Application of Monte Carlo Simulation to Quantify Uncertainties in Petrophysical Deliverables

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Introduction

The requirement for quantification of petrophysical uncertainty is not a recent development. Many papers in the literature describe functions for uncertainties definitions. Uncertainties in petrophysical deliverables have been attempted by various methods but work such as that of Hooper, H. T. (2001)[1] provides an excellent methodology.

Use of Monte Carlo technique to quantify uncertainties dates as early as 1964 where the technique was applied to business decisions[2]. The published example was a case of manufacturing company considering a new product line. Experts estimated probability distributions of input parameters such as manufacturing cost and product marketability. The distributions were then combined through simulation to calculate a probability distribution of economic parameters. Since then, Monte Carlo has been used to help simulate the economic model for exploration prospects[3], to estimate risk and manage performance associated with drilling[4,5] and to estimate reservoir properties[6].

Typically petrophysical deliverables include net reservoir porosity, permeability, water saturation and contact locations. These deliverables are required to compute in-place volume of hydrocarbon and reservoir modeling which provides input to operational decision-making. Often this has been observed that these data are provided without quantitative determination of uncertainties. Although excellent work such as that of Amaefule & Keelan[7] (1989), Chen and Fang[8] (1986) and Hook[9] (1983) provides foundation on how to compute uncertainties. However the methodologies presented are both time consuming to program and inflexible with regards to interpretation model.

With the computing power available on desktop PCs, Geoscientists are no longer required to use the analytical techniques outlined by Amaefule & Keelan[7] (1989), Chen and Fang[8] (1986) and Hook[9] (1983) to derive uncertainty. In this paper an attempt to highlight the ease with which uncertainties can be derived using Monte Carlo simulation method using advanced interpretation software***** available on PC is made.

Understanding Monte Carlo Simulation and basic assumptions

When a petrophysical property such as porosity or water saturation is calculated, an interpretation model is assumed. Usually, this model is implemented in a mathematical equation. Petrophysicists typically calculate properties using their most likely estimates of each input required in said equation. In reality though, there is an uncertainty range associated with the inputs used. Uncertainties in the inputs will result in uncertainty in the output, although the magnitude of that uncertainty can be difficult to quantify. As an example, if a simple density porosity calculation is considered, as shown in the equation below:

$$\phi_d = (\rho_{ma} - \rho)/(\rho_{ma} - \rho_{fl})$$

where ρ_{ma} is the matrix density, ρ is the density log measurement and ρ_{fl} is the density of the fluid in the pore space of the zone investigated by the density tool and ϕ_d is the log-derived density porosity. The input values (ρ_{ma} ,,) all have uncertainties associated with them, so the resulting output will also have an uncertainty.

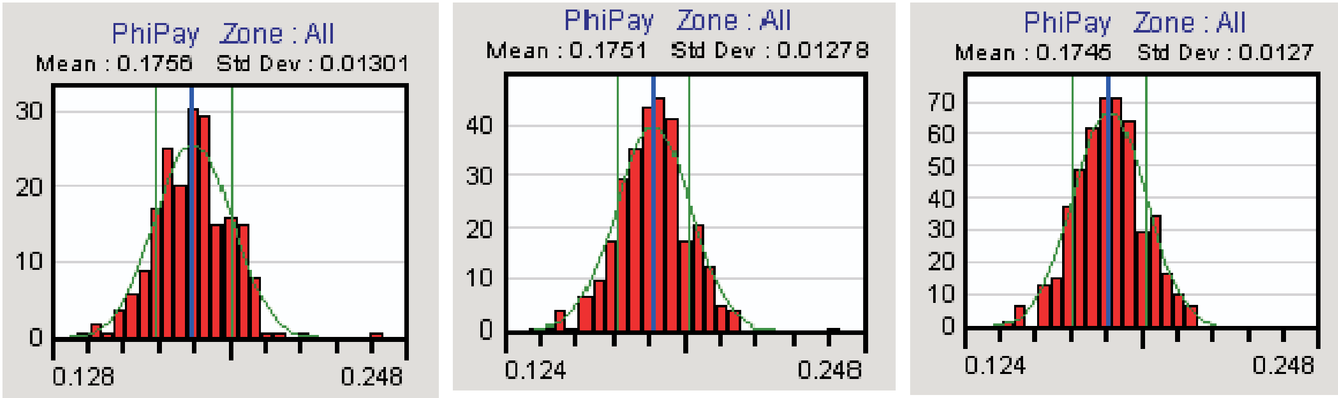
Monte-Carlo simulation provides a simple means by which uncertainties in inputs can be translated into uncertainties in the calculated petrophysical properties. This simulation is done by selecting a random value from the distribution of likely values for each input parameter required for the interpretation model. Once a value has been selected for all inputs, the interpretation equations are calculated and the result are stored. Then the process is repeated for all the different input values and all the results stored. When the requested number of cycles has been completed, the results can be sorted and histograms created allowing the derived petrophysical property at any given probability level to be found.

Monte Carlo modeling is very flexible, allowing different interpretation models to be built and the uncertainties tested quickly. Dependencies between input variables may also be accounted for in the input value determination.

The downside to Monte Carlo simulation is that a large number of cycles (>500) Adams[10] are typically required for meaningful statistics to be developed.

Methodology

To illustrate the significance of the assumptions and models used for uncertainty quantification, the basic petrophysical interpretation was done. This involved mainly



(a.) (b.) (c.)

Fig. 1. Histogram of the porosities derived using Monte Carlo Simulation through various pay sands. a. after 200 iterations, b. after 300 iterations, c. after 500 iterations.

calculation of volume of clay followed by porosity and water saturation determination and finally summing up for net pay, net reservoir and gross thickness and finally creating a model and assigning the shift increments to complete the simulation.

Calculating various petrophysical deliverables in the order displayed in the Figure. 2 performs simulation analysis. A shift (Linear, Reciprocal and Percent) is then applied to various parameter used and finally a random distribution (Gaussian, Square or Triangular) is applied.

Fig. 2 : The setting of the Monte Carlo simulation model, wherein the basic input are taken from clay volume determination, Porosity and water saturation and summation of the reservoir properties.

Results

1. Tornado Plot

The '***Tornado Plot***' error analysis display shows the relative importance of each parameter in the overall error associated with a result parameter.

In order to calculate the errors, a set of workflow runs is made. For each parameter in the Monte Carlo analysis, two runs are made; one with the parameter set to its low value and one set to its high value (± 2 standard deviations for Gaussian distributions). All other parameters are kept to their default values. This can take a little time to run, but once completed, a tornado plot can be made for any output

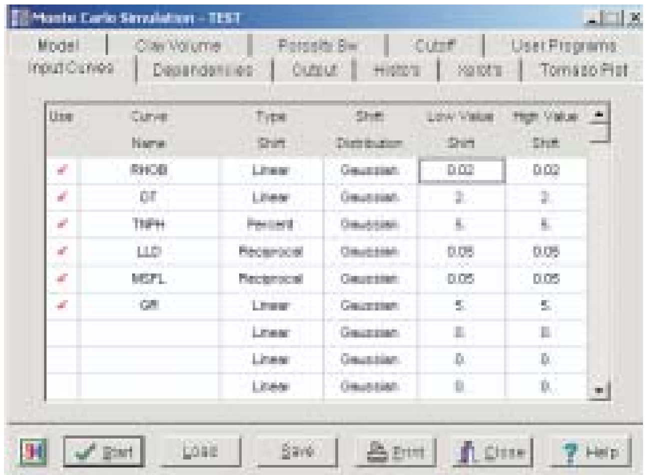


Fig.3 : The Monte Carlo simulation model showing the input curves and the corresponding shift values.

parameter without having to re-do the simulation runs. The '***Tornado Plot***' displays the errors associated with any of the output parameters. The plot is displayed with all selected input parameters shown in the Y axis with decreasing importance towards the bottom of the plot. The red bands show the effect of the selected input parameter on the output parameter. The Monte Carlo error ranges for each parameter, along with their starting values, are displayed on the right of the plot. A '***%***' sign indicates that the shift for the parameter is in percent. An '***R***' character indicates that this is a reciprocal

Summary Results

The summary results gives the output in various percentiles values e.g. P10, P50 and P90.

Conclusions

From the above discussion, it is apparent that the uncertain ranges estimated using Monte Carlo simulation are interpretation model dependent. It is still possible for calculated uncertainty ranges not to include the actual reservoir properties for which the best way out is to have a comparison with core data and other validation mechanisms. However, even in the absence of core data, Monte Carlo simulation is still suited to uncertainty quantification.

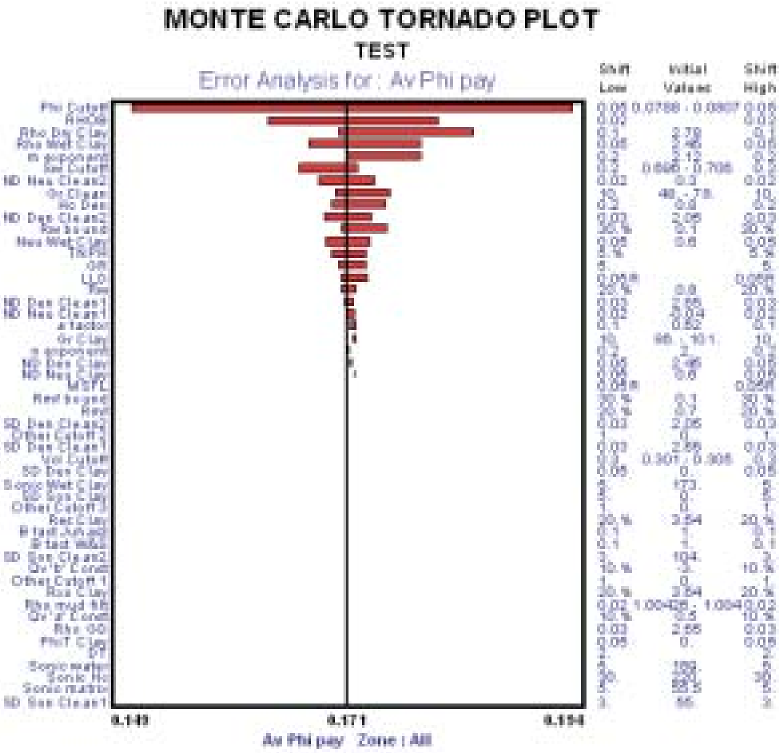


Fig. 4: Tornado Plot

MONTE CARLO SUMMARY RESULTS

Well : TEST
Date : 06/19/2005 6:14:02 PM
Number of Simulation : 504

NET RESERVOIR ROCK SUMMARY

Zn #	Zone Name	Top	Bottom	Gross	Net	N/G	Av Phi	Av Sw	Phi*H	Phi*So*H
1		300.00	739.98	439.98	334.75	0.761	0.212	0.628	70.878	26.376
	Mean				334.38	0.760	0.213	0.625	70.726	26.475
	P10.				279.81	0.636	0.198	0.782	61.370	15.015
	P50.				334.29	0.760	0.213	0.610	70.488	26.887
	P90.				393.73	0.895	0.229	0.468	80.331	37.422
2		739.98	763.91	23.93	23.32	0.975	0.181	0.142	4.231	3.630
	Mean				23.02	0.962	0.182	0.164	4.201	3.503
	P10.				22.17	0.927	0.171	0.362	3.867	2.699
	P50.				23.32	0.975	0.182	0.121	4.198	3.628
	P90.				23.47	0.981	0.194	0.023	4.522	4.096
3		763.91	775.03	11.13	11.13	1.000	0.149	0.179	1.654	1.357

Fig. 5. Summary Results

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