SCA2003-35: GENETIC PETROPHYSICS APPROACH TO CORE ANALYSIS – APPLICATION TO SHOREFACE SANDSTONE RESERVOIRS

David K. Potter[1], An H. Le[1], Patrick W. M. Corbett[1], Clive McCann[2], Solomon Assefa[2], Tim Astin[2], Jeremy Sothcott[2], Barry Bennett[3], Steve Larter[3], and Arnaud Lager[3]
[1]Institute of Petroleum Engineering, Heriot-Watt University, Edinburgh, EH14 4AS, UK
[2] Institute of Sedimentology, University of Reading, Reading, RG6 2AB, UK
[3]Fossil Fuels and Environmental Geochemistry, NRG, University of Newcastle upon Tyne, NE1 7RU, UK

This paper was prepared for presentation at the International Symposium of the Society of Core Analysts held in Pau, France, 21-24 September 2003

ABSTRACT

Shoreface reservoirs are characterized by coarsening up sequences of fine to medium grained sandstone. Single coarsening-up parasequences are often easily recognizable within stacked shoreface sequences. These elements are the fundamental building blocks (representative genetic units) of such reservoirs. We identify such a package in a North Sea oil well, and show how the detailed characterization of this single shoreface unit can be used to predict, via neural networks, a range of parameters throughout the rest of the well and an adjacent well in the same oilfield. We have termed the approach "Genetic Petrophysics" as it emphasizes the genetic aspects of the sandstone body in both the sampling and prediction strategies. The work presented has both extended our previous studies on permeability prediction, and has also applied the approach to the prediction of other diverse parameters. A key new result is that excellent predictions can be made from extremely limited but representative conventional or SCAL core plug data. This provides a very cost effective sampling strategy, and paves the way for rapidly predicting a whole range of other parameters of interest from minimal core data.

INTRODUCTION

Acquisition and analysis of core is very costly and time consuming. The industry standard practice is to sample conventional horizontal plugs every foot (about 0.3m), conventional vertical plugs every 3 feet, and SCAL plugs perhaps every 6 feet, over a large cored interval (generally a few hundred feet). This approach is not based on geological criteria and can inadvertently bias the sampling so that some lithologies (or hydraulic units) may be over-sampled, whilst others may be substantially under-sampled. Corbett et al [1] provide a short review of the geological, petrophysical and statistical issues involved.

In contrast, we have advocated a sampling strategy [1-4] that is based on selecting a small representative genetic unit (RGU) from the available wireline log data and drill cuttings, and then performing a detailed analysis of the core in this RGU. Figure 1 shows a schematic diagram indicating the essential elements of this sampling strategy. The measured RGU provides data that is used to train a genetically focused neural net (GFNN), which is then used to predict a variety of properties in the other RGUs throughout the rest of the well and adjacent wells in the same oilfield. There are several reasons for advocating this approach:

- The RGU sampled is selected on the basis of geological criteria.
- The RGU is representative of the other units in the well, and adjacent wells in the same oilfield. The RGU may be even more generic in that it could be representative of similar depositional units in other oilfields.
- It is very cost effective in terms of core acquisition, core measurement, and data processing. The neural net need only be trained on this limited 'smart' dataset. In situations where core is scarce, it maximises the potential usefulness of that core.
- All multi-disciplinary studies use this common sample set.
- Data collection can be rapid yet comprehensive at multi-scales (at the probe, plug, and whole core scales), due to the short intervals involved.
- Rapid parameter prediction can be extended beyond permeability to acoustic properties (suitable for time-lapse geophysical and engineering studies), stress sensitivity, and several other key parameters of interest from minimal initial measurements on the training core sample set. This allows field development decisions to be made at a much earlier stage.

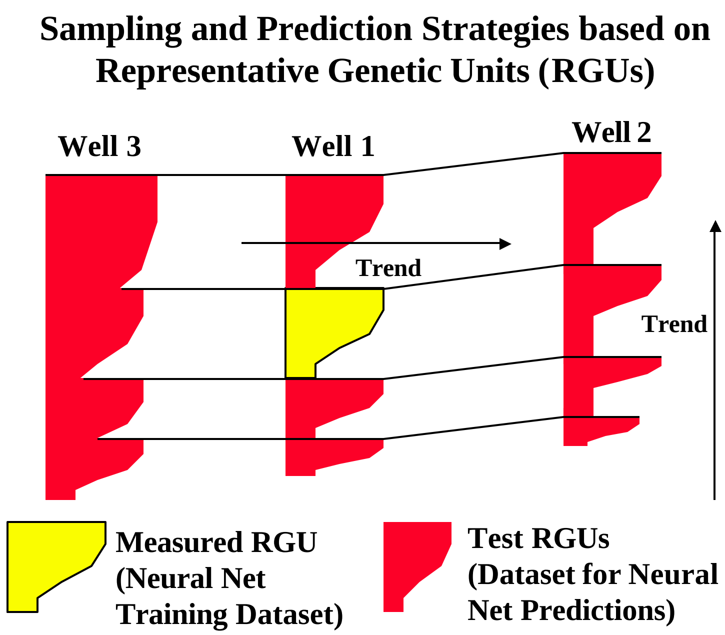

Figure 1. Schematic of coarsening upwards shoreface representative genetic units (RGUs) in 3 wells. The measured RGU provides the training dataset for predicting parameters in the other RGUs.

We recently demonstrated this approach by successfully predicting permeability throughout the cored intervals of a number of North Sea oil wells [5,6], primarily in an oilfield where permeability prediction had previously been problematic due to a very poor relationship between porosity and permeability. We previously showed [3,7] that microporous illite rims around quartz grains in core material from these wells resulted in porosity remaining almost constant, whilst permeability could vary by several orders of magnitude depending upon the illite content. We trained a GFNN predictor on the permeability values from just 24 conventional core plugs, along with the associated wireline log data, within one short 7m shoreface RGU [5,6]. The predictor was successfully tested throughout the cored interval of the same oil well (129m), cored intervals in adjacent wells in the same oilfield, and in a shoreface interval in a completely different oilfield. The latter result suggests that the approach might be truly generic, and that our predictor might be applied more generally to other oilfields, with similar depositional units, where there is no core data. If core data is available, however, one would normally train a GFNN predictor on the relevant data within the oilfield of interest.

Prior to our work [5,6] described above, another study had shown some success in predicting permeability in other localities (without using a genetic approach), from what was then considered "limited" core data involving 45 core training plugs [8]. We now test whether we can dramatically reduce the number of training data points still further within our RGU (to one representative point per hydraulic unit), and still achieve comparable predictions to our prior work. The strategy is also extended to test whether other parameters can be successfully predicted using this genetic methodology.

METHODOLOGY

A short 7m RGU was chosen on the basis of standard wireline log data in PEGASUS Well 2. The core in this interval has been comprehensively analysed using a variety of conventional and novel techniques (for a review see [7]). This dataset formed the basis for training various neural nets in order to predict petrophysical, geophysical, and geochemical parameters in larger intervals both in the same well and elsewhere. For the neural net itself, we employed a combination of 3 algorithms (back propagation, Cascade-Correlation and TACOMA) in a committee neural network, rather than using a single algorithm. This allowed slightly better overall predictions than our previous work [5,6], which had only used a back propagation algorithm.

We first trained a GFNN permeability predictor using data from minimal horizontal core plug permeability values in the RGU, plus the associated data from just 3 key wireline logs (gamma ray, bulk density and sonic transit time). This generated predictions in the test intervals using data from the 3 key wireline logs in those intervals. We previously showed [5,6] that this combination of wireline logs gave comparable results to predictors which used all 6 available wireline logs (the others being neutron porosity, medium and deep induction logs). No nuclear magnetic resonance (NMR) logs were run in this field. The gamma ray log was directly linked to the content of the permeability controlling illite clay, whilst the bulk density and sonic logs accounted for the effect of low porosity and permeability (mainly barite) cemented regions. We significantly reduced the amount of initial core training data within the RGU from 24 plugs in our previous work [5,6] down to only one plug per hydraulic unit (in this case just 5 plugs). If we had no other core data, we would normally have done this by plotting our available RGU data on a global hydraulic element grid [9] and selecting a core plug from each hydraulic element. In this instance, however, since we had the conventional core plug porosity and permeability data for the entire 129m cored interval of the well (297 horizontal plugs), we decided to use the methodology of [10] to firstly categorize all the plugs in the well into their respective hydraulic units. It turned out that there were essentially 5 hydraulic units in the well, and the 24 conventional core plugs in the RGU contained representatives from each hydraulic unit. We therefore decided to train the neural net using the permeability values from just 5 of these conventional horizontal plugs, one representative from each of the hydraulic units (see Figure 2), along with the associated depth matched wireline log data from the 3 key logs at those depths. The predictions were then compared with the measured core plug values in the test intervals, and also compared with a neural net predictor trained on the substantially larger dataset comprising the entire 129m cored section of the well. We subsequently trained neural nets to predict other parameters using a slightly different combination of wireline logs as detailed in the results section.

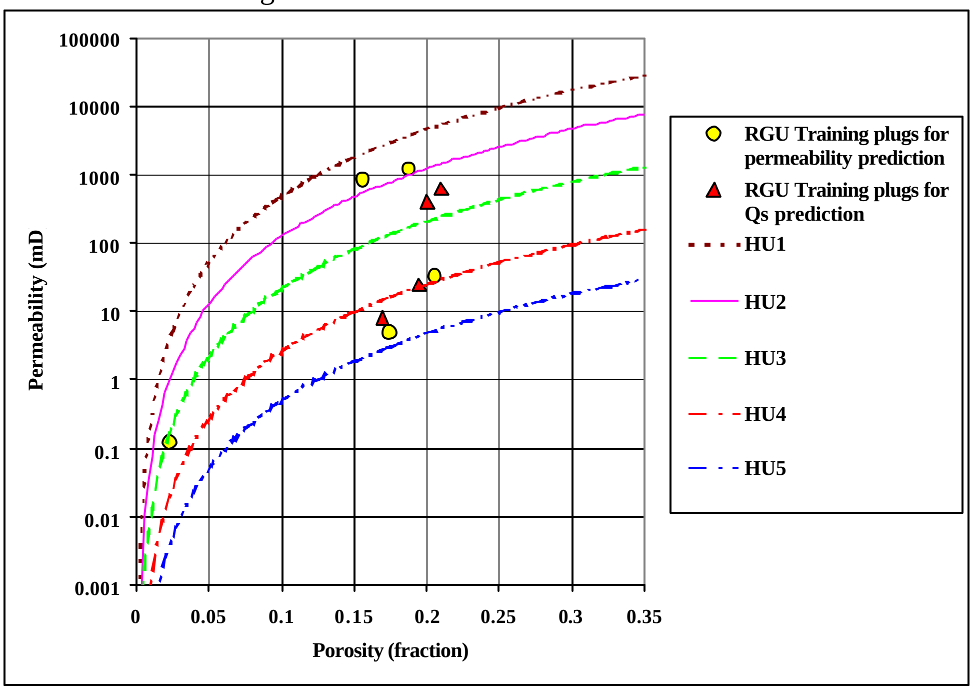

Figure 2. The lines represent the mean trends of the 5 hydraulic units (HU) determined using the porosity and permeability data of all the 297 horizontal conventional core plugs in PEGASUS Well 2. The 5 training plugs for permeability prediction all come from the RGU and represent each of the 5 hydraulic units. Likewise, the 4 plugs from the RGU for

the prediction of shear wave quality factor (Q_s) represent a reasonable range of the hydraulic units in the well.

RESULTS

Genetic Permeability Prediction in PEGASUS Well 2

Figure 3 shows a comparison of neural net predicted and measured core plug permeabilities with depth for the entire cored interval of PEGASUS Well 2. Figure 3 (a) shows the results where the neural net was trained using data from the 3 key wireline logs (gamma ray, bulk density and sonic logs) and routine horizontal core plug air permeability values from ***just*** 5 discrete depths within the RGU (one from each of the 5 hydraulic units).

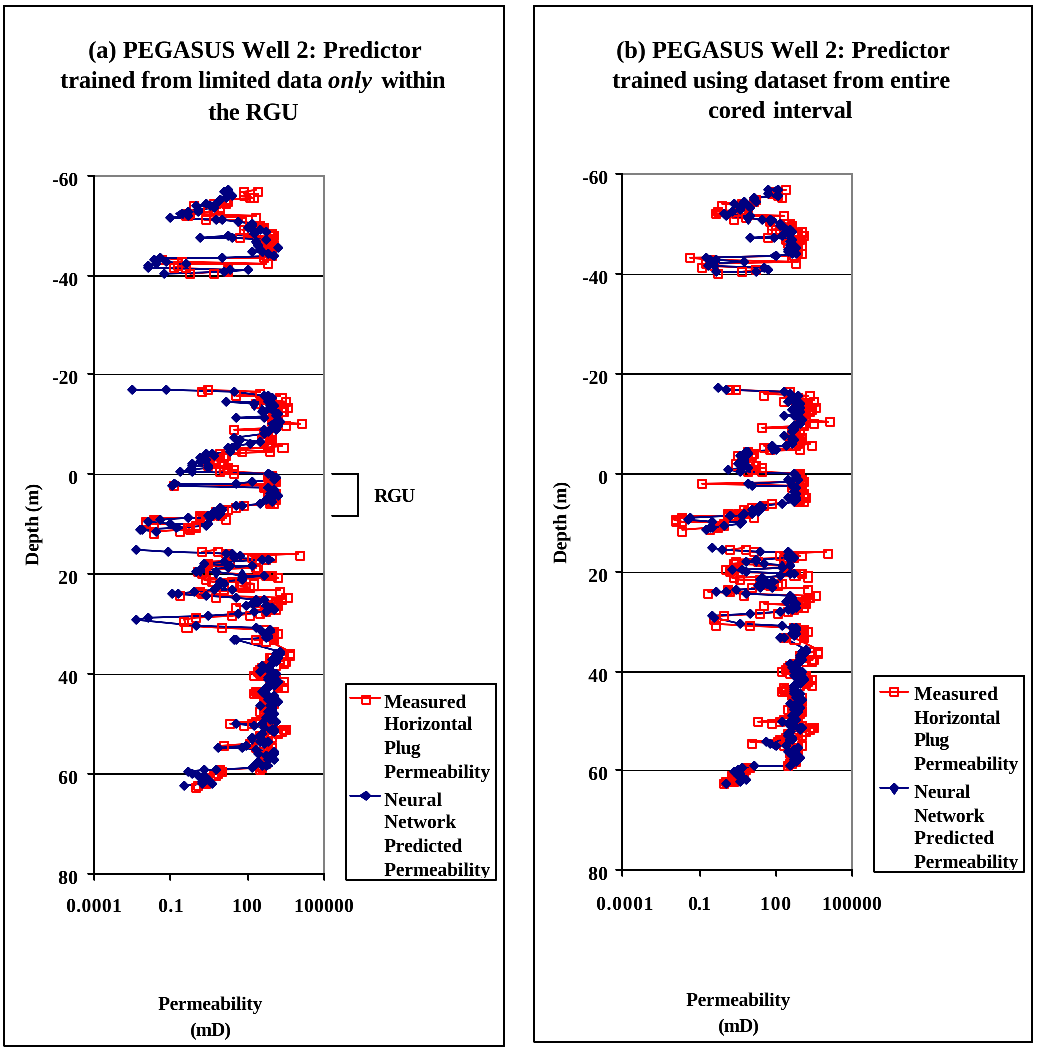

Figure 3. A comparison of neural net predicted permeability and measured values in PEGASUS Well 2 using predictors trained on (a) Just 5 representative plugs in the RGU, and (b) All 297 plugs throughout the interval. Each predictor also used data from 3 key

wireline logs (GR, RHOB, DT) in the training and test intervals. Depths are from top of RGU (actual depths are confidential).

The position of the RGU is shown on the figure. Figure 3 (b) shows the results where the neural net was trained using the 3 key wireline logs and routine horizontal core plug air permeability data throughout the entire 129m cored interval of PEGASUS Well 2. This meant that 297 values of each wireline log and core plug permeability were used to train the neural networks in this case. Remarkably, the predictor trained on the very limited RGU dataset was almost as good as that based on the substantially larger (by a factor of 60) full dataset. Crossplots of the logarithms of the measured versus predicted permeabilities for the predictors based on the limited and full datasets gave values of 0.72 and 0.85 respectively for the power regression coefficient r^2. The RGU predictor is a considerable improvement on any predictor based on the core porosity – permeability relationship (in PEGASUS Well 2 the porosity – permeability crossplot has a power regression coefficient $r^2 = 0.25$). The results from the limited dataset (5 plug) RGU predictor are also comparable to our previous results [5,6] using all 24 plugs in the RGU, where $r^2 = 0.71$ using a neural net predictor based on one algorithm (back propagation). The predicted versus measured correlation coefficients for the RGU predictors compare favourably (particularly considering the large number of our predicted points) compared to other reported values for neural net permeability prediction studies. Moreover, previous authors often either quote values of r rather than r^2, for example [11] report r values between 0.49 and 0.86 (i.e., $r^2 = 0.24 – 0.74$), or they may not give any correlation coefficient [8]. We have pointed out [6], however, that values of the regression coefficient should be treated with some caution, as the presence of just two outliers can reduce the r^2 value by 0.1 or more. Also, the core validation dataset can sometimes miss key features (due to the industry standard 1 core plug per foot sampling strategy) that are predicted by the neural net and confirmed from other data such as core photos, resulting in a potentially good predictor having an anomalously low r^2 value.

Genetic Permeability Prediction Using PEGASUS Well 2 Predictors In An Adjacent Oil Well

Figures 4 (a) and (b) show the results of testing the PEGASUS Well 2 permeability predictors in an adjacent well (PEGASUS Well 2b). The predictions based on the limited RGU training dataset (Figure 4 (a)) are again very similar to those based on the much larger dataset (Figure 4 (b)), and both successfully predict the general trends of permeability with depth. Crossplots of the logarithms of the measured versus predicted permeabilities show that the power regression coefficient r^2 is actually slightly better for the predictor based on the limited RGU dataset in this case, the values being 0.68 and 0.65 for the limited RGU and entire core datasets respectively.

Genetic Prediction Of Other SCAL Parameters

Since permeability was successfully predicted using very limited training data, then the genetic petrophysics approach could potentially allow a whole variety of other parameters to be predicted in this way. We tested this idea by training neural nets on data from the PEGASUS Well 2 RGU, to predict other special core analysis (SCAL) parameters in adjacent PEGASUS Well 2b, and compared the predictions with the measured values on intervals of core made ava ilable to us.

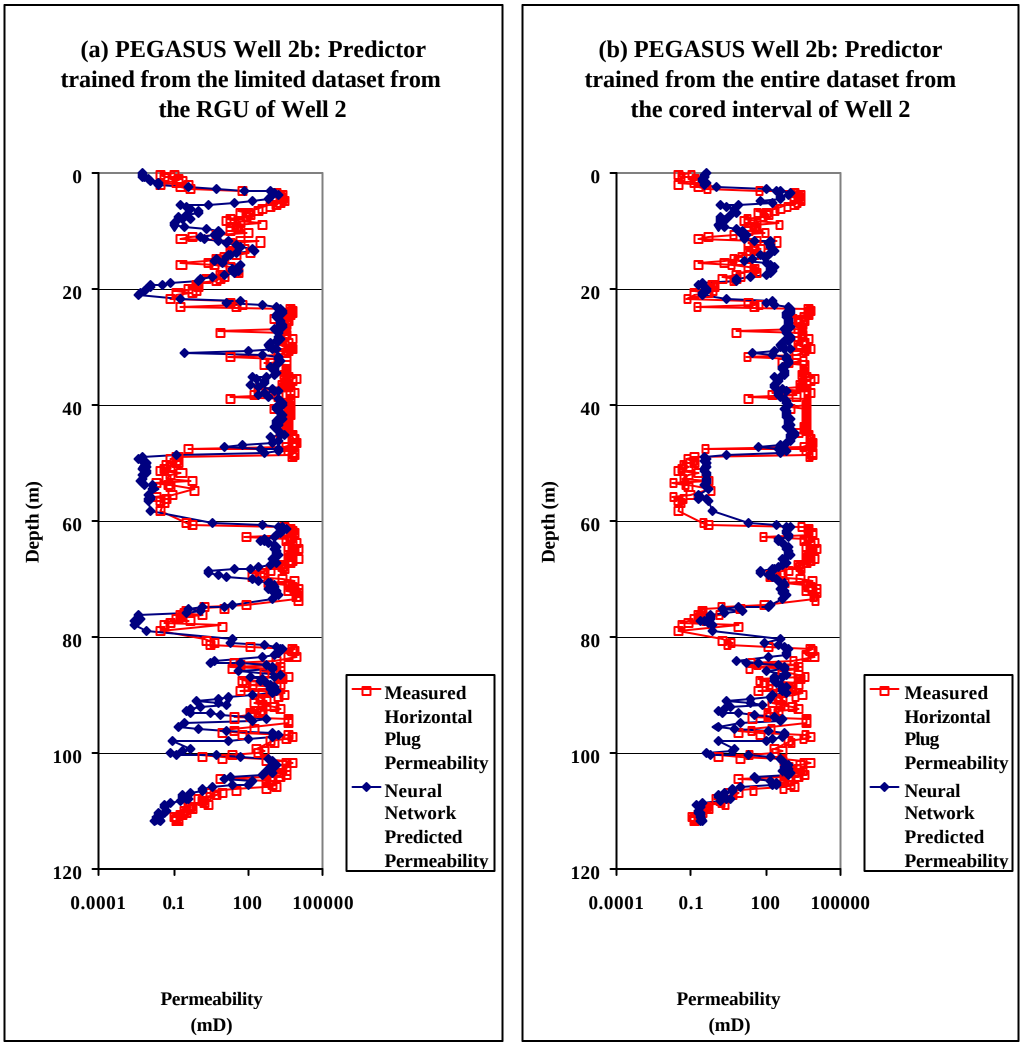

Figure 4. A comparison of neural net predicted permeability and measured values in PEGASUS Well 2b using predictors trained from adjacent PEGASUS Well 2 on (a) The 5 representative plugs in the RGU, and (b) All 297 plugs throughout Well 2. Each predictor used data from 3 key logs (GR, RHOB, DT) in the training and test intervals. Depths are from top of cored section.

<u>(a) Genetic Prediction Of An Acoustic Parameter – Shear Wave Quality Factor</u>

We genetically predicted the shear wave quality factor (Q_s), which is reciprocally related to acoustic attenuation, for crude oil saturated samples at stress sensitive conditions (30 MPa) close to ***in-situ*** reservoir pressures. In this case we trained a neural net using data from ***only*** 4 SCAL plugs that had previously been cut for these measurements from the

PEGASUS Well 2 RGU. These plugs were representative of a reasonable range of the Well 2 hydraulic units (see Figure 2), and the training dataset of Q_s measurements was made at ultrasonic frequencies under the same conditions as detailed above. We would have preferred to have some more plugs to encompass the full range of hydraulic units, however it was not possible in this case, mainly because much of the rest of the core was used for other studies.

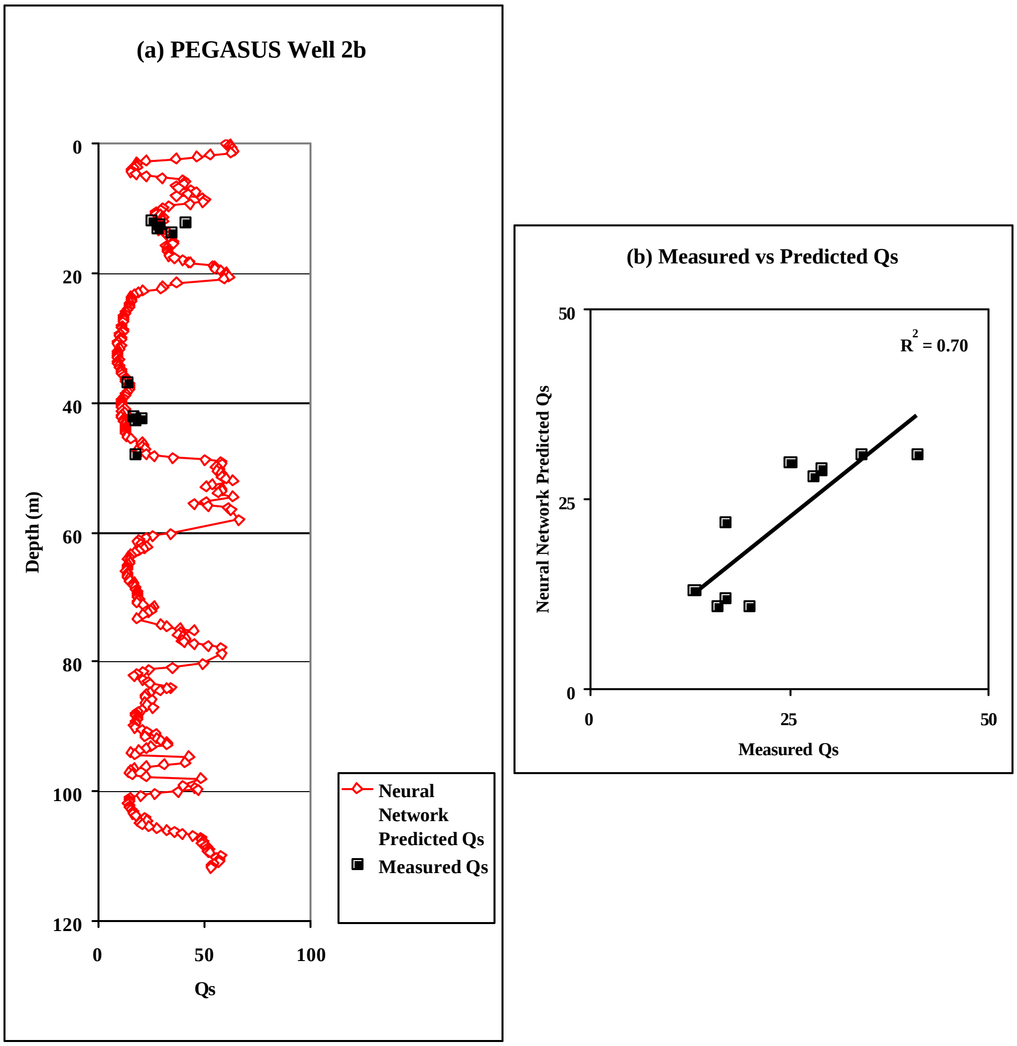

Figure 5. (a) Neural net predicted values of the shear wave quality factor (Q_s) at 30 MPa close to ***in-situ*** pressures for crude oil saturated samples in PEGASUS Well 2b. The predictor was trained on ***just*** 4 SCAL plugs from the PEGASUS Well 2 RGU, along with associated wireline log data. Our measured values on core plugs cut from intervals of the slabbed core are also shown. (b) Crossplot of the predicted versus measured Q_s values.

The neural net predictors in this case were trained without using any acoustic wireline log data in the training well (PEGASUS Well 2) or the test well (PEGASUS Well 2b), i.e. without using the sonic log data. This was to test whether we could provide good acoustic predictions merely from the limited SCAL training data in conjunction with some non-acoustic wireline logs. We chose to train the neural net using the gamma ray, bulk density and deep induction logs. Figure 5 (a) shows the neural net predictions of Q_s at 30 MPa for crude oil saturated samples throughout the cored interval of PEGASUS Well 2b, using the predictor based on the PEGASUS Well 2 RGU limited SCAL dataset.

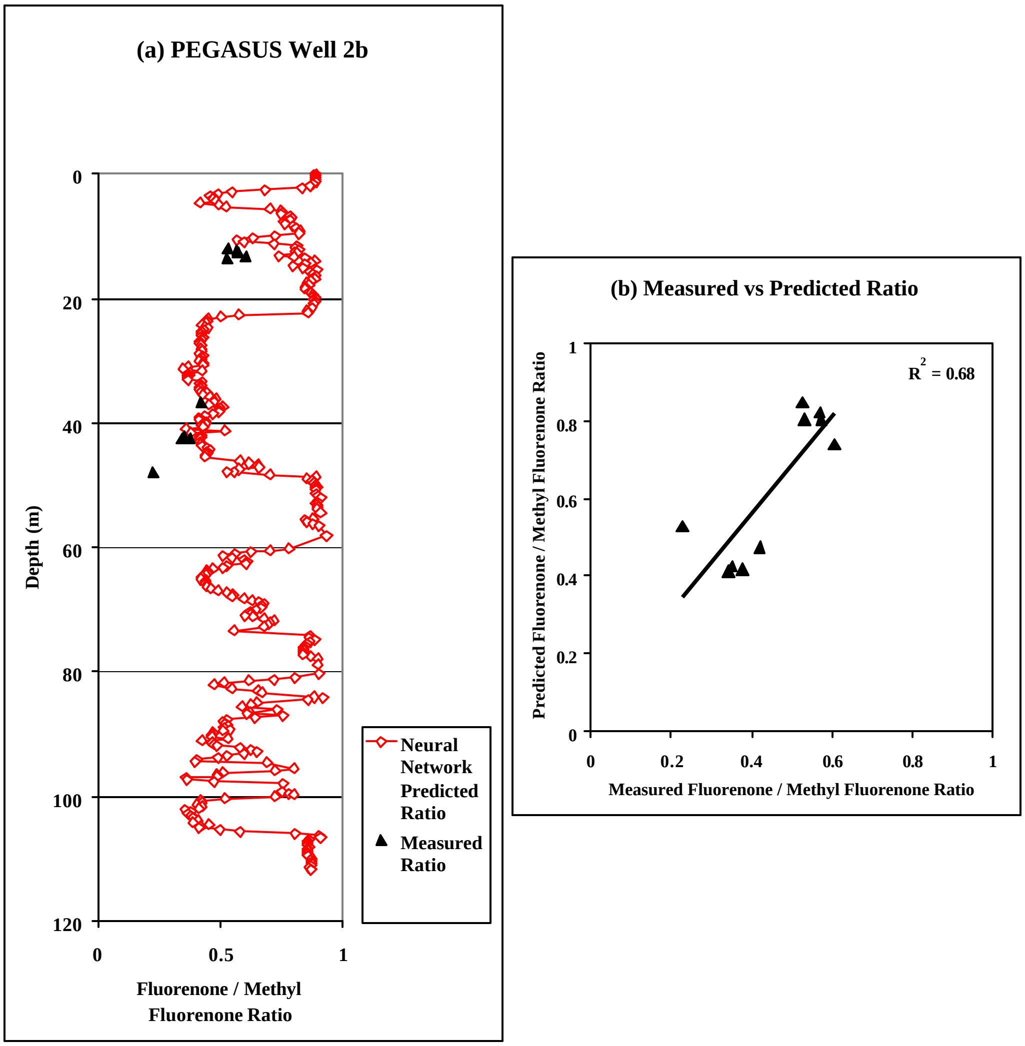

Figure 6. (a) Neural net predicted values of the fluorenone / methyl fluorenone ratio in PEGASUS Well 2b using the PEGASUS Well 2 RGU predictor based on data from 37 small rock chips and associated wireline log data. Our measured values on 10 core chips

made available to us are shown for comparison. (b) Crossplot of the predicted versus measured values of the fluorenone / methyl fluorenone ratio.

We were allowed access to 4 short intervals of core in PEGASUS Well 2b to test our predictions. The sections contained core with a variation in properties from both clean sand and muddy sand intervals. From these intervals 10 plugs were cut (5 cm in diameter and 2.5 cm in height). They were then saturated in the relevant crude oil, and the values of Q_s at 30 MPa were measured. The results are also plotted on Figure 5 (a) and show good agreement with the neural net predictions. The distinct measured differences between the low values of Q_s in the clean sand and the higher values in the muddy sand were successfully predicted by the neural net. Figure 5 (b) shows a crossplot of the neural net predictions versus the measured Q_s values. The linear regression coefficient $r^2 = 0.70$ and the trendline is very close to a line of unit slope passing through the origin.

<u>(b) Genetic Prediction Of A Geochemical Parameter – Fluorenone / Methyl Fluorenone Ratio</u>

We genetically predicted the ratio of two non-producible geochemical compounds, fluorenone / methyl fluorenone, throughout the cored interval of PEGASUS Well 2b using geochemical data acquired from 37 small chips of core from the PEGASUS Well 2 RGU. These chips spanned the full range of hydraulic units within PEGASUS Well 2. In this case we trained the neural net predictor using the gamma ray, neutron porosity and medium induction logs. Figure 6 (a) shows the neural net predictions of the fluorenone / methyl fluorenone ratio, along with the measured values taken on 10 small rock chips, in PEGASUS Well 2b. The predictions are generally in good agreement with the measurements, and Figure 6 (b) shows that a crossplot of the values gives a linear regression coefficient $r^2 = 0.68$. The predictions, however, are generally slightly higher than the measured values. Recent research (Lager, Bennett and Larter, personal communication) has shown that fluorenones and methyl fluorenones exhibit decreases in concentration with time under certain conditions due to oxidation. However, the methyl fluorenones are more stable and decrease less rapidly, so that the ratio can decrease with time. The measured ratios in the test well were made a few years after the original measurements in the neural net training well, possibly explaining why the predictions are slightly higher than the measured values in the test well. At present the significance of these compounds is unclear. However, they may turn out to be potentially useful as their concentration and ratio does show correspondences with clay content, the gamma ray log, the induction logs, water saturation, and wettability [12].

CONCLUSIONS

This work strongly supports the genetic petrophysics approach, and has resulted in the following conclusions:

- It has extended our recent work on genetic permeability prediction to demonstrate that extremely limited, but representative, data can be used to train a neural net to rapidly predict key petrophysical (or geophysical, or geochemical) parameters throughout the uncored intervals in a well, or an adjacent uncored well in the same oilfield. The methodology potentially allows rapid prediction of virtually any parameter of interest, even at in-situ pressures (like the predictions of acoustic quality factor), from a handful of measurements on representative core samples. Our previous work [5,6] also suggested that our genetic shoreface predictors may be even more generic since they provided good predictions in a shoreface interval in a completely different oilfield.

- In particular, the results on genetic permeability prediction have demonstrated that training a neural net on the permeability data from ***just*** 5 initial conventional core plugs (one from each hydraulic unit) in a short representative genetic unit (RGU), along with associated minimal wireline log data from 3 key logs, can produce excellent predictions in shoreface environments. The predictions in PEGASUS Well 2 were equally as good as our previous ones based on using all 24 plugs in the RGU [5,6], and, significantly, were almost as good as those which used the entire dataset (297 plugs) from the 129 m cored interval of the training well. Moreover, the predictions in adjacent PEGASUS Well 2b using the limited training dataset (5 plugs from the PEGASUS Well 2 RGU, plus the associated wireline log data) were actually slightly better than those generated using the entire PEGASUS Well 2 dataset.
- Predictions of the shear wave quality factor (Q_s), at close to in-situ pressures, were made throughout the cored interval of PEGASUS Well 2b from a limited training dataset comprising ***just*** 4 SCAL plugs in the RGU of adjacent PEGASUS Well 2 (plus the associated data from 3 wireline logs). The predictions agreed well with measured values, where these were possible. Moreover, the neural net predictor did not make use of any acoustic wireline log data in the training or test wells.
- A close association between the petrophysics and fluid rock interactions are indicated by the apparent ability of the neural network to predict the behaviour of a petroleum geochemical parameter, the ratio of fluorenone / methyl fluorenone [12], which probably tracks clay content and may have a surrogate role as a wettability prediction parameter. The geochemical log was predicted in the test well (PEGASUS Well 2b), using a training dataset acquired from a series of rock chips from the RGU in adjacent well PEGASUS Well 2, together with the associated data from 3 wireline logs. The predictions agreed well with measured values, raising the possibility that calibrated geochemical wettability logs derived from standard log suites may be possible.
- The results have implications for petrophysical sampling. The sampling of conventional and SCAL plugs could be more effectively done by sampling a small RGU rather than a large cored interval at regular arbitrary spacings. Minimal representative SCAL plugs (which could be used for genetic prediction purposes) could be selected by plotting the available data on a global hydraulic element grid [9]. Alternatively, if a significant amount of conventional core data is already available, then the selection of minimal representative SCAL plugs could be done using conventional hydraulic unit analysis [10].
- The genetic petrophysics approach is very cost effective and less time consuming in terms of core acquisition, sampling, measurement, and parameter prediction purposes.

ACKNOWLEDGEMENTS

We thank the PEGASUS Phase II sponsors (Amerada Hess, BG, Schlumberger, Halliburton, EPSRC, the DTI) for funding and for access to wireline log and core datasets, plus support from Robertson Research Int., Core Labs, and Core Magnetics.

REFERENCES

1. Corbett, P. W. M., Potter, D. K., Mohammed, K., and Liu, S., 2001a. Forget better statistics - concentrate on better sample selection. *DiaLog*, **9**, Issue 2 (June 2001).
2. Potter, D. K., Wright, J.M., and Corbett, P. W. M., 1999. A genetic petrophysics approach to facies and permeability prediction in a PEGASUS well. *European Association of Geoscientists and Engineers 61st Conference*, Extended Abstracts, **Volume 1**, paper 2-53, EAGE meeting, Helsinki, June 8-11.
3. Potter, D. K., and Corbett, P. W. M., 2000. Genetic petrophysics and data integration in PEGASUS – improved prediction of key parameters. *European Association of Geoscientists and Engineers 62nd Conference*, Extended Abstracts, **Volume 1**, paper X-12, EAGE meeting, Glasgow, May 29 - June 2.
4. Corbett P. W. M., Potter, D. K. and Bowen, D. G., 2001b. A new petrophysical sampling strategy for a model-dominated user group using an experimental design checklist approach. *Proceedings of the 2001 International Symposium of the Society of Core Analysts*, paper SCA 2001-01.
5. Le, A. H. and Potter, D. K., 2003. Genetically focussed neural nets for permeability prediction from wireline logs. *European Association of Geoscientists and Engineers 65th Conference*, Extended Abstracts, **Volume 1**, paper F-28, EAGE meeting, Stavanger, June 2 -6.
6. Le, A. H. and Potter, D. K., 2003. Genetically focussed neural nets for permeability prediction from wireline logs in some North Sea shoreface reservoirs. (Submitted to *Geophysical Prospecting*).
7. Potter, D. K., 2000. PEGASUS: Petrophysics, Engineering, Geophysics, And Support to end UserS. *DiaLog*, **8**, Issue 2, 1-4 (July 2000).
8. Arpat, G. B., Gumrah, F., Yeten, B. 1998. The neighborhood approach to prediction of permeability from wireline logs and limited core plug analysis data using back propagation artificial neural networks. *Journal of Petroleum Science and Engineering*, **20**, 1-8.
9. Corbett, P. W. M., Ellabad, Y., Mohammed, K, and Posysoev, A., 2003. Global hydraulic elements – elementary petrophysics for reduced reservoir modeling. *European Association of Geoscientists and Engineers 65th Conference*, Extended Abstracts, **Volume 1**, paper F-26, EAGE meeting, Stavanger, June 2 -6.
10. Amaefule, J. O., Altunbay, M., Tiab, D., Kersey, D. G., and Keelan, D. K. 1993. Enhanced reservoir description:using core and log data to identify hydraulic (flow) units and predict permeability in uncored intervals / wells. *SPE paper* **26436**, 205 – 220.
11. Huang, Z., Shimeld, J., Williamson, M., and Katsube, J., 1996. Permeability prediction with artificial neural network modeling in the Venture gas field, offshore eastern Canada. *Geophysics*, **61**, 422-436.

12. Bennett, B. and Larter, S.R., 2000. Significance of non-producable petroleum compounds in reservoirs: influence on petrophysical / core parameters. *DiaLog*, **8**, Issue 2 (July 2000).