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# PERMEABILITY MODELING FROM WELL LOGS USING ARTIFICIAL NEURAL NETWORKS

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**Abstract:** Permeability, the ability of a rock to transmit fluid, is one of the most important properties of hydrocarbon bearing formations. Formation permeability is generally measured in laboratory from cores. It can also be evaluated from well test data. This study discussed a rigorous approach for permeability determination from well logs of the Habiganj Gas Field (HGF). This is a “Virtual Measurement” method and makes use of Artificial Neural Networks (ANN). ANN can predict permeability values for entire wells without prior exposure to their log and core data with accuracies. The ability of neural networks to learn from experience and then to generalize these learning for solving new problems sets it apart from all conventional methods. One developed well of HGF was considered under this study. The permeability model was developed from the data set consisting of core permeability and logs from the well. The model was then applied to that well and the result (i.e. predicted permeability) was compared with the core permeability.

***Keywords:*** *Permeability, ANN, Well log, HGF*

## NOMENCLATURE

ANN = Artificial Neural Network
BD = Bulk density log
BGFCL = Bangladesh Gas Field Company Ltd.
BPNN = Back Propagation Neural Network
DI = Deep induction log
GR = Gamma ray log
HGF = Habiganj Gas Field
HBJ#7 = Well No. 7 of Habiganj Gas Field
MVR = Multiple Variable Regression
Neu = Neutron log
PMML = Predictive Model Markup Language
por = Corrected log porosity
SPSS = Statistical Package for the Social Sciences
SNNS = Stuttgart Neural Network Simulator
Sonic = Sonic compressional transit time
XML = Extensible Markup Language
$b$ = Connection weight of the input layer
$b_o$ = Bias weights of the input layer
$K$ = Permeability
$n_1$ = Dimension of the input vector
$n_2$ = Number of hidden neurons
$w$ = Connection weight of the hidden layer
$w_{ij}$ = Weight for the $i$ neuron in the hidden layer $j$
$w_{oj}$ = Bias weights of the hidden layer
$x_i$ = Input variables
$y$ = Output variable
$X$ = Input vector of one dimension for any input variable
$Y$ = Output variable
$\phi$ = Corrected log porosity

## 1. INTRODUCTION

There are several ways to measure formation permeability [1,2]. Three methods are available to determine permeability from well logs namely Empirical, Multiple Variable Regression (MVR) and Artificial Neural Networks (ANN) [3–5].

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Empirical models were developed based mainly on porosity and water saturation of a formation. Thus it is often limited to provide accurate estimation of permeability [6]. To overcome such limitation MVR was introduced and frequently used to develop permeability model from well log [7]. But MVR is not able to predict permeability for entire domain of interest. ANN shows the consistency to predict permeability from well logs [8,9].

## 2. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) is a computational tool modeled on the interconnection of the neuron in the nervous systems of the human brain and that of other organisms. ANN is the type of non-linear processing system that is ideally suited for a wide range of tasks, especially tasks where there are no existing algorithm for task completion. ANN can be trained to solve certain problems using a teaching method and sample data. In this way, identically constructed ANN can be used to perform different tasks depending on the training received. With proper training, ANN is capable of generalization, the ability to recognize similarities among different input patterns. ANN is essentially simple mathematical model defining a function f:X →Y or a distribution over X or both X and Y, but sometimes models also intimately associated with a particular learning algorithm or learning rule. One of the more popular algorithms is the back-propagation algorithm [10,11].

A typical back propagation neural network (BPNN) is composed of three layers namely input, hidden and output layers. Each layer has a number of processing elements which are called neurons. Neurons of different layers are connected together by a simple weighted link (Fig. 1).

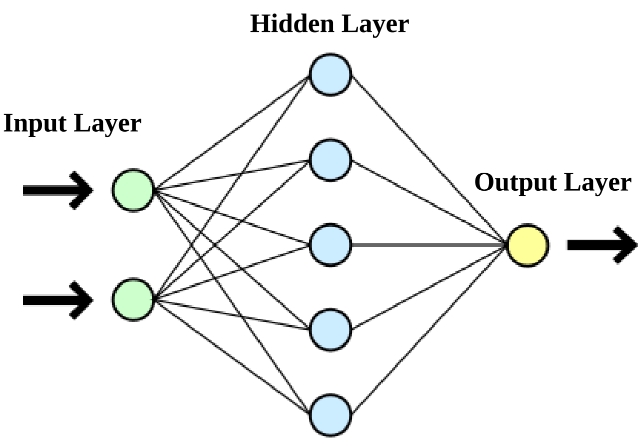


Fig. 1: Typical Neural Network Architecture.

BPNN uses the following mathematical function:

$$\boldsymbol{y = f\left[b_0 + \sum_{j=1}^{n_2} b_j f_j\left(w_{oj} + \sum_{i=1}^{n_1} w_{ij} x_i\right)\right]} \quad (1)$$

where $y$ is the output variable, $x_i$ are the input variables, $b$ and $w$ are the connection weights, $n_1$ is the dimension of the input vector, $n_2$ is the number of hidden neurons, $b_0$ and $w_{oj}$ are called the bias weights.

The output, y, depends on the particular transfer function that is chosen. All the values of the input variables and target variable are normalized or scaled in the range of (–1, 1). In this study, the input variables are different well logs ($\phi$, GR, Sonic, Neu, BD, DI) and the output variable is the target which is permeability (K).

Neural network simulators are software applications that are used to simulate the behavior of artificial or biological neural networks. They focus on one or a limited number of specific types of neural networks. They are typically stand-alone and not intended to produce general neural networks that can be integrated in other software. Commonly used artificial neural network simulators include the Stuttgart Neural Network Simulator (SNNS), Emergent, Java NNS and Neural Lab. The majority implementations of neural networks available are however custom implementations in various programming languages and on various platforms. Basic types of neural networks are simple to implement directly. There are also many programming libraries that contain neural network functionality and that can be used in custom implementations. A common language is necessary for neural network models to be shared by different applications. Recently, the Predictive Model Markup Language (PMML) has been proposed to address this need.

PMML is an XML-based language which provides a way for applications to define and to share neural network models (and other data mining models) between PMML compliant applications. PMML applications provide a vendor-independent method of defining models so that proprietary issues and incompatibilities are no longer a barrier to the exchange of models between applications. It allows users to develop models within one vendor's application, and use other vendors' applications to visualize, analyze, evaluate or otherwise use the models. Previously, this was very difficult, but with PMML, the exchange of models between compliant applications is now straightforward. A range of products are being offered to produce and consume PMML. *SPPS* is one of them and was preferred to develop permeability model.

## 3. RESERVOIR DESCRIPTION

Habiganj Gas Field (HGF) is located in the north-eastern part of Bangladesh. This area belongs to Madhobpur Upazilla under the District Habiganj & Division Sylhet. Habiganj structure lies in the north-eastern part of Bengal Foredeep and in the south central part of Surma Basin. It is the northern culmination of Baramura anticline of Tripura (India), is separated by a saddle. The structure is almost symmetrical and trending SSE. Seismic and well data of Habiganj structure have proved that the structure has entirely separate closure. Including Baramura it is a giant structure of about 130 km long. In Habiganj structure, the exposed rock is Dupi Tila and the topographical height is about 20 m above mean sea level. No fault has been detected on flanks.

Habiganj structure has one of the largest producing gas fields of the country. This field comprises two sands namely: Upper Gas Sand (1320–1530 m) in Bokabil and Lower Gas Sand

(3014–3022 m) in Bhuban formation. The upper structure is about 10 km long towards North-South and 5 km wide in the direction of East-West. In the crest, reservoir has very good permeable sand. The Upper Gas Sand is fine grained, clean, unconsolidated and well sorted. Lack of clay matrix and presence of glauconite in Upper Gas Sand indicate the deposition in high-energy littoral to sub littoral environment. The sand indicates a beach and barrier bar characteristic.

## 4. DEVELOPMENT OF PERMEABILITY MODEL

For developing the permeability model using ANN, information about the field were collected. Required data were selected to be used in the ANN model. Section 4.1 describes the data used in ANN model. The developed permeability model is given in section 4.2.

### 4.1 Data Description

Permeability is usually modeled using ANN based on the core and log data. Core data of only well no. 7 of HGF (HBJ#7) for an interval of 1500–1518 m depth were available during this study. Fig. 2 shows log and core data of HBJ#7. Permeability modeling requires the following well logs –

- Density log
- Neutron log
- Sonic log
- Gamma ray log and
- Resistivity log

### 4.2 Application to the HGF

Core and log data from HBJ#7 were used to construct the network model. A total of 31 core measurements for porosity and permeability and their corresponding well logging responses were available for network training and testing. The well log responses that have been used include bulk density (BD), gamma ray (GR), sonic compressional transit time, neutron porosity (Neu), and deep induction (DI). The permeability model is given by

$$K = f\,(\phi,\ GR,\ Sonic,\ Neu,\ BD,\ DI) \qquad (2)$$

23 data samples were chosen by a random number generator for network training. The remaining 8 samples were put aside to be used for testing the network's integrity and robustness. The available data were randomly divided into two groups. The first group was used for the process of network training which represent 74.2% of the total sample points, and the rest 25.8% were used for network testing. Finally, the training process data were divided into validation process (30%) and forward training process (70%). The final architecture of the neural network to predict permeability contained six input variables and one hidden layer with 2 neurons (as shown in Fig. 3). This configuration and the proper use of the validation set were sufficient to ensure fast convergence after about 60 iterations.

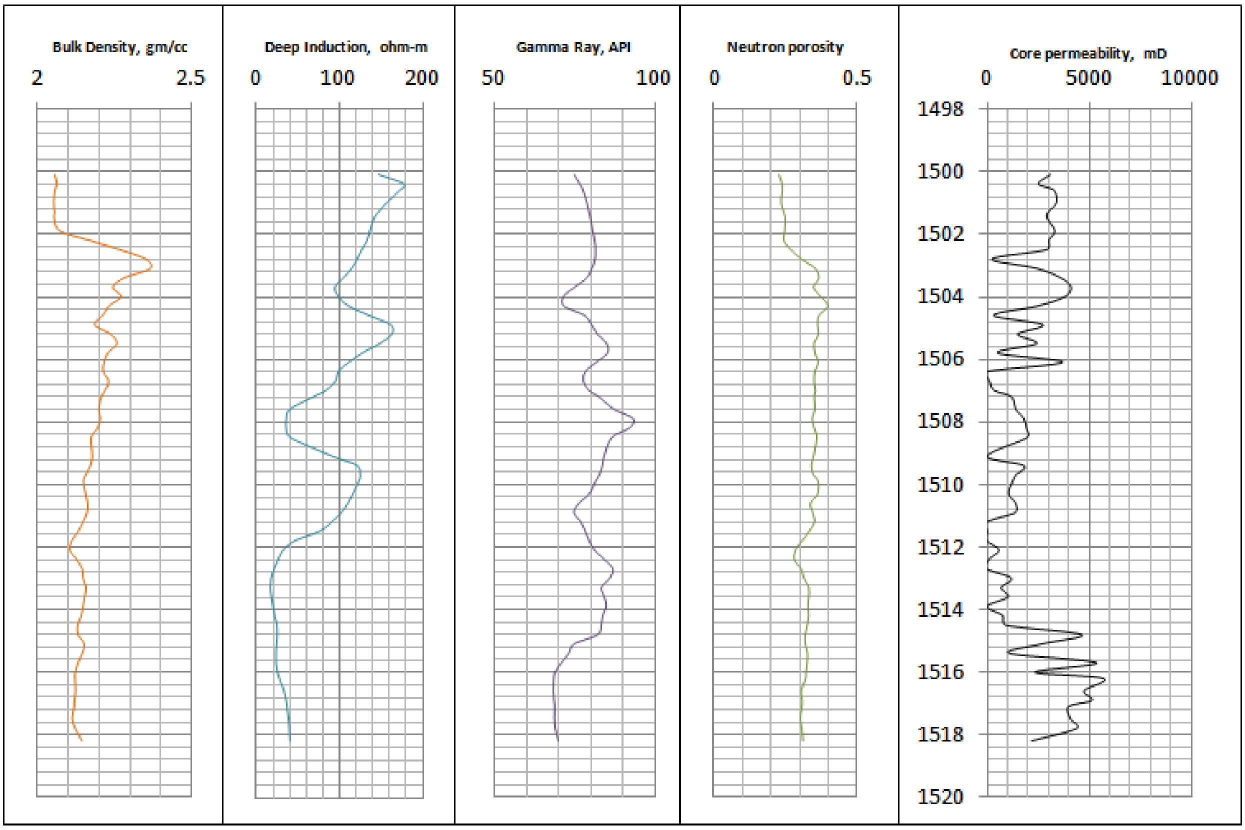


Fig. 2: Log and core data of HBJ#7 (courtesy: BGFCL).

## 5. RESULTS AND DISCUSSION

ANN has a correlation coefficient of 0.813 (Fig. 4), where 1.0 is a perfect match. Permeability models need both core and log data for several wells to give a consistent result. But, in this study permeability model was developed based on only one well data. The fact that core data of only one well of HGF was available during this study. This model can be updated using more than one well data whenever core data of the wells of interest are available. It can be done such a way that the $n$ (where $n = 2, 3, 4 \ldots$) developed well of HGF will be considered under this study. The permeability model will be developed from the data set consisting of core permeability and logs from $n$-1 well. The model will then be applied to the $n^{th}$ well. However, the permeability model based on HBJ#7 can be applied in other wells of this field to determine permeability from well logs.

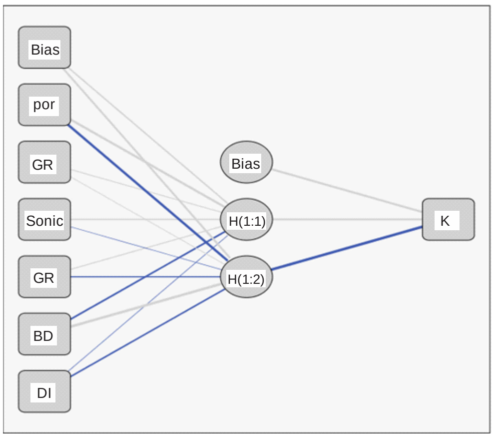


Fig. 3: *SPSS* generated Neural Network Architecture.

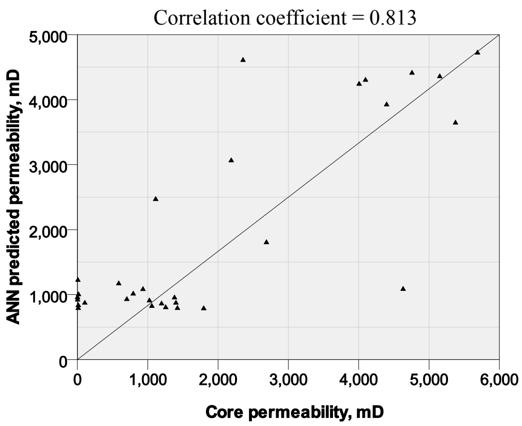


Fig. 4: ANN permeability vs. core permeability of well HBJ#7.

## 6. CONCLUSIONS

A rigorous methodology has been presented here which has the potential to significantly reduce the cost of permeability determination from well logs. This methodology uses the conventional well logs and generates predictive model for all the wells in a field. The development process requires a handful of wells in a field. Then the log data generated from those wells are used to develop an intelligent, predictive permeability model. The process can help engineers to acquire a better handle on the reservoir characteristics. This is especially beneficial for the fields which have many newly drilled producing wells.

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