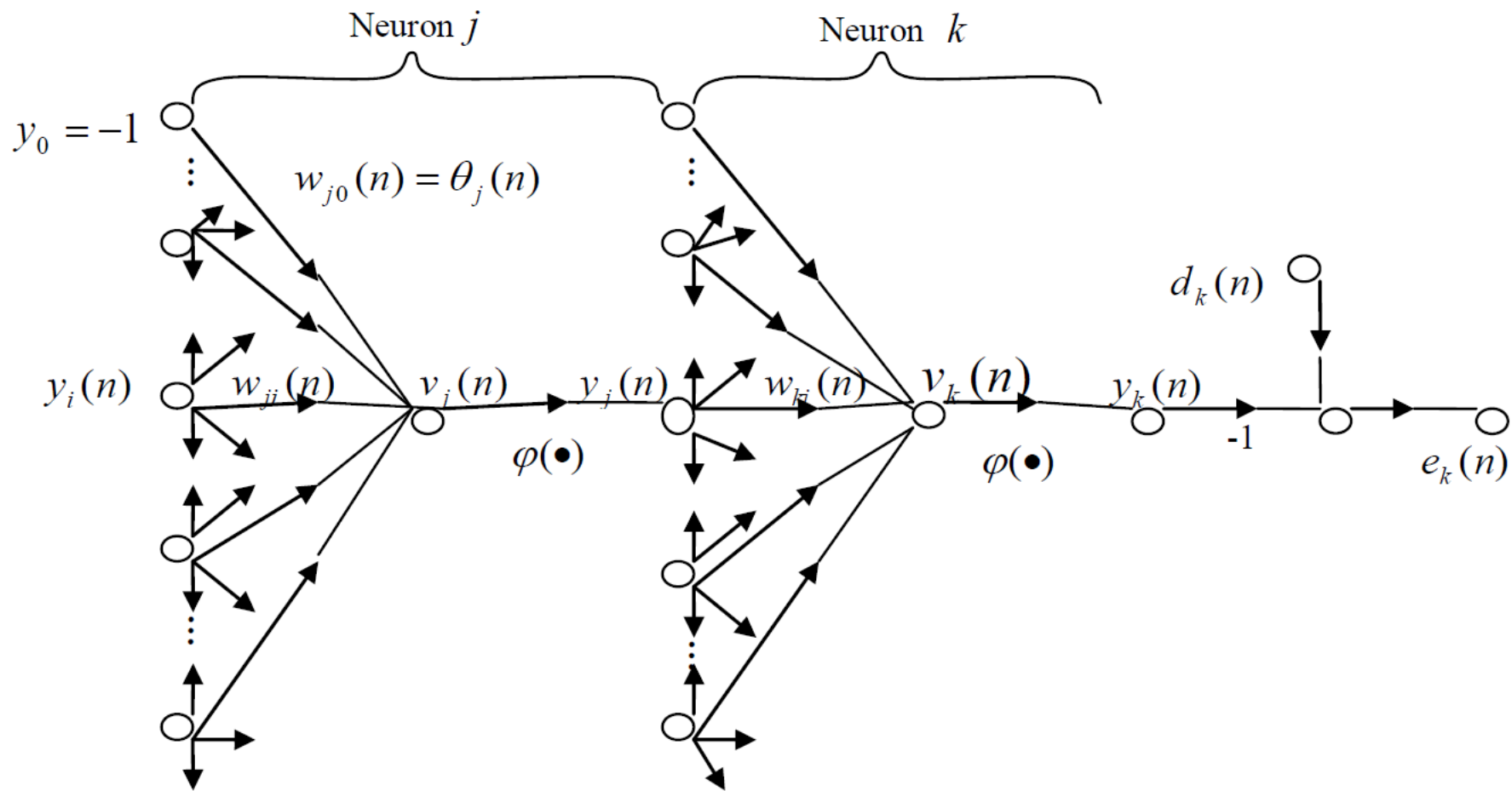


Figure 2. Sign circulation of the unit and the next unit.