UNCERTAINTIES IN PRODUCTION CHARACTERISTICS DUE TO GEOLOGICAL UNCERTAINTY

Lars Holden, Norwegian Computing Center and University of Oslo, and
Henning Omre, Norwegian Institute of Technology and Norwegian Computing Center

One of the major objectives of reservoir evaluation is to predict future production of hydrocarbon from the reservoir under study. In an idealistic setting with everything completely known it may be expressed by:

$$q_p(t) = w(r(x), p(t)); \quad t \epsilon [t_0, \infty) \tag{1}$$

with

- $q_p(t)$ being the production characteristics of interest. It will be a function of time, t, from production start. The subindex, p, indicates that the production will depend on the recovery strategy, ie development plan and depletion strategy.

- $r(x)$ being the initial reservoir characteristics prior to production. It will of course be a function of location, x, in the reservoir. It represents the variability of porosity, various permeabilities and fluid saturations in the reservoir.

- $p(t)$ being the recovery variables defining the development variables specified through the well locations and production constraints, and the depletion variables defining the injection strategy. This will be time dependent.

- $w(.,.)$ being the set of differential equations representing fluid flow. These physical processes are assumed to be correctly modeled and they link the reservoir characteristics and recovery variables to the production characteristics for the future. This function will usually be based on Darcy's Law and expressions for conservation of mass and is represented by reservoir production simulators in the petroleum sector.

The production characteristics, $q_p(t)$, is the variable to be determined, hence the objective of the study. The reservoir characteristics prior to production, $r(x)$, is largely unknown but it is being explored through seismic surveys, exploration wells and production testing. The reservoir characteristics is given by nature and will remain a partial secret to man. The recovery variables, $p(t)$, however, is completely controlled by the reservoir management and is used to optimize production. The fluid flow model, $w(.,.)$, is for simplicity assumed to be completely known in this paper. Improvement in the numerical models for fluid flow is an important and intensive area of research. Inaccuracy in the fluid flow model is probably one of the most important contributions to the error in the estimates presented in this paper.

The component containing uncertainty is the reservoir characterization since it is neglected the uncertainty due to our limited understanding of fluid flow. In order to represent this uncertainty, the initial reservoir characteristics are assigned a stochastic interpretation, and denoted $R(x)$. The actual uncertainty is modeled by the corresponding probability density function, pdf, denoted $f_R(r(x))$. This pdf assigns a probability to each outcome $r(x)$ of the reservoir characteristics. The aim of stochastic reservoir description is to define $f_R(r(x))$ and to estimate model parameters involved in it. This is the only stochastic component in the evaluation and expression (1) appears as:

$$Q_p(t) = w(R(x), p(t)) \quad ; \quad t \epsilon [t_0, \infty) \tag{2}$$

with $Q_p(t)$ being the production characteristics now being stochastic due to the dependence on the stochastic reservoir characterization. Note that since $Q_p(t)$ is stochastic a corresponding pdf, $f_{Q_p}(q_p(t))$, exists. This pdf can in principle be determined by taking $f_R(r(x))$ through the function $w(.,.)$. Since $w(.,.)$ consists of a set of differential equations, this will entail solving stochastic differential equations. Very few analytical results are available for this and a Monte Carlo sampling approach remain the only feasible way to assess $f_{Q_p}(q_p(t))$. See e.g. Holden and Risebro (1991)

The definition of the stochastic reservoir characteristics must be based on two types of information:

- geological inference information, containing general geological knowledge about the type of reservoirs present. Moreover, observations from representative outcrops and comparable reservoirs are included. This type of information can be considered to provide general understanding of the reservoir characteristics.

- reservoir specific information, containing observations made at specific locations in the reservoir. This includes seismic data, observations and measurements in wells, well test data and production history. This type of information is specific to the reservoir under study and is denoted, O. It will be stochastic since the reservoir characteristics are considered to be stochastic, and a stochastic model for the sampling procedure must be defined through the pdf $f_{O|R}(o|r(x))$. This entails specifying the probability model for the observation whenever the reservoir characteristics were completely known. Let the observations actually made be denoted o.

The geological inference information must be used to defined the stochastic model for the reservoir characteristics through the pdf $f_R(r(x))$. The model of interest, however, is the one conditioned on the reservoir specific information. The conditional reservoir characteristics are $(R(x)|O = o)$, with associated pdf $f_{R|O}(r(x)|o)$. Realizations from this model will ensure that the reservoir specific information is honored according to the sampling model $f_{O|R}(o|r(x))$ since from Bayes formula

$$f_{R|O}(r(x)|o) = c f_R(r(x)) f_{O|R}(o|r(x)).$$

In the GRUS-study, see Lia et al (1995) an extensive evaluation of the production uncertainty was made. One realization from the conditional reservoir characterization model is presented in figure 1. Three petrophysical variables are displayed: porosity, horizontal absolute permeability and irreducible water saturation. The model contains structural components defining the outline of the reservoir and the six formations being present. Moreover, most formations contain facies models underlying the petrophysical variables. Note that in the figure the observations in the wells are reproduced.

By imposing the conditional reservoir characteristics $(R(x)|O=o)$ on expression (1), one gets:

$$(Q_p(t)|O=o) = w\left((R(x)|O=o),\, p(t)\right)\ ;\ t\epsilon[t_0,\infty) \tag{3}$$

with $(Q_p(t)|O=o)$ being the stochastic production characteristics conditional on the reservoir specific information available. An increasing amount of reservoir specific information will tend to reduce the uncertainty in the production characteristics. The associated pdf is $f_{Q_p|O}(q_p(t)|o)$, and the ultimate objective of the study is to determine this pdf. As mentioned previously, few analytical results is available for this problem, hence the assessments has to be made by Monte Carlo simulation. This entails: generate a set of realizations from $f_{R|O}(r(x)|o)$, displays of one realization being presented in figure 1; take each realization through the set of differential equations represented by $w((r(x)|O=o),\, p(t))$ to obtain a set of realizations of production characteristics representing $f_{Q_p|O}(q_p(t)|o)$. In figure 2, a set of such realizations is presented. The results are produced in the GRUS study and the characteristics are total oil production with time. The corresponding best prediction for the production characteristics at a specific time $t=t'$ is the expected value at that point in time:

$$E\{Q_p(t')|O=o\}$$

with associated prediction variance

$$Var\{Q_p(t')|O=o\}$$

The best prediction can be estimated by the average of the set of realizations being generated. The prediction variance can be estimated by the empirical variance of the realizations.

Note in particular that:

$$\begin{aligned} E\{Q_p(t')|O=o\} &= E\{w\left((R(x)|O=o),\, p(t)\right)\} \\ &\neq w[E\{R(x)|O=o\},\, p(t)] \end{aligned}$$

with the inequality being true due to the non-linearity of the fluid flow equations represented by $w(.,.)$. Hence the expected production characteristics will not be equal to the predictions made by solving the fluid flow equations on a reservoir characterization provided by the best guess based on available information.

STOCHASTIC RESERVOIR DESCRIPTION

The initial reservoir characteristics will be largely unknown and is given a stochastic interpretation. The characteristics, $R(x)$, must contain information sufficient for activating $w(.,.)$ in order to compute $q_p(t)$. One may say, that the reservoir variables needed in the description are the ones required by the fluid flow model in order to compute the production characteristics. This will of course vary from reservoir to reservoir dependent on the geology and hydrocarbon phases present. In an oil reservoir the reservoir variables needed will typically be:

$$R(x) = (\Phi(x), K_h(x), K_v(x), S_{wir}(x), S_{or}(x), S_{ow}(x), T)$$

with $\Phi(x)$ being spatial distribution of porosity; $K_v(x)$ and $K_h(x)$ being spatial distribution of vertical and horizontal absolute permeability respectively; $S_{wir}(x)$ being spatial distribution of irreducible water saturation; $S_{or}(x)$ being spatial distribution of residual oil saturation; $S_{ow}(x)$ being spatial distribution of initial oil/water saturation; and T being a list of other non-spatial variables like standardized relative permeability curves, fluid properties etc. All these variables are, as indicated by the capital letters, in principle stochastic variables since they will not be completely known. In practice, the geoscientist must judge whether the uncertainties in the individual variables will have significant influence on the overall uncertainty. If the influence is neglectable the model can be simplified by treating these variables as constants.

The stochastic reservoir description entails assigning a probability model to the stochastic reservoir variables, $R(x)$. This must be done by defining the associated probability density function, pdf, $f_R(r(x))$. The pdf specifies the probability associated with an arbitrary realization of the reservoir variables, $r(x)$. The reservoir geology usually appear as complex spatial patterns and simple spatial stochastic models like Gaussian random functions will normally not be representative. The stochastic model for reservoir description should be built as a two-stage model, see Damsleth et al (1992). The stochastic underlying model should contain the large scale architectural elements of the reservoir, and can be divided into a structural, sedimentary and fluid model. Superimposed on this architecture is the stochastic reservoir variable model containing the small scale variability of $R(x) = (\Phi(x), K_h(x), K_v(x), S_{wir}(x), S_{or}(x), S_{ow}(x))$.

The stochastic underlying models are:

- the structural model containing two modules: geometry and fault module. The geometry module include models for the formation border horizons dividing the reservoir into a number of formations each of them created by one sedimentary process. Examples are fluvial, deltaic, shallow marine and turbidite formations. The border horizons can be modeled by Gaussian random functions and the models can integrate information from observations in wells, seismic data on reflectors and subjective guesses on formation thickness. Gaussian random functions are defined as spatial generalization of the linear Gaussian theory. In Abrahamsen et al (1991) a stochastic structural model, including seismic depth conversion is presented. In figure 3, a predicted formation thickness map with associated uncertainties is displayed.

Moreover the location of other large scale features as laterally extensive shale barriers may be included in the geometric module.

- The fault module includes both large scale fault zones identifiable from seismic data and sub-seismic fault patterns. The fault zones will have offsets determined by the stochastic geometry module, while the individual faults in the zone cannot be identified. In Omre et al (1992), a Marked point random field model is used for modeling these fault units. This type of model defines geometrical objects and models their geometries and interactions in a probabilistic manner. In figure 4 a top view and a front view of a fault zone realization are presented. The model was used for evaluating the flow characteristics a cross a fault zone. The sub-seismic fault pattern in the reservoir matrix can also be modeled stochastically. In Munthe et al (1993), a Marked point model was used for this purpose. In figure 5, a realization of such a fault pattern based on geological understanding of fault processes and seismic data is presented.

  The stochastic modeling of sub-seismic fault patterns appears as a very interesting and challenging problem with considerable impact on the production characteristics of the reservoir.

- the sedimentary model defined within each formation and containing the stochastic model for facies architecture generated by the sedimentary processes. A large variety of models are need to cover the possible facies patterns, of course. In the following, the mostly used model formulations are reported.

  Markov random fields are parameterized by specifying the probabilities of the combinations of facies neighborhoods. In Fält et al (1991) the facies architecture of a reservoir of coastal marine origin was modeled by Markov random fields. Eight facies types were involved in the model, and a couple of cross sections from one realization are displayed in figure 6. Note how the facies interact to fill the total reservoir without defining a background facies. Conditioning on well observations is simple to perform.

  Truncated random fields are generated by discretization of a continuous realization of a Gaussian random function. The cut-offs for the discretization are such that the proportions of the individual facies are reproduced. In Matheron et al (1987) this approach was used to model the facies architecture of a fluvial-deltaic reservoir, actually an extensive outcrop. Three facies types where defined: sandstone, shaly sandstone and shale. In figure 7, a cross section from a realization is presented. Note that the facies transitions are ordered with shale content. The lateral variations of facies proportions are introduced by the geoscientist as parameters. The conditioning on well observations can relatively simply be made.

Indicator random field is defined by assigning an indicator to each facies type and then to model the correlations between these indicators. In Suro-Perez and Journel (1990) the indicator model was used to model various shale lenses and other barriers in a sandstone reservoir. Six different facies types, including sandstone, was used. A cross section of a realization of the facies architecture is shown in figure 8. Note the frequent transitions from one facies to the other. The conditioning on well observations is straight forward.

Marked point random fields is based on a probabilistic model of geometrical objects, their size, orientation and relative positioning. The approach is often termed object based models. In Clemetsen et al (1990) and Egeland et al (1993) Marked point random fields are used for modeling river channel geometries sedimented in fluvial environments. Four different facies are modeled: fluvial plains, river channel, sheets plays and barriers In figure 9, a horizontal cut through a realization of a fluvial reservoir is displayed. Note how the various facies interacts in a hierarchical manner. The conditioning on well observations can be difficult unless clever parameterizations of the objects are used.

In addition to stochastic models for the large scale facies architecture, models for sub-facies as shale and calsite sheets are required. This was actually the initiation of heterogeneity modeling as presented in Haldorsen and Lake (1984). They used a simple Marked point random field model for representing shale units in a sand matrix, see figure 10. This shale model is extended and refined in order to suit more complex conditioning by well observations, see Syversveen and Omre (1994) see figure 10. These models can be used for other small scale facies types like calsite segmentation as well. Shale horizons which location should be modeled as a part of the structural model can be represented by two dimensional Markov random fields as reported in Høiberg et al. (1990). In figure 11, a realization of the shale horizon is presented. The shale is nonexistent in some areas and the thickness varies. A similar approach can be used for other facies with large lateral extensions, like for example calsite sheets, see Omre et al (1990).

The facies architecture is expected to have considerable impact on the production characteristics of the reservoir. Stochastic modeling of discrete variables in a spatial setting is difficult, and the need for conditioning on well observations make the problem even more challenging.

- the fluid model represents the hydrocarbon saturations and phase properties. The hydrocarbon contact surfaces are usually modeled spatially, Gaussian random functions are most frequently used. In faulted reservoirs individual models in each fault segment can be used, see Abrahamsen et al. In figure 12, a realization of a hydrocarbon in place map over a segmented reservoir is displayed.

- The fluid model concerns presence or absence of hydrocarbon in the individual segments and is therefore of utmost importance in reservoir evaluation. Surprisingly few thorough stochastic studies of this problem can be found in literature and many challenging problems are still to be worked out.

The stochastic reservoir variable model represent the variables directly involved in the fluid flow differential equations. Their model will be dependent on the realization of the underlying model in the sense that the latter determines the parameters in the reservoir variable model. The large scale fault pattern will for example define the location of fault sealing if this is assumed to be present; the expected porosity will normally be higher in sand facies than silt facies; there will be an upward fining trend in river beds in fluvial environments; the variance of permeability is smaller in coarse sand facies than shaly sand facies; the saturations are differently defined above and below the hydrocarbon contact levels; etc. Most frequently Gaussian random functions are used as models for the reservoir variables superimposed on the underlying models, see Fält et al (1991). In figure 13, the simulated permeability values superimposed on the facies architecture in figure 6. In cases where no underlying sedimentary model us used, ie. the same facies is used for the total formation, Fractal random functions and Indicator random functions have been used. In figure 14 and 15 examples of these from Hewett (1986) and Journel and Alabert (1988) are presented. In Doyen the reservoir variables are simulated with support of seismic data. The following table gives an overview over the most used stochastic random functions used in reservoir models:

Structural	Sedimentary	Fluid	Petrophysics
Horizons:	Trunc. Gaussian	Gaussian	Gaussian
Gaussian	Markov	Discrete	Fractal
Faults :	Indicator		Indicator
Marked Point	Marked Point		

In a case study it is in addition to using the stochastic models necessary to include:

- The reservoir is usually described in a much finer grid in the stochastic model than it is possible to use in the fluid flow model. The geologists prefer to model properties on the meter scale while the blocks in the fluid flow model typically is 10-100m scale. It is therefore necessary with a change of scale or an upscaling of the reservoir parameters. Methods are typically based on the same fluid flow model but with simplified local boundary conditions, see e.g. Holden and Lia (1992)

- The fluid flow model traditionally takes most of the time of the geoscientists and the CPU time.
- The model must then be fitted to the production data. This is called history matching. It is based on repeated use of the fluid flow model with perturbed input data. See e.g. Eide et al. (1994)
- It is very important to validate the model. The model is based on very many different and possibly conflicting data. There are many different validation techniques e.g. visual inspection, different statistics, and matching production data.

EXAMPLE

In the GRUS-study previously mentioned, see Lia et al (1995), an oil reservoir inspired by the Brent group of the Veslefrikk field in the Norwegian sector of the North Sea, see Pedersen et al (1994) and Damsleth and Holden(1994), was evaluated. This is a part of the PROFIT initiative in Norway. The objective was to evaluate the impact of the uncertainty in the reservoir description on the total production uncertainty. In figure 1, the reservoir variables of one realization of the stochastic reservoir description model are displayed. The model is in three dimensions but only a fence diagram is shown. The actual variables are $[r(x)|O = o] = [(\varphi(x), k_v(x), k_h(x), s_{wir}(x), s_{or}(x))|O = o]$ Only three of these variables are shown in the figure. The reservoir contains five major formations, from top to bottom: Tarbert, Ness, Etive, Rannoch and Oseberg.

The structural underlying model contain seismic depth conversion to two seismic reflectors, but also stochastic models for the formation borders and two major shale horizons in the Oseberg formation were included. A Gaussian random function model was used. Hence the uncertainty in the overall geometry of the reservoir was modeled. Note, however, that in the figure the displays are relative to base Oseberg and are hence not reflecting the geometry correctly. The fault module of the structural model did only consider large scale fault zones identifiable on seismic.

The sedimentary model was activated within each formation segment. Note however that it is the reservoir variables themselves be indirectly observed on figure 1. The shallowest formation, Tarbert, consist of marine sand sheets deposited during progradation in times of an overall regression. It is very thin and contains only a minor part of the resources. A simple one facies model with a barrier at the bottom was used. The next formation, Ness, is deposited as river channels facies are modeled as Marked point random fields with predominant directions approximately 30^0 off the direction of the fence diagram in the figure. The fluvial plain is considered to be almost impermeable. The high heterogeneity can be observed in the figure. The Etive and Rannoch formations are deposited in a high energy beach or barrier bar complex and lower marine delta respectively. The heterogeneity is extremely high and no underlying facies structure can be identified. Hence the underlying sedimentary model contain one facies in each of the formations only. The deepest formation, Oseberg, was rapidly deposited by various sediment gravity flows from a continental area. The formation is thick and constitutes excellent reservoir properties, in spite the content of some shale and calsite segmentation. An underlying facies model containing three facies, sand shale and calsite, was used. The sand facies was considered a background facies overlayed by shale and calsite facies. The shale facies was located in the two major barrier horizons modeled in the structural model. A Markov random field model was used and the shale horizons can be identified, one thin one close to the top of Oseberg and one thicker one close to the bottom. The calsite sheets are spread all over Oseberg although with a higher frequency to the north-east. A Marked point random field model was used. Note that the underlying facies model do reproduce the facies observations made in the wells.

The fluid model consisted of three pressure regimes. One in the Tarbert formation, one in upper Ness and the major Brent regime covering lower Ness, Etive, Rannoch and large parts of Oseberg. The corresponding oil/water contacts were modeled as horizontal with the depths.

The stochastic reservoir variable model defining

$$(R(x)|O = o) = [(\Phi(x), K_v(x), S_{wir}(x), S_{or}(x))|O = o]$$

is conditional in the stochastic underlying model defined above. The reservoir variables are defined with no spatial heterogeneity in Tarbert, in Ness each of the facies are assigned values without spatial variability also. Etive and Rannoch is modeled with high spatial variability and distinct horizontal anisotropy. Moreover, Etive has a vertical trend with best flow properties in the middle, while in Rannoch the vertical trend has best flow properties on the top. In Oseberg, the sand facies is assigned excellent reservoir properties without spatial variability while shale and calsite are considered to be impermeable. Gaussian random function are used as model for the reservoir variables in all facies. Moreover, a stochastic model for the permeability, or sealing transmissibility, across the fault zones defined in the structural model was defined. The initial phase saturations was defined to be physically perfect saturations of oil and water in the respective phase zones. All observations in wells were reproduced. Note that it is a realization of the reservoir variables

$$(R(x)|0 = \sigma) = ((\Phi(x), K_h(x), K_v(x), S_{wir}(x), S_{or}(x))|O = o)$$

which is displayed in figure 1. The underlying facies model can only be indirectly identified.

The GRUS-study took the realization of the reservoir variables, $(r(x)|O = o)$, through a rescaling procedure to prepare an input suitable for the fluid flow simulator, $w(.,.)$. A set of recovery variables, $p(t)$, including seven injecting and four producing wells with water injection in the water zone was defined. Based on this the predicted production characteristics, $(q_p(t)|O = o) = w[(r(x)|O = o), p(t)]$, can be obtained by simulation of fluid flow. By generating more realizations of the reservoir variables more realizations of the predicted production characteristics can be obtained. In figure 16, a collection of 57 such realizations for predicted characteristics production over 30 years is presented. The characteristics displayed are: accumulated oil production; oil production rate and water cut. This represents the uncertainty in the predictions. An interesting feature of the GRUS-study is that simulation of reservoir descriptions through simulation of fluid flow to obtain predictions of production is performed completely automatically, without any human interference. Each realization all the way required approximately 5 cpu-hours on a medium size work station.

Additional 200 full simulations were performed. With so many simulations it is possible to explore the model quite thoroughly. Figure 17 shows the probability densities for total production, recovery and recovery of mobile oil. It is possible to find which input parameters which contributes most to the uncertainty in production. In this case study the sealing of the large faults contributed most to the uncertainty. Figure 18 shows how important this parameter is in this case study.

FUTURE TRENDS

The need for assessing uncertainties in order to make better and more robust reservoir management decisions will be emphasized in the future. This entails ensuring that all available information is used in a balanced manner in the reservoir evaluation. Focus will hopefully be on construction of the stochastic reservoir models and on estimating their parameters reliably. The representativity of the model governs the representativity of the results. It will be required that the models can be automatically explored on a computer, but this is merely a technical problem.

In the near future, user friendly computer systems will be available to help geoscientist in this modeling task. These systems will bridge the between existing systems for well log interpretation, seismic data interpretation etc. and the reservoir production simulations.

Special topics which required more thorough work are:

- assessment of uncertainties in hydrocarbon in place by refining the fluid model. It should be possible to pin down the available resources much better than one does today.
- modeling of sub-seismic fractures and faults. Their influence on fluid flow is large, and their presence can change the anisotropy directions of the reservoir which is crucial when EOR is used.
- improved use of the available data e.g. seismic, well test, outcrops, well data in sedimentary modeling, particularly in modeling the facies architecture which has large influence on fluid flow.

- use of production history in reservoir characterization. This is the familiar history matching problem.
- tools for combining the different models and using the uncertainty information for improving the reservoir management decisions.
- improvements in the fluid flow models.

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