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Design and Development of an Artificial Neural Network for Estimation of Formation Permeability

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Abstract

Permeability is one of the most important characteristics of hydrocarbon bearing formations. An accurate knowledge of permeability provides petroleum engineers with a tool for efficiently managing the production process of a field. Furthermore, It is one of the most important pieces of information in the design and management of enhanced recovery operations. Formation permeability is often measured in the laboratory from cores or evaluated from well test data. Core analysis and well test data, however, are only available from a few wells in a field, while majority of wells are logged.

In this study, an artificial neural network has been designed that is able to predict the permeability of the formations using the data provided by geophysical well logs with good accuracy. Artificial neural network, a biologically inspired computing method which has an ability to learn, self-adjust, and be trained, provides a powerful tool in solving pattern recognition problems.

Using well logs to predict permeability has been attempted in the past. The problems with previous approaches were two-fold. Namely, the number of variables used (only one variable - porosity), and using regression analysis as the main tool for correlations. The approach introduced in this paper attempts to overcome these short comings. This is done, first, by using many variables from well logs that may provide information about the permeability. Second, by recognizing the existence of possible patterns between these variables and formation permeability using artificial neural networks. Neural nets are analog, inherently parallel, distributive systems. These characteristics enable artificial neural networks to be successful in predicting the permeability in rocks using well log information.

Introduction

Acquiring knowledge on formation permeability has remained one of the fundamental challenges to petroleum engineers. This important piece of information about porous rock, provides engineers with the ability to design and manage efficient processes in the development of oil and gas fields. Using coring tools and bringing samples of the pay zone to the surface and measuring their permeability under simulated downhole conditions is one of the oldest practices for estimating the formation permeability. Coring every well in a large field can be very expensive. It is necessary and inevitable to core some wells no matter how small or large a field. On the other hand, trying to get a representative sample from every single well, especially in fields with hundreds of wells, requires a large amount of capital. In a heterogeneous field where permeability values tend to change rapidly with spacial coordinates, such practices (coring every well), although expensive, would provide valuable information. Having a representative value for permeability in different locations, especially where wells (injection or production) are drilled, could be used effectively in reservoir simulation studies.

Another popular way of obtaining reservoir permeability is well testing. The data that becomes available after a carefully designed well test helps petroleum engineers calculate a volumetric average of the formation permeability, among other parameters such as skin and wellbore storage. Although a valuable and necessary procedure, well testing is not a viable procedure for small developers. Due to its high cost, (the cost of performing the test in addition to loss of production during the test) only a limited number of well tests is advisable in any field.

Geophysical logging is performed in almost all wells, either during or immediately after the drilling process. There is a plethora of information that is available to engineers and log analysts from different well logs. It is the goal of the authors to extract formation permeability values from information provided by well logs. As will be shown in this paper, the preliminary studies conducted by the authors, and currently continued studies, establishes the fact that such an effort is indeed a fruitful one. It will be shown that the sixth generation computing methodology (artificial neural networks) facilitates this task.

Background

It has been a fairly common practice to plot permeability versus porosity for several wells and generate a correlation between these variables for estimating formation permeability in other wells, from which cores are not available. For fairly homogeneous reservoirs, this effort may or may not prove to be adequate. As the degree of heterogeneity of a reservoir increases, such correlations lose credibility. Figure 1 is a plot of porosity versus permeability of several samples from the five wells that have been studied in this paper. The scatter of this plot shows the inadequacy of this type of approach to heterogeneous reservoirs. Some engineers will not accept results of such correlations even for fairly homogeneous reservoirs. The major shortcoming with this methodology is that permeability, although dependent on porosity, has a highly complex and non-linear relationship with it. There are other factors that contribute to permeability besides porosity. Therefore, plotting porosity versus permeability and drawing a straight line over the data (no matter how scattered it might look) is a gross approximation. The authors believe that petroleum engineers can do much better than this, using advanced information technology.

Network Design and Development

Artificial neural networks resurfaced in the mid 1980's after neuroscience had made some major advances. Known as the sixth generation computing, neural networks are widely used in many disciplines from Wall Street to airport security devices. Neural networks are non-algorithmic, analog, distributive and parallel information processing methods that have proven to be powerful pattern recognition tools. Since they process data and learn in a parallel and distributed fashion, they are able to discover highly complex relationships between several variables that are presented to the network. As a model-free function estimator, neural networks can map input to output no matter how complex the relationship. There are several paradigms that can be used to generate neural networks. To achieve the goal of this study, a feed-forward, back propagation neural network (which adopts a supervised training scheme) has been used. A description of this process is provided in the Appendix.

During the design and development of the neural network for this study, it was determined that a three-layer network with 15 neurons in the hidden layer would be most appropriate. The learning rate of the network was adjusted so that training time was minimized. During the training, several parameters had to be closely watched. It was important to train the network long enough so it would learn all the examples that were provided. It was also equally important to avoid overtraining, which would cause memorization of the input data by the network. A network that has memorized all of its training data will perform poorly when exposed to a new set of data for testing. Another important factor is local minima. During the course of training, the network is continuously trying to correct itself and achieve the lowest possible error (global minimum) for every example to which it is exposed. Most of the time, there are locations on the error surface that will cause temporary convergence, even before sufficient learning has taken place by the network. It is important to design the network in a way that it can scape out of local minima and reach the global minimum in every case. Figure 2 is a schematic diagram of local and global minima during training. Please note that this two dimensional drawing is very simplistic and is presented for demonstration purposes. The actual error surface for this problem has 90 dimensions (same as the number of synaptic connections). Visualization of such a surface is impossible.

Core and log data from five different wells were chosen. These wells were 1107 - 1108 - 1109 - 1110 and 1126 in Granny Creek Field in Clay and Roan Counties, West Virginia. Figure 3 shows the location of Granny Creek field. Granny Creek is a well-documented, highly heterogeneous reservoir[1-4] that has been producing from Big Injun sandstone for the past 70 years. In this part of the study, as a preliminary trail, only the most productive zone of the Big Injun sand, known as Section C, was used. Section C of the Big Injun sand has an approximate thickness of 30-40 feet (the bottom 75% of the total sand thickness), and is further divided into three subsections, C_1, C_2, and C_3. It should be noted that the division of the Big Injun sand into these sections and subsections has been made by geologists prior to this study using well logs and no core observations were made for their classification.

For supervised training of the three-layer, feed-forward, back propagation network, log and core data were used. In this case, there were 151 pieces of core data available. Twenty-three examples (log and core data combined) were chosen by a random number generator and put aside to be used for testing the network's integrity and robustness after training. The remaining examples, which included depth, gamma ray, bulk density, deep induction log responses, zonal subdivision specification, and permeability measurements from cores for each example were used to train the network.

During the supervised training, it was necessary to provide the network with the correct permeability value for each example. The network will converge to the correct permeability value by back propagating the error between its prediction and the actual permeability value. The principal for this back propagation of error is known as modified delta rule. Once a network has reached a stable state (converged) and has learned all the examples that were provided, it is time to test the network. As previously stated, fine-tuning the network to avoid memorization as well as stop in local minima is required for a well trained neural network. There are other techniques that should be used in order to achieve acceptable results from a neural network. This expertise will only be achieved through continuous education on the fundamentals of neurocomputing. It has been said that after a certain amount of experience with neural networks, successful use and implementation of neurocomputing is an art more than it is a science.

Results and Discussions

Figures 4 and 5 show the relationship between formation permeability with bulk density, gamma ray, and induction log responses, respectively. The scatter of these plots suggest no apparent relationship between these parameters and formation permeability.

The trained network was tested to see if it was able to estimate-/predict permeability values from the five wells in Big Injun Sand. The 23 examples that were separated at the beginning of this study for this purpose included a wide range of permeability from 0.05 to 47.3 md. This further indicates the high degree of heterogeneity of this formation. Figure 6 shows the actual permeability values that were measured in the laboratory (and were never seen by the network during training) in comparison with the network's estimation/prediction for each sample. Although permeability values cover a wide range, the network is able to follow the trend very closely. After plotting core measurements versus network predictions, one can see the divergence of the predictions from a perfect match, which is the unit slope line. Permeability estimations/predictions presented in this paper have a correlation coefficient of 0.963, where 1.0 is a perfect match (Figure 7). Comparing the results presented in Figures 6 and 7 with that of Figures 1, 4 and 5 reveals the power of artificial neural networks in pattern recognition. One might comment on the input variables that were used in this study in the following fashion: depth of the formation is an indication of reservoir pressure that might effect permeability. Gamma ray log response is an evidence of clay presence which has an impact on permeability. Rock density is an inverse function of porosity and 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 geologic time and, therefore, been influenced by permeability. Using these log responses in this study stems from the fact that they were available for all wells that were of interest to us.

The results presented here are from 23 randomly selected samples out of a total of 151 samples taken from five wells. A few points about these results need to be mentioned. Our experience with the design and development of a neural network for permeability prediction/estimation has shown that it is essential to have enough data to train the network properly in order to see acceptable, as well as repeatable, results. The questions of how much data is enough and whether there exists a threshold below which neural nets will not be effective are currently under investigation. The results are as good as the data available. With proper data more can be done with neural networks than any other tool.

This study establishes the fact that neuro-estimation of formation permeability from geophysical well log data is feasible. Using this methodology to actually predict/estimate the permeability for an independent well without core measurement information (which will be the more realistic approach) is currently being investigated[5]. At this point, our study shows that these methods will produce field specific or formation specific results. The universality of these methodologies and approaches are also under investigation.

Conclusions

This study showed that neuro-estimation of formation permeability using well log data is a feasible methodology. An artificial neural network that is capable of predicting/estimating formation permeability using geophysical well log data was presented. It was shown that the trained network was able to predict/estimate permeability comparable to that of actual core measurements. Availability of reliable core data for training process was proven to be essential. At this point, this type of study is capable of producing field specific results.

Adequate knowledge on fundamental theories and practices of artificial neural networks are required to achieve acceptable and repeatable results. Treating neural nets as black boxes may prove to be disappointing.

References

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Appendix

An artificial neural network is a system of several simple processing units known as nodes, neurons or processing elements. These processing elements are associated with one another through simple connections known as synaptic connections. The strength of the synaptic connections changes with attaching a weight to them. Figure 8 is a schematic diagram of a typical artificial neural network. Neurons in a network are organized in layers. Each layer is responsible for a particular task. Typically there are three kinds of layers in an artificial neural network. Input layer is responsible for presenting the network with the neccesary information from the outside world in a normalized manner. Hidden layers (there may be more thatn one hidden layer in a network, this is a problem dependent factor) contain hidden neurons that are responsible for main part of the input to output mapping. These neurons are responsible for feature extraction from the input neurons and subsequently passing the information to the output neurons. Output layer contains output neurons that communicate the outcome of the neural networks computation with the user. During a supervised training procedure, for example back propagation that was used in this study, the strength (weight) of all synaptic connections are initialized. Information is provided to the network through input neurons. Input values are multiplied by synaptic connection weights. Sum of the product of all input neurons and their corresponding synaptic connection weights are then forwarded to each hidden neuron. Each hidden neuron will perform a simple computation by mapping the sum to an output using a non-linear function (usually sigmoid function). The result is then multiplied to the synaptic connection weight between the hidden neuron and each output neuron. Sum of the product from all the hidden neurons will then be used to determine the final network output. This is called the feed forward process.

At this point the network output is subtracted from the actual or desired output of the problem. The resulting error is then back propagated through the network and synaptic connection weights are altered accordingly. This process continues until the network output reaches an acceptable value. To create an artificial neural network, after deciding on the paradigm one needs to program the proper algorithm using any computer language (most of the algorithms are available in the literature). Two models were developed for this study. One using Visual Basic and one using C.

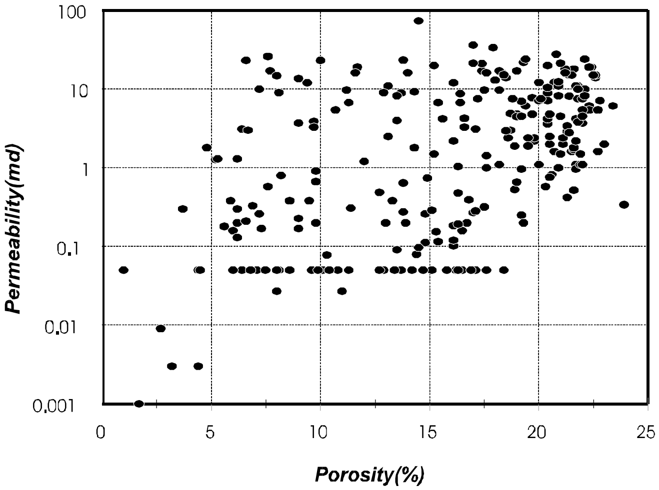

Figure 1. Relationship between porosity and permeability for wells used in this study

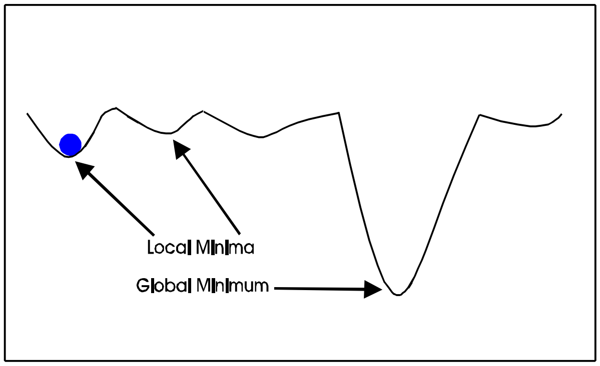

Figure 2. Local and global minima in a 2D error surface.

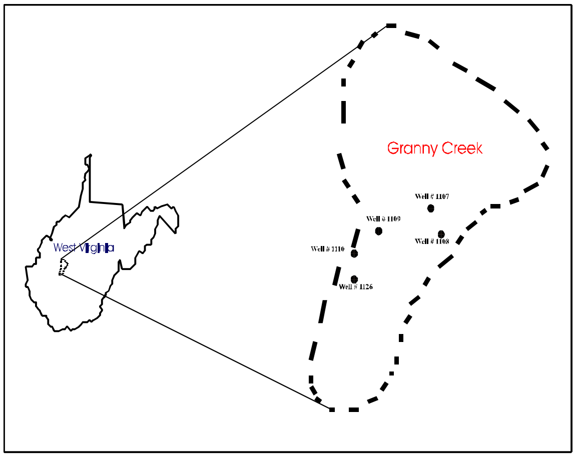

Figure 3. Granny Creek field in West Virginia.

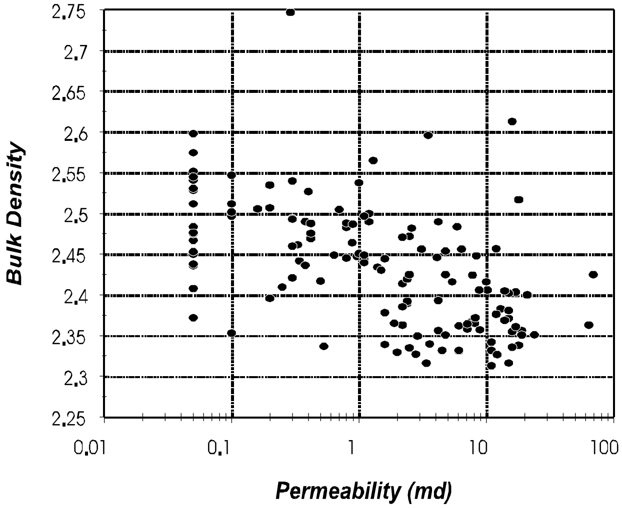

Figure 4. Permeability vs. Bulk density log responses for wells used in this study.

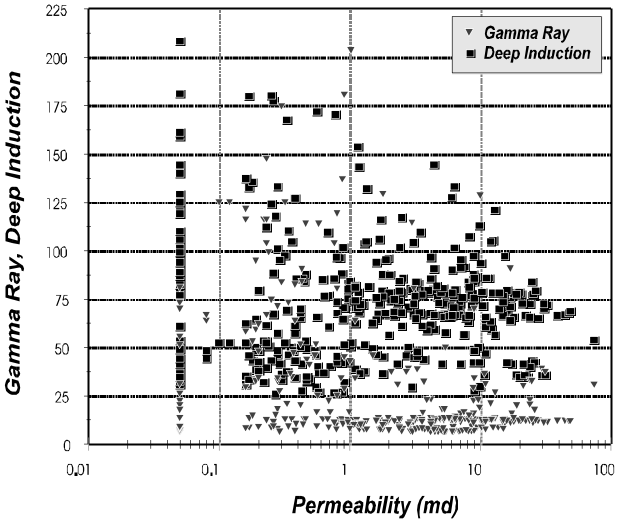

Figure 5. Permeability vs. Gamma ray and deep induction log responses for wells used in this study.

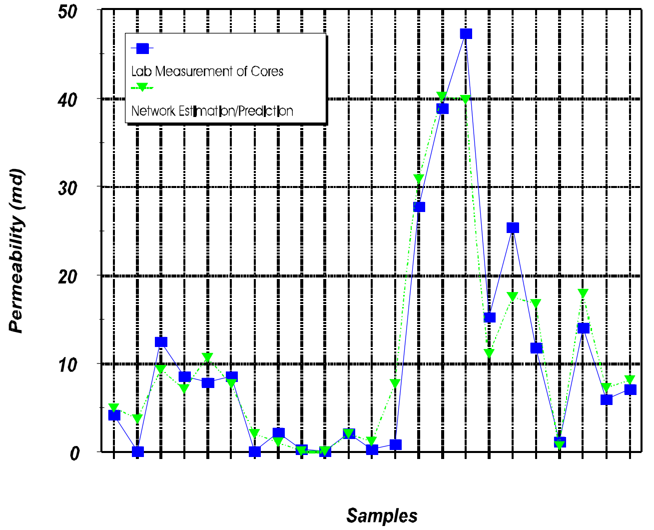

Figure 6. Permeability values measured in the laboratory compare to those predicted using neural networks developed for this study.

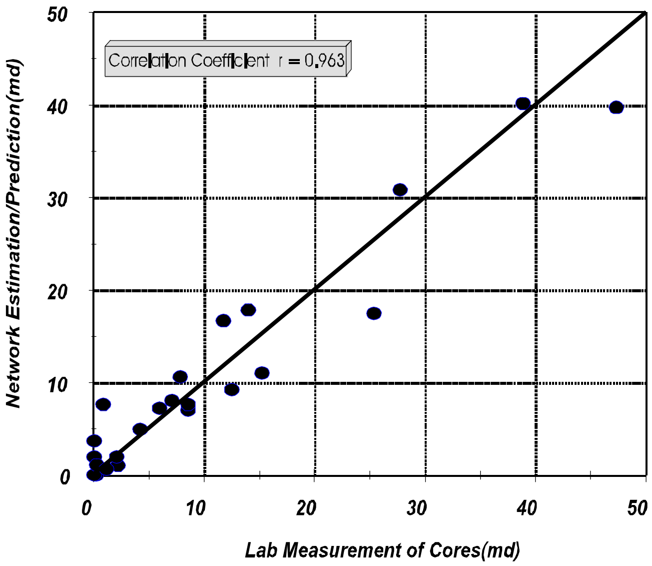

Figure 7. Scatter plot of measured permeability values vs. Predicted values.

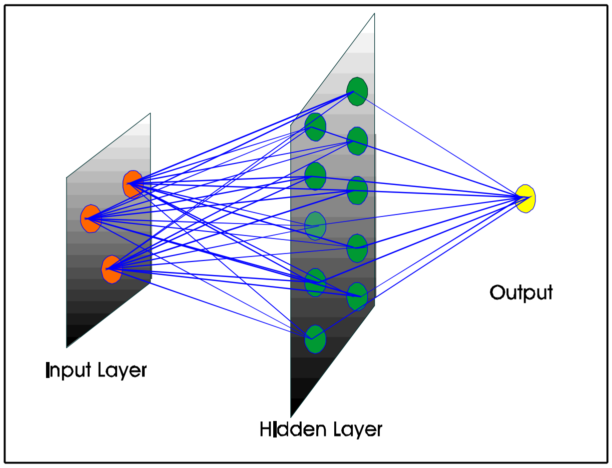

Figure 8. Neural network architecture used in this study.