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Artificial Neural Network As A Valuable Tool For Petroleum Engineers

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ABSTRACT

Artificial neural networks are rapidly gaining popularity. This paper discusses the importance of this new tool to petroleum engineers, and the advantages that this computing process has over other conventional methods. The mechanics by which neural networks achieve their objective are also discussed. Artificial neural networks can assist petroleum engineers in solving some fundamental petroleum engineering problems, such as formation permeability prediction from geophysical well log responses with accuracy comparable to actual core analysis and well test interpretations. They are also capable of addressing case specific problems that may be encountered in the field. An example of each of these situations with successful results are discussed in this paper. The main goal of this paper is to put the artificial neural network in perspective from a petroleum engineering point of view and encourage engineers and researchers to consider it as a valuable alternative tool in the petroleum industry.

INTRODUCTION

Production and management of oil and gas in today's highly competitive environment require the use of high tech tools. These tools provide the means by which the cost of exploration, production, and management of hydrocarbon resources may be reduced. Engineers find themselves in a never ending race to catch up with new advancements in information technologies. Employing computers in the work place, incorporating sophisticated simulation models in decision making processes, and digital control and monitoring of equipment that were regarded as state of the art only a few years ago, are now normal day-to-day procedures. The phrase "Advanced Technologies" has a highly dynamic meaning.

In recent years, artificial neural networks and fuzzy set theory with its application in artificial intelligence have assumed the new meaning of the phrase "Advanced Technologies." These tools are providing engineers and scientists with the foundation upon which intelligent machines can be developed. Instruments will soon be evaluated according to their MIQ (Machine IQ) rather than bit processing bandwidth and clock speed. There is a great potential for these types of tools in exploration, production and management of hydrocarbons. Although the expert system is only one member of a family called artificial intelligence, it has been used as a synonym for artificial intelligence. Actually many AI scientists believe that neural networks, in their relatively short life, have accomplished far more than expert systems have, during their entire life. Neural network, a non-algorithmic, non-digital, intensely parallel and distributive information processing system, is being used more and more every day. The financial community (Wall street, insurance companies, banks, credit card companies) has been quietly using this tool for some time,[1] and since using neural networks prediction capabilities appears to be profitable they don't want the competition to know about it.

A handful of articles on the use of neural networks in the petroleum industry has appeared in SPE conference and related proceedings and publications in the past two years[2-4]. These articles can be divided into two categories. First, those that use neural nets to analyze formation lithology from well logs, and second, those that use neural networks to pick a reservoir model to be used in conventional well test interpretation studies. Automation of these tasks, which are usually performed by log analysts and reservoir engineers, using a fault tolerant process, may prove valuable. In this paper, it is intended to show that neural networks are able to solve quite complicated problems that have been encountered in the petroleum industry. Neural networks can help engineers and researchers overcome difficulties in addressing some fundamental petroleum engineering problems as well as specific ones which conventional computing methods have been unable to solve. To show the power of this tool an example for each case will be presented in a brief manner.

BACKGROUND

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 network 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 a panacea for 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. This paper will concentrate on neural network. Neural network, a biologically inspired computing scheme, is an analog, adaptive, distributive, and highly 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 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].

It has been only a few years since neural networks first gained popularity. In the past two to three years banks, credit card companies, manufacturing companies, high tech companies and many more institutions have adopted neural nets to help them in their day-to-day operation. Within the past few years, several software companies have surfaced that work solely on neural net products. Most researchers believe that artificial neural networks may be able to produce what rule based artificial intelligence (expert systems) have promised for so long but failed to deliver.

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 we do not know the form of the functions[8].

MECHANICS OF A NEURAL SYSTEM

In a typical neural data processing procedure, the data base is divided into two separate portions called training and test sets. The training set is used to develop the desired network. In this process (depending on the paradigm that is being used), the desired output in the training set is used to help the network adjust the weights between its neurons or processing elements (supervised training.) Once the network has learned the information in the training set and has "converged," the test set is applied to the network for verification. It is important to note that, although the user has the desired output of the test set, it has not been seen by the network. This is to ensure the integrity and robustness of the trained network. In order to clarify the actual functionality of a neural system, a short discussion on the mechanics and components of artificial neural network seems necessary. Our experience with neural networks on the estimation of formation permeability from well log data and prediction of gas storage well performance after hydraulic fracturing, has been that, one will get <u>some</u> sort of results by treating neural network as a black box, where one inputs the data, trains the network and gets some output. It has been the authors' observation that a fundamental understanding of theory and application of artificial intelligence in general and neural networks specifically is essential in achieving meaningful results and repeatable outcomes. The following discussion is meant to be a contribution to such an understanding.

A neuron is a nerve cell with all of its processes. Neurons are one of the main distinguishing features of animals. Figure 1 is a bipolar neuron, which means it has two processes. The cell body contains the *nucleus*. Leading into the nucleus are one or more dendrites. These branching, tapering processes of the nerve cell, as a rule, conduct impulses toward the cell body. The *axon* is the nerve cell process that conducts impulses away from the cell body.

Bundles of neurons, or nerve fibers, form *nerve structures*. In a simplified scenario, nerves conduct impulses from receptor organs (such as eyes or ears) to effector organs (such as muscles or glands). The point between two neurons in a neural pathway, where the termination of the axon of one neuron comes into close proximity with the cell body or dendrites of another, is called a *synapse*. At this point, a microscopic gap, the relationship of the two neurons is one of contact only. The impulse traveling in the first neuron initiates an impulse in the second neuron. Signals come into the synapses. These are the inputs. They are "weighted." That is, some signals are stronger than others. Some signals excite (are positive), and others inhibit (are negative). The effects of all weighted inputs are summed. If the sum is equal to or greater than the threshold for the neuron, then the neuron fires (gives output). This is an "all-or-nothing" situation. Either a neuron fires or it doesn't fire.

Within the last few years, hardware improvements have made computer simulation of artificial neural network possible. Although it may seem strange to simulate a parallel process on a sequential machine, there have been many benefits. It has bought time for the real objective of implementing neural networks in hardware, and it has illuminated problems in earlier models. Simulations have allowed us to better understand and improve the technology, and to tell in advance how well a particular neural network will perform in a given application. In addition to simulations, analog neural network circuits have been built and tested.

In neural computing the artificial neuron is called a *Processing Element* or *PE* for short. The word *node* is also used for this simple building block, which is represented by circles in Figure 2. These artificial neurons bear only a modest resemblance to the real thing. They are barely a first order approximation of biological neurons. Neurons in the human brain perform at least 150 different processes, where as Processing Elements model approximately three of those processes. The PE handles several basic functions. It must evaluate input signals and determine the strength of each one. Next, it must calculate a total for the combined input signals and compare that total to some threshold level. Finally, it must determine what the output should be. Just as there are many inputs (stimulation levels) to a neuron, there should be many input signals to a PE. All of them should come into PE simultaneously. In response, a neuron either "fires" or "doesn't fire," depending on some *threshold* level. The PE will be allowed a single output signal, just as in a biological neuron - many inputs, one output.

In addition, just as real neurons are affected by things other than inputs, some networks provide a mechanism for other influences. Sometimes this extra input is called a *bias term*, or a *forcing* term. It could also be a forgetting term, when a system needs to unlearn something. Each input will be given a relative *weighing* which will affect the impact of that input. This is similar to the varying synaptic strengths of biological neurons. Some inputs are more important than others in the way they combine to produce an impulse. Weights are adaptive coefficients within the network that determine the intensity of the input signal. One might think of them as a measure of the connection strength. The initial weight for a PE could be modified in response to various inputs and according to the network's own rules for modification.
Mathematically, we could look at the inputs and the weights on the inputs as vectors, such as $(I_1, I_2 \ldots I_n)$ and $(W_1, W_2 \ldots W_n)$. The total input signal is the dot, or inner, product of the two vectors. The result is a scalar, not a vector. Geometrically, the inner product of two vectors can be considered a measure of their similarity. If the vectors point in the same direction, the inner product is maximum; if the vectors point in opposite directions (180 degrees), their inner product is minimum. What was discussed before about signals coming into biological neuronal synapses applies here as well: signals can be positive (excitatory) or negative (inhibitory). A positive input promotes the firing of the PE, whereas a negative input tends to keep the PE from firing. If some local memory is attached to the PE, one can store results of previous computations and modify the weights used as the process continues. This ability to change the weights allows the PE to modify its behavior in response to its inputs, or *learn*. For example, suppose a network identifies a production well as "an injection well." On successive iterations, connection weights that respond correctly to a production well are strengthened; those that respond to others , such as an injection well, are weakened until they fall below the threshold level. It is more complicated than just changing the weights for production well recognition; the weights have to be adjusted so that all objects are correctly identified. When weight adjustments are made in preceding layers of feedforward networks by "backing up" from outputs, the term *back propagation* is used. This is an important concept, because a high percentage of all networks today employ back propagation algorithms.

Now, suppose that this processing element is combined with other PEs to make a layer of these nodes. Inputs could be connected to many nodes with various weights, resulting in a series of outputs, one per node. The connections correspond roughly to the axons and synapses in a biological system, and they provide a signal transmission pathway between the nodes. Several layers can be interconnected. The layer that receives the inputs is called the *input layer*. It typically performs no function other than the buffering of the input signal. The network outputs are generated from the *output layer*. Any other *layers* are called *hidden layers* because they are internal to the network and have no direct contact with the external environment. Sometimes they are likened to a "black box" within the network system. But just because they are not immediately visible does not mean one can not examine what goes on in those layers. There may be zero to several hidden layers. The connections are multiplied by the weights associated with that particular interconnect. They convey analog values. Note that there are many more connections than nodes. The network is said to be *fully connected* if every output from one layer is passed along to every node in the next layer. This description of components of a neural system was mainly from a book by Nelson and Illingworth[9].

APPLICATIONS IN PETROLEUM ENGINEERING

Neural networks can address some fundamental petroleum engineering problems as well as specific ones which conventional computing has been unable to solve. Petroleum engineers may benefit from neural networks on occasions when engineering data for design and interpretations are less than adequate. This is an especially common occurrence in the basins and fields that have been producing for a long time. Lack of adequate engineering data may also be encountered due to the high cost of coring, well testing and so on. Neural networks have shown great potential for generating accurate analysis and results from large amounts of historical data that otherwise would seem to be useless, or irrelevant in the analysis. Following are two examples of applying artificial neural networks to petroleum engineering problems. As the primary investigators in these projects, the authors believe that these problems are representative of the power that neural networks possess in solving some fundamental as well as special petroleum engineering problems. Neural networks are shown to be a viable alternative in addressing many problems we face in petroleum engineering.

Permeability Prediction/Estimation:

Permeability is the most important rock parameter in the flow of reservoir fluids. From a reservoir engineering, reservoir management, and enhanced recovery design point of view, knowledge of rock permeability and its spatial distribution throughout the reservoir is of utmost importance. Such information could prove quite valuable in any reservoir simulation studies. Conventionally core analysis and well test data interpretations are the most reliable way of acquiring permeability values of a formation. There have been attempts to correlate permeability with porosity. These efforts have produced some satisfactory results when the formation under investigation has been fairly homogeneous. In heterogeneous formations such attempts will result in poor correlations. Figure 3 is a plot of porosity versus permeability for such a formation in West Virginia. On the other hand wells are logged on a regular basis during and immediately after drilling. Although well logs provide a wealth of information about the rock, they fall short in measurement and calculation of its permeability. Dependency of rock permeability on parameters that can be measured by well logs have remained one of the fundamental research areas in petroleum engineering. Using the conventional computing tools available, scientists have not been able to prove the existence of such dependency or relationships in a rigorous and universal manner. Authors suggest that if such dependency exists, artificial neural networks are the tool to find them.

Neural nets' distributive and highly parallel processing characteristic allows them to literally discover highly nonlinear and fuzzy relationships that might exist between information provided by well logs (namely bulk density of the rock, gamma ray response, and induction) and rock permeability, that could be hidden and unfindable by conventional point-wise, sequential computing methods such as regression analysis. Using their recognition without definition property, neural networks can recognize patterns that we cannot even define[8].

Using geophysical well log data, authors have been successful in predicting/estimating the permeability of a highly heterogeneous formation in West Virginia[10-11]. Results of this study are shown in Figure 4. It is noticeable that permeability data in both Figures 3 and 4 belong to the same formation and the same field.

Hydraulic Fracturing:

Many opinions exist regarding optimum hydraulic fracture design. Two and three dimensional models are frequently used for fracture design and monitoring. Use of these models, however, requires detailed information about rock mechanics and reservoir characteristics. Obtaining this information may be difficult due to heterogeneities or excessive costs.

Basic well information such as reservoir thickness, porosity, depth, tubular design, initial open flow, offset production, flow tests, fracture design and treating parameters is usually readily available without additional cost. This information is generally not useful engineering data for hydraulic fracture design and post-fracture well performance prediction. Given enough pertinent historical data, a neural network may be used to predict the benefit of specific fracturing treatments.

A gas company in Ohio operates a 762 well gas storage field in the Clinton-Medina formation of Northeastern Ohio. All wells have been stimulated by hydraulic fracturing at least one time. A refracturing program was initiated in 1974 to counter declining field deliverability. Approximately twenty-five wells have been refractured each year since 1974 for a total of around 500 treatments.

Determining accurate reservoir and rock properties in the Clinton sandstone for hydraulic fracture design is difficult due to reservoir heterogeneity and natural fracturing. A neural network was used to optimize fracture design and predict well performance from abundant historical information in a close geographical area with multiple and varied hydraulic fractures.

Successful prediction of such problems can be very lucrative for any company, since it can reduce the cost by not performing frac jobs on wells that will not show production enhancement. Such predictions may also result in savings by predicting the same production enhancement even if a less expensive frac job is performed. The value of such accurate predictions is better understood once it is noted that the available data are not sufficient for actual engineering design and calculation of frac jobs. Figure 5 shows post-fracture well performance prediction made by neural network versus actual post-fracture results. Please note that Q100 is just a well performance yardstick used by the company. Detailed results of this study will soon be published.

CONCLUSIONS

Artificial neural networks are parallel distributed information processing models that can recognize highly complex patterns within available data. Other authors have discussed neural network power in helping to automate tasks that are currently done by log analysts and reservoir engineers such as formation lithology recognition/classification and determining the proper reservoir model for well test interpretations[2-4]. It was briefly discussed in this paper that due to their parallel distributed information processing capabilities that mimic that of a biological system, neural networks are capable of performing far more complicated tasks than just automation of different processes. It was shown that neural networks can predict formation permeability even in highly heterogeneous reservoirs using geophysical well log data with good accuracy. Neural networks' capability in predicting gas storage well performance after a hydraulic fracture was also shown. Artificial neural networks can help petroleum engineers when the problem in hand can be addressed through pattern recognition. It has also proven to be a valuable tool in cases where adequate engineering data are not available, but where large amounts of historical data can be acquired.

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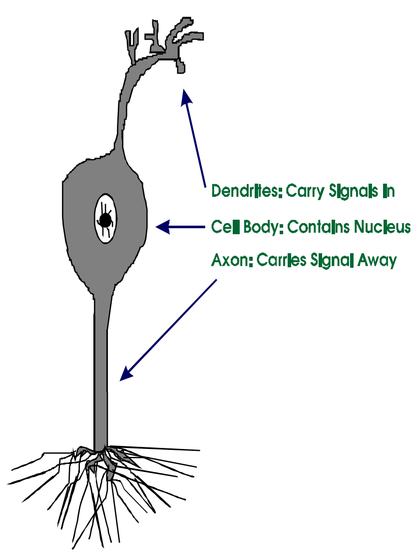

Figure 1. Three parts of a typical nerve cell.

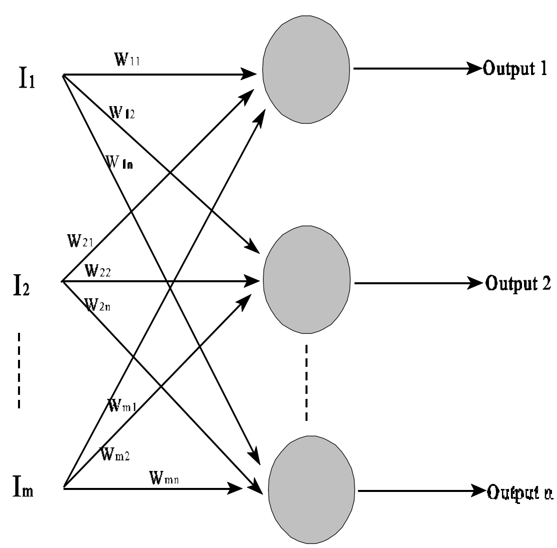

Figure 2. Inputs could be connected to many nodes.

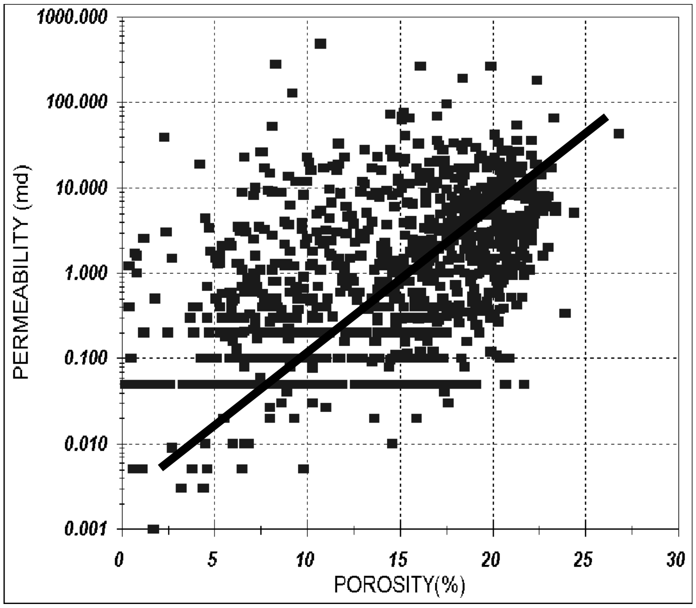

Figure 3. Permeability vs. Porosity using linear regression.

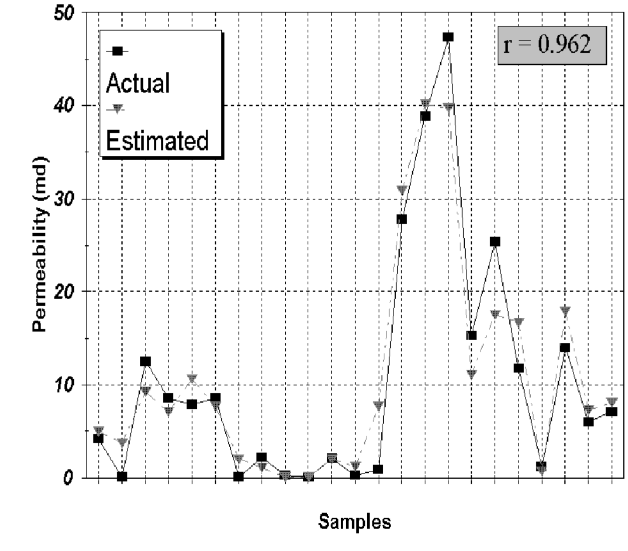

Figure 4. Core permeability vs. neural network's prediction.

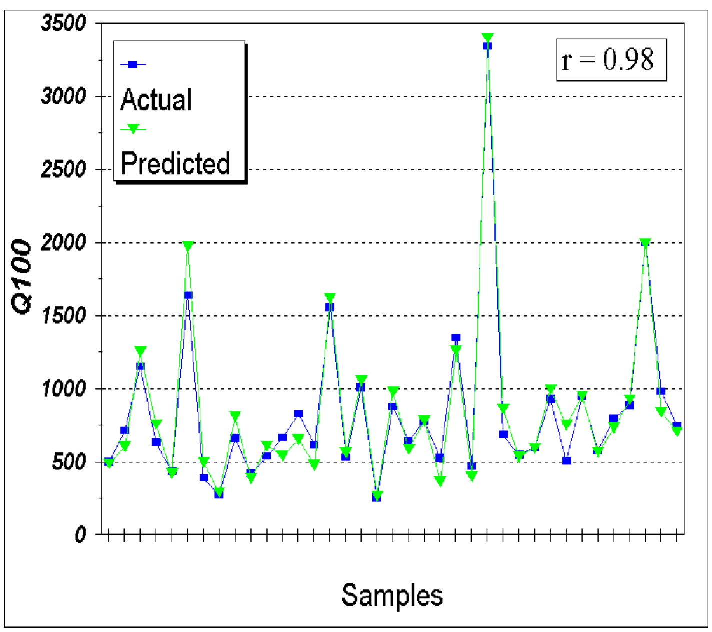

Figure 5. Comparison of neural network's prediction vs. Actual post-fracture well performance.