USING QUANTIFIED 'MODEL BASED' PETROPHYSICAL UNCERTAINTY TO AID IN CONFLICT RESOLUTION

J. Kennedy and Pujiyono, Hess Oil and Gas Malaysia, A. Cox and R. Aldred, Paradigm

This paper was prepared for presentation at the SPWLA 51st Annual Logging Symposium held Perth, Australia, June 19-23, 2010.

ABSTRACT

When a number of different petrophysical interpretations are presented by interested parties in a reservoir development it is essential to understand whether the differences are significant or within the bounds of the uncertainties of each model.

Petrophysical uncertainty can be attributed to three sources, random uncertainty from measurement noise and formation heterogeneity, systematic uncertainty from possible measurement or calibration errors, incorrect parameters or lack of knowledge of true formation properties, and model based uncertainty from the reasonable use of different interpretation techniques. The third of these has traditionally been the hardest to quantify and therefore the least analysed and understood, but it often has the biggest impact on the results.

In the case where multiple interpretations have been performed by different parties involved in a development, quantified model based uncertainty can clearly indicate whether the differences are within the tolerances of each model's uncertainty range, and therefore not significant, or are greater than those tolerances and further information is required in order to resolve the differences.

A case study is presented here where there were significant discrepancies between the results derived from different petrophysical interpretations in the reservoir model for a South East Asian field development. The paper describes the method used to quantify the differences in terms of reserves estimates and identify possible techniques for the resolution of those differences.

This technique cannot determine which of the models is the most appropriate, but it can show the significance of the differences and provide an indicator of the value of the information required to resolve the differences and eliminate the model based uncertainty.

INTRODUCTION

When working with the same well data set it is common for two Petrophysicists to provide two quite different interpretations. This is understandable when one considers the wide range of analysis models currently available and the variability and complexity of geology. Even with the extensive data set of present-day log data and routine and special core analysis the analyst can chose to handle ambiguous data in a variety of ways.

In the past it was common practice for the petrophysicist to deliver to the customer geoscientists and reservoir engineers a single computed data set of what can be best described as a most likely realistic outcome which is dependent on personal experience and beliefs. In reality however, due to the measurement uncertainty on the full range of input variables, a range of reasonable analysis outcomes could be presented, as well as an even wider range of less likely results. It is preferable therefore to capture that range of uncertainty in not only the provision of a selection of results but to also identify where the most significant uncertainty lies so that the relevance of this can be addressed and a decision made on how best to handle the uncertainty in subsequent field modelling and simulation work.

CASE STUDY OVERVIEW

The situation in the case study is a familiar one - with more infrastructure in place locally as a result of nearby field developments, an opportunity arose to develop a gas accumulation, discovered during a previous exploration programme, into a commercial gas field. As part of this development activity, a new well was drilled and new data were acquired, including some whole core, density, neutron, array induction logs, as well as wireline formation tester (for pressure and gas samples), and magnetic resonance. Available core was logged, photographed and sampled for porosity, permeability, grain density, and Archie parameters “m” & “n”. Unfortunately the core was collected from a smaller non-connected sand above the main reservoir, and the exact geological similarities are unclear.

The reservoir is a shaly sand, predominantly quartz, although nearby fields have up to 10% feldspars - the core in this well was not analyzed for mineralogy.

There are occasional coals and carbonaceous shales. The resistivity log and WFT gradients show a clear water contact, at the very base of the main reservoir. The raw data is displayed in Figure 1 below.

The bulk of the hydrocarbons are found in Zones 1 and 2, highlighted in red and magenta respectively. The lithology from the mudlog only indicates that both zones are “sandstone” and the mud gas readings show similar response. Zone 1 shows a low gamma ray indicating low shale content, and the resistivity & neutron/density logs show the presence of gas.

In Zone 2, however, the resistivity shows this interval probably contains significant gas amounts, and the neutron/density displays occasional gas cross-over, but does the gamma ray log indicate this interval contains significant shale volumes? The presence of gas means that neutron/density cannot be directly used to compute a shale volume.

The relative thickness of Zone 2 indicates that it may contain a significant portion of the reserves of this field. Applying even very optimistic cutoffs to an industry-standard deterministic interpretation with shale volume from gamma ray, porosity from hydrocarbon-corrected neutron/density, and saturation from common saturation equations leads to most of this zone being excluded from net pay.

Multiple interpretations were presented for this interval by different interested parties. Each person used different models to calculate shale content, porosity and saturations or a different combination of these models. It was found that each model had its merits based on possible formation characteristics present, but with the data available there was no way of determining which was most appropriate. It was decided to consider the range of results from all the models combined as the overall uncertainty range for the project.

INTERPRETATIONS

In subsequent re-interpretations, two models for shale volume calculation (gamma ray linear & non-linear), two techniques for porosity computation (neutron-density (Bateman and Konen, 1977) and Density-Magnetic Resonance (Freedman *et all* 1998)) and two saturation models (Indonesian (Poupon, and Leveaux, 1971) and Juhasz (1981)) were used.

These particular models were chosen by the petrophysicists as they represent two different geological assumptions for this formation; the complications include apparently inconsistent radioactive levels for the shales and the possible presence of radioactive feldspars, competing effects of gas and shale on the porosity logs and the structure of the shales and their effects on resistivity measurements.

As each of these models may be applicable at each of the steps of a deterministic interpretation, they may be used in any combination. In fact to properly estimate the complete range of possible equivalent hydrocarbon column, the pessimistic models for each step in the process should be combined into one interpretation, the optimistic models into another and a base case combination into a third.

In this study there were only eight possible combinations of models, so as this was a manageable number, all eight have been generated for these zones.

Each model uses the same interpretation parameters where valid - for example gamma ray, neutron and density shale parameters and the water resistivity - and other “model-specific” parameters were used according to industry best practice. In this way, any differences between results are attributable directly to the different models themselves.

Note that the suitability to these formations of each of the different models is still unknown and all eight results are plausible.

The measure of hydrocarbon in place used to compare the results was the cumulative computation of equivalent hydrocarbon column (EHC),

$$\Sigma\, \varnothing_t \,(1 - Sw_t)$$

where: $\varnothing_t$ = total porosity, Sw_t = total water saturation, and the values are accumulated over the interval in question.

The values of equivalent hydrocarbon column for each of the models has been computed, and displayed in the histogram of Figure 2.

The histogram shows an EHC range from 17ft up to 29ft, but, this does not display the true uncertainty on the EHC for the well. The individual model results - termed the “base cases” - can only be correct if particular assumptions about the formation, which guided the choice about which 8 models to use, end up being true.

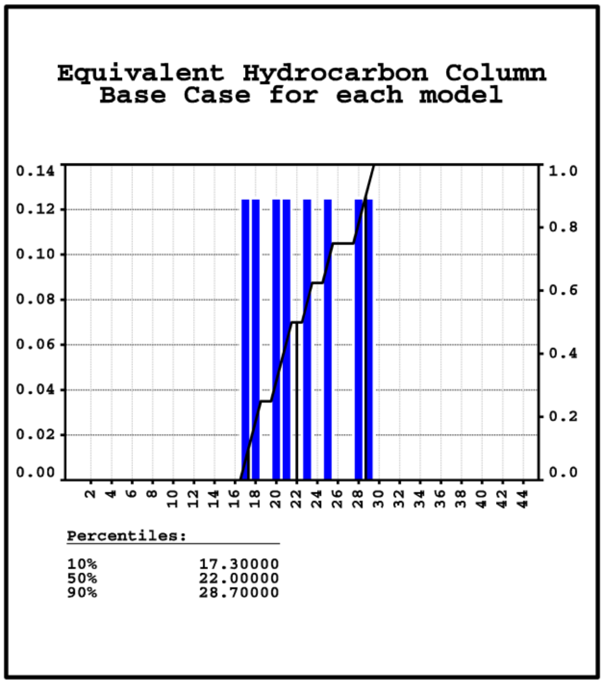

Figure 2 – *Individual EHC of 8 separate petrophysical models does not show the true uncertainty of the equivalent hydrocarbon column*

Each of the logs and parameters used in these models will have an uncertainty associated directly with it, and when these are incorporated into the interpretation, the output will be a range of EHC for each model. Combining these will give the true range of uncertainty for EHC for this interval given that the ambiguity exists on some aspects of the formation and thus on our choice of interpretation model.

In order to fully understand the range of EHC for each model, a full uncertainty analysis was carried out on each interpretation model.

MODELLING PETROPHYSICAL UNCERTAINTY

The Monte Carlo technique was chosen to evaluate the effects of measurement and parameter uncertainty on the petrophysical results. This technique involves processing the complete interpretation model many times while randomly varying parameters and log values, within defined distributions, to reflect the uncertainties the analysts had with each. Using this technique we obtained a large number of possible computations for Vsh, porosity, water saturation, permeability and hydrocarbons in place.

A separate value of EHC was computed for each Monte Carlo iteration over each interval and these results were ordered, generating a cumulative distribution function from which the P10, P50 and P90 values for the reservoir models could be determined. The results were a series of EHC measurements, net to gross ratios, zone average porosities, saturations and permeabilities, for the base case, mean, and the three user selected percentile cases.

In addition to these results we also used a sensitivity analysis to generate a ‘tornado chart’ for each interpretation. This is a simple plot where the impact on the final result due to each variable parameter and input log can be visualised.

DIFFERENT TYPES OF PETROPHYSICAL UNCERTAINTY.

Fylling (2002) provides a comprehensive description of the nature and origins of petrophysical uncertainty. To summarise his paper we see that the different aspects can be grouped into uncertainty related to possible errors in the measurements used and uncertainty related to the interpretation model, both in terms of the choice of model and parameters used. We can further divide these uncertainties into random, systematic and model based.

Uncertainty in a measurement can be due to random effects, such as statistical variation in count rates or signal noise, or it can be due to systematic errors, arising from calibration issues, the logging environment or possible uncertainty in the parameters used for environmental corrections.

Interpretation uncertainty can arise due to parameters being based on an uncertain or uncalibrated lithological model (mineralogy, facies, *etc*), as well as when multiple interpretation models could be applicable, depending on the lithology present.

For example, the incorrect calculation of shale volume (Vsh) in clastic formations can lead to large potential errors for porosity calculation and resistivity interpretation. Vsh is highly variable, with changing composition, clay types, clay content, porosity, compaction, electrical anisotropy, radioactive sands, *etc*., meaning that techniques such as a linear gamma ray model can be misleading over short intervals or totally incorrect over complete sections. Occasionally information is available with which to calibrate, such as core mineralogy, but in many cases this is insufficient for a full calibration and often the ‘hottest’ part of an interval is called 100% shale, while the lowest measured gamma ray in the interval is used to represent clean sand.

Such lack of knowledge can lead to systematic uncertainties, based on a range of possible parameter values, and often more significantly, to model based uncertainties, where it is not clear which interpretation model best applies the measurements to the formation properties.

MEASUREMENT UNCERTAINTY

Most logging companies publish figures for repeatability and accuracy of their measurements.

In terms of petrophysical measurements, repeatability is the difference between a value measured at a specific depth and the value at the same depth in a repeat measurement (Theys, 1994). This provides an indication of the amount of random error that would be observed in a series of measurements at the same depth. Accuracy, on the other hand, is the difference between the mean value of that series of measurements and the true value (Theys, 1997). Therefore, while considering uncertainty due to possible measurement error, we can relate measurement precision to random uncertainty and accuracy to systematic uncertainty, as illustrated in Figure 3.

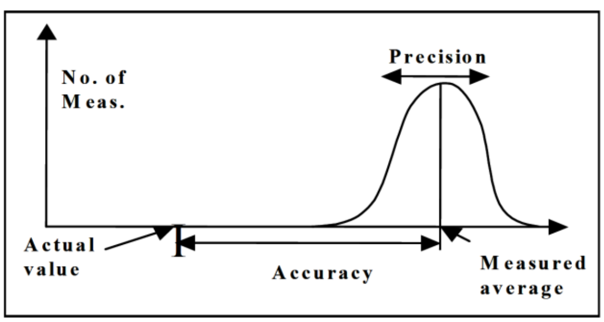

Figure 3 - *Accuracy and Precision (from Fylling 2002)*

In this study uncertainties in the results were quantified based on the overall hydrocarbon content in each interval. This means that any effects of random error in measurements are mostly cancelled out in the zone summary process. Care was taken when setting reservoir and pay cutoffs, and when picking certain parameters, as random errors in measurements can still have an impact, though in most cases these effects were small.

In terms of petrophysical uncertainty, the accuracy of a measurement is much more important than the precision as this contributes a potential systematic error in the interpretation results. Furthermore, it is not just the accuracy of the measurement itself which must be considered, but also the uncertainty surrounding the parameters used to correct the measurement for any effects of the logging environment.

Part of the data preparation for this study was to run the input log data through a Monte Carlo process which incorporated the published accuracy for each measurement as well as environmental corrections which had error bars applied to all environment parameters such as temperature, salinity, *etc*. The result of this process was a series of three curves for each input log, with the corrected curve as normally calculated, a high version and a low version based on the range of results from the Monte Carlo processing. These three curves were then used as input to the main part of the deterministic processing, with a random number generator selecting an offset version of each curve, for each iteration, based on a user defined distribution.

PARAMETER UNCERTAINTY

In the type of sequential deterministic interpretation process that was used in this study, the uncertainty in the early stages of the process affects the input to the later stages. It has been recognised (Ventre, 2004) that it is inappropriate to deal with uncertainties in porosity and saturation separately because the saturation computations must include any uncertainties in the porosity input. To truly model the effects of all uncertainties on the end result the complete interpretation process must be run, for a complete interval of the well, through each Monte Carlo iteration. This effectively passes the actual uncertainty distributions from one interpretation step to the next.

This process does lead to one complication which is the fact that some parameters are picked from logs and crossplots which are generated in the early stages of the interpretation. The problem here is that as the Monte Carlo process randomly changes parameters and measurements within the given distributions, so the logs from which the picks are made are constantly changing. Clearly it is impractical to re-pick each parameter set for each iteration so instead a process was used whereby the initial picks were automatically adjusted for each iteration based on the amount of movement of each measurement. In this way the initial picks made by the analyst are honoured, while still moving the input data and parameters within the given distributions.

An example of this process used in this study was the picking of wet shale points from neutron-density crossplots. There was a large variation between the high and low versions of the neutron log, so every time a new Monte Carlo iteration was run the points on the crossplot would have moved significantly. By using auto-adjustment, new picks were generated for each iteration. These new picks marked the same point within the data cloud as it moved around the crossplot. Uncertainties in the neutron and density values for that wet shale point were applied after this auto-adjustment.

SETTING ERROR BARS - MORE DATA LESS UNCERTAINTY

One of the most difficult aspects of this work was setting the error bars for each parameter. There are no standard values that can be used as each parameter and each formation are different. Even if there was a standard value for the error on, for example, the grain density of a certain formation type, this would still have to vary based on whether any additional data were used to calibrate the result or to support the initial value.

One issue that arose while modelling uncertainty in this complex series of calculations was the effect of the number of parameters in those calculations. For example, if one log measurement is used to determine porosity, with a small number of parameters involved, a much lower uncertainty would result than if two or more measurements were used with similar parametric uncertainties. This effect seems to be counter-intuitive because additional information should result in lower, rather than higher, uncertainty in the results.

For this reason it was important to carefully examine, not only the information available for setting each parameter, but also any corroborating or conflicting information that was available. When corroborating information, such as measurements on core, is available the error bars can be decreased to reflect the reduced uncertainty, while bearing in mind the inherent uncertainties associated with those laboratory measurements (Hook, 1983). If the additional data conflicts with the initial results, however, either the parameters must be altered or the error bars must be increased to cover both possible answers.

The interpretation models chosen also have an impact on the uncertainty in the results. For instance, Vsh uncertainty has a much larger effect on sonic porosity than it has on neutron-density porosity. Therefore, adding sonic porosity to an interpretation can initially raise the apparent overall uncertainty, even if it confirms the neutron-density approach. It is then reliant on the analyst to adjust the error bars accordingly.

DISTRIBUTIONS

In this study a choice of statistical distributions for use in the Monte Carlo random number generation was available, including normal, log-normal, uniform and asymmetric triangular. Normal and log-normal distributions were chosen for the initial log measurements, while for the parameters used in the interpretation asymmetric triangular distributions were used as these better reflected the nature of the uncertainty.

NUMBER OF MONTE CARLO ITERATIONS.

The number of iterations required in the Monte Carlo process is determined by the complexity of the interpretation model, the number of measurements used and range of the error bars applied. Initial repeatability tests showed that the results for this interpretation began to stabilise somewhere over 2000 iterations. This means that when the interpretation model is run multiple times the differences in the final EHC distribution became negligible once the number of iterations was set to over 2000. If a smaller number of iterations is used the final EHC distribution and its average will change significantly from one run to the next and the results are therefore not reliable. It was decided to use 5000 iterations for our Monte Carlo processing to ensure this effect had no impact on the study results.

MODEL BASED UNCERTAINTY

The Monte Carlo technique allowed effective modelling of the random and systematic uncertainties in the interpretations. As already described, the random uncertainties were mostly accounted for in the zone averaging and the interval based results process, but the issue of model based uncertainties remained. Multiple interpretation models were assessed, all of which were feasible given the evidence and data available, but these models gave markedly different results. These differences are just as much a part of the overall uncertainty as the variability in results due to parameter changes.

In order to address this issue the Monte Carlo processing was run separately on each of the conflicting models and the effect of the model in terms of the impact each had on the hydrocarbon in place estimates was judged. Using the equivalent hydrocarbon column estimates, which feed directly into the reservoir models and the reserves estimates, the percentage change in final P10, P50 and P90 reserves estimates for each interval due to each model were evaluated.

There is a tendency to judge the relative merits of each of the models based on the uncertainty that it generates; however, this is not appropriate. Basically this is like using a measurement of precision to define accuracy. A number of possible answers are at hand and it is uncertain as to which of these is closest to the true value. If sufficient data was available to define our formation exactly, then the Monte Carlo process alone would effectively produce a measure of the uncertainty in the equivalent hydrocarbon column that could be used in a reserves estimate. In this case study, however, such data does not exist so it must be accepted that the multiple results are all valid and form part of a larger, more complete measure of uncertainty.

By considering the combined uncertainties, and their impact on this project's economics, it became easier to determine a financial basis on which to justify the collecting of the extra data sets required to resolve these uncertainties.

UNCERTAINTY ANALYSIS

As mentioned above, the uncertainties for the input logs including gamma ray, density, and neutron were generated during the environmental corrections processing. However as array induction logs are computed from proprietary processing algorithms which integrate environmental effects, the published maximum accuracy of 2% was used to compute the high and low versions for resistivity. Ventre, (2004) has called for service companies to provide the true uncertainty ranges of the logs they provide to allow more robust uncertainty analysis

Following this, each of the interpretation parameters used in the original models was assigned an uncertainty based on the concrete knowledge obtained from the limited hard data such as core & samples, and from the standard interpretation tools (crossplots, histograms, *etc*.). The parameters were entered as a "base case" value along with a low-side and high-side error bar and a statistical distribution.

For example, for gamma ray shale, the value thought to best represent the gamma ray measurement in a shale was used as the base case. The low-side error was small because realistically the value cannot be lower than the actual reading in the shaly rock, but the high-side error was large because it could be ascertained whether or not a formation of pure shale was present. Owing to the asymmetry in the uncertainty regarding this parameter the triangular distribution was used for the random number generator.

Core analysis data included a series of electrical measurements to determine the Archie "m" & "n" parameters. With these measurements it becomes possible to assign the parameters for certain saturation equations with a high degree of confidence and low error bars. However, as other saturation models use "m-star" & "n-star", for which no core measurements were made in these wells, default values of "2" & "2" were used, along with a large uncertainty range.

Using similar logic, uncertainties were assigned to all input parameters, and the 5000 iteration evaluation was performed to calculate the EHC for each of the models.

UNCERTAINTY RESULTS

The results for one of the models are shown in Figure 4. The first four log tracks (labelled Gamma Ray – Density – Neutron – Resistivity) display the input logs and the uncertainty associated with each.

In the following four tracks, the main log analysis curve outputs (the "base case") are displayed in blue in the tracks labelled Shale Volume – Porosity – Water Saturation – Bulk Volume Hydrocarbon, overlying a distribution. This distribution displays the results of all 5000 iterations as a histogram, and can be used to visualise the amount of uncertainty associated with each of the base case analysis outputs at a particular depth.

The yellow flag in the porosity track indicates sands which pass both the shale volume and the porosity cutoffs, whilst the red flag in the water saturation track indicates net pay.

The final track displays the equivalent hydrocarbon column on two scales. Both overlie the distribution of EHC from the 5000 iterations (once again on two scales). This distribution has been enlarged to a single histogram for the cumulative distribution for the entire interval in Figure 5.

This histogram shows the maximum possible range of EHC for Model-6 to be 20 to 39ft, with a P90 value of 24.9ft and a P10 value of 32.5ft and a mean value of 28.5ft. The base case EHC for Model-6 (from Figure 2) is 28.25ft.

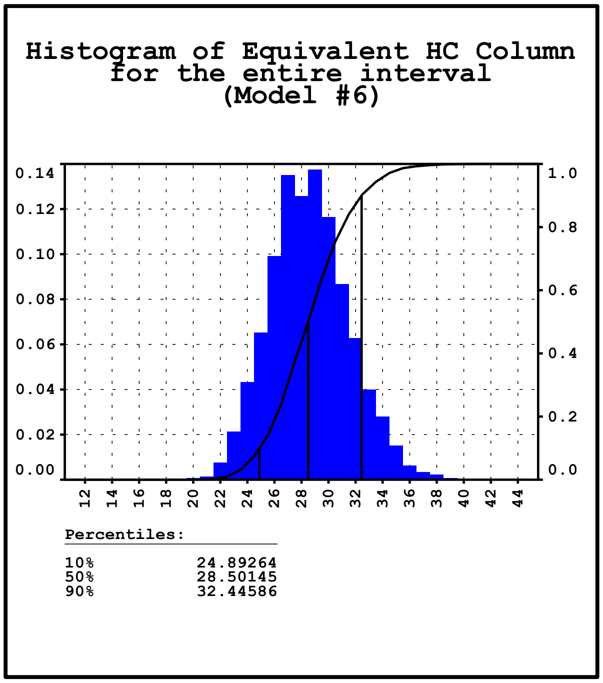

Figure 5 – *EHC results for one model, 5000 iterations, showing the uncertainty associated with one particular model.*

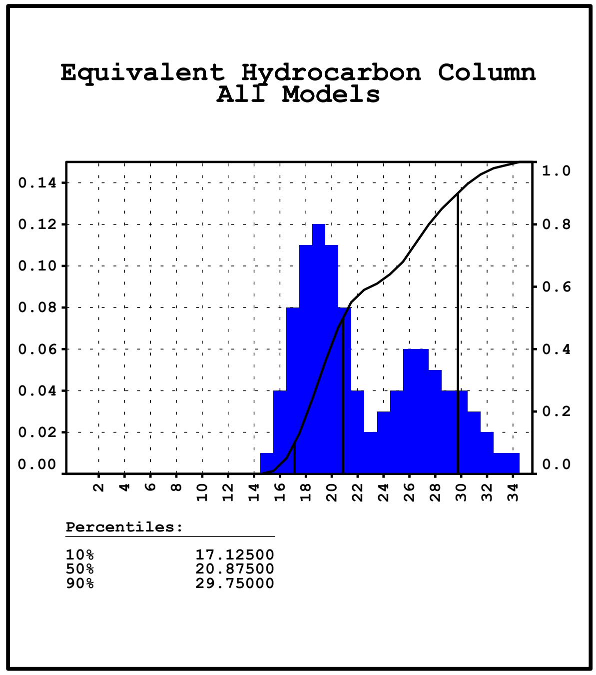

Figure 6 - *This shows the true uncertainty results, the equivalent hydrocarbon column for all possible models and combinations. The upper lobe is predominantly non-linear Vsh, and Juhasz saturation equation models.*

Given that there are still important characteristics of the formation about which we are unsure, all interpretation models that were run are possible valid interpretations and each of these has a similar uncertainty range. The combination of all of these models and their uncertainties is the true range of possible EHC for this interval.

Figure 6 shows the full range of uncertainty on this well given the current level of knowledge on the formation and the uncertainty on the logs and interpretation parameters. The lowest possible EHC is 15ft, the highest 34ft, P90 is 17.1ft, P50 is 20.9ft and P10 is 29.75ft.

The bimodal nature of the data in Figure 6 is driven predominantly by the decision of whether Zone 2 is pay or not pay. The lower lobe consists of Zone 1 as pay, whilst the higher lobe consists of Zones 1 and 2 denoted as pay. Hence the main question controlling the higher EHC numbers is whether Zone 2 is a producible reservoir. The upper lobe is made up predominantly of data from models of non-linear shale volume and Juhasz saturation equations.

PARAMETER SENSITIVITY

A sensitivity analysis was carried out on each of the eight models, to see which inputs (both parameters and logs) affected the computed EHC most significantly.

Each parameter for each model was ranked depending on its overall impact on the computed EHC. Tornado charts were then created showing the 15 parameters with most effect on the results. Two charts for Model Five and Model Two are typical and displayed in Figure 7 and Figure 8.

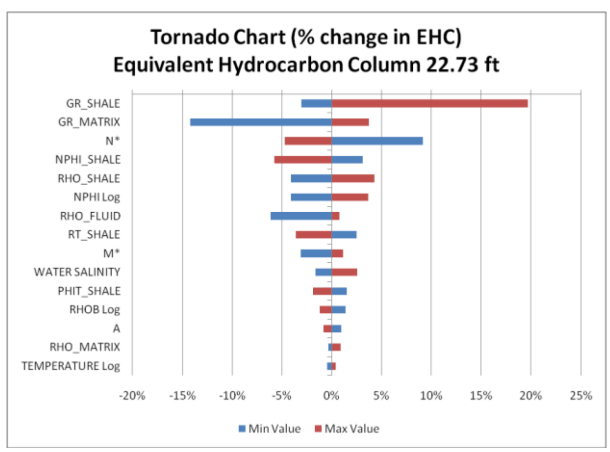

Figure 7 - *Tornado chart showing the inputs with the greatest affect on the calculated EHC for Model #5*

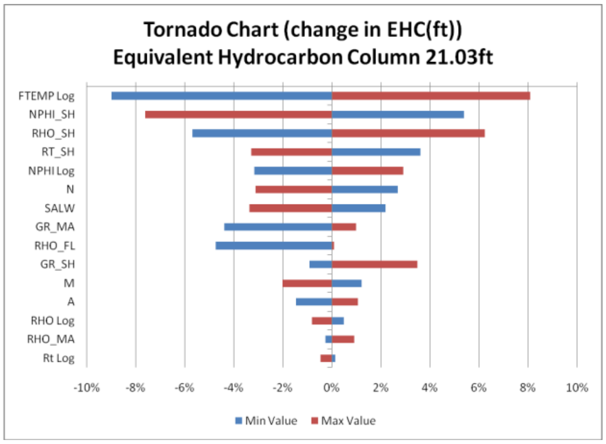

Figure 8 - *Tornado chart showing the inputs with the greatest effect on the calculated EHC for Model #2*

To judge the most influential parameters for all eight models combined, a histogram, Figure 9, was created to display the top 16. The shale parameters significantly influence the EHC computed in seven of the eight models, both in the computation of shale volume from gamma ray end points and through the shale resistivity parameter.

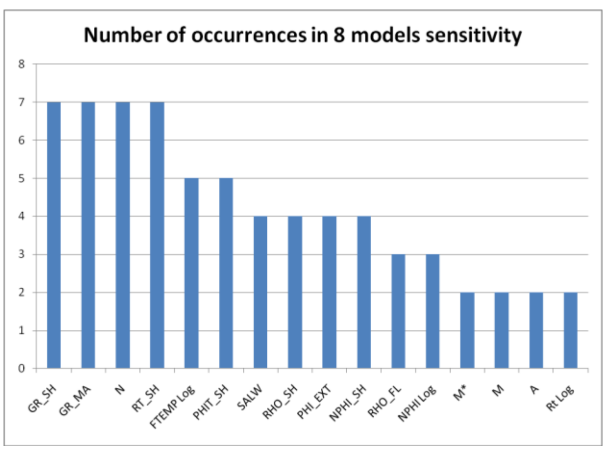

Figure 9 - *Inputs which have more that 10% effect on the EHC in each of the models*

Often the parameters m and m* have a strong impact on the EHC results; however, here it is apparent that they are not as important as usual. This is because the main changes in pay in the different models are due to the shale content in the marginal formations and secondly because these individual parameters only appear in half of the eight models.

DISCUSSION

The overall uncertainty for the equivalent hydrocarbon column for the well can be defined by the P90, P50 & P10 displayed in Figure 6, and listed in Table 1.

It appears to be rather significant especially to the upside. This data has been passed onto the geological and economics modellers. The true impact on the development potential for this gas field can only be ascertained when those calculations are complete.

	P90	**P50**	**P10**
EHC	15 ft	20.9 ft	34 ft
% Change	- 28%		+ 63%

Table 1 - *The uncertainty of the EHC based on eight different petrophysical models.*

If the economic modelling suggests that the field development may be marginal based on the wide range of 1P, 2P, 3P, the requirement would be to reduce this range.

The uncertainty analysis carried out in this case study has identified that the biggest petrophysical uncertainty is driven by the lack of knowledge of the shales in Zone 2. This lack of knowledge has not allowed a specific petrophysical model to be chosen with certainty.

Hence, suggested collection of new data includes X-Ray Diffraction (XRD) with clay volume measurements on the present core. This will allow, at limited cost, calibration of shale volumes from log analysis with hard data.

The suspected presence of feldspars, which have been observed in neighbouring fields, may reduce the accuracy of using solely the gamma ray for shale volume calculations. The XRD study should also allow clarification of feldspar types and quantities, and hence give higher certainty to interpretation parameters associated with shale volume calculation.

The question of which resistivity model is truly applicable in Zone 2 would also reduce the range of possible EHC values (as seen in Figure 6). Selection of a resistivity model is largely driven by the distribution of the shales.

To choose the appropriate saturation model, a more extensive core study should be performed (as it has minimal cost) but will have a significant effect on the EHC uncertainty. The main purpose would be to ascertain the distribution of the shales and allow one particular saturation model to be utilized. Questions to be clarified include, are the shales predominantly continuous laminar or clasts or are the clays themselves dispersed?

If this core study does indicate that the Juhasz saturation equation is more appropriate in Zone 2 laboratory measurements of “m-star” and “n-star” would reduce the uncertainty on EHC. This can be seen in Figure 7 which shows an effect of 5% & 15% respectively on the EHC given the current error bars on these parameters in the current interpretations.
Several other interpretation inputs have shown to impact the computed EHC, but at less than 10% (as seen in the tornado charts in Figures 7 and 8), these may not have as big an impact as the above parameters. This says that the costs of obtaining the information to improve the uncertainty on these parameters would not justify the rewards in the reduction of EHC uncertainty.

SUMMARY

When interpreters disagree it is important to consider their differences in an objective manner. To do this the impact of the differences on overall project economics must be ascertained first. In petrophysics this is best done by correctly applying quantitative uncertainty modelling.

Once the impact of different interpretation decisions is understood, the discrepancy can be examined in each model and the additional information required to resolve the conflicts can be determined. When the financial impact of the uncertainty is taken into account it becomes easier to justify the additional expense of appropriate data gathering.

In this case study, the differences were large, and should have a significant impact on the development plans. Once the project economics are completed it will be straightforward to justify, if needed, additional laboratory work to resolve the major issues and to reduce the uncertainty to manageable levels

ACKNOWLEDGMENTS

The authors would like to thank Hess Oil and Gas, Malaysia and their partners for allowing publication of this work.

REFERENCES SECTION

Bateman, R.M., and Konen, C.E., 1977, The Log Analyst and the programmable pocket calculator. Part II - crossplot porosity and water saturation, The Log Analyst, Nov-Dec 1977.

Freedman, R., Minh, C.C., Gubelin, G., Freeman, J.J., McGinness, Th., Terry, B. and Rawlence, D., 1998, Combining NMR and density logs for petrophysical analysis in gas bearing formations, SPWLA 39th Annual Logging Symposium, Paper II.

Fylling, A., 2002, Quantification of petrophysical uncertainty and its effect on in-place volumes estimates: numerous challenges and some solutions, SPE 77637.

Hook J.R., 1983, The Precision of core analysis data and some implications for reservoir evaluation, SPWLA, 24th Annual Symposium, Paper Y.

Juhasz I., 1981, Normalised Qv - the key to shaly sand evaluation using the Waxman-Smits Equation in the absence of core data, SPWLA, 22nd Annual Symposium, Paper Z.

Poupon, A. and Leveaux, J., 1971, Evaluation of Water Saturations in Shaly Formations, SPWLA 12th Annual Logging Symposium, Paper O.

Theys, P., 1994, A serious look at repeat sections, SPWLA 35th Annual Logging Symposium, paper F.

Theys, P., 1997, Accuracy – Essential information for a log measurement, SPWLA 38th Annual Logging Symposium, paper V.

Ventre, J.B., Terpolilli, P., and Chaffe, W., 2004, Dependencies and ranking: two keys for an efficient petrophysical uncertainty evaluation, SPWLA 45th Annual Logging Symposium, paper KKK.

“ABOUT THE AUTHOR” SECTION

Since graduating with a Bachelor of Science in Geology from University of Birmingham, John Kennedy has spent 19 years in formation evaluation related work, initially in wireline before moving to petrophysics. He has worked for several operator companies in the UK and internationally before joining Hess Malaysia in 2005 as Petrophysics Advisor for the South East Asian Region.

Pujiyono is currently a Geological Advisor with Hess Malaysia. He has spent 14 years in the oil industry, with Caltex in Sumatra, in Jakarta with Unocal, and with Petronas Carigali in Kuala Lumpur. He has a Bachelor of Science (Geology) from UPN `Veteran` Yogyakarta

A
A

and a Masters Degree in Reservoir Geology from the Institut Teknologi Bandung in Indonesia.

Andrew Cox graduated in 1990 from the University of Adelaide with a Bachelor of Science (Honours) in Petroleum Geology. He immediately joined Schlumberger as a wireline field engineer, where he spent 7 years in the field, then another 6 years as Petrophysicist in Egypt, Venezuela and Australia. In 2004 he joined Paradigm where he currently performs commercial consulting work and acts as a technical liaison with R & D. He is a member of SPWLA.

Rick Aldred is a petrophysicist with 30 years oil industry experience, including 15 years with operating oil companies, 10 years with logging companies, providing petrophysical consulting services, and 5 years in petrophysical software development. He has a bachelor's degree in Geology from Keele University in the UK and has subsequently worked in the North Sea, North Africa, Middle East, Indian Subcontinent, South East Asia and Australia. He currently works with the Geolog R&D team in Brisbane, Australia. He is a member of SPWLA.

A
A

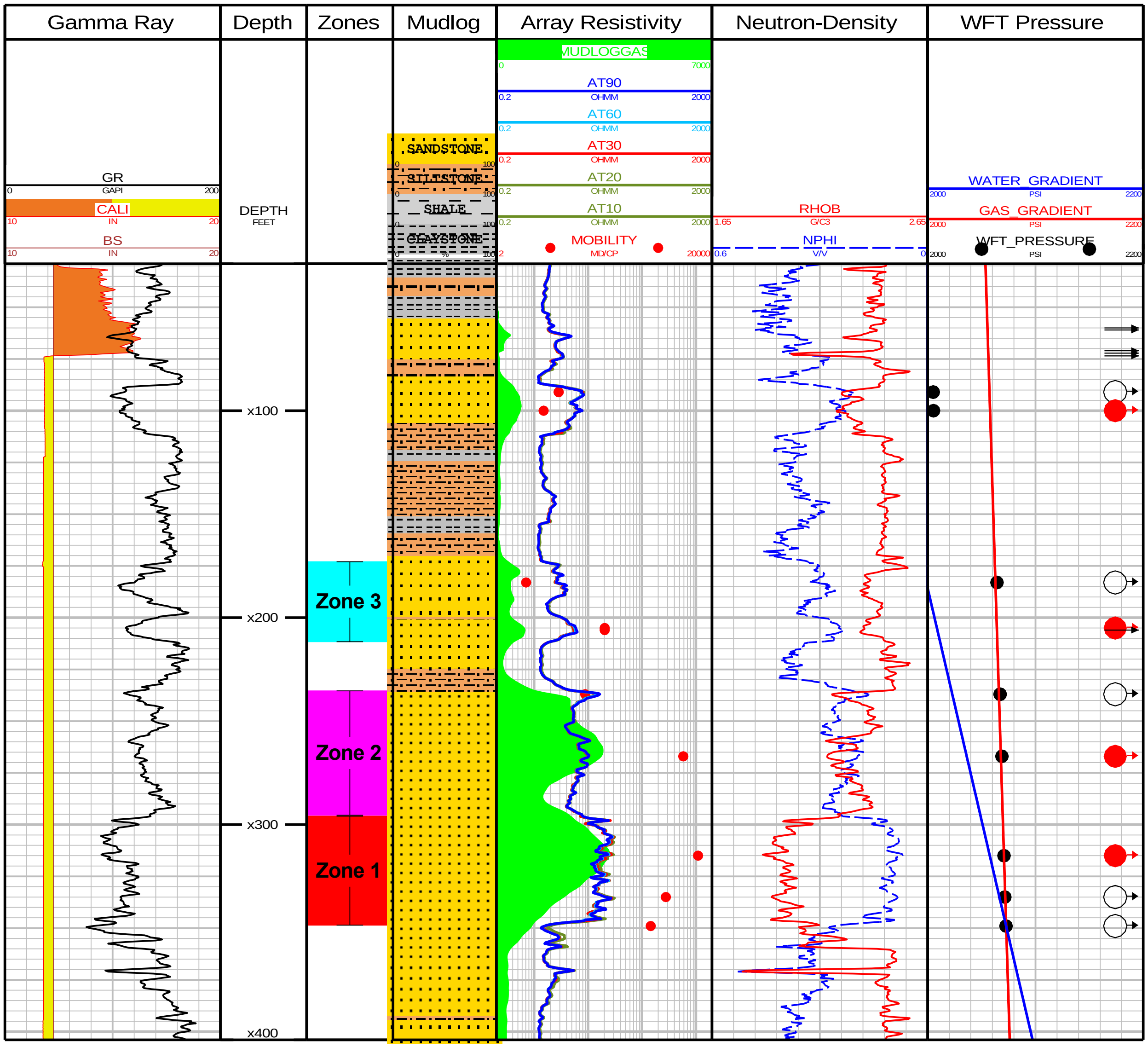

Figure 1– *The standard logs show that Zone 1 contains significant gas, but with how much certainty can the amount of gas in Zone 2 and Zone 3 be quantified? The last track displays the WFT results; the gas gradient (in red) shows that the top reservoir is not in pressure communication with Zones 1, 2 or 3. The arrows indicate WFT pressure tests, clear circles successful pressures and red circles gas samples*

A
A

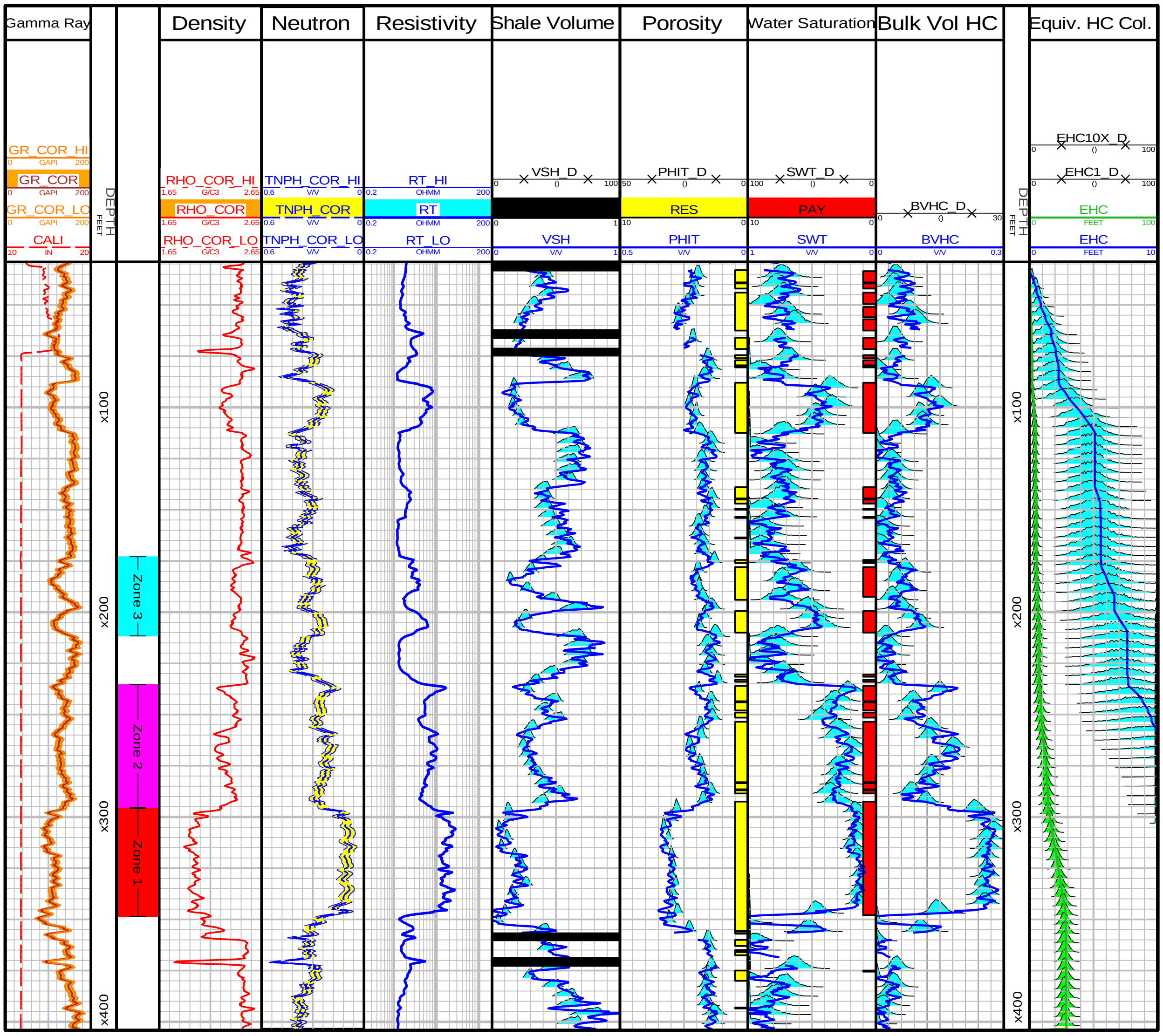

Figure 4 - *Uncertainty results for one model, showing input logs with their ranges and computed results with their distributions*