The Application of ANN for Zone Identification in a Complex Reservoir
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INTRODUCTION
Advanced computer models are available for simulating the fluid flow in increasingly complex reservoirs for the purpose of determining hydrocarbon recovery and appraising the economic success of reservoir management and development methods. However, an accurate description of the reservoir is necessary for the model to predict the performance of the reservoir reliably. Nearly all reservoirs contain several zones due to the existence of contrasting lithologies, digenesis, or sedimentological complexity. These zones usually influence the hydrocarbon movement, distribution, and production. Therefore, recognition of the zones has economic implications in reservoir management. As a result, the reservoir description cannot be realistically determined without accurate prediction as to how the zones are distributed in the reservoir. The prediction and identification of the zones are complex problems which require integration and interpretation of various geological and engineering information. The major problem in determining the distribution of the zones stems from the fact that the core data that are required for zone identification are available only from a few wells in a reservoir.

The objective of this study is to investigate the feasibility of using an Artificial Neural Network as a tool for zone recognition and identification in a heterogeneous reservoir utilizing geophysical well logs. Neural networks, 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. Known as sixth generation computing, neural networks are widely used in many disciplines from Wall Street to airport security devices. 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 might be. There are several paradigms (supervised, unsupervised, and reinforced) that can be used to generate neural networks.

One of the key issues in the description and characterization of heterogeneous formations is the distribution of various zones and their properties. In this study, several artificial neural networks (ANN) were successfully designed and developed for zone identification in a heterogeneous formation from geophysical well logs. Granny Creek Field in West Virginia has been selected as the study area in this paper. This field has produced oil from Big Injun Formation since the early 1900’s. The water flooding operations were initiated in the 1970’s and are currently still in progress. Well log data on a substantial number of wells in this reservoir were available and were collected. Core analysis results were also available from a few wells. The log data from 3 wells along with the various zone definitions were utilized to train the networks for zone recognition. The data from 2 other wells with previously determined zones, based on the core and log data, were then utilized to verify the developed networks predictions. The results indicated that ANN can be a useful tool for accurately identifying the zones in complex reservoirs.

ABSTRACT
Reservoir characterization plays a critical role in appraising the economic success of reservoir management and development methods. Nearly all reservoirs show some degree of heterogeneity, which invariably impacts production. As a result, the production performance of a complex reservoir cannot be realistically predicted without accurate reservoir description. Characterization of a heterogeneous reservoir is a complex problem. The difficulty stems from the fact that sufficient data to accurately predict the distribution of the formation attributes are not usually available. Generally the geophysical logs are available from a considerable number of wells in the reservoir. Therefore, a methodology for reservoir description and characterization utilizing only well logs data represents a significant technical as well as economic advantage.

One of the key issues in the description and characterization of heterogeneous formations is the distribution of various zones and their properties. In this study, several artificial neural networks (ANN) were successfully designed and developed for zone identification in a heterogeneous formation from geophysical well logs. Granny Creek Field in West Virginia has been selected as the study area in this paper. This field has produced oil from Big Injun Formation since the early 1900’s. The water flooding operations were initiated in the 1970’s and are currently still in progress. Well log data on a substantial number of wells in this reservoir were available and were collected. Core analysis results were also available from a few wells. The log data from 3 wells along with the various zone definitions were utilized to train the networks for zone recognition. The data from 2 other wells with previously determined zones, based on the core and log data, were then utilized to verify the developed networks predictions. The results indicated that ANN can be a useful tool for accurately identifying the zones in complex reservoirs.
system is composed of neurons switching at speeds about a million times slower than logical computer gates'. 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.

Granny Creek Field in West Virginia has been selected for detailed analysis in this study. The producing horizon in the Granny Creek Field, the Upper Pocono Big Injun sandstone, is characterized by severe heterogeneity due to a complex interplay of stratigraphic, structural, and diagenetic factors.

BACKGROUND
Granny Creek Field is located approximately 25 miles northeast of Charleston, in Clay and Roane Counties, West Virginia (see Figure 1). It produces from the Lower Mississippian Pocono Big Injun sandstone, a prolific oil producer (nearly 60 fields) in West Virginia. Structurally, the field is situated on the northwest flank of a syncline, which strikes N 15–20 degrees east to S 15–20 degrees west, and is surrounded to the west, south, and southeast by fields producing from the same interval. The western extent of the field might be limited by a gas cap and the northeast extent by erosional thinning of the reservoir. The field is roughly five miles long, has a maximum width of a little over two miles, and has a total productive area of about 3,000 acres.

Granny Creek Field was developed over a period of nearly 30 years, beginning in 1924. Production has continued throughout most of the field until the present day. The well spacing commonly is 400 feet. The crude oil in Granny Creek Field is a paraffin base, Pennsylvania Grade oil. It has a viscosity of 3.14 cp and a liquid gravity of 45.4 °API. Total oil production is estimated to be between 6,500,000 and 6,750,000 barrels. During the late 1970's and early 1980's, water flooding operations in Granny Creek Field were initiated. The water flooding has been moderately successful. However, the areal and vertical sweep efficiencies have been poor due to the heterogeneous nature of the formation. An enhanced oil recovery CO₂ pilot project was conducted beginning in 1976. Because of the extremely heterogeneous nature of the reservoir, less that 4 percent of the injected CO₂ entered the pattern. However, even this small amount was responsible for the production of over 4,000 barrels of oil from within the pattern. This recovery was considered very good under the circumstances. A minitest CO₂ project was conducted in a part of the same pattern several years later with a small amount of oil recovery. The CO₂ flood has not been expanded because of poor economics.

GEOLOGY
The producing horizon in the Granny Creek Field is the Pocono Big Injun sandstone of Lower Mississippian age. The Pocono Big Injun sandstone in the Granny Creek Field area can be divided into the upper coarse-grained fluvial channel facies and the lower fine-grained distributary mouth bar facies (see Figure 2). The diagenetic features in the upper and lower parts of the channel facies are sufficiently different to warrant its further subdivision into A and B members. Typically, the porosity in the upper A member is preserved due to the presence of chlorite coating on the grains, which prevented quartz cementation. The lack of coatings in the lower fluvial channel sandstones (the B member), however, resulted in quartz cementation during burial, which drastically reduced the porosity and permeability. The pre-Greenbrier unconformity erosion has removed the A and B members eastward across the field.

The basal fine-grained C member laterally consists of prograding tongues, numbered from oldest to youngest respectively, as C1, C2, and C3 (see Figure 3). The C member and its tongues represent a facies deposited in a deltaic river mouth bar environment and the subfacies are the distal and proximal parts of the bar, further distinguished by whether they are dominated by marine or fluvial processes. The C member exhibits progradational intertonguing with shales toward the west with pinch outs of C1 and C2. The development of well formed chlorite coatings that restricted quartz cementation was the main factor in porosity preservation in the proximal mouth bar interval. However, a combination of factors lowered porosity of the distal mouth bar facies to some extent and drastically reduced its permeability. The analysis of thin sections, cores, and well logs, have revealed that the marine influenced proximal mouth bar subfacies of the C member to be the primary pay zone and the tightly cemented B member to be the seal (5). The initial oil potential data and production data indicate that the areas of high production occur where C2 is thick, has good porosity and permeability (the marine influenced proximal mouth bar subfacies), and is capped by the impermeable B member. Where C2 is thin, has low permeability and porosity (where the mouth bar subfacies changes from marine to fluvial dominated), or where the B member is absent, the production appears to be low.

The previous investigations in Granny Creek Field for the purpose of predicting permeability from well log data had lead to a quantitative zone definition that integrated the geological descriptions of the various zones, geophysical well log responses, and the trend of the permeability variations. As a result of the trends of log responses and permeability, several zones were delineated in terms of log responses and annotated as Gamma Ray-Induction-Density (GRID) zones, A, B, Transition, and C (see Figure 2).

METHODOLOGY
The overall goal of this study was to investigate the feasibility of utilizing ANN for identifying various zones from the well log data. More specifically, the objective was to design and develop ANN to predict various geological zones in the Big Injun sandstone in Granny Creek Field. The methodology utilized in this study consisted of 3 steps, which follow:

1. Data collection
2. Training of ANN for zone identification
3. Verification
The following sections describe each step in detail.

1. Data Collection
In order to properly train the artificial neural networks (ANN), it is necessary to utilize the wells that have sufficient data. During this study, it was concluded that the sufficient data included the geophysical suite of logs consisting of Gamma Ray, Deep Induction, and Bulk Density as well as core descriptions and core analysis. Five wells, scattered throughout the field (see Figure 1), were then identified to have all the necessary data. The well log and core data were collected and compiled on all these wells.

2. Training of ANN for Zone Identification
The collected data on 3 wells (1110, 1130, and 1134) were utilized for network training. In this process, the network was provided with the log data (the input) as well as the definition of the various zones (the output). After a number of iterations, the networks recognized a pattern between the input and output. At this point, the network can predict the output for any given set of input.

In this study, the four sets of zone definitions as discussed previously (Depositional Environments, Lithofacies, Stratigraphic, and GRID), were utilized to develop four separate networks. It should be noted that Depositional Environment and Lithofacies zones are strictly core based definitions. Stratigraphic zones are log-based definitions and GRID zones are dependent on log and core data.

In our investigation, it was found that the network cannot recognize the zones if only the various log values are provided as input. To alleviate this problem, for every data point (depth), the slopes of the log plot (log reading vs. depth) prior and after that point were also included as a part of the input. The inclusion of the slopes allowed the network to recognize the changes in the shape of the various log plots. This lead to successful development of the networks.

3. Verification
The data for the other two wells (1126 and 2410) were utilized to verify the accuracy of the network predictions. The log data as well as the slopes were provided to each network (for each set of zone definitions) and the network predictions were compared with zones previously identified from core and log data. The results are shown in Figures 4-7 for well 1126 and 8-11 for well 2410. The results, as illustrated in Figures 4-10, generally verify the accuracy of the network prediction. It should be noted that the network results are given in the form of strength (as a percent) of the prediction.

DISCUSSION
A detailed scrutiny of Figures 4-11 reveals that there some differences between the networks’ prediction and the zones defined from core and log data. Some of the more pronounced differences will be discussed here. It should be noted that well 1126 is in the general vicinity of the 3 wells used for training and the network predictions appear to be more accurate. Well 2410 is a significant distance away from the training wells, yet, the network predictions are relatively accurate.

It appears that the Depositional Environment Network cannot predict the Fluvial Influenced Point Bar (FIPB) zone. This may be the result of very limited data (thin zone) available for training of the network. There is generally a decline in strength of prediction when moving from the upper Coarse Grained Channel Facies to Fine Grained Marine Facies. This is the zone which generally corresponds to GRID Transition zone. Indeed, the network’s prediction in this area generally is inconclusive as represented by the lack of any prediction except for GRID Network predictions. This confirms the presence of the GRID Transition zone, although the network predicts a thinner transition zone than the core and log data. It should be noted that the GRID Network fails to predict the second transition zone in well 2410. However, the data from the wells used for training only contained one transition zone. At the same time, there is a decline in network predictions in this general area in well 2410.

It should be noted that limited data (3 wells) were utilized to train various networks in this study. This was a preliminary study to evaluate the feasibility of ANN for zone identification. More accurate ANN can be developed utilizing the entire available data for training purposes which will provide more accurate predictions.

CONCLUSIONS
The following conclusions were reached in this study:

1. It is feasible to utilize ANN for zone identification in heterogeneous reservoirs.

2. The networks were developed that can predict Depositional Environments, Lithofacies, Stratigraphic, and GRID zones in Granny Creek Field utilizing only well log data.

3. The inclusion of slopes prior and after each point is necessary for the ANN to recognize the pattern.

4. The ANN predictions confirmed the presence of a transition zone in the Big Injun sandstone in Granny Creek Field.

REFERENCES


Figure 1. Grannu Creek Field in West Virginia.

Figure 2. The Pocono Big Injun Sandstone Zonal Interpretation.

Figure 3. The C member and its tongues (After reference 2).
**Figure 4.** The comparison of GRID Zones and NN predictions.

**Figure 5.** The comparison of Lithofacies Zones and NN predictions.

**Figure 6.** The comparison of Stratigraphic Zones and NN predictions.

**Figure 7.** The comparison of Depositional Environment Zones and NN predictions.
Figure 8. The comparison of GRID Zones and NN predictions.

Figure 9. The comparison of Lithofacies Zones and NN predictions.

Figure 10. The comparison of Stratigraphic Zones and NN predictions.

Figure 11. The comparison of Depositional Environment Zones and NN predictions.