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Value of information analysis of geophysical data for drilling decisions

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SUMMARY

Value of Information (VOI) analysis is performed for different geophysical data (seismic and electromagnetic data). VOI is a concept in decision theory for analysing the value of obtaining additional information, before purchasing and revealing the data. Gathering the right kind and amount of information is crucial for resolving difficult reservoir decision situations. We focus on drilling decisions, and structure situations according to the spatial decision alternatives and value function complexity.

Introduction

Where should a petroleum company drill wells? Making decisions in the petroleum industry can be challenging: There is often notable uncertainty pertinent to the decision and there could be a lot at stake as investments may be considerable. What is the value of acquiring different geophysical data? Additional information almost always comes at a price, so when is the information worth its price? Reliable information could go a long way towards improving the overall quality of decisions. The decision theoretic notion of value of information (VOI) is useful for evaluating and analyzing various sources of data. Recent examples for petroleum applications include Eidsvik et al. (2008), Bhattacharjya et al. (2010) and Martinelli et al. (2013).

The power of analysing information sources using VOI is that: i) it allows the decision maker to perform a reasonable evaluation before the information is purchased and revealed, and ii) if the decision maker can model value using monetary units, then VOI is also in monetary units. Compared with the traditional use of VOI in the petroleum industry, we stress the spatial aspects of the uncertain reservoir variables, the alternatives, and the potential information gathering schemes.

Value of information analysis

Denote uncertain reservoir variables by $\boldsymbol{x} = \{x_i : i = 1,2,...,n\}$ and alternatives by $\boldsymbol{a} = \{a_j : j = 1,2,...,N\}$, where indexes are associated with spatial locations, i.e. $x_i = x(\mathbf{s}_i)$ and $a_j = a(\mathbf{s}_j)$. The spatial locations $\mathbf{s}_*$ could for instance represent cells or units in a reservoir model. Each cell has uncertain facies, saturation or porosity variables. The decision maker must choose drilling or development alternatives from an available set $\boldsymbol{a} \in \boldsymbol{A}$.

We make a distinction between high and low decision flexibility. When there is high decision flexibility, the decision maker has many spatial alternatives to choose from. We can exemplify this situation by selection at $N = n$ reservoir units, where the petroleum company must drill or not, giving 2^n number of alternatives. The case with low decision flexibility can be exemplified by the decision of committing to one drilling plan or not. The injection and production wells are associated with geographic locations, but alternatives are simply $a \in \{0,1\}$, without need for spatial subscripts.

Let $v(\boldsymbol{x},\boldsymbol{a})$ be the value obtained by the decision maker. This is a function of both the spatial variable $\boldsymbol{x}$ as well as the chosen alternative $\boldsymbol{a}$. We make a distinction between coupled value and decoupled value. When the value function decouples, there are no complex interactions. If one selects different reservoir units, the value is simply the sum obtained from individual units. When there is coupling, the value computation involves interactions of several variables (e.g. fluid flow simulation).

Assuming a risk neutral decision maker, the prior value is defined by the optimal expected value:

$$PV = \max_{\boldsymbol{a} \in \boldsymbol{A}} \left\{ E\left(v(\boldsymbol{x},\boldsymbol{a})\right) \right\},$$

where the expectation is over the uncertain reservoir variable $\boldsymbol{x}$. Suppose next that the decision maker can purchase data $\boldsymbol{y}$ before making the decision. The posterior value is

$$PoV(\boldsymbol{y}) = \int \max_{\boldsymbol{a} \in \boldsymbol{A}} \left\{ E\left(v(\boldsymbol{x},\boldsymbol{a}) \mid \boldsymbol{y}\right) \right\} p(\boldsymbol{y}) d\boldsymbol{y},$$

where the expectation inside the max term is conditional on the data, while the outer sum is over the possible data outcomes, assuming a continuous sample space and probability density function $p(\boldsymbol{y})$

for the data. Under the assumption of a risk neutral decision maker, the VOI is the difference between posterior and prior value (Howard and Abbas, 2015):

$$VOI(\boldsymbol{y}) = PoV(\boldsymbol{y}) - PV.$$

VOI analysis is used to evaluate an experiment $\boldsymbol{y}$ before it is acquired. If the price of an experiment is larger than the VOI, the data are not economic, and the decision maker should not purchase the data. Customarily, VOI analysis is conducted to compare various experiments over different price ranges. There can be several opportunities for spatial information gathering in the petroleum industry. By embedding the VOI analysis in a unified framework involving spatial uncertainties and spatial alternatives one can address and evaluate a range of information gathering schemes more realistically.

Examples

Suppose there is post-stack seismic amplitude data at top-reservoir, which can be inverted to get saturation and porosity predictions. Now, the company considers purchasing pre-stack data or electromagnetic data. See also Eidsvik et al. (2008) and Bhattacharjya et al. (2010). Here, a grid of 25×25 reservoir units is defined at the top reservoir, and the total number of cells is $n = 625$. We assume the decision maker can freely select drilling sites. At every reservoir unit, the company decides whether to drill a well or not, i.e. alternatives are $a_i \in \{0,1\}$, $i = 1,\ldots,625$. This means there are 2^{625} alternatives and high flexibility. The value is a sum over cell values, so it decouples.

Our modeling approach is based on a prior model for the porosity and saturation along the top reservoir horizon. The saturation is two-phase brine or oil dominated. Brine saturation at cell $i = 1,...,n$ is denoted by $s_i \in (0.1, 0.9)$. The porosity is $\phi_i \in (0.15, 0.4)$. Saturations and porosity are both spatially dependent. Note that porosity is accurately defined from the post-stack data, while saturation remains more uncertain. Profits $\boldsymbol{x} = (x_1,\ldots,x_n)$ associated with drilling wells and producing oil from the n reservoir units are hence largely a function of the uncertain saturation. At unit i, set $x_i = \mathrm{Rev}_0\, \varphi_i (1 - s_i) - \mathrm{Cost}$, where the constant Rev_0 incorporates factors such as the unit area, the assumed reservoir thickness, recovery factor and oil price, and where the subtracted cost of drilling is assumed fixed and constant for all units. We assume these profits are Gaussian in the prior model $p(\boldsymbol{x})$, with different mean and variance parameters and with spatial correlation.

Is it worthwhile for the petroleum company to process pre-stack amplitude versus offset (AVO) data or electromagnetic (EM) data? These will give imperfect information about the reservoir variables (and profits) at all cells, but it comes at the large price of data acquisition and processing. In the geophysical modeling we use well-known rock physics relations (Mavko et al., 2009) for the seismic AVO data and the electromagnetic resistivity data as a function of profits (porosity and saturation). The likelihood model for the data, $p(\boldsymbol{y} \mid \boldsymbol{x})$, is a linearized Gaussian model.

The VOI is the difference in posterior and prior value:

$$VOI(\boldsymbol{y}) = \sum_{i=1}^{n} \int \max\{0, E(x_i \mid \boldsymbol{y})\}\, p(\boldsymbol{y}) d\boldsymbol{y} - \sum_{i=1}^{n} \max\{0, E(x_i)\}$$

where the conditional expectation varies with the data, allowing the informed petroleum company to change the decisions at reservoir units, depending on the data. The probability density function for the seismic AVO or EM data $p(\boldsymbol{y})$ is Gaussian, inheriting properties from both prior and likelihood.

Figure 1 shows decision regions computed for three possible information gathering schemes; only seismic AVO data, only EM data, or both. This is displayed as a function of the price of processing AVO data (first axis) and the price of EM data (second axis). When the prices of data are low, it is optimal to purchase both data types because the VOI is larger than the added prices. The diagram clearly depends on the spatial correlation in the reservoir variables (left and right displays). Data are more valuable when there is high spatial correlation in the uncertain reservoir profits.

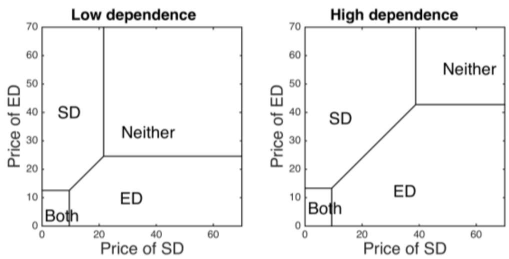

Figure 1: Decision regions for pre-stack seismic AVO data (SD price on first axis) and EM data (ED price on second axis) for the high flexibility drilling decisions. The left display has small correlation in the profits, while the right display has more spatial correlation.

Consider next a more complex value function including fluid flow, but limit scope to a simplified decision situation where the decision maker can either develop the reservoir by drilling a fixed configuration of wells ($a=1$), or avoid development ($a=0$). This represents low decision flexibility. A petroleum company could have limited flexibility for various reasons: say, existing infrastructure making a (few) well configuration alternative(s) much less expensive than others.

The petroleum reservoir is modeled with geologic scenario x as the main uncertain variable, see e.g. Trainor-Guitton et al. (2011). We consider two geologic scenarios: a meandering channel system and a delta system, equally likely a priori. In the value calculation we condition on the geologic scenario, and account for spatial heterogeneity by drawing multiple realizations of facies, porosity and permeability (Figure 2). These are drawn using a multiple-point geostatistical algorithm (SNESIM) on a training image created from boolean object based modeling, as well as rock physics relations connecting the reservoir variables (Mavko et al., 2009), and Gaussian process modeling.

The production profiles of 1000 realizations are computed. The average production, assuming no discounting in the economic model, is 113 monetary units for the delta, while it is 60 monetary units for the meandering channel scenario. This gives a prior value of $PV = \max\{0, 86.5 - \text{Cost}\}$, where 86.5 is the average value for the two scenarios, and where the cost of development is subtracted.

The data scheme considered involves the interpretation of seismic amplitude data, which are informative of the reservoir properties. For assessing the posterior value we must know the accuracy of the seismic interpretation y for each scenario; the reliability measure. One approach for deriving this is to study the misclassification rate from summary statistics (Trainor—Guitton et al., 2011). Together with the prior model this gives the posterior probabilities of the geologic scenarios. We have

$$PoV(y) = \sum_{y \in \{0,1\}} \max\left\{0, E\left(v(x, a=1) \mid y\right)\right\} p(y).$$

Table 1 shows the VOI for a range of production and development costs; high (100), medium (85) and low (70), and three different reliability measures (assuming equal rates of misclassification in the reliability). The VOI is largest for the medium cost range as this is close to the average expected production in the prior model. For high and low costs the VOI is 0 for the lowest reliability measure considered in this example, and the interpreted data is for sure not worthwhile. For intermediate costs and more accurate interpretation of the seismic data the VOI increases, but note that the price of obtaining a more accurate interpretation is likely much larger.

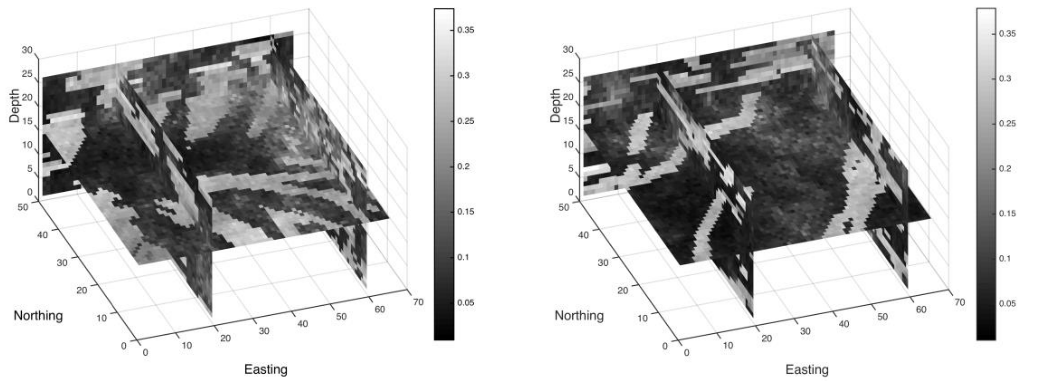

Figure 2: Porosity maps for the two geologic scenarios. Left: delta system. Right: meandering channel system.

	Perfect information	Reliability 0.9	Reliability 0.7
VOI, low cost (70)	**5**	**2.4**	**0**
VOI, medium cost (85)	**12.5**	**9.9**	**4.6**
VOI, high cost (100)	**6.5**	**3.9**	**0**

Table 1: VOI as a function of production costs (rows) and accuracy of the seismic interpretation (columns).

Conclusions

We show examples of conducting VOI analysis in petroleum applications that exhibit spatial dependence. A distinction is made between high and low decision flexibility, depending on the number of alternatives in the decision situation. We also distinguish between situations with coupled versus decoupled value functions. Several decision situations in the petroleum industry are characterized by high decision flexibility and coupled value, and we anticipate more research on resolving such complex decision situations and VOI analysis in this context (Barros et al., 2014). There is a wealth of opportunities for creative spatial information gathering schemes in the petroleum industry, and we believe these are more realistically gauged by framing the spatial decision situation in a unified framework including multivariate statistics, geo-modeling and decision analysis.

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