Uncertainty Quantification in 1d Pore Pressure Prediction of Exploratory Wells

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Abstract. The pore pressure model serves as a subsidy for the well project, predicting potential risk events. Events such as stuck pipe and inflow of fluids into the well result in a high cost in exploratory oil projects, either due to the time spent fighting them, or the complete loss of the well. Unfortunately, in exploratory projects we do not have enough data, nor the indirect data have good reliability, therefore, these models have high uncertainties. The present work proposes the application and evaluation of the uncertainty and sensitivity analysis methodology in the 1D pore pressure models used in the drilling of exploratory oil wells, to quantify and measure their impact. For this purpose, data from wells drilled in the Santos Basin, southeastern Brazilian margin, were used.

Keywords: Pore Pressure, Uncertainty Quantification, Sensitivity Analysis.

1 Introduction

The prediction of the pore pressure using ndirect methods use the concept of effective stress, the stress that will control changes in volumes or rupture of porous media saturated with water described by Terzaghi [1] apud Skempton [2]. In regions with abnormal pore pressure, there is a deviation in the transit time of the acoustic wave from what is considered normal for the same region, geology, and depth. The transit times are abnormal due to the formations being undercompacted, presenting porosities greater than those estimated for the rock compaction by the effective tension with normal pore pressure.

For pore pressure predictions affected by undercompaction we use Eaton's equation [3]:

$$P_p = \sigma_v - (\sigma_v - P_h)\left(\frac{\Delta t_N}{\Delta t_m}\right)^E \tag{1}$$

Where P_p is the pore-pressure pressure, σ_v is the overburden stress, the pressure exerted by the weight of the overlying rock, and P_h is the hydrostatic pore pressure, which is derived from the expected weight for a fluid column to the calculated depth. Δt_m is the measured acoustic transit time and Δt_N is the expected value of the normal compaction line of the acoustic transit time. E is the Eaton's exponent; it tells how much a difference between the measured property and the equivalent of a region without overpressure are equivalent in terms of excess pore pressure. This exponent is calibrated with the measured data and varies according to the region studied and the geophysical data used.

During exploratory drilling campaigns, we do not have data measured in the target reservoirs to calibrate the pore pressure model, therefore, we use theoretical and/or empirical models and data from regions considered analogous. As this choice is made through the experience of the professional, this model is surrounded by uncertainties and more susceptible to errors. This work proposes the analysis of the impact of uncertainties in the 1D pore pressure models of exploratory wells and the analysis of the sensitivity of the variables used. The quantification of the uncertainties and sensitivity analysis of the pore pressure models should make it possible to understand the importance of the prediction variables, show the influence of the precision of the input variables, improve the predictions, and increase the productivity and safety of exploratory well projects.

For the analysis of uncertainties in oil and gas drilling operations the most used approach consists of taking the model that is used for pore pressure prediction and propagating the uncertainties of the input variables to the output through a Monte Carlo simulation (MC) [4]. Several times the uncertainties of the input variables, the theoretical probability distributions and parameters, are chosen without even observing whether they are consistent with empirical data. To deal with this, we used data from 416 wells in the Santos Basin in 79 field/sites.

2 Data and Methodology

The standard 1D pore pressure prediction workflow using Eaton's equation and seismic velocities for exploratory wells can be summarized by the following steps: 1) use of the density curve to estimate total vertical stress, overburden. As there is no direct measurement for exploratory wells, a correlation with the seismic interval velocity is used; 2) generation of the normal compaction trend in terms of the seismic interval velocity. 3) Eaton's coefficient calibration with measured pressure data; 4) and with the results of the previous steps, calculate the estimated pore pressure for the planned exploratory well.

As we were unable to obtain seismic data for this project, we had to create a synthetic seismic velocity data from the transit time data measured in the wells.

The Monte Carlo method was chosen to obtain the final probability distribution and samples for sensitivity analysis. Using 10000 samplings for each of the Eaton's equations inputs, we performed several deterministic models to obtain the uncertainty of the Eaton exponent and prediction of the pore pressure. For the uncertainty modeling of the input variables, we chose ten of the most common distributions to test: Cauchy, chi-squared, exponential, exponential power, gamma, lognormal, normal, power-law, Rayleigh and uniform. To choose which one best fits the measured data, we chose two metrics: the sum of the squared errors of (SE), the Kullback-Leibler divergence (KLB). The SE tells how far the fitted values are from the measured values and KLB is a measure of how much information was lost when approaching the data by the theoretical distribution.

2.1 Overburden Stress

The overburden stress σ_v is determined from the integration of the density profile. For exploratory well projects we do not have direct density measurements, density is estimated through correlation with interval velocities. To obtain the density from seismic velocities we used a regression proposed by Gardner et al. [5]:

$$\rho = \alpha V^{\beta} \tag{2}$$

Where ρ is the estimated density, V is the measured interval velocity and α, β are the coefficients obtained by the regression.

The factors that most contribute to the uncertainty of the calculation of the overburden's densities in exploratory wells are the interval velocity model obtained by the seismic and the regression used to transform velocity into density. The seismic uncertainty is complex and varies according to the techniques used during data acquisition, its processing, available resources and the geological peculiarities of the region. As we did not find data and bibliographies to satisfactorily substantiate this quantification of uncertainty in the velocity model, we chose to quantify only the uncertainty related to well measurements and the respective transformation of velocity data into density.

Linearizing the Gardner et al. equation, that is, applying the logarithmic function, we obtain the following result:

$$log\,(\rho) = log\left(\alpha V^{\beta}\right) = log(\alpha) + \beta\, log(V) \tag{3}$$

Therefore, to obtain the coefficients of the equation we only need to perform a linear regression of the type:

$$log\,(\rho) = log(\alpha) + \beta\, log(V) + \varepsilon,\;\; min\,(\varepsilon^2) \tag{4}$$

Where ε are the regression residuals that are minimized according to ε^2. The consequence of this regression is that these residuals follow a normal distribution of zero mean and constant variance over $x = \log(V)$:

$$\varepsilon = \mathcal{N}(0, \sigma(\varepsilon)^2) \quad (5)$$

The theoretical distribution of this density estimator, log $(\hat{\rho})$, will be a normal distribution with mean equal to $\log(\alpha) + \beta \log(V)$ and variance equal to the residual ε (Fig. 1):

$$log\ (\hat{\rho}) = \mathcal{N}(log(\alpha) + \beta\ log(V)\ , \sigma(\varepsilon)^2) \quad (6)$$

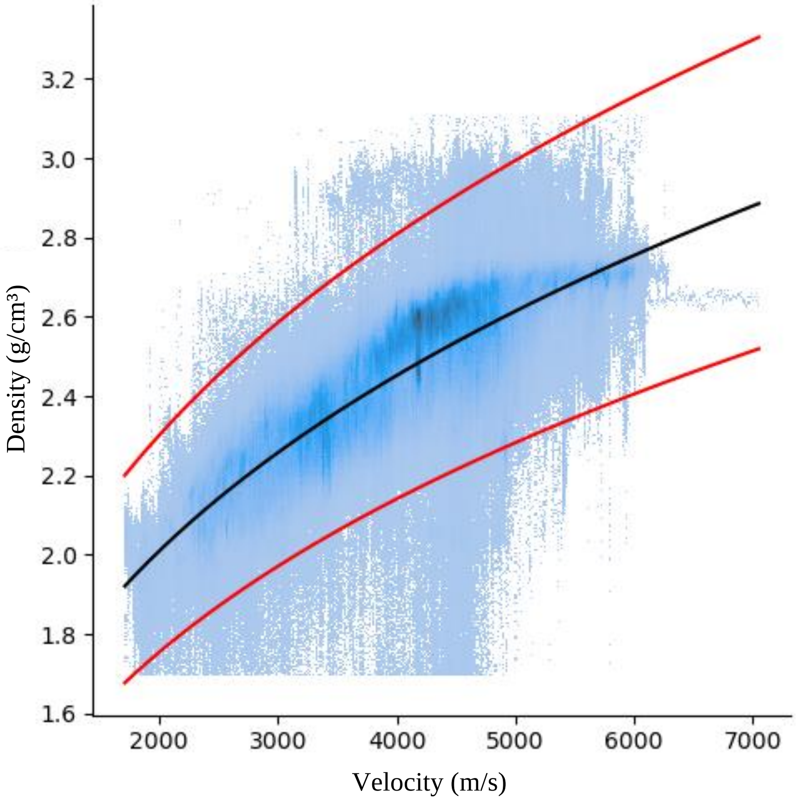

Figure 1. Velocity regression with density, black line is the regression result and red lines represent the 1st and 99th percentile of the density uncertainty model.

2.2 Normal Pore Pressure

The normal pore pressure model follows the same proposal as the overburden stress but using the formation water density. Its magnitude is obtained through the integration of the density profile of the formation water, which occurs naturally in the pores of the rocks, and the seawater, in offshore wells.

Despite the Cauchy distribution being the one that best adjusts the formation water densities, according to the criterion of the sum of squared errors, we opted for the Exponential Power distribution. It was the one that best represented the distribution both by the KDL criterion and by the histogram (Fig. 2), it was able to portray the wider tail and the asymmetry to the left of the data.

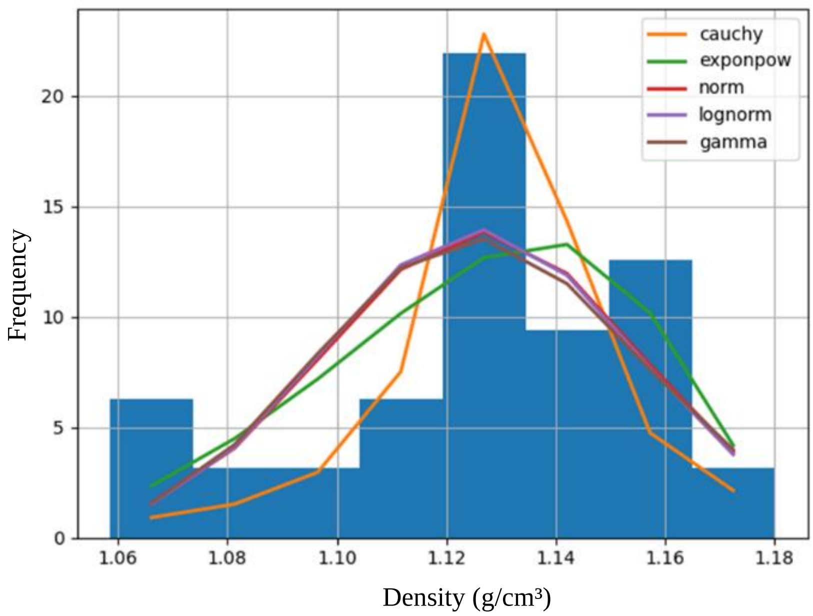

Figure 2. Histogram of formation water densities with the five distributions that best fit the data by the sum of squared errors criterion.

2.3 Normal compression trend

For the calculation of normal compaction trend lines, we used the method proposed by Hottmann and Johnson [6] to draw a linear line on the logarithmic transit time graph plot. A conventional linear regression was performed on the transit times profiles in normal pore pressure zones:

$$log(\Delta t_N) = a - bz,\ \ top\ of\ normal\ P_p\ zone < z < base\ of\ normal\ P_p\ zone \qquad (7)$$

Where a and b are regression coefficients and z is the burial depth, vertical depth subtracted from the water depth. In the same way as the linear regression of the density by velocity explained earlier, we can calculate its theoretical uncertainty distribution.

One of the sources of uncertainty that can generate quite divergent results is the choice of the top and bottom of the zone considered to have normal pore pressure. Based on the pore pressure measurements by stratigraphy, on the percentage of fields with overpressure measurements and on the stratigraphic chart of the Santos Basin, we chose to always include in the trend regression of normal pore pressure the Marambaia Formation and the base of the regression is going to be one drawn randomly among all the other tops of remaining formations.

2.4 Eaton exponent optimization

Using the Monte Carlo method, Eaton's equation, the uncertainties of the input variables and the pressures measured in the wells, we obtained the uncertainty of the Eaton coefficient. From the distribution of these results (Fig. 3) we conclude that according to the criterion of the sum of squared errors, the curve that best describes the behavior of the Eaton Exponent is the log-normal distribution.

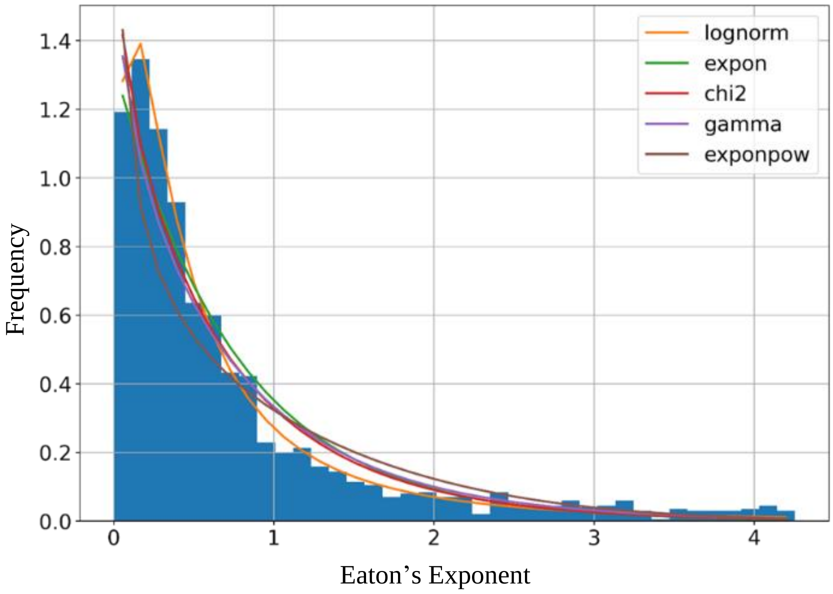

Figure 3. Histogram of Eaton's Exponents with the 5 distributions that best fit the data by the criterion of sum of squared errors.

2.5 Sensitivity Analysis

For linear trends, the measures that work well are Pearson's correlation coefficient. Pearson's correlation coefficient measures the strength and direction of linear relationships between pairs of variables, in this case the input and output variable of the uncertainty model. It varies from -1 to +1, the closer to 0 the lower the correlation of the variables and the closer to -1 or 1 the greater it is.

For non-linear non-monotonic trends, methods based on the decomposition of the variance of the model output are the most suitable, such as the Sobol method [7]. The variance-based sensitivity analysis indices are between 0 and 1. A high index indicates a strong relationship between the variation of input and output.

The Sobol method is computationally expensive if the number of input variables is large. To get around this we chose the RBD-FAST method, Random Balance Design of Fourier Amplitude Sensitivity Test [8], to estimate the first-order sensitivity indices. It is based on the combination of the RBD sampling technique, Random Balance Design [9], with the Fourier transform to decompose the model output variance, FAST, Fourier Amplitude Sensitivity Test [10] [11].

3 Results

From the Fig. 4 and the analysis using the RBD-FAST sensitivity index we obtained that the uncertainty of the Eaton exponent is the variable that most impacts the uncertainty of the pore pressure model by undercompaction in Santos Basin and the second is the transit time variable.

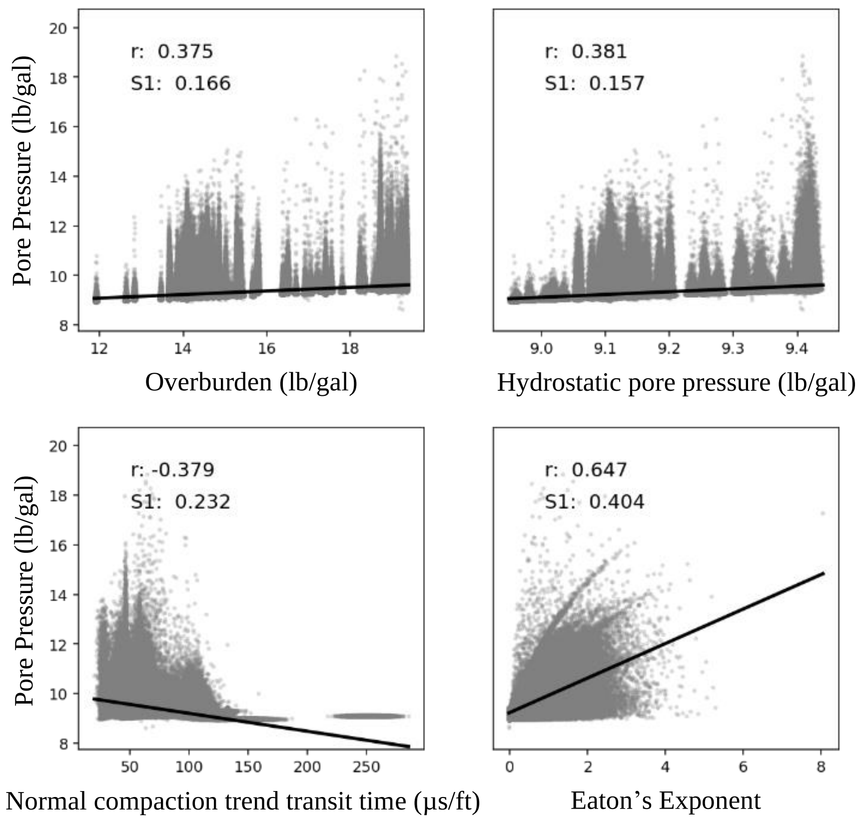

Figure 4. Scatter plots between input variables and pore pressure the pore pressure modeled. In black, linear regression, r is Pearson's correlation coefficient, and S1 is the first-order sensitivity index of RBD-FAST.

Carvalho et al. [12] evaluated two overpressure mechanisms in the Guarujá Formation of the Santos Basin that do not involve the undercompaction model. Of the nine fields/sites of Fm. Guarujá studied, six have high pressures (>10 lb/gal). All measurements of high-pressure fields/sites are within our uncertainty quantification of the Eaton's model (Fig. 5).

Granitoff [13] studied the high pore pressures in the Itajaí-Açu Formation and applied the Eaton's method. His interpretation is that the Eaton's method with a coefficient of 3, the standard coefficient of the methodology, was sufficient to calibrate satisfactorily with the well data he had. Of the 17 fields/sites of Fm. Itajaí-Açu, only 2 have high pressures (>10 lb/gal). Both are within the uncertainty modeled (Fig. 5).

Picolini and Chang [14] used Eaton coefficients from 3 to 5.5 in their work studing the Itajaí-Açu Formation, Juréia, Formation and Ilha-Bela Member. Of the 33 fields/locations with those formation 4 have high pressures (>10 lb/gal). All of them are within the uncertainty modeled (Fig. 5).

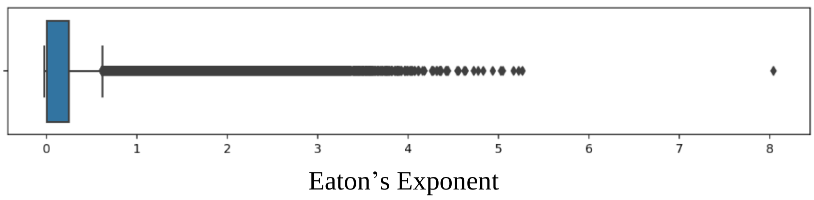

Figure 5. Box diagram of modeled Eaton's

4 Conclusions

Given the epistemological and practical limitations of this type of work, the results were satisfactory. We were able to assess that the variables that most impact the overcompaction models of the Santos Basin are the Eaton coefficients and the transit time of the normal compaction curve. With this we have an idea of what needs to be improved in the models that are currently made. This, added to the development of an automated methodology for this model construction process and Eaton and its respective uncertainties allow a greater gain in the workflow of exploratory well projects, either by the gain in scalability, of being able to work with a large number of wells, as well as the removal of interpretive bias and greater coherence of some work steps.

Eaton's method [3] has limitations, which may have impacted the results and should be analyzed in future research. They are: i) we do not consider breaking the normal compaction trend, despite the studies on geological evolution in the Santos Basin indicating this; ii) other overpressure generation mechanisms; iii) transit time is not a direct measurement of porosity, low transit times may be indicative of lithological or compositional changes in the rock [15]; iv) mechanisms of overpressure in carbonate rocks, as is the case of Guarujá Formation, are poorly understood and do not have a clear signature in transit time [15]; v) seismic transit times/velocities are not reliable in some regions. We did not have access to real seismic, we believe that this should have a significant impact, and perhaps the seismic uncertainty is even more important than those mapped in this study.

Finally, it should be noted that these conclusions are specific to the models, assumptions and data used. It is not guaranteed that, using data from other Basins or other types of overpressure models, the results will be the same.

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