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Application of Committee Machines in Reservoir Characterisation While Drilling: A Novel Neural Network Approach in Log Analysis

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Abstract
We have applied a new parallel architecture of the neural network, the committee machine (CM), that represents a powerful extension of the neural techniques for log analysis in petroleum geosciences. The new approach, initially applied to wireline (WL) data, is further developed and tested on measurements while drilling (MWD) data.

Prediction of porosity, permeability and fluid saturation from MWD data is feasible and thus can be made while drilling to provide reservoir properties for real-time reservoir simulation and geosteering. The flexibility of the CM architecture permits attached gating networks that constraint output based on prior data or specified range limits. We show that prior data, supplied by the gating networks, significantly enhance the power of the neural network techniques by eliminating ambiguities in the identification of lithofacies.

The CM approach for quantitative log conversion is more robust than the single neural network. Since while training the individual networks reach slightly different minima of the objective function, the overall accuracy is improved by combining output from a number of nets.

Once properly trained and tested, the networks are fast and more accurate than classical methods based on linear multivariate regression. The trained networks have been used successfully in bulk conversion of WL and MWD logs to reservoir properties.

Introduction
Porosity, permeability and fluid saturation are the key variables for characterising the reservoir and for determining flow patterns in order to optimise production of a field. Reliable predictions of porosity and permeability are also crucial for evaluating hydrocarbon accumulations in a basin-scale fluid migration analysis and to map potential pressure seals for reduction of drilling hazard.

Several relationships have been offered which can relate porosity to wireline readings such as the sonic transit time and density logs. However, the conversion from density and transit time to equivalent porosity values is not trivial. The common conversion formulas contain terms and factors that depend on the individual location and lithology, e.g. clay content, pore fluid type, grain density and grain transit time for the conversion from density and sonic log, respectively. In general, these are unknown quantities that remain to be determined from rock sample analysis.

Permeability is also recognised as a complex function of several interrelated factors such as lithology, pore fluid composition and porosity. Thus, estimates from well logs often rely upon porosity e.g. through the *Kozeny-Carman* equation that also contains adjustable factors

such as the *Kozeny* constant that varies within the range 5-100 depending on the reservoir rock and grain geometry (Rose and Bruce, 1949). Nelson (1994) gives a detailed review of these problems.

Evaluation of fluid saturation and identification of fluid type also constitute complex tasks. In a uniform lithology the resistivity and neutron logs are normally sufficient indicators of the fluid type whereas in a mixed lithology such as shaley sandstone the common methods suffer from ambiguity. Similarly, a quantitative interpretation of fluid saturation in a mixed lithology is a non-trivial problem that involves several steps of log interpretation in order to determine the input variables such as porosity and clay content. Moreover, accurate evaluation of fluid saturation requires the use of core data to determine key parameters in the conversion scheme such as that of the commonly used *Indonesian Equation* of Poupon *et al*. (1971).

Neural networks for quantitative analysis of reservoir properties from well logs have been demonstrated in several practical applications and the artificial neural network (ANN) approach is shown to be an accurate and pragmatic alternative for converting well data to the commonly used reservoir parameters (Huang *et al*., 1996; Huang and Williamson, 1997; Helle *et al*., 2001). In previous work single multi-layered ANNs have been used to convert log readings to formation properties. In this study we apply a new type of network called a committee machine (CM), where the simple ANNs are interconnected in parallel structures. The CM for quantitative prediction of reservoir properties consists of a number of identical networks (experts) trained on the same pattern or a subset. The underlying philosophy is that of dividing a complex problem into a number of computationally simple tasks, and then combining the solutions of those tasks into a solution of the complex computational task (see e.g. Haykin, 1999). Here, a number of artificial neural networks for each property, i.e. porosity, permeability and partial fluid saturation have been trained and tested. For each property the output from the network branches are combined using the optimal linear combination approach (OLC) of Hashem (1996) enabling improved accuracy and robustness compared with the single network approach.

In this work we have applied the CM approach to reservoir characterisation using measurements while drilling (MWD) data from highly deviated and horizontal wells. For technical and economical reasons cores are normally not collected in highly deviated and horizontal wells. Core data for calibrating the petrophysical analysis of MWD data are thus not commonly available. On the other hand, a pilot well is often drilled through the reservoir where both MWD and wireline (WL) data have been acquired, allowing for a calibration of the MWD networks based on the formation properties established from the WL data and calibrated neural nets for the actual field. In this study the patterns for training the MWD networks are based on the networks established for WL data by Helle *et al*. (2001).

The ultimate objective is to provide the complete reservoir characterisation while drilling in order to perform a real-time reservoir simulation of the near-bore fluid flow for optimisation of well completion. Partial fluid saturation predicted by neural nets and the normalised relative permeability curves from laboratory studies are in turn used to generate the relative permeability logs for each fluid type. The power of the CM approach is further demonstrated when applied to identification of lithofacies from well logs.

Committee Machines

The back propagation artificial neural network (BP-ANN) is a relatively new tool in petroleum geoscience that is gradually emerging into several practical applications including seismic analysis. It simulates the cognitive process of the human brain and is well suited for

solving difficult problems which are not amenable to conventional numerical methods such as character recognition (Lawrence, 1994; Patterson, 1996; Haykin, 1999). The ANN functions as a non-linear dynamic system that learns to recognise patterns through training. The network (Figure 1) has two major components: *nodes* (or neurons) and *connections* (which are weighted links between the neurons). Upon exposure to training examples (*patterns*) the neurons in an ANN compute the activation values and transmit these values to each other in a manner that depends on the learning algorithm being used. The learning process of the BP-ANN involves sending the input values forward through the network, and then computing the difference between the calculated output and the corresponding desired output from the training data set. This error information is propagated backwards through the ANN and the weights are adjusted. The process is iterated until the calculated output values best approximate the desired values. The similarities between BP-ANN and the common geophysical inversion techniques are obvious.

Committee machines belong to a new class of neural network architecture (Haykin, 1999) that has a potential to improve the accuracy and expand the practical application of neural networks. Basically, the CM combines knowledge acquired by a group of experts to arrive at an overall decision that is superior to that of the individual expert acting alone. Here we have applied the simple version of the CM consisting of *K* individual BP-ANN (Figure 1) which share a common input and whose individual outputs are combined to produce an overall output as shown in Figure 2. This technique is referred to, as an *ensemble averaging method* and the motivations for its introduction are the following:

- If a single network replaces the combination of experts in Figure 2, this network would have a correspondingly large number of adjustable parameters. The training time for such a large network is likely to be longer than for training all the experts in parallel.
- The risk of over-fitting the data increases when the number of adjustable parameters is large compared to the number of training facts (*cardinality*).
- While single networks are prone to errors caused by ambiguity in the minima of the objective function (Figure 1) the weighted ensemble output from the CM implies reduction in errors.
- A gating network can conveniently be attached to the CM (Figure 3) to split the permeability range for improving the over-all resolution. Similarly, *prior* data can conveniently be added through a gating network to help in resolving closely spaced or overlapping clusters in lithofacies identification using local model constraints.

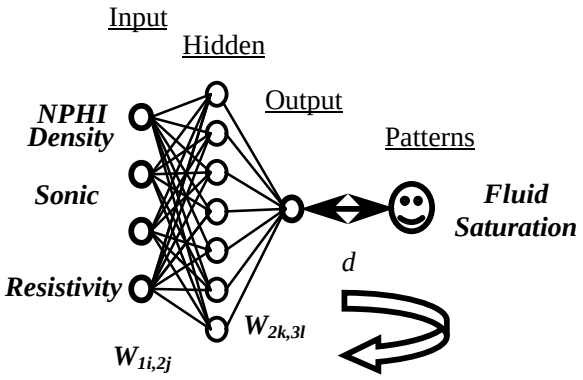

Figure 1. Architecture of a *BP-ANN*. The symbols $W_{1i,2j}$ and $W_{2k,3l}$ are the weights connecting the input and hidden layer, and output and hidden layer, respectively. The networks used in this study have the same architecture but differ in the number of hidden neurons according to the complexity of the problem; i.e. 10 neurons in the networks for porosity and water saturation, and 15 in the permeability network.

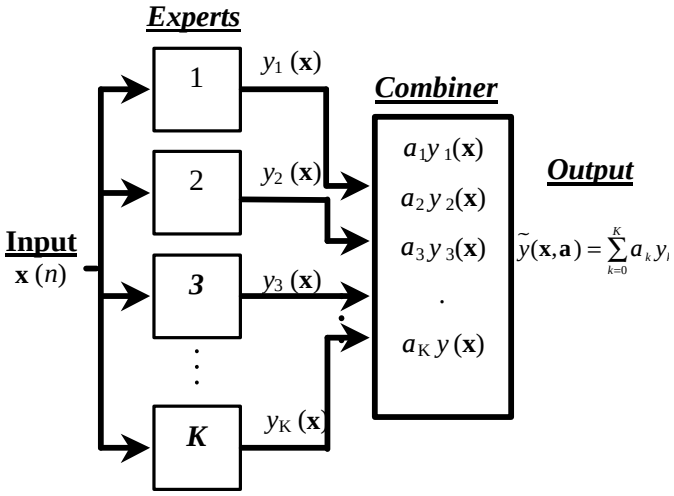

Figure 2. Block diagram of a *committee machine* based on *optimal linear combination* of networks. Each of the experts is a *BP-ANN* as shown in Figure 1. The networks are individually trained by using identical patterns, but with individually randomised initial weights $W_{i,j}$.

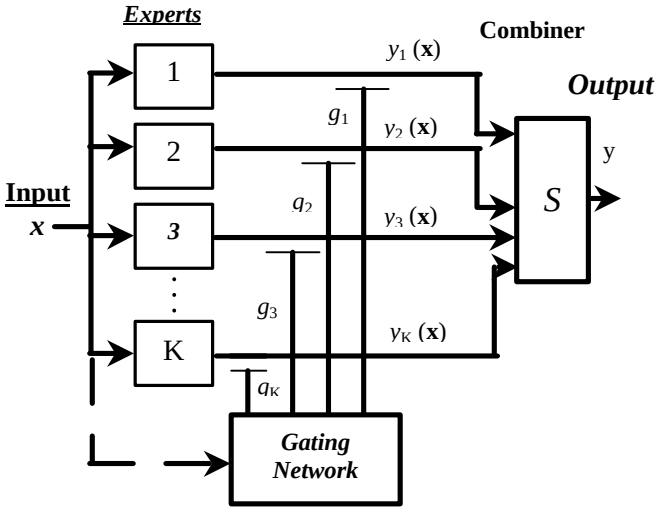

Figure 3. Block diagram of a *committee machine* using a *gating network* to trigger the output from individual experts. In the case of permeability, each expert constitutes an OLC-CM as shown in Figure 2. In the case of lithofacies prediction (Figures 12-13), the gating network contains the prior data of the local geology.

In using the committee machine in quantitative prediction, the expectation is that the differently trained experts converge to different local minima on the error surface, and the overall performance is improved by combining the outputs in some way. As demonstrated in the error analysis of Naftaly *et al*. (1997):

- The bias of the ensemble averaged-function $F_I(\mathbf{x})$ pertaining to the committee machine is exactly the same as that of the function $F(\mathbf{x})$ pertaining to a single neural network.
- The variance of the ensemble-average function $F_I(\mathbf{x})$ is less than that of the function $F(\mathbf{x})$. These theoretical findings point to a training strategy for reducing the overall error produced by the committee machine due to *varying initial conditions* (i.e. random initial weights).
- The individual expert should be purposely over-trained to reduce the bias at the cost of the variance (Figure 4).
- Subsequently, the variance is reduced by ensemble averaging the experts over the initial conditions, leaving the bias unchanged.

According to Hashem (1996) the ensemble averaging technique can be further improved by an optimal combination of the individual networks in the ensemble (Figure 2). By assigning different weights to the output of the individual network the combined output from the *K* experts may be expressed by the weighted sum

$$\tilde{y}(\mathbf{x},\mathbf{a}) = \sum_{k=1}^{K} a_k y_k(\mathbf{x}) \qquad (1)$$

where $y_k(\mathbf{x})$ is output from the individual network, $a_k, k = 1, K$ are the weights and $\mathbf{x}=\{x_i; i = 1..N\}$ is the input vector. The requirement is to evaluate a_k so that $\tilde{y}$ provides a least-squares estimate of the desired response *r*(x). Given a set of training data *r*(x) the approximation error is $d(x;a) = r(x) - \tilde{y}(x;a)$. In order to correct for any bias Hashem *et al.* (1994) extended the definition of $\tilde{y}(x;a)$ to include a constant term a_0. Thus, the modified $\tilde{y}(x;a)$ is expressed by

$$\tilde{y}(\mathbf{x},\mathbf{a}) = \sum_{k=0}^{K} a_k y_k(\mathbf{x}) = \mathbf{a}'\mathbf{y}(\mathbf{x}) \qquad (2)$$

where $\mathbf{a}'$ and $\mathbf{y}(\mathbf{x})$ are $(K+1)\times 1$ vectors and $\mathbf{y_0(x)=1}$. As demonstrated by Hashem (1996) the unconstrained mean-squared error (MSE) optimal linear combination (OLC) of weights as given by eq. 2 is equivalent to regression of $r(\mathbf{x})$ against $y_k(\mathbf{x}); k = 1, K$ with an intercept term a_0, i.e.

$$r(\mathbf{x}) = a_0 + \sum_{k=1}^{K} a_k y_k(\mathbf{x}) + e \qquad (3)$$

where *e* is a random error with zero mean. From a selection of alternative MSE-OLC investigated by Hashem (1996) this particular form exhibits minimum theoretical error. A comparison of bias and variance for 9 individual networks for water saturation is shown in Figure 5. Using the OLC approach the bias is effectively removed and variance reduced compared to that of the simple averaging.

The problems of log conversion

Porosity

Geophysical well logs generally provide a better representation of *in situ* conditions in a lithological unit than laboratory measurements because they sample a larger volume of rock around the well and provide a continuous record. However, as with most well logging measurements, the log does not directly measure the parameter with which it has become associated, e.g. the sonic and density logs do not measure the porosity directly but instead porosity can be calculated from the measurements given knowledge of the grain and the fluid properties. A discussion of the problem is given in Helle *et al.* (2001). It thus seems obvious that no single log measurement is sufficient to obtain reliable values of porosity. Additional data would be required of the pore fluid and grain material, which normally are not at hand except for special studies in cored reservoir intervals. This is demonstrated in Figure 6 where we have combined wireline readings of sonic velocity and laboratory data of grain density r_g. A more consistent velocity-porosity transform can clearly be obtained if clay content is taken into account. Moreover, by including the total organic content *TOC* as the third independent variable we have demonstrated that the linear least squares fit can be further improved. However, these relations are of limited practical value because they require the clay content and organic content to be accurately estimated, which is hard to do in practice given the limitations in the semi-empirical relations based on the gamma-ray and resistivity logs. In Helle *et al.* (2001) we demonstrate that several logs combined in an artificial neural network

provide accurate porosity estimates for any combination of grain material and pore fluid. In this paper we extend this technique to CM and application to MWD data.

Permeability

While porosity is fairly linearly related to the sonic and density readings, the common permeability transforms indicate non-linear relations between permeability and the same physical measurements, e.g. the standard *Kozeny-Carman* equation. The relation between log readings and permeability is more complicated than that for porosity and, moreover, additional physical measurements are required to represent its value. Schlumberger (1989) provides various published forms of the relationship between porosity and permeability. In the following sections we will show that accurate conversion from MWD data to permeability can be obtained by using the neural network alternative rather than the semi-empirical transforms. A more complex network may be required for permeability compared to porosity in order to account for the non-linearity.

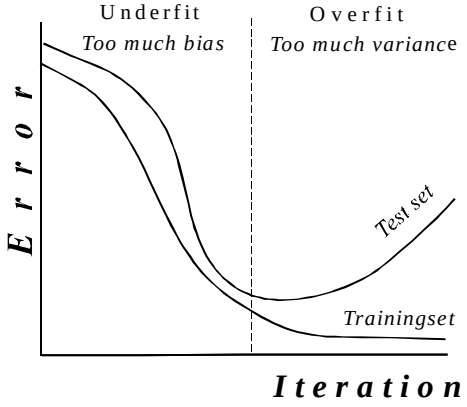

Figure 4: Generalisation versus training error for a single neural network. Training error can be reduced below any level by over-fitting the training data at the cost of increasing error when applied to the unknown test data.

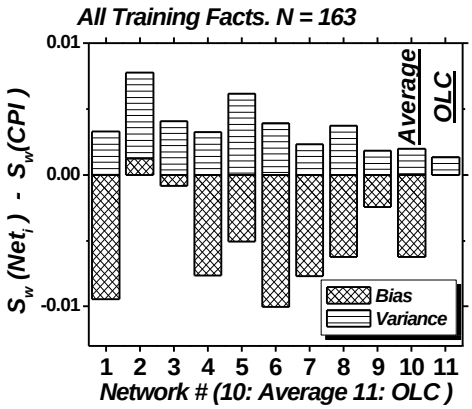

Figure 5: Comparison of bias and variance of the 9 individual networks in the CM. Ensemble average and *OLC* are shown for comparison.

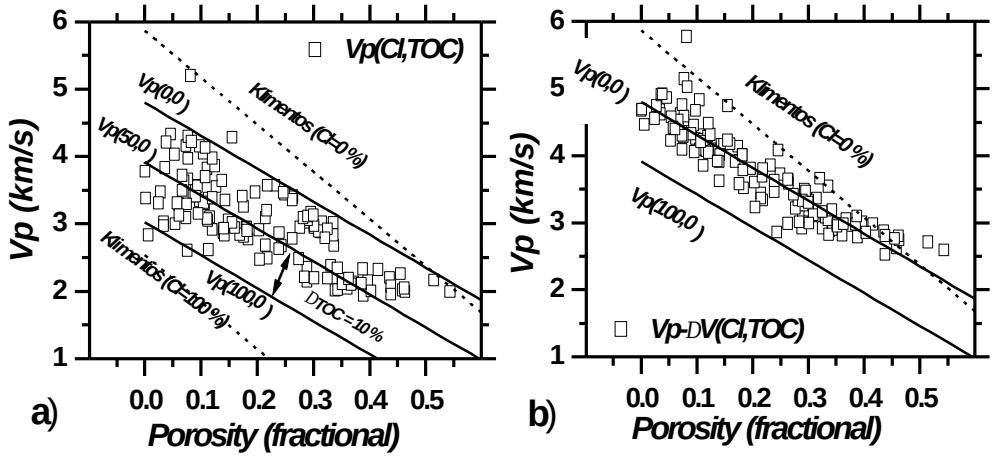

Figure 6: (a) Empirical velocity-to-porosity transform obtained from linear regression by combining logs (sonic, density) and laboratory data (grain density, clay content and total organic carbon) from Northern Viking Graben. A change of 50% (vol.) in clay content *Cl* has approximately the same effect on V_p as a change of 10% (vol.) in total organic carbon *TOC* as indicated by the arrow. (b) By accounting for *Cl* and *TOC* the velocity-porosity transform may be significantly improved. The result the equation of Klimentos (1991) is shown for comparison.

Water saturation

Water saturation in clean (non-shaly) formations with inter-granular porosity is determined by Archie's equation.

$$S_w^n = \frac{FR_w}{R_t} \tag{4}$$

where R_w is the formation water resistivity, R_t is the true formation resistivity and F is the true formation resistivity factor. F is usually obtained from the measured porosity of the formation by the relationship

$$F = \frac{a}{f^m}. \tag{5}$$

In shaley formations the determination of water saturation is a more complicated task. One of the models commonly used in the North Sea for calculating effective water saturation S_{we} in shaley formations is that provided by Poupon *et al*. (1971) who claim that their model is independent of the clay distribution. Based on a modified Archie's equation the relationship between the true resistivity and the formation parameters has been established by the equation

$$\frac{1}{\sqrt{R_t}} = \left(\frac{V_{sh}^{\left(1-V_{sh}/2\right)}}{\sqrt{R_{sh}}} + \frac{f_e^{m/2}}{\sqrt{aR_w}} \right) S_{we}^{n/2} \tag{6}$$

where R_t is the true resistivity of the formation as evaluated from the deep resistivity log, R_w is the resistivity of the formation water (brine) at formation temperature, R_{sh} is the resistivity of the shale and V_{sh} is the volume fraction of shale in the formation. as determined from the shale sensitive logs such as gamma ray, or from a combination of neutron and density. Here f_e is the effective porosity of the formation, i.e. excluding shale porosity. f_e is calculated by using the bulk density values from the density log, the grain density measurements for matrix density and the fluid density using the standard density-to-porosity transform.

The factor a and the exponents m, n are the constants that remain to be determined. The exponent m is the so-called cementation factor that depends on the shapes and distribution of pores and n is the saturation exponent. These unknowns are in principle determined from measurements of resistivity on core plugs fully saturated (S_{we}=1.0) with pure water (R_0) and formation water (R_w), respectively, and then using Archie's equation (4)

$$\frac{R_0}{R_w} = \frac{a}{f_e^m} \tag{7}$$

to determine m by assuming a=1.0. From partially water saturated core plugs and resistivity measurements at ambient conditions the saturation exponent n is determined experimentally and, again by using Archie's equation (4),

$$\frac{R_t}{R_w} = S_{we}^{-n}. \tag{8}$$

Determination of water saturation thus implies a series of complex and time-consuming steps for a skilled log analyst. In addition to laboratory data for grain density and resistivity, an accurate log interpretation for porosity and clay content is required. However, when saturation data for a field already has been established we will demonstrate below that the knowledge of a skilled log analyst, and valuable laboratory data from special core analysis, conveniently can be imbedded in a neural network system and applied to future wells in the field.

The Porosity Network

Since cores for calibrating the petrophysical analysis of MWD data are not commonly available, the calibration of the MWD networks rely on the formation properties established from the WL data and the calibrated neural nets for the actual field. Thus training patterns for the MWD network are the output from WL network of Helle *et al*. (2001) in wells where both MWD and WL data were acquired. This network uses density, resistivity and sonic logs as input. The majority of the porosity values are based on grain density laboratory measurements and bulk density from wireline data (Lucas, 1998) which were carefully selected to obtain a range of values appropriate for most sediments in the Viking Graben (Bhatt, 1998). Since the main objective was basin-scale fluid flow analysis, the training facts were dominated by non-reservoir intervals from Tertiary to Jurassic levels, including reservoir intervals of the Brent formation where standard core data were available. We added some points from the hydrocarbon bearing interval of reservoir which contained patterns from the Helium core porosity measurements from the laboratory. The training patterns cover the porosity range 0.02-0.55. The network for predicting porosity from MWD data consists of 3 input neurons corresponding to the density, neutron porosity and resistivity logs. The hidden layer has 10 neurons and the output layer has a single neuron (Figure 1). The training patterns were selected from water and hydrocarbon bearing intervals of the reservoir, as well as non-reservoir sections. The selected training patterns cover the porosity range 0.02-0.32. We trained the K=9 identical networks with the same input data, but with individual randomised initial weights. The slightly different output from these networks were combined using the OLC technique of (Hashem, 1996). A comparison of the porosity predicted by the MWD network, the WL network and helium core porosity in a training well is shown in Figure 7. This is a unique data set where all data types are available within the same depth range. The difference between the measured helium core porosity and that predicted by the MWD network gives a mean error of 0.009 and a standard deviation of 0.02 porosity fractions which are probably better figures than in general can be expected in wells unknown to the network.

The Permeability Network

While porosity is a scalar quantity, permeability is a tensor with significant anisotropy. Even in a good reservoir rock the in-bedding permeability K_h may be twice the bedding-normal permeability K_v. For well sections non-normal to the sediment layers this is an obvious problem since we use the K_h values from core in training our networks. On the other hand, since permeability anisotropy is confined to a much smaller scale (~0.1m) than the spatial resolution of logging tools (~1m) we believe that anisotropy is not a major source of errors for log based predictions. Errors in core permeability due to pressure effects and core sampling procedures comprise a more serious problem (Jacobson, 2000). We have used the K_h core values to represent the formation permeability throughout this study.

The MWD permeability network has 3 neurons in the input layer, i.e. density, neutron porosity and gamma ray logs, 15 neurons in the hidden layer and 1 neuron in the output layer. The training patterns cover the permeability range of nD to about 7 D (–6.6 to 3.82 in logarithmic mD). Like the porosity network, the patterns for training the MWD networks are based on the predicted values from the networks established for WL data by Helle *et al*. (2001). In the WL network the input layer consisted of 4 neurons, i.e. density, neutron porosity, gamma ray and sonic log. The hidden layer has 12 neurons and a single neuron in the output layer. The patterns for the WL network are Klinkenberg corrected air permeability measured on cores. Data points from oil, water and gas bearing sections of the reservoir have

been included. Low permeability shale points have been added to increase the dynamic range of the data set. The problems and errors involved in combining air permeability data at room conditions with log measurements at downhole conditions are discussed in more details by Worthington (1991) and Helle *et al*. (2001).

The numerical range of the permeability values within a reservoir, i.e. a few orders of magnitude, is another problem that we have attempted to overcome by the following procedure:

- We split the range into several (N=3 by experience) sub-ranges by sorting the patterns into N overlapping subsets. For each sub-set we establish a CM with K nodes using the OLC approach (Figure 2).
- Then the K number of CMs are combined into a new CM with N nodes, each representing the permeability in its sub-range. A gating network (Figure 3) was used to trigger the range selection and the final output. In this case the gating network is simply a permeability network with low resolution but which is valid for the entire range.

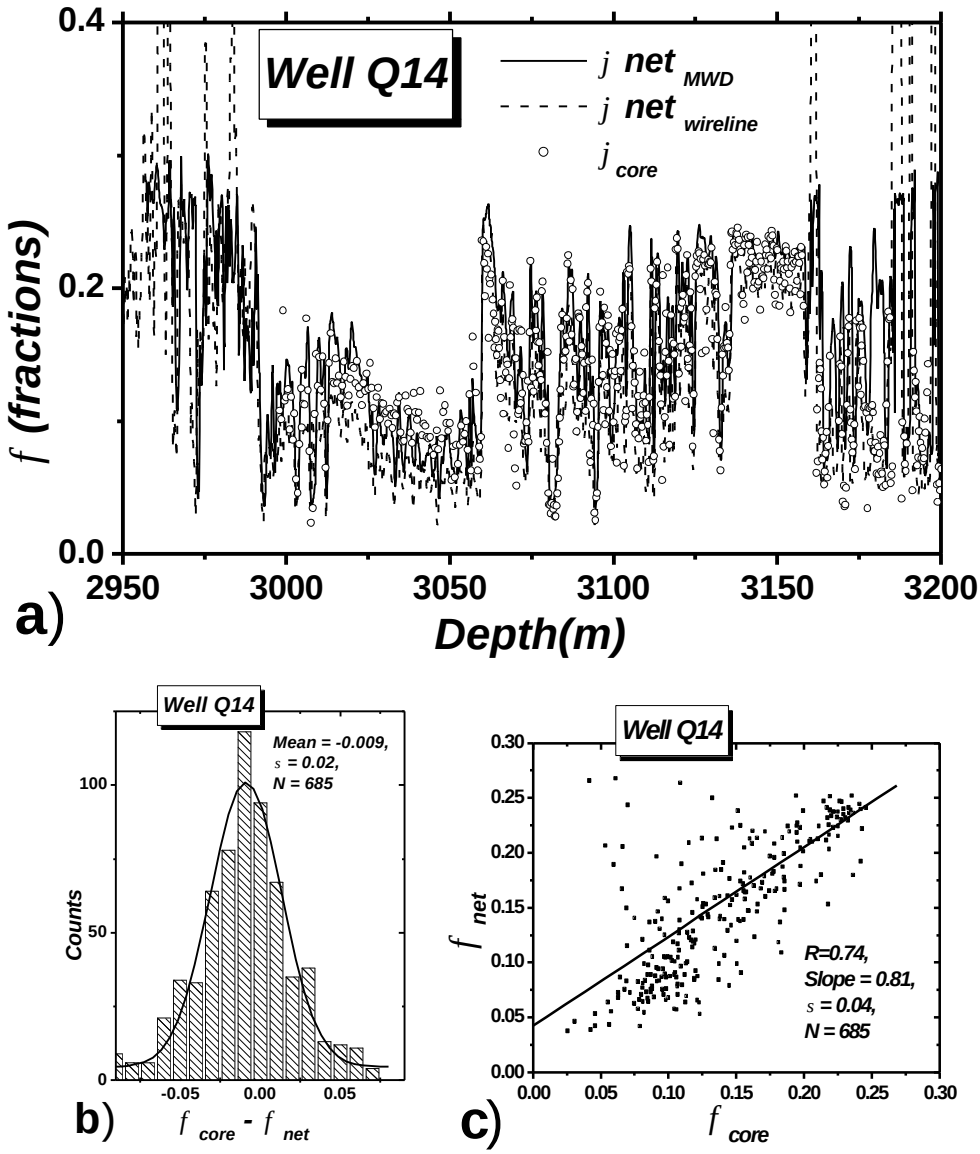

Figure 7: (a) Comparison of porosity predicted from MWD data with standard helium core porosity values. (b) Error histogram and (c) crossplot.

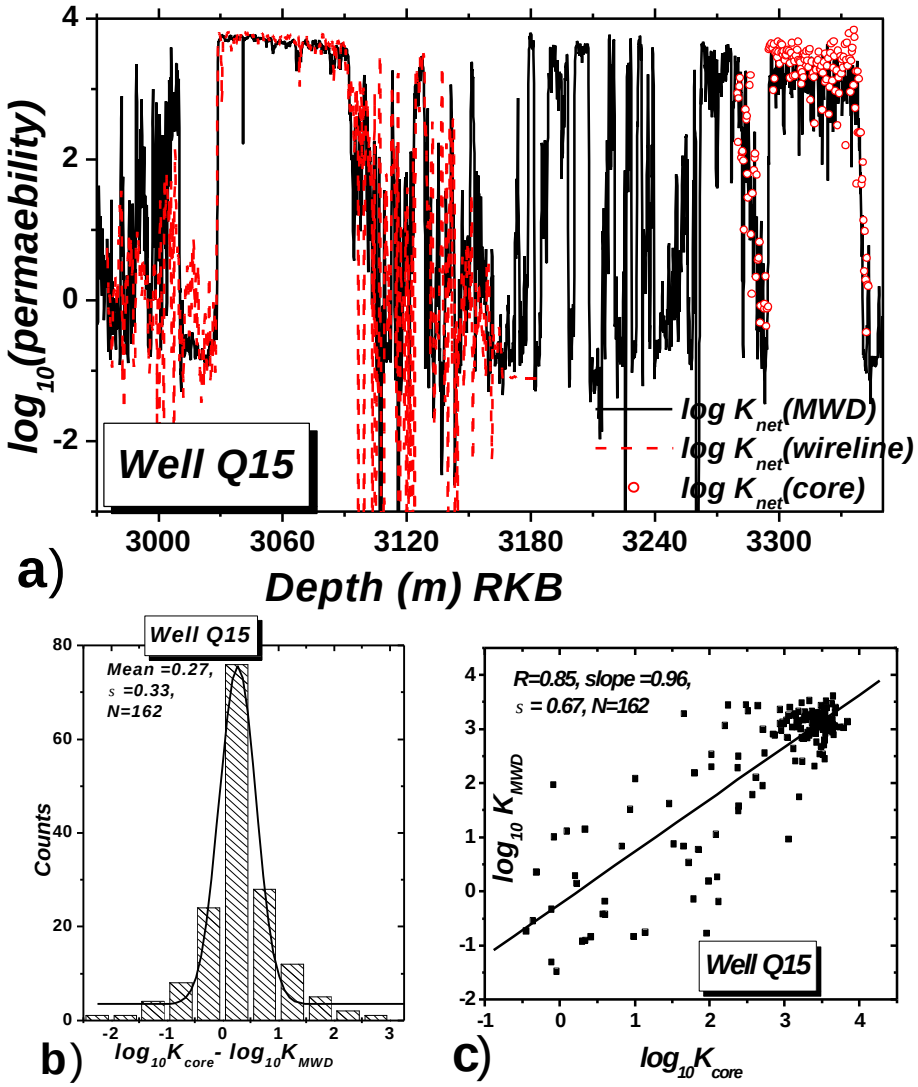

Figure 8: (a) Comparison of permeability prediction using MWD, wireline and core data in a training well. (b) Error histogram and (c) crossplot.

A comparison of permeability predicted by the WL network, the MWD network and core permeability is shown in Figure 8. The difference between the logarithm of core permeability and the predicted permeability gives a mean error of 0.27 and a standard deviation of 0.33.

By introducing the CM approach with range splitting we experience in general an improvement in accuracy in the permeability prediction, compared to the single network and the results based on linear multivariate techniques. A comparison has been made between the permeability predicted by using single neural network, parallel neural networks (OLC) and the classical multivariate techniques in Figure 9. From the error analysis (Figure 9b) the bias is the same for the single ANN and the OLC prediction, and the standard deviation shows only minor improvements in the favour of OLC. However, by inspecting the details in logs, e.g. around 2690 m and 2740 m depths we see that the OLC prediction reproduces more details of the core data.

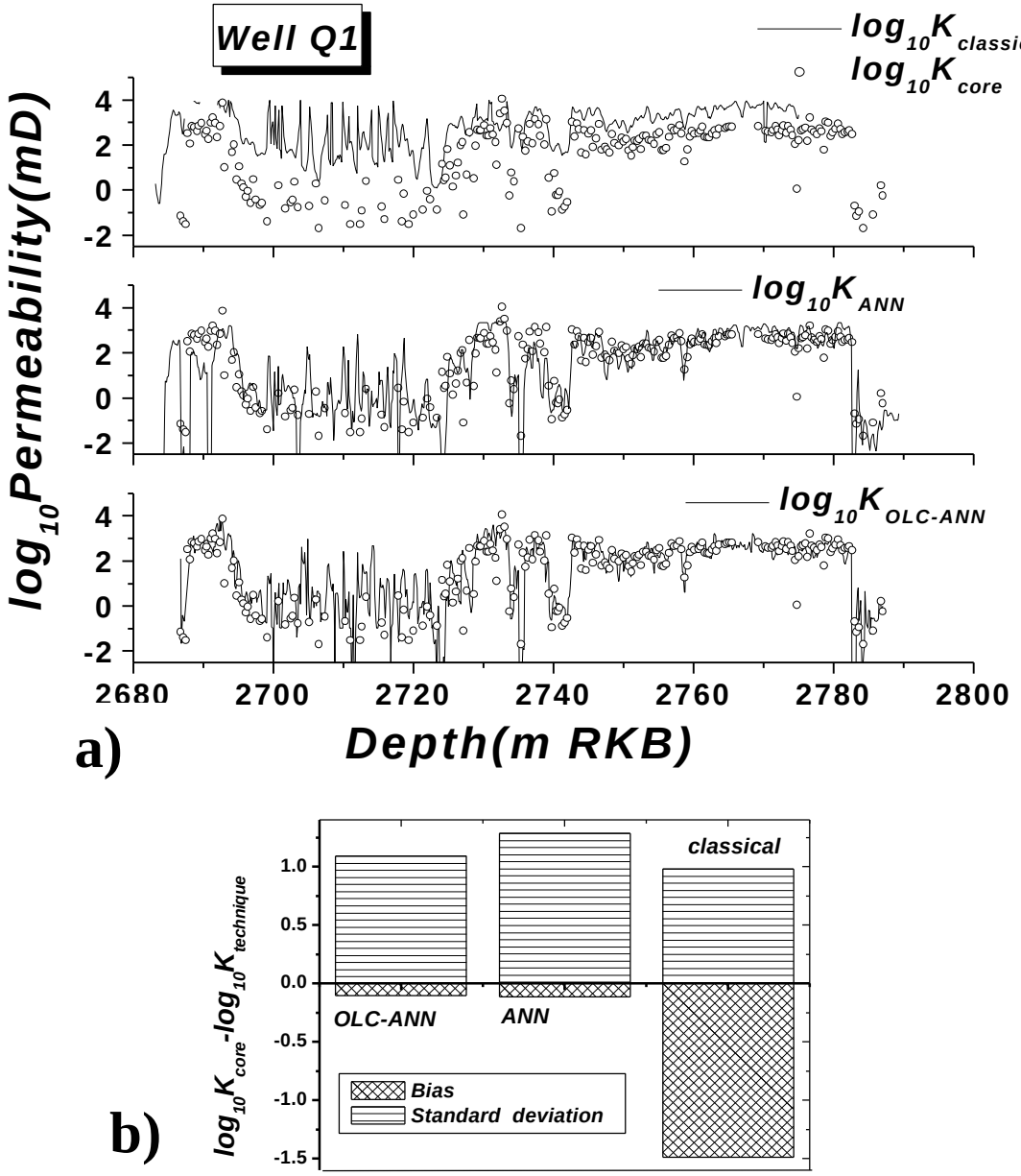

Figure 9: (a) Comparison of logarithmic permeability using OLC and a single neural network. Permeability curves taken from the database are calculated by classical technique using multiple linear regression. (b) Bias and standard deviation are compared.

The water saturation Network

The basic architecture network for predicting water saturation is the same as for porosity (Figures 1 and 2) and the OLC approach has been applied. The individual CM (K=9) members has 3 neurons in the input layer, i.e. density, neutron porosity and resisitivity logs, the hidden layer has 10 neurons and there is a single neuron in the output layer. The patterns used for training are a selection of water saturation values (CPI logs) extracted from the petrophysical database. These values are based on the interpretation by an individual petrophysicist of the MWD data using the method of Poupon *et al.* (1971) as standard procedure. Thus, in this case there was no need for using WL data as an intermediate step to calibrate the MWD networks. Training patterns were selected from reservoirs with different dominant pore fluids, i.e. water, oil and gas, to assure a sufficient dynamic range. The

resulting MWD network for water saturation by OLC method has been tested on several wells with excellent performance. Figure 10 shows a comparison between the water saturation predicted by the MWD network using the OLC approach and the corresponding S_w values from CPI logs in well Q6 which are unknown to the network. Since both test data (CPI) and the predictions by neural nets are based on essentially the same log data, except for the more qualitative interpretation added by the petrophysicist, it is no surprise that that the results are very similar. In this well there is an oil/water contact (OWC) around 5850 m (RKB) with a transition zone from oil to water of around 20 m thick. Using the predicted value of water saturation and the normalised relative permeability curves for the Q-field, the relative permeability logs for the oil/water system have been generated (Figure 11). The latter is an important input to reservoir simulation while drilling. Similar results were obtained for a gas/oil with partial water saturation based on a network that outputs the three fluid saturation logs.

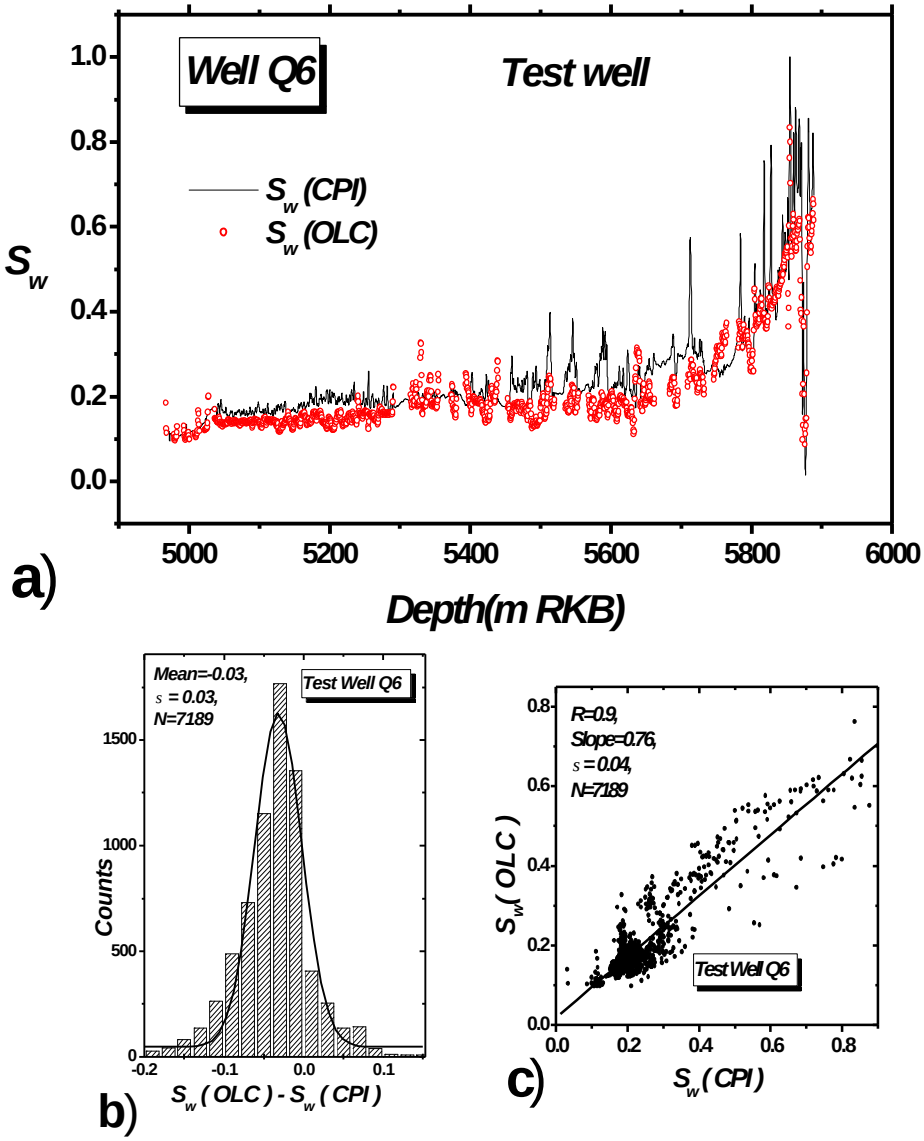

Figure 10: (a) Comparison of water saturation predicted from MWD with the CPI logs from the database. (b) Error histogram and (c) crossplot. The data is unknown to the network.

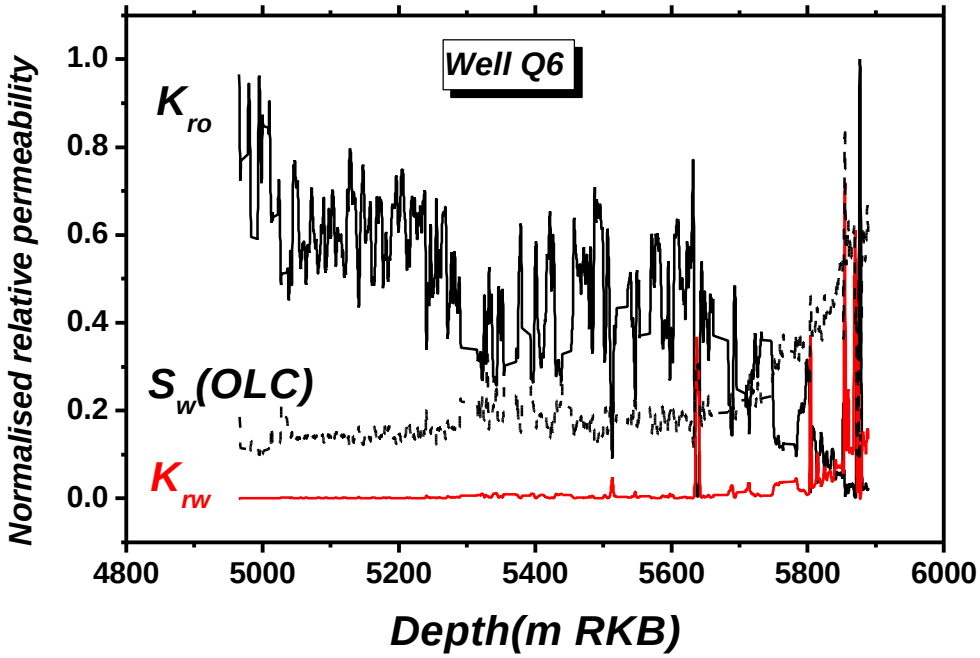

Figure 11: Relative permeability logs using normalised relative permeability curves from laboratory and predicted fluid saturation by the network using MWD data.

Neural nets for lithofacies prediction

The manual identification of lithofacies is time consuming, requires much work and significant geological skill. Classical multivariate statistics methods suffer from the disadvantage that they are inflexible, need a large amount of statistical data and a complex dimension reduction technique. A critical comparison between lithofacies prediction by discriminant analysis and neural networks has been made (Wong *et al.*1995) and the latter provided superior estimates. The use of fuzzy logic is another way of identifying lithofacies since there is an abundance of uncertainty and imperfection in geological data, which cannot be well defined by crisp boundaries (Saggaf *et al.*, 2000).

We have developed a CM approach for lithofacies prediction from WL data which in principle can be used for MWD data as well.

- We use the architecture shown in Figure 3, where each of the *K* members is trained to be an expert in identifying only one lithofacies. Others are rejected. The output of these experts is sent to the gating network containing prior knowledge of the geology, i.e. the local stratigraphy of the field (Figure 12). The purpose of the gating network is to impose constraints on the predictions. In principle, the gating network may even contain the full 3-D geological model provided in UTM co-ordinates. Even simple and obvious geometrical constraints significantly increase the resolution power of the network by eliminating ambiguity in overlapping clusters in the multi-valued log domain.
- Based on the best available geological zonation of the Brent group we have trained the *experts* to discriminate the zonation of Brent using all available logs. According to this zonation (Figures 12 and 13) the Tarbert formation is divided into the middle and lower Tarbert (MT and LT), the Ness formation into 3 levels, Upper Ness 2, Upper Ness 1 and Lower Ness (UN2, UN1 and LN), Etive (Et), Rannoch (Rn) and two lobes in the Oseberg formation (OseT and OseB).

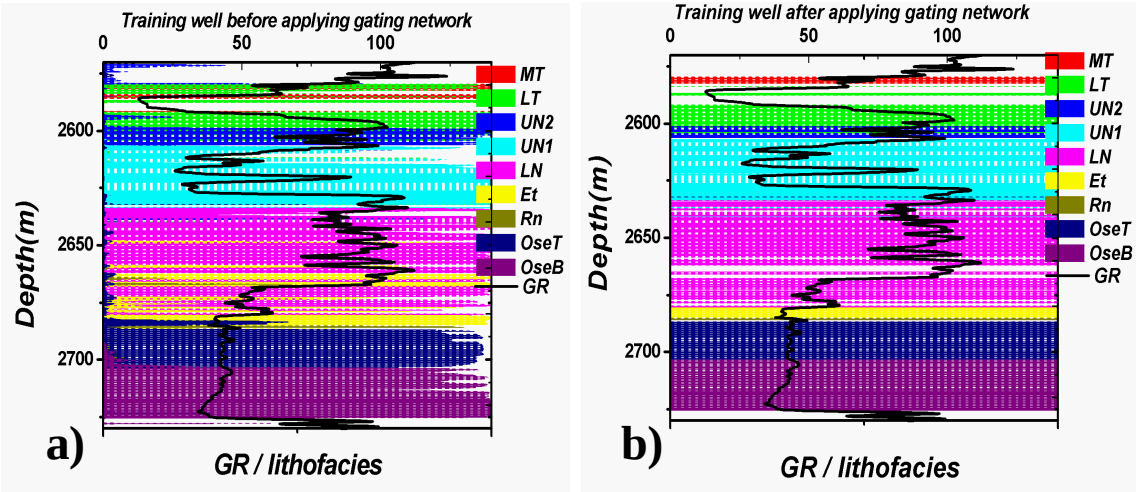

Figure 12: Prediction of lithofacies in a training well (Q21) before (a) and after (b) applying the gating network.

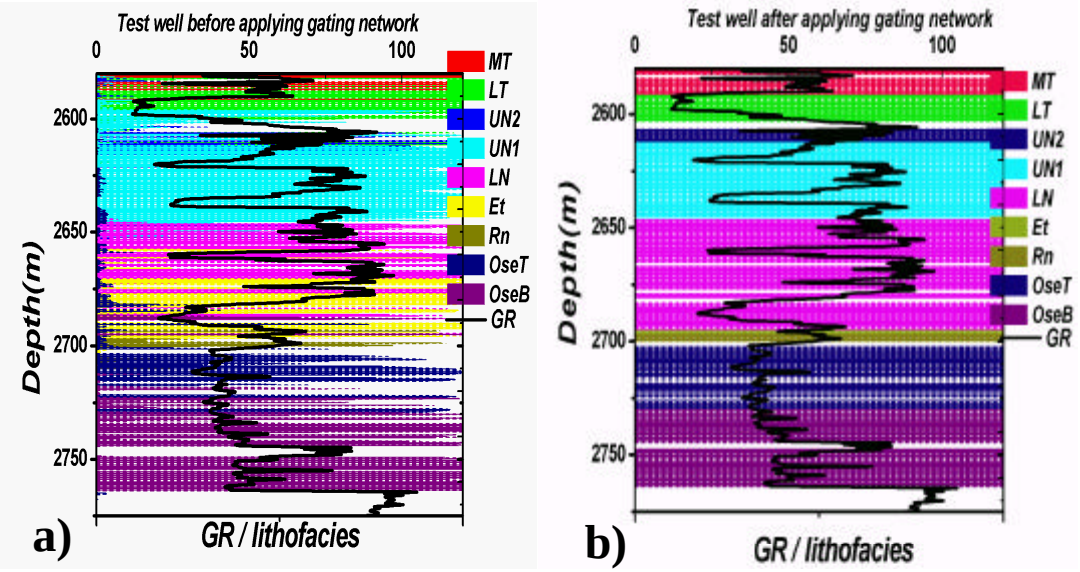

Figure 13: Same as in Figure 12 but applied in a test well (Q2) unknown to the network.

Figure 12a shows the output from the individual experts in the training well before connecting the gating network, and Figure 12b shows the result after its application. The gamma-ray log is shown for comparison. In the first case we see that a layer of LT and UN2 has been misplaced above MT and that Et has been misinterpreted within LN, in conflict with local stratigraphy. The other lithofacies are reasonably well identified by the experts and placed in correct position.

Figure 13 displays the same features for a test well unknown to the network. Here, the impact of the gating network is more pronounced and the streaks of misplaced layers are properly transferred to their correct positions, resulting in the clearly defined lithological column shown in Figure 13b.

Conclusions

The parallel architecture of the neural network in the committee machine approach, combined with optimal linear combination and gating networks, significantly enhance the power of the neural network techniques for application in petroleum geoscience. Prediction of porosity, permeability and water saturation from MWD data is feasible and thus can be made while

drilling. Once properly trained and tested, the networks are fast and more accurate than classical methods based on linear multivariate regression. The trained networks have been used successfully in the field for predicting the reservoir properties.

The CM approach for quantitative log conversion is more robust than the single neural network. Since the individual networks while training reache slightly different minima of the objective function, the combined output from a number of nets improve the overall accuracy.

The use CM for lithofacies prediction is a novel technique that has a significant potential in practical log analysis and geo-steering applications. The method remains to be evaluated on MWD data.

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