Make decisions using stochastic models

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Abstract:
The ultimate aim of stochastic modelling in reservoir evaluation is making better decisions. This paper illustrates how stochastic models may be used in enhancing decision making. In order to quantify the decision making, it is necessary to formulate an object function such as net present value, production etc. The optimal decision is the decision that maximises the object function. The objective function should include the most important aspect of the decision including expenses if necessary. Since the decision is made under uncertainty, it is also necessary to specify whether one maximises the expected value of the object function, the probability for the object function to be larger than a particular value or another deterministic quantity. This is illustrated in several examples. For some of the examples it is possible to perform a thorough evaluation. In other examples time is the most crucial limitation. In all the examples it is defined an objective function. Then the function is quantified within the constraint in the project.

1 Introduction

This paper focus on how to use stochastic models in order to make better decisions in reservoir exploration and exploitation. This is in contrast to the traditional use where the ambition is to make predictions. We will argue that when the focus in on the decisions, this has influence on the choice of stochastic model and the evaluation of this. There is a large variety of decision situations. Some are important decisions involving large investments and requires advanced models to reach a good decision. The opposite is the more ordinary decision where a simple model is satisfactory and where it may be important to make the decision fast and with limited use of resources. In some cases there are a sequence of decision that can be made based on the same model such as the position of the next infill well, while other decisions are more unique such as determine whether to build or not build a platform.

We have found it necessary to formulate a precise criteria, an object function, when comparing different alternative decisions. Possible object functions could be net present value, maximum production after n years, and length of a well in a productive zone. The "best" decision is the decision that maximises the object function. The purpose of the stochastic model is to evaluate the object function and find the reservoir management variables (i.e. well position, injection rates) that maximises the object function. This evaluation should be performed with as few assumptions as possible. In most practical decisions however, it is necessary to make severe assumptions. Typical assumptions are that the seismic interpretation is correct and neglect certain parts of the problem like strategic aspects. The authors believe that the formulation of a precisely specified object function helps the manager in the final decision making which may be different from the optima of the object function. The object function is particularly useful in comparing different alternatives where it is no reason to believe that the assumptions have influence on the ranging of the alternatives. This approach is demonstrated in four different cases presented in sections 3-6.

The stochastic model may lead to a stochastic object function. However, it is necessary to prioritise between two alternatives where the stochastic function for the two alternatives have overlapping distributions. Hence, the object function should be the expected value or a quantile of a stochastic function, i.e. the expected net present value instead of the net present value. Expectation and quantiles can be estimated by generating realisations of the model and evaluate the stochastic function for each realisation. If the distribution is approximately symmetric, only few realisations are necessary in order to estimate the expectation or quantiles central in the distribution. It is also necessary to take the expectation at the correct level since most object functions are not linear. This may be illustrated by positioning of a an infill well. It is better to use expected production from the well than expected thickness of the productive zone since the productivity may be larger per meter for thin zones.

Some decisions are robust in the sense that it is not necessary with an advanced model in order to make a good decision. Other decisions are more sensitive such that it is necessary with thorough scientific work in order to chose between the different alternatives. In reservoir evaluation the object function often depends on a very large number of variables, i.e. permeability in all grid blocks in a reservoir. Experience is however that the object function does not depend critically on all variables. It is crucial to choose a parameterisation that limits the number of critical variables and treats this variables properly. Section 2 illustrates these point for a fluvial reservoir.

The authors favour to formulate a stochastic model using prior distributions for the most important variables. The model is then conditioned on the available data including measurement uncertainty and expected model errors such that the variables follows posterior distributions. Realisations of the conditioned model are generated by a simulation algorithm. The simulation algorithm can be verified by checking whether the realisations are distributed according to the model. By using this formal approach the model assumptions are separated from the approximations in the simulation algorithm. There is a tendency to drop the formal model and use an ad hoc simulation algorithm directly. It is easy to give examples where simulation algorithms that seem reasonable have pitfalls that may be difficult to observe. Tjelmeland (1998) gives one example within history matching. The use of a formal stochastic model is also discussed in section 2. There is a separate section with typical assumptions by using this approach.

The purpose of the stochastic model is to find the values of the reservoir management variables that maximises the object function. In some cases this optimisation may be performed by evaluating the function for all combinations of the variables. In most cases this is not feasible due to the number of combinations. Then one may use traditional numerical methods using gradients, genetic algorithms or experimental design, see Damsleth et al. (1992) and Egeland et al.(1992).

2 Critical properties in fluvial reservoirs

Fluvial reservoirs are deposited by rivers. The reservoir consists of high permeable sand bodies in a non-permeable shale matrix. The sand bodies are called channels since they are of limited width and thickness and are continuous through the reservoir. Fluvial reservoir with medium sand/gross may have a very complex connectivity pattern. See figure 1. Fluvial models and simulation algorithms are reported in Holden et al (1998).

Assume that the position of the sand bodies in a reservoir are not known. Then the probability for a vertical well to penetrate a particular channel is proportional to the width of the channel. In order to model correctly the probability for a well penetrating the channel it is essential to have correct average width of the channel. It is not important to model thickness, variation in width or vertical and horizontal sinuosity of the channel.

Assume a certain channel already is penetrated by a producing well. The challenge is to find a position for an injector penetrating the same channel and maximise the volume in the channel between the two wells. The optimal decision is obviously to put the injector in the most likely direction of the channel from the producer, but it may be more difficult to find the distance between the two wells. As a first order approximation, the volume increases linearly with the distance between the two wells and the probability for penetrating decreases linearly with the distance. Hence, the expected volume between the wells is approximately independent of the distance. If the distance is large, the injector will only penetrate the channel with a small probability, but if it is penetrating, the volume is large. Also in this case it is not necessary with a complex model for the thickness, width and vertical and horizontal sinuosity of the channel.

Assume that channel facies is observed in two wells and the decision depends critically on the probability that the same channel is observed in both wells. It is assumed that the probability is only based on the geometry and it is not possible to use other data like geochemical analysis or production data. This is a complex problem that can not be solved analytically. It can only be evaluated by a realistic model that includes the most important properties of the reservoir. This included width distribution for the channels, depth and thickness variation, possible interaction between channels and realistic sand/gross ratio in the reservoir. A similar problem is to find a correct width distribution of channels that is penetrated and channels not penetrated by wells. These distributions are not similar since it is more likely to penetrate wide channels than narrower channels. Another problem is to generate an expected sand/gross map conditioned on several wells.

An ad hoc simulation algorithm that is not based on a formal model, but only generates channels that fits well observations is not likely to handle these challenging problems correctly. A correct simulation algorithm gives the same result when it generates a large number of realisations and the realisations that satisfies the actual well observations are selected, as by directly conditioning the simulation algorithm on the observations. A simulation algorithm is also likely to have approximations, but it is easier to control the approximation. It is essential to have the correct probability for the same channel being penetrated by several wells and the correct width distribution in the penetrated and non-penetrated channels in order to perform good reservoir management in fluvial reservoirs

3 Position of an infill well in a fluvial reservoir

In a fluvial reservoir with 6 wells, two channels in different layers are penetrated by two wells. In order to maximise production from these wells an injector is planned in the reservoir. The problem is to find the best position of the injector. There is no cost difference between the different positions so the optimal decision is to find the position that maximises production. The object function is the expected production from the field. It is considered more important to get a good model for the geometry of the channels, than to model the flow for a particular position by a reservoir simulator. The volume in the channels between an injector and producer is considered as a satisfactory estimate for the production instead of using a reservoir simulator. If the injector does not penetrate the channel, it is assumed that there will be no production from the producer. The model presented in Hektoen and Holden (1996) is used for representing the geology. It uses Bayesian updating of channel dimensions and directions. 50 realisations from the reservoir conditioned on the well data is generated. For each realisation, 30 different well positions are evaluated. See figure 2. For each position it is found whether the well penetrates either of the channels, and if it penetrates, the volume between the producer and the new well position is calculated. By interpolation between these well positions, it is made a map over the probability for penetrating either of the channels and the expected volume between the producer and the new well. See figure 3. The optimal position is the position where the expected volume is highest.

It is also made an alternative model with faults that disconnect the flow in the channel. It is assumed that if there is a fault in the channel between two wells, the producer will not produce anything. It is assumed that the probability for fault is proportional with the distance between the two wells. By including faults in the model, the optimal position of the injector is closer to the producer. See Aanonsen et al (1995) for more details.

4 Infill wells in history matched reservoir

The question is to drill or not drill 5 infill wells in a reservoir with 8 years production history. The problem is whether the additional production is large enough to compensate for the additional expenses. The object function is chosen to be the expected net present value of the field. The main uncertainty is in the reservoir properties of the field. It is assumed that the additional costs with the infill wells, the oil price and the optimal position of the infill wells are known. In order to calculate the difference in net present value for the two alternatives, it is necessary to find the additional production from the 5 infill wells. The main challenge is to perform a history match of the reservoir. The additional production is the difference between reservoir simulations with and without the 5 infill wells.

The reservoir consists of 5 layers. It is used a correlated transformed Gaussian fields to model the porosity and vertical and horizontal permeability in each layer separately. The reservoir consists of 1761 blocks and has 8 years production history from 6 wells. A Bayesian approach in the history matching was used, with a model for the uncertainty in the production measurements. It is assumed a model with independent Gaussian noise in each measurement with zero expectation and with variance based on reservoir simulation experience. This error should include both the measurement error and the model error, i.e. the precision in the reservoir simulator, upscaling, reservoir description etc. It is then generated realisations of the reservoir that satisfies the prior model, the well data and the production data. It was chosen an adaptive genetic Metropolis-Hastings simulation algorithm. This work is reported in Holden et al (1999). The evaluation is performed as a part of the EU project PUNQ; see Floris et al. (1999).

5 Dimension of platform in appraisal stage

In the appraisal stage of a field, it is necessary to dimension the platform. An important part is the number of drainage points. It is natural to use net present value as object function. In this study it is assumed that the dominating uncertainty is connected to the production as a function of drainage points. Hence, it is assumed that the cost including both investment and maintenance of the platform, as a function of drainage points are known in addition to the oil price. A pragmatic argument for these assumptions is that these assumptions make the geoscientist focus on the important aspects of the reservoir model which improves the input from the geoscientist to the economical model.

The reservoir under study has many faults and there are two different models for the contact between the segments. There is a large uncertainty in the depth conversion and the properties of each segment. The large number of segments also makes reservoir simulation not feasible. The stochastic model for the reservoir focusing on the depth conversion of the horizons is based on the software Horizon, see Abrahamsen et al.(1992). A large number of realisations of the horizons are generated from the model conditioned on the seismic and the available wells. The geometry for each segment in each realisation is found from the horizons and a model for the faults. It is also made a model for the average value of the most important variables for each compartment.

Based on a limited number of reservoir simulations it is estimated the production from a segment with uncertainty as a function of the average properties of the segment, the dimension of the segment, and the number of drainage points in the segment. This function is used in order to find the expected production and the uncertainty in the production as a function of drainage points in the field, see figure 4. The calculation is based on the following approach:
Assume some wells already are positioned. Then it is found the segment that gives the largest expected production if the next well is positioned in this segment. This expectation is calculated by evaluating the function for the production from a segment in each of the realisations of the reservoir.

This evaluation is performed under the two alternative assumption that each segment is isolated and that there is contact in the gas between the segment. The difference between theses two assumptions is that the function for the production from each segment is different. This study is based on a real field study reported in Abrahamsen et al. (1992). In the object function each of these alternatives is given a probability.

6 Modelling while drilling

In the three previous sections it was focused on a single decision. The same stochastic models may also be used for other decisions by continuously updated it as new information become available. There is a continuous decision making while drilling a well. The most important decision is to determine the direction of the well path. Also in this case stochastic modelling may help. It is assumed that the facies information from the drilling already performed is updated in steps and included in the stochastic model. At these steps the model is updated and used in the decision making in order to find the optimal direction of the well path.

In this example from a shore-face reservoir the challenge is to drill a well such that as much as possible of the well path is in a certain layer. It is assumed that it is possible to interpret which layer the well is penetrating during drilling. For every L'th meter of the well path, there is made a set of stochastic realisations of the layers based on the same stochastic model, but for each time with increased well information. Based on the set of realisations, the direction of the well path is found that maximises the expected length of the well path in the particular layer; see figure 5. The evaluation is based on a truncated Gaussian stochastic model and a small program that evaluates the different well paths.

7 Typical assumptions

It is necessary to make some assumptions in order to formulate a stochastic model for the reservoir. Since the assumptions are quite similar in most cases this is discussed in a separate section. It is important to remember that there is only one reservoir. Any quantification of the uncertainty only describes the precision in our knowledge. It is natural that different scientists quantify the uncertainty differently if they have different knowledge or make different assumptions. All manual work includes subjective decisions and a possibility for errors.

The model is based on a seismic, geological and petrophysical interpretations of the reservoir. It is difficult to evaluate the quality of the interpretations. Several different possibly conflicting interpretations can integrated by giving each scenario a probability. Several scenarios increase the manual work. This type of assumptions can only be verified by comparing with (new) data that is not used in the interpretation. An indication may be found by letting other scientists make an independent interpretation and by comparing the interpretation from previous fields with the data obtained after the interpretation was performed.

The stochastic model makes assumptions on the structure of the data. Typical assumptions are that the permeability, porosity and saturations are transformed correlated Gaussian fields and facies are objects with particular geometric properties. This is a considerable simplification of the variability of the reservoir properties. Another important assumption is that it is possible to represent the effective properties in a grid. It is possible to use different stochastic models and find out whether these assumptions seem critical.

In all stochastic models it is necessary with parameters. Parameters like average porosity and trends in the sound velocities are important for the reservoir performance. It is easy to check the consequences of different assumptions. But the scientists have to give a best estimate on the distribution for the parameters. A Bayesian formulation helps in the quantification. The Bayesian interpretation is based on a prior distribution without using data from the field. One of the advantages of this approach is that it handles the problem of decreasing the uncertainty as the knowledge increases in a proper way.

In order to make realisations from the model, it is necessary to use a simulation algorithm. The simulation algorithm is a purely mathematical problem separated from the geology. Most simulation algorithms use approximations and for iterative methods convergence towards the specified distribution should be checked.

In order to simulate the flow in a reservoir, it is necessary to represent the reservoir properties in an upscaled grid. The reservoir simulator makes assumptions regarding the physics of the flow and the partial differential equations are solved numerically. One may get an impression on the quality by refining the grid, use different simulators and compare with previous predictions and history matching.

The reservoir uncertainty will in most cases be combined with models that includes the economy of the field and uncertainties like oil price, currencies and interest rates. In some cases these parameters may be represented by expected values. However, it is important to be aware of that the upside usually is not symmetric with the downside. Hence, including the uncertainty in these variables may be crucial. In most cases one consider alternative decisions in a reservoir or similar reservoirs. Then the uncertainties in the economical variables are less likely to be important for reservoir management decision.

Most of the above assumptions are difficult to verify or even quantify the probability of being correct. It is easier to check the consequences by replacing one assumption by another assumption, i.e., use a different stochastic model or a different distribution for a parameter. Some of the above assumptions are known to be wrong, i.e. that the permeability is transformed Gaussian and the physics in the reservoir represented in the reservoir simulator. The important question is whether this is important or not. Does the Gaussian field have sufficient flexibility to represent the heterogeneity of the field? Is the flow represented sufficiently good in a reservoir simulator to make prediction of further performance?

8 Concluding remarks

The authors opinion is that stochastic models may improve decisions. This is illustrated in four examples. It seems natural to formulate an object function in order to compare different decisions. It it recognised that the object function is based on certain assumptions that may be wrong and that not all aspect of the decision may be represented in a single function. However, it is believed that this will help in the decision making process at least when comparing different alternatives. If the manager is not choosing a solution that is close to the optimum of the object function, it should be necessary with an argument either based on the assumptions or a strategic aspect not represented in the object function.

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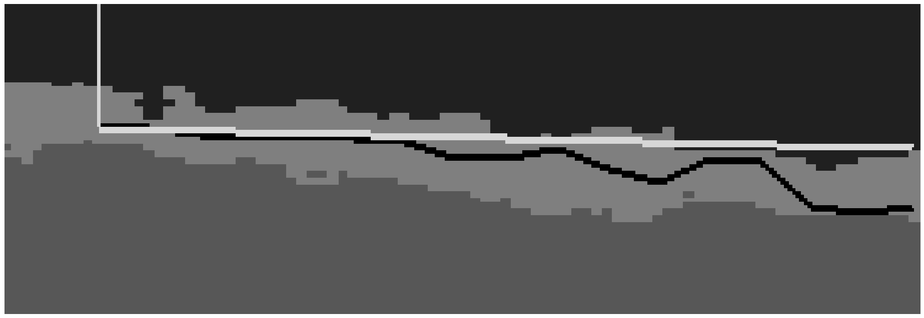

Figure 5 Vertical cross section with three layers in a shore-face reservoir and two possible well paths that are 4000m vertically. The light well path is determined only on the first observation of the middle layer, while the dark well path is determined also on an updated model for the layer for every 250m of the well path.