Introduction

Operating digital oil fields is one of the most exciting challenges for the new generation of E&P decision making software. Just as a powerful and up-to-date GPS system assist you in safely driving your car in time with your plans, the digital oil field operating software will "enable producers to extract a larger percentage of the oil from a field at a lower cost" (Ref1_ Jacobs and Ward 2006)

Digital oil field of course refers to Big (Geo) Data and real time Cloud computing and that will make the difference with current geo data processing and modelling workflows. But the main issue when making E&P decision remains: Oil is a natural resource that is out of direct reach and there is no such thing as an exact representation of the subsurface that would allow for making "ideal" E&P decisions.

So, even with terabytes of data flowing per second, how can we optimize E&P decision making and how can we best design these Big Geo Data processing workflows in order to best benefit from them?

DOOS : Digital Oilfield Operating System

I like the comparison with the driving GPS systems. I was recently driving to Brittany at night for 3 hours through heavy fog with less than 50m visibility. I have two GPS systems in my car: An old "built in" one useful to map the itinerary and locating the car position on it in real time and at various scales. It was useless as I could not simultaneously look at the road and the map and interpret it at reasonable driving speed. The other one is the most popular that you stick on your windshield. It shows the car position and the next 100m road ahead updating it in real time according to the car speed. I started driving paying more attention to the GPS road indication than to the road itself (to some extent of course!) and I eventually could drive at nearly the speed limit allowed on the highway (110 km/h) and arrived in Brittany with less than 15mn delay when compared to the forecasted time in standard conditions.
I realized that this driving experience was very similar to operating oil fields and that the analogous of the GPS was the digital oil operating system, let's call it the DOOS.

Optimizing E&P decision making: Cost cutting and producing more barrels per $ invested

Let's B be the profit of a project, Nb the number of barrels produced, P the oil price per barrel and C the cost for producing a barrel. Then very schematically B = Nb* (P-C).
Now let the same X be the percentage of cost reduction for producing the same Nb barrels in case 1 and the percentage of additional barrels produced at the same cost C in case 2
Case 1: The additional profit of the cost reduction is Δ B1 = Nb*X*C
Case 2: The additional profit of the "more barrel per $" is Δ B2 = Nb* X *(P-C)
The sum of cases 1and 2 equals to Δ B= Nb*X*P

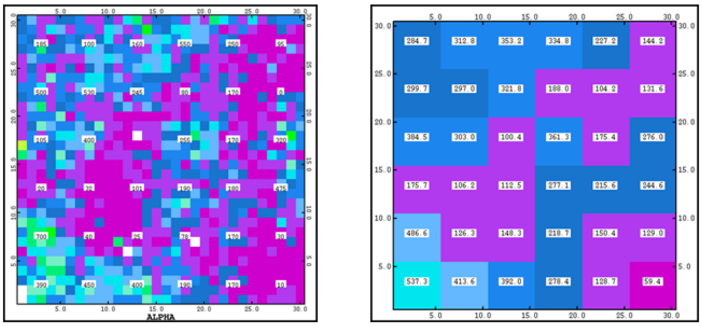
For usual values of P, C, and X, the benefit of the cost reduction is of the same order (higher when P <2C) than the "more barrel per $ option". Surprisingly, for the same X, their sum no longer depends on C but only on P that is the oil price.

The conclusion is that cutting costs or producing more barrels for the same cost equally contributes to improving the profitability of a project. A smart and costless way of producing more barrels per $ invested is to increase efficiency of the decision-making process by reconciling E&P expectations and realizations, meaning less exploration failures and more oil recovery. It is smart and costless because it only depends on the DOOS supporting the decision-making process, that is on algorithms and software.

A stochastic engine for the DOOS : The kriging algorithm

In the oil industry, kriging is known as a mere interpolator, it is in fact much more than that: It is a mathematical optimizer for decision making as it is actually designed to minimize the unknown difference that always occurs between expectations on reservoirs characteristics and their actual values. This difference is called the estimation error and kriging minimizes the estimation variance (Ref 2 Matheron 1970). Let’s illustrate kriging on a case study coming from real agricultural data collected after cropping a 90m*90m millet field by individual 3*3 m² spots.

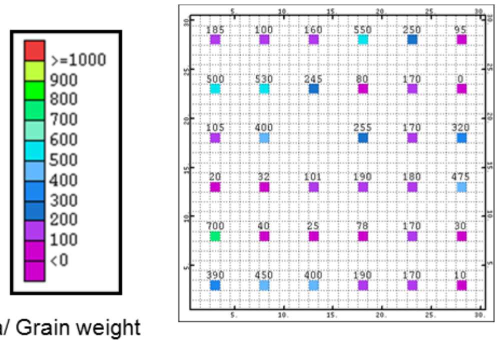
The weight of millet grains was measured for each 9m² spot thus leading to an exhaustive data set (Figure 1a, 3 were missing over 900)



a/ Grain weight 3m*3m spots   b/ Grain weight 15m*15m panels

Figure 1 *Cropping a millet field by 3m*3m spots Exhaustive data set allowing for validating field operating decision*

In the following we ‘ll be considering a 5*5 spot sampling of the field leading to 35 data displayed in Figure 2.

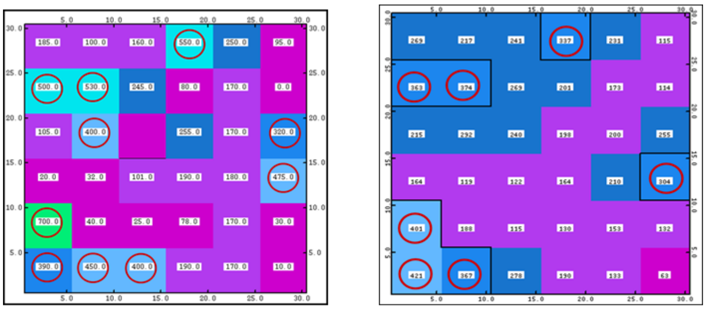


a/ Grain weight color scale   b/ 35 Grain weight samples

Figure 2 *Regular sampling of the millet field 3m*3m spots on a 15m*15m grid Available data set at the time of making decisions*

The operational decision to be made from the 35available data is:
a-How many 5*5 (15m*15m) panels contain more than 7.5kg of grains that is the average of the 25 spots they contain is above 300g?
b-What is the expected weight of grain contained in these panels?
c-What is the profitability of the operation knowing that cropping cost for one 15m*15m e average of the grain content per 15*15m panels.

Figure 3a *displays an intuitive deterministic evaluation of the panel contents consisting in extending the central 3m*3m spot grain weight to the whole surrounding 15m*15m panel.*
Figure 3b *displays a stochastic (kriging) estimation of the average weight of grain content in the panels (the quantified confidence indicator on the estimation or kriging variance is another output of the kriging process that is not discussed here)*



a/ extending the central 3m*3m spot grain weight to the whole surrounding 15m*15m panel   b/ stochastic (kriging) estimation of the average weight of grain content in the panels

Figure 3 *evaluations of the weight of grains contained in 15m*15m panels from 35 samples*

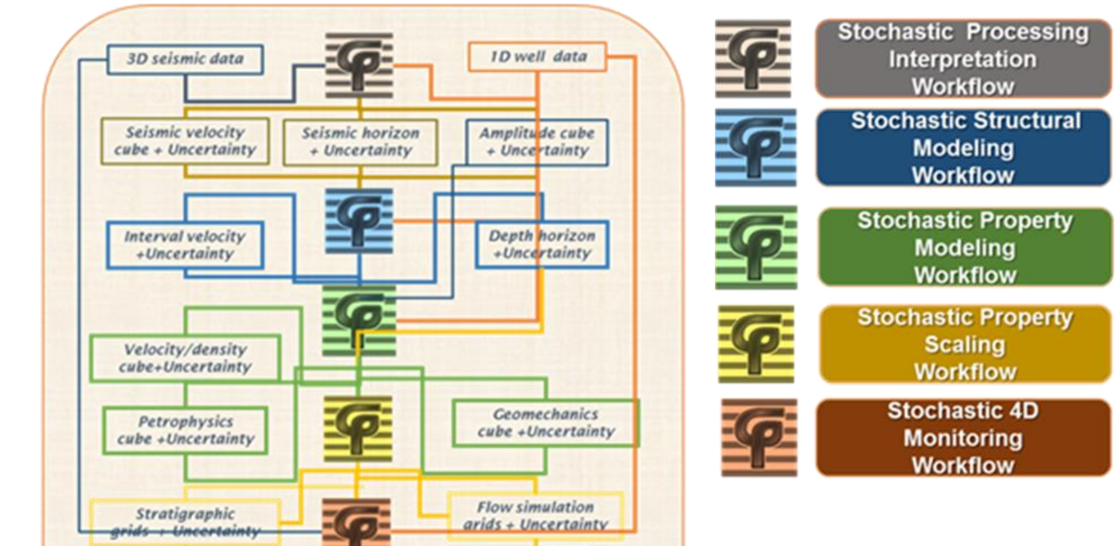
When the operating decision is made from deterministic map 3a: 10 panels are cropped, expected yield is 117,9kg and expected profit is 42,9$.
When the operating decision is made from stochastic map 2b: only 7 panels are cropped, expected yield is 64.2 kg and the expected profit is 11,7$

Figure 1b displays the actual average grain content per panels computed by averaging the 25 actual 3m*3m spot values contained in the panels. The comparison with expectations is striking:
Deterministic case: 10 panels cropped yield is 89.6kg and profit 18.6€ (expectation divided by 3!) operating cost 75$, that is a grain produced /$ spent ratio of 1195 g/$.
Stochastic case: 7 panels cropped yield 64.5kg profit 12,9$ (consistent with expected 11,7$) operating cost 52.5$ that is a grain produced /$ spent ratio of1228g/$

When making decision from the kriged panel values, the operating cost has been cut by 30% while increasing the Nbg/$ invested increased by 3%. The reason is that the optimization criterion of the Kriging (the cost function) is indeed the minimization of the estimation error (unknown true value – kriged value), which is only possible by using a probability model.

Examples of DOOS

Similar although more sophisticated kriging algorithms have been developed to support decision making throughout the E&P cycle (3_Abrahamsen 1993). For each E&P decision, the way it works is to translate usual deterministic and empirical geophysical processing and modelling workflows supporting the decision into their mathematical stochastic equivalent. (4 L.Sandjivy 2014) . Kriging enables optimization and automation of stochastic workflows.,
Figure xx displays a sketch of the full DOOS stochastic engine, starting from seismic pre stack data amplitude and velocity input and integrating to with well data down to the reservoir model.
Dynamic workflow building + traceability + interactive control points + parallel computing + quasi real time updates result in “live” delivering of 1P 2P 3P scenarios required by E&P decision makers.



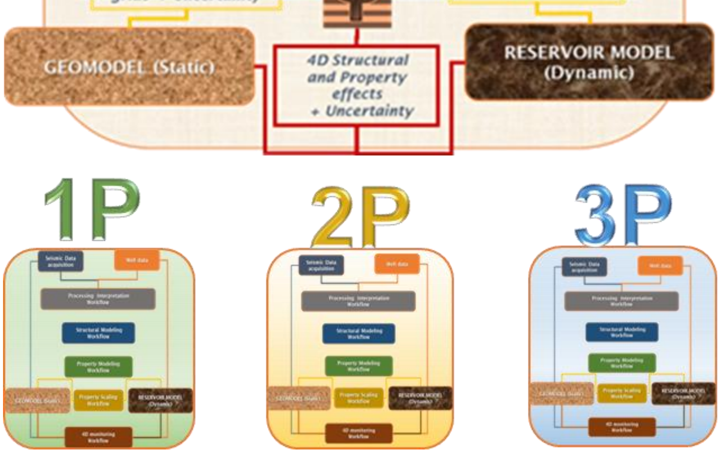
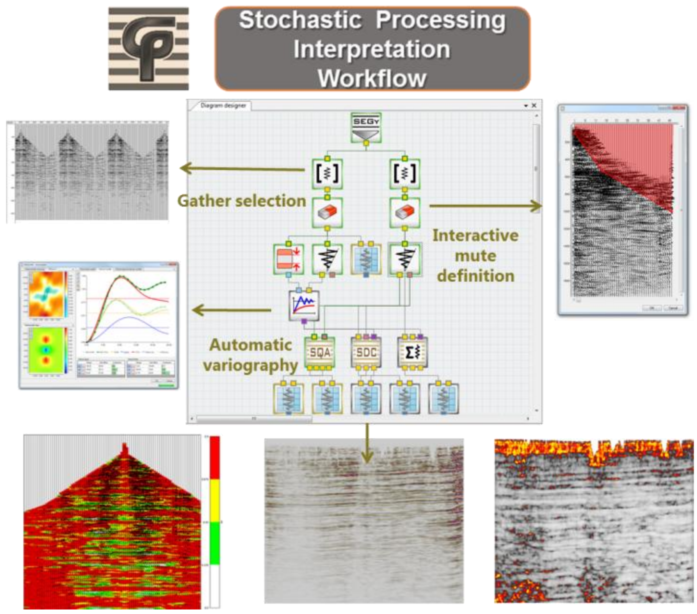


Figure 4: *DOOS linking successive stochastic workflows from seismic and well data reservoir qualification down to reservoir monitoring. Depending of the data selection and the parametrisation of the workflows 3 scenarios can be simultaneously run and compared representing 1P 2P and 3P cases required by risk management when making E&P decisions*



a *b* *c*

Spatial quality index *Stack* *Confidence interval*

Figure 5: *detailed pre stack gather data qualification automated workflow*

Figure 5 details an automated stochastic processing workflow for reservoir qualification of pre stack data, useful when supervising processing, interpretation or inversion. In a first parametrisation run, a number of individual gathers are interactively analysed for defining the mute function and variogram modelling. A second automated run will process the whole gather data set, updating the parameters accordingly, and perform the spatial quality assessment (a) of the gathers and of the stochastic stack (b and c). The output of the workflow is then automatically input to the next stochastic structural or property modelling workflow.

Conclusion

The coming of age of digital oil field operations in oil companies implies the conversion of today empirical data processing and modelling workflows into automated ones. Digital oilfield operation systems or DOOS must be designed for optimizing workflows performance and turnaround times, enabling real time and safer decision making. Kriging based stochastic workflows will be the engine of these DOOS as they are designed to minimize the difference between E&P expectations and realizations. As Scotty Salamov, a skilled geophysicist in Houston said when introducing stochastic workflows on the 2014 Surge day presentation "The statistical approach to many of the geological and geophysical problems we face will be the norm in less than a decade".

References

1) Digital oil field of the future Judson Jacobs and Richard Ward, Cera , Wall street journal Feb 7 2006 Copyright Cambridge Energy Research Associates 2006.

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3) P. Abrahamsen (1993), "Bayesian Kriging for Seismic Depth Conversion of a Multi-layer Reservoir" in A. Soares (ed.) "Geostatistics Troia '92". Kluwer Academic Publ., Dordrecht, pp. 385-398 76th EAGE Conference & Exhibition 2014

4) L.Sandjivy F. Merer : Plea for a consistent uncertainty management in geophysical workflows to better support E&P decision making EAGE 2014 Amsterdam RAI