Submitted to DIALOG. 17.09.02

Novel methods of permeability prediction from NMR tool data

S.R. Ogilvie[1*], S. Cuddy[1,2], C. Lindsay[2] and A. Hurst[1].

1. Department of Geology & Petroleum Geology, Meston Building, Kings College, AB24 3UE, Aberdeen, U.K.

2. Helix-RDS Ltd, Westhill, Aberdeen, U.K.

* Current address: Statoil ASA, Arkitekt Ebbellsvei 10, Rotvoll, N-7005 Trondheim, Norway.

Permeability governs the movement of fluids through pore networks of porous media. Applications include enhancement of hydrocarbon recovery, management of water resources, improved geothermal energy strategies and the safe design of toxic and radioactive waste repositories. It is an elusive parameter in hydrocarbon reservoirs as it is very difficult, if not impossible, to determine directly using current sub-surface logging technology. It is a complex interplay of porosity, pore connectivity, grain packing, grain size, rock electrical properties and rock diagenesis. From these data, empirical equations are popularly used in the oil industry to calculate permeability. Nelson (1994) suitably divided these into (i) surface area (e.g., Coates *et al*. 1991), (ii) pore size (e.g., Kozeny-Carmen; Swanson, 1981) and (iii) grain size (e.g., Berg 1970; Van Baaren 1979) models.

The popular Kozeny-Carmen model has been modified many times since the 1930s but the working equation is,

$$K_{KC} = \frac{cd^2\phi^3}{(1-\phi)^2} \quad (1)$$

where, c = constant, d = median grain size (μm), ϕ = porosity.

From mercury injection capillary pressure (MICP) data, Swanson (1981) created a relation based on 319 cleaned sandstone and carbonate samples from 74 formations,

$$K_S = 339\,(S_{hg}/P)_{apex}^{1.691} \quad (2)$$

where, (S_{hg}/P) is the value of the mercury saturation divided by the pressure that corresponds to the apex of the mercury saturation divided by pressure against pressure.

The scatter in cross-plotting permeability and porosity is primarily a result of variable grain size, which has a large influence upon the total wetted surface properties of rocks. Therefore, Berg (1970) suggested that permeability should be predicted using the square of grain size and raising the porosity to an exponent of ~5,

$$K_B = 8.4 \times 10^{-2} \times d^2 \phi^{5.1} \tag{3}$$

where, d = grain size (μm), ϕ = porosity.

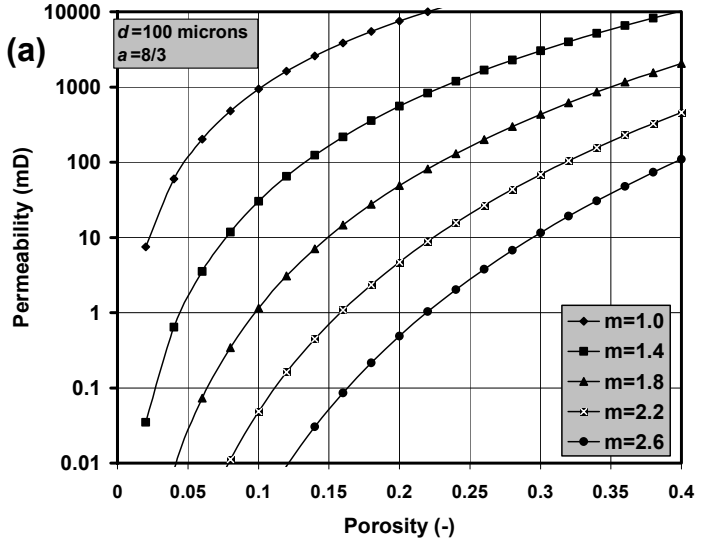
Here we introduce the use of an improved (analytical) method, the RGPZ model named after its authors, Revil, Glover, Pezard and Zagora (Revil *et al*. 1997; Revil & Glover 1998,1999), which considers the link between electrical conductivity and fluid permeability of a porous rock. The relationship requires a mean grain size, d, for the rock, a packing parameter, a, effective porosity, ϕ, and Archie's exponent, m, and is analytically very simple. We show that the relationship is a clear improvement upon the above prediction laws based on grain size estimation, including the Kozeny-Carmen relationship (1). The difficulty in applying the model to down-hole measurements is how to obtain the grain size upon which the model depends. We demonstrate that NMR measurements are able to provide a mean grain size with sufficient accuracy to produce good permeability estimations. The working equation is,

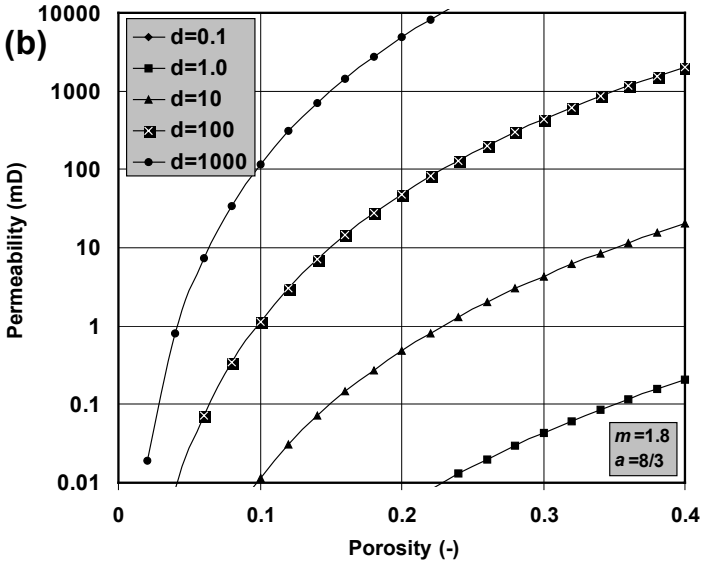
$$K_{RGPZ} = \frac{d^2 \phi^{3m}}{4am^2} \tag{4}$$

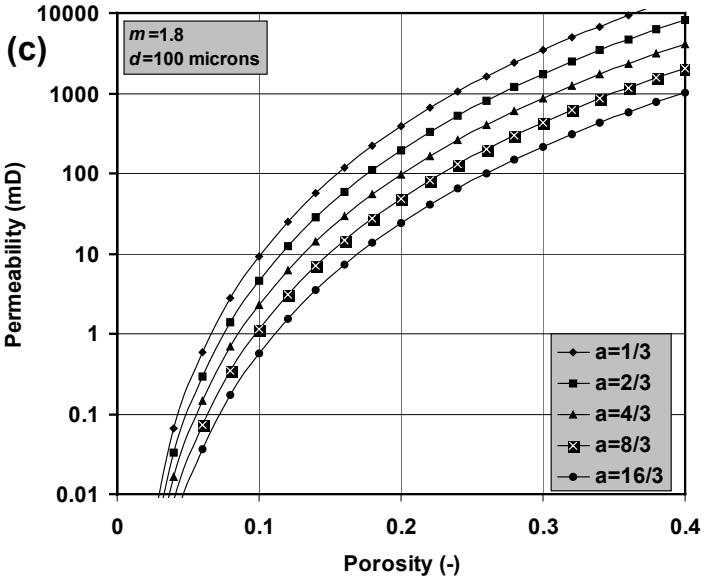
where, K_{RGPZ} = RGPZ predicted permeability, d = mean grain size (μm), ϕ = porosity, m = cementation exponent, a = packing parameter.

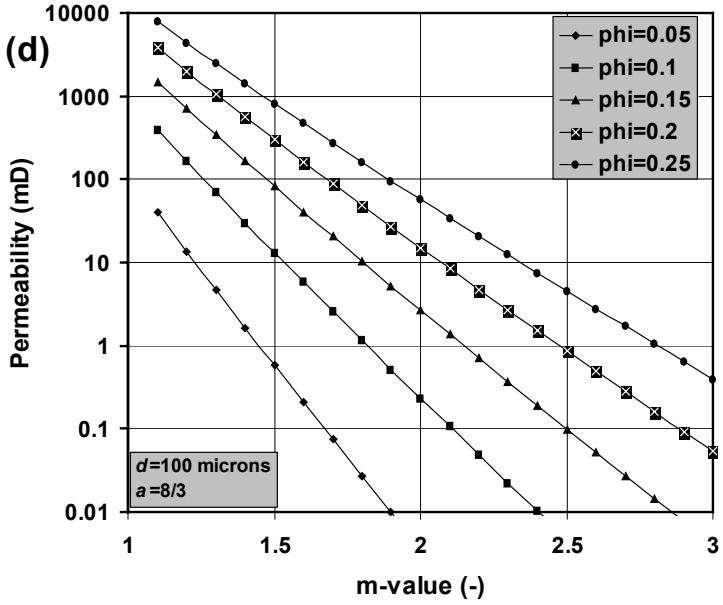
Figure 1 shows the RGPZ model implemented as a function of its major parameters, over ranges exceeding those commonly encountered in reservoir rocks. The shape of the poroperm plots (a) to (c) is convex-up in a similar way to many poroperm plots for similar lithologies. The model is highly sensitive to changes in ϕ, m and d, but not to a. Therefore a constant is used for a.

Figure 1 Behaviour of the RGPZ model as a function of its major parameters. (a) Predicted permeability as a function of porosity for various values of cementation exponent. (b) Predicted permeability as a function of porosity for various values of grain size. (c) Predicted permeability as a function of porosity for various values of the packing parameter. (d) Predicted permeability as a function of cementation exponent for various values of porosity.









We have examined this model using high quality routine core analysis (RCAL) data from a set of carbonate and clastic reservoir rocks from a suite of wells (Table 1).

Table 1 RCAL inputs for the RGPZ model

	Grain Size, *d* (microns)	**Packing parameter, *a***	**Porosity ϕ**	**Cementation exponent, *m***	**Permeability (mD)**
Carbonates	Mercury Injection Porosimetry	Constant	Mercury Injection Porosimetry	Electrical measurements $=F/\phi$	Nitrogen gas
Clastics	Mercury Injection Porosimetry	Constant	Mercury Injection Porosimetry	Electrical measurements $=F/\phi$	Nitrogen gas

RGPZ Core predictions

The NMR experiment conducted on core is almost identical to the NMR log measurement (Coates *et al*. 1999), therefore once tested on RCAL data we have tested the RGPZ model using log input parameters from NMR logs.

The grain size is calculated at each injection pressure from MICP data, and a modal grain size derived for each individual sample (5). Where no MICP data is available, mean grain sizes are determined from thin-section images. These are checked against thin-section photographs and are very accurate.

Grain size determinations on powdered samples using MICP analysis are fairly routine (Carli & Motta, 1989); these are less common for rock samples:

$$Grain\ diameter = KP * AC / 1000 / P \quad (5)$$

where, KP = packing constant (i.e. 4.65 for cubic packing as recommended for use in the porosimeter manual), AC = parameter defined by a conical model for pore-size calculations, P = pressure (bars). This equation is a slight modification to the Washburn equation for calculating pore sizes from MICP data; it is highly relevant to carry out a sensitivity analysis of this equation to packing parameter variation.

The success of permeability prediction is gauged with reference to a 1:1 line between predicted and measured permeabilities (Figs. 2,3). A constant packing parameter, a, of 8/3 (for perfect spherical grains) is used in the RGPZ model as it is insensitive to a (Fig. 1c). The model performs better over five orders of magnitude than $K_{KOZENY\text{-}CARMEN}$ for a range of clean and immature reservoir analogue rocks (Fig. 2). It is also better for the subsurface clastics than for the carbonates (Fig. 3). However, the use of cementation exponent, m, causes a considerable shift of the carbonate predictions towards the 1:1 line of predicted vs measured permeabilities. Also, the model tends to slightly overpredict the permeability of the more poorly sorted quartz wackes (Fig. 3). For the subsurface samples, it is clear that the Swanson (2) and Berg (3) models vastly underpredict and overpredict permeability respectively (Fig. 3).

Figure 2 RGPZ permeability predictions for a range of outcrop sedimentary rocks (i.e. variable grain sizes and sorting) from onshore U.K. compared to measured permeabilities (i) Fascally sandstone (Jurassic), Brora, Scotland, (ii) Lochaline Sandstone (Cretaceous), Morven, Scotland, and (iii) Portland and Purbeck Limestones. The Kozeny-Carmen model shows much greater scatter than the RGPZ model around the 1:1 line.

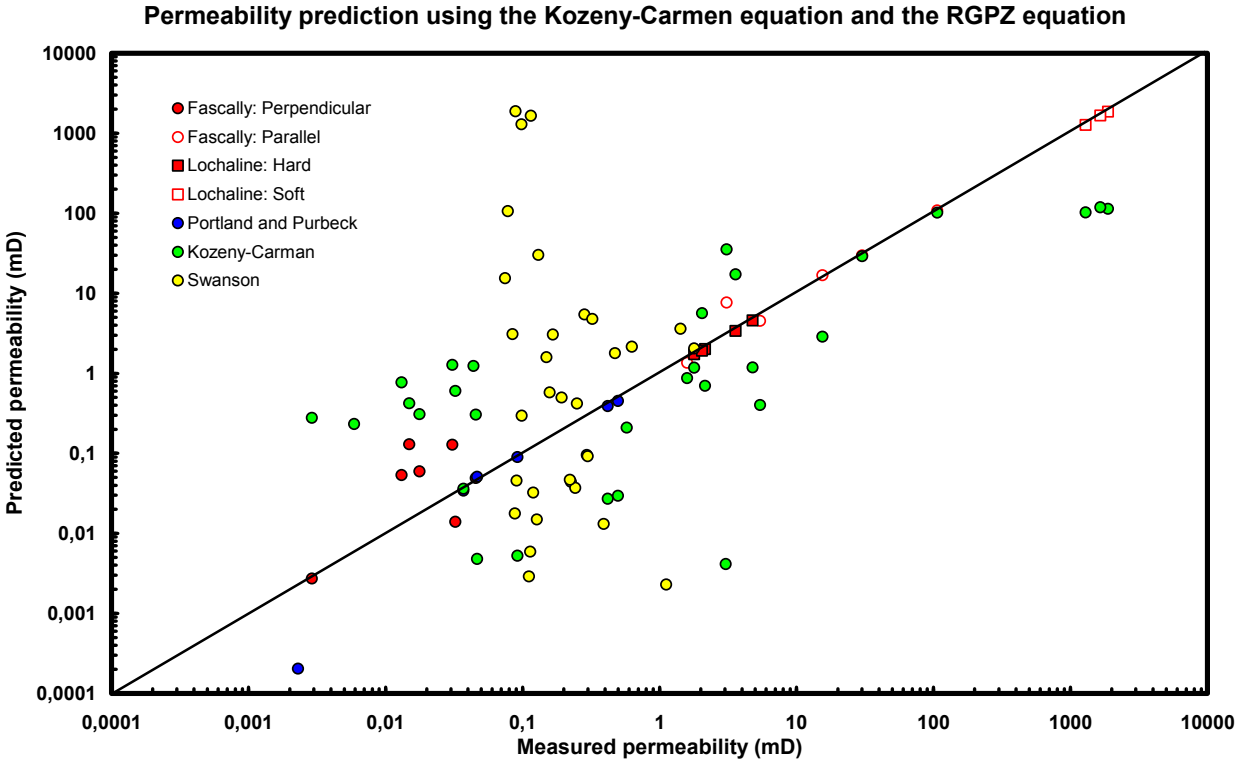
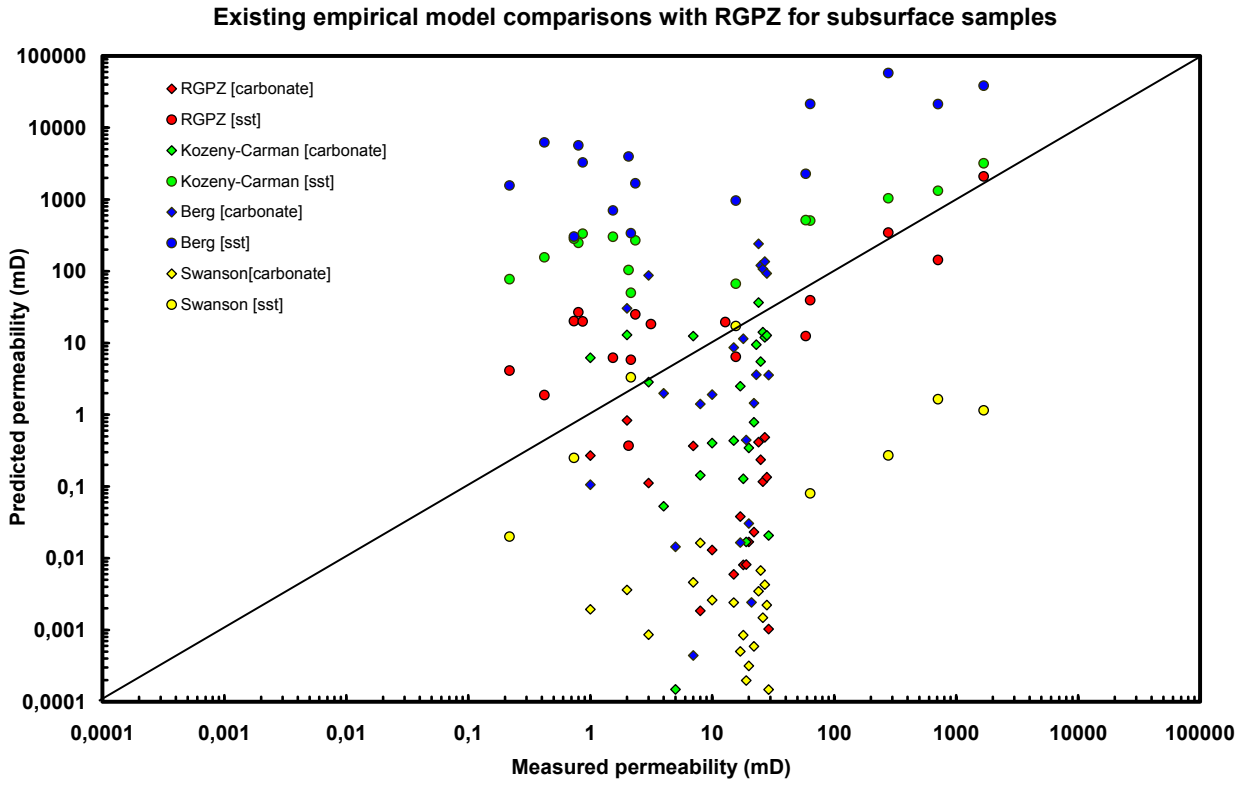


Figure 3 Comparison of best scenario for RGPZ model (i.e. variable *m*, packing parameter 8/3, MICP modal grain size & ϕ) with common grain size (Berg) model and pore-size (Swanson & KC) models. For the Swanson model, only data from samples with MICP data are used as this model relies upon MICP data. For the clastics, quartz arenites are closer to the 1:1 line than more poorly sorted quartz wackes.



RGPZ Log Predictions

Extracting pore and grain sizes from NMR core data.

Now that we have fully and successfully tested the model with routine core analysis (RCAL) input parameters, we have inputted log data into the model. The aim is to replace the standard Coates model for permeability prediction on *Geolog 6.4* (NMR module) with the RGPZ model. The parameters and logs are

(i) *Porosity* by conventional methods directly from the electrical logs.

(ii) *Cementation exponent* from special core analysis (SCAL) data.

(iii) Constant *packing parameter* from established rock matrix models.

(iv) *Grain size* from NMR core and log data.

We have developed a method to obtain grain sizes (iv) from NMR data as described below. To obtain pore size distributions from NMR T_2 distributions, we obtained a pore-scaling factor using (mercury injection) capillary pressure data, by methods described by Basan *et al*. (1996) and Coates *et al.* (1999), (Fig. 4).

To derive pore throats from NMR core data we calculated the effective relaxivity (ρ_e) from 2 parameters,

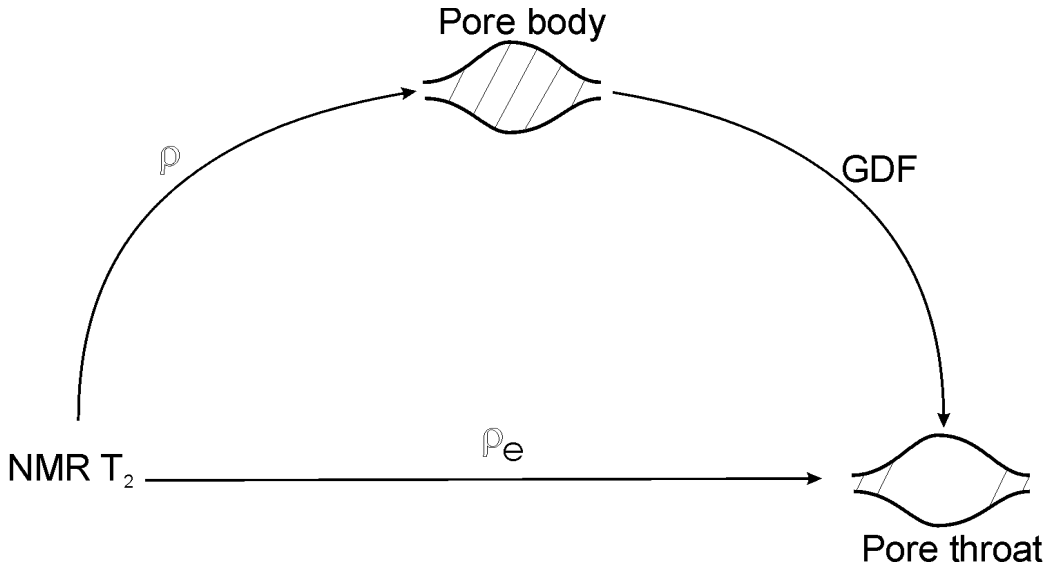
$$\rho_e = \rho / GDF \tag{6}$$

where:

ρ = the intrinsic surface relaxivity i.e., the conversion from T_2 distributions to pore body size. A constant of 50 μm/sec is commonly used for this purpose and used for all lithologies in this study.

GDF = geometric dimensionless constant, i.e., the ratio of pore throat size to pore body size; the conversion of pore body size to pore throat size. This is greater for mud-dominated dolomites and limestones than grain-dominated lithologies.

Figure 4. The derivation of pore throats from NMR T_2 amplitude data. This is the effective relaxivity (ρ_e), which is a product of the conversion of T_2 data to pore bodies i.e., the intrinsic surface relaxivity, ρ, and the ratio of these pore bodies to mercury-injection derived pore throats, the geometric dimensionless factor, *GDF*.



From MICP data, mean grain diameter (d) is calculated using,

$$d = \log y.\ \rho_e. \tag{7}$$

Where, y = gradient of the relationship between MICP-derived grain sizes (5) and pore-throat sizes (~22.8), ρ_e = effective relaxivity.

We can now directly relate these mean grain diameters (related to pore throat size by 22.8 i.e. *y*, gradient of the line) to the NMR derived pore size using the GDF.

Mean grain diameter can now be calculated using,

$$d = 22.8\ (T_2.50/GDF) \tag{8}$$

where, d = mean grain diameter, T_2 = Logarithmic mean T_2 (ms) from NMR tool.

Genetic Algorithms and Fuzzy logic (GAFL) Techniques

Two branches of soft computing known as genetic algorithms (GA) and fuzzy logic (FL) have emerged over the last decade offering complementary but robust techniques to analyse non-linear systems. We have applied these in order to develop a better permeability prediction technique for the NMR tool.

Fuzzy logic is an analytical technique that asserts that the reservoir consists of several litho-types, each having characteristic distributions for permeability and electrical log values. It attempts to uncover the relationship

between these distributions. Genetic algorithms are models of computer learning, which derive their behaviour from an analogy of the processes of evolution in nature. Genetic algorithms, is a feedback technique, that asserts that there is a continuous functional relationship between the log values and permeability and attempts to "evolve" this relationship. They can provide the functional form of the equation as well as the constant parameters of the relationship.

Conventional permeability prediction from the NMR using the Coates or SDR models use very little of the wealth of information contained in the T_2 distribution. The Coates method compares two areas, FFI and BVI, beneath the T_2 distribution separated by an arbitrary cutoff whereas the SDR method only uses a single piece of information, the logarithmic mean T_2. GAFL techniques analyse the entire shape of the T_2 distribution, attempting to unlock any information such as pore throat sizes or grain size diameters that could be related to permeability.

The Applications of Fuzzy Logic to Permeability Prediction

Permeability prediction using fuzzy logic asserts that a particular electrical log value can be associated with any formation attribute, but some are more likely than others. For instance, clean aeolian sand is most likely to have a high bulk density reading, although there is a finite probability that the sand has low density reading. Fuzzy logic attempts to uncover the relationship between these attributes.

Rather than using a single value from the T_2 distribution, such as the logarithmic mean value, fuzzy logic uses the shape of the distribution. The shape of T_2 distribution is processed by slicing it into a 30 point numerical array *t1,t2, t3, t4,…t30.*

The entire core permeability database is scanned by the fuzzy logic software and divided into twenty equally sized bins. That is to say that the bin boundaries are determined so that the number of core permeabilities in bin 1 represents the twentieth percentile boundary of the core permeability data. Bin 2 represents the nineteenth percentile boundary and so on. The formation is thereby divided into 20 bins or litho-facies types each representing a range in permeability. The range in permeability is different for each litho-facies type but each are all assumed to be equally likely to found in the formation as they represent an equal number of core points.

We assert that each slice of the T_2 array may belong to any of the permeability litho-facies, but some are more likely than others. The fuzzy logic software attempts to determine these probabilities by comparing each of the litho-facies bins to the T_2 distribution array. The array data associated with levels in the well corresponding to bin 1 (very low permeability) are analysed and their mean and standard deviation calculated. In this way, not only is the average or most probable *t* value associated with bin 1 calculated, but also some idea of the uncertainty in the measurement or fuzziness is obtained. Each litho-facies has its own mean and standard deviation, such that for the 20 litho-facies types there are 20 pairs of μ and σ. In this way the T_2 distribution is calibrated or conditioned to permeability. This 20 x 30 calibration array is stored in computer memory in order to make permeability predictions.

The fuzzy possibility, $F(t1_f)$ of the first point in the T_2 distribution array, *t1* belonging to litho-facies type *f* compared to the fuzzy possibility of measuring the mean value μ_f is

$$F(t1_f) = e^{-(t1-\mu_f)^2/2\sigma_f^2}. \qquad (9)$$

This is the fuzzy possibility $F(t1_f)$ based on the first slice in the T_2 array. This is done separately for each slice of the T_2 distribution by repeating the process for the second slice of the T_2 distribution array, *t2*. This will give $F(t2_f)$, the fuzzy possibility of the measured volume of *t2* belonging to litho-facies type *f*. This routine is repeated for *t3* etc. At this point we have thirty fuzzy possibilities ($Ft2_f$, $F(t2_f)$, $F(t3_f)$ ... $F(t30_f)$) from different the measurement slices *t1, t2, t3 ….t30* suggesting if that litho-facies type *f* is most probable. The fuzzy possibilities are combined harmonically to give the likelihood that the T_2 distribution is associated with the first litho-facies type (*f=1*). This procedure is repeated for all twenty litho-facies types and as the permeability bins are of equal size, the probabilities can be directly compared to predict the most likely litho-facies and hence permeability associated with the shape of the T_2 distribution at that depth in the well. The associated fuzzy possibility or "greyness" assesses the confidence of this prediction. The computer program then repeats the entire process at the next depth increment in the reservoir. Further information on this technique is described by Cuddy (2000).

The Applications of Genetic Algorithms to Permeability Prediction

A genetic algorithm comprises variables and constants. The variables are, in this application, the thirty slices of T_2 distribution that are typically recorded on a regular half-foot sample rate (i). A genetic algorithm attempts to evolve a relationship between the T_2 distribution and core permeability by changing the constants. Our objective is to construct empirically a function $g(t1, t2, t3…t30)$ which predicts permeability at each depth, i given $(t1, t2, t3…t30)$ at each depth. We are therefore searching for an appropriate function of the form

$$Permeability = g(t1, t2, t3…t30) = a1.t1 + a2.t2 + a3.t3….a30.t30 \quad (10)$$

where $a1…a30$, are unknown constants. The next step is to provide a method for determining how good a given $f(t1, t2, t3…t30)$ which is as a predictor of *permeability*. The approach we adopt is to sum deviations in prediction over all depth levels for a given borehole. We seek a function of the form Equation 10 which minimizes this sum. Mathematically, the problem can be stated as:

$$\underset{f}{Minimise} : \sum_{i=1}^{i=N} [Permeability - g(t1_i t2_i, t3_i….t30_i)] \quad (11)$$

The genetic algorithms were constructed as follows. An initial population of individuals is picked randomly in the solution space. Each individual has randomly chosen constants $a1…a30$. The fitness criterion of each of these individuals is determined by Equation 11. The best existing algorithm for minimising Equation 11 starts with a randomly generated g and uses local search by mutating the coefficients one at a time. The coefficients are initially allowed to undergo large mutations in order that the individuals search all of the solution space. After a number of generations, a pool of individuals is selected, by linear ranking, for mutating and cloning. Mating is achieved by coefficient merging. Some of the best individuals are cloned to add more individuals, where solutions are most promising. After a number of generations the percentage change in mutated coefficients is gradually reduced. The algorithm stops when the percentage improvement in evaluation reaches a predefined lower limit or a maximum number of iterations has been reached.

In the language of genetic algorithms we have a *CHROMOSOME* which is a vector of length 30. The *CHROMOSOME* is as in genetics, a structure than contains all the genes. The genes are floating point values that represent the coefficients $a1…a30$. The initial population is generated by creating chromosomes with random floating point numbers for the coefficients $a1…a30$. The gene is modified by multiplication by a randomly

picked value from a certain range. This range decreases in value as the number of generations increases. This provides a method that allows the search to become more local towards the end of the algorithm as better solutions emerge. Further information on this technique is described in Brown *et al.* (2000).

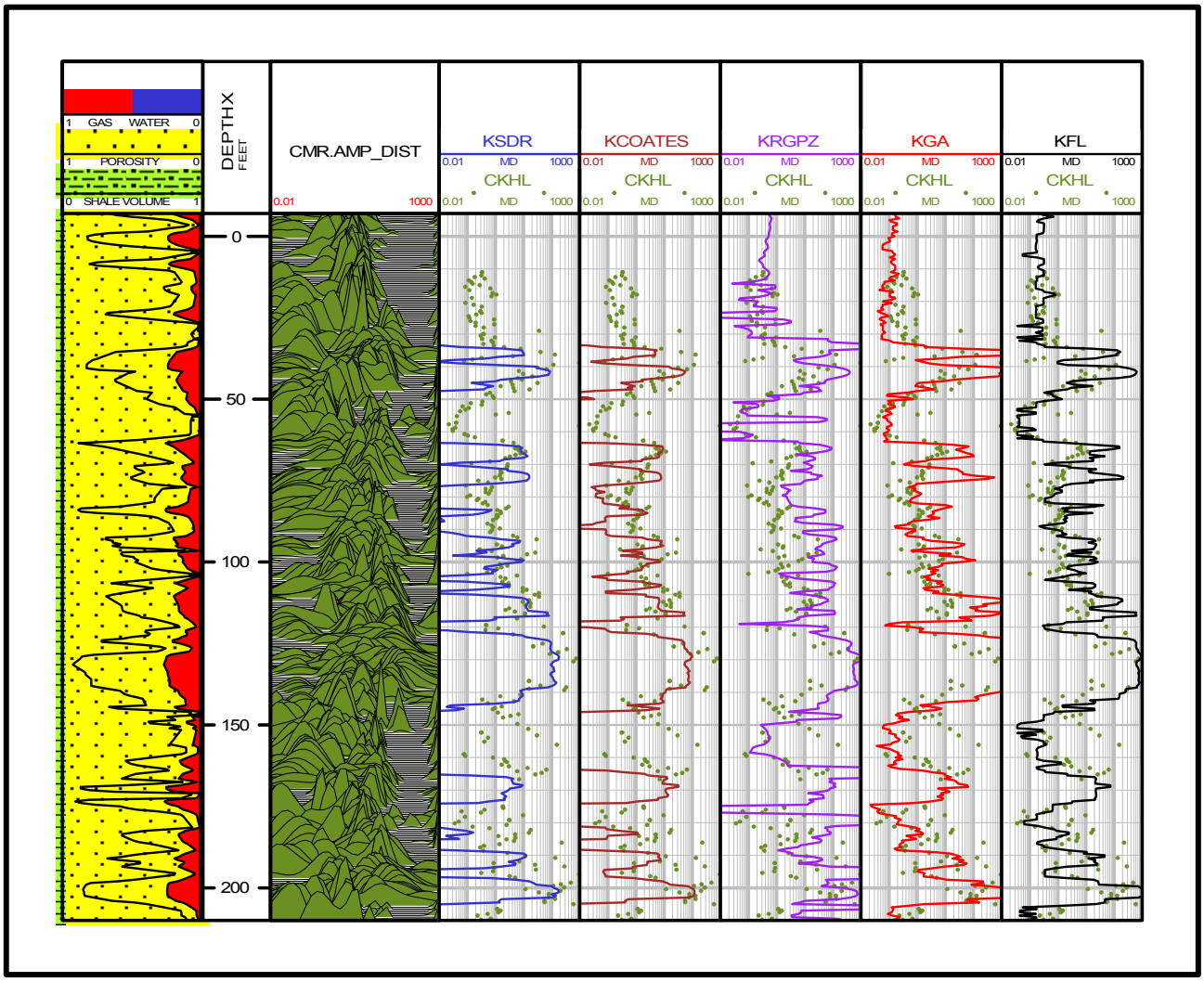
Comparison between Models

A comparison between the RGPZ model implemented for the clastics with predictions by (i) Coates, (ii) SDR and GAFL (genetic algorithm-fuzzy logic) methods is shown in Figure 5. All methods are conditioned to the core data in this well.

For the sandstone interval, the log mean T_2 is 419 ms and the standard cut-off is 32 ms. From this, the mean grain size is calculated as 14500 μm^2 (120 x 120 μm) and where bound water exists it is 1100 μm^2. This is a realistic grain size for the studied sandstones as verified by core analysis data.

Clearly, the RGPZ model works better over the interval than the standard NMR models, and in certain intervals, compared to GAFL (genetic algorithm - fuzzy logic) methods. The RGPZ model does not work so well in the mid section (65-100 ft). This is likely a result of the cementation exponent being held constant. Current SCAL studies may help us understand how this varies throughout the reservoir. We are working to refine the RGPZ model with additional core analysis data in order to improve the permeability predictions further.

Figure 5. Permeability prediction in the study well using
(i) SDR, (ii) Coates, (iii) RGPZ, (iv) Genetic Algorithm and (v) Fuzzy Logic methods



Conclusions

The RGPZ and GAFL models work exceptionally well as a permeability predictor on core and log data, performing better overall than the SDR and Coates models. The following constraints for the RGPZ model do not preclude its use for permeability prediction in the reservoir:

1. the F and m values are derived from saline water bearing rock,
2. the rock is unfractured such that $F >> 1$ (also Coates/SDR do not account for fractures),
3. the model is not used in the limit $\phi \rightarrow 1$ (i.e. 100% porosity).

References:

Basan, P.B. Lowden, B.D, Whattler, P.R. and Attard, J.J. 1996. Pore-size data in petrophysics: a perspective on the measurement of pore geometry. From Lovell, M.A & Harvey, P.K. (eds) 1997, Developments in Petrophysics, Geological Society Special Publication No 122, 47-67.

Berg, R.R. 1970. Method for determining permeability from reservoir rock properties: Transactions, Gulf Coast Association of Geological Societies 20, 303-317.

Brown, D.F, Cuddy S.J, Garmendia-Doval A.B and McCall J.A.W. 2000. "The Prediction of Permeability in Oil-Bearing Strata using Genetic Algorithms" 3rd IASTED International Conference Artificial Intelligence and Soft Computing, Banff, Canada.

Carli, F and Motta, A. 1989. Particle Size Distrbution of Reference Materials by Microcomputerised Mercury Porosimetry. In. Carlo Erba Instruments (Porosimeter 2000 Series) Instruction Manual, 1989.

Coates, G.R., Hardwick, R.C.A. and Roberts, D. 1991. The magnetic resonance imaging log characterised by comparison with petrophysical properties and laboratory core data: Paper 22723, *Proceedings of the Society of Petroleum Engineers 66th Annual Technical Conference and Exhibition*, 4 p.

Coates, G.R, Xiao, L and Prammer, M.G. 1999. NMR principles and applications, Haliburton Energy Services, Houston.

Cuddy, S.J., 2000. "The Prediction of Permeability and Litho-Facies from Electrical Logs using Fuzzy Logic." *SRE Reservoir Evaluation and Engineering Magazine*. SPE Paper Number 65411. August, Vol. 3 No. 4.

Nelson, P.H. 1994. Permeability-Porosity Relationships in Sedimentary rocks. *The Log Analys*t, May-June, 38-41.

Revil, A and Glover, P.W.J. 1997. Theory of ionic surface electrical conduction in porous media, *Phys. Rev.B*, 55 (3), 1757-1773.

Revil, A and Glover, P.W.J. 1998. Nature of surface electrical conductivity in natural sands, sandstones and clays, *Geophysical Research Letters*, 25 (5) 691-694.

Revil, A and Glover, P.W.J. 1999. Streaming potential in porous media 1. Theory of the zeta potential. *Journal of Geophysical Research*, 104, B9, 20201-20031.

Swanson, B.F. 1981. A simple correlation between permeability and mercury capillary pressure, *J. Pet. Tech*., 33, 2498-2504.

Van Baaren, J.P. 1979. Quick-look permeability estimates using sidewall samples and porosity logs, 6th annual European logging symposium transactions: *Society of Professional Well Log Analysts*, 19p.