Integrating Multiple Log Measurements for Uncertainty Reduction in Reservoir Evaluation

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Abstract.

The methodology presented in this work aims at reducing uncertainties in the petrophysical evaluation using machine learning, statistics, and physics-driven methods to increase the level of confidence in advanced workflows in complex formations.

The proposed method saves days in repetitive processes when compared to traditional workflows and quantifies the level of confidence associated with the answers considering multiple uncertainty sources.

This methodology enables the petrophysicist to provide an analysis containing one final porosity, water saturation, and permeability estimation with minimized uncertainty considering the multiple measurements available for the well and the multiple sources of uncertainties in a reproducible and fast manner.

Keywords: Reservoir Characterization, Uncertainty Analysis, Unsupervised Clustering, Data Analytics

1 Introduction

The high costs associated with deep-water offshore wells often drive logging with multiple/advanced tools including dielectric, NMR (Nuclear Magnetic Resonance), dipole acoustics, resistivity, and density logs to improve the confidence in the reservoir evaluation. We propose a new and fast integrated method to improve log evaluation results in complex reservoir scenarios (anisotropy, high heterogeneity, and complex mineralogy) that can be used in conjunction with a mineralogy estimation, for estimating uncertainty, improving results precision, and obtaining more information on the pore structure.

This richness in available data results in an apparent redundancy when estimating formation properties, as multiple wellbore log data responding to the same output. One approach is deriving the petrophysical properties for each tool individually and from that qualitatively understand the fluid effect in the near wellbore region, this approach is subjective and part of the knowledge is lost in the process to deliver the interpretation for the reservoir engineer.

In the proposed method, the data richness is used by the petrophysicist to improve the confidence in the interpretation by associating appropriate weights to each data. This methodology contains a stochastic approach to assign those weights semi-automatically in a reproducible manner capable of capturing variation in the uncertainties depending on formation type. The randomness in the solution comes from the multiple realizations that are performed to extract the influence of information and parameters on the different logs that naturally varies depending on formation type and physics of measurement.

The objective is to capture more information from the multiple logs to reduce uncertainties in the petrophysical evaluation and with the improved resulting estimation, be able to infer more information on pore structure which affects both fluid flow and the relationship between porosity and elastic properties. The tool saves days in repetitive processes when compared to traditional workflows.

2 Methodology

This methodology is based on propagating uncertainty in the petrophysical interpretation using a computationally efficient method that uses machine learning and statistics combined with physics-driven methods.

One measurement that is used in multiple steps of this methodology is the Nuclear Magnetic Resonance (NMR) T2-distribution measurement. For more details about the application of magnetic resonance for reservoir characterization see [1], that represents the fitting of the magnetization T2 decay times containing primarily information about hydrogen nuclei mainly present in the formation and invaded fluids which are associated to total total porosity, and fluid properties, and secondly information from pore size distribution.

The first step in applying the method is estimating an unsupervised cluster using auto encoder and k-means using the multidimensional information extracted from the NMR T2 distribution, which by the nature of the measurement should reflect the pore systems. The second step is generating multiple scenarios considering the inherent uncertainty of each input curve, mineral properties, and model parameters. The third step is calculating the variance and covariance by cluster for each answer, and the fourth step is estimating the final output curves that minimize the combined variance. Those steps represent the base of how information is extracted from the tool measurements as can be seen in Fig. 1, that indicates the user interface for changing the uncertainty levels as necessary, the uniform distribution assumed for the multiple inputs, the output distribution from the multiple scenarios and the final integration using statistics.

All steps are performed in the C++/ Python-based module to help the petrophysicist arrive at a reservoir property that honors the different logs and cores using a fast integration method, parallel computing, and statistics are used to reduce the computational time to allow for local processing and not requiring cloud computing capabilities.

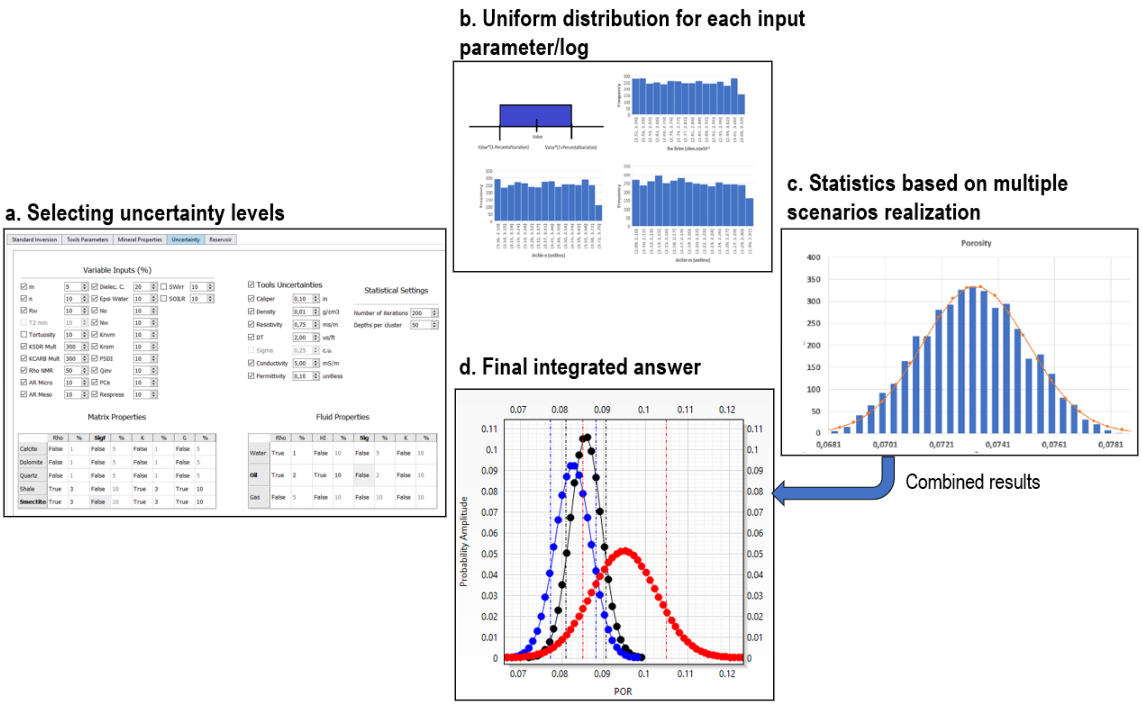

Figure 1. After grouping similar depths, the proposed workflow contains the following parts: it starts with the user-defined input uncertainty (a), which defines the uniform distribution for mineral properties, input parameters, and the normal distribution for input logs (b). The following step consists of multiple integrated simulations considering parameters and data uncertainties (c), from that simulations the distribution associated with the main petrophysical responses are estimated together with a final response with minimum associated uncertainty (d).

2.1 Step 1- Cluster the reservoir depths according to similarity

In our methodology, we include uncertainty on seven tool measurements and up to thirty- seven input parameters, and to get a reasonable level of confidence with all those varying variables, we need to run multiple scenarios that would require a long computational time if we performed the simulation for all depths in the reservoir. On the other hand, if we decided to run only a few depths in the reservoir and propagate randomly to other depths, that would be computational efficient but could provide a biased standard deviation depending on the random samples chosen.

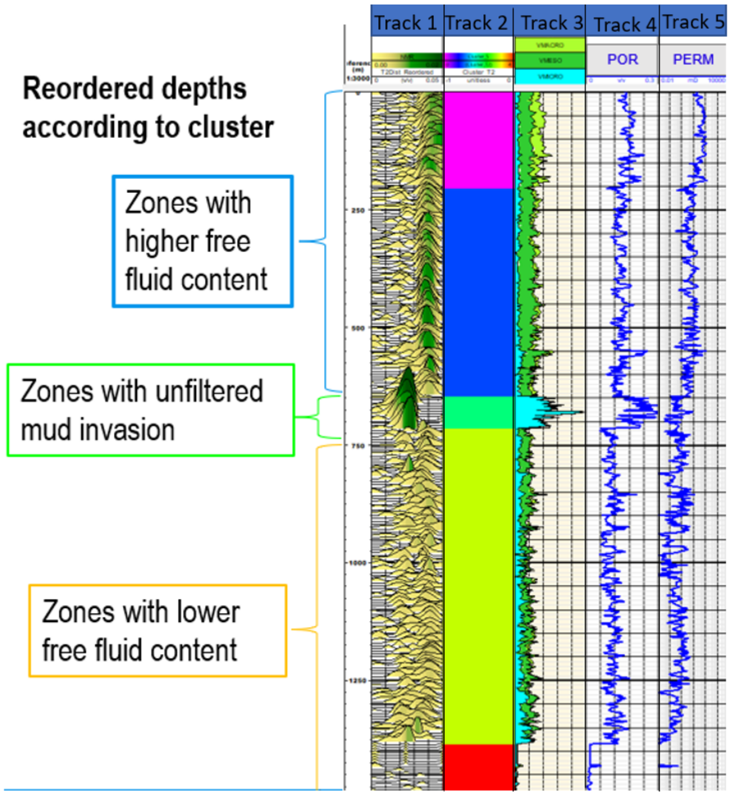

Figure 2. Logview with T2 distribution information, cluster, partitioned porosity, total porosity and permeability. The logview shows how the cluster is used to rearrange well depths according to similar porosity system. Each color in track 2 represents a set and assumes that uncertainty has similar behavior for each depth within a set.

To obtain a time-efficient answer considering the behavior for each depth, the reservoir depths are clustered according to similarities in the pore size. To illustrate the expected result from the unsupervised clustering, Fig. 2 contains the results of the methodology applied to a complex carbonate well containing high-quality reservoir rock typed in magenta and dark blue, in regions with high free fluid volume, a short interval with the T2 distribution being influenced by non-filtered drilling fluid effects in the near wellbore region, and light green and red colors indicating zones with low free fluid volume.

The methodology can automatically identify possible anomalies in the T2 distribution due to non-filtered drilling fluid effect or in zones with break out, and when the density correction is low, it is possible to reduce the propagation of error to the final interpretation, the weight associated with NMR porosity is decreased and while the weight for density porosity is maintained, providing a final porosity that has lower impact of possible anomalies in the T2 Distribution. This capability is important for complex carbonate reservoirs with presence of vugs and for improving automation on well log interpretation.

2.2 Step 2– Using Monte Carlo to generate multiple possible scenarios

An appropriate definition of clusters is important, as it is assumed that the behavior in the distribution of uncertainty is similar within each group, it is important to emphasize that the method does not assume the variable mean is constant in each group, it only assumes the uncertainty behavior is similar.

The computation uses a fixed number of depths per cluster and for these samples, we generate several scenarios using Monte Carlo simulation. In these simulations, each input parameter has a uniform distribution centered on the user's input and with user-defined limits, as seen in Fig. 3.

This step is the most computationally intensive and requires running the inversion multiple times per depth, by default we run 400 scenarios in our simulations, and to reduce the computational time of our method and taking advantage of the independence of different scenarios, we use a parallel computation. With this effective way to calculate the integration and considering the clusters in our modeling.

This step takes about 1300 s to run 4000 scenarios at 200 depths using a high performing computing PC (32 GB RAM). Each multiple scenarios obtained is associated with the estimated petrophysical properties and, for each depth, these results are organized in the distribution.

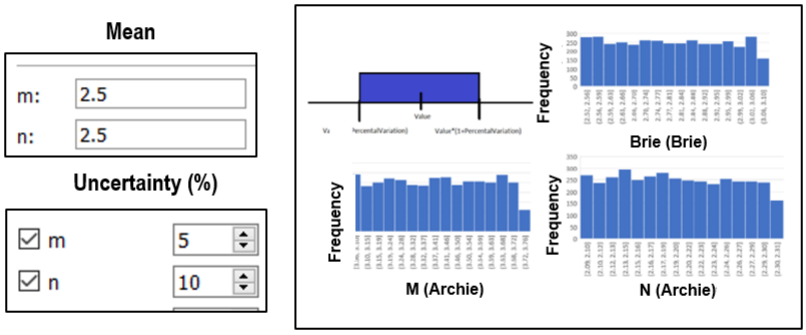

Figure 3. Uniform distribution based on user input mean and uncertainty interval, and simulated assuming independence among different input parameters.

2.3 Step 3 Deriving the variance-covariance matrix for the formation petrophysical properties

By the nature of the measurement and the physics, it is not possible to assume independence between the multiple derived answers and also not possible to assume a fixed uncertainty.

To include the variable dependencies in the modeling, the statistics from the various scenarios are combined to obtain the variance and covariance matrix, this matrix contains the input information that will be used to estimate the final output of the formation's petrophysical properties. As part of our method, the variance and covariance of the main calculated petrophysical curves are estimated using multiple scenarios according to eq. (1) and eq. (2).

$$var(X) = \sum_{i=1}^{n} \frac{(X - \bar{X})^2}{n}. \tag{1}$$

$$covar(X, Y) = \sum_{i=1}^{n} \frac{(X - \bar{X}) * (Y - \bar{Y})}{n}. \tag{2}$$

In these equations, n represents the number of scenarios considered, the response variables of our method are combined two by two forming X and Y, in our variance and covariance matrix X are the rows and Y each column of the matrix.

Using the 4 variables DPHI (density porosity), NMR_POR (NMR porosity), SW_Res (water saturation by resistivity), and SW_Sigma (water saturation by Sigma measurement), we can create the variance and covariance matrix for each cluster. These quantities are defined as the mean of variance and covariance of the selected samples. For each variable, we derive the best fit for the normal distribution using the sample's mean and standard deviation, as in Fig. 4, that contains a histogram (right) indicates the porosity distribution from the multiple scenarios in blue and the fitted normal distribution in orange showing a high similarity between fitted and original distribution. For the permeability(κ), the fit is performed in $log(\kappa)$.

2.4 Step 4 Derive the final petrophysical answers with minimized combined uncertainty

After calculating the variance and covariance matrix of porosity and water saturation, it is possible to estimate the combination of different sources of porosity and water saturation to provide the final estimated response that

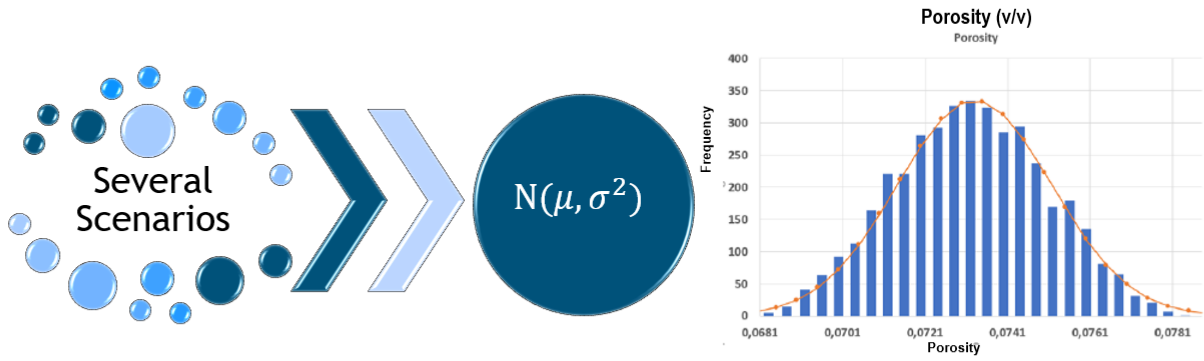

Figure 4. Normal porosity distribution test, differentiating various input parameters and including standard tool uncertainty.

minimizes the final uncertainty according to the linear equation eq. (3):

$$Z = \bar{\alpha}X + (1 - \bar{\alpha})Y. \tag{3}$$

Where $\bar{\alpha}$ is defined as in Equation eq. (4)::

$$\bar{\alpha} = (2var(Y) - covar(X, Y))/(2 * (var(X) + var(Y) - covar(X, Y))). \tag{4}$$

Assuming that X and Y have a normal distribution with standard deviation equal to the square root of the variances $var(X)$ and $var(Y)$, respectively, the final estimate of Z follows a normal distribution with standard deviation defined by eq. (5):

$$var(Z) = \alpha^2 var(X) + (1 - \alpha)^2 var(Y) + \alpha * (1 - \alpha) * covar(X, Y). \tag{5}$$

The final estimated curve Z is the linear combination of X and Y that reduces the final uncertainty to the standard deviation,as indicated in Fig. 5. The standard deviation (σ) represents the parameters that define the output uncertainty. Therefore, if the assumptions of a normal distribution for X and Y are valid, the Z output will contain minimal uncertainty. The hypothesis of porosity and saturation extracted from the multiple simulations was tested in complex carbonate wells, and the experiments indicate that when including tool uncertainties and varying multiple input parameters following a uniform distribution, with a sufficiently high number of scenarios, there is a good approximation of the calculated numerical distribution of extracted porosity and saturation with a normal distribution with mean and sigma extracted from the samples.

The first output minimized uncertainty is porosity, the porosity is estimated using a linear combination of density porosity and NMR porosity. The combined porosity estimated is used as input for water saturation. In the model considered in this work, if sigma and resistivity are available, these estimations will be combined following a methodology similar to porosity, and the combined estimation with reduced uncertainty indicated in Fig. 6 is calculated and can be used by the petrophysicist to deliver a result considering multiple measurements.

The main scenario of interest that was widely used to develop and test the methodology is complex carbonates, whose different types of porosity and high heterogeneity have a strong effect on permeability, fluid saturation, and elastic properties, which represents a challenge for seismic interpretation, understanding of well drilling using logging data, reservoir modeling, and production estimation.

The second scenario of interest is laminated formations with intrinsic anisotropy due to thinly laminated beds, this scenario has been covered in-depth in the paper Shetty et al. [2], which describes how acoustics and resistivity measurements can be combined to describe zones with intrinsic anisotropy.

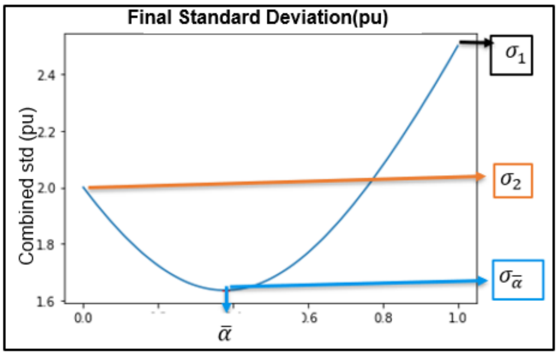

Figure 5. The plot indicates the standard deviation of the linear combination of two variables, the optimal point selected in the methodology is the one that minimizes the final uncertainty.

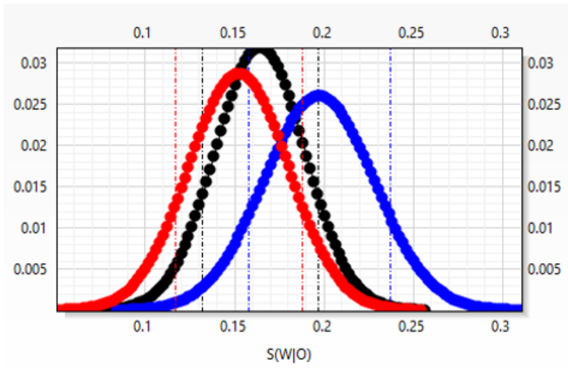

Figure 6. The plot indicates the distribution of estimated water saturation using sigma (blue) and resistivity (red) and a final estimation (black) using the linear combination of the two measurements.

The presence of shale increases the uncertainty about the density and sigma of the formation, and this will naturally reflect the weight associated with that measurement.

The second scenario of interest covers the improvement of petrophysical interpretation considering the near-wellbore alteration due to drilling fluid effects containing contrast compared to the formation fluid, this application has been covered in depth in Simoes et al. [3].

The improvement of information estimation precision was an enabler that allowed to include complex scenarios reducing the uncertainty from models and tool measurements.

3 Conclusions

This is a methodology that reduces the uncertainty of the output curves (for porosity, saturation, permeability, and elastic properties) and allows the users to be aware of the uncertainty range, so they can be conscious of all open scenarios to work with. The tool is fast and easy to use and can reduce the time spent on conventional evaluation by 50%.

This method aims to contribute to quantify and reduce uncertainty in well log interpretation and helps to separate rock and fluid volumes that are used in reserve estimation and rock physics model calibration. It is a methodology that moves in the direction of automation and digitization of the oil industry, enabling high quality and standardized petrophysical interpretations in a highly reduced time.

The base of the method is a combination of traditional statistics and machine learning. Using artificial intelligence methods to cluster the reservoir depths into clusters with similar porosity distribution and Monte Carlo simulation for estimating uncertainty associated with each basic petrophysical measurement, we can provide a final estimation of porosity, water saturation, and most of the conventional petrophysical properties including inferring Archie parameters, while minimizing uncertainty.

All of the above steps are performed internally in the method to help the petrophysicist provide a reservoir characterization honoring different profiles optimally and without adding too much additional effort. By integrating different measures and reducing the final uncertainty, we reduce the user's influence on the final results, we include a multiple quality control mechanism that allows the petrophysicist to understand how the inputs are being reconstructed and we perform a statistical analysis that provides the probability distribution of final petrophysical properties.

The proposed methodology used for estimating uncertainties in the petrophysical interpretation enabled the sensitivity analysis developed in [4] to calculate the uncertainty on predicted clean up time during fluid sampling jobs, an important estimation for field job planning.

Acknowledgements.

This research was carried out in association with the concluded Research and Development project registered as ANP 20024-6, ”Phase II Multi-Sensor Inversion” (Schlumberger / Shell Brasil / ANP), sponsored by Shell Brasil under the ANP Research and Development law as ” Commitment to Investments with Research and Development”. We would like to thank Austin Boyd for his vision of proposing the research project on integrating multiple measures for petrophysical characterization and his guidance during the project.

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