A STATE-OF-THE-ART REVIEW OF NEURAL NETWORKS FOR PERMEABILITY PREDICTION

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ABSTRACT

This paper reviews the state-of-the-art of neural networks for permeability prediction from well logs. Good prediction of permeability is necessary for reservoir characterisation and is important for improving the reliability of the asset value of oil and gas companies. Two particular models, known as backpropagation and radial basis function networks, have been applied. From previous work, six innovative aspects are identified:

1. **choice of inputs;**
2. **outlier detection and removal;**
3. **data splitting;**
4. **scaling;**
5. **multiple networks; and**
6. **prediction confidence.**

We have also provided a list of future research directions in the area, reflecting the current deficiencies of the use of neural networks. The topics are:

1. **the quality and quantity of core data;**
2. **the maximum use of the logs;**
3. **the compatibility of scales;**
4. **the use of soft computing; and**
5. **the management of prediction confidence.**

The current applications are certainly the beginning of a new era. It is important for petrophysicists to take advantage of the advanced technologies.

KEYWORDS

Permeability, neural networks, well logs, core, scales, soft computing, confidence.

INTRODUCTION

Reservoir modelling and production forecasting requires accurate permeability measurements. Well logs are used frequently to predict permeability in the uncored intervals. The use of empirical equations has been common since the early 1950s. Examples include Wyllie and Rose, Timur and Raymer and Freeman (Bateman, 1985). Most of these equations require the estimation of other variables (e.g. porosity and irreducible water saturation) before they can be applied. This is not an easy task. If cores are available, the coefficients and exponents of the equations can be adjusted until a reasonable match with the core permeability is obtained. However, it becomes unreliable when these equations are extrapolated to the uncored intervals, especially in heterogeneous reservoirs. The use of these equations is generally tedious and time consuming.

In the late 1980s, many people started to apply statistical techniques in searching for relationships between well logs and core permeability (Wendt et al, 1986; Sakurai and Melvin, 1988; Jian et al, 1994). This bypasses the need to estimate other petrophysical logs and to assign the coefficients and exponents. The use of linear relation and distribution-driven (or parametric) models is fast and simple. However, most techniques require the assumption and satisfaction of multi-normality, linearity and independence of inputs (Davis, 1986; Size, 1987). In an uncertain geological environment with a small sample set, the use of assumptions will reduce the reliability of the predictions, and they must be applied with great caution.

In the early 1990s, some petrophysicists revisited the application of an assumption-free approach for well logging, namely artificial neural networks. This approach presents a suite of advanced pattern recognition techniques, which are inspired by the biological neural system in the human brain structure (Wasserman, 1989; Zurada, 1992). These techniques have the ability to 'learn from experience' and are now well accepted in many engineering practices. The popularity has resulted in the establishment of international societies, the organisation of regional and international conferences, the publication of peer-reviewed journals and the development of commercial software. This applies also to related technologies such as fuzzy computing (Cuddy, 1997; Fung et al, 1997c; Huang et al, 1999) and evolutionary computing (Huang et al, 1998b).

In the past 10 years, neural networks have been applied to many areas in reservoir evaluation. Examples include lithology recognition (e.g. Smith et al, 1991; Rogers et al, 1992), porosity and permeability prediction (e.g. Wong et al, 1995b; Malki et al, 1996) and reservoir mapping (e.g. Wang et al, 1999). In this paper, we will focus on permeability prediction from well logs. We will first revisit the basic models of neural networks for permeability estimation, followed by a review of previous work. We will also provide a list of future research directions in the area.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are universal approximators inspired by some working functions of the brain and nervous system. They operate as non-linear dynamic systems that learn to recognise patterns after being 'trained'. A 'trained' ANN has been presented with training data, which consist of a number of observed input signals (e.g. well logs) paired with target signals (e.g. permeability). Once trained, new input data can be applied to it, allowing prediction of output values.

The major components of ANNs are neurons and connections. The connections are weights between the neurons. Neurons are also often referred to as units or nodes. Each neuron, except the input neurons, uses a transfer function to process the input values passed on from the preceding neurons. This arrangement allows the calculation of a final output for a given set of input values. The final output is compared with the desired output, and the connection weights are adjusted using a learning algorithm in order to minimise the total error of the system. In this section, we will revisit the basic concepts of two supervised neural network paradigms, that have been applied to permeability prediction.

Back propagation neural networks

Back propagation neural networks (BPNNs) are the most popular types of ANNs to date. The architecture of a BPNN consists of an input and output layer of neurons as shown in Figure 1. There is also at least one hidden layer, sitting between the input and output layers, which has a certain number of neurons (often determined by trial and error). All neurons of adjacent layers are fully interconnected by weights and biases. A bias is a fixed input value (often set at one) added to each connection in the hidden and output layers, that is analogous to the intercept used in linear regression. There are no interconnections between neurons of the same layer. The forward propagation step sends input signals through the network to create an output value. A mathematical function called a transfer function is applied at each connection. Mathematically, the estimator can be expressed as follows:

$$Y = f\left[\alpha_0 + \sum_{j=1}^{n2} \alpha_j f_j\left(\beta_{0j} + \sum_{i=1}^{n1} \beta_{ij} x_i\right)\right]$$

where Y is the output (e.g. permeability), x_i are the inputs (e.g. well logs), α_j and β_{ij} are the connection weights, α_0 and β_{0j} are called the bias weights, $n1$ is the number of inputs (e.g. number of well logs used) and $n2$ is the number of hidden neurons. $fj(.)$ is the transfer function. A typical function used is the sigmoid function $f(z)=1/(1+e^{-z})$. This mathematical model allows complex combination of inputs (i.e. well logs) and hence avoids manual manipulation of coefficients and exponents in most empirical equations.

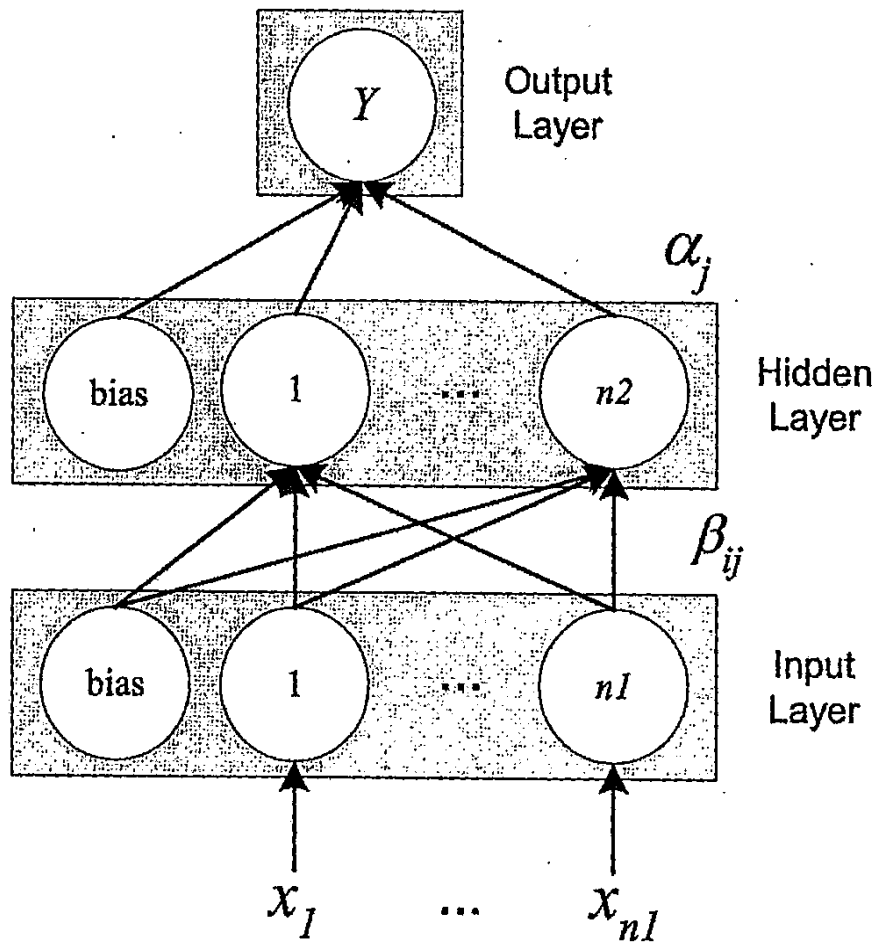


Figure 1. A schematic diagram of a backpropagation neural network. ($x_1 \ldots x_{n1}$) are the inputs, Y is the output, α_j and β_{ij} are the connection weights.

Initial weights (usually small random values) provide a starting point for training. A gradient-descent algorithm is used to recalculate the weights until the total error for all the training patterns is below a tolerance value. At the end of training the weights are saved and the network can be used for prediction. More details are given in Bishop (1995).

It is important to note that, if a network is trained for too long, it will memorise the training patterns and fail to generalise. This situation is known as 'overtraining'. An overtrained network often gives a large error on unseen data. The method to avoid overtraining is a continual area of research. One popular method is the use of a validation data set, which is usually a subset of the original training data set. This data set is used to test the performance of the trained network at a specific number of iterations or 'epochs'. In general, the validation error reduces with epochs and increases beyond a certain epoch. At this point, we may terminate the training process before the performance deteriorates (Fig.1). This process of avoiding overtraining is called 'early-stopping', and while it is easy to implement, it does require a large number of training patterns.

Radial basis function neural networks

Radial basis function neural networks (RBFNNs) present a data-interpolation procedure by non-linear functions in a multi-dimensional space (Bishop, 1995). These networks use the centre-weighted response of a

radial basis function (RBF), which is a symmetrical function (e.g. Gaussian), to learn from the training patterns. The general estimator can be expressed in the following manner:

$$Y = \sum_{j=1}^{n} \alpha_j f_j\left(\left\|\mathbf{x} - \mathbf{r_j}\right\|\right)$$

where α_j are the connection weights, n is the number of RBF centres and denotes the distance between the input vector $\mathbf{x}$ and the reference vector $\mathbf{r}_j$, or the Euclidean norm. The $f_j(.)$ in this case represents a RBF.

Figure 2 shows a schematic diagram of a RBFNN. A distinct characteristic of RBFNN is the use of only one hidden layer. The number of RBF centres determines the exactness of the estimator. If all the training patterns are used as the reference vectors, it is straightforward to see that the weights can be obtained analytically by solving a system of linear equations with unknowns. Hence, the desired outputs of the training set can be reproduced exactly in the model. This type of network is sometimes known as 'interpolation neural network' (Wong and Shibli, 1998). If however, only a portion of the training patterns is retained as the RBF centres, a numerical method (e.g. gradient-descent) is required to iteratively estimate the weights as in BPNNs. The desired outputs can only be approximated (i.e. inexact) in the model. This model is known as 'approximation neural network' (Wang et al, 1999). In practice, both networks are useful, depending on the objectives of the modelling study.

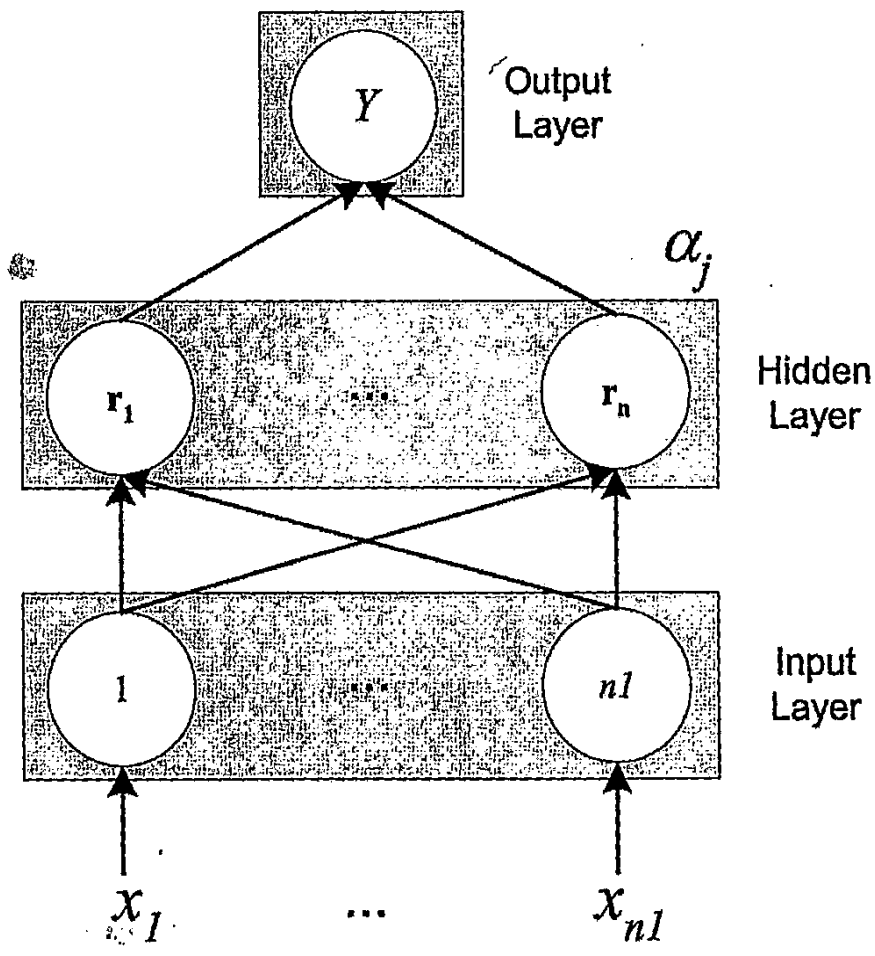


Figure 2. A schematic diagram of a radial basis function neural network. (x_1...x_{n1}) are the inputs, Y is the output, α_j are the connection weights and **r** are the reference vectors.

PREVIOUS WORK

There are many examples of the use of ANNs to estimate permeability from well logs (e.g. Zhang, 1998; Huang, 1999). Some provide advanced models addressing specific problems in well logging, while others put the neural networks into real practice. So far all the published works have shown improvement over conventional methods, including the use of empirical equations and multiple regression. Case studies have been concluded in a number of places, including Australia, Canada, China, India, Indonesia and North and South America. In this paper, we will summarise the innovative aspects of these case studies in six subsections.

Choice of inputs

It is conceptually correct to relate in-situ permeability to permeability-related well log measurements. In practice however, the relationships are too complex and too non-linear. For example, the photoelectric factor log (PEF) is a lithology indicator and the caliper reflects the mud cake thickness. These two logs are in fact related to permeability, but the exact relationships are difficult to derive. This is the major reason for applying the self-adaptive neural networks. It becomes a redundant exercise if neural networks are used to model data generated from a well-defined function. If the networks learn successfully, they will show a stronger connection to the more significant well logs than those which are less significant (Wong et al, 1995a; Fung et al, 1997a). In Wong et al (1998), it was proposed that the caliper and PEF logs had the second and third highest contributions to permeability respectively, while bulk density had the highest contribution.

Apart from well logs, other information can also be included in the network. Rogers et al (1995), Mohaghegh et al (1996) and Huang et al (1996b) used the spatial coordinate of the well log values (including the well positions) as inputs to the network. This is particularly useful for analysing multi-well data as it allows the network to learn the spatial relationships of the data. Garrouch and Smaoui (1998) included the weight fractions of various minerals (quartz, chert, plagioclase and feldspar, calcite and dolomite, chlorite and kaolonite, illite and smectite) together with the mean pore size radius and porosity as inputs.

The generation of additional well logs is also useful for permeability prediction. Combining original well logs can accomplish this. Additional input neurons are required (Fig. 3). It may improve the network performance (Lippmann, 1989). In Wong et al (1998), the average matrix grain surface area (a function of total porosity and shale fraction) and the difference between density and neutron porosity were used as additional inputs. The use of other combinations or even log-derived properties is also possible. Examples include ratio of travel time of the sonic over gamma ray, ratio of the deep and shallow resistivity values, apparent total porosity and apparent

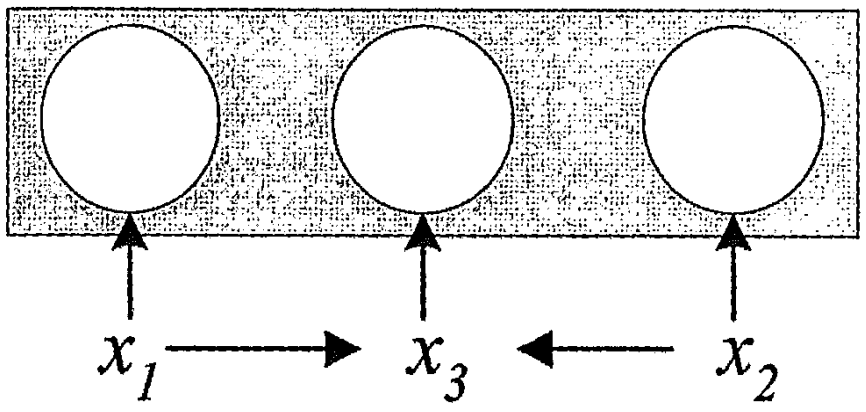


Figure 3. Use of an additional input x_3 at the input layer, where $x = f(x_1, x_2)$.

matrix density (Zhang and Salisch, 1998). The use of non-linear inputs may reduce the complexity of the network topology.

Outlier detection and removal

The presence of outliers in the training set is an important issue in petrophysical evaluation. Most reservoir data are noisy in nature. Generally speaking, the use of noisy data in neural learning has two detrimental effects: slow learning of the good patterns and unnecessary fitting of the outliers. It is therefore desirable to remove the outliers in the training set where possible. Techniques such as 'error sign testing' or EST (Wong and Gedeon, 1995) and Bayesian neural networks (Cho et al, 1999) have been proposed.

The EST technique examines the learning profile of each training pattern. The patterns are classified based on the number of negative signs when taking the difference between the errors at the current epoch and the previous epoch. A bad pattern will have a small number of negative signs showing that the error increases with epochs, or each presentation of the training patterns. The identified bad patterns can then be discarded.

In Cho et al (1999), the authors proposed the use of a recent neural network paradigm, namely Bayesian neural networks (MacKay, 1992), for outlier detection. The unique feature of such networks is the use of a distribution of weights. This allows the calculation of error bars for each training pattern. A pattern with a small error bar may be considered a good pattern. The paper showed that discarding the bad patterns improved porosity prediction by 56% and permeability prediction by 30%.

In Wong and Gedeon (1999), the authors proposed the use of fuzzy reasoning concept (Zadeh, 1993) for training a backpropagation neural network. The technique automatically discounts the contribution of the pattern having a large error during training. This advanced concept avoids the use of an either-or decision on whether a pattern is bad or not, and uses a 'membership function' to quantify the merit of each pattern. Unlike the previous outlier detection methods there is no definite boundary to separate good and bad patterns. This technique is fast and easy to implement for practical field studies (Wong et al, 1998).

Data splitting

The use of BPNNs and RBFNNs requires a training data set. On many occasions, it is important to optimise the configuration of the networks. For example, in BPNNs, it is necessary to obtain the optimum number of hidden neurons. In RBFNNs, it is desirable to use the best type of RBF with the best functional parameters (e.g. the variance in Gaussian function). One method of optimising a network is the use of a validation data set, as discussed in early-stopping. This is only possible if a reasonable number of training patterns is available. A decision must be made as to whether the data set is large enough to sacrifice patterns from training for validation.

If the number of training patterns is sufficiently large, the next technological challenge is how to split the whole data set into two. A number of ways have been proposed in the literature. Firstly, if many wells are available, some wells may be used for training and the rest for validation (White et al, 1995; Wong and Shibli, 1998). There is no theoretical guideline on how many patterns should be used in each data set. The rule of thumb is that the training set should be at least of the same size as the validation set.

However, if the characteristics of the training and validation sets are too different, this poses another problem in early-stopping. The optimum stopping point will tend to bias the patterns in the validation set (Wong et al, 1997). In Wong et al (1996) and Crocker et al (1999), a clustering algorithm, namely self-organising maps or SOMs (Fung et al, 1995; Kohonen, 1995), was applied to divide all the patterns into two groups. The training set was constructed by selecting 50% of the patterns in the first group and 50% in the other group. The remaining patterns were used as the validation set (Fig. 4). This practice ensures that the two data sets contain similar characteristics, and avoids the modelling bias in early-stopping.

Scaling

The incompatibility of the measurement scales of well logs and core data is a significant and well-known problem in core-log integration studies (Ahmed et al, 1989; Worthington, 1997). This is commonly referred to as the 'scaling' problem. Core data typically represent reservoir

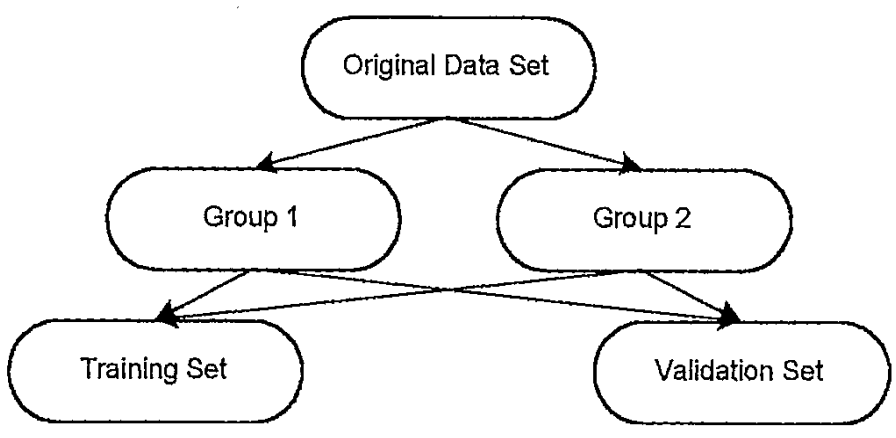


Figure 4. A data splitting procedure.

properties within one-inch plugs. Log data, however, represents averages over a much larger rock volume both radially and vertically. Hence, direct integration of core and log data without any quality control may lead to inaccurate results. In Wong et al (1995c, 1998), they added statistical noise to the permeability estimates. The final values mimicked the core data distribution successfully. However, this technique does not handle the scaling effect in a direct fashion.

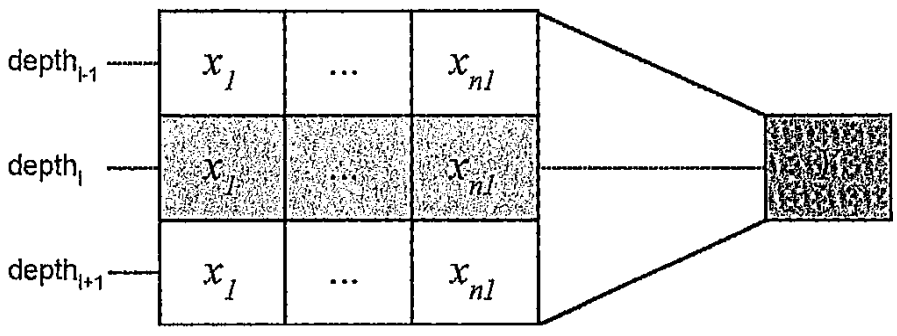
A few techniques to incorporate the scaling effect have been proposed and implemented in neural networks (Fig. 5). Many researchers (Liu et al, 1992; Jenner and Baldwin, 1994; Rogers et al, 1995; Arpat, 1997; Goncalves et al, 1997) used neighbouring log data (points above and below) to predict permeability at the centred-depth (Fig. 5a). This technique uses additional input neurons to encode the neighbouring signals, and has the capability to compensate for any minor depth-matching error between log and core data and also allows matching of the measurement scales. The size of the depth windows depends on the vertical resolution of the well logs used. In Huang et al (1996b), they averaged the neighbouring core permeabilities and related the averaged permeability to the log data (Fig. 5b). This technique is common in many current practices. Recently, Wong (1999) introduced an improved technique to relate the well logs directly to the neighbouring, and often closely spaced, core permeabilities (Fig. 5c). The technique incorporates the averaging effect of the log data and avoids the calculation of average permeability. More discussion is presented in the later sections of this paper.

Multiple networks

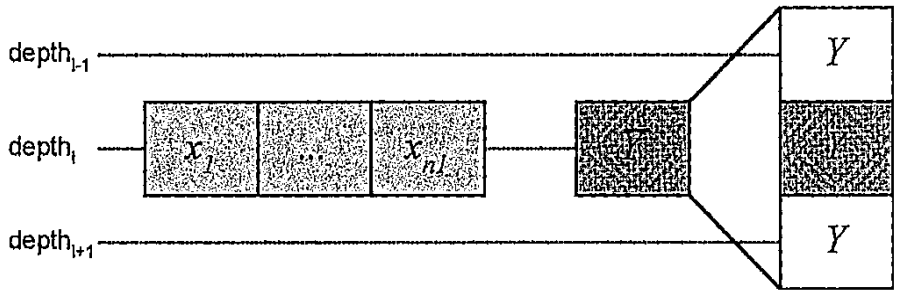
The use of multiple networks aims to subdivide a complex problem into a number of simpler problems (Fung et al, 1997b). There are two ways to connect the individual modules in the system: 1) in series; and 2) in parallel. This section will describe the connection in series, and the next section will discuss the connection in parallel under the heading 'Prediction confidence'.

In multiple networks, each network acts as an individual module to tackle specific problems. Figure 6 shows an example of two networks in series. In this case, they create a result through the first ANN and reassign the output as an input neuron (often along with the original training inputs) into the second ANN. The reassigned output value when applied as an input neuron has the effect of mimicking the shape of the target values. This method avoids averaging by essentially adding a constraint.

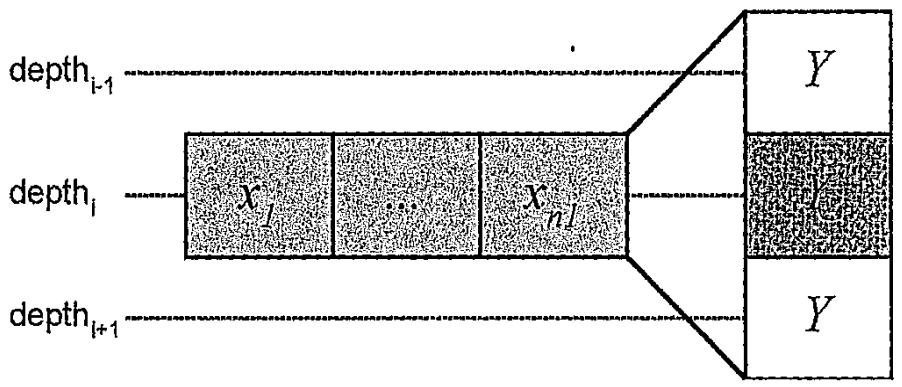
Wong et al (1995b; 1995c) used the concept of multiple networks to predict permeability via lithology. The first network used for lithology, a classification based on conventional well logs. The lithology indicator was subsequently used for permeability prediction in the second network. The lithology information was used as constraints for improved predictions. This concept also follows the geological practice which does not treat the



a) Use of neighbouring logs.



b) Use of average permeability.



c) Use of neighbouring core permeabilities.

Figure 5. Use of neighbouring patterns. (x_1...x_{n1}) are the well logs (inputs) and Y is the permeability (output).

whole reservoir as a single flow unit, but subdivides the reservoir into a number of distinctly different units.

Zhang and Salisch (1998) also used two networks to estimate permeability values. The first network estimated the permeability range, which is essentially a network for classification. The output values of this network were reassigned as an input neuron into the second network that predicted the actual permeability value. The permeability range was used to constrain the quantitative estimate of permeability.

Prediction confidence

Permeability prediction throughout the uncored intervals based on the estimators developed at the cored intervals involves a great deal of uncertainty. It is unrealistic to use a single number to represent the permeability at a particular location. Therefore, it is best to produce a measure of prediction confidence (e.g. prediction range) for each and every prediction. It is a matter of fact that the confidence measure should attach to even the training pattern. This is because of the

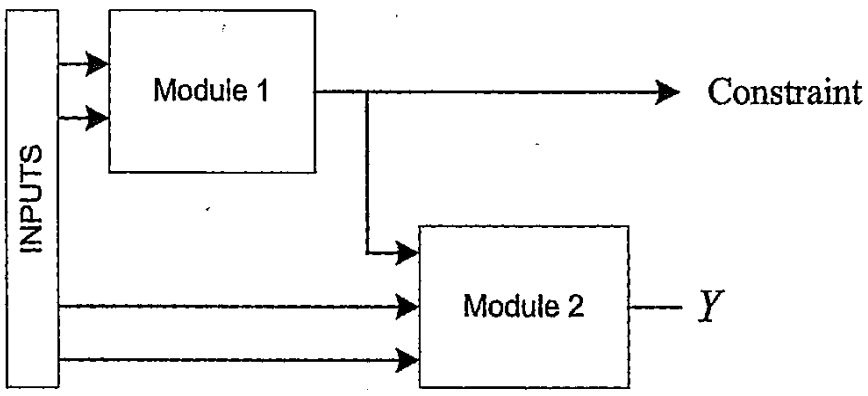


Figure 6. An example of two multiple networks.

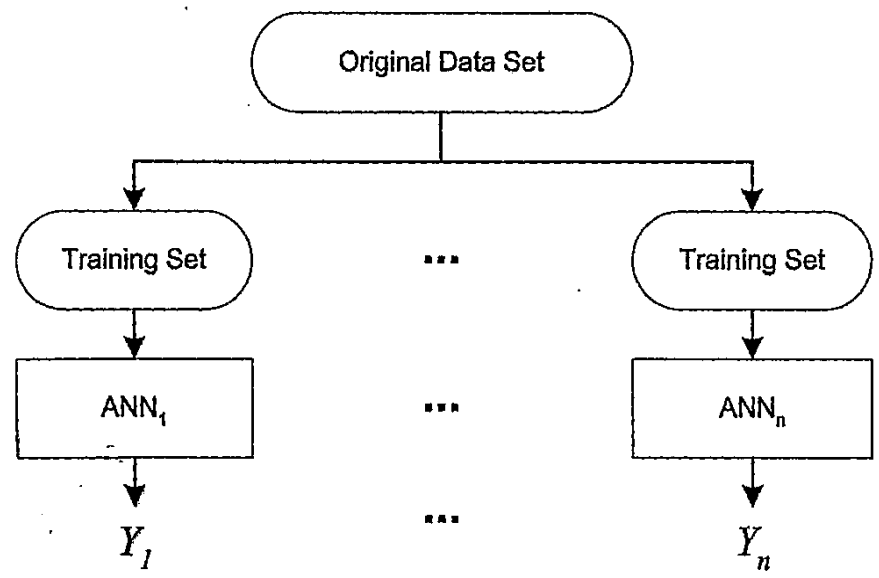


Figure 7. Use of multiple training sets with multiple networks.

presence of errors in the well logs and the core permeability values, and the fact that the core and log-derived permeability values are not of compatible scales. The confidence measure may in fact indicate the quality of each training pattern (Cho et al, 1999).

There are currently three general approaches in neural networks to generate a range of predictions for the same input vector (Figs 7–9): 1) use of multiple training sets; 2) use of multiple networks; and 3) use of error bars.

MULTIPLE TRAINING SETS

In Wong et al (2000), an observational learning algorithm was used to create multiple permeability predictions using the same input logs. The algorithm generates additional training patterns from the original training set (Cho et al, 1998). This is followed by the use of bootstrapping to randomly select training patterns with replacement. This sampling process provides different training sets for training different networks, and hence multiple predictions are obtained (Fig. 7). The technique was applied to two oil and gas wells in an Australian reservoir, and the results showed a 39% to 43% improvement (in terms of errors) in a blind test compared to multiple linear regression. The permeability range also provided valuable information into the reliability of the predictions.

MULTIPLE NETWORKS

The previous section discussed the multiple networks in series. This section shows how connection in parallel generates multiple predictions. Multiple networks use the same training set to train networks with different configurations. The configuration parameters include initial weights, number of hidden neurons and learning the algorithms. The purpose is to capture the uncertainty of the model parameters. The arrangement in parallel produces multiple predictions for the same input data. The difference between the maximum and minimum predictions provides a measure of prediction confidence: the smaller the difference (or range), the smaller the uncertainty, and vice versa. If desirable, the final solution can be combined by a simple weighted method (Huang et al, 2000).

In Bruce et al (1999), the above concept was extended and used multiple training sets to train multiple networks. The approach was applied to a sandstone reservoir in Sumatra, Indonesia. In this case, well log and core data were available from four wells. Since the log responses and the statistics of the core permeability values exhibit different behaviour, a network was trained for each well using its own data set. After training, the well logs of each well were applied to the four networks. The maximum and minimum of the four predictions indicated the complexity of the training patterns. Ideally all the predictions should be identical. The permeability range provides a measure of prediction confidence. This approach avoids averaging and is able to indicate the uncertainty of extrapolation to the uncored intervals.

The permeability profiles of one of the four wells are shown in Figure 8. The profiles show that the permeability range is relatively small in the core intervals and becomes large in some uncored intervals. For example, the clean interval between 4,370 feet to 4,400 feet has a large range value. This is mainly due to the fact that most of the training patterns come from the relatively shaly regions and the clean patterns were under-sampled. The range value is important for indicating the risk for extrapolation or the degree of similarity to the training patterns.

ERROR BARS

Other networks have confidence or error bars built into their algorithms. One example is Bayesian neural networks, which implements backpropagation in Bayesian learning (MacKay, 1992). The model is able to provide a mean and a standard deviation (or error bar) for each prediction. Qu et al (2000) used a Bayesian neural network to estimate permeability for the same data set as in Bruce et al (1999). The results for the same well are shown in Figure 9. The sigma (i.e. standard deviation) profile indicates the prediction confidence, which gives a similar message as in the multiple networks approach.

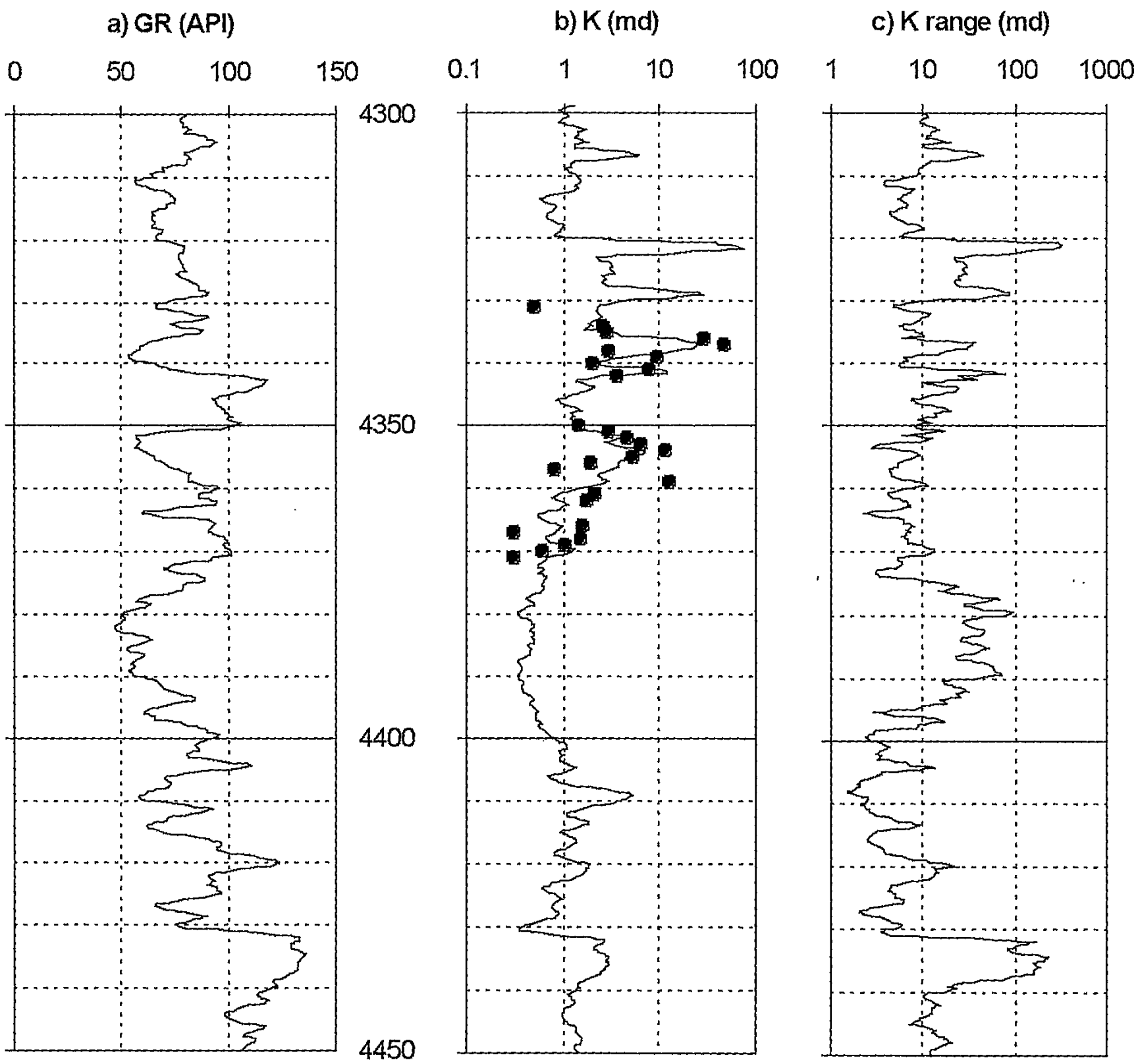


Figure 8. Permeability profiles from multiple networks: a) gamma ray curve; b) permeability prediction with core data; and c) permeability range.

FUTURE TRENDS

The progress shown in previous work encourages further investigation. It is important to understand the limitations of neural networks in petrophysical evaluations. This final section outlines five key research directions for the future use of neural networks.

Core data

The size of the core data set is generally small. It becomes an important issue for the application of any non-parametric techniques. The distributions of training data may not be representative for the whole field. This problem can be further complicated if there is a strong bias in core sampling strategy (e.g. coring in only high permeability sands) in heterogeneous cores. Further work should be focussed on the generation of additional training patterns and the identification of outliers (e.g. Cho et al, 1999).

Well logs

The current neural networks can only use the common well logs available for all wells. The application of such networks in new wells will certainly require the same types of well logs used for training. In practice, however, it may be difficult to conduct the same logging program

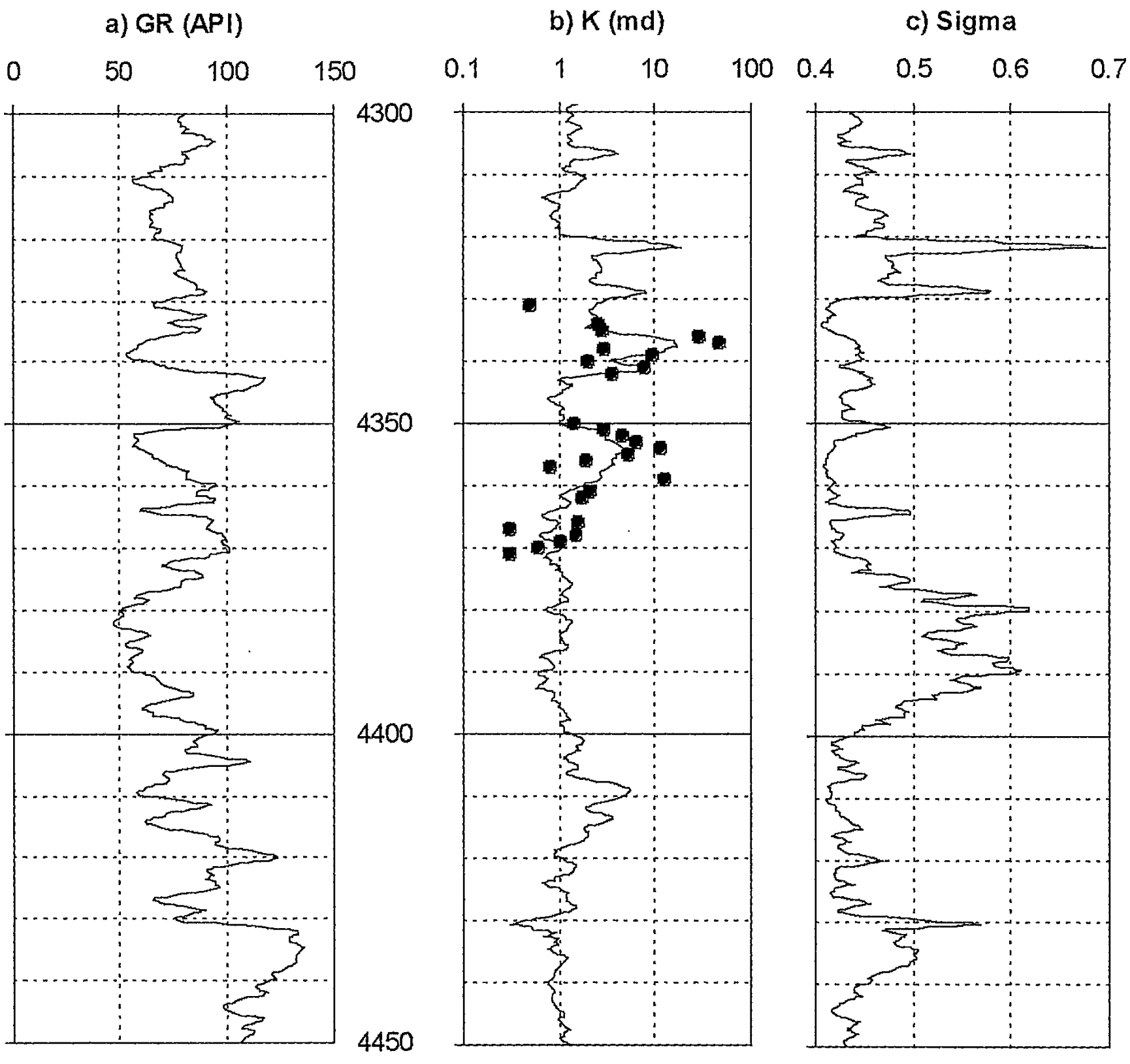


Figure 9. Permeability profiles from Bayesian network: a) gamma ray curve; b) permeability prediction with core data; and c) sigma (standard deviation) curve.

for all wells. Mud logs also contain valuable information, but they are currently under-utilised in this problem domain. It is therefore important to develop improved techniques to maximise the use of all well data.

Scaling

The incompatibility of the measurement scales of well logs and core data will remain a physical problem for any core-log correlation studies. The development of better logging tools will reduce the extent of the scaling problem. Nevertheless, direct integration of core and log data at a given depth may lead to inaccurate and unrealistic results. It becomes necessary to incorporate the vertical trends and fluctuations of the log curves and the boundary effects across beds with distinct characteristics. More studies are required to investigate the contribution of the neighbouring beds.

Soft computing

Neural networks are increasingly used together with other intelligent techniques (e.g. fuzzy computing and evolutionary computing) for performance enhancement. The various disciplines of artificial intelligence are no longer competing with each other, but rather providing

capability and flexibility to each other. Such hybrid use is now known as 'soft computing' (Zadeh, 1993; Tamhane et al., 2000). Techniques such as neural-fuzzy (Huang et al, 1996a; Huang et al, 1997), neural-genetic (Huang et al, 1998b) and neural-fuzzy-genetic (Huang et al, 1998a; Huang et al, 2000) are emerging for industrial applications. The future work includes the use of advanced techniques to incorporate prior geological knowledge (including the permeability from the empirical equations) and to provide reliable extrapolation from the cored intervals to the uncored intervals.

Prediction confidence

Uncertainty is an important issue in permeability prediction. The present approach to quantify the uncertainty is to examine the closeness of the permeability estimates from, at least, two independent predictors. This approach is in fact not valid because it implicitly assumes the validation of the assumptions behind the two predictors that are often contradictory. It is important to understand the sensitivities of a predictor before comparing the performance of various predictors. It becomes necessary to provide a range of predictions, rather than a single prediction.

Some techniques have been proposed to produce a range of permeability values using the same input pattern. The range or standard deviation of the prediction provides a quantitative measure of prediction confidence. The change of such measures with depth may indicate the degree of heterogeneity in the reservoir (Bruce et al, 1999; Wong, 1999; Qu et al, 2000). The future research lies on the correlation of the uncertainty measures with the well logs and the regional geology.

CONCLUSIONS

This paper summarises the current state-of-the-art of permeability prediction using artificial neural networks. Two models, known as backpropagation and radial basis function networks, have been applied. Five major research directions in the future are identified:

1. the quality and quantity of core data;
2. the maximum use of the well logs;
3. the compatibility of scales;
4. the use of soft computing; and
5. the management of prediction confidence.

These areas deserve special attention from academia and industry. The current applications are certainly the beginning of a new era. It is important for petrophysicists to take advantage of the advanced technologies.

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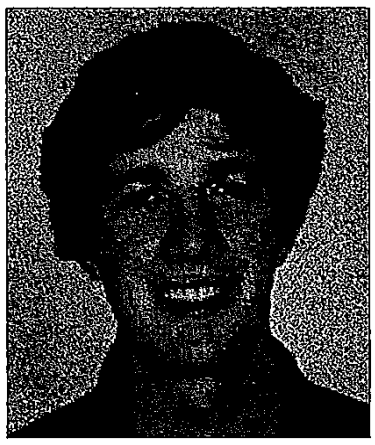
Authors' biographies over page.

APPEA

THE AUTHORS



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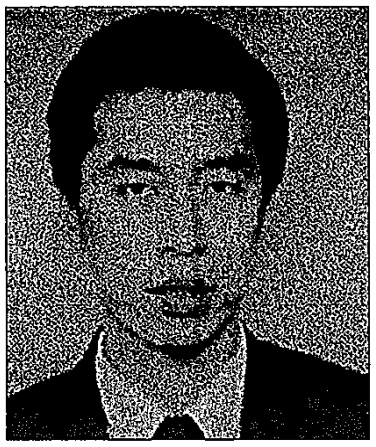

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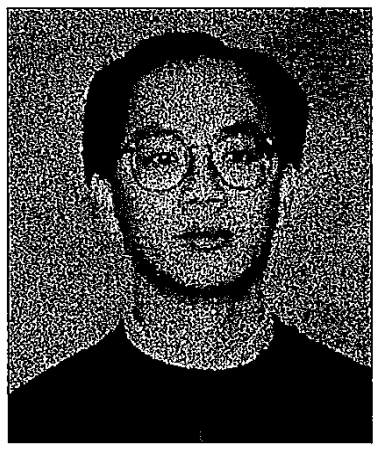

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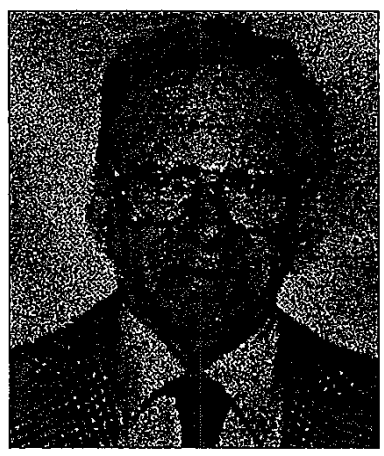

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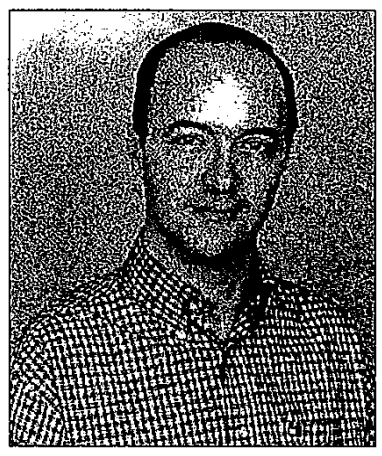

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