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# Prediction of coal-bed permeability from well logs using artificial neural network

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***Summary***

*Prediction of permeability from well logs in heterogeneous formation is a difficult and complex problem to solve by conventional statistical methods. The correlation between parameters like porosity with permeability for different wells alone may be a crude approximation for permeability estimation, even for homogeneous formations. Recently artificial neural networks have been successfully used for solving many complex problems in reservoir permeability estimation. In this work, the neural network technique is utilized for the permeability estimation of coal formations. The back propagation neural network (BPNN) permeability prediction model has been developed from a data set consisting of well test permeability and well log data from "well A" located in the Damodar valley coalfield, India. The bulk density, gamma ray, long normal resistivity and neutron porosity logs have been used as the inputs for the modelin g. The model is tested with well log data from the "well A" as well as another "well B" which was withheld from the modeling process. The results of this study reveal that the BPNN predicted coal-bed/ coal seam permeability is consistent with the well test permeability data.*

***Key words****: Back propagation neural network, coal permeability, neural network, well log*

## Introduction

Permeability is a critical factor in Coal-bed Methane (CBM) reservoir characterization and engineering. Due to costs associated with extensive core extraction and subsequent laboratory analysis of core samples, considerable efforts have been made to relate other physical properties to the available well test data, so that the transformations developed can be applied to predict the permeability of coal-beds in un-cored intervals or well sections. In un-cored intervals and well sections, the reservoir description and characterization methods of permeability estimation utilizing well logs represent a significant technical as well as economic advantage, because well logs can provide a continuous record over the entire well. The correlation of well logs and core permeability had been widely studied in many oil/gas fields of the world (Huang et al., 1996, Mohaghegh et al., 1996, Wong et al., 1998, Wong, 1999, Lim et al., 2006, and Ho and Ehara, 2007).

Permeability estimation from conventional well logs in coaly formation is a difficult and complex problem to solve by statistical methods. The parametric methods like statistical regression require the assumption for the satisfaction of multi-normal behavior and linearity. Therefore, an artificial neural network (ANN), as a non-linear and non-parametric tool, is becoming increasingly popular in well log analysis. ANN is a computer model that attempts to mimic simple biological learning processes and simulate specific functions of human nervous system. Recently ANN has been successfully utilized for reservoir permeability estimation using the transformation between well logs and core analysis data (Lim et al., 2006).

Main objective of the paper is to use back propagation neural network, which is a specific type of ANN, to model the inter-relationships between four different well logs: bulk density, gamma ray, long normal resistivity and neutron porosity, and well test permeability data for selected major coal bearing layers in a Damodar valley coalfield, in India.

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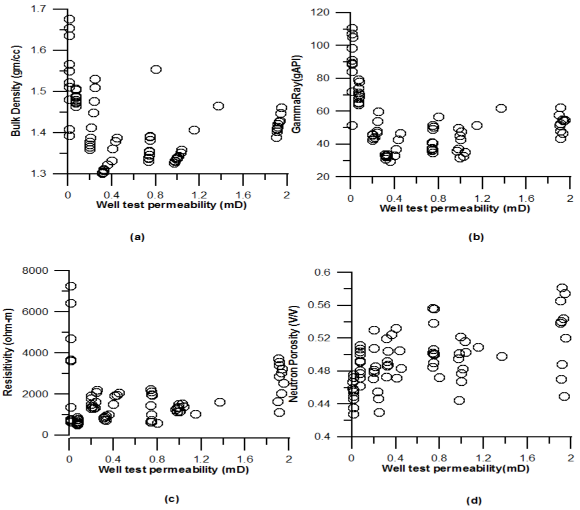


Figure 1: Displays scattered cross-plots of (a) Bulk density, (b) Gamma ray, (c) Resistivity analysis. ANN is a computer model and (d) Neutron porosity w ith well test permeability for coal seams of wells of the Damodar valley coalfield, India.

## Background

The ineluctable need of estimation of permeability for reservoir characterization has urged the need to devise approximate methods of permeability estimation by rock physicists. Among the most conventional method for estimation of permeability in homogeneous reservoir is the cross-plot between permeability and other log parameters like porosity, resistivity, and others. The cross-plots of several wells are used to generate a correlation between the parameter and permeability. This correlation is used in permeability estimation for wells where core is absent. Permeability, however, follows a very complex relation, with its dependence on various parameters and not just one, like porosity. Cross-plots between various physical parameters, like bulk density, gamma ray, long normal resistivity and neutron porosity from coal seams of several wells of the Damodar valley coalfield w ith well test permeability obtained for the same coal seams was constructed. It showed non-linear correlation of these well log parameters with the well test permeability (Figure 1). All of these cross-plots show scattered distribution. A straight line fit through these scattered points will be a crude approximation to relate permeability with these parameters, which may not be adequate solution even for fairly homogeneous reservoirs.

However, using advanced start-of-art network development and optimization techniques, a better correlation can be made between permeability and combination of several physical/petrophysical parameters. The dependence of permeability on all of these parameters can be considered a better way of permeability estimation from wells where core data is absent.

## Neural network: design and development

Neural networks are composed of simple elements operating in parallel, which mimic a simple biological learning process. The network function depends on the relationship between the elements of the network. The network is developed based on the training process, where it learns from examples or experiences. It is extremely useful in pattern recognition and mapping problems. Because the network process data and learn in parallel and distributed fashion, they are able to identify complex relationships between parameters associated in the network. Neural networks can map from input to output for an y relationship owing to the fact that it is a model-free function estimator. There are various methods of developing a neural network. In this study, feed-forward back propagation neural network (BPNN) has been used for permeability estimation.

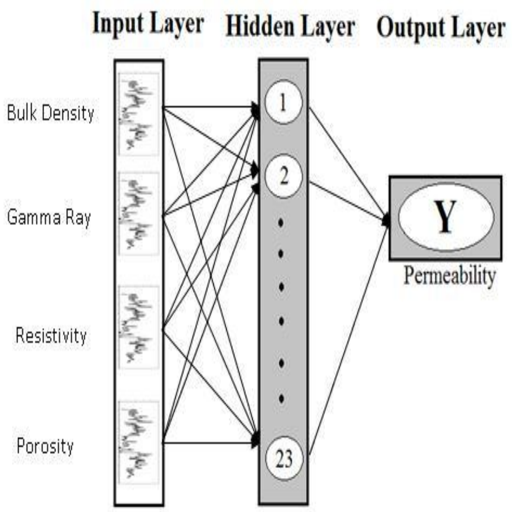


Figure 2: Network architecture of BPNN showing input layer, hidden layer, and output layer, and connecting weights. back propagation neural network (BPNN) has been used for permeability estimation.

## Network topology: back propagation neural network

The back propagation algorithm using the gradient descent method is the most commonly used method to reduce the model error (Dayoff, 1990) in a network. 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. A typical BPNN network consists of three layers: input, hidden and output layer (Figure 2). Each layer consists of a number of processing elements or neurons. Each neuron is connected to every other neuron in the preceding layer by a simple link represented by the weights. The input and the output layers consist of the values which help in training the network, until it can approximate a function. The input layer is normally biased, the hidden layer is a sigmoid function, and the output layer is a linear layer. With these three layers it is possible to approximate any function with a finite number of discontinuities. The BPNN network uses a training pattern in which the first step is the forward propagation step followed by the back-propagation step. The forward propagation step sends the input through the neurons of each layer, resulting in an output value. The BPNN uses the follow ing expression for the output calculation:

$$Y = f[\alpha_0 + \sum_{j=1}^{n_2} \alpha_i f_j(\beta_{0j} + \sum_{i=1}^{n_1} \beta_{ij} x_i)], \qquad (1)$$

where $Y$ is the output variable, $x$ are the input variables, $\alpha$ and $\beta$ are the connecting weights, $n_1$ is the dimension of the input vector, and $n_2$ is the number of hidden neurons. $\alpha_0$ and $\beta_{0j}$ 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.

The function $f$(z) used in this work is the log-sigmoid transfer function. It is given by the following expression:

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

The log-sigm oid function generates output between 0 and 1 as the neuron inputs goes from negative to positive infinity.

The BPNN calculates the error vector by comparing the calcu lated outputs and the target values. The weights are calcu lated again in the reiteration process until a minimum overall error is reached. The Levenberg-Marquardt algorithm, which is a type of gradient descent method, is used as the back-propagation algorithm as it converges to a faster solution to the problem of minimizing a function.

## Development of the network

Major coal seams have been identified from the correlation of the bulk density (RHOB), gamma ray (GR), long normal resistivity (LN), and neutron porosity (NPhi) logs from two CBM wells under study located at the Damodar valley coalfields. The well permeability data for these seams were then collected from well hydro-fracture data. Well test permeability, essentially a single value for a particular coal seam was extrapolated. The extrapolation was done on the basis of variation of the permeability values obtained for the same seam using cleat volume (Yang et al., 2006, Chatterjee and Pal, 2010), with the mid of the seam being assigned the exact well test permeability obtained from hydro-fracture data, and the other values extrapolated accordingly using the cleat volume permeability. This method is adapted to assign a different value of permeability at each sample point, deviating slightly fromthe actual well test permeability, so that the network is trained properly and is not biased. The well logs of RHOB, GR, LN, and Nphi for selected major coal seams at varyin g depths from 315m to 1165m are served as input whereas the well test permeability for these selected seams at the same depths has been provided as the target values to the network train ing. The hidden layer has 23 neurons, which is chosen using trial and error method based on the performance of the network. Preprocessing of the data was done to a certain extent to do away with outliers. A total of 264 values were considered for train ing the network after the preprocessing. First these values were randomized to eliminate the biases. Out of these randomized input values, 60% of the values were used for the train ing, 20% of the values were used for validation of the network. Once the weights were decided on the basis of the minimization of the error function, the remaining 20% of the values were used to independently test the network. The performance plot (Figure 3) shows how the error decreases with the number of epochs, which is a step in the training process. This clarifies that the network is learning. The network developed in this study required 100 epochs for the error function to stabilize at a value of 0.005. The set of connection weights were obtained after the iteration process was complete.

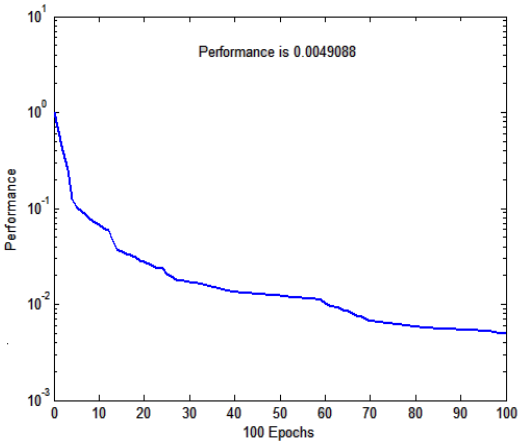


Figure 3: Performance plot of BPNN with number of epochs.

The connection weights were analyzed after train ing using the following equation (Wong et. al., 1995):

$$A_i = \frac{\sum_{j=1}^{n_2} |\beta_{ij}|}{\sum_{k=1}^{n_1}\sum_{j=1}^{n_2} |\beta_{kj}|} * 100\%, \qquad (3)$$

where $A_i$ is the average contribution of the input variable $i$, $\beta_{ij}$ is the connection weight from input neuron $i$ to hidden neuron $j$. The contribution of each log in the network is shown in Figure 4, with bulk density log having the greatest contribution of around 30% to the network while gamma ray log having the least contribution of 20%.

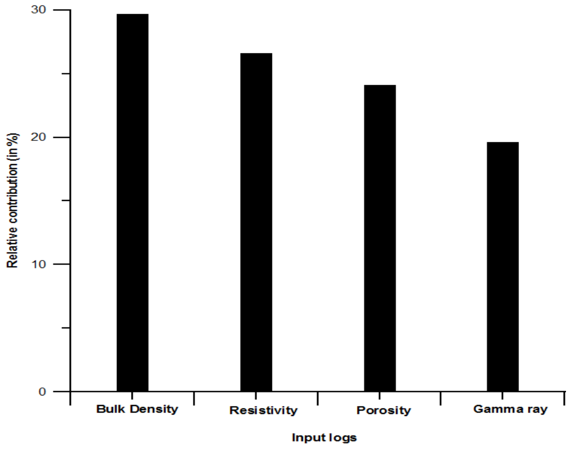


Figure 4: Contribution of input logs to permeability estimation.

## Testing of the network

The trained network described in the previous section is applied on the entire dataset used for training purpose from well A. Data from an adjacent well B has been also used for testing the network. Table 1 lists few training data as well as test data of input log parameters for selected depth values, well test permeability, network estimated permeability and errors for well A. The best fit linear curves between the well test permeability and network estimated permeability for well A (Figure 5) and well B (Figure 6) showed excellent correlation (correlation coefficient = 0.98 for well A, and 0.97 for well B) with goodness of fit (R2) ranging from 0.94 (well B) to 0.97 (well A). Figure 7 displays network predicted and well test coal-bed permeability with depth for few selected major

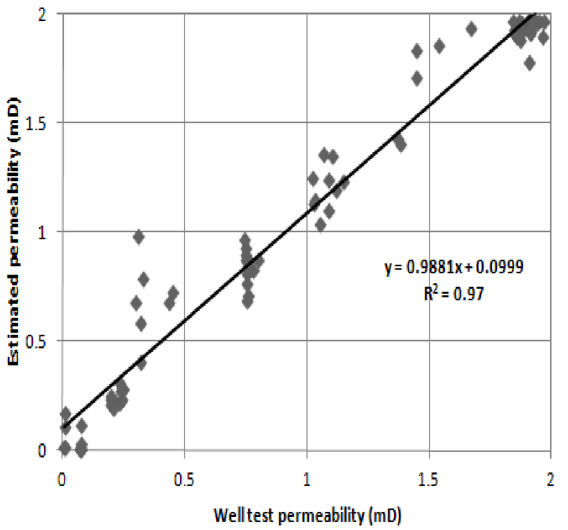


Figure 5: Best fit relation between well test coal-bed permeability and network predicted coal-bed permeability for well A.

seams from well B. The well test permeability values (lyin g within a range) are chosen based on the variation of other log parameters. It is observed from Figure 7 that the network predicted coal-bed permeability value matches well with the well test permeability data for this test well.

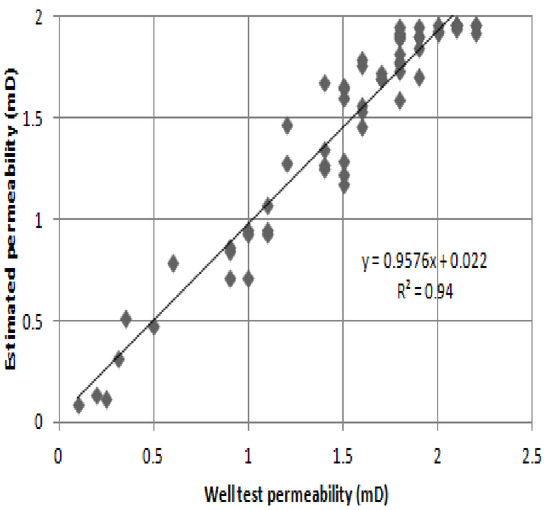


Figure 6: Best fit relation between well test coal-bed permeability and network predicted coal-bed permeability for well B.

## Conclusions

Bulk density, gamma ray, resistivity and neutron porosity log responses have been used as input to the neural networks. They helped in predicting permeability of the major coal-beds/coal seams. By testing the developed neural network against field data, it is shown that a carefully designed neural network is able to predict coal- bed permeability. The coal-bed permeability predictions made by this BPNN are quite close to the well test permeability data. This demonstrates that it is possible to attain reliable coal-bed permeability values for all wells covering the CBM fields of this Damodar valley coalfield under study, though only a few well test data are available for permeability measurement.

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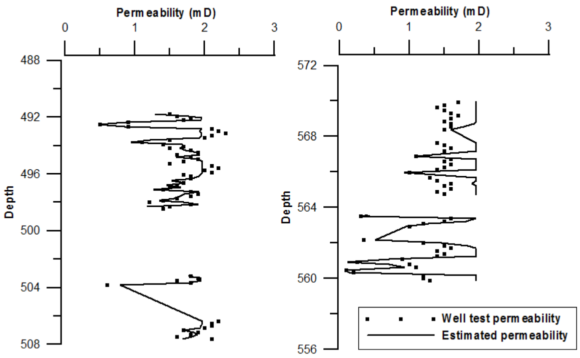


Figure 7: Permeability vs. depth profile of coal seams of well B.

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Table 1: Some of the input log values and the corresponding estimated permeability values (training data and test data) for well A. Error estimation of the permeability values with respect to the well test permeability values at a particular depth are also shown.

| Depth (m) | Bulk density (gm/cc) | Gamma ray (gAPI) | Long normal resistivity (ohm-m) | Neutron porosity (V/V) | Well test permeability (mD) | Network estimated network (mD) | Error in estimation (mD) | |
|---|---|---|---|---|---|---|---|---|
| 315.6 | 1.4072 | 62.173 | 1107.933 | 0.5403 | 1.91 | 1.9297017 | 0.019702 | **Training data** |
| 319.2 | 1.2844 | 35.0365 | 1727.742 | 0.5902 | 1.85 | 1.9649863 | 0.114986 | |
| 602.2 | 1.3781 | 42.6137 | 1952.314 | 0.505 | 0.435 | 0.675867 | 0.240867 | |
| 615.1 | 1.3903 | 50.4004 | 1950.237 | 0.5006 | 0.752 | 0.685383 | -0.06662 | |
| 1062.8 | 1.3438 | 42.5157 | 650.3777 | 0.497 | 1.011 | 1.3487151 | 0.337715 | |
| 1152.2 | 1.3652 | 42.2668 | 1296.116 | 0.4789 | 0.2 | 0.5533676 | 0.353368 | |
| 316.2 | 1.447 | 54.1519 | 3230.571 | 0.5745 | 1.94 | 1.965 | 0.025 | **Test data** |
| 319.8 | 1.4125 | 43.6861 | 2003.93 | 0.5235 | 1.915 | 1.8956677 | -0.01933 | |
| 602.4 | 1.3028 | 32.3347 | 755.241 | 0.5106 | 0.317 | 0.9123125 | 0.595313 | |
| 660.6 | 1.3678 | 42.4864 | 2270.031 | 0.5141 | 0.747 | 0.8783621 | 0.131362 | |
| 1100.1 | 1.356 | 55.5075 | 1878.923 | 0.4976 | 0.195 | 0.3159914 | 0.120991 | |