The Use of Genetic Algorithms and Fuzzy Logic in the Prediction of Permeability and Shear Velocities; and in the Determination of Shaly Sand Saturation Equations

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Abstract

We have developed new techniques for the prediction of rock physical properties based on genetic algorithms and fuzzy logic. These methods are statistically very different and therefore provide alternative methods of prediction to existing methods. Fuzzy logic is an analytical technique that asserts that a reservoir can be broken down into several lithotypes, each having characteristic distributions for electrical log values and permeability. Fuzzy logic attempts to uncover the relationships between these distributions. Genetic algorithms use a feedback technique that assumes a continuous functional relationship between the electrical log values and rock properties, generating and testing equations that fit predicted and observed responses. Complex non-linear equations are "evolved" until the best fit is obtained. Genetic algorithms provide the functional form of the equation as well as the constant parameters of the relationship.

Permeability governs the movement of fluids through reservoir rocks and is therefore critical input into 3D reservoir models. Permeability prediction is extremely challenging, as it is nearly impossible to measure directly using current sub-surface logging technology. It is useful to complement current technology and to gain insight to older wells without core and extensive logging programmes. This contribution describes improved permeability prediction from conventional electrical logs and Nuclear Magnetic Resonance (NMR) data using genetic algorithms and fuzzy logic (GAFL) techniques.

The measurement of shear sonic velocities is important for understanding reservoir rock properties. Shear sonic velocities are required for rock strength analysis to determine fracture propagation and formation breakdown characteristics. They provide improved porosity prediction as it is largely unaffected by fluid type. It is also becoming important for enhanced geophysical interpretation such as AVO. Because the value of shear velocity data is only now being realized and the high cost of acquisition, there is limited amount of information available in the North Sea. Fuzzy logic and genetic algorithms are used to find correlations between shear sonic logs and conventional logs like the gamma-ray and density logs. In a recent study, calibration data from four wells with shear velocity data were used to predict Vs in all the wells in the field. This gave the oil company a cost effective method of building a 3D reservoir model that resulted in the better location of wells.

We use genetic algorithms to evolve shaly sand equations from Dean and Stark water saturations. This method derives the form of the shaly sand equation and gives an independent calculation of special core analysis (SCAL) parameters such as the cementation exponent, *m* and the saturation exponent, *n*.

We demonstrate, using several field examples, how these new predictive methods can be applied in a variety of ways to enhance the understanding of rock physical properties. A high degree of predictive confidence can be obtained by combining predictions made by these two disparate techniques, especially in uncored wells. The new techniques give better predictions compared to conventional methods such as multiple linear regression, neural networks and cluster analysis.

Keywords

Fuzzy logic genetic algorithms

Introduction

A challenge to the oil industry is to build a reservoir model for cost-effective well placing and economic hydrocarbon production. This problem involves using sparse data from linear boreholes to build a 3D model of the reservoir. The aim of this study is to understand the relationship between reservoir parameters and measurements from core and electrical logs. These correlations are used to extract as much information as possible from the well data in order to improve formation evaluation, reservoir characterization and modelling.

This paper describes how we can improve the understanding of the relationship between geological attributes as observed in oil and gas reservoirs and the responses to borehole conveyed electrical logs. This boosts the oil industry's ability to predict reservoir parameters such as permeability, litho-facies and shear velocities especially in uncored areas of the field. To complement this description of the formation rock fabric, our research has also developed a technique to understand the distribution of fluids throughout the reservoir. From this research, methods were developed to improve the resolution and quality of electrical log data itself. This contribution uses two soft computing techniques, fuzzy logic and genetic algorithms, to help with this endeavour.

There are many statistical techniques for making predictions from data in the geological and other sciences. These techniques can be divided into conventional techniques, which include least squares regression and cluster analysis **[Freund, 1980]** and 'soft computing' techniques **[John, 2001]** which include fuzzy logic, genetic algorithms and neural networks. The soft computing techniques take advantage of powerful, relatively cheap computers that are now available **[Cuddy, 2000(a)]**. Fuzzy logic and genetic algorithms are considered, for reasons given later, to be the most promising for making geoscience predictions and are the main tools used in this research.

The Philosophy of Genetic Algorithms

Genetic algorithms (GAs) are models of computer learning, which derive their behaviour from an analogy of the processes of evolution in nature. The individual organisms in this analogy are possible solutions to some given well-defined problem in formation evaluation. The analogy is implemented by the creation within a computer of a population of individuals represented by GA-chromosomes that are analogous to the DNA chromosomes **[Mitchell, 1999]**. These GA-chromosomes take the form of mathematical equations relating the solution to a set of input data. The individuals in the population then go through a process of evolution. Mutation, achieved through random number generation, can play an important part in the process. After a number of generations, the computer uses a fitness function to select individuals probabilistically to undergo genetic operations analogous to sexual reproduction and cloning. The fitness function assesses how close the individual comes to solving the problem **[Back, 1996]**. Genetic algorithms use stochastic processes, and as they are not random searches for a solution to a problem, they perform better than classical optimisation routines. As in nature, poorly performing individuals die or their species become extinct, the computer discards poor solutions. The computer then iterates using the new population, with one iteration being one generation. Mutation plays a role in the process, though it is not the dominant role that is traditionally believed to be the process of evolution, i.e., random mutation and survival of the fittest. It is important to stress that the genetic algorithms are not a "random search" for a solution to a problem (highly fit individual). The genetic algorithm uses stochastic processes and random number generators but the result is distinctly non-random (better than random) **[Back, 1996]**.

Many scientists believe that the use of computer genetic algorithms is not analogous to evolution but merely a variation. Oxford University evolutionary biologist Richard Dawkins saw the border between life and machine start to blur more than 15 years ago. In his 1986 book, *The Blind Watchmaker* **[Dawkins, 1986]**, Dawkins wrote:

> "What lies at the heart of every living thing is not a fire, not warm breath, not a 'spark of life.' It is information, words, instructions. There is very little difference, in principle, between a two-state binary information technology, like ours, and a four-state information technology like that of the living cell."

Evolution has been clearly demonstrated to work by the diversity of life on this planet. There are no reasons why the same principles applied to computer software shouldn't work equally well, but in minutes rather than in geological time. Genetic algorithms are not restricted to the rules we observed in nature. For instance mating can involve several parents rather than two and individuals can pass on to their offspring characteristics that they have acquired during their lifetimes.

Genetic algorithms have been developed and applied for the last forty years **[Fang, 1996].** They are only now being used extensively as they require fast computers, which are now more readily available as they are cheaper. They have several advantages over conventional problem solving. Genetic algorithms 'invent' the equation as well as the parameters involved. For instance if we were attempting to predict water saturation from resistivity logs genetic algorithms will derive the special core analysis parameters (SCAL) but may also reinvent Archie's saturation equation, a modified version of it, or indeed a better equation more fitting to the particular dataset. The GA technique is therefore fundamentally empirical. If we were attempting to predict permeability from the nuclear magnetic resonance tool genetic algorithms may re-invent the Coates equation or something similar or better. Prior knowledge of the equations is therefore not necessary. The method does not fall into the group called 'Black Box' techniques such as neural networks as the equations they uncover clearly show the relationship between variables **[Gurney, 2000]**. The equations can be transferred easily between computer systems, say to a spreadsheet. Genetic algorithms avoid the problems of conventional problem solving techniques as they escape easily from local minima and are relatively insensitive to data outliers and noise.

The Philosophy of Fuzzy Logic

Fuzzy logic is an analytical statistical technique whereas the use of genetic algorithms is a feedback technique. Fuzzy logic is an extension of conventional Boolean logic (zeros and ones) that has been developed to handle the concept of "partial truth", i.e., truth values that lie between "completely true" and "completely false". Dr. Lotfi Zadeh of UC/Berkeley introduced it in the 1960s as a means to model uncertainty **[Zadeh, 1965]**. Science and our way of thinking is heavily influenced by Aristotle's laws of logic formulated by the ancient Greeks and developed by many scientists and philosophers since then **[Kosko, 1993]**.

Aristotle's laws are based on "X or not-X"; a thing either IS, or IS NOT. This has been used as a basis for almost everything that we do. We use it when we classify things and when we judge things. Managers want to know whether something is ‘this’ or ‘that’, and even movies have stereotype goodies and baddies. Conventional logic is an extension of our subjective desire to categorize things. Life is simplified if we think in terms of black and white. This way of looking at things as true or false was reinforced with the introduction of computers that only use the binary digits 1 or 0. When the early computers arrived with their machine-driven binary system, Boolean logic was adopted as the natural reasoning mechanism for them.

Conventional logic forces the continuous world to be described with a coarse approximation; and in so doing, much of the fine detail is lost.

We miss a lot in the simplification. By only accepting the two extreme possibilities, the infinite number of possibilities in between them is lost. Reality does not work in black and white, but in shades of grey. Not only does truth exist fundamentally on a sliding scale, it is also perceived to vary gradually by uncertainties in measurements and interpretations. Hence, a grey scale can be a more useful explanation than two end points. For instance, we can look at a map of the Earth and see mountains and valleys, but it is difficult to define where mountains start and the valleys end.

This is the where mathematics of fuzzy logic comes in. Once the reality of the grey scale has been accepted, a system is required to cope with the multitude of possibilities. Probability theory helps quantify the greyness or fuzziness. It may not be possible to understand the reason behind random events, but fuzzy logic can help bring meaning to the bigger picture. Take, for instance, a piece of reservoir rock. Aeolian rock generally has good porosity and fluvial rock poorer porosity. If we find a piece of rock with a porosity of 2 porosity units (pu), is it aeolian or fluvial? Since this has a low porosity value we could say it is definitely fluvial and get on with more important matters. But let's say it is probably fluvial but there is a slim probability that it could be aeolian. Aeolian rocks are generally clean (i.e., contain little or no clay minerals) and fluvial rocks shalier (i.e., contain clay minerals). The same piece of rock contains 20% clay minerals. Now, is it aeolian or fluvial? We could say it is approximately equally likely to be aeolian or fluvial based on this measurement. This is how fuzzy logic works. It does not accept something is either ‘this’ or ‘that’. Rather, it assigns a greyness, or probability, to the quality of the prediction on each parameter of the rock, whether it is porosity, shaliness or colour. There is also the possibility that there is a measurement error and the porosity is 20 pu not 2 pu. Fuzzy logic combines these probabilities and predicts that, based on porosity, shaliness and other characteristics, the rock is most likely to be aeolian and provides a probability for this scenario. However, fuzzy logic says that there is also the possibility it could be fluvial, and provides a probability for this to be the case too.

In essence, fuzzy logic maintains that any interpretation is possible, but some are more probable than others. One advantage of fuzzy logic is that we never need to make a concrete decision. In addition, fuzzy logic can be described by established statistical algorithms. Computers, which themselves work in ones and zeros, can do this effortlessly for us.

Geoscientists live with error, uncertainty and fragile correlations between data sets. These conditions are inherent to the geosciences, because of the challenge of designing and building sensors to measure complex formations in hostile environments. Even in the laboratory it is difficult to relate a log response to a physical parameter. Several perturbing effects such as mineralogy, fluids and drilling fluid invasion can influence a simple measurement, say porosity. Conventional techniques try to minimize or ignore the error. Fuzzy logic asserts that there is useful information in this error. The error information can be used to provide a powerful predictive tool for the geoscientist to complement conventional techniques.

How the Concept of Fuzziness helps Predict Litho-facies

There are two causes of the fuzziness in reservoir rocks. The first is measurement error and the second is due to classification. It is clear that random error in a measurement of a variable like porosity will give arise to fuzziness in the answer. However, we assert it is the second cause, classification, is the main cause of fuzziness, and fuzzy logic deals with this directly. If the rock type is sub-divided into more detailed classifications such as dune, fluvial or sabkha sands, each classification or bin becomes more crisp, the opposite of fuzziness **[Kosko, 1993]**.

Take two classifications of reservoir rock, aeolian dune and sabkha sandstones. In this example the aeolian dune sandstones are considered to have good reservoir potential with an average porosity of 20 pu **[Schlumberger, 1997]** and the sabkha are considered to be poorer reservoir sandstones with an average porosity of 10 pu. Now consider a third specimen of reservoir sandstone exhibiting a porosity of 15 pu. This could belong to a third independent classification, but if we are forced to select whether this specimen is associated with the good aeolian or the poor sabkha reservoir there is a problem. This is because the sample porosity of 15 pu is equidistant from the 20 pu aeolian sandstone and the 10 pu sabkha sandstone. However, Figure 1 shows that the sabkha sandstone has a wider and fuzzier distribution of possible porosity values than the aeolian sandstone. A reason for this could be that the sabkha sandstone contains more sub-types than the aeolian sandstone, which by comparison has been defined more precisely. As a consequence Figure 1 shows that 15 pu is more likely to be associated with sabkha sandstone rather than the aeolian sandstone as 15 pu is seen to occur higher on the probability distribution of the sabkha sandstone that of the aeolian sandstone. This example demonstrates how the understanding of the fuzziness of a classification is as valuable as knowing its average value.

This paper describes how our research led to the development of techniques to apply the theory of fuzzy logic to geoscience problems such as formation evaluation and reservoir characterisation. These techniques have been incorporated in petrophysical software packages and tested on several and gas fields by the major oil companies.

Fuzzy Mathematics of Litho-facies Prediction

This paper describes how we developed the philosophical ideas, concepts and practical software techniques of fuzzy logic to build a novel and original mathematical framework. This new mathematics is the basis of software that we developed to solve formation evaluation and reservoir characterisation problems. Many of the ideas deviate from conventional statistical theory, such as Bayes Theorem, but have been shown to work on the many oil field databases available to this research.

We start with the mathematics of the normal distribution **[Freund, 1980]**. This is given by

$$P(x) = \frac{e^{-(x-\mu)^2/2\sigma^2}}{\sigma\sqrt{2\pi}} \qquad (1)$$

where *P(x)* is the probability density that an observation *x* is measured in the data-set described by the arithmetic mean μ and its standard deviation σ.

In conventional statistics the area under the curve described by the normal distribution, say between x_1 and x_2, represents the probability of a variable *x* falling into that range,. The curve itself represents the relative probability of variable *x* occurring in the distribution. That is to say, the mean value is more likely to occur than values 1 or 2 standard deviations away from it. This curve is used to estimate the relative probability, or fuzzy possibility, that a data value belongs to a particular data set. If a litho-facies type has a porosity distribution with a mean μ and standard deviation σ the fuzzy possibility that a well log porosity value *x* is measured in this litho-facies type can be estimated **[Freund, 1980]**. The mean and standard deviation are estimated from the calibrating or conditioning data set, usually core data in our applications.

Where there are several litho-facies types in a well, the porosity value *x* may belong to any of these litho-facies, but some are more likely than others. Each of these litho-facies types has its own mean and standard deviation, such that for *f* litho-facies types there are *f* pairs of μ and σ. If the porosity measurement is assumed to belong to litho-facies *f*, the fuzzy possibility that porosity *x* is measured (logged) can be calculated using Equation 1 by substituting μ_f and σ_f. Similarly, the fuzzy possibilities can be computed for all *f* litho-facies. These fuzzy possibilities refer only to particular litho-facies and cannot be compared directly as they are not additive and do not sum to unity.

We solved the problem of comparing the fuzzy possibilities between the *f* litho-facies as follows. We would like to know the ratio of the fuzzy possibility for each litho-facies to the fuzzy possibility of the mean or most likely observation. This is achieved by de-normalizing Equation 1, which simplifies the equation and is necessary if information about the relative occurrence of the facies is to be used in the prediction.

The fuzzy possibility of the mean observation μ_f being measured is

$$P(\mu) = \frac{e^{-(\mu_f - \mu_f)^2 / 2\sigma^2}}{\sigma\sqrt{2\pi}} = \frac{1}{\sigma\sqrt{2\pi}} . \qquad (2)$$

The relative fuzzy possibility $R(x_f)$ of a porosity *x* belonging to litho-facies type *f* compared to the fuzzy possibility of measuring the mean value μ_f is Equation 1 divided by Equation 2

$$R(x_f) = e^{-(x-\mu_f)^2 / 2\sigma_f^2} . \qquad (3)$$

Each fuzzy possibility is now self-referenced to all possible litho-facies types. The different litho-facies possibilities still cannot be compared directly as the calibration of each litho-facies may be based on a different sample size. For instance the four litho-facies types; aeolian, fluvial, sabkha and shale may have relative abundances in the reservoir section of 70%, 15%, 10% and 5% respectively. To compare the computed possibilities derived using Equation 3 would give undue weighting to the less frequently occurring litho-facies, sabkha and shales.

We solved this problem by devising a method to compare different bin sizes, which is described below.

The relative occurrence of each litho-facies type in the formation must be taken into account in order to compare these fuzzy possibilities between litho-facies. We propose that this can be achieved by multiplying Equation 3 by the square root of the 'expected occurrence' of litho-facies *f.* The expected occurrence is the percentage occurrence of the specimens in the calibrating sample. This assumption is based on the observation that rare litho-facies in the calibrating data set, say limestone stringers or coal beds, it will not be a predominant facies elsewhere in the field. This assertion is support by sensitivity studies.

Therefore if the expected occurrence is denoted by n_f, the fuzzy possibility of measured porosity x belonging to litho-facies type f is:

$$F(x_f) = \sqrt{n_f}\, e^{-(x-\mu_f)^2/2\sigma_f^2} . \qquad (4)$$

This square root term was determined from sensitivity studies on a number of fields. We introduced the term 'fuzzy possibility' to differentiate and contrast it from the conventional statistical term ‘probability’ to emphasis that fuzzy logic is drifting subtly away from conventional statistics.

The next challenge is to use not one curve to predict a litho-facies type, but several, and perhaps dozens. We solved this problem by devising a novel way to combine fuzzy possibilities, as described below.

So far we have described how it is possible to calculate the fuzzy possibility $F(x_f)$ is based on the porosity measurement (log), x, alone. This process can be repeated for a second log type such as the volume of shale, y. This will give $F(y_f)$, the fuzzy possibility of the measured volume of shale y belonging to litho-facies type f. This process can be repeated for another log type, say z, to give $F(z_f)$. At this point we have several fuzzy possibilities ($F(x_f)$, $F(y_f)$, $F(z_f)$ ….) based on the fuzzy possibilities from different measurements (x, y, z ….) predicting that litho-facies type f is most probable. We propose that these fuzzy possibilities should be combined harmonically to give a combined fuzzy possibility C_f, where

$$\frac{1}{C_f} = \frac{1}{F(x_f)} + \frac{1}{F(y_f)} + \frac{1}{F(z_f)} \ldots \tag{5}$$

Combining the fuzzy possibilities harmonically is repeated for each of the f litho-facies types. The litho-facies that is associated with the highest combined fuzzy possibility is taken as the most likely litho-facies for that set of logs. The associated fuzzy possibility $C_f(max)$ provides the confidence factor for the litho-facies prediction.

Litho-facies prediction using fuzzy logic is based on the assertion that a particular litho-facies type can give any log reading although some readings are more likely than others **[Kosko 1993]**. For instance, clean aeolian sand is most likely to have a high porosity, although there is a finite probability that the logging tool could measure a low porosity. It is important to have a comparable set of logs between wells, although accuracy is not essential.

For the prediction of rock attributes across a reservoir containing several or several hundred wells it is necessary to ensure that all curves are normalised and comparable between wells. The physics of each tool measurement requires different normalisation procedures.

Even after careful calibration and normalisation the log curves may still contain residual systematic errors. This could be due to use of different logging contractors, the vintage of the logging tools and nature of additives to the borehole fluid (mud). This is where the fuzzy logic technique excels because it uses the fuzziness of each calibration bin rather than merely trying to minimise it. As several wells are used in the fuzzy logic calibration any systematic error is reflected in an increase in the fuzziness of each calibration bin. As a result the technique will naturally favour any logging measurement which is less fuzzy, or crisp. Crispness is defined as the opposite of fuzziness **[Kosko, 1993]**.

During the calibration of the fuzzy logic technique the mean and standard deviation for each litho-facies type and each log response are determined. Consequently the calibration uses an array of data as shown in Figure 2.

The Fuzzy Mathematics of Permeability Prediction

Litho-facies prediction using fuzzy logic is based on the assertion that a particular litho-facies type can give any log reading, although some readings are more likely than others. Fuzzy logic is used for litho-facies prediction by assigning a data bin to each litho-type. The challenge for litho-typing is how to combine the fuzzy possibilities between the litho-types as the litho-facies are not equally frequent in the cored section of the well. Predicting aperiodic data (i.e., not occurring at regular intervals) such as permeability using fuzzy logic avoids this problem by ensuring, at the outset, that the bins are of equal size (i.e., contain the same number of samples or occurrences). First the core permeability values are scanned by the program and divided into ten (or more) equal bin sizes. That is to say that the bin boundaries are determined so that the number of core permeabilities in Bin 1 represents the tenth percentile boundary of the logged permeability data. Bin 2 represents the twentieth percentile boundary and so on. In this example there are ten divisions in the data but there is no reason why there could not be twenty or more. Each one of these bins is then compared to the electrical logs. The log 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 log value associated with Bin 1 calculated, but also some idea of the uncertainty in the measurement is obtained. Fuzzy logic asserts that a particular electrical log value can be associated with any permeability, but some are more likely than others. Fuzzy logic is applied to the prediction of other rock attributes by a similar manipulation of the bins.

The program uses any number of permeability bins with any number of input curves. The distribution of bin boundaries depends on the range of expected permeabilities, as described above. The number of bins depends on the number of core permeabilities available for calibration, the statistical sample size. A reasonable minimum sample size for fitting a normal distribution is around 30 **[Freund, 1980]**. Consequently the number of bins is determined so that that there are at least 30 sample points per bin. For a well with 300 core permeabilities it would be appropriate to use 10 permeability bins. This description assumes that we are dealing with horizontal core plugs and the prediction of horizontal permeability. Vertical permeability can be predicted simultaneously by simply comparing the core vertical permeabilities with the logs in a similar manner.

The Fuzzy Mathematics of Shear Velocity Prediction

We have described how fuzzy logic was first applied to litho-facies prediction and how this was modified for permeability prediction. We further developed fuzzy logic to predict continuously varying values such as shear velocities. The measurement of shear velocities is important for understanding reservoir rock properties **[Boonen, 2001]**. Shear sonic data (*Dts*) is required for rock strength analysis to determine fracture propagation and formation breakdown characteristics, and for improved porosity prediction as *Dts* is largely unaffected by fluid type. Shear sonic data are also becoming important for enhanced seismic interpretation **[Boonen, 2001]**. Because the value of shear velocity data is only now being realized, and because such data is expensive to acquire, there is limited amount of information available.

Fuzzy logic is used for litho-facies prediction by assigning a data bin to each litho-type. The challenge for litho-typing is how to combine the fuzzy possibilities between the litho-types as the litho-facies are not equally frequent in the cored section of the well. As with permeability prediction, shear velocity prediction avoids this problem by ensuring, at the outset, that the bins are of equal size. Unlike core data, shear velocity data is regularly sampled. Shear velocity data is periodic data whereas core data is aperiodic. This allows the shear velocity data to be displayed on plots as a continuous curve against depth unlike the core data, which contains many gaps between depths, must be displayed as large dots.

First the continuous shear velocity log is scanned by the program and divided into around ten equal bin sizes on a linear scale. That is to say that the bin boundaries are determined so that the number of shear velocity data points in Bin 1 represents the tenth percentile boundary of the permeability data. Bin 2 represents the twentieth percentile boundary and so on. Each one of these bins is then compared to the electrical logs. The log data associated with levels in the well corresponding to Bin 1 (slow velocities) are analysed and their mean and standard deviation calculated. In this way, not only is the average or most probable log value associated with Bin 1 calculated, but also some idea of the uncertainty in the measurement is obtained. Fuzzy logic asserts that a particular electrical log value can be associated with any shear sonic value, but some are more likely than others.

Why Permeability Prediction is Important for Field Studies

Knowledge of permeability, the ability of rocks to flow hydrocarbons, is important for understanding oil and gas reservoirs. Permeability is best measured in the laboratory on cored rock taken from the reservoir **[Glover, 1998]**. However coring is expensive and time-consuming in comparison to the electronic survey techniques most commonly used to gain information about permeability. In a typical oil or gas field all boreholes are "logged" using electrical tools to measure geophysical parameters such as porosity and density. Samples of these are cored, with the cored material used to measure permeability directly. The challenge is to predict permeability in all boreholes by calibration with the more limited core information.

In principle, determining permeability from electrical measurements is a matter of solving equations in rock physics **[Glover, 1998]**. In practice, there are numerous complicating factors that make a direct functional relationship difficult or impossible to determine. One problem is that permeability is related to the aperture of pore throats between rock grains, which logging tools find difficult to measure. Several perturbing effects such as mineralogy, reservoir fluids and drilling fluid invasion can influence the permeability measurement. Litho-facies determination is a clear application of fuzzy logic as the litho-facies types are described in clear "bin" types such as aeolian or fluvial. One of the main drivers behind litho-typing is to understand permeability, as the different litho-facies exhibit different permeabilities. We soon realized that fuzzy logic could be used to predict permeability directly, by-passing the litho-facies step. This paper describes that application to a North Sea field.

Permeability is a very difficult rock parameter to measure directly from electrical logs as it is related more to pore throats rather than pore size. Permeability is essentially a dynamic quantity whereas the electrical logs are static measurements. There is a weak correlation between porosity and permeability that explains the spread of points on poroperm cross-plots. Determining permeability from logs is further complicated by the problem of scale; most well logs measure several cubic metres of rock whereas core plugs, from which actual permeabilities are measured, contain only a few cubic centimetres of reservoir rock. In addition to these issues, there are measurement errors on both the logs and core. When you add these problems together it is surprising that predictions can be made at all. The mathematics of fuzzy logic provides a way of not only dealing with the errors, but also using them to improve the prediction. Genetic algorithms give an alternative method of predicting permeability. This application is also described, and contrasted with fuzzy logic, in this paper.

The objective of this application of GAFL (Genetic Algorithms and Fuzzy Logic) was to predict permeability in all the wells in a North Sea field based on calibration to core from the cored wells. This work was required by the oil company in order to select intervals for perforation. The determination of a permeability curve, with considerable confidence, enabled the oil company to focus on key intervals for perforation, resulting in a significant cost saving for each well. Permeability was predicted using both the fuzzy logic and genetic algorithms techniques

Permeability Prediction using Genetic Algorithms

Our objective was to construct empirically a function $f(\phi, Vsh)$ which predicts permeability at each depth, given ϕ, Vsh and at each depth. We were therefore searching for an appropriate function of the form,

$$Permeability = f(\phi, Vsh) = [a\ \phi^{b}] \bullet_1 [c\ Vsh^{d}] \bullet_2 [e]\ . \tag{6}$$

where $\bullet_1$, $\bullet_2$ represent the algebraic operators addition and multiplication, *a, c* and *e* are unknown constants, and *b* and *d* are unknown constant exponents.

Each of the wells was divided into three zones: An upper zone with good reservoir quality, a middle zone of poorer porosity and a thinly bedded lower zone. A separate genetic algorithm was evolved for each zone. These are:

Zone	a	b	c	d	e	$\bullet_1$	$\bullet_2$
1	-5.3588	-0.0268	-3.1070	0.0855	10.261	"+"	"+"
2	-6.7399	-0.0108	-1.8061	0.3572	9.7143	"+"	"+"
3	-4.4857	-0.0009	-0.8341	0.0267	5.3503	"+"	"+"

The genetic algorithm constants show that permeability is influenced by both reservoir porosity and shaliness. The permeability predicted by this genetic algorithm is shown in track 4 (4th column from the left) of Figure 3.

Permeability Prediction using Fuzzy logic

In the study field all curves were assessed for their suitability to predict permeability by analysing the correlation coefficients of the log variables and core permeabilities. Although all logs are have some degree of interdependence the six best curves are: PHIE, PHIT, VSH, NLITH, DT and the HEIGHT above the free-water-level. The effective porosity, PHIE, derived from the density log, has the best correlation coefficient. The sonic transit time, DT, gives a different form of effective porosity, perhaps indicating any secondary porosity. VSH and PHIT provide shaliness information and NLITH is a lithology indicator. The HEIGHT above the free water level is included as it is believed that there is a relationship between height and permeability as the reservoir fill reduces diagenetic effects. Again RHOB is not used as it was used in the PHIE determination and SW was not appropriate as it is product with PHIE is a constant at a particular depth in the reservoir. As with the genetic algorithms technique, fuzzy logic uses stratigraphic and flow unit information.

Fuzzy logic asserts that the reservoir consists of several litho-types, each having characteristic distributions for permeability and electrical log values. Fuzzy logic attempts to uncover the relationship between these distributions based on calibration to core data from the five cored wells. Permeability is predicted based on these calibrations and is shown in track 5 of Figure 3.

The Value of Shear Velocity Data

The measurement of shear velocities is an important parameter for understanding reservoir rock properties. Shear sonic data is used in strength analysis to determine fracture propagation and formation breakdown characteristics, and for improved porosity prediction **[Boonen, 2001]**. Shear sonic data are also becoming important for enhanced seismic interpretation **[Debski, 1995]**.

There is limited amount of shear data information available in the North Sea as it is expensive to acquire and he value of shear velocity data has only been recently realized and because such data **[Chen, 1998]**. This lack of data has been especially acute in this field where only six wells acquired shear data whilst logging. Shear data acquisition requires special technology and is difficult to obtain especially in deviated wells. Two of the shear logs from the field being analysed were subsequently discounted as the data was shown to be suspect. .

Using Genetic Algorithms to Predict Shear velocities

A genetic algorithm comprises of variables, constants and algebraic operators. The variables are, in this application, the borehole electrical logs that are typically recorded on a regular half-foot sample rate (i). For this description consider, for example, 4 variables or electrical logs: shear velocity dts, formation porosity ϕ, formation resistivity Rt, and the volume of shale Vsh. A genetic algorithm attempts to evolve a relationship between shear velocities dts, and porosity ϕ, formation resistivity Rt, and the volume of shale Vsh. Note that porosity is the measure of pore space in the rock matrix that is filled with reservoir fluids such as oil, gas and water. Formation resistivity is the inverse of the electrical conductivity of the fluid-saturated rock. The volume of shale, in this context, is a normalized measure of the radioactivity of the rock matrix by measuring the formation gamma-ray background. Porosity ϕ, Rt and Vsh are measured by borehole electrical logs.

Our objective is to construct empirically a function $f(\phi,Rt,Vsh)$ which predicts shear velocities at each depth, i given ϕ, Rt, Vsh at each depth. We are therefore searching for an appropriate function of the form

$$Dts = f(\phi,Rt,Vsh) = [a\ \phi^{b}] \bullet_1 [c\ Rt^{d}] \bullet_2 [e\ Vsh^{g}] \bullet_3 [h] \tag{7}$$

where $\bullet_1$, $\bullet_2$, $\bullet_3$ represent the algebraic operators addition and multiplication, a, c, e, and h are unknown constants, and b, d, and g are unknown constant exponents. The algebraic operators represent addition and multiplication and determine how the constants are actually used. The constants are allowed to be negative which allows that the algebraic operators to also represent subtraction and division.

The next step is to provide a method for determining how good a given $f(\phi, Rt, Vsh)$ is as a predictor of *Dts*. The approach we adopt is to sum absolute deviations in prediction over all depth levels for a given borehole. We seek a function of the form Equation 7 which minimizes this sum. A more standard way to do this might be to use least squares rather than absolute values of residuals. The reason for the approach that we take is that the borehole data is noisy and includes many "outliers". These can only be removed by extensive manual editing of the data sets and rechecking of measurements. By using the absolute value of residuals, one diminishes the effect of noise and outliers and produces more appropriate predictor functions. Mathematically, the problem can be stated as:

$$\underset{f}{Minimise} : \sum_{i=1}^{i=N} \left| Dts_i - f(\phi_i, Rt_i, Vsh_i) \right| \tag{8}$$

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 *a* ,*b* ,*c* ,*d* , *e, g, h* and operators $\bullet_1$, $\bullet_2$, $\bullet_3$. The fitness criterion of each of these individuals is determined by Equation 7. The best existing algorithm for minimising Equation 8 starts with a randomly generated *f* and uses local search by mutating the coefficients one at a time or flipping the operator between an addition and a multiplication. 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 mathematical operators are fixed and 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 10. The *CHROMOSOME* is, as in genetics, a structure than contains all the genes. Three genes are binary integer values that represent the mathematical operators $\bullet_1$, $\bullet_2$, $\bullet_3$. The rest of the genes are floating point values that represent the coefficients *a, b, c, d, e, g, h*. The initial population is generated by creating chromosomes with a random binary numbers for $\bullet_1$, $\bullet_2$, $\bullet_3$ and random floating point numbers for the coefficients *a, b, c, d, e, g, h*. If the gene represents the operator $\bullet$, its value is binary and it will be switched. If the gene represents one of the real variables, it will be 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.

The following equation was derived for the prediction of Vs using Genetic Algorithms.

$$Dts = \left(a\phi^{b}\right) + \left(cRt^{d}\right) + \left(eVsh^{g}\right) + h \qquad (9)$$

Where:

a	b	c	d	e	g	h
0.014120	2.033557	0.002983	-2.729030	-6.741331	1.354442	56.006934

Equation 9 is the form of the equation evolved using genetic algorithms. It is possible that an alternative equation of the form of Equation 10 could have been suggested by the software.

$$Dts = a\frac{\left(\phi \cdot Rt\right)}{Vsh^{b}} \qquad (10)$$

It is important to stress that the genetic algorithms returns the form of the equation as well as the constants. The form of the equation is controlled by the mathematical operators $\bullet_1$, $\bullet_2$, $\bullet_3$. The results are shown in Figure 4.

The Prediction of Shear Velocities using Fuzzy Logic

Fuzzy logic was used to predict shear velocities. Fuzzy logic is particularly useful in predicting shear velocities because of its nature as a binning technique. In this application the reservoir can be thought of consisting of between twenty litho-facies types each of which has a characteristic shear velocity. Each of this litho-facies will have a characteristic set of petrophysical values for density, shaliness and formation resistivity.

The fuzzy logic program first scans the entire reservoir interval for all wells containing shear data. This data is divided into fifteen equal bin sizes on a linear scale. That is to say that the bin boundaries are determined so that the number of shear velocity data points in Bin 1 represents the fifteenth percentile boundary of the permeability data. Bin 2 represents the fourteenth percentile boundary and so on. Each one of these bins is then compared to the electrical logs. The log data associated with levels in the well corresponding to Bin 1 (slow transit time) are analysed and their mean and standard deviation calculated. In this way, not only is the average or most probable log value associated with Bin 1 calculated, but also some idea of the fuzziness in the measurement is obtained. Fuzzy logic asserts that a particular electrical log value can be associated with any shear sonic value, but some are more likely than others.

It is intuitive that litho-facies with low transit times (fast velocities) will generally have different densities and gamma-ray readings compared to litho-facies with high transit times. This is reflected by the mean value for the density log readings associated with the 100 to 110 μsec/ft bin being different than that of the fourteen other bins. The fuzzy logic program determines the mean and variance for each of the bins. The variance represents the fuzziness of each distribution. The fuzzy logic program analyses all the wells with shear data and creates an array of means and variances.

This array of data represents the relationship, or calibration, between the input curves: DTP, NLITH, MLITH, VSH, RT, RHOMA and DTS. The array was used to predict DTS in all wells in the study field.

Water Saturation Modelling using Genetic algorithms

Genetic Algorithms can used to derive a shaly sand equation. The input curves for this equation include conductivity, normalised gamma-ray and the porosity. Genetic algorithms were used to evolve the form of the shaly sand equation as well as the constants *a*, *m* and *n*.

The objective is to determine an equation so that the predicted water saturations are as close as possible to core derived water saturations. Equations 11 and 12 are example of possible results.

$$Sw = \sqrt[n]{\frac{aRw}{Rt\phi^m}} \qquad (11)$$

$$\frac{1}{\sqrt{R_t}} = \left[\frac{V_{cl}^{(1-V_{cl}/2)}}{\sqrt{R_{cl}}} + \frac{\phi^{m/2}}{\sqrt{aR_w}}\right] S_w^{n/2} \qquad (12)$$

Where:

Sw	= Water saturation
f	= Porosity
Rt, Rsh, Rw	= Resistivities
Vsh	= Volume of shale
a, m, n, Rw	= Constants (the genes)

The results are shown in track 4 of Figure 5. Here we use genetic algorithms to evolve shaly sand equations from Dean and Stark water saturations. This method derives the form of the shaly sand equation and gives an independent calculation of special core analysis (SCAL) parameters such as *m*, the cementation exponent, and *n*, the saturation exponent.

Discussion and Conclusions

Both the Fuzzy Logic and Genetic Algorithms predictors are broadly similar, providing confidence in the premise that it is possible to derive permeability from the electrical logs. This was not obvious as permeability is essentially a dynamic measurement whereas the electrical logs are static measurements. It is important to note that both genetic algorithms and fuzzy logic are empirical techniques and requires a calibrating data set. As with other techniques a consistent set of curves is required. Even after careful calibration and normalisation the log curves may still contain residual systematic error. This could be due to use of different logging contractors, the vintage of the logging tools and nature of additives to the borehole fluid (mud) **[Schlumberger, 1997]**.

The genetic algorithms technique produces a clear mathematical relationship that can be used in spreadsheets and other programs. Genetic algorithms do not require prior knowledge of the structure of this relationship. The equations produced by genetic algorithms indicate the most important input parameters by comparing constants and power functions. In contrast, fuzzy logic requires analysis of a look up table.

Genetic algorithms give a more continuous output compared to fuzzy logic, which is a binning technique. Genetic algorithms are less sensitive to outliers and noise compared to fuzzy logic because absolute rather than least squares minimisation is used. This speeds up data input as the calibration datasets do not require extensive manual editing before they can be used.

Fuzzy logic is self-calibrating technique. For most applications it is not necessary to select and optimise parameters to ensure that is best result. There are no crossplots to make or parameters to pick. However, careful thought is required to the design of the fitness function which determines whether the genetic algorithms are improving and fit for survival. Mathematically these are easy to program but a clear understanding of what is required from the genetic algorithms to achieve is not a simple task.

Because genetic algorithms use absolute minimisation and because fuzzy logic is a binning technique they both give good predictions at the extremes of high and low permeabilities whereas other techniques, by their nature, regress towards their mean values. In formation evaluation knowledge of extreme values is important as these often the main conduits to flow and barriers to production. In other words, the technique retains the natural heterogeneity of the measured system, compared to other techniques which tend to artificially homogenise the data, which amounts to a scale change, bearing in mind that some of the parameters we want to extract such as permeability are not scale invariant.

Genetic algorithms require all the curves to exist to make a prediction and will 'fall-over' if one curve is missing. This is important as oil and gas wells often have missing and incomplete log suites. For this reason the genetic algorithms in this example used only the porosity and shaliness logs as these exist, with confidence, in all wells over the entire reservoir. Even where all curves exist, genetic algorithms can be sensitive to one rogue input. In contrast fuzzy logic is an analytical technique and provides a statistical best answer based on all the input data.

Both the fuzzy logic and genetic algorithms techniques required only a couple of minutes of computer time to reach an answer. Genetic algorithms become more cumbersome when the number of variables (electrical logs) increases. In contrast, adding extra curves to fuzzy logic is a trivial, if not an automatic task. Fuzzy logic can effectively deal with an unlimited number of input curves and processing time is virtually independent of number of inputs variables. Computing time to reach an acceptable solution for genetic algorithms is proportional to number of genes to be determined. Due to speed of modern computers this is not a serious disadvantage.

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Figure 1 Using Fuzziness to Compare Probabilities

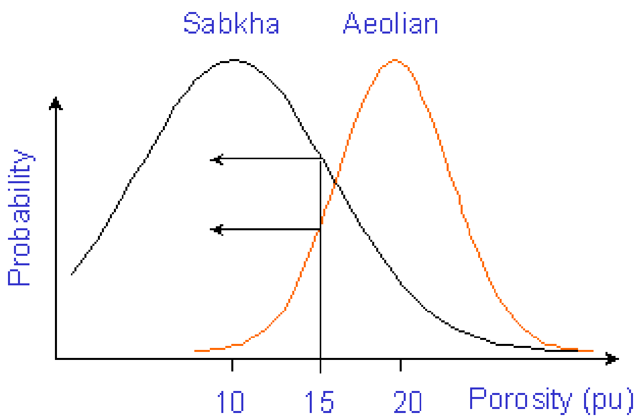

Figure 2: The Calibration of the Fuzzy Logic Technique

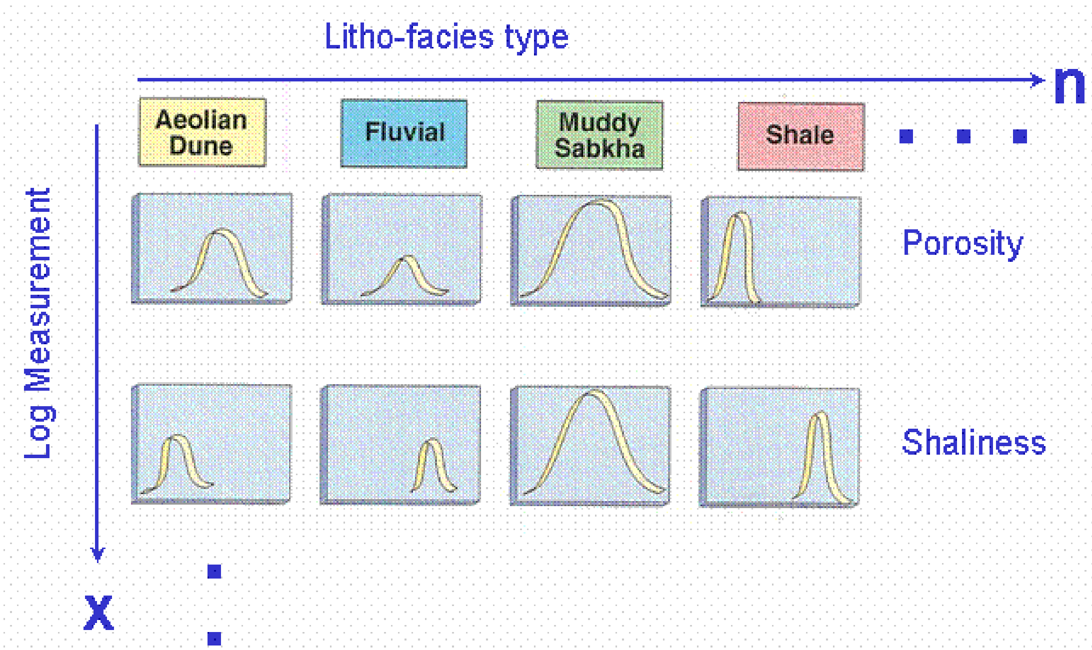

Figure 3: The Prediction of Permeability using Genetic algorithms and Fuzzy Logic

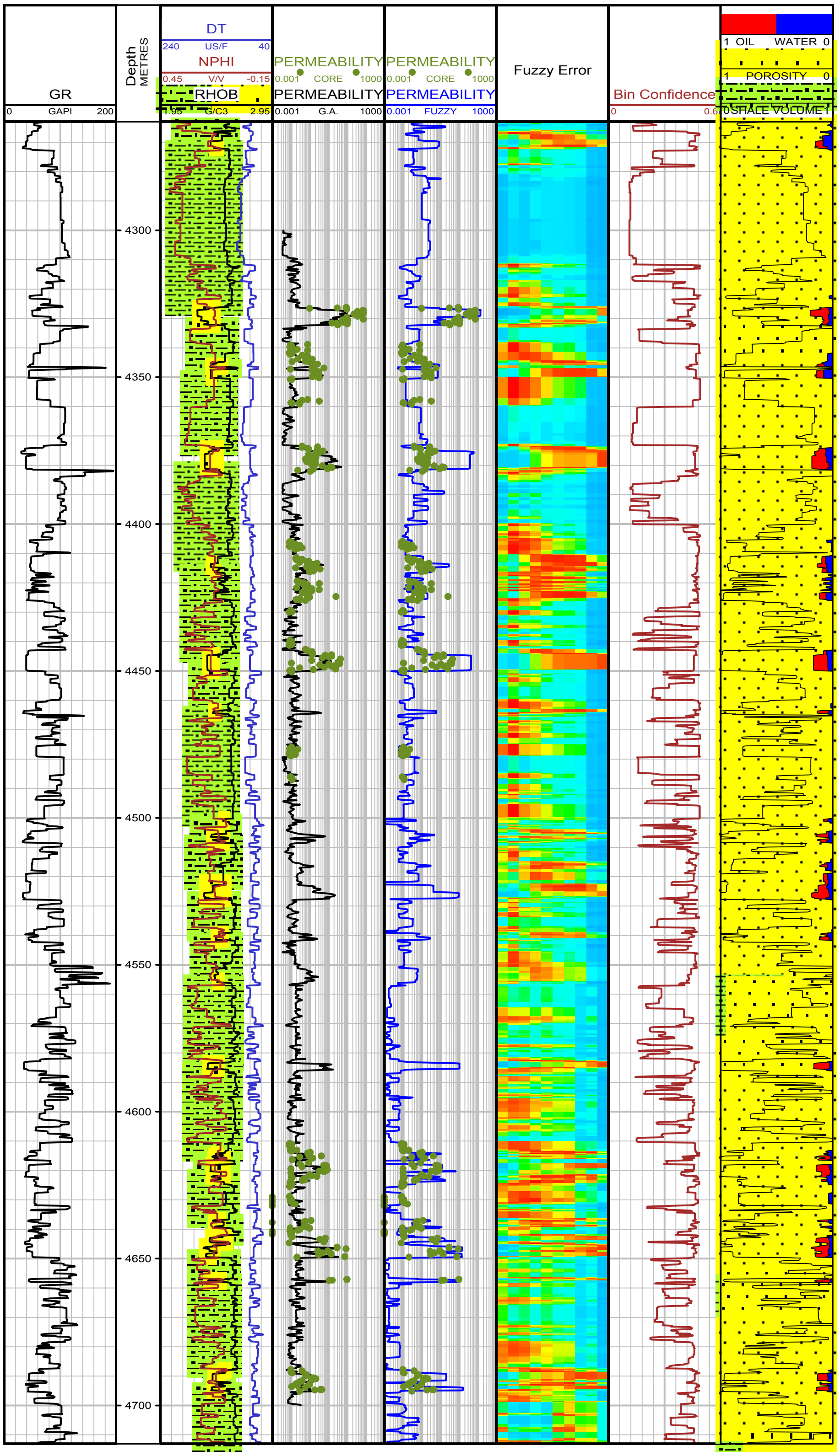

Figure 4: The Prediction of Shear Velocities using Fuzzy Logic & Genetic Algorithms

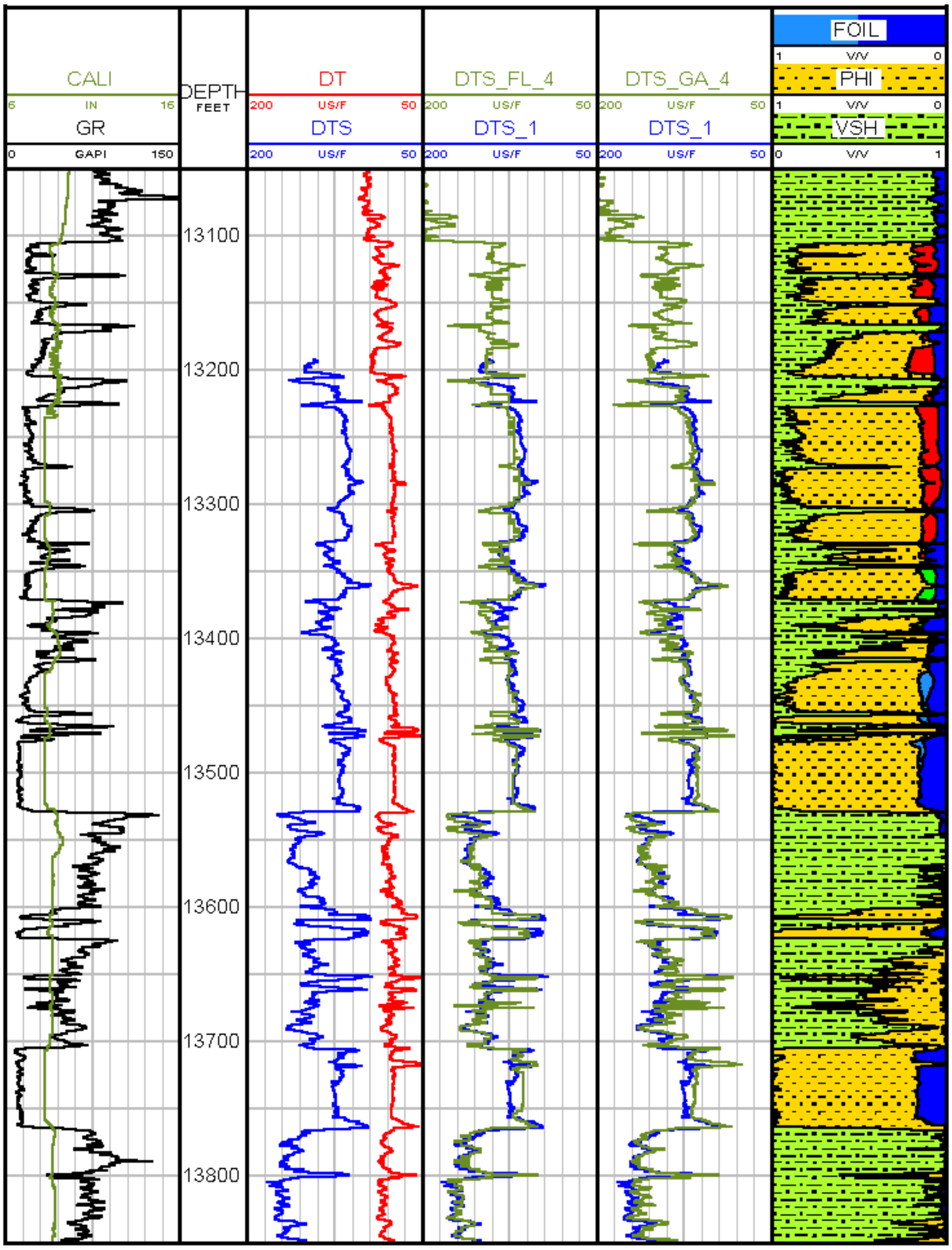

Figure 5: Determination of Shaly Sand Saturation Equations