A MODULAR SIGNAL PROCESSING MODEL FOR PERMEABILITY PREDICTION IN PETROLEUM RESERVOIR

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Abstract:
The use of Artificial Neural Network (ANN) especially Backpropagation Neural Network (BPNN) has been a promising tool for well log analysis in predicting permeability. However, due to the range of permeability data, it is normally converted using logarithmic transform before being used for data analysis by the BPNN. This has an impact on the accuracy of the permeability prediction. This paper suggests a model for improving the permeability prediction. It first divides the whole sample space of the permeability values according to their logarithmic region, and then generates individual BPNNs for each logarithmic region. In this initial study, Learning Vector Quantisation (LVQ) is used for this purpose for separating the data. After that, each region is then handled by each BPNN. This method not only preserves the resolution of the permeability, but at the same time, increase the prediction accuracy. The contributions of this paper are to identify the problems in the signal processing of permeability prediction, and exploit new direction of improving permeability prediction using well logs.

INTRODUCTION

One of the key issues in reservoir evaluation using well logs is the prediction of petrophysical properties such as porosity and permeability. Of these petrophysical properties, permeability is one of the more important properties. Over the life of the reservoir, many crucial decisions depend on estimates of formation permeability. Permeability is widely used to determine the well production rate of the hydrocarbon, such as oil or gas. It is used to measure the fluid mobility that flows through the porus media when a pressure gradient is applied. However, the prediction of such properties is complex as the measurement sites available are limited to isolated well locations.

Normally boreholes are drilled at different locations around the region. Well logging instruments are then lowered into the borehole to collect data at different depths known as well log data. Well logging instruments used in the measurement

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of well log data broadly fall into three categories: electrical, nuclear and acoustic [1]. Examples are Gamma Ray (GR), Resistivity (RT), Spontaneous Potential (SP), Neutron Density (NPHI) and Sonic interval transit time (DT). Beside the well log data, samples from various depths are also obtained and undergo extensive laboratory analysis. This laboratory analysis data is known as core data in the well log analysis process. In well log analysis, the objective is to establish an accurate interpretation model for the prediction of petrophysical properties for uncored depths and boreholes around that region [2].

There are three main widely used approaches for permeability prediction; namely empirical, statistical and ANN [3]. Recently, the use of fuzzy system [4] and fuzzy neural networks [5] have also emerged. Although the methods used are different, their objective is similar. It is mainly to establish an interpretation model by ways of linear or non-linear curve fitting. The ways they handle the processing of permeability data is also quite similar regardless of the method used. The next section of this paper will examine some of the possible problems in handling the permeability data. Section three will present a model that will improve the permeability prediction. Section four will examine the possible use of Learning Vector Quantisation (LVQ) in establishing the model discussed. Results and discussion of the test cases are also presented in this paper to show the proposed modular signal processing model could improved the accuracy of the permeability prediction.

PROBLEMS OF PREDICTING PERMEABILITY

Among most methods used in permeability prediction, ANN especially BPNN seems to be the most promising one in the literature [6],[7]. BPNN is the most popular among all ANN techniques in permeability prediction mainly because it is quite similar to Multiple Regression [8]. The analysis of the problems presented in this section will be based on the BPNN approach. However, most problems discussed here are also valid in other approaches used in permeability prediction. The problems mentioned in this section are discussed without taking any geology and petrophysics theory into consideration as these have been investigated in the geophysics literature. The analysis presented here is mainly viewed from the perspective of signal processing.

The problems can mainly be divided into the following three areas:-

1. The normalisation of permeability values

In most cases for ideal operation, BPNNs should only take values between 0 and 1 as input. Permeability values have to be normalised before they can be used in BPNN. There are normally two ways of performing normalisation in permeability prediction; they are linear or logarithmic transform.

The equation that is used for linear transformation is:

$$Y = \frac{X - \min val}{\max val - \min val} \tag{1}$$

where Y is the normalised permeability value
X is the actual permeability value
minval is the minimum permeability value in the data set
maxval is the maximum permeability value in the data set

For logarithmic transform, the permeability values normally undergo base-10 logarithm before performing the above linear transformation, which can be represented by the following equation:

$$Y = \frac{\log_{10} X - \log_{10} \min val}{\log_{10} \max val - \log_{10} \min val} \tag{2}$$

For permeability prediction, the logarithmic transform is normally used, as linear normalisation present too small a resolution to be modelled correctly by the BPNN. From Table 1 for example, BPNN will have difficulties in modelling permeability values from 0.01 to 5 correctly as their resolution is too small.

TABLE 1: LINEAR TRANSFORMATION OF PERMEABILITY VALUES

Permeability Values	Linear Transformed Values
0.01	0.000000
0.05	0.000020
0.1	0.000045
0.2	0.000095
1	0.000495
5	0.002495
100	0.049995
150	0.074995
1000	0.499997
1500	0.749999
2000	1.000000

Conventionally, permeability analysis has adopted logarithmic transformation and has been shown in most literatures to be the correct way of modelling permeability values. However, when the range of the permeability values is too wide, it will suffer from a similar problem as in the linear transformation with uneven distribution of the resolution. This is shown in Table 2. From Table 2, it can be observed that the resolution of the permeability transform is quite good between 0.01 and 1000 but starts to degrade from 1000 and above. It is basically quite difficult for the BPNN to realise the big difference between 1000 and 2000 as they are about the same when presented in the logarithmic normalised value.

TABLE 2: LOGARITHMIC TRANSFORMATION OF PERMEABILITY VALUES

Permeability Values	Logarithmic Transformed Values
0.01	0.000000
0.05	0.116495
0.1	0.166667
0.2	0.216838
1	0.333333
5	0.449828
100	0.666667
150	0.696015
1000	0.833333
2000	0.883505
10000	1.000000

2. The resolution of permeability prediction

In BPNN training, the training error is calculated using sum of squared error. The total error, *TE*, for the BPNN and for all training patterns K is defined as the sum of squared differences between the actual network output and the target output T at the output layer L:

$$TE = \sum_{k=1}^{K} \left(\frac{1}{2} \sum_{i=1}^{N_L} T_i(k) - O_i^L(k)]^2 \right) \tag{3}$$

The aim of course is to minimise *TE* by adjusting all the weights in the BPNN.

If the permeability values in Table 2 are used for training, the difference in values of 1000 and 2000, which is 0.83333 and 0.883505 respectively, will be considered as a very small error.

Besides training, prediction of the permeability will also have a large impact even when the difference between the predicted result and the actual result in normalised form is small [3]. For example, if the predicted output generated from the BPNN is 0.8 and the actual output should be 0.9, the difference could be considered small. When converted back into the actual permeability values, the difference is actually about 1880.9, as 0.9 will correspond to 2511.9 and 0.8 corresponds to 631.0. This can be a serious problem as the prediction actually goes from one logarithmic region to another.

3. The presentation of the prediction results

Most of the literature when presenting results make use of the logarithmic representation [3], this can be very inaccurate when comparing prediction accuracy as shown in Figure 1. The dots on the plot correspond to core permeability and the solid line corresponds to the predicted permeability. The difference between the predicted and core permeability in the normalised scale pointed by the arrow is only 0.4773, while in normal scale the difference is 125.3.

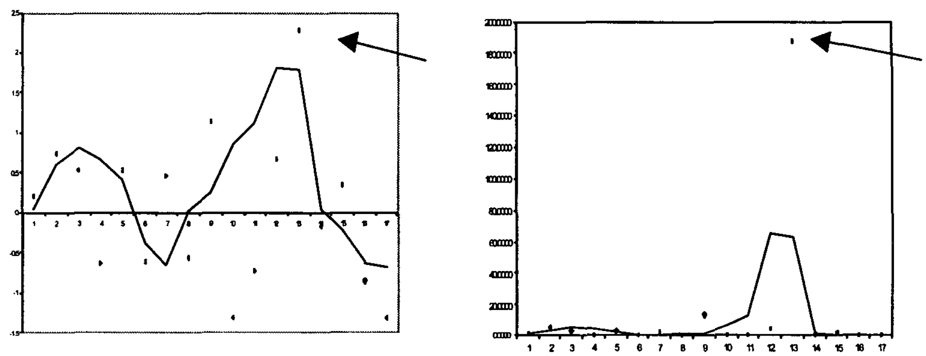

FIGURE 1: REPRESENTATION OF PERMEABILITY VALUES IN NORMAL AND LOGARITHMIC SCALES

MODEL FOR BETTER PERMEABILITY PREDICTION

From the previous analysis, the following deductions can be made in order to improve the signal processing of the permeability prediction:

1. Use the original permeability values without normalising when building the interpretation model.
2. Allow linear transformation without losing much of the resolution

The first solution is difficult to accommodate as BPNN can only deal with values between 0 and 1. Our model proposed in this section will address the second solution.

As shown in Table 1, if linear transformation is used to normalise the permeability data, the resolution of the data will be lost if the range of the data is large, e.g. 0.01 to 10000. However, if some modular signal processing techniques can be applied to separate the whole distribution of permeability values, according to their logarithmic region, the resolution of the result can then be increased.

Figure 2 shows the block diagram of the proposed modular signal processing model. Some kind of modularisation technique can be used to separate the permeability values according to their logarithmic regions. For example, permeability values falling between 10 and 99 will be forced into the *lg 1 BPNN*, and values between 100 and 999 will be forced into the *lg 2 BPNN* and so on. After all the permeability values have been separated, individual BPNNs that handles just one logarithmic region can then be trained.

As each BPNN just take care of data in one logarithmic region, the linear normalisation can be applied. This will in turn increase their resolution, as each BPNN will only see data in the same logarithmic region.

This proposal is quite similar to the genetic approach proposed by Jian et al. [9]. The genetic approach basically separates the whole sample space according to different lithohydraulic units based on their petrophysical, depositional and diagenetic properties. However, in the genetic approach, in each lithohydraulic classes, the permeability values may spread over three logarithmic scales. This has again reduced the resolution of the permeability values.

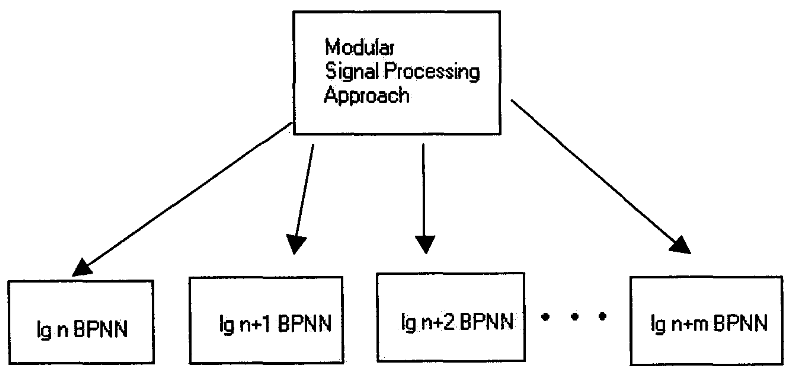

FIGURE 2: BLOCK DIAGRAM OF THE MODULAR SIGNAL PROCESSING APPROACH

THE USE OF LVQ

In this initial study, a supervised clustering ANN can be used as the modularisation technique shown in Figure 2. An ANN with supervised learning is chosen here as the logarithmic region already gives the clustering boundary, and it is desired that the ANN can learn the clustering boundary to be used for any new data.

The Learning Vector Quantization (LVQ) is a supervised learning network, which can be used to define class regions in the input space [10]. The training data given is a set of well logs along with correct class labels that correspond to the logarithmic region. LVQ is well known in applying to statistical classification or used for pattern recognition. LVQ makes use of competitive learning rule to define decision boundaries in the input space. It creates a codebook that has similarly labelled vectors that define the class borders. Once the network is trained, the codebook vectors for each class remain within the class region. They are then used to classify any subsequent inputs according to the codebook vectors.

LVQ corrects the codebook vectors $m_i(t)$, $t = 0,1,2...$ according to the rule:

if x and the closest codebook vector belong to the same class:

$$m_c(t+1) = m_c(t) + \alpha(t)\,[\,x(t) - m_c(t)\,] \tag{4}$$

if x and the closest codebook vector belong to different classes:

$$m_c(t+1) = m_c(t) - \alpha(t)\,[\,x(t) - m_c(t)\,] \tag{5}$$

for $i \neq c$

$$m_i(t+1) = m_i(t) \tag{6}$$

where m_c is closest codebook vector
x is random input sample
α is $0<\alpha<1$ and is decreasing with time

The LVQ network is easier to set up compared to BPNN. Typically, only two parameters are required to be determined by the user. First, the size of the codebook has to be selected. The second parameter to be determined is the number of learning steps. In [10], they are some formulas used to calculate them. As the training time required by LVQ is short, optimisation of these parameters can be done quickly with trials of values close to the initial calculated parameters. In addition, any new set of input data can be used to retrain the network in a short period of time.

CASE STUDY

The input logs used are gamma ray (GR), bulk density (RHOB), neutron (NPHI), photoelectric (PEF), and sonic travel time (DT). By observing the permeability values, four logarithmic regions are involved in the data. They are assigned to class labels according to Table 3. For comparison, a conventional method of using BPNN with logarithmic transformation was generated with 10 hidden nodes.

As for the proposed modular signal processing approach, the LVQ was trained with the input logs and their corresponding class label. There are a total of 166 data used for the training process. The linear transformation is then used to normalise the data for each BPNN before training. There are a total of four BPNNs to be trained in this case.

TABLE 3: CLASS LABEL FOR PERMEABILITY VALUES

Permeability Values	Class Label
0.01 – 0.099	1
0.1 – 0.99	2
1 – 99	3
100 – 999	4

After the LVQ and the four BPNNs have been trained, another set of testing data that comprises of 222 data points are used to test the approach. The input logs were first fed into the LVQ for classification. After the input logs have been classified, they are then fed into the corresponding BPNN used for prediction. When comparing the classification output of the LVQ to the actual permeability values, a classification accuracy of 90.54% was determined. This will suggest that certain data may fall into the wrong BPNN that could generate results in the wrong logarithmic region.

The results generated by the proposed model as compared to the conventional BPNN approach are tabulated in Table 4. A few measurements of differences between the predicted permeability and core permeability are used. They are:

Mean Squared Error:

$$MSE = \frac{\sum_{i=1}^{P}(T_i - O_i)^2}{2P} \tag{7}$$

Mean Character Difference Distance:

$$MCD = \frac{\sum_{i=1}^{P}| T_i - O_i |}{P} \tag{8}$$

Percent Similarity Coefficient:

$$PSC = 200\frac{\sum_{i=1}^{P}\min(T_i, O_i)}{\sum_{i=1}^{P}(T_i + O_i)} \tag{9}$$

For comparison with conventional presentation of permeability results, a logarithmic comparison is also carried out. Results from Table 4 shows that even when the permeability prediction is compared using the log scale, this proposed approach can also generate better results. Figure 3 shows part of the graphical plot (using normal scale) of the permeability prediction generated from the two models developed in this case study.

TABLE 4: SUMMARY OF COMPARISON RESULTS

Model	MSE	MCD	PSC
Conventional BPNN (log scale)	0.00993	0.658	4.818
Modular SP (log scale)	0.00535	0.406	50.284
Conventional BPNN (normal scale)	3582.7583	27.312	40.404
Modular SP (normal scale)	1437.54114	19.055	73.399

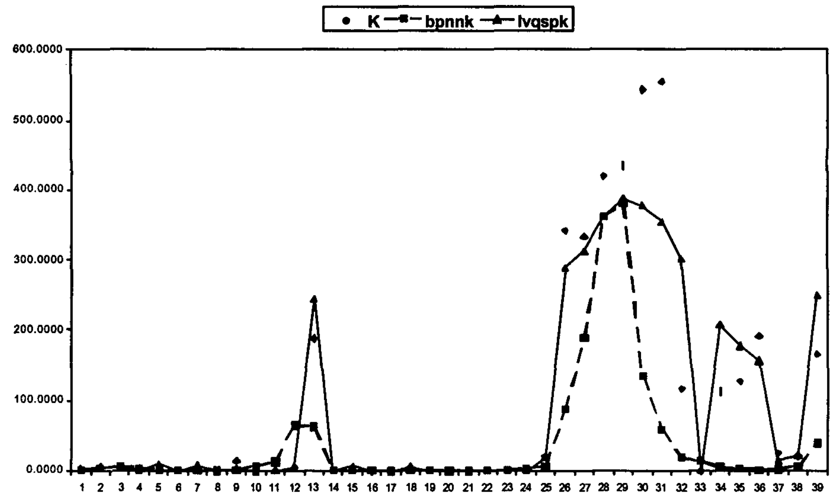

FIGURE 3: GRAPHICAL PLOT OF THE PREDICTION RESULTS TO THE CORE

CONCLUSION

This paper has examined the problems of permeability analysis and proposed a modular signal processing model to increase the accuracy of the prediction of permeability. This initial work has used LVQ as the modularisation technique, and the results shown in the case study has generated promising results. However, further investigation of better modularisation techniques will be carried out as the success of this approach is directly related to the classification accuracy of the modularisation technique used. The proposed modular signal processing model is important as this will exploit new directions of improving permeability prediction from the perspective of signal processing.

ACKNOWLEDGEMENT

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