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A Methodological Approach For Reservoir Heterogeneity Characterization Using Artificial Neural Networks

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Abstract

For the past few years Artificial Neural Networks (ANN) have made a strong comeback to the scientific community. They are used in a variety of tasks where adaptive computing can enhance process performance. There has been a handful of papers suggesting the use of artificial neural networks in the petroleum industry[1-3]. These papers can be classified into two major categories. First category includes papers that recommend the use of ANN in classification of lithologies from well logs. Second category includes papers that employ ANN to pick the proper reservoir model for well testing purposes.

This paper introduces a new implementation of the neuro-computing technology in petroleum engineering. It is shown in this study that artificial neural networks possess numerous capabilities, and can be much more useful to petroleum engineers than previously thought. An implementation of artificial neural networks in characterization of reservoir heterogeneity is presented in this paper. A methodology is introduced through which different rock properties in highly heterogeneous reservoirs can be predicted with good accuracy using information deduced from geophysical well logs. Examples of such networks are presented using field data for verification.

The underlying reasons (theories) that make achievement of such complex tasks possible are discussed. The notion that artificial intelligence and neural networks in particular have immense potentials in solving complex engineering and scientific problems are addressed. The innovation now lies on the creativity of the researchers to recognize and define petroleum engineering problems that can be addressed by artificial intelligence technology.

Introduction

Heterogeneity in a hydrocarbon reservoir is referred to non-uniform, non-linear spacial distribution of rock properties. Characterization of porosity, permeability, oil, gas and water saturation of hydrocarbon bearing rocks is the focus of this technical paper. Calculating formation porosity and water saturation from geophysical well logs has been practiced since well logging tools became available. These calculations assume a linear or modeled non-linear relationship between porosity and water saturation with density and resistivity log responses. The term modeled non-linearity has been used here to emphasize that in these calculations it is assumed that a known function (linear or non-linear) is sufficient for modeling the relationship between these rock parameters and the aforementioned well log responses. A thorough investigation of such relationships and a comparison of their results with those produced by an artificial neural network will be addressed in a separate paper. Here, simply some preliminary results and a short discussion on the performance of artificial neural networks in predicting rock porosity as well as water, gas and oil saturations in heterogeneous reservoirs, where all three phases exist, is presented.

Characterizing rock permeability and its spacial distribution in a heterogeneous reservoir is a problem with no direct and known solution. To date, there are only two generally reliable ways of acquiring knowledge on rock permeability. These are laboratory measurements and well test interpretation. Laboratory measurement of the cores attained from the field or core archives, provides precise (assuming adequate equipment) permeability values that are used in reservoir simulation studies as well as any other design and development studies on the field. The second method for permeability determination is pressure transient analysis which provides a volumetrically averaged permeability for the volume of the reservoir that has been investigated during the test. It should be noted that during the well testing procedure the length of the test is an important issue. Test should be designed so that it is long enough to achieve reliable and usable data. On the other hand, the longer the test time, the larger the volume represented by the calculated permeability. In this paper the authors introduce a new method for permeability determination. This technique is quite inexpensive. It does not require production interruption and provides permeability values that are comparable to those obtained by laboratory measurements of cores. In a feasibility study on this method of permeability prediction/estimation, Mohaghegh, et. al.[1] showed that such efforts are indeed fruitful. In that study, Mohaghegh, et. al. demonstrated that with a limited number of data, a carefully designed and developed artificial neural network can provide acceptable results.

Methodology

Petroleum engineers have shown a high degree of open-mindedness in utilizing new technologies from different disciplines to solve old and new petroleum engineering problems. Use of CT-Scan, MRI, Microwave, and even expert systems are good examples. Artificial Intelligence in general and neural networks specifically are no exceptions. The key in using artificial neural nets in petroleum engineering, or in any other discipline for that matter, is to observe, recognize, and define problems in a way that will be addressable by neural nets. It is obvious that neural network is not a panacea for petroleum industry, but it very well may help solve problems that conventional computing has not been successful in solving.

Artificial Intelligence is generally divided into two basic categories, rule based (expert) systems and adaptive (neural) systems. Neural network, a biologically inspired computing scheme, is an analog, adaptive, distributive, and massively parallel system that has been used in many disciplines and has proven to have potential in solving problems that require pattern recognition. The main interest in neural network has its roots in the recognition that the brain processes information in a different manner than conventional digital computers. Computers are extremely fast and precise at executing sequences of instructions that have been formulated for them (algorithm). A human information processing system is composed of neurons switching at speeds about a million times slower than logical computer gates[5]. Yet, humans are more efficient than computers at computationally complex tasks such as speech understanding and other pattern recognition problems. Artificial neural systems, or neural networks, are physical cellular systems which can acquire, store, and utilize experiential knowledge. The knowledge is in the form of stable states or mapping, embedded in networks that can be recalled in response to the presentation of cues.

This statement means that, unlike a digital, sequential computer with a central processor that can address an array of memory locations, neural networks store knowledge in the overall state of the network after it has reached some equilibrium condition (stable state.) In other words, knowledge in a neural network is not stored in a particular location. One can not look at memory address 1354 to retrieve the value of permeability. Knowledge is stored both in the way processing elements are connected, and in the importance of each input to the processing element (embedded mapping.) Knowledge is more a function of the network's architecture or structure than the contents of particular locations[6].

Pattern recognition has proven to be one of the neural nets' strong points. The essence of pattern recognition is the concurrent processing of a body of information, all of which are available at the same time. The parallel distributed information processing characteristics of neural networks accommodate this necessity. The science of pattern recognition is concerned with three major issues; 1) The appropriate description of objects, physical or conceptual, in terms of representation space, 2) The specification of an interpretation space, and 3) The mapping from representation space into interpretation space[7]. Another important characteristic of neural nets is their adaptability. Neural nets do not use algorithmic processes. They respond (like humans) to things learned by experience. Therefore, it is necessary to expose the net to sufficient examples, so it can learn and adjust its links and connections between different neurons. Neural networks can be programmed to train, store, recognize, and associatively retrieve patterns or database entries; to solve combinatorial optimization problems; to filter noise from measurement data; and to control ill defined problems; in summary, they estimate sampled functions when the form of the functions is not known[8].

In order to obtain the results that are shown here several different paradigms were used. The authors have concluded that a three layer feed forward, back propagation network is probably the ideal paradigm for this type of problems. As a methodology the authors suggest the use of General Regression Neural Networks as a first step toward identifying the optimum network design. GRNN usually goes through a large set of training data and reaches a stable state in a short period of time. It may even generate results that are better and more accurate than what back propagation network would eventually converge to. The major shortcoming of GRNN's application to these type of problems is that they may perform well with the test set, but the final generated network can not reproduce acceptable results with other sets of data. Therefore, although back propagation seems to be slower in convergence to an optimum network, it will produce reliable, and repeatable results. Therefore, it is suggested to use GRNN to identify the design structure of the optimum network and then use this design structure in a back propagation network for the final result.

The Case Study

Big Injun formation, in the Granny Creek field in West Virginia was chosen for this study (Figure 1.) Located approximately 25 miles northeast of Charleston, West Virginia, Granny Creek field is structurally situated on the northwest flank of a syncline which strikes N 15-20 degrees east to S 15-10 degrees west. Upper Pocono Big Injun sandstone is the oil producing formation in the Granny Creek field. Big Injun sandstone has been sub-divided into several sections. Using grain-size distribution and bulk density variations it has been sub-divided into A, B and C members. In an engineering and geological study of this field, Big Injun formation has also been subjected to other sub-divisions. Using depositional environment, the formation was sub-divided into 5 separate sections and using lithofacie it was sub-divided into two sections[9] (Figure 2.) In a preliminary study using neural networks, the authors concluded that the sub-division with respect to grain-size distribution as well as bulk density variation (the A, B, C sub-divisions) should be incorporated in this work.

Development of this field started in 1916 and continued for 30 years. Production throughout the field has been continued until the present day. The crude produced in this field is a paraffin based Pennsylvania Grade oil. It has been estimated that this field has a total production of 6.5 to 6.75 million barrels of oil. A moderately successful water flooding operation was initiated during 1970's and early 1980's. A tertiary recovery CO_2 pilot project was conducted beginning in 1976. The Pocono Big Injun sandstone is a well documented heterogeneous formation. Its severe heterogeneity and availability of some core data were the main reason for choosing it as the formation for this study.

The data presented in this study have been gathered from wells 1107, 1108, 1109, 1110, 1126, 1128, 1130 and 1134. The distance between wells 1110 and 1134 is approximately 2 miles. The relative locations of these wells are shown in Figure 1. The logs and core data were obtained from companies that are currently involved in the water flooding project in the field. Some cores were obtained and consequently were measured for permeability in the laboratory in the West Virginia University. Well logs were carefully digitized and exported to LAS (Log AScii) format to be used as inputs to the neural networks.

Results and Discussions

Depth, gamma ray, bulk density, and deep induction log responses were used as input to the neural networks. In order to demonstrate the degree of heterogeneity of this formation and to show the chaotic status of the information that the authors were faced with, a cross plot of permeability versus gamma ray and deep induction log responses is presented in Figure 3. Figure 4 shows permeability variation with respect to bulk density well log responses. Looking at Figures 3 and 4 there seem to be no apparent relationships between these log responses and the permeability.

Since bulk density may be regarded as a symbol of porosity of the rock, (regardless of how linear or non-linear this relationship might be) it may contribute to the permeability of the formation. Gamma ray log responses are an indication of shalyness or clay content of the formation. This property of the rock may have some impact on its ability to conduct fluid. Deep induction is usually used to calculate water saturation in rocks. Since water saturation may or may not be an indication of water movement (migration) in the rock throughout the geologic time, it might have some contribution to rock permeability. These possible relationships together with the fact that, due to the age of the field, bulk density, gamma ray and deep induction were the only logs available for all of these wells, constituted them as inputs to the networks.

As was mentioned in the methodology section of this paper, GRNN was used to identify the optimum design structure of the networks. After identification of the blue prints of the optimum networks, the back propagation neural networks were designed. Back propagation neural networks use supervised training schemes. In all cases a set of data data was chosen randomly (using a random number generator) and put aside. The data were not shown to the network during the training period. This data, called the test set, is used to check the integrity and robustness of the network after it has reached some stable state. The training period is the phase during which the network is exposed to the available data. The available data is organized as input and output. In this case well log responses as well as the geological sub-divisions were inputs to the network and rock parameters (permeability, porosity, oil and water saturations) were the outputs.

Using this data, neural networks try to discover possible patterns that might exist between inputs and the corresponding output. After learning the data and recognizing the possible noises that might exist in the data, the network will eventually converge. It should be noted that one may encounter many different problems throughout this process. But a good understanding of the fundamentals of the problem, the tool, and their interaction can be of great help in overcoming these difficulties.

Figure 5 through 8 display the major findings of this study. In these figures following conventions in the presentation of the results have been used. Out of 8 wells in the case of permeability and 5 wells in the case of porosity and saturations, only two wells have been randomly chosen for the presentation of the results. Similar results for the remaining wells are available and may be requested from the authors. In these figures neural network's predictions are compared with the actual core measurements. Neural network's predictions are represented as solid lines while actual rock parameters (laboratory measurements from the cores) are shown by either circles or triangles. The circles are core measurements that were used to train the neural network. The triangles on the other hand were not used in the training and therefore, were never seen by the network.

Figure 5 is the permeability predictions made by the neural network that was designed for this study, in comparison to permeability values measured in the laboratory. It is important to notice the degree of heterogeneity that is clearly shown in this figure. Most of the core measurements are quite close to network's predictions. Figure 5 shows the results for wells 1107 and 1126. This method enables researchers to attain reliable permeability values for the entire pay zone while only few samples are available for laboratory measurement.

Figure 6 shows the porosity values predicted by neural network in comparison to those measured in the laboratory for wells 1109 and 1126. Similar results are shown for oil and water saturations for wells 1109, and 1128, in Figures 7 and 8, respectively. It is interesting to note that for comparable amount of efforts to neuro-process porosity, oil and water saturations, better results have been achieved for porosity and water saturation in comparison to that of oil saturations. This is also true in traditional calculations of these rock parameters from resistivity and density logs. Using Archie's formula to calculate porosity and water saturations is usually more straight forward than calculating oil saturations in a three phase system, where more assumptions must be made.

Conclusions

A new method for prediction of hydrocarbon reservoir rock parameters was introduced. This method utilizes the pattern recognition capabilities of artificial neural networks. Using this methodology researchers and engineers will be able to characterize reservoir heterogeneity using readily available geophysical well logs. It was shown that a carefully designed neural network is able to predict rock permeability, porosity, oil, water and gas saturations with accuracies comparable to actual laboratory core measurements.

This methodology can provide an intelligent front end to reservoir simulators. It will add a whole new dimension to the usage of geophysical well logs. It further proves that there may be a relationship, no matter how complex in nature, between gamma ray, bulk density, and deep induction log responses with formation permeability. This approach also indicates that there may be more information embedded in these logs that previously thought.

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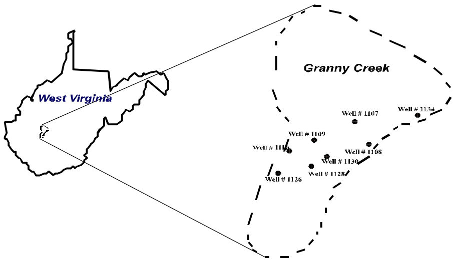

Figure 1. Granny Creek Field in West Virginia.

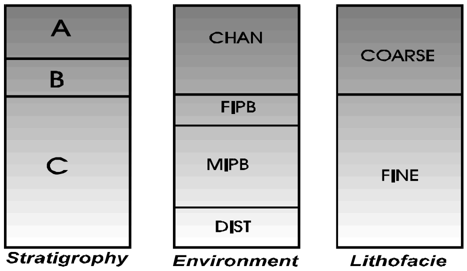

Figure 2. Various geological interpretations in Granny Creek.

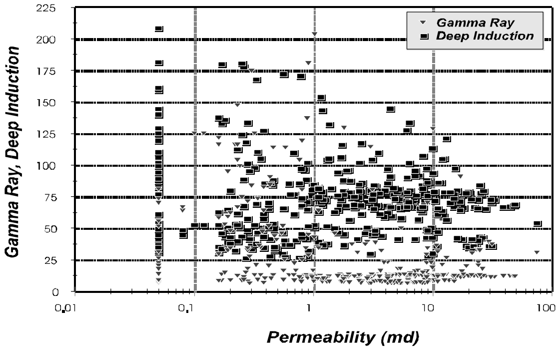

Figure 3. Permeability vs. Gamma ray and deep induction log responses for wels used in this study.

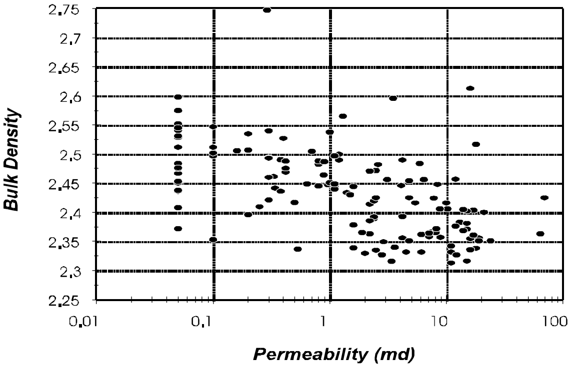

Figure 4. Permeability vs. Bulk density log responses for wells used in this study.

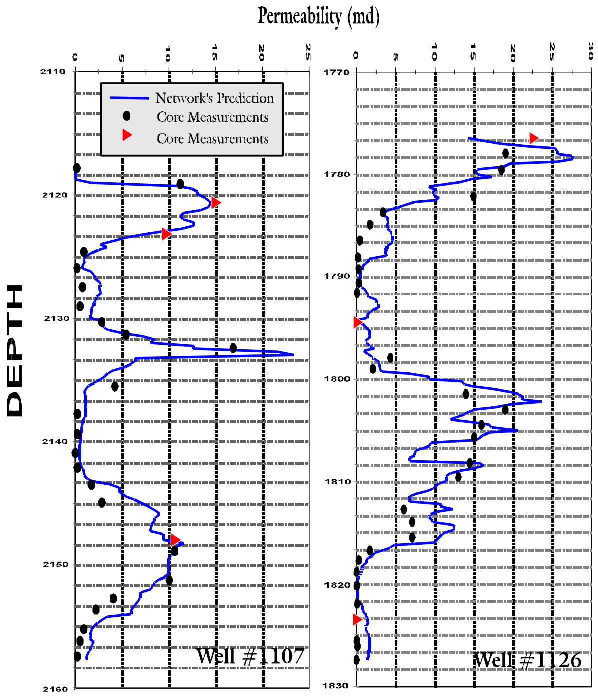

Figure 5. Neural network's permeability prediction vs. Actual laboratory measurements for wells 1107 and 1126.

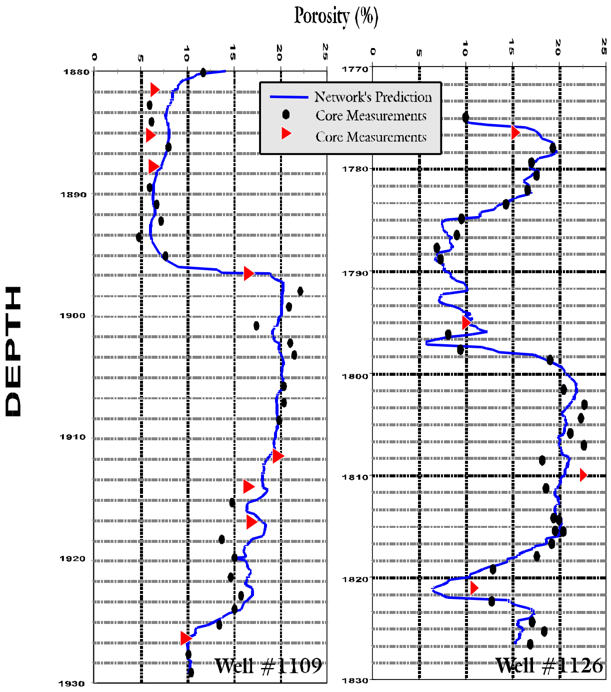

Figure 6. Neural network's porosity prediction vs. Actual laboratory measurements for wells 1109 and 1126.

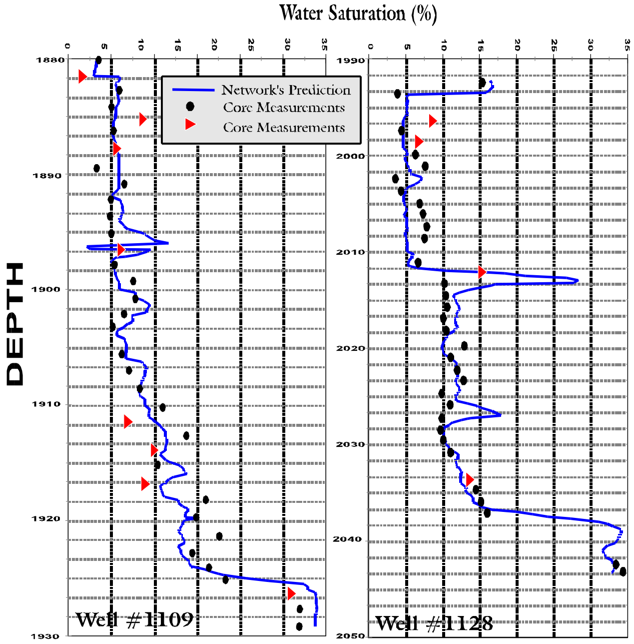

Figure 7. Neural network's oil saturation prediction vs. Actual laboratory measurements for wells 1109 and 1128.

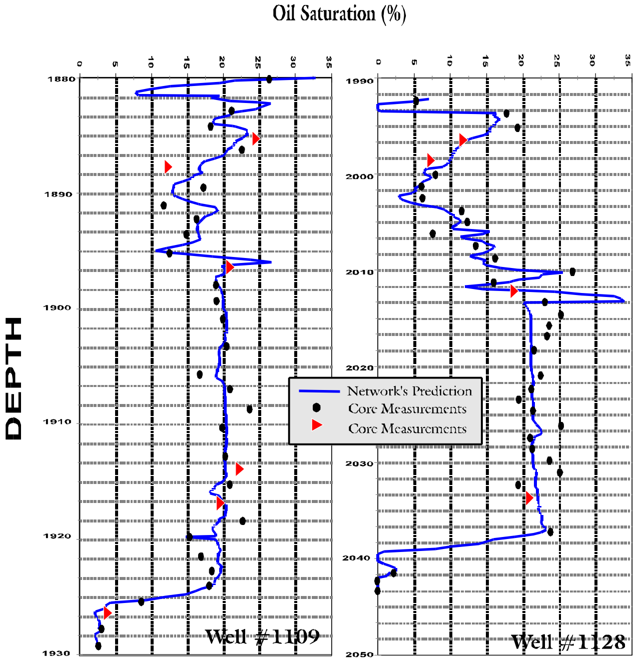

Figure 8. Neural network's water saturation prediction vs. Actual laboratory measurements for wells 1109 and 1128.