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Use of Neural Network Methods to Predict Porosity and Permeability of a Petroleum Reservoir

(Running Head: Neural Net to Predict Porosity and Permeability)

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ABSTRACT

Accurate determination of porosity and permeability values at given well locations is a central problem in petroleum reservoir characterisation. Recent studies have shown that identification of individual rock types, or lithofacies, prior to calculating por-perm data can lead to improved estimates. This paper uses the genetic approach in predicting porosity and permeability values from wireline logs and lithofacies information in reservoirs, using a backpropagation neural network method. In order to reproduce the fine-scale variability known to exist in core por-perm data, separate neural nets are used for porosity, followed by permeability prediction. A simulation technique for adding fine-scale noise is also used. For the reservoir data considered, the fine-scale simulation approach combined with the use of neural networks provides realistic and accurate por-perm predictions when compared to the core data.

INTRODUCTION

This paper is concerned with the use of neural net techniques, combined with a geological description or classification of rock type to give improved predictions of key rock properties in petroleum reservoirs. In particular we are concerned with porosity and permeability predictions which are as precise as possible yet retain variability typical of that which exists within a given lithofacies, or rock type. These predictions are based at well locations where available wireline log suites have been suitably calibrated to available core sample measurements. In order that advantages offered by the proposed neural network application can be clearly understood, it is helpful to first outline key concepts and practices relevant to petroleum reservoirs. This is followed by an outline of the contribution made by the present paper.

A. Petroleum Reservoirs

A petroleum reservoir is a volume of porous sedimentary rock which has been filled, over geologic time scales, by oil migrating upwards from organic sources. Oil accumulates where barriers to further upward oil migration occur. The oil exists, along with varying amounts of water and possibly gas, in the pore spaces of the rock. Typical pore space dimensions are 1-100 microns. The two most important properties of reservoir rock are its porosity and permeability. Porosity is the fraction, or percentage, of the total rock volume which exists as pore space (typically in the range of 5-30%) whilst permeability is a measure of the mobility of fluid flow through this pore space when subjected to applied pressure gradients (measured in millidarcy, or md). Overall porosity levels control the amount of oil that can be contained in a reservoir,

whilst the average permeability level dictates the rate at which this oil can be recovered by imposed pressure gradients (e.g. water injection). One of the first tasks when assessing potential petroleum reservoirs is to determine the porosity and permeability properties (or por-perm data) of the reservoir rocks. This process is complicated because the measurement sites available to petroleum reservoirs are generally limited to isolated well locations. At these locations, measurements take the form of actual rock samples and wireline log readings. Rock samples, or core samples, are obtained by using a special coring barrel to recover intact cylindrical samples of reservoir rock. Wireline log readings are obtained every 150 mm or so of depth, by lowering various sondes in the drilled wells. These measure formation and fluid properties in and around the wellbore location. Typical sondes generate electrical signals from measurements of the acoustic, radioactive, resistivity and neutron attenuation and scattering properties of the formation and its contained fluids. Some measurements respond more to the rock itself (e.g. the density log or RHOB), whilst others are more sensitive to the pore space and fluids contained there-in (e.g. the neutron porosity log or PHIN). Further details on logging are given by Bateman (1985). Because coring is a relatively time consuming and expensive process, much effort is made to relate the electrical log measurements to available core porosity and permeability measurements so that the transformations developed can be applied to predict por-perm data in uncored intervals.

B. Genetic and Non-Genetic Classification of Reservoirs

The rocks which constitute a petroleum reservoir are far from homogeneous. Heterogeneity exists both within and between the different rock types, or lithofacies, which make

up a reservoir. Understanding the form and spatial distribution of these heterogeneities is fundamental to the successful characterisation of petroleum reservoirs (Haldorsen and Damsleth 1993). Heterogeneities occur on many scales from the cement found between individual sand grains at the pore scale, through laminations caused by fine silting at the centimetre scale, through to variations at reservoir scales caused by meandering river belts, deltas and marine shelves which controlled and directed the large scale deposition of sediment. This study is focussed on the estimation of por-perm data at the log scale of 150-1000 mm. Whilst fluid saturation is an equally important parameter, its estimation is beyond the scope of this paper. An estimation as to the degree of reservoir heterogeneity present in an oil reservoir can be seen in Figure 1 which shows a RHOB log, which represents the result of a log measurement transformed to a porosity scale. Note that the RHOB plot is a very crude estimate of (core) porosity, and that no adjustment has been made for variations in rock type.

There are two broad ways in which geologists, petrophysicists and engineers approach the problem of reservoir characterisation. These two methods can be described as non-genetic and genetic approaches (Jian et al. 1994). The non-genetic approach is the older, more established process to reservoir characterisation. This technique does not recognise different rock types and instead seeks to determine transformations to give porosity and permeability valid for any rock type. The genetic approach is a newer concept which seeks to identify and treat each dominant lithofacies type separately. Note that our use of the term "genetic" in this paper refers to the geological classification of rocks, and is in no way related to the different meaning of "genetic" in the artificial intelligence literature in general. The genetic approach to reservoir characterisation implicitly believes that each lithofacies type has distinguishing hydraulic properties, such as lithofacies-specific relationships between porosity and permeability (Hearn

et al. 1984, Stiles and Huthilz 1992) and therefore must be treated individually. Application of genetic characterisation is two-fold; firstly the dominant rock types or lithofacies must be identified, secondly lithofacies-specific transformations to porosity and permeability must be developed. The reason why a genetic approach is to be preferred over a non-genetic approach is that a non-genetic approach results in poorer quality predictions of reservoir properties. Figure 2a is an example plot of core permeability versus porosity for petroleum reservoir. Whilst simple analytical models, based on capillary tubes (Carmen 1937), suggest that logarithmic permeability may be linearly related to porosity, in practice correlations are developed for each individual reservoir. A non-genetic approach seeks to correlate the data in Figure 2a using one transformation whilst a genetic approach breaks the plot up into individual units, and develops relationships for each one. Clearly by following a genetic approach, the scatter in permeability values is much reduced at a given porosity level. This approach is depicted in Figure 2b. Note however, that even when following a genetic approach, that significant scatter remains. From the flow prediction viewpoint such variations within a lithofacies, or flow unit, are important and need to be captured as part of the characterisation process (Haldorsen and Damsleth, 1993). This feature is discussed later in regards the separate configuration of neural nets for porosity and permeability prediction as well as the use of fine-scale simulation (noise addition) methods to ensure that predicted por-perm data display this same variability.

C. Neural Nets and Genetic Classification

Whilst neural network methods have been applied to the problem of supervised lithofacies classification (Derek et al. 1990, Baldwin et al. 1990, Rogers et al. 1992), few studies

have considered the use of neural nets to the integrated problem of genetic classification from wireline log readings, whereby lithofacies prediction at a given depth is followed by the estimation of porosity and permeability values. Supervised learning requires training data which has been labelled with the desired outcome for each pattern of inputs. In the case of lithofacies predictions from logs, the available well log data is labelled with the lithofacies group names obtained from analysis of the appropriate core sample. This step is not a trivial one and can be complicated by the different resolution of core samples and log signals. This aspect will be discussed in a later section of the paper. The neural net can be trained to recognise and predict a given lithofacies from an input set of wireline log readings. Input features are selected from the data available in well logs based on geological expert knowledge and examination of each feature versus core porosity crossplots. Unlike traditional statistical classification techniques, such as discriminant analysis, neural networks can simultaneously output both discrete (lithofacies) and continuous (porosity) data. Wong et al. (1994b) have recently presented a comparison study on lithofacies, porosity and permeability predictions from wireline logs using neural network techniques and that of discriminant analysis followed by a regression stage. The results showed that the neural network approach provided superior estimates to those based on the discriminant analysis approach.

This work aims to implement the genetic approach using a neural network method for the purposes of porosity-permeability predictions. In the examples considered here, we assume that the lithofacies classification step is already complete, either by hand (a geologist) or as the result of a supervised classification scheme (e.g. another neural net). The following sections will first review the basic properties of neural networks. Then we will apply the genetic approach to porosity-permeability predictions from a suite of wireline logs and core-derived lithofacies

information. The data set used comes from a reservoir located in the Carnarvon Basin of the North West Shelf in Australia. Some of the available data is used to provide the training patterns, and the remaining data is used as a validation data set to test the performance of the trained network. Due to the heterogeneous nature of the formation, a fine-scale simulation technique is used in this study for better porosity and permeability predictions, and this technique is also reviewed in the later sections.

NEURAL NETWORK

An artificial neural network, or simply a neural net, is a computer model which attempts to mimic some parts of the workings of the human brain (Caudill 1988, Dayhoff 1990). It can learn and generalise from examples, and is extremely useful in solving pattern classification and mapping problems.

Training, or learning, is an essential part of using neural nets. This process requires training patterns which consist of a number of input signals paired with target signals. The inputs are presented to the net and the corresponding outputs are calculated. The aim of training is to minimise the differences between the output and target values (i.e. errors) for all the training pairs. By training, a set of parameters are produced and can be used for classifying data or predicting property values in situations where the actual output is unknown. Note, however, that this set of parameters is problem-specific because each training data set results in a unique neural net.

A. Basic Architecture

A typical neural net is composed of three kinds of layers: input, hidden and output layers. Each layer is made of a number of nodes, or processing elements. The input layer nodes are different from other nodes by only receiving input signals from the outside world and no mathematical operations are performed. Each of these inputs layer nodes are connected, via weighted links, to every node in the hidden layer. Unlike the input and output layers, the number of hidden layers can be any positive number (including zero). Recent studies show that one hidden layer is generally sufficient to solve complex problems if enough nodes are available (Hornik et al. 1989, Lippmann 1989) and hence this study was limited to the one hidden layer structure. The decision of how many nodes should be present in the hidden layer, however, is difficult to determine a-priori and is usually determined by trial-and-error (Derek et al. 1990, Bischof et al. 1992). The determination of the number of nodes present in input and output layers is more straight forward and is usually dictated by the particular application. In some cases, non-linear input variables (Lippmann 1989, Widrow and Lehr 1990) may also be used (see later sections). Output layer nodes receive output signals from hidden layer nodes and therefore provide responses to a given set of input signals.

Figure 3 shows a schematic diagram of a network architecture for porosity predictions using (core-derived) lithofacies with the density (RHOB) and neutron (PHIN) logs. An additional non-linear input, using RHOBxPHIN, is also displayed. In this figure, the input and hidden layers are composed of four nodes, and output layer contains only one node which gives the predicted porosity value. The magnitude of the output depends on the weights on all connections which are represented by the lines as shown in the figure. Bias nodes are usually

included for faster convergence and better decision boundaries (Dayhoff 1990). The weights on the bias nodes are treated the same as the others except the inputs are always equal to one (i.e. fixed).

B. Learning Algorithm

The backpropagation (BP) algorithm is the most widely used learning procedure for supervised neural nets. Before beginning training, small random numbers are used to initialise each weight on each connection. BP requires pre-existing training patterns, and involves a forward-propagation step followed by a backward-propagation step. The forward-propagation step begins by sending the input signals through the nodes of each layer until the actual output values are calculated. The backward-propagation step calculates the error vector by comparing the actual and target outputs. New sets of weights are re-iteratively calculated, by modifying the existing weights based on these error values (Rumelhart et al. 1986, Caudill 1988). Sending all of the input patterns in the training set through the network and modifying the weights is called an epoch of training. As weights are adjusted slowly to allow the network to generalise among the input patterns in the training set, normally some thousands of epochs of training are required.

In order to improve the generalisation capabilities of the net, a validation data set (i.e. a set of known input-output pairings which were withheld from the training set) is usually used to stop training before generalisation degrades (Morgan and Boulard 1990). Performance of the trained net can be evaluated by some simple statistical functions, such as root-mean-square-error (*rmse*), on the validation data. If the error value on the validation set begins to increase, training is halted and the results are examined to determine whether they are acceptable. If the results are

unacceptable, then it is possible to re-train the network, by either modifying some network parameters (e.g. by varying the number of nodes in the hidden layer over a reasonable range), or changing the number of training patterns (Mehrotra et al. 1991, Gedeon and Bowden 1992). To maintain a balance between being able to generalise from a training set but to not memorise it, some reasonable relationship between the number of parameters and number of training patterns must be maintained. A rule-of-thumb is that there should be at least 10 times as many as weights in the net. This clearly limits the number of hidden layer nodes used. Once acceptable results are obtained, the net is ready for use in solving real problems, using the input data for which the output is not known.

C. Practical Considerations

A major drawback to the use of the neural net approach is the problem of convergence. Convergence in the BP algorithm means that the global minimum (smallest error) of the error function is obtained in a reasonable amount of iterations, or epochs. The iterative process may require long training times of the order of several hundreds of thousands of epochs. Sometimes the net may get stuck in a local minimum during training which means that the net has failed to learn acceptably and gives large errors. Developing faster learning algorithms and local minimum detection and avoidance are active areas of research for neural nets (Gedeon and Harris 1992, Gori and Tesi 1992, Scalero and Tepedelenlioglu 1992).

The use of the genetic approach in porosity-permeability predictions requires lithofacies information as input data. All the inputs (logs and lithofacies) and target (porosity or permeability) data is then normalised in the interval (0,1) and (0.1,0.9) respectively (Eberhart and

Dobbins 1990). The advantage of using lithofacies information in predicting porosity-permeability values (i.e. the genetic approach) is to provide additional information allowing the separation of patterns in the input pattern space, and hence training time will be significantly reduced (Wong et al. 1994a). Also, generation of non-linear input variables may also reduce training time (Wong et al. 1994a) and improve generalisation capabilities of the trained net in some cases.

We have used two separate neural nets for porosity-permeability predictions. One is for the porosity and the other one is for the permeability. That means only one output node is used in each net. It is possible to use two output nodes (i.e. porosity and permeability) in only one net, however, in our experiments, we could not get this net to perform as well as the separate networks reported here. It is possible that different features need to be extracted to predict porosity and permeability, which could explain the reduced performance of a single network.

CASE STUDY

A. Objective

The objective of this study was to implement the genetic approach in well log interpretation using backpropagation neural networks. Using the genetic concepts, predicting porosity and permeability values require not only the use of the wireline logs, but also the lithofacies information as input data. As discussed in the previous section, two separate neural nets were used for porosity-permeability predictions in this study. The predicted results were

compared to the actual core data and the performance of the technique was then evaluated.

B. Training and Test Data

The data used in this study was from ten cored wells of a reservoir in the Carnarvon Basin in Australia. This data set was constructed from 1303 core data, including lithofacies, porosity and permeability values, with the corresponding log responses, which consist of bulk density (RHOB) and neutron (PHIN) logs. This formation is a lithologically complex reservoir which was diagnosed by a geologist to consist of 11 dominant lithofacies with distinct porosity and permeability relationships. The lithofacies were named as facies 1 to facies 11 for simplicity purposes.

The data set was divided into a training set and a validation set. The training data set was formed by selecting the patterns with density log values falling between the 25th and 75th percentiles for each lithofacies. Five hundred and seven (507) samples were finally chosen as training patterns. This was done in order to choose representative samples for the training set and to reduce the regions of overlap for different lithofacies. The use of data between the 25th and 75th percentiles is consistent with the standard statistical approach and can be considered a sure way of ensuring that no outliers are included in the training set. The validation set was then constructed using the remaining 796 patterns. The assumption we made was that these patterns deviate from the rest largely due to noise. Thus, the neural net will return results consistent with its training set, and effectively map patterns into the 25th to 75th percentiles range. Our results discussed in the later sections show that this was a valid assumption in this case.

In this study, non-linear input was also generated using RHOB and PHIN as

RHOBxPHIN. The input data was then normalised using the minimum and maximum values from the whole data set in the interval (0,1). Porosity values were determined in the first net, and permeability values were then estimated in the second net using the same non-linear input as the first net, plus the previously predicted porosity values as an additional input. Figure 4 also shows the prediction process in simple block diagrams.

C. Neural Network Architecture

1. Porosity Prediction

The training patterns were constructed by a set of 4-dimensional input vectors (i.e. RHOB, PHIN, RHOBxPHIN and lithofacies) and 1-dimensional target vectors (i.e. porosity). Four hidden layer nodes were found to produce the best results. The training data was used to train the network for 10,000 epochs. The validation data set was also used to record the lowest *rmse* during the training phase. The *rmse* was minimised at 3,648 epochs with a value of 0.112 on the validation set. The contribution of each input variable to the system (Wong et al., 1994a) was also calculated and is tabulated in Table 1. This contribution is the relative magnitude of the weights from an input unit to all hidden units with respect to the sum of all weights of the inputs to hidden units. It shows that lithofacies was a very important input variable in porosity determination as it is characterised by a high contribution percentage. The weight matrix defining the network at epoch 3,648 in this example would be used to predict porosity values in practice.

Due to the heterogeneous nature of the formation, the wireline logs were not able to

resolve most of the thin beddings of the reservoir, and resulted in smoothed porosity predictions from the neural net, relative to that obtained from core measurements. Therefore, a fine-scale simulation technique was used in order to simulate the variability of the porosity values observed from the core data (Jian et al. 1994). The objective of the fine-scale simulation is to mimic the appearance of the core data. This is useful because geologists have a great deal of expertise developed over time to interpret such data. A smooth curve produced from neural net predictions appears different and can be less well interpreted than the same curve with the addition of appropriately fine-scaled noise to re-introduce an indication for them of the expected scatter.

The fine-scale simulation technique requires the use of lithofacies-specific standard error value derived from the target porosity values (from the training patterns) and the predicted porosity values (from the trained net). A simulated noise was calculated by multiplying the standard error by a normally distributed probability field with zero mean and unit variance. This noise was then added to the porosity value obtained from the neural net. This fine-scale simulation technique with the use of neural net estimates is referred to as the simulated neural net method in the rest of this paper.

The statistics of the porosity predictions based on the standard (i.e. no fine-scale simulation) and the simulated neural net methods are tabulated in Table 2. The results showed that the standard neural net method gave a lower *rmse* compared to the simulated method (0.6% difference). This was because the standard method aims to minimise the differences between the actual and predicted values. The simulated method, however, aims to reproduce statistics of the actual data which is usually considered to be one of the most important goals in petrophysical property prediction. As shown in Table 2, the simulated method produced better statistics compared to the standard method. Figure 5a shows the predicted porosity profiles using the

standard and the simulated methods with the core data in one of the ten wells, named Well A. Note that approximately one-third of the data points in this well were chosen as training patterns. Due to the heterogeneous nature of the reservoir, the standard neural net technique resulted in smoothed predictions as can be observed by a low standard deviation displayed in Table 2. The predicted porosity values for all the wells (i.e. 1303 core data) are also displayed in Figure 5b as histograms. The simulated neural net porosity produced a similar distribution to the core data. The porosity derived from the standard method, however, tended to smooth out the profile and produces a high frequency content in the 14-16% interval.

2. Permeability Prediction

For consistency, the training data set for permeability predictions was composed of the same 507 patterns with the additional porosity information as input data. This way the 796 withheld data points could be used to assess both porosity and permeability predictions. Logarithmic permeability was used at the output node because this variable reduced the amount of training time and also showed better results compared to using only permeability. One of the reasons is that logarithmic permeability is linearly related to porosity in general (see Figures 2a and 2b). The results were optimised by using three hidden layer nodes. The training patterns were trained for 10,000 epochs. The same validation data set was again used to record the lowest *rmse* during the training phase. The results were best at 6,975 epochs and a *rmse* of 0.115 on the validation set was obtained. The contribution of each input variable to the system is tabulated in Table 1.

The simulated neural net method was also used to simulate the fine-scale variations of

the permeability predictions. The results of the standard and simulated methods are tabulated in Table 2, and the predicted permeability profiles at Well A are shown in Figure 6a. Histograms of all predictions are also displayed in Figure 6b. As discussed earlier for porosity prediction, the simulated results produce more realistic estimates compared to the standard method.

CONCLUSIONS

A technique for porosity and permeability predictions from wireline log signals within a genetic framework is presented using backpropagation neural networks. The technique is also applied to a data set, already classified into lithofacies type, from a heterogeneous petroleum reservoir. Based on the results obtained from the example problem, the major findings are listed below:

1. Genetic well log interpretation can be implemented using a backpropagation neural network.
2. The accuracy of porosity and permeability predictions depends strongly on lithofacies information.
3. The fine-scale simulation technique can be used in conjunction with the neural network method to reconstruct small scale por-perm variability as part of the overall predictive process.

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