This paper presents a new approach to quantify the uncertainties which exist in reservoir description. We focus particularly on the uncertainties due to geostatistical modeling. Our approach, which relies on both experimental design theory and statistics, allows efficient and reliable production forecasts in a strongly uncertain environment.

Several approaches have been dedicated to the estimation of uncertainty, but few of them address the problem of combining the impact of both stochastic (geostatistical context) and deterministic uncertainty on production forecasts. Typically, geostatistics allows to obtain a realistic reservoir description, which honors geological properties and takes into account rock heterogeneities. But, in terms of production forecasts, this modeling induces a large uncertainty since several equiprobable realizations may fit the available data, but each of them leads to a different production behavior. Furthermore, this uncertainty increases with the scarcity of data, since the geostatistical realizations are then poorly or not constrained.

In this framework, we suggest an approach which integrates both "classical reservoir uncertainties" (petrophysical parameters, aquifer strength …) and the uncertainty due to geostatistical modeling. This approach combines the experimental design technique, which has already proven its efficiency in terms of uncertainty quantification, with a new concept: the Joint Modeling method, which is dedicated to the quantification of the geostatistical uncertainty.

In particular, since the production response behavior can be modified by the uncertainties on "classical parameters" (like permeability, porosity, aquifer strength …), and by the uncertainty due to the multiple equiprobable geostatistical realizations, we suggest to quantify the uncertainty on production forecasts using two statistical models:

- A mean model, which allows to quantify the uncertainty due to classical parameters,
- A variance model, which characterizes the dispersion of the production response, due to the uncertainty on the set of equiprobable realizations.

In such a way, the production response behavior can be estimated using a prediction interval which encompasses both the classical and the geostatistical uncertainty.
This methodology was successfully applied to a synthetic case derived from a real field case. The objective was to quantify the impact of both the main reservoir uncertainties (horizontal and vertical permeabilities, aquifer strength) and the geostatistical modeling on the cumulative oil production. Using the Joint Modeling method we were able to predict variation intervals for the cumulative oil production, within a risk prone environment. Finally, we validate the accuracy of the predictions by performing a posteriori reservoir simulations to check if the corresponding cumulative oil production falls into the prediction intervals.

INTRODUCTION

The objective of this work is to present a new approach to quantify the uncertainties which exist in reservoir description. Indeed, it is crucial to quantify uncertainty in reservoir studies to be able to safely predict the production behavior.

The experimental design theory is particularly well suited to estimate uncertainty on reservoir parameters, such as permeability, porosity, or aquifer strength. However, with the increasing complexity in reservoir modeling increasing sources of uncertainty must be accounted for.

Typically, geostatistics allows to obtain a more realistic reservoir description, which honors geological properties and takes into account rock heterogeneities. But in terms of production forecasts, this modeling induces an increasing difficulty for uncertainty quantification since several equiprobable geostatistical realizations describe the same model but may lead to significantly distinct production behaviors. Indeed, the classical experimental design theory does not provide solution to quantify both classical uncertainty and uncertainty due to geostatistics in a global framework.

A high interest is devoted to the estimation of uncertainty in reservoir studies [6], but very few works have tried to quantify the impact of the uncertainty due to geostatistical modeling in using experimental designs [5][10]. That is why, in this paper, we focus particularly on the uncertainties due to geostatistical modeling.

Uncertainty quantification on production forecasts

Even when considering the continuous improvement of reservoir characterization methods, uncertainty still remains a key issue when engineers want to evaluate production forecasts. In order to quantify the impact of these uncertainties, it is crucial to consider production forecasting from a probabilistic point of view. In this way, the reservoir engineer can easily quantify the impact of each parameter uncertainty on production forecast and take decision in a risk prone environment.

One of the goals of uncertainty quantification is to obtain a quick diagnostic on the effect of each uncertain parameter. Thus, the uncertainty on some parameters can be neglected, since it does not significantly affect the production forecasts, while particular attention should be paid to some other uncertain parameters which induce a large variation on production forecasts.

The geostatistical context

Geostatistical simulation is currently widely used to give a realistic reservoir description. Although geostatistics is clearly well suited to model geological information, it leads to an uncertain framework since the geostatistical model properties make it possible to produce not one geological model but a set of equiprobable realizations of the geological model.
Some major questions induced by this geostatistical context are: which equiprobable realization should be used for production forecasts? How the possible choice between equiprobable realizations will affect the final production forecasts?

Indeed, the multiplicity of the possible geological models must be taken into account in a reservoir risk analysis since it can strongly affect the range of uncertainty for the production.

Thus, the necessity of handling the geostatistical context as a full uncertainty appears clearly. One can imagine to treat several possible realizations like several production scenarios [5]. In this manner, the possible interactions between the classical uncertain parameters (permeability, porosity, …) and the geostatistical context is clearly neglected in a such approach, since the classical parameter effects are estimated for several geostatistical realizations, which were previously chosen for fixed values of these classical uncertain parameters.

An integrated methodology to deal at the same time with several sources of uncertainty, particularly the classical reservoir uncertainties and the geostatistical context, is then one of the most important concern for a safe and accurate risk analysis.

A specific treatment

The first step of uncertainty quantification consists in listing the possible uncertain parameters without any a priori, and then in fixing a range of uncertainty for each listed parameter.

In most reservoir studies, one can distinguish three kinds of uncertain parameters:

- The "physical parameters" which are intrinsic properties of the reservoir, but remain uncertain because of the poor knowledge of the field. Typically, they can be permeabilities, porosities, facies volume fractions, correlation lengths, …These "physical parameters" are not controlled by engineers, and have no random effect on production (production is directly correlated with parameter variations).

- The "production parameters" which are involved in the production scheme development. Typically, they can be the well perforated length, the well locations, …These "production parameters" have no random effect on production too, but we must distinguish them from "physical parameters" since they can be controlled by engineers and would thus be set to optimize the field production forecasts.

- The "discontinuous parameters" which gather all uncertainties which have a random effect (non-smooth) on production. Typically, they can correspond to several geostatistical realizations with different seeds (stochastic parameters), several possible structural maps, several possible fracture networks, several matched models [7][13] …

To better distinguish this different kind of uncertainties, Figures 1, 2 and 3 illustrate the evolution of a production response, the cumulative oil production, as a function of several parameters. Here, all realizations are constrained by the facies values at well locations. Figures 1 and 2 address the illustration of "physical parameters"(in this example it is the horizontal permeability and the porosity). One can see that the evolution of the production is quite smooth when the parameter varies smoothly. The effect of "production parameters" is not illustrated here, but it is quite similar to the "physical parameters".

Figure 3 illustrates the evolution of the cumulative oil production for several geostatistical realizations of the top layer of the model. Here, the production response varies randomly when the seed varies. That is because this kind of uncertainty will affect the production on a non-continuous manner. As a consequence, a specific approach is necessary to quantify this kind of uncertainty: the Joint Modeling Method [11][12].
Contrary to the classical "physical" or "production" parameters, the uncertainty due to the geostatistical context cannot be taken into account through experimental design, since the unique parameter which could describe this uncertainty (the geostatistical seed) does not affect smoothly the production behavior (cf. Figure 3).

![Figure 1: Cumulative oil versus uncertain permeability](image1)

![Figure 2: Cumulative oil versus uncertain porosity](image2)

![Figure 3: Cumulative oil versus several geostatistical models](image3)

**Necessity of a dual modeling**

The main goal of this approach is to be able to quantify the impact of uncertainties on "physical parameters", "production parameters" and the impact of the geostatistical modeling.

Several studies [6][12] devoted to the quantification of uncertainty due to "physical parameters" and "production parameters" have shown that those uncertainties generally affect smoothly the production behavior. Then, they can be quantified using the experimental design method and regression analysis. In such a way, one can model the behavior of the production as a function of the uncertain parameters using a simple analytical model, typically a polynomial.

On the other hand, if we focus on a risk analysis study while keeping in mind that several equiprobable geostatistical models can describe the reservoir, the production behavior becomes slightly different.

As shown on Figure 4, the production behavior is affected by the geostatistical model choice. Indeed, each equiprobable geostatistical realization leads to a different production behavior. From the statistical point of view the main issue is then to define a way for handling this dispersive behavior of the production response which is due to the geostatistical context.
As shown on Figure 5, the production behavior can be split up in a mean behavior (the red solid line) and a dispersive behavior (the 2 yellow arrows). The most logical way to catch such a behavior is then to perform a statistical dual modeling, that is a modeling of the mean behavior of the production response, and a modeling of the dispersive behavior of the production response.

To draw a parallel with classical risk analysis performed with experimental design (without handling the geostatistical framework), the mean model corresponds exactly to the quantification of uncertainty due to the classical "physical" and "production" parameters. Moreover, the dispersion model allows to describe the dispersive behavior of the production due to the geostatistical context.

The next section of this paper is devoted to present a way of performing this dual modeling: the Joint Modeling Method.
Before going into details in the Joint Modeling principle, we briefly present the basis of experimental design theory.

The experimental design theory

This theory [2][3] allows to study and to quantify the impact of uncertain parameters on a given process.

Let us consider a production response of interest, (typically, the cumulative oil production, the recovery factor, the gas-oil ratio), denoted by \( y \), and some uncertain reservoir parameters which can be "physical parameters" or "production parameters", denoted by \( x_1, x_2, \ldots, x_n \).

The primary goal of experimental design theory is to provide the right set of simulations to perform to estimate the behavior of \( y \) as a function of the uncertain parameters \( x_1, x_2, \ldots, x_n \).

Especially, it allows to:

- identify the parameters that are actually influential on the production response \( y \). This step is crucial since it allows to eliminate parameters that have a negligible impact on the response and to focus on the influential ones.
- build a regression model which links the production response \( y \) to the influential uncertain parameters.

The regression model can be considered as an accurate approximation of the production response behavior, and in this way, it quantifies safely the effect of all the uncertainties on the production response. Usually, a polynomial model is sufficient to catch the production response behavior as a function of the uncertain parameters:

\[
y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{12} x_1 x_2 + \ldots + \beta_n x_n^2 \quad (1)
\]

This simple analytical model can be used to bypass the reservoir flow simulator (for the uncertainty quantification) to finally provide fast evaluation of production forecasts in an uncertain environment. One of the most obvious uses of the regression model is clearly the intensive computation, for Monte-Carlo sampling for instance. On the other hand, if the uncertain parameters are "production parameters", a simple optimization of the regression model will provide the optimal production condition (well locations, flow rates ...) to optimize the final recovery.

The Joint Modeling principle

The Joint Modeling Method [9][11][12] allows to quantify the impact of both classical parameters (production and/or physical parameters) and the geostatistical context. This approach is mainly based on experimental design theory. Indeed, it requires to run a set of simulations to catch the behavior of \( y \) as a function of the uncertain parameters \( x_1, x_2, \ldots, x_n \), but it allows to characterize as well the effect of having several equiprobable geostatistical realizations to describe the reservoir.

In such a case, the production behavior can be split up in a dual variation.

To catch this specific behavior, the Joint Modeling method models the production response with two regression models:
- A mean model which describe the production response as a function of the physical or production parameters (smooth behavior),

\[ y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_2 x_1 x_2 + \ldots + \beta_n x_n^2 \] (2)

- A dispersion model which describe the dispersion of the production response due to geostatistics:

\[ Dispersion(y) = \exp(\gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_1 x_1 x_2 + \ldots + \gamma_n x_n^2) \] (3)

In equation (3), an exponential transformation is required to ensure the positivity of the dispersion. These two regression models are linked using generalized linear models. To illustrate the principle of this methodology, Figure 6 represents the two resulting models for two uncertain parameters.

The blue surface located in the middle represents the mean behavior of the production as a function of the two uncertain parameters, and the two orange boundary surfaces represent the dispersion due to geostatistical modeling. This figure illustrates clearly one of the main power of this innovative approach: it can catch the possible interactions between classical parameters and geostatistical uncertainties. Indeed, the thickness of the orange envelope is not constant when the classical parameters vary. Thus, this approach federates the sources of uncertainty.

This innovative approach is essential in quantifying uncertainty on production forecasts since the effect of geostatistics is often at least as important as the effect of classical other reservoir parameters.

![Figure 6: The Joint Modeling principle](image)

**The Joint Modeling algorithm**

From the statistical point of view, the joint models are theoretically the followings:

Model of the production response \( y \):

\[
\begin{align*}
    E(y) &= \mu = X\beta, \\
    \text{Var}(y) &= \text{diag}(\sigma^2)
\end{align*}
\] (4)

where \( \mu \) is the mean of the response \( y \), \( X\beta \) is the matrix notation for the polynomial (2) and \( \sigma^2 \) is the variance of the production \( y \), mainly due to the geostatistical context.

We should note that \( \sigma^2 \) is constant without geostatistics, and must be estimated in a geostatistical framework.
It is precisely performed via the model of the dispersion $d$ of the production response $y$:

$$
\begin{align*}
E(d) &= \sigma^2 = \exp(\gamma y) \\
\text{Var}(d) &= \tau I_d
\end{align*}
$$

(5)

In both models (4) and (5), the parameter $\mu$, represents the mean behavior of the production and the parameter $\sigma^2$, represents the dispersion due to geostatistics. These parameters are unknown.

An iterative process, described in Figure 7, is then required to estimate those two parameters and then to reach the final joint models of the production. The model fitting is performed using a classical statistical technique: the weighted least-squares method.

The fact that those two models are linked in this way is crucial since it allows to treat together the classical uncertainty (continuous parameters) and the stochastic one, in order to finally obtain a probabilistic production in an integrated chain of uncertainty quantification.

**Figure 7**: Joint Modeling Algorithm
THE FIELD CASE STUDY

In order to illustrate the interest of taking into account the uncertainty due to geostatistics in an integrated process, we present an application of the Joint Modeling method to a synthetic case derived from real field data.

Reservoir Description

The full field is made of 3 geological units: a Senonian unit where gas was detected, a Turonian unit with oil and a Cenomanian reservoir. The following study will only deal with the Cenomanian reservoir.

At the top of the Cenomanian, the structure is an anticlinal along a NW-SE axis. This reservoir contains three units: C1, C2, C3. We are mainly interested in the top of Cenomanian series, the C1 level, which is described using a continuous lognormal geostatistical model.

The top of the Cenomanian reservoir (C1 unit) is located at a depth of 545 meters sub-sea and the Water-Oil Contact is at 645 meters sub-sea. The thickness of C1 varies between 10 and 45 meters with a maximum near the center of the structure. The C2 unit is made of thick dolomitic sandstone with a mixture of fine to medium grain sandstone both inter-bedded with shale. The C3 unit is made of thick aquifer sands and is about 250 meters thick.

Reservoir Characteristics

The Cenomanian reservoir properties follow the two main units C1 and C2. Indeed, the C1 unit appears to be of good reservoir quality, whereas the C2 unit is of poor quality. The main petrophysical properties of C1 and C2 are summarized in table 1.

<table>
<thead>
<tr>
<th></th>
<th>C1</th>
<th>C2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Porosity (%)</td>
<td>25</td>
<td>5</td>
</tr>
<tr>
<td>Horizontal Absolute Permeability (mD)</td>
<td>1000</td>
<td>10</td>
</tr>
<tr>
<td>Vertical Absolute Permeability (mD)</td>
<td>10</td>
<td>0.01</td>
</tr>
<tr>
<td>Waterflood Residual Oil Saturation (%)</td>
<td>23</td>
<td>23</td>
</tr>
</tbody>
</table>

*Table 1: Porosity, Permeability and Sorw*

The initial temperature in the reservoir is 48 °C, and the initial pressure is 59.1 bars at 583 meters sub-sea, whereas the bubble point pressure is 57 bars.

Geostatistical and Numerical Models

For the development phase, a numerical 3D black-oil model was built. The horizontal grid which is oriented NE-SW is 31 by 12 cells in x and y directions. Each cell is 250 m by 250 m. Since no zonation was established in C1 reservoir, this unit was divided in three layers with same petrophysical properties.

The C1 unit permeability distribution is simulated using a lognormal geostatistical model. The correlation lengths are respectively 4500 meters and 1750 meters along the main anisotropy axis.
main anisotropy direction is diagonal with respect to the reservoir grid. The mean value of the permeability distribution is 1000 mD. The variogram is spherical.

On the other hand the C2 unit is assumed to be fully homogeneous. Thus, the quantification of uncertainty due to geostatistical modeling will only be due to the C1 description.

The reservoir production is accomplished through 12 production wells mainly located at the top of the structure, as shown on figure 8. Here, no injection process was investigated since the aquifer in unit C3 ensures satisfactory pressure maintenance.

![Figure 8: Pressure at and well locations](image)

In order to provide safe production forecasts for this reservoir, an uncertainty quantification step was necessary. Thus, before going further in details in the impact of uncertainty on production, we listed the existing uncertainties on both classical parameters and geostatistical modeling.

**Reservoir Uncertainty**

The objective of this study was to predict the behavior of the cumulative oil production (named Cumoil) for 10 years, overall the 12 wells, while taking into account the uncertainties due to classical reservoir parameters and to the geostatistical modeling.

A sensitivity study allowed to determine 4 influential uncertain parameters:

- The horizontal permeability for the unit C2, says $k_{hc2}$;
- The vertical permeability for the unit C2, says $k_{vc2}$;
- The horizontal permeability for the unit C1, says $k_{hc1}$;
- The analytical aquifer strength in unit C3, says $caq$;

As said in the previous section, the permeability distribution in the C1 unit is described using a geostatistical lognormal model. Thus, the parameter $k_{hc1}$ represents the mean of the geostatistical realization of the permeability in this top unit.

For each of these 4 parameters, the table 2 summarize a range of uncertainty.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum Value</th>
<th>Most probable Value</th>
<th>Maximum Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Khc2</td>
<td>5 mD</td>
<td>27.5 mD</td>
<td>50 mD</td>
</tr>
<tr>
<td>Kvc2</td>
<td>$10^2$ mD</td>
<td>$10^1$ mD</td>
<td>1 mD</td>
</tr>
<tr>
<td>Caq</td>
<td>$10^5$</td>
<td>$10^6$</td>
<td>$10^7$</td>
</tr>
<tr>
<td>Khc1</td>
<td>500 mD</td>
<td>1000 mD</td>
<td>1500 mD</td>
</tr>
</tbody>
</table>

**Table2: Parameters Range of uncertainty**

Beyond the uncertainty on these 4 physical parameters, the uncertainty due to geostatistical modeling remains. Indeed, several equiprobable realizations of the geostatistical lognormal model describe the same reservoir properties. As an illustration, the production profiles shown on Figure 4 were obtained with 12 possible realizations of the permeability of the C1 unit, when the 4 uncertain parameters were fixed at their most probable value (only the geostatistical seed changes). On the left part of Figure 4 out of these 12 realizations are drawn.

Once the possible uncertainties are listed, the risk analysis phase allows to quantify the impact of these uncertainties on cumulative oil production forecasts.

**Risk Analysis on production forecasts: the Cumulative Oil Joint Modeling**

In order to proceed to the Joint Modeling, we need first a sample of the cumulative oil production which is representative of the effect of all the sources of uncertainties described above. To obtain this sample, we have made some simulations (geostatistical + reservoir flow simulations) according to an experimental design. To catch the uncertainty due to the physical parameters (separately from the geostatistical effect), an accurate experimental design for 4 parameters requires 25 simulations, that is 25 distinct combinations of $(khc1, khc2, caq, kvc2)$ values in their range of variation. On the other hand, to account for the geostatistical context, 10 equiprobable model realizations were simulated for each of these 25 combinations. Finally we get 250 values of the cumulative oil production.

According to experimental design theory, this resulting sample allows to safely cover the uncertainty domain to fully characterize the cumulative oil production behavior. This 250-sample of the cumulative oil production was then used to perform a joint modeling process. Five iterations of the algorithm shown on Figure 7 were sufficient to obtain accurate joint models.

The mean model for the cumulative oil is:

$$Cumoil = 1.676 + 0.374 \, khc1 - 0.022 \, khc2 - 0.025 \, caq - 0.067 \, kvc2 - 0.139 \, khc1^2 - 0.042 \, khc2^2 + 0.013 \, caq^2 - 0.016 \, kvc2^2 + 0.015 \, khc1 \times khc2 - 0.028 \, khc1 \times caq - 0.028 \, khc1 \times kvc2 - 0.029 \, khc2 \times kvc2 - 0.048 \, caq \times kvc2.$$

And the following dispersion model completes it:

$$Disp_{Cumoil} = \exp(-3.43 - 0.613 \, khc1 + 0.17 \, khc2 - 0.079 \, caq + 0.043 \, kvc2 - 0.46 \, khc1^2 + 0.53 \, khc2^2 - 0.026 \, caq^2 - 0.2 \, kvc2^2 - 0.15 \, khc1 \times khc2 - 0.22 \, khc1 \times caq + 0.035 \, khc1 \times kvc2 + 0.042 \, khc2 \times caq - 0.1 \, khc2 \times kvc2 - 0.19 \, caq \times kvc2).$$

These two models can then be used for intensive computation, particularly for Monte-Carlo sampling, at a very low cost, since it only requires the computation of such simple polynomials.
Main results of the study

Using these two models, we can build the probabilistic distribution of the cumulative oil production at 4 years (Figure 9), at 6 years (Figure 10), at 8 years (Figure 11) and at 10 years (Figure 12), while taking into account the effect of both the geostatistical modeling and the petrophysical uncertain parameters (red solid curves). A comparative study was realized without taking into account the geostatistical effect (a random realization was chosen and fixed for all the simulations), and the resulting probabilistic cumulative oil production is presented as blue curves.

These figures allow a good description of the cumulative oil evolution in a risk-filled environment. The contribution of geostatistics in the uncertainty quantification is quite significant since as time increases, the difference between the blue and the red curves increases. Figure 13 represents the predicted interval of variation of the cumulative oil production over the time. The blue area model the effect of taking into account geostatistics. The contribution of the geostatistical context in the uncertainty on cumulative oil is almost the same as the uncertainty due to the 4 other uncertain parameters. Indeed, the thickness of the blue envelope is quite close to the width of the white interval.

Moreover, the green crosses on Figure 14 represent the cumulative oil for confirmation runs which have been performed (for random values of \((k_{hc1}, k_{hc2}, c_{aq}, k_{vc2})\) and for some equiprobable geostatistical realizations). This figure highlight the efficiency of the Joint Modeling, since most of the simulations fall in the variation intervals at any time.

![Figure 9: Probabilistic Cumoil at 4 years (10^6 m^3)](image)

![Figure 10: Probabilistic Cumoil at 6 years (10^6 m^3)](image)

![Figure 11: Probabilistic Cumoil at 8 years (10^6 m^3)](image)

![Figure 12: Probabilistic Cumoil at 10 years (10^6 m^3)](image)
Thus, neglecting the geostatistical context in a risk analysis can lead to a very underestimate prediction of the production, and as a consequence to a higher uncontrolled risk-taking.

CONCLUSIONS

The quantification of uncertainty in a reservoir development is becoming one of the main preoccupation of reservoir engineers, since a under-estimated or upper-estimated prediction of the production would lead, from an economical point of view, to huge errors in decision making.

In such a context, one should take into account all sources of uncertainty, whether coming from reservoir characterization or geological modeling. To deal with this problematic, we have proposed the Joint Modeling method which is mainly based on experimental design principles. This approach, conversely to a dual modeling which models mean and dispersion separately, allows to quantify both the classical uncertainties and the geostatistical uncertainty in taking into account the possible interactions between classical parameters and non-continuous ones.

To illustrate the efficiency of this method we have presented a field case study were both classical reservoir uncertainties and uncertainty due to geostatistical modeling, are taken into account in a global risk analysis approach. This study has highlighted the necessity to not neglect uncertainty due to geostatistical modeling since it may have almost comparable effect on production with any other uncertainty sources.

The proved efficiency of the Joint Modeling method to deal with "non-continuous" uncertainties, such as the geostatistical context, encourages us to extend this methodology to other sources of uncertainties: several possible fracture network, several possible top of a structure, several matched models [7][13], and potentially to deal with geological or production scenarios.

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