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Permeability Estimation From Well Log Responses

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Abstract

Permeability is one of the most important characteristics of hydrocarbons bearing formations. Formation permeability is often measured in laboratory from cores or evaluated from well test data. However, core analysis and well test data are usually only available from a few wells in a field. On the other hand, almost all wells are logged.

This paper presents a nonparametric model to predict reservoir permeability from a conventional well logs data using artificial neural network (ANN). The ANN technique is demonstrated with an application to one of Saudi oil fields. This field is the largest offshore oil field in the world and was deposited in a fluvial dominated deltaic environment.

The use of conventional regression methods to predict permeability in this case was not successful. The ANN permeability prediction model was developed from some of the data set consisting of core permeability and well logs data from three early development wells. The ANN model was built and trained from some of the well logs data and their corresponding core measurements by using a back propagation neural network (BPNN). The resulted model was blind tested using data, which was withdrawn from the modeling process. The results of this study show that ANN model permeability predictions are consistent with actual core data. It could be concluded that the ANN model is a powerful tool for permeability prediction from well log data.

Introduction

Many oil reservoirs have heterogeneity in rock properties. Understanding the form and spatial distribution of these heterogeneities is fundamental to the successful exploitation of these reservoirs. Permeability is one of the fundamental rock properties, which reflect rock ability to transmit fluids when subjected to pressure gradients. While this property is very important in reservoir engineering, there is no specific geophysical well log for permeability, and its determination from conventional log analysis is often unsatisfactory [1].

In general, porosity and permeability are independent properties of a reservoir. However, Permeability is low if porosity is disconnected, whereas permeability is high when porosity is interconnected and effective. Despite this observation, theoretical relationships between permeability and porosity have been sought, such as the Kozeny-Carmen theory which relates permeability to porosity, and specific surface area of a porous rock which is treated as an idealized bundle of capillary tubes. This theory, however, ignores the influence of conical flow in the constrictions and expansions of the flow channels and treats the highly complex porous medium in a very simple manner. Empirical relationships based on the Kozeny-Carmen theory have also been developed that relates permeability to other logs and/or log-derived parameters such as resistivity and irreducible water saturation [2]. These relationships are applied only either to the region above the transition zone or to the transition zone itself. Since core permeability data are available in most exploration and development wells, statistical methods have become a more versatile alternative in the solution of this problem domain. Therefore, regression is widely used as a statistical method in searching for relationships between core permeability and well logs parameters [3,4]. This parametric method requires the assumption and satisfaction of multinomial behavior and linearity. It is a model-based technique, and hence it must be applied with caution. Details of the uses and abuses of statistical methods in geosciences can be found in literature (e.g. see references 5 and 6).

Besides statistical methods, a relatively new nonlinear and nonparametric tool, namely Artificial Neural Networks (or simply neural nets), has become increasingly popular in petroleum industry [7-12]. In this work, the neural network is applied to determine reservoir permeability from the knowledge of conventional well log responses. Core permeability and well logs data from three early development wells from one of the Saudi oil reservoirs were used to develop an ANN permeability prediction model. These core permeability data and their corresponding well logs data are randomly distributed and divided into two parts. The first part was used for training and building the network model. The second part was used as a "blind test" of the model.

Artificial Neural Networks (ANN)

Artificial neural networks are computational devices whose conception has been motivated by our current knowledge of biological nervous systems. As such, neurocomputing, or computation by using artificial intelligent neural networks, offers an alternative to the traditional computational approach based on sequential and algorithmic processing.

Probably the main feature that characterizes the artificial neural networks approach is the simultaneous use of a large number of relatively simple processors, instead of using very few powerful central processors, as is nowadays the standard in most man-made computers. This is also the computational architecture for the central nervous systems of the most developed animals, where the basic computational unit is the neuron.

The use of a large number of simple processors makes it possible to perform parallel computation and to have a very short response time for tasks that involve real-time simultaneous processing of several signals. Furthermore it is also possible to have a decentralized architecture, which is much more fault tolerant to loss of individual processors than centralized architectures.

Another important feature of artificial neural networks is that, although each processor is very simple in terms of computational power and memory, they are adaptable nonlinear devices. Consequently, artificial neural networks can be used to approximate nonlinear models, an essential property for solving many real-world problems. The adaptable parameters of artificial neural network models are the connections that link the processors. This is similar to "learning" in biological neural networks that is supposed to be the result of changes in the strength of the connections between neurons [13-18].

Nowadays artificial neural network model is the subject of study in many areas as diverse as medicine, engineering and economics, to tackle problems that cannot be easily solved by other more established approaches.

Reservoir Description

The field understudy is located in the Northern Area of the Arabian Gulf. It is an anticline structure with productive area about 65 km long and 15km wide. It is one of a series of structures trending southwest to northeast produced by uplift movement that is reflecting deep-seated basement faults. This reservoir is a thick sequence of sandstone, siltstone and shale with thin intervals of limestone, coal and varying amounts of ironstone. One of the most important observations about the reservoir of interest is the gradual decrease in sand content from Southwest to Northeast. It has been convenient to plot core permeability versus core porosity for several wells and generate a correlation to estimate formation permeability in wells from which cores are not available. For homogeneous reservoirs, this method may prove adequate. As the degree of heterogeneity of a reservoir increases, such correlation loses its reliability. Figure 1 shows a semilog plot of core permeability versus core porosity measurements from three wells. The scatter of this data shows the high degree of heterogeneity in this reservoir.

Neural Network Model

Data Description

Core and log data from three development wells (namely A, B, and Well C) were used to construct the network model. A total of 700 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 gamma ray (GR), bulk density (RHOB), sonic compressional transit time (DT), thermal neutron apparent porosity (NPHI), and deep induction log (ILD). Due to the lateral discontinuity of the formation beds over the lateral extension of the reservoir, as mentioned earlier, a 460 data samples were chosen by a random number generator for network training. The remaining 240 samples were put aside to be used for testing the network's integrity and robustness.

Back Propagation Neural Network Architecture

A typical back propagation neural network (BPNN) is composed of three layers: input, hidden and output layers. Each layer is made of a number of processing elements or neurons. Each neuron is connected to each neuron in the preceding layer by a simple weighted link. Figure 2 shows a schematic diagram of the designed BPNN. It has n1 input neurons that represent n1 types of well logs. There are n2 hidden neurons and one output neuron. The output is the permeability. The solid lines represent the strength or weights of the connections between neurons. The number of input and output neurons is usually straightforward and is determined by the particular application. On the contrary, the optimum number of hidden neurons is usually obtained by trial and error

Network Training

The BPNN requires the use of training patterns, and involves a forward-propagation step followed by a backward-propagation step. The forward propagation step sends input signal through the neurons at each layer resulting in the calculation of an output value. BPNN uses the following mathematical function:

$$y = f\left[b_o + \sum_{j=1}^{n2} b_j f_j \left(w_{oj} + \sum_{i=1}^{n1} w_{ij} x_i \right) \right] \quad (1)$$

Where y is the output variable, x_i are the input variables, b and w are the connection weights, n1 is the dimension of the input vector and n2 is the number of hidden neurons. Note that b_o and w_{oj} are called the bias weights (analogous to the intercept used in statistical regression). Small random numbers are used to initialize all the connection weights (including the bias weights) and the final values are determined by iteration process.

The output, y, depends on the particular transfer function that is chosen. The common transfer functions used in multilayer network are log-sigmoid ($y=f(x)=(e^x/(1+ e^x))$) and tan-sigmoid or $\tanh^{-1}$ ($y=f(x)=(e^x - e^{-x})/(e^x + e^{-x})$). These functions are sometimes called the "squashing function" as it squashes the values into the range of (-1,1). Therefore, all the values of the input variables (ϕ, GR, RHOB, DT, NPHI, and ILD) and target (K) variable must be normalized or scaled in the range of [–1, 1].

Consequently, different normalization formulas were tested to normalize the input variables. The following formulation was adapted because it gave a better performance index for the neural network model.

$$X_{new} = \left\lfloor \left(X - X_{averag} \right) / STDEV \right\rfloor \quad (2)$$

$$X_{normalized} = X_{new} / \left| (X_{new})_{\max} \right| \quad (3)$$

Where, X is the input vector of one dimension for any input variable

On the other hand, logarithmic scale has been used instead of the absolute value of the target variable (K) and the normalization has been made by using the following formula:

$$K_{new} = \log(K) \quad (4)$$

$$K = K_{new} / (K_{new})_{\max} \quad (5)$$

The objective of the neural network is to obtain optimal weights to give a best value for the neuron (node of the dependent variable) of the output layer. There are three steps involved in the development of a neural network model. The first step is to define the dominant input variables, the number of hidden layers and the number of neurons in each hidden layer. The second is to define a quantitative measure of network performance, called the performance index, which is small when the Network performs well and large when the Network performs poorly. It represents the calculated mean squared error as the difference between the target output, y_k^{actual}, and the network output, y_k^{ANN}:

$$e = \frac{1}{q} \sum \left(y_k^{actual} - y_k^{ANN} \right)^2 \quad (6)$$

where q is the number of training pairs in the training set. The third step is to adjust the network weights and biases in order to reduce the performance index. The most common method used to adjust the weights and bias is the back propagation. This method takes the error (difference) from each iteration (training cycle) and uses it to change the weights on the neural network interconnections:

$$w_{ij}(t) = \eta \frac{\partial e}{\partial w_{ij}} + \alpha \Delta w_{ij}(t-1) \quad (7)$$

where w_{ij} is a weight for the i neuron in the hidden layer j; e is the error from the current training cycle; _ is the learning rate (a number between 0 and 1 that controls how much the weights can change in each iteration); α is the momentum (a constant on the momentum term that uses the previous weight change to keep the errors changing in the right direction); and t reflects the current iteration (t-1 is the previous iteration).

One of the problems that occurred during neural network training is overfitting problem. The error on the training set is driven to a very small value. But when new data is presented to the network the error increases. One method for improving generalization is by early stopping. As mentioned earlier the available data are randomly divided into two groups. The first group is used for the process of network training which represent 66% of the total sample points, and the rest 34% 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 19 neurons (as shown in Figure 2). This configuration and the proper use of the validation set were sufficient enough to ensure fast convergence after bout 60 iterations.

Neural Network Permeability Model Results

The developed model up to this stage was able to reproduce the 460 training data. Table 1 shows the statistical description of the input data used for training process. Table 2 shows the statistical description of the input data used for testing.

The trained network was finally tested to estimate permeability values from the three wells in the reservoir understudy. These are including the 240 sample pairs that were separated from the three available wells for testing purpose. These involve a wide range of permeability (0.1-9000md). This further indicates the high degree of heterogeneity of this reservoir. The cross plots of core measurements against network prediction results shown in Figure 3 show a good match. The permeability prediction results yielded correlation coefficients of 0.9969 for Well A, 0.9897 for Well B, and 0.982 for well C. Figure 4 shows the actual core permeability values in comparison with the network's estimation, for each well sample points. From Figure 4, it is obvious that although permeability values cover a wide range, the ANN model is able to follow the core permeability trend very closely. One might comment on the input variables that were used in this study in the following fashion. Gamma ray log response is an evidence of clay presence that has an impact on permeability. Rock density , sonic, and neutron logs are an inverse functions of porosity and shale content. Deep induction log response demonstrates resistivity from which fluid saturation is deduced. Fluid saturation may be a function of fluid migration in the rock during the geological time and, therefore, the migration may have been influenced by permeability.

Conclusions

1. The ANN model for predicting permeability is perfect when training the network with all six input variables (ϕ, GR, RHOB, DT, NPHI, and ILD).
2. Artificial neural network is capable of estimating formation permeability with high accuracy, by use of a geophysical well-log data, comparable to that of actual core measurements.
3. The ANN model results yielded excellent correlation coefficients (0.9969, 0.9897, and 0.9820 for A, B, and C wells respectively).
4. The developed ANN model does not incorporate depth as part of input parameters which means that it is applicable to any field.
5. This study shows that neuro-estimation of formation permeability by use of well-log data is a highly feasible technique.

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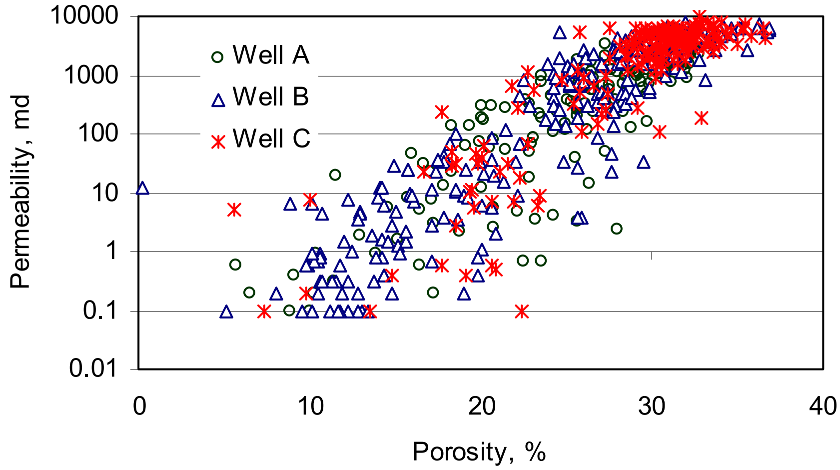

Figure 1: Permeability Versus Porosity Measurements Plot from Three Wells in the Reservoir Understudy.

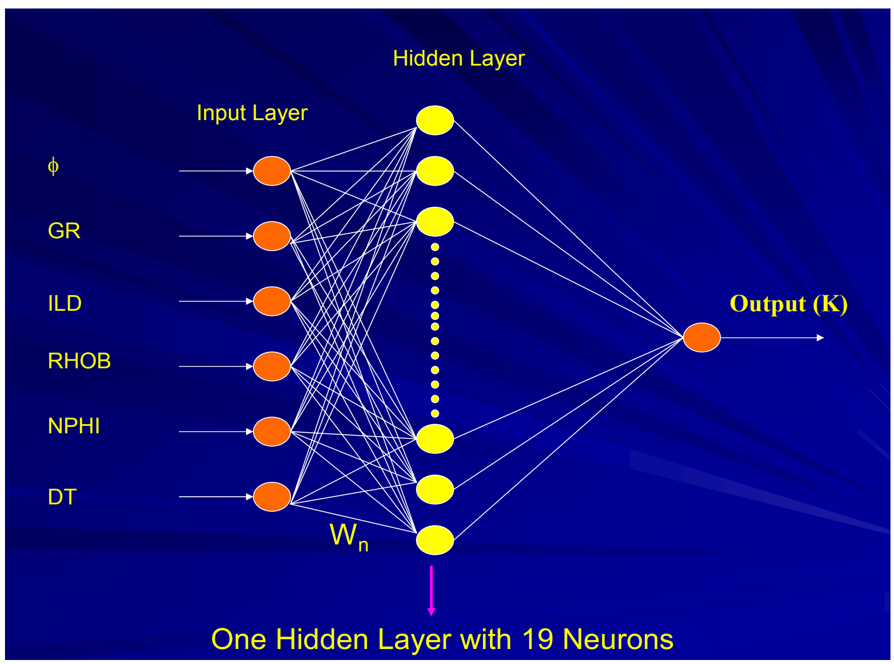

Figure 2: Neural Network Architecture

Table 1 Statistical distribution of the input data used for network training process.

Variable	Min	Max	Average	St. Dev.
Porosity, (Φ)	5	36.9	26.77688	6.588722
Gamma ray (GR)	7.934	83.586	28.29141	15.59948
Sonic	80.7	109.3	93.88557	4.303568
Neutron	0.213	0.519	0.298479	0.039343
Bulk density (NPHI)	1.873	2.6274	2.226158	0.103319
Deep induction log (ILD)	0.1702	2000	54.57274	229.4703

Table 2 Statistical distribution of the input data used for network testing process.

Variable	Min	Max	Average	St. Dev.
Porosity, (Φ)	5.1	36.8	25.90846	7.211273
Gamma ray (GR)	7.643	74.306	30.09125	16.78414
Sonic	80.1	108.2	92.84418	4.457518
Neutron	0.227	0.484	0.298806	0.042535
Bulk density (NPHI)	1.84	2.7028	2.247061	0.129651
Deep induction log (ILD)	0.169	2000	89.21511	359.5711

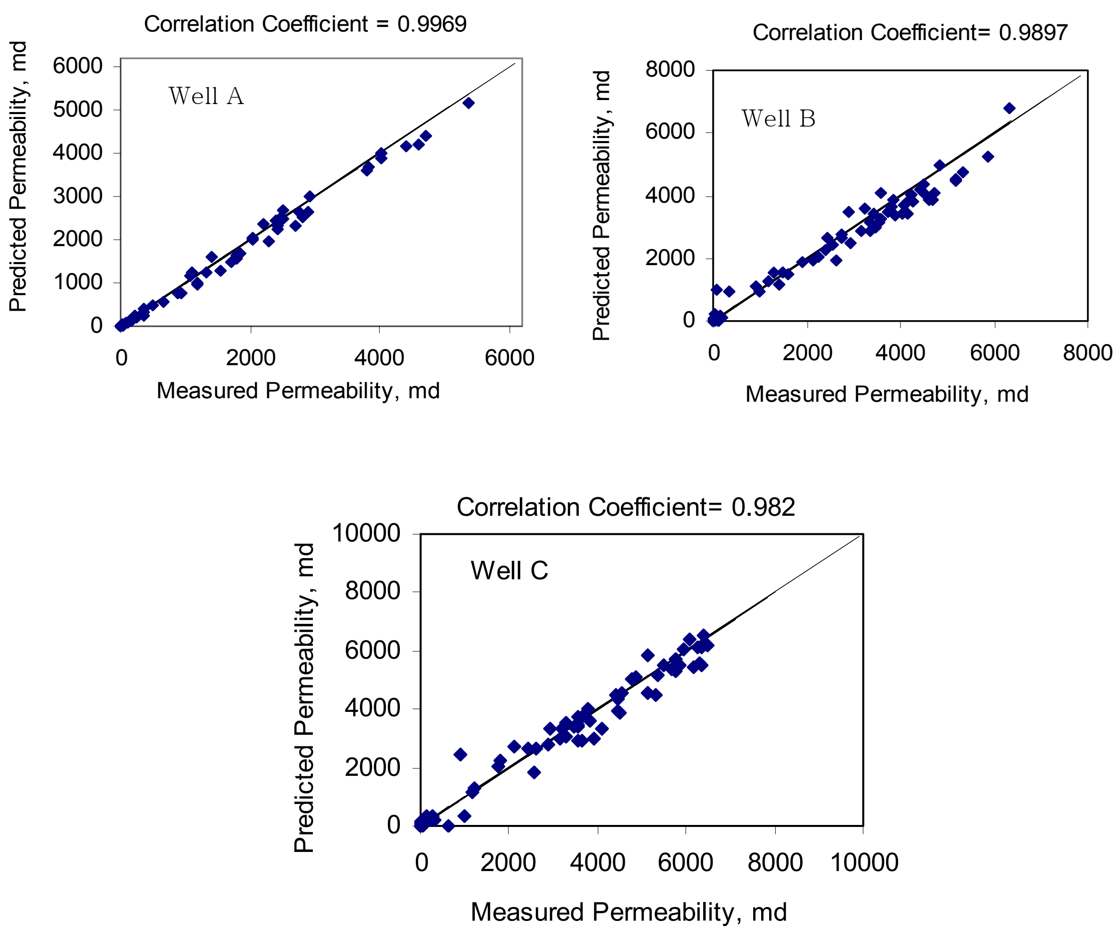

Figure 3: Cross-Plot of Measured Permeability vs. ANN predicted permeability for wells A, B, C

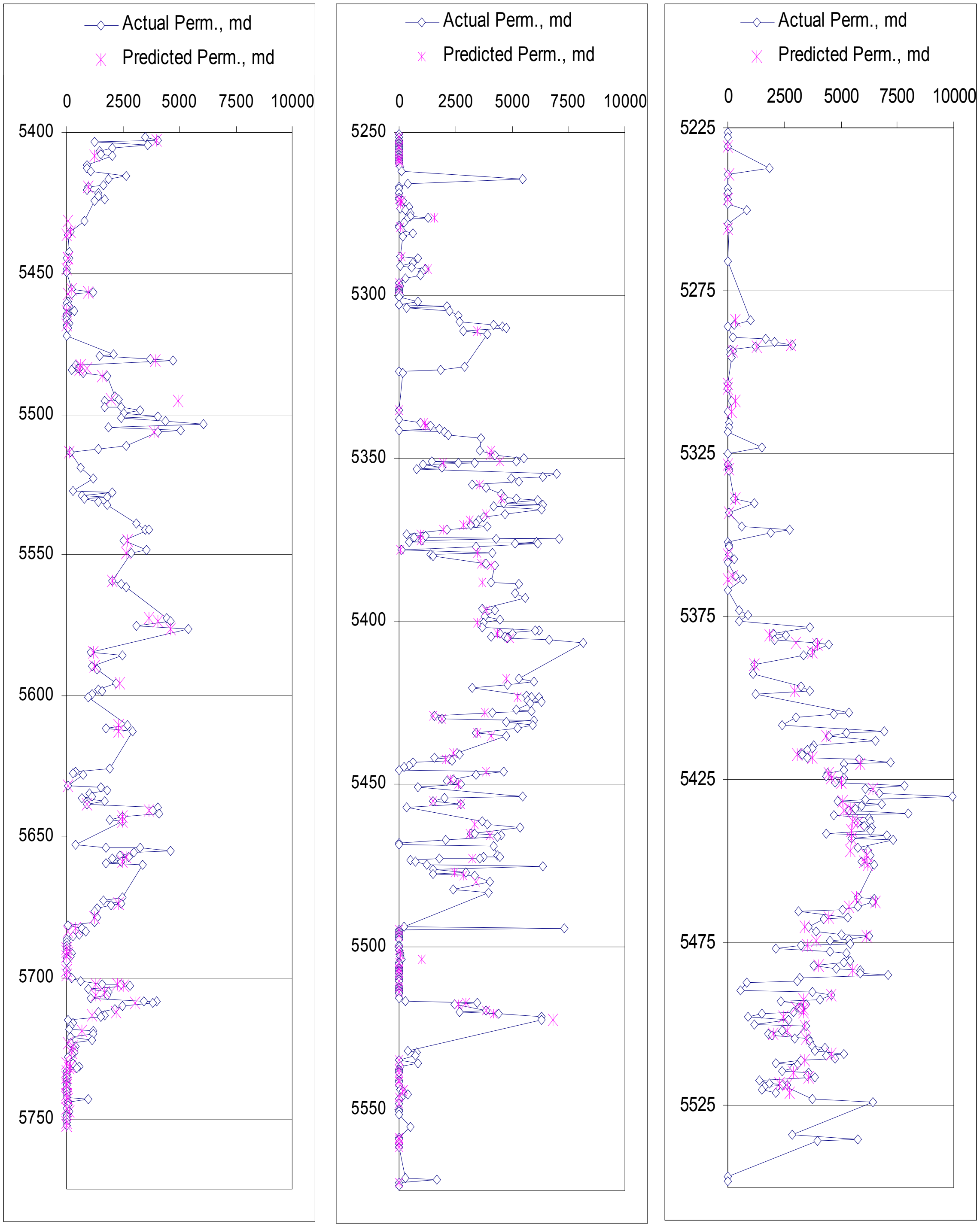

Figure 4: The actual permeability and ANN predicted permeability vs. depth for wells A, B, C.