

Facies Recognition Using Neural Networks

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Abstract

The Maui Field in New Zealand has recently been petrophysically reviewed. Following detailed sedimentological descriptions of core, a geologically based facies scheme was made. Significant differences in porosity, permeability, grain density and capillary pressure behaviour were evident between facies. A neural network was designed and trained to predict the facies using basic wireline log responses. The use of a neural network has allowed several variables to be included in the prediction procedure, resulting in a better match with core data than a deterministic approach would allow.

Introduction

The Maui Field, discovered in 1969 and operated by Shell Todd Oil Services Ltd, lies in the offshore Taranaki Basin on the West Coast of the North Island, New Zealand (Figure 1). To date seven exploration/appraisal wells and 24 development wells have been drilled. Gas, condensate and oil are trapped in two separate low relief structural culminations (the A and B-Areas, Figure 2) with the hydrocarbon bearing intervals further subdivided into the C, Upper D, Lower D and F Sands. In this paper we describe the integration of core and log data in the petrophysical review of the gas/condensate bearing column in the C Sands, and the utilisation of neural network techniques to enable improved prediction of reservoir facies. There are two main ways to approach the problem of reservoir characterisation. One approach treats an entire reservoir as a whole in the prediction of petrophysical properties, while the second approach seeks to identify and treat different lithofacies of a reservoir separately.

The latter approach implies that each lithofacies has distinguishing petrophysical properties, such as facies-specific porosity-permeability relationships, and must therefore be treated separately.

Two quantitative pattern recognition techniques for reservoir characterisation are available, discriminant analysis and neural networks. The biggest difficulty with treating different lithofacies of a reservoir separately is ensuring the reliable identification of these lithofacies. Both approaches derive classification rules, which are established in cored wells, to identify lithofacies from log signatures. Once patterns have been established in cored wells, the prediction of lithofacies are made in other (non-cored) wells.

This paper compares the discriminant analysis and neural network techniques in identifying and predicting lithofacies, in the Maui C sand gas-condensate field.

Discriminant Analysis

The discriminant analysis, or graphical, technique requires core data to act as a training set to enable development of a set of classification rules, based on log responses, which can be used to identify lithofacies.

A very simple example of the discriminant method is given in Figure 3, where the classification of two lithofacies is made based on a crossplot of Gamma Ray vs Formation Density. Both facies exhibit overlapping formation density values, but each can clearly be identified on the basis of Gamma Ray alone. Multiple crossplots are made in two or three dimensions, incorporating sufficient log responses to optimise the classification accuracy. This conventional method of identifying lithofacies by cross-plotting pairs of logs is adequate for identification of simple mineral mixtures, but fails in more complex and heterogeneous reservoirs due to the extreme difficulty in deriving classification rules in more than two dimensions.

Neural Network

Neural networks, which do not assume normality and linearity of data yet are fairly easy to use and offer an alternative to the more traditional pattern recognition approach. They have proved to be valuable pattern recognition tools and are capable of finding highly complex patterns within large amounts of data because of their true multi-dimensional ability.

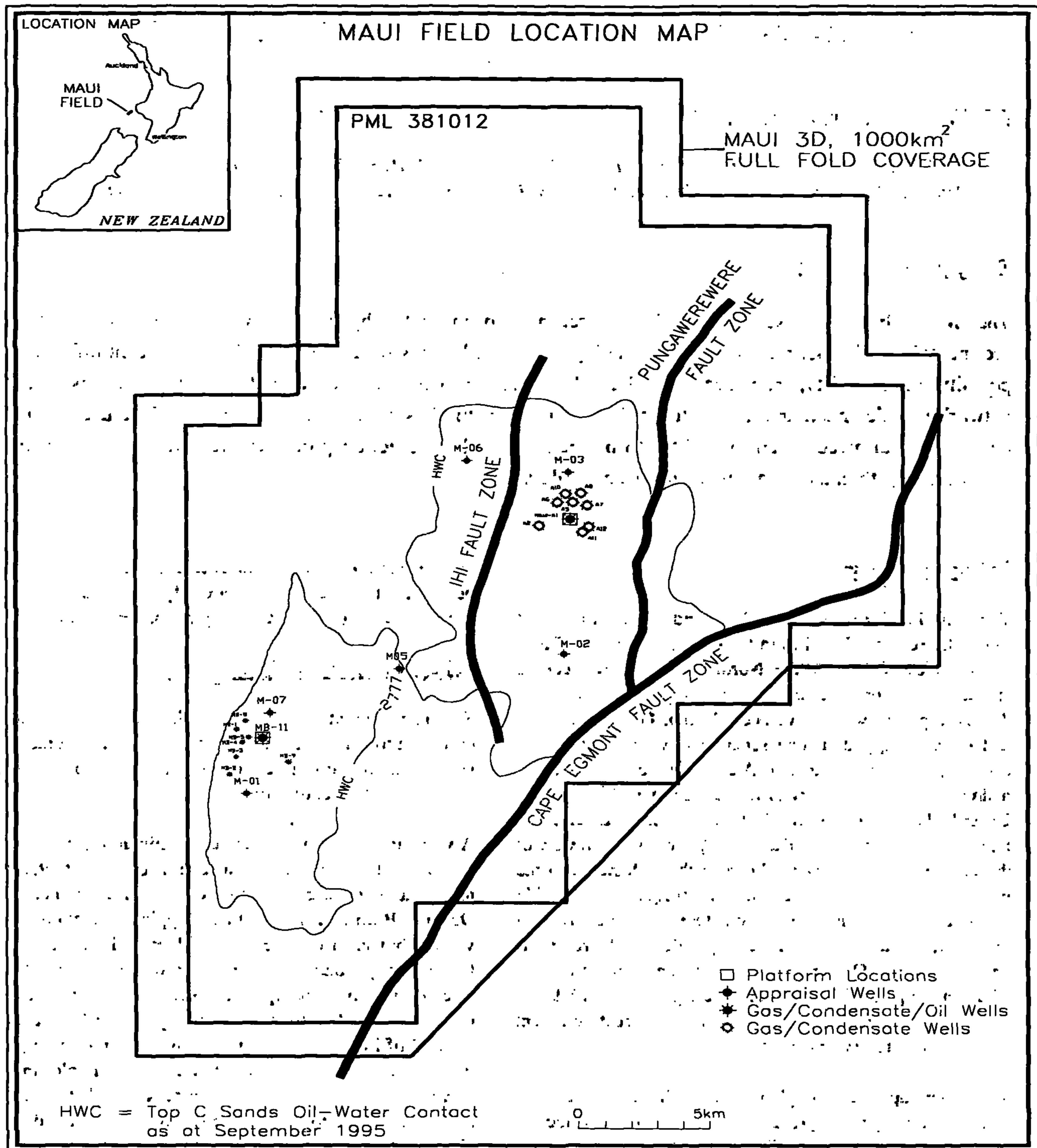


Figure 1. Maui Field location map.

In wireline log recognition, some applications are:

- classification of lithofacies
- classification of fluid types
- estimation of porosity
- estimation of permeability

The input variables are log readings and the output variables – the properties to be estimated – are

probabilities of lithofacies or fluid type, porosity or permeability. The neural network has to learn the task at hand by showing it example inputs and outputs (in cored wells). These samples form a training set which are presented to the network repeatedly.

Each time the network is adapted such that the output of the network matches the target output (core parameter) a little better. Eventually, the network output is close enough to the core description to allow application to new-well data, for which no core is present. As long as the data used to train the network is representative for the

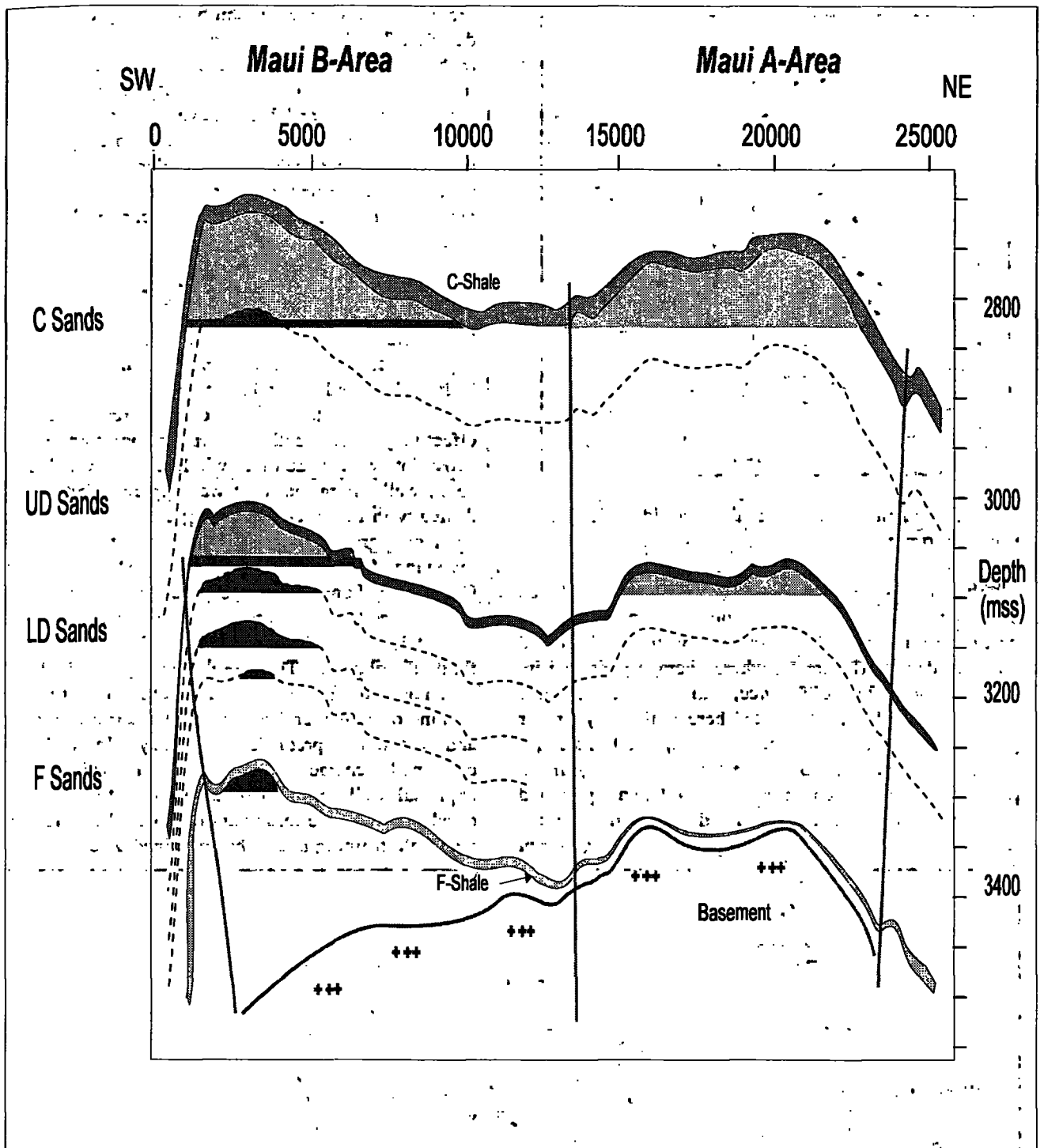


Figure 2. Generalised cross section Kapuni Group.

task at hand, the network output will be a good approximation of the desired property. The network components are depicted in Figure 4. The basic processing element of a neural network is a neuron. It receives information from one or more fellow neurons, or from the outside world. This information is weighted, integrated and, after a non-linear transformation, passed on again to other neurons, or the outside world, providing an answer. The neurons are ordered in layers: an input layer, one or more intermediate layers and an output layer. Connections between neurons have weightings, positive or negative, which determine the impact of the information passed over

that line. The problem specific information is stored in these weights. Various techniques, beyond the scope of this paper are available to ensure an optimally designed network.

Lithofacies Grouping

After exhaustive analysis of all core data twenty genetic facies, based predominantly on grain size, were determined. Since it was unlikely that individual facies would be identified, by either pattern recognition method, the individual facies were classed into petrophysically

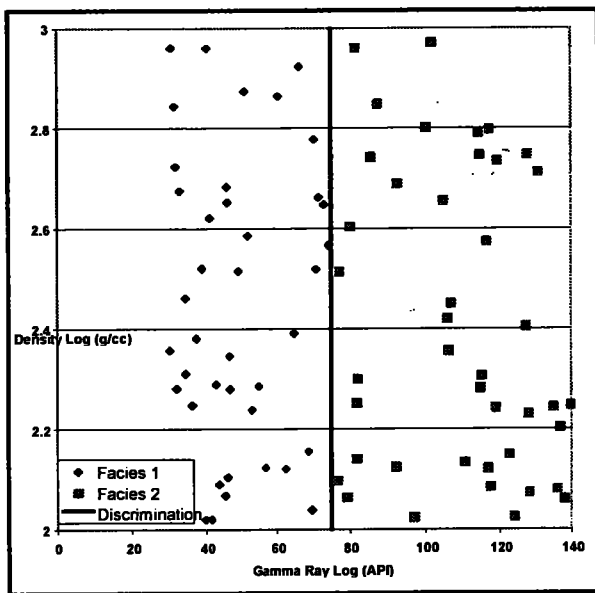


Figure 3. Example of a simple lithofacies identification using discriminant analysis.

significant bins, resulting in six facies groups (numbered 0-5) with the lower numbered groupings representing the best quality reservoir. The groupings were initially based on grain density (Figure 5), where average grain density varies from 2.66-2.78 g/cc, to ensure accurate determination of porosity. Noted here is the very similar grain density values for lithofacies groups 0, 1 and 2. As well as grain density, two other petrophysically significant parameters, porosity-permeability relationships and capillary pressures were considered in determining the final geologically and petrophysically significant

groupings. Porosity-permeability data approximately two decades. The binning of facies was optimised to ensure each grouping had similar porosity-permeability relationships as well as grain density. The resulting data for two groups (0 and 2) that have similar grain density is shown in Figure 7. The difference in porosity-permeability is approximately one decade. A similar approach was used to ensure consistent capillary pressure data for each grouping in order to derive accurate hydrocarbon saturation.

Lithofacies Recognition

In the Maui C sands there are five cored wells, with approximately 550 m of core, evenly split between hydrocarbon and water bearing sands. This amount of data was felt to be sufficiently representative to effectively train both pattern recognition methods. Crossplots were made of all wireline logs available in the cored wells. Immediately it was apparent that there was difficulty in accurately discerning clear recognition of all six facies groups. A classification scheme was derived involving Gamma Ray, Formation Density, Neutron, Caliper and Sonic logs. Two prediction schemes can be derived, one treating hydrocarbon and water bearing sands separately, and a scheme combining all sands regardless of fluid distribution. The combined approach has the advantage of using all core data to optimise the training of both neural network and discriminant analysis and maximise prediction accuracy. In addition, a combined scheme can be used in exploration and appraisal wells prior to fluid interpretation. The major disadvantage of the former approach is the reduction in available training data. The combined prediction scheme

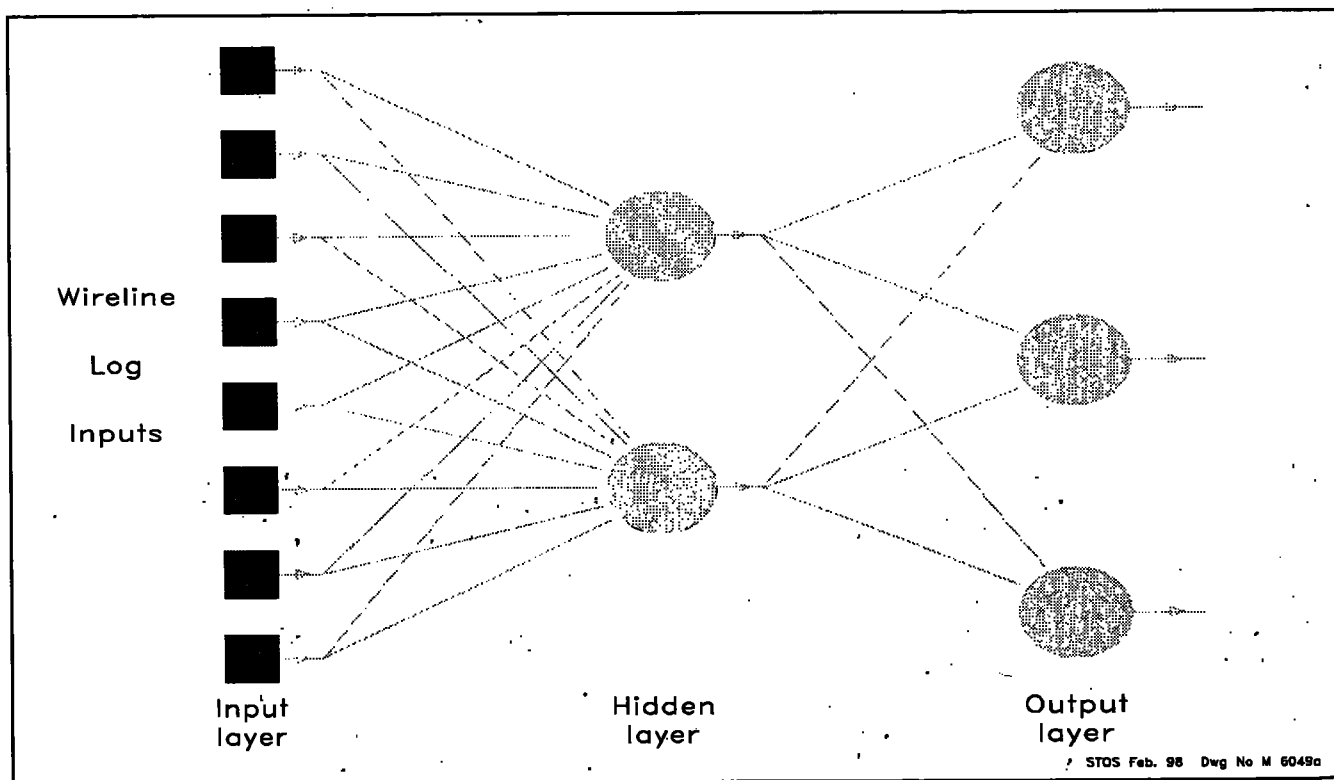


Figure 4. Neural network architecture.

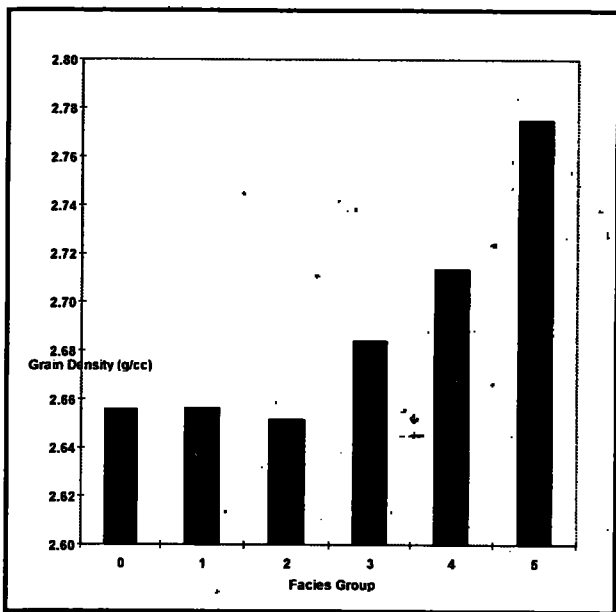


Figure 5. Grain density per lithofacies group.

was adopted in the C sands because of two reasons. Firstly, the core data is evenly split between hydrocarbon and water bearing sands and it is likely there would be severe degradation in lithofacies prediction accuracy if separate schemes were adopted.

Secondly, residual saturations are present throughout the water leg in the C sands due to a process of imbibition. Since the wireline log inputs chosen to discriminate groupings have minimal differences in log response across the hydrocarbon and "water" sands the combined scheme is unlikely to significantly affect the prediction accuracy. Multiple neural networks were designed and tested to optimise network performance.

Prediction of Lithofacies

Figure 8 compares the performance of both methods in predicting lithofacies. The discriminant analysis technique predicts the correct facies on 48% of occasions, and predicts the neighbouring, and hence most similar, facies group 27% of the time. The neural network technique predicts the correct facies 65% of the time and nearest neighbour facies group on 21% of occasions. An example of the difference in prediction methods is illustrated for one cored well, MA-01, in Figure 9. Throughout the interval the neural network method outperforms the discriminant analysis method, especially across the interval 2820-2835 m, where the discriminant method fails to fully characterise the high quality layers (Group 0 facies). The neural network approach does, however, predict the high quality layers very accurately.

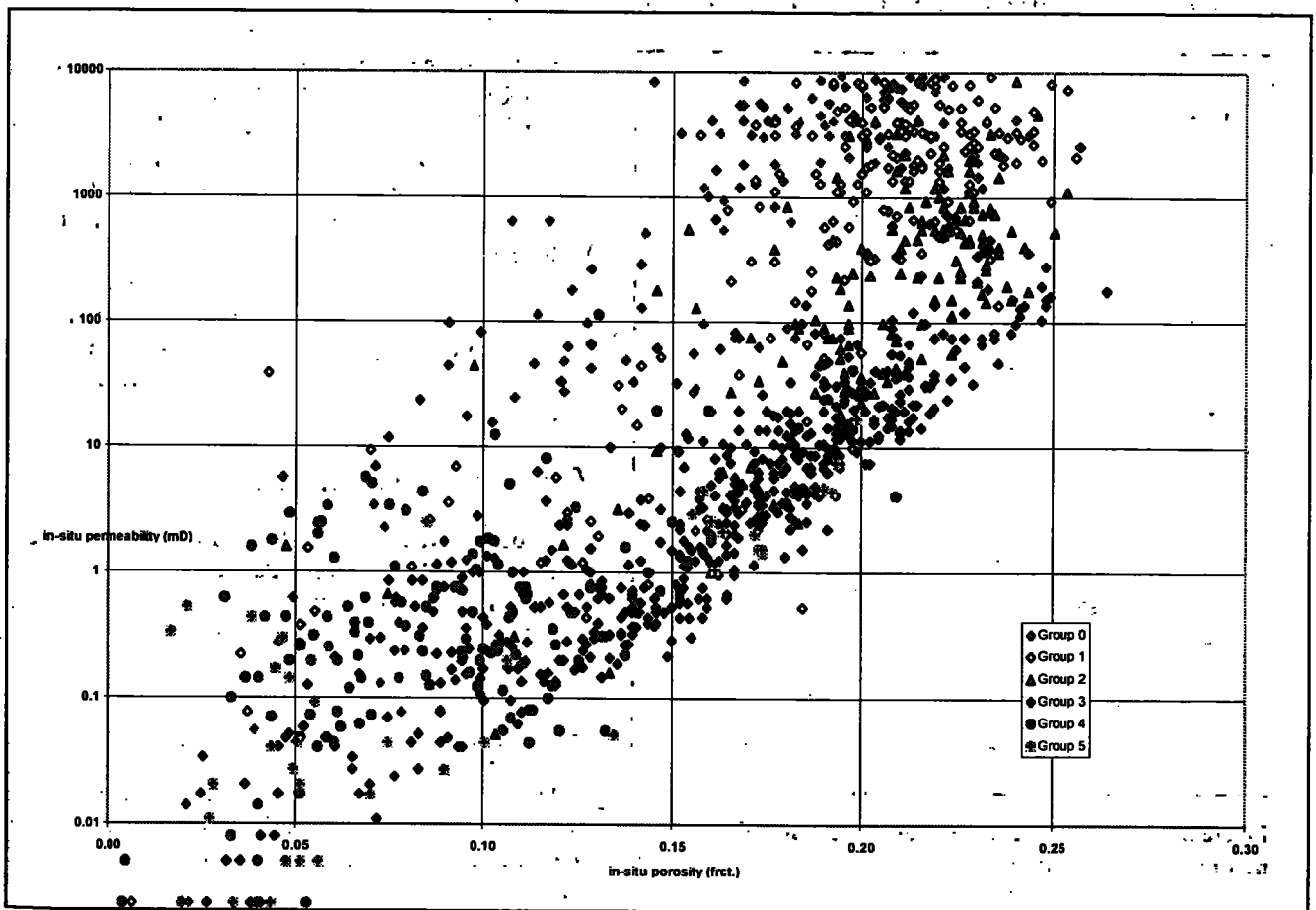


Figure 6. Porosity and permeability data coded by lithofacies group.

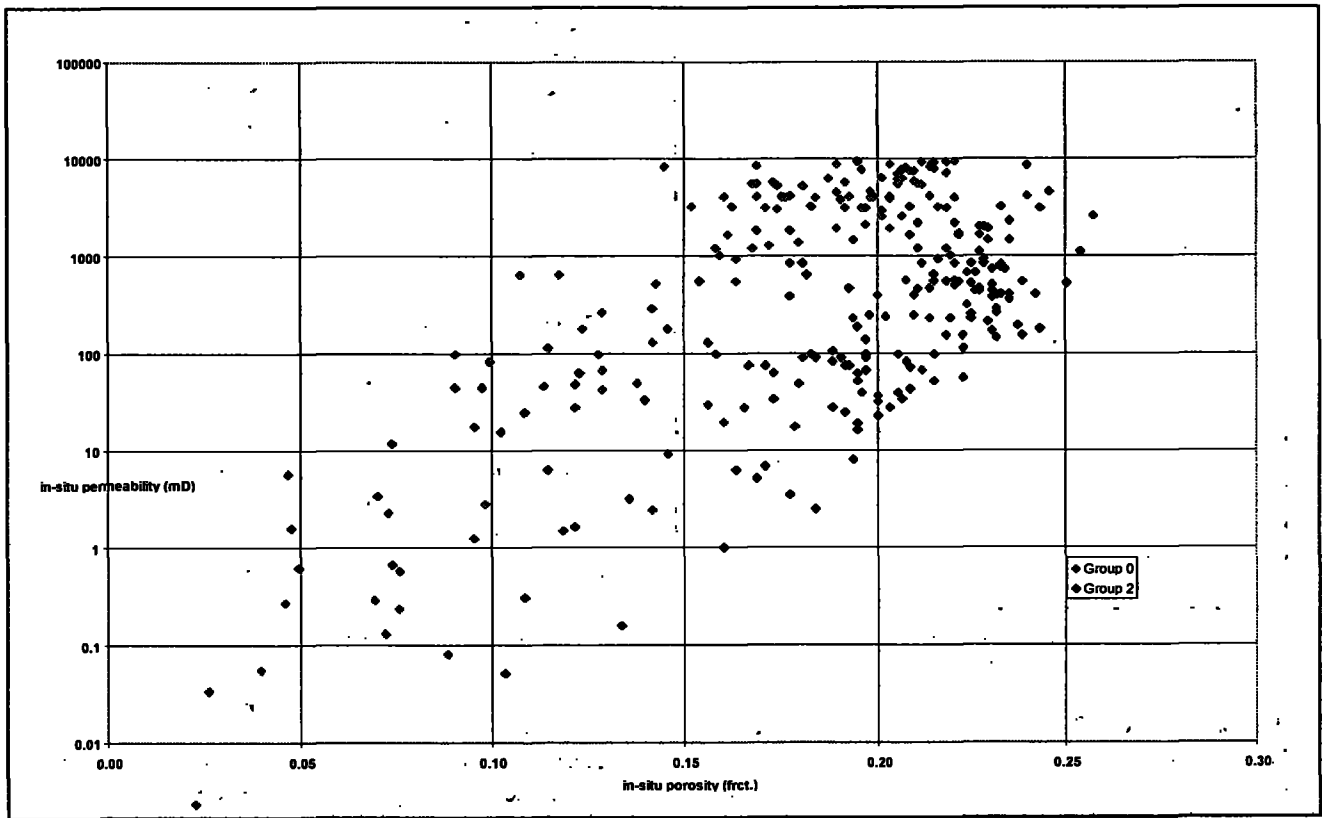


Figure 7. Porosity and permeability for lithofacies group 0 and group 2.

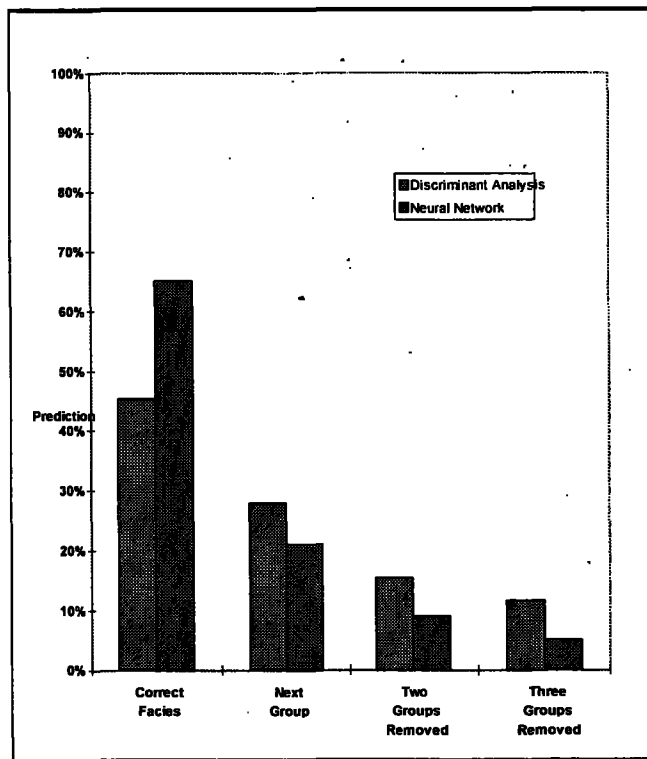


Figure 8. Prediction accuracy of discriminant and neural network analysis – all facies.

Conclusions and Recommendations

We have demonstrated the neural network approach is successful in lithofacies recognition in the Kapuni

Formation of the Maui Field. The neural network approach is superior to a graphical approach because the dimensionality shortcomings of the graphical technique are eliminated. Improved lithofacies prediction can be used in quantification of porosity, permeability and hydrocarbon saturations. Other potential applications of this technique include pore-fluid identification, analysis of image logs, determination of depositional environments and enhancement of well log correlation. Consideration should be given to extending the approach presented in this paper to other reservoirs where sufficient training data is available.

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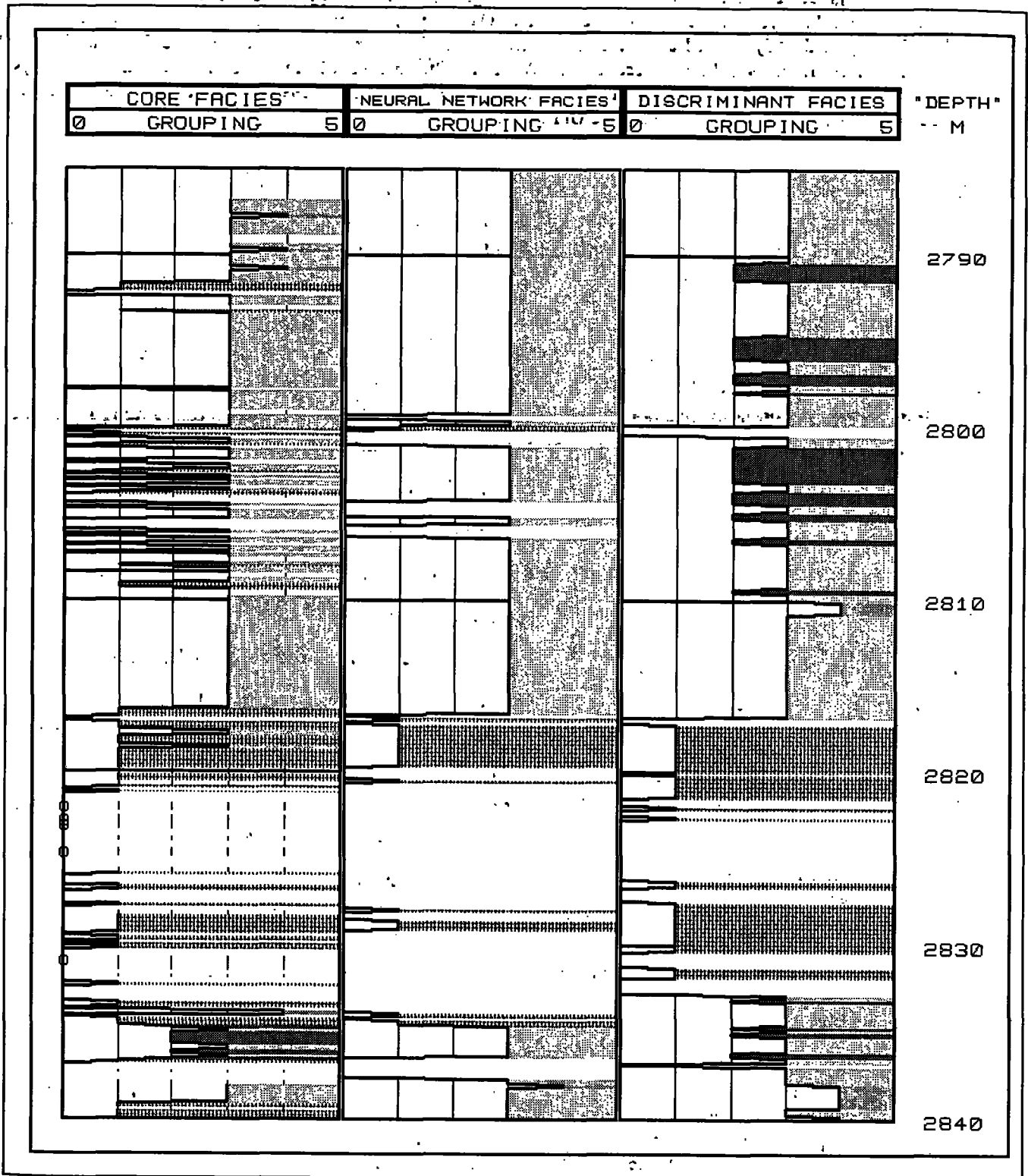


Figure 9. Comparison of core described facies with lithofacies predicted from neural network and discriminant analysis in well MA-01.

Author

Russell Farmer graduated with a BSc (Hons) in Applied Physics from the University of Durham, England. He joined Shell International in 1989 and then worked in The Netherlands as an operational petrophysicist in the Nederlandse Aardolie Maatschappij offshore business unit. In 1994 he was transferred to the Shell Salym operating unit where he worked exclusively on Russian Log Interpretation. In 1996 he was transferred to Shell Todd Oil Services where he is working as a petrophysicist.

Stephen Adams graduated with a MSc (Hons) from the University of Auckland in 1986. He joined Shell International in 1987. Steve spent three years working in the Sultanate of Oman as a petrophysicist supporting operational activities and working in integrated study teams. He was then transferred to the Shell Technology Development unit in The Hague, The Netherlands in 1991. In 1993 he was seconded to Woodside Offshore Petroleum in Perth as a senior petrophysicist, working on oil and gas/condensate developments. Since resigning from Shell in 1994 to work as a consultant, Steve has worked in Asia, Australia, New Zealand and the United Kingdom.