Identification of Coal Litho-units for Coal Bed Methane Exploration from Well Logs using Artificial Neural Network Techniques

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Keywords

Artificial Neural Network, Back Propagation Neural Network, Cross-plot, Lithology, CBM Exploration

Summary

Coal lithology is predicted from back propagation neural network in Jharia coalfield. Three wells which are viable for coalbed methane exploration are chosen for this study. This work demonstrates the utilization of multilayered feedforward neural network for identification of coal litho-units such as: coal, shaly coal, carbonaceous shale and jhama. The input parameters from well logs for this network are bulk density, gamma ray, long normal resistivity and neutron porosity. Output parameter is litho-unit for coal, shaly coal, carbonaceous shale and jhama. Different litho-codes are assigned to these litho-units. The network is optimized with minimum sum-squared error of training and testing dataset for 150 epochs and 3 hidden nodes. The model predicted litho-codes for other two wells matches well with the observed litho-codes with $R^2 = 0.99$.

Introduction

Steady increase in coal bed methane (CBM) within energy industry claim that the resources of methane, trapped within coal are greater than the total reserves of all known conventional gas fields (Bachu and Bell, 2001; Peng et al., 2006). Carbonaceous shale may occur in the overburden and within the inter-seam partings. Coal and carbonaceous shale are potential CBM gas reservoir for commercial exploitation. Well log responses can be used to delineate coal and carbonaceous shale from other non-potential litho-units by cross-plotting technique. Identification of lithologies above and below coal seams is important to know the variation in permeability, velocity and elastic properties of rocks immediately overlying and underlying CBM reservoir for identification of the best targets for CBM exploration and production (Ayers, 2002; Bachu and Michael, 2003; Bell and Bachu, 2003; Gentzis, 2010; Ross and Zoback, 2008).

Cross-plotting or statistical techniques enable evaluation of lithology on both regional and detailed reservoir scale (Chatterjee and Paul, 2012; Hunze and Wonik, 2007; Lamont et al., 2008). Anderson and Gray (2001) as well as Gray and Andersen (2000) had demonstrated that many different lithologies like coal, shale, sandstone, gas saturated sands and carbonates can be identified by cross-plots.

The main objective of this paper is to use Back Propagation Neural Network (BPNN), which is a specific type of Artificial Neural Network (ANN) technique, to model the inter-relationships between four different well logs: bulk density, gamma ray, long normal resistivity and neutron porosity and to identify different litho-units for selected coal bearing horizons of Jharia coalfield using the proposed BPNN model.

Theory and/or Method

The BPNN litho-unit prediction model has been developed from a data set consisting of well log data and then the litho-units are identified using the proposed BPNN model for three wells: J1, J3 and J4 located in the central part of Jharia coalfield, India (Figure 1). The bulk density, gamma ray, long normal resistivity and neutron porosity logs have been used for the inputs for BPNN modeling. The model is tested with well log data from the wells J7 and J8 which were withheld during the modeling process.

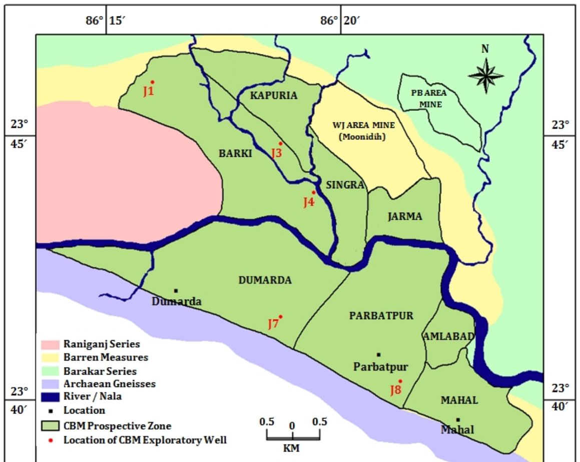

Figure 1: Showing locations of wells in the central part of Jharia coalfield, India.

Network Topology: BPNN

The back propagation algorithm using the conjugate gradient descent method is the most commonly used method to reduce the model error (Dayoff, 1990) in a network**.** Multilayered feedforward neural network (MLFN) consists of neurons that are ordered into three layers, namely, input layer, hidden layer and output layer. The network is trained to predict four coal litho-units such as: coal (litho-code 10), shaly coal (litho-code 20), carbonaceous shale (litho-code 30) and jhama (litho-code 40) from bulk density, gamma ray, long normal resistivity, and neutron porosity logs. Figures 2(a) and (b) are showing examples of log responses against coal, shaly coal, carbonaceous shale and jhama from well J2.

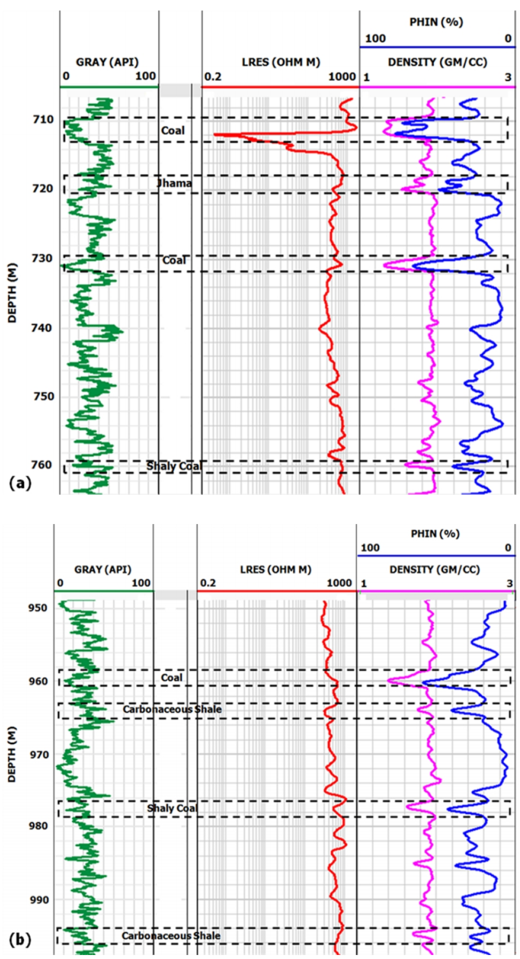

Figure 2: Showing well log responses against coal, shaly coal, carbonaceous shale and jhama for the depth intervals (a) 706-764m and (b) 948-998m from Well J2 located in Jharia coalfield, India.

The MLFN architecture is shown in Figure 3. Each layer consists of nodes, and the nodes are connected with weights. The weights combine the inputs to produce a result at the output layer. The network is trained with known answers to derive an optimal set of weights. The training algorithm is essentially a gradient descent local optimization technique which involves backward error correction of the network weights.

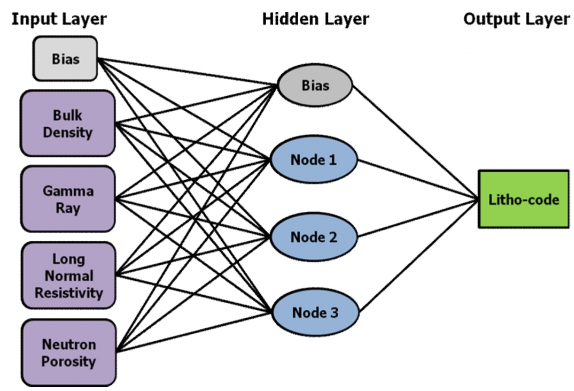

Figure 3: MLFN architecture showing input layer, hidden layer, and output layer, and connecting weights.

The back propagation uses the following expression for the output calculation:

$$Y = f[\sim_0 + \sum_{j=1}^{n_2} \sim_i f_j(\ _{0j} + \sum_{i=1}^{n_1}\ _{ij} x_i)] \ldots (1)$$

where Y is the output variable, x are the input variables, α and β are the connecting weights, n_1 is the dimension of the input vector, and n_2 is the number of hidden neurons. α_0 and β_{0j} are called the bias weights. Small random numbers are used to initialize all the connecting weights and the biases, and the final values are determined using the iteration process. During MLFN training, each hidden and output neuron process inputs by multiplying each input by its weights. The products are summed and processed using the activation function. The function f used in this work is the sigmoidal transfer function. It is given by the following expression,

$$f(z) = \frac{1}{1+e^{-z}} \ldots (2)$$

The back propagation calculates the error vector by comparing the calculated outputs and the target litho-code. The weights are calculated again in the reiteration process until a minimum overall error is reached. The problem of estimating the weights can be considered a nonlinear optimization problem, where the objective is to minimize the sum-squared error between the actual litho-code values and the predicted litho-code values. The process of obtaining appropriate weights in a neural network design utilizes two sets of equations. First, the feed-forward equations are used to calculate the error function, i.e. the objective function to be minimized. This is a differentiable function. The feedback equations are next used to calculate the gradient vector, which is then used for defining search directions in order to minimize the error function using conjugate gradient method. The networks which utilize this algorithm are called back propagation feed-forward network. The training process can be made to create the network such that it can predict a property value even in situation where the actual output is absent.

The number of neurons in the hidden layer generally varies as required for optimum performance, which could be decided on trial and error basis. Initial weights are assigned at random in the range suitable for the activation function at neurons. The signal is feed-forward through the network as shown in Figure 3.

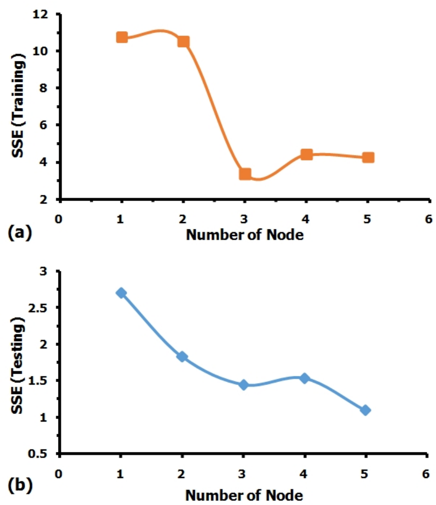

Figure 4: Sum-squared error (SSE) versus nodes in hidden layer for optimization with (a) training dataset and (b) testing dataset for 150 epochs.

The learning cycle begins with the updating of the weights of output layer and utilized to adjust the input weights and to obtain the desired output, known as a back propagation (Rumelhart et al., 1986). To initialize the hidden layer weights, sum-squared error (SSE) for trial models are computed by repeating steps for 150 epochs. Weights are selected with the lowest SSE to provide a good starting point for the optimization process. The results of weight initialization in Figure 4 show a simple way to determine how many hidden neurons are required to create a satisfactory computational model. We have conducted 150 trials for one to five neurons with resulting SSE plotted in Figure 4. The lower value of SSE results at beginning 3 neurons. The number of hidden layer neurons has been chosen as 3 on the ground of good generalization. In our modeling, we have taken the input from Figure 4 of the BPNN architecture with 3 hidden neurons using IBM SPSS version 21 software. Training dataset of 600 data points are generated from three wells J1, J3 and J4 from coal, shaly coal, carbonaceous shale and jhama layers. The network is trained with 60% of the total available data, then tested on remaining 30% data and hold out is remaining 10% data. The training dataset accounts for 60% of the entire dataset and is used to calculate errors and adjust connection weights and bias. The validation i.e., test dataset is used to avoid over-training or over-fitting through detecting the predicted results in validation group.

Validation and Testing

The different network parameters like number of hidden layers and neurons, learning rate and momentum ratio are optimized in a trial and error basis. Maximum epoch is set on the basis of training convergence as well as the testing performance. Figure 5 is showing the SSE versus epoch for training and validation/testing dataset. It is observed that the training error is undulating in the beginning then starts decreasing with less variation from 100 to 200 epochs, while for validation SSE starts decreasing followed by increasing trend and decreasing at epoch 150 then again increased at 200 epochs slightly. Since it becomes minimum at 150 epoch, so the training have been optimized with 150 epoch.

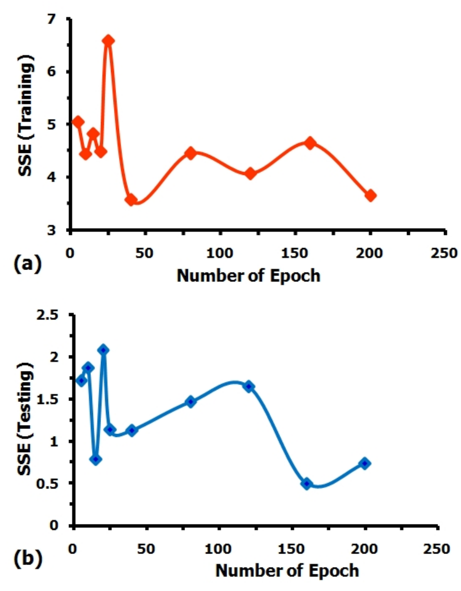

Figure 5: Sum-squared error (SSE) versus epochs for model network optimization for (a) training dataset and (b) testing dataset with 3 hidden nodes.

Trained network is applied to the new dataset containing 819 data points from Well J7 and J8. Figure 6 is showing the predicted litho-code and observed litho-code for these wells. The regression equation is showing the best fit line with goodness of fit (R^2 =0.99). Standard error is observed for this predicted value as 0.91. Standard Error of the estimate is referred to as the root mean squared error. It is the square root of the mean square for the residuals (Koch and Link, 1970).

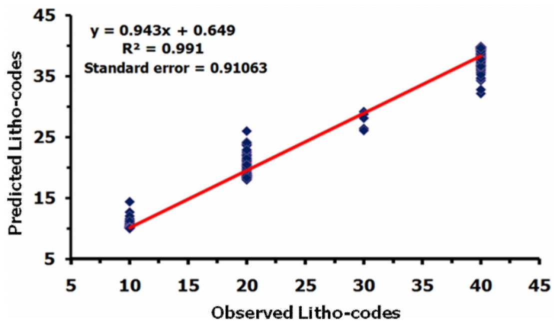

Figure 6: Showing the Predicted Litho-codes versus Observed litho-codes from two wells J7 and J8 with standard error and R^2 = 0.99.

Conclusions

This work demonstrates the identification of coal litho-units from coal bearing horizons with the help of multilayered feedforward neural network (MLFN) model developed using well log data. Network error is observed minimum at 150 epoch as validated with test dataset. This model is able to identify coal, shaly coal, carbonaceous shale and jhama from the well logs of any well located in the same or nearby areas of present study area. This network prediction may be useful for huge dataset for CBM exploration.

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