Production History

Well Observations, Seismic Data and Reservoir Characterization Integrating

Berlin, Björn and Omre, Henning

Department of Mathematical Sciences
Norwegian University of Science and Technology

Trondheim, Norway

September 1998
Preface

This is the final report from the project "Reservoir Characterization in Integrating Well, Seismic and Production Data". The goal for this project is to establish a stochastic model integrating all kinds of information in reservoir characterization and to develop a corresponding sampling procedure. A symbolic test case is used to explore the model and how much different sources of information increase accuracy and reduce uncertainty.

Bjørn Kåre Hegstad and Henning Omer

September 1998

The project is financed by Norsk Hydro A/S.

We would like to thank Alfhild Eide for allowing us to use her work on integration of seismic data as a base for the current work. Without her results we would not have a starting point to base our work on integration of uncertainly.

We wish to thank Halvor Tjelmeland and Alfhild Eide for allowing us to use their software for fast generation of large Gaussian fields. Also our contacts in Norsk Hydro, Charlotte Tjølsen and Eivind Damsleth, have been giving us valuable feedback and help on how reservoir characteristics are modeled.

Charlotte Tjølsen and Eivind Damsleth have been giving us valuable feedback and help on their software for fast generation of large Gaussian fields. Also our contacts in Norsk Hydro, Charlotte Tjølsen and Eivind Damsleth, have been giving us valuable feedback and help on how reservoir characteristics are modeled.

The project is financed by Norsk Hydro A/S.

Bjørn Kåre Hegstad and Henning Omer
A stochastic model for the local nature of well observations to some extent.

The simulation study demonstrates that even when well observations carry little information

The simulation study demonstrates that the global structure of the true reservoir is well reproduced when

In some cases the ratio of accepted realizations is doubled when conditioning on seismic data.

A stochastic model for a 3D reservoir integrating well observations, seismic data and production history is presented.

A stochastic model for a 3D reservoir integrating well observations, seismic data and production history is presented.
In this work, it is assumed that the production characteristics are largely unknown at the stage of evaluation. Let the reservoir characteristics be implicitly assumed and not visible in the notation. Thus, the production forecast is linked to the reservoir characteristics through a fluid flow simulator. The production forecast is linked to the reservoir characteristics through a fluid flow simulator. The production forecast is linked to the reservoir characteristics through a fluid flow simulator.

1.1 Prior stochastic model


Mention should be made of different sources of information into reservoir characterization.

Hence both future production characteristics and reservoir characteristics can be forecasted through a fluid flow simulator.

The goal in reservoir characterization is to forecast production characteristics under varied recovery strategies. The production forecast is linked to the reservoir characteristics through a fluid flow simulator. The production forecast is linked to the reservoir characteristics through a fluid flow simulator.
general geological knowledge a priori stochastic model for the reservoir characteristics can be defined. The model is represented by the probability density function $f_R(x)$, and the variable $R$ is a stochastic field representing the reservoir characteristics. The prior model must be consistent with the prior knowledge of the geological reality of the formation which is a stochastic field representing the reservoir characteristics. The prior model can be obtained by using a fluid simulator.

Finally, the link between the production characteristics and the reservoir characteristics can be modeled as

$$ m_R + (d) m^R = [d = d^R] $$

Similarly, for the link between reservoir characteristics and well observations

$$ m_R + (d) m^R = [d = d^R] $$

$$ [D_s j R] $$ is a stochastic variable representing the seismic observations given that the reservoir characteristics are $R$. This variable is often termed $D_s$ conditioned on $R$ or $D_s$ given $R$.

The link between reservoir characteristics and seismic data can be modeled as

$$ [D_s j R] = g_s(R) + U_s $$

where $g_s(R)$ is a forward model, and $U_s$ is the error term.

Similarly for the link between reservoir characteristics and well observations

$$ [D_w j R] = g_w(R) + U_w $$

where $g_w(R)$ is modeling the well observations process and $U_w$ is the error term.

Finally, the link between the production characteristics and time domain observations can be modeled as

$$ [D_p j P] = g_p(P) + U_p $$

where $g_p(P)$ is modeling the production characteristics process and $U_p$ represents modeling and measurement error.
The link between the observations and the reservoir characteristics and production characteristics is represented by the likelihood function
\[ f(d_j p;; r) \]
expressing how likely it is to observe \( d \) given that the true reservoir characteristics are \( r \) and the true production characteristics are \( p \).

The three types of observations \( D_p, D_s, \) and \( D_w \) are obtained by different tools and procedures, and hence can be regarded as conditionally independent given the reservoir characteristics \( r \) and the production characteristics \( p \). Moreover, the production observations depend only on \( p \) and the space domain observations depend only on \( r \). Hence the likelihoods in the production model are obtained from

\[ f(d_j p;; r) = f(d_p j p) f(d_s j r) f(d_w j r) \]

The likelihood for the well observations \( f(d_w j r) \) is usually simple to obtain since it involves

\[ f(p j r) \]

Note that the pdf \( f(p j r) \) may be extremely time consuming to evaluate since it involves

\[ V(f(r; t)) \]

distribution through Bayes rule also as

\[ f(p; r) = \int f(d_p; p) f(d_s; r) f(d_w; r) f(p; r) \cdot \text{const} = f(p; d_p) \]

The variables of interest are now \( P_j D = d \) and \( R_j D = d \) with associated pdfs \( f(p j d) \) and \( f(r j d) \), respectively. These pdfs express the uncertainty about \( P \) and \( R \) after all reservoir specific observations are taken into account, the so-called posterior pdfs. The challenge is to include these observations in a consistent and effective way.

The posterior distribution \( f(p; d, r) \) is expressed through Bayes rule as

\[ f(p; d, r) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are derived such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(d_p; p) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(p; d_p) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(p; d_p) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(p; d_p) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(p; d_p) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(p; d_p) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(p; d_p) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(p; d_p) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(p; d_p) \]

The likelihood for the well observations \( f(d_w; r) \) is simple if the prior model is defined such that sampling the posterior is tractable. All assumptions and simplifications are expressed through Bayes rule also as

\[ f(p; d_p) \]
The prior stochastic model. As a result, the true reservoir turns out to be in an extremely low-probable area of the prior stochastic model. The differences from more typical and probable realizations from the prior model are discussed.

In Section 5 and Section 6 the properties of the stochastic model are explored. In these sections the change in properties of reservoir characteristics and production characteristics when the amount of data included is varied, is studied. In Section 7 the information contents of the well observations are made more local by introducing the concept of local information. This is not necessary for the validity of the stochastic model. Also other assumptions as e.g. zero expectation on noise variables, can be relaxed with the model still being valid. These model choices and simplifications are done to make sampling from the stochastic model as simple as possible. Also of the choice of functional stochastic model is illustrated by a directed graph in Figure 1. The details are explained.

2 Stochastic model

Consider a three-dimensional Gaussian field with expectation vector \( \mathbf{\mu} \) and covariance \( \mathbf{\Sigma} \).

\( \mathbf{\Sigma} \)

\[ \mathbf{\Sigma} = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \]

where \( \Sigma_{ij} = \text{Cov}(X_i, X_j) \).

The prior stochastic model is illustrated by a directed graph in Figure 1. The details are explained.

A note on notation

made and subjected to further research are proposed.
Figure 1: A directed graph representing the stochastic model. A double arrow from $A$ to $B$ implies that the conditional distribution of $B$ given $A$ is defined a priori in the model. An arrow from $A$ to $B$ implies that $B$ is deterministic given all of the variables $A$, and $A'$. A circle indicates a stochastic variable.

Variables:
- $\Theta$: History
- $K$: Permeability
- $\phi$: Porosity
- $\theta$: Porosity
- $\Omega$: Permeability
- $\rho$: Porosity
- $\Phi$: Permeability
- $\Psi$: Permeability
- $\Omega$: Permeability
- $\rho$: Porosity
- $\Phi$: Permeability
- $\Psi$: Permeability
- $\rho$: Porosity
- $\Phi$: Permeability
- $\Omega$: Permeability
- $\rho$: Porosity
- $\Phi$: Permeability
- $\Omega$: Permeability

Observed variables:
- $S$: Reservoir observations
- $C$: Connection coefficients
- $Z$: Acoustic impedance
- $Z_w$: Well observations of acoustic impedance
- $Z_{top}$: Acoustic impedance on top of the reservoir
- $\phi$: Porosity
- $K$: Permeability
- $\phi$: Porosity
- $K$: Permeability
- $\phi$: Porosity
- $K$: Permeability
- $\phi$: Porosity
- $K$: Permeability

Conditional distributions:
- The conditional distribution of $B$ given $A$ and $A'$ is defined a priori in the model.
Let the reservoir characteristics be $R$ where $K$ is permeability, porosity and acoustic impedance. The prior distribution of acoustic impedance $Z$ is discussed in relation with connection coefficients $C$. The crucial point is that the prior model of both permeability and porosity are defined conditioned on $Z$. This is illustrated by the arrow from $Z$ to $K$ in Figure 1.

Given acoustic impedance $Z = z$, the porosity is modeled as

$$\log K | Z = z, \theta = \Theta, \Sigma = Z \Phi$$

where $\Phi$ is a known function of $z$ with model parameter $\theta$, but else arbitrary. Hence, conditioned on $Z = z$ and $\theta = \Theta$, the stochastic variable $\log K$ is Gaussian:

$$\mathcal{N}(\mu, \Sigma)$$

This is illustrated by the arrow from $Z$ to $K$ in Figure 1. The corresponding pdf is in general denoted $f(\log K | Z = z)$. Data from the Troll field, Tjølsen and Damsleth (1998) suggest no correlation between permeability and acoustic impedance within the corresponding pdf is in general denoted $f(\log K | Z = z)$. Data from the Troll field, Tjølsen and Damsleth (1998) suggest no correlation between permeability and acoustic impedance within a facies, i.e. $z$ is a known function of $z$ with model parameters $\mu$ and $\Sigma$ where the variance may vary with acoustic impedance. The model parameters $\mu$ and $\Sigma$ are defined conditioned on $Z$.

The corresponding pdf is in general denoted $f(\log K | Z = z)$. Data from the Troll field, Tjølsen and Damsleth (1998) suggest no correlation between permeability and acoustic impedance within the corresponding pdf is in general denoted $f(\log K | Z = z)$. Data from the Troll field, Tjølsen and Damsleth (1998) suggest no correlation between permeability and acoustic impedance within a facies, i.e. $z$ is a known function of $z$ with model parameters $\mu$ and $\Sigma$ where the variance may vary with acoustic impedance. The model parameters $\mu$ and $\Sigma$ are defined conditioned on $Z$.
where $Z_{o} = \frac{1}{Z + 1} = \frac{1}{Z} - \frac{1}{Z}$

$$Z + 1/Z = \frac{1}{Z - 1}$$

In acoustic impedance, the relation can be inverted and expressed as

where increasing index indicates increasing depth. It can be interpreted as a relative change

$$\frac{Z + 1/Z}{Z - 1/Z} = \gamma$$

The reflection coefficients are modeled as a Gaussian field with expectation zero and covariance $C_{ij}$.

2.1.3 Prior model: Reflection coefficients $C_i$

The corresponding pdf is in general denoted $f_{C_i}$ as input for the stochastic model. The relation can be inverted and expressed as a relative change.

$$Z_{i} = \frac{1}{C_i + 1}$$

where increasing index indicates increasing depth. It can be interpreted as a relative change.

$$Z_{i} = \frac{1}{C_i + 1}$$

The corresponding pdf is in general denoted $f_{C_i}$ as input for the stochastic model.

2.1.2 Prior model: Production characteristics $d$

Hence the stochastic variable $d$ is a Gaussian field.

$$d = N(\mu_d, \Sigma_d)$$

where $\mu_d$ and $\Sigma_d$ are the mean and covariance matrix of $d$, respectively. Hence the mean log-permeabilities are in general unknown. Hence the mean log-permeabilities are modeled as independent Gaussian variables with expectation $\mu_{C_i}$ and covariance $\Sigma_{C_i}$.

$$\mu_{C_i} = \frac{1}{C_i + 1}$$

where $\mu_{C_i}$ and $\Sigma_{C_i}$ are some threshold values. Hence faces I tends to have an acoustic
In Figure 1, the corresponding prior model for \( Z \) is a subset of \( z \). This deterministic relation is illustrated by the double arrow,

\[
(z)^{\Phi} = [z = Z \circ Z]
\]

where \( (z)^{\Phi} \) is a subset of \( z \).

The corresponding prior model for \( Z \) is therefore uniquely determined by the prior model for \( C \) and \( Z \), note that by relation (7) the corresponding posterior \( C^{\circ Z} \) is a Gaussian field.

In Figure 1, the posterior pdf is discussed below.

In addition all well observations of different reservoir characteristics are supposed to be point

from \( Z \) to \( Z \). The observations are assumed to be exact to simplify the posterior

where \( (z)^{\Phi} \) is a subset of \( z \). This deterministic relation is illustrated by the double arrow,

\[
(z)^{\Phi} = [z = Z \circ Z]
\]

For acoustic impedance the well observations are modeled as

\[
\phi \circ \gamma \circ \phi = [\gamma = Y \circ Y]
\]

Similarly for porosity and measurements error, this is illustrated by the double arrow from \( \phi \) to \( \phi \).

\[
\phi \circ \gamma \circ \phi = [\phi = \Phi \circ \Phi]
\]

However well observations are modeled as

\[
\Phi \circ \gamma \circ \Phi = [\gamma = \Phi \circ \Phi]
\]

Porosity well observations along the well trajectories.

Recall that well observations are point observations.

Likelihood model

Likelihood model

The problem is therefore a subject for further research.

In addition all well observations of different reservoir characteristics are supposed to be point

from \( Z \) to \( Z \). The observations are assumed to be exact to simplify the posterior

where \( (z)^{\Phi} \) is a subset of \( z \). This deterministic relation is illustrated by the double arrow,

\[
(z)^{\Phi} = [z = Z \circ Z]
\]

For acoustic impedance the well observations are modeled as

\[
\phi \circ \gamma \circ \phi = [\gamma = Y \circ Y]
\]

Similarly for porosity and measurements error, this is illustrated by the double arrow from \( \phi \) to \( \phi \).

\[
\phi \circ \gamma \circ \phi = [\phi = \Phi \circ \Phi]
\]

However well observations are modeled as

\[
\Phi \circ \gamma \circ \Phi = [\gamma = \Phi \circ \Phi]
\]

Porosity well observations along the well trajectories.

Recall that well observations are point observations.

Likelihood model

Likelihood model

2.2.1 Prior model for layer of acoustic impedance

2.1.4 Prior model for layer of acoustic impedance

\( Z \) is a hidden variable in the transformation from acoustic coefficients to acoustic impedance

\( Z \) is a hidden variable in the transformation from acoustic coefficients to acoustic impedance
Production history can be all kinds of production characteristics observed at observations.

$$D_p$$

Produce data are on the form

$$P_o j P_o = p / g$$

where $$U_p o$$ is an error term with expectation zero and covariance matrix $$P_o$$ representing observation errors and modeling errors introduced by using $$g P / (p /)$$. This is illustrated by the arrow from $$P$$ to $$P_o$$ in Figure 1. The transfer function $$g P / (p /)$$ could be production characteristics at observation times up to time $$t_0$$.

The corresponding likelihood function is in general

$$f(d / p) = f_[d / p] / \tilde{f}_{d / p}$$

where $$f$$ is an error term with expectation zero and covariance matrix $$P$$ representing production errors and modeling errors introduced by using $$d /$$. This is illustrated by the arrow from $$d /$$ to $$d /$$ in Figure 1. The likelihood function $$f(d / p)$$ could be production characteristics at observation times up to time $$t_0$$. In this study the observed production characteristics are all production

$$d /$$

Likelihood model: derived reflection coefficients well observations $$C_o$$.

For reflection coefficients, the well observations are modeled as

$$C_o / C / c = g C / c$$

where $$g C / c$$ is a subset of $$c /$$. This deterministic relation is illustrated by the double arrow from $$C$$ to $$C_o$$ in Figure 1. The well observations of reflection coefficients are in practice calculated from $$z_o$$ given $$z_{top} /$$. Hence $$c_o$$ is uniquely determined when $$z_o$$ and $$z_{top}$$ are known. Hence, if $$c_o$$ is uniquely determined when, and $$z_o$$ and $$z_{top}$$ are given, calculated from $$z_o$$ given $$z_{top}$$, then $$c_o$$ is uniquely determined when, and $$z_{top}$$ are given, calculated from $$z_{top}$$ given $$z_o$$.

Note that in this study the seismic data $$D_s$$ are also denoted $$S /$$, see Figure 1. Seismic amplitude data are modeled as a convolution between a seismic wavelet and a vertical sequence of reflection coefficients, and corrupted with noise. The seismic data are covering the complete reservoir. The stochastic model for the seismic data conditioned on the reflection coefficients is in general

$$S_o j C / c = g S / c$$

where $$S_o$$ is seismic amplitude data, $$A$$ is a matrix defined by the seismic wavelet and $$C$$ is the field of reflection coefficients. This relation is illustrated by the arrow from $$C$$ to $$S_o$$ in Figure 1. The error term $$U_{S_o}$$ is a Gaussian field with expectation zero and covariance matrix $$S_o$$, that is

$$S_o j C / c = N - [ = C S_o]$$

The corresponding likelihood function is Gaussian hence the conditional pdf

$$f(c / j d_s)$$ representing the variable $$[C / D_s = d_s]$$ is a Gaussian pdf as well.
partial model

impedance Gaussian. This is the case in this study.

production characteristics and reservoir characteristics;

deep seismic data variables given posterior pdf, these variables should, however, be included. Hence the pdf

from this pdf, the latter pdf can be factorized as

where are the set of all possible values of, c, and respectively. Note


Reservoir characteristics

Consider the last pdf in expression (9). Note that the variables , and are not

where is conditionally independent of all other variables of interest and hence not in the target pdf. To define a worthwhile productization of the

The simplification in the last equality can be reached by inspecting Figure 1: Consider the first line

Production characteristics and production characteristics

The joint posterior pdf of the production characteristics and the reservoir data is given by:
The simplifications in the last equality can easily be verified by inspecting Figure 1. Considerally independent given the first and second pdf after the last equality sign. Permeability and porosity are conditionally independent given permeability and porosity are conditionally independent of connection coefficients minimistically determined given probability mass on the value. Note furthermore, that this is not a traditional pdf but a Dirac delta function putting all probability mass on the value. The stochastic parameter is clearly defined conditional on the stochastic parameters. Since all important terms in the conditioning are conditionally independent of the last pdf on the right hand side of equation (10). Hence the right hand side of equation (11) corresponds to the last pdf on the right hand side of equation (110). Since $Z$ is conditionally independent to $f$ given both $Z$ and $f$ are omitted in all these pdfs. Hence both $Z$ and $f$ are conditionally independent of $C$. $Z$ and $D$ are conditionally independent of $C'$. $Z$ and $D$ are conditionally independent of $C'$. Hence $Z'$ is omitted in this pdf. The sequence of the fourth and fifth and the third pdf on the right hand side of equation (1/1) can be written as

\[
\begin{align*}
(\phi, \theta, \gamma) & \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
\end{align*}
\]


Consider the last pdf in the right hand side of equation (11). This demonstrates that samples from $f$ and $\theta$ are conditionally independent given $\theta$, and that the right hand side of equation (11) is conditionally independent of connection coefficients. Since the right hand side of equation (11) is conditionally independent of connection coefficients. Hence both $Z$ and $f$ are conditionally independent of $C$. $Z$ and $D$ are conditionally independent of $C'$. Hence $Z'$ is omitted in this pdf. The sequence of the fourth and fifth and the third pdf on the right hand side of equation (1/1) can be written as

\[
\begin{align*}
(\phi, \theta, \gamma) & \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \quad \text{f(x, y, z)} \\
\end{align*}
\]


Consider the last pdf on the right hand side of equation (1/1) corresponding to the last pdf on the right hand side of equation (1/1). It is assumed that the properties of the right hand side of equation (1/1) are omitted in both pdfs. Consider the third pdf after the last equality sign. The stochastic parameter $Z$ is clearly defined conditional on the stochastic parameters. Since all important terms in the conditioning are conditionally independent of the last pdf on the right hand side of equation (10). Hence the right hand side of equation (11) corresponds to the last pdf on the right hand side of equation (110). Since $Z$ is conditionally independent to $f$ given both $Z$ and $f$ are omitted in all these pdfs. Hence both $Z$ and $f$ are conditionally independent of $C$. $Z$ and $D$ are conditionally independent of $C'$. Hence $Z'$ is omitted in this pdf. The sequence of the fourth and fifth and the third pdf on the right hand side of equation (1/1) can be written as

\[
\begin{align*}
(\phi, \theta, \gamma) & \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
\end{align*}
\]


Consider the first three pdfs on the right hand side of equation (1/1) corresponding to the first three pdfs on the right hand side of equation (1/1). Since $Z$ is conditionally independent to $f$ given both $Z$ and $f$ are omitted in all these pdfs. Hence both $Z$ and $f$ are conditionally independent of $C$. $Z$ and $D$ are conditionally independent of $C'$. Hence $Z'$ is omitted in this pdf. The sequence of the fourth and fifth and the third pdf on the right hand side of equation (1/1) can be written as

\[
\begin{align*}
(\phi, \theta, \gamma) & \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
\end{align*}
\]


Consider the last pdf on the right hand side of equation (1/1) corresponding to the last pdf on the right hand side of equation (1/1). It is assumed that the properties of the right hand side of equation (1/1) are omitted in both pdfs. Consider the first three pdfs on the right hand side of equation (1/1) corresponding to the first three pdfs on the right hand side of equation (1/1). Since $Z$ is conditionally independent to $f$ given both $Z$ and $f$ are omitted in all these pdfs. Hence both $Z$ and $f$ are conditionally independent of $C$. $Z$ and $D$ are conditionally independent of $C'$. Hence $Z'$ is omitted in this pdf. The sequence of the fourth and fifth and the third pdf on the right hand side of equation (1/1) can be written as

\[
\begin{align*}
(\phi, \theta, \gamma) & \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
\end{align*}
\]


Consider the last pdf on the right hand side of equation (1/1) corresponding to the last pdf on the right hand side of equation (1/1). It is assumed that the properties of the right hand side of equation (1/1) are omitted in both pdfs. Consider the first three pdfs on the right hand side of equation (1/1) corresponding to the first three pdfs on the right hand side of equation (1/1). Since $Z$ is conditionally independent to $f$ given both $Z$ and $f$ are omitted in all these pdfs. Hence both $Z$ and $f$ are conditionally independent of $C$. $Z$ and $D$ are conditionally independent of $C'$. Hence $Z'$ is omitted in this pdf. The sequence of the fourth and fifth and the third pdf on the right hand side of equation (1/1) can be written as

\[
\begin{align*}
(\phi, \theta, \gamma) & \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
\end{align*}
\]


Consider the last pdf on the right hand side of equation (1/1) corresponding to the last pdf on the right hand side of equation (1/1). It is assumed that the properties of the right hand side of equation (1/1) are omitted in both pdfs. Consider the first three pdfs on the right hand side of equation (1/1) corresponding to the first three pdfs on the right hand side of equation (1/1). Since $Z$ is conditionally independent to $f$ given both $Z$ and $f$ are omitted in all these pdfs. Hence both $Z$ and $f$ are conditionally independent of $C$. $Z$ and $D$ are conditionally independent of $C'$. Hence $Z'$ is omitted in this pdf. The sequence of the fourth and fifth and the third pdf on the right hand side of equation (1/1) can be written as

\[
\begin{align*}
(\phi, \theta, \gamma) & \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
& \quad \text{f(x, y, z)} \\
\end{align*}
\]
Rejection Sampling

1. Accept the pair \((p, r, d)\) if \(f(p, r, d) f(z, \phi | \theta, \gamma, \eta) \geq \text{const}\).

2. Generate \(d\) from \(f(d | p)\) derived by expression (6). The corresponding production performs

\[ f(p, r, z, \phi | \theta, \gamma, \eta) \]

since \(d\) is conditionally independent of \(Z\).

3. Accept the two-pair \((p, r, d)\) by some rule involving \(z\) and \(r\), or \(z\) only. The corresponding production performs

\[ f(p, r, z, \phi | \theta, \gamma, \eta) \]

since \(d\) is conditionally independent of \(z\) and \(r\).

4. Accept the two-pair \((p, r, d)\) by some rule involving \(z\) and \(r\), or \(z\) only. The corresponding production performs

\[ f(p, r, z, \phi | \theta, \gamma, \eta) \]

since \(d\) is conditionally independent of \(z\) and \(r\).

Rejection Sampling

1. Accept the pair \((p, r, d)\) if \(f(p, r, d) f(z, \phi | \theta, \gamma, \eta) \geq \text{const}\).

2. Generate \(d\) from \(f(d | p)\) derived by expression (6). The corresponding production performs

\[ f(p, r, z, \phi | \theta, \gamma, \eta) \]

since \(d\) is conditionally independent of \(Z\).

3. Accept the two-pair \((p, r, d)\) by some rule involving \(z\) and \(r\), or \(z\) only. The corresponding production performs

\[ f(p, r, z, \phi | \theta, \gamma, \eta) \]

since \(d\) is conditionally independent of \(z\) and \(r\).

4. Accept the two-pair \((p, r, d)\) by some rule involving \(z\) and \(r\), or \(z\) only. The corresponding production performs

\[ f(p, r, z, \phi | \theta, \gamma, \eta) \]

since \(d\) is conditionally independent of \(z\) and \(r\).

Rejection Sampling
Note that the stochastic model is defined on a uniform 30 x 30 grid in the two horizontal and the vertical direction respectively. All correlation functions unless otherwise stated, are exponential.

The stochastic model is following the arrows in Figure 1 illustrating the stochastic model. A trained statistician can by only looking at this figure and knowing where Gaussian and/or linear relations are made, suggest this sampling scheme. More general Metropolis algorithms can be used giving more complex acceptance probabilities.

The specific sampling scheme used in this study is rejection sampling defined by

\[ \left\{ \frac{d}{d} \right\}, \frac{d}{d} \]  

where \( d \) is

\[ \left\{ \frac{d}{d} \right\}, \frac{d}{d} \]  

on the form

\[ \left\{ \frac{d}{d} \right\}, \frac{d}{d} \]  

The stochastic model and production conditions are presented, and base case parameter values are defined.

The base case geological model and production conditions are presented, and base case parameter values are defined.

2.1 Geostatistical model

Comment on the stochastic model

Exported models see literature on image analysis Ripley (1988), and references therein.

Exported models will be close to the truth, even if the truth is poorly represented by the prior model. Realizations will be close to the truth, even if the truth is poorly represented by the prior model. Having enough high-quality data will help the information contained in the data. By conditioning to data through the likelihood function, realizations from the stochastic model derived above can absorb all relevant aspects of the reservoir to produce a realistic realization. However, in order to condition consistently on several sources of reservoir specific observations, however, the model defined above, is different, and the prior model becomes better suited. Object based models are model defined above. An object based model seems more realistic and feasible. However, the model defined above, is different, and the prior model becomes better suited. Object based models are model defined above. An object based model seems more realistic and feasible. However, the model defined above, is different, and the prior model becomes better suited. Object based models are model defined above. An object based model seems more realistic and feasible.

2.2 Comments on the stochastic model

\[ \left\{ \frac{d}{d} \right\}, \frac{d}{d} \]  

Accept the pair \( \left\{ \frac{d}{d} \right\}, \frac{d}{d} \) with probability

\[ \left\{ \frac{d}{d} \right\}, \frac{d}{d} \]  

production characteristics.

\[ \left\{ \frac{d}{d} \right\}, \frac{d}{d} \]  

no modeling error is assumed. See Table 2 for

\[ \left\{ \frac{d}{d} \right\}, \frac{d}{d} \]  

1. Generate \( \theta, \frac{d}{d} \) from \( f^d \) as described above
(1 + \sum_{i,j} x_i x_j) d - (x_1 x_2) d - (x_3 x_4) d - (x_5 x_6) d = \text{const}

\begin{array}{|c|c|}
\hline
L & \text{Reflection coefficients: } C \\
\hline
0 & 0 \\
0 & (z) w_h \\
\phi & (\phi) w_h \\
\hline
\end{array}

Table 3: Base case parameter values for reflection coefficients.

Table 1: Base case parameter values for reservoir characteristics.
Seismic data

\[
D = \begin{cases} 
0 & \text{if } i = j \\
/ & \text{otherwise} 
\end{cases}
\]

Seismic pulse peak frequency \( \leq 40 \) Hz

Grid cell thickness

Table 4: Upscaling and base case parameter value for production characteristics. The latter

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Form</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Porosity</td>
<td>Arithmetic</td>
<td>( p )</td>
</tr>
<tr>
<td>Permeability</td>
<td>Harmonic</td>
<td>( k )</td>
</tr>
<tr>
<td>Reservoir</td>
<td>Procedure</td>
<td>( \rho )</td>
</tr>
<tr>
<td>Characteristics</td>
<td>Logarithmic</td>
<td>( n )</td>
</tr>
</tbody>
</table>

Table 2: Base case parameters for seismic data.

<table>
<thead>
<tr>
<th>( d )</th>
<th>( p_r )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>0.7</td>
</tr>
<tr>
<td>1.0</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 5: Upscaling and base case parameter value for reservoir characteristics. The latter
Note that according to Table 2 the well observations are assumed to be without error. If

Production

The fluid flow is modeled on a \( 10 \times 10 \times 15 \) grid upscaled from the \( 50 \times 50 \times 15 \) geological grid. The injection well is perforated in the top five grid layers only, while the production well is perforated in the entire trace. Fluid flow is modeled by using ECLIPSE, see the model file in Appendix A. An outline of the reservoir with injection and production well is

Upscaling

Reservoir characteristics

<table>
<thead>
<tr>
<th>Porosity</th>
<th>Arithmetic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Permeability</td>
<td>Harmonic</td>
</tr>
<tr>
<td>Reservoir</td>
<td>Procedure</td>
</tr>
<tr>
<td>Characteristics</td>
<td>Logarithmic</td>
</tr>
</tbody>
</table>

Table 4: Upscaling and base case parameter value for production characteristics. The latter

\[
\text{Upscaling: } D = \begin{cases} 
0 & \text{if } x \neq 0 \\
/ & \text{otherwise} 
\end{cases}
\]

Note that according to Table 2 the well observations are assumed to be without error. If
The true reservoir is inspired by the Troll-field. It has a layered structure with alternating high-permeable and low-permeable layers called C-sands and M-sands. The background of the reservoir is shown in Figure 2. Outline of the reservoir model. The thick lines indicate where the wells are perforated.

4. Background

4. The true reservoir

The construction of the true reservoir is inspired by the Troll-field. It has a layered structure with alternating high-permeable and low-permeable layers called C-sands and M-sands. The background of the reservoir is shown in Figure 2. Outline of the reservoir model. The thick lines indicate where the wells are perforated.

| Table 6: Observed production characteristics and base case parameter values. Note that gor_1 and gor_2 are only used to give information on breakthrough time. Hence the absolute value of gas/oil ratio is not used. |
|---|---|
| 2.3% of observed bhp | Oil production rate in Well 1 (opr_1) |
| 2.3% of observed bhp | Oil production rate in Well 2 (opr_2) |
| 50 days (from breakthrough time) | Gas/oil ratio in Well 1 (gor_1) |
| 50 days (from breakthrough time) | Gas/oil ratio in Well 2 (gor_2) |
| 50% of observed opr_1 | Bottom hole pressure in injection well (bhp) |
| 50% of observed opr_2 | Oil Production rate in Well 1 (op_1) |
| Oil Production rate in Well 2 (op_2) | Oil Production rate in Well 1 (op_1) |
| Observation period > 1.216 or 1.42 days | Observation period > 1.216 or 1.42 days |

Variables

- opr_1
- opr_2
- gor_1
- gor_2
- bhp
- op_1
- op_2
- Observation period

Figure 2: Outline of reservoir model. The thick lines indicate where the wells are perforated.
true reservoir consists of three layers having the highest permeability in the middle. A grid with a constant grid cell size of value 6.73 on the top of this grid. A histogram of the acoustic impedance is calculated according to equation (8) on the 30 x 30 x 11-grid displayed in Figure 4. Figure 3 illustrates the extended grid used for seismic data generation. The central grid corresponds to the base case reservoir. The numbers indicate the number of grid cells in each interval. High negative and positive values are added at the interfaces of the top and middle layer of grid cells. The central grid corresponds to the base case reservoir. Figure 2 shows the outline of extended grid used for true reservoir. The numbers indicate the number of grid cells in each interval.

4.2 Construction

The reservoir is constructed by generating three independent fields of reflection coefficients with standard deviation $C=0.03$. The histogram of the reflection coefficients on the central grid is displayed in Figure 4. A histogram of the reflection coefficients on the central grid is displayed in Figure 4. A histogram of the reflection coefficients on the central grid is displayed in Figure 4. A histogram of the reflection coefficients on the central grid is displayed in Figure 4. The acoustic impedance is calculated according to equation (1) on the 30 x 30 x 11-grid with a constant field of value 6.73 on the top of this grid. A histogram of the acoustic impedance is calculated according to equation (8) on the 30 x 30 x 11-grid displayed in Figure 4.
In this section the model parameters $\Theta = (\Theta_1,\Theta_2)$ are used in place of the log-probability $\log p(\Theta)$.

5 Exploring the stochastic model conditioned on the model parameters $\Theta$

Reservoir specific data are explored and discussed.

The most realistic prior stochastic model would hence be an object-based model with one

...
This section are observed with seismic pulse peak frequency 80 Hz, compared with 40 Hz in
the reservoir. For noiseless data, the reservoir is observed and conditioned with noiseless data
in the reservoir. The reservoir is conditioned with noiseless data in the stochastic model conditioned on \( \theta \).

2.3 Exploring the stochastic model conditioned on high-frequency, low-noise seismic amplitude data

not similar to a typical realization from the stochastic model. The production response from the true reservoir is different from the reservoir conditioned with the true model parameters. The production response from the prior stochastic model is different from the prior model parameters. The production response from the prior model parameters is different from the production response from the stochastic model conditioned on \( \theta = \Theta \).

2.2 Exploring the stochastic model conditioned on seismic amplitude data

In this section, properties of realizations from the stochastic model are explored and compared with the true reservoir. In Figure 15, a realization displaying a cross-section of realizations from the stochastic model conditioned on \( \theta \) and high-frequency, low-noise seismic amplitude data is displayed. The realization is qualitatively different from the true reservoir displayed in Figure 9, by having a mosaic of high-permeable and low-permeable facies.

2.1 Exploring the prior stochastic model

In this section, properties of realizations from the prior stochastic model are explored and displayed.

\( (p, \theta|d), (p, \theta|u) \)
In this section properties of realizations from the stochastic model conditioned on well observations are explored and compared with results above. Consider Figures 2/5, 2/6 and 2/7. Note that the structure of the middle layer can be recognized. The uncertainty in production characteristics is drastically reduced and there is a good fit in bottom hole pressure the first 1000 days. There seem to be a tendency of too early breakthrough. The well observations are explored and compared with results above. Consider Figures 2/8, 2/9 and 3/0. Note that the structure of the middle layer is well reproduced and better correlated around the time value compared with the case with base case reservoir and better correlated around the time value compared with the case with reservoir parameter and observations.

In this section properties of realizations from the stochastic model conditioned on seismic amplitude data and well observations are explored and compared with results above. Consider Figures 2/8, 2/9 and 3/0. The structure of the middle layer is well reproduced and there is a good fit in bottom hole pressure the first 1000 days. The production characteristics seems to be similar to a typical realization. The production response from the reservoir seems to be similar to a typical realization.
In this section the model parameters are the expected level of the log-permeability in the high-permeable and low-permeable areas respectively, are regarded as stochastic. Production history are always included, that is all realizations are history matched. To explore the influence of different information sources different combinations of well observations and seismic data are considered. The behavior of production characteristics is discussed and plots of production characteristics in Section 3 should be studied. The acceptance rate is almost zero. Hence the true reservoir is in a low probability area. The acceptance rate is still unacceptably low, even for short production histories. The fraction of accepted proposals is hence a measure of how well features important for fluid flow are reproduced when conditioning on these information sources only. High acceptance rate for a short production history indicates that important features near the wells are well reproduced. The acceptance rate is almost zero. Hence the true reservoir is in a low probability area. To include the production history in the conditioning, the accept/reject step is taken in the simulation algorithm outlined in Section 2.1. Recall that the proposed realizations are condition on production data and well.

| 6.1 Exploring stochastic model conditioned on production data only. |

| 6.2 Exploring stochastic model conditioned on production history and seismic data. |

| 6.3 Exploring stochastic model conditioned on production data and well. |

| 6.4 Exploring stochastic model conditioned on production history only. |
The well observations are giving much information on features important for now areas near the wells.

For the model parameters consider Figures 3/4, 3/5 and 3/6 for 2/5, 3/3 and 4/5 years of production history respectively. In each plot the first display shows the mean conditional estimate of \( f(\theta|d) \) being the smooth curve with the lowest model evidence. The second display is similar but for \( f(\theta|p,d) \) being the other smooth curve with the highest model evidence. The third display is a cross plot of the accepted samples from the posterior model. The parameter values in the true reservoir are 0.65 and 0.55 respectively. The fourth display is a cross plot of the accepted samples from the posterior model. For 2/5, 3/3 and 4/5 years of production history the acceptance rate is increased when seismic data are added to well observations. Note however, that even when well observations, seismic data and 5 years of production history are included, the long term behavior of the first production well is qualitatively different from the observed production history, see the first and fourth displays in Figure 3/9. The discrepancy is probable due to the fact that the true reservoir is not constructed by generating a realization from the prior model and some features of the true reservoir are difficult to capture with the stochastic model. To investigate this further a randomization over true reservoir models should be performed.

In this section the true reservoir is unchanged, but the information contents of the well observations are made more local in the stochastic model. This is achieved by halving the correlation lengths of the reservoir characteristics. This corresponds to use a bigger reservoir volume. 

### Section 6.4
Exploring stochastic model conditioned on all available data:

\[ (p|\theta)f, (p|d)f, (p|a)f \]
Compared with the corresponding results with longer correlation lengths discussed in Section

7.2 Exploring stochastic model conditioned on well observations and seismic data

7.3 Exploring stochastic model conditioned on all available data.

and not changing correlation lengths, but this can not be performed without changing the

presentation of the true reservoir, making comparison difficult. Hence the correlation lengths in the previous stochastic model is halved from 100 to 50 in the

horizontal directions and from 50 to 30 in the vertical direction. It is intuitive that the more

reliable information is available from the seismic data, the less influence on the reduction of uncertainty in the posterior model. The model parameters \( \theta = (\theta_1, \theta_2) \) being the expected level of the log-permeability in the high-permeable and low-permeable areas respectively are fixed at the true values (8.5, 5.3) in the

blended extended local or the log-permeability in the horizontal direction and from 0 to 2 in the vertical direction. It is intuitive that the more

observations of the low-permeable area are fixed at the true value 0, the less influence of the well

local information contents of the well observations on the posterior model. Hence the correlation lengths is halved from 100 to 50 in the

horizontal directions and from 50 to 30 in the vertical direction. It is intuitive that the more

reliable information is available from the seismic data, the less influence on the reduction of uncertainty in the posterior model. The model parameters \( \theta = (\theta_1, \theta_2) \) being the expected level of the log-permeability in the high-permeable and low-permeable areas respectively are fixed at the true values (8.5, 5.3) in the

favour of not changing correlation lengths, but this can not be performed without changing the

reliable information is available from the seismic data, the less influence on the reduction of uncertainty in the posterior model. The model parameters \( \theta = (\theta_1, \theta_2) \) being the expected level of the log-permeability in the high-permeable and low-permeable areas respectively are fixed at the true values (8.5, 5.3) in the

favour of not changing correlation lengths, but this can not be performed without changing the
Not unexpectedly, production characteristics are significantly better reproduced when well correlation is reduced, especially for longer production histories. By reducing the correlation lengths the predictive properties are, not unexpectedly, reduced. The reduction in acceptance ratio is however, not as dramatic as for the case with no seismic data in Section 7.

Hence when well observations are mainly containing local information, only reservoir characteristics close to the wells and short term production history may be well reproduced. A longer production history is thereby more difficult to reproduce using local information. Wells close to the wells and short term production history may be well reproduced, not necessarily close to the wells and short term production history may be well reproduced.

The simulation study demonstrates that even when well observations carry little information, the prediction of production characteristics is improved. The prediction of production characteristics is improved, since the reservoir is well reproduced when seismic data are included.

The stochastic model for a 3D reservoir integrating well observations, seismic data and production history is presented. The stochastic model is illustrated by a directed graph. Simplifying assumptions are introduced and utilized to define a sampling algorithm. The algorithm is defined by sequential sampling of Gaussian and log-Gaussian fields, and an accept-reject step where Markov chain Monte Carlo or rejection sampling can be used. The time consuming part in the algorithm is the evaluation of a fluid flow simulator.

Including seismic data adds valuable global information on the reservoir characteristics and reduces the number of fluid flow simulations required for each accepted realization. Including seismic data reduces the number of fluid flow simulations required for each accepted realization.

A true reservoir is defined. Data are observed from this reservoir and various simulation studies including different amounts of data are performed. The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The stochastic model for a 3D reservoir integrating well observations, seismic data and production history is presented. The stochastic model is illustrated by a directed graph. Simplifying assumptions are introduced and utilized to define a sampling algorithm. The algorithm is defined by sequential sampling of Gaussian and log-Gaussian fields, and an accept-reject step where Markov chain Monte Carlo or rejection sampling can be used. The time consuming part in the algorithm is the evaluation of a fluid flow simulator. Including seismic data adds valuable global information on the reservoir characteristics and reduces the number of fluid flow simulations required for each accepted realization. Including seismic data reduces the number of fluid flow simulations required for each accepted realization.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.

The simulation study demonstrates that the global structure of the true reservoir is well reproduced, even if it has nearly zero probability density in the prior model. The prior model is flexible and adapted to the data. A more realistic model may be developed, but on the expense of complexity and slower algorithms in some general cases. Production characteristics for the first few years are well reproduced with the stochastic model, even if it has nearly zero probability density in the prior model. The prior model is not well reproduced when seismic data are included.
Observations are carrying more global information, even when only well-observed wells are included.

To further investigate this methodology generally and this stochastic model specifically, the number of wells should also be varied. In addition to qualitative aspect of production characteristics from full-field models, the quality of seismic data is also important for the results, and this should be investigated further.

To draw more general conclusions, several reservoir models should be constrained and the exercises repeated. The quality of data and well data from the full field should be constrained and the stochastic model conditioned to seismic data and well data. This would allow for a broader assessment of the probabilities and uncertainties.

References


Professors in E. Y. New and N. A. Stock (1979), Geostatistics in Petroleum Engineering and Geology.


Figure 4: Histogram for reflection coefficients in the reservoir.
value $z_{th}$ in the stochastic model. The first histogram is from the entire true reservoir. The second is from the high-impedance layers at top and bottom. The last histogram is from the middle layer with low impedance. The vertical line indicates the threshold value $z_{th}$ in the stochastic model.

Figure 5: Histograms for acoustic impedance. The first histogram is from the entire true reservoir. The second is from the high-impedance layers at top and bottom. The last histogram is from the middle layer with low impedance. The vertical line indicates the threshold value $z_{th}$ in the stochastic model.
Figure 6: Histograms for porosity. The first histogram is from the entire true reservoir. The second is from the low-porosity layers at top and bottom. The last histogram is from the middle layer with high-porosity.
Figure 8: Cross plot of acoustic impedance and log-permeability in the true reservoir. The vertical line indicates the threshold value \( \gamma \) in the stochastic model.

Figure 7: Histograms for permeability. The first mode displays values in the low-permeable layer in the middle, the second mode displays values from the high-permeable layer in the top and bottom layers.
Figure 9: Cross section from the true reservoir displaying reflection coefficients, acoustic impedance, porosity, and log-permeability respectively.
Figure 1: Trace plots of reflection coefficients and acoustic impedance corresponding to the cross plot in Figure 4. The vertical traces are the first, tenth, twentieth, thirtieth, fortieth and fiftieth trace respectively. The vertical lines indicate the threshold value $z_{th}$. In realizations from the stochastic model acoustic impedance below $z_{th}$ is interpreted as high-permeable facies according to expression (15).
Figure 11: True but unobserved production characteristics from the true reservoir corresponding to the variable $P$ in Figure 1.
Figure 12: Observed acoustic impedance and log-permeability in the wells. The first two displays on the right hand side corresponds to observations from the same horizontal well.
Figure 13: Cross section from the true reservoir displaying seismic data and reflection coefficients.
Figure 14: 4.5 years of observed production characteristics from the true reservoir. Each dot represents an observation. The vertical lines correspond to 2.5 years and 3.33 years respectively.
Figure 15: Cross section from a realization from the prior model displayin reflection coefficients, acoustic impedance, porosity and log-permeability respectively.
Figure 16: Trace plots of reflection coefficients and acoustic impedance corresponding to the cross plot in Figure 15. See also Figure 10 for detailed explanations.
Figure 17: Production characteristics from one hundred realizations from the prior model conditioned on $\theta$ set to true values. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 1.8: A cross section from a realization from the stochastic model conditioned on seismics.
Figure 19: Trace plots of reflection coefficients and acoustic impedance corresponding to the cross plot in Figure 18. See also Figure 10 for detailed explanations.
Figure 20: Production characteristics from one hundred realizations from the stochastic model conditioned on seismics and $\theta$. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 21: A cross section from a realization from the stochastic model conditioned on high-quality seismics and 

See also Figure 10 for detailed explanations.

Figure 22: Trace plots of reflection coefficients corresponding to the cross plot in Figure 21.
Figure 23: Trace plots of acoustic impedance corresponding to the cross plot in Figure 21. See also Figure 10 for detailed explanations.
Figure 24: Production characteristics from one hundred realizations from the stochastic model conditioned on high quality seismics and $\theta$. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 25: A cross section from a realization from the stochastic model conditioned on well observations and \( \theta \).
Figure 26: Trace plots of reflection coefficients and acoustic impedance corresponding to the cross plot in Figure 25. See also Figure 10 for detailed explanations.

"Trace plot in Figure 25." See also Figure 10 for detailed explanations.
Figure 27: Production characteristics from one hundred realizations from the stochastic model conditioned on well observations and $\theta$. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 28: A cross-section from a realization from the stochastic model conditioned on well observations, seismics and $\theta_i$. 
Figure 29: Trace plots of reflection coefficients and acoustic impedance corresponding to the cross plot in Figure 28. See also Figure 10 for detailed explanations.
Figure 30: Production characteristics from one hundred realizations from the stochastic model conditioned on well observations, seismics and $\theta$. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 31: Production characteristics from 100 realizations from the stochastic model conditioned on well observations and 2.5 years (911 days) of production history. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 32: Production characteristics from 95 realizations from the stochastic model conditioned on well observations and 3.33 years (1216 days) of production history. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 33: Production characteristics from 14 realizations from the stochastic model conditioned on well observations and 4.5 years (1642 days) of production history. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
of second display is similar to the first, but with the curve is a density estimate for years of production history. The curve is a density estimate for when production history are included. The smooth curve is the pdf for \( \Theta \) conditioned to well observations. The irregular years of production history. The curve with the lowest mode is the prior pdf. The other years of production history. The curve with the lowest mode is the prior pdf. Where \( \frac{\partial^2 p}{\partial \theta^2} \mid \theta \) and \( \frac{\partial^2 p}{\partial \theta^2} \mid \theta \) where \( \frac{\partial^2 p}{\partial \theta^2} \mid \theta \) and \( \frac{\partial^2 p}{\partial \theta^2} \mid \theta \).
See Figure 3.4 for details.

See Figure 3.5 for details.

Figure 3.6: Plots of $f(p)$, $f(j)$, and $f(y)$ where $d_p$ is 4.7 years of production history.

See Figure 3.4 for details.
Figure 37: Production characteristics from 100 realizations from the posterior model conditioned on well observations, seismics and 2.5 years of production history. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 38: Production characteristics from 100 realizations from the posterior model conditioned on well observations, seismics and 3.33 years of production history. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 30: Production characteristics from 30 realizations from the posterior model conditioned on well observations, seismics and 4.5 years of production history. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 4.0: The first display shows plots of production history. The curve with the lowest mode is the prior pdf conditioned to well observations, i.e., when production history and estimates are included. The second display is similar, but with $\theta_2$ instead of $\theta$. The irregular curve is the pdf for $\theta_1$ conditioned to well observations, i.e., $f(\theta_1|\theta_2)f(\theta_2)$. The other smooth curve is the pdf with the lowest mode is the prior pdf for $\theta_1$ where $f(\theta_1)f(\theta_2)$ and $f(\theta_1|\theta_2)f(\theta_2)$.
Figure 4.1: Plots of $f(p \theta)$ and $f^{(m)}(p \theta)$, where $d_p$ is the years of production history. See Figure 4.0 for details.

Figure 4.2: Plots of $f(p \theta)$ and $f^{(m)}(p \theta)$, where $d_p$ is 3.5 years of production history. See Figure 4.0 for details.
Figure 43: Production characteristics from one hundred realizations from the stochastic model having shorter correlations lengths, conditioned on well observations and $\theta$. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 44: Production characteristics from one hundred realizations from the stochastic model having shorter correlation lengths, conditioned on well observations, seismic data and $\theta$. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 45: Production characteristics from 100 realizations from the posterior model conditioned on well observations, seismics and 2.5 years of production history. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 46: Production characteristics from 100 realizations from the posterior model conditioned on well observations, seismics and 3.33 years of production history. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
Figure 47: Production characteristics from 7 realizations from the posterior model conditioned on well observations, seismics and 4.5 years of production history. The production characteristics from the true reservoir are indicated by black circles overlayed by a white line.
A The ECLIPSE model file

GRID

INCLUDE 'ECLIPSE//PORO U/.dat'

INCLUDE 'ECLIPSE//PERMXU/.dat'

EQUALS

'MULTZ/' /0/./6/4 /1/1 /0/1/1 /0/5 /5/

'MULTZ/' /0/./2/6 /1/1/0 /1 /1/0 /1/0 /1/0 /

ENDBOX

THE Y AND Z DIRECTION PERMEABILITIES ARE COPIED FROM PERMX SOURCE DESTINATION BOX

COPY 'PERMX/' 'PERMY//' /1/1 /0/1/1 /0/1 /1 /5/

'PERMX/' 'PERMZ/'

OUTPUT OF DX/, DY/, DZ/, PERMX/, PERMY/, PERMZ/, MULTZ/, PORO AND TOPS DATA IS REQUESTED, AND OF THE CALCULATED PORE VOLUMES AND X/, Y AND Z TRANSMISSIBILITIES

RPTGRID

0/0 /0/1 /0/0 /0/1 /

6/9

A The ECLIPSE model file
The PROPS section defines the relative permeabilities, capillary pressures, and the PVT properties of the reservoir fluids. Water relative permeability and capillary pressure are tabulated as a function of water saturation. Similarly for gas, oil relative permeability is tabulated against oil saturation for oil-water and oil-gas-connate water cases. PVT properties of water include reference pressure, compressibility, reference volume, compressibility, and surface densities of reservoir fluids. PVT properties of dry gas (no vaporised oil) are specified using PVTG.
PVT PROPERTIES OF LIVE OIL (WITH DISSOLVED GAS)

We would use PVDO to specify the properties of dead oil for each value of RS, the saturation pressure, FVF, and viscosity are specified. For RS = 1.27 and 1.618, the FVF and viscosity of undersaturated oil are defined as a function of pressure. Data for undersaturated oil may be supplied for any RS, but must be supplied for the highest RS (1.618).

OUTPUT CONTROLS FOR PROPS DATA

Activated for SOF/3, SWFN, SGFN, PVTW, PVDG, density and rock keywords RPTPROPS

SOLUTION = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = =

The solution section defines the initial state of the solution variables (phase pressures, saturations and gas-oil ratios).

DATA FOR INITIALISING FLUIDS TO POTENTIAL EQUILIBRIUM

DEPTM DATUM OWC OWC GOC GOC RSVD RVVD SOLN

VARIATION OF INITIAL RS WITH DEPTH

DEPTM RS

= = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = =

OUTPUT CONTROLS (SWITCH ON OUTPUT OF INITIAL GRID BLOCK PRESSURES) RPTSOL

SUMMARY = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = =

This section specifies data to be written to the summary files and which may later be used with the Eclipse graphics package.

SCHEDULE = = = = = = = = = = = = = = = = = = = = = = = = = = = = = =

The schedule section defines the operations to be simulated.

SE / = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = =

The following is a partial listing of the contents of the file.

/ 0

/ 1

/ 2

/ 3
<table>
<thead>
<tr>
<th>Date</th>
<th>Month</th>
<th>Year</th>
<th>Type</th>
<th>Operation</th>
<th>Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>3/1</td>
<td>Jan</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Feb</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Mar</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/0</td>
<td>Apr</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>May</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/0</td>
<td>Jun</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Jul</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Aug</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Sep</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/0</td>
<td>Oct</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Nov</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/0</td>
<td>Dec</td>
<td>1997</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Jan</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/0</td>
<td>Feb</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Mar</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/0</td>
<td>Apr</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>May</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/0</td>
<td>Jun</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Jul</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Aug</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/0</td>
<td>Sep</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Oct</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/0</td>
<td>Nov</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
<tr>
<td>3/1</td>
<td>Dec</td>
<td>1998</td>
<td>PROD</td>
<td>OPEN</td>
<td>4.0</td>
</tr>
</tbody>
</table>
Derivation of \( z^\text{top} \) in the presence of horizontal wells

Recall that the reservoir characteristics observed in wells are permeability, porosity and acoustic impedance. Reconnection coefficients are calculated from vertical changes of impederance. Hence it is not clear how reconnection coefficients can be found in horizontal wells. Acoustic impedance is sampled as indicated in Sections 2/1/1/3 and 2/1/3/2. A simple sampling scheme is: let \( z^\text{top} \) be a constant field, simulate reconnection coefficients conditioned on seismics and well observations of reconnection coefficients; then calculate the acoustic impedance field by the relation \((8)\) in all vertical traces. This procedure does however not reproduce acoustic impedance observations in horizontal wells. Hence \( z^\text{top} \) has to be chosen so that observed acoustic impedance is reproduced also in horizontal wells. An ad-hoc procedure where \( z^\text{top} \) is found by kriging is defined as follows:

1. Generate a field of reconnection coefficients from \( f(\cdot, c, p) \).
2. Calculate impedance upwards from vertical wells and all observations in horizontal wells.
3. Let \( z^\text{top} \) be the kriged surface conditioned on the calculated \( z^o \)’s.

According to the prior model both \( f \) and \( [c = C] \) are Gaussian fields. Hence also the acoustic impedance \( Z(\cdot) \) is Gaussian. Note that also by using kriging, Gaussianity is implicitly assumed. Gaussian assumptions are however not in accordance with the resulting field of acoustic impedance \( Z(\cdot) \), defined in Section 2/1/1/3.

C Generation of Gaussian fields conditioned on seismic data

According to the prior model both \( S_0 \) and \( C_0 \) are Gaussian fields, hence also the variables \( C_j S_0 = d_s \) and \( C_j C_0 = c_o \) with corresponding pdfs \( f(\cdot, c \mid d_s) \) and \( f(\cdot, c \mid c_o, d_s) \). Since all horizontal wells are running in the horizontal direction on the contour plot and from left to right on the 3D-plot, the irregularities originating from the well observations are clearly visible on the plots. The \( /\text{hill/} \) is due to large values of acoustic impedance observed in the first half of one of the horizontal wells. Simple kriging is used with kriging equal to the calculated by this procedure. The horizontal wells are running in the horizontal direction on the contour plot and from left to right on the 3D-plot. Hence the function putting all mass in the \( z^\text{top} \) calculated by this procedure is represented by a Dirac delta function putting all mass in the \( z^\text{top} \) calculated by this procedure. The horizontal wells are running in the horizontal direction on the contour plot and from left to right on the 3D-plot.

Recall that the reservoir characteristics observed in wells are permeability, porosity and acoustic impedance.
Another example is used in faces classification.

A model for the parameters $f(a,g)$ is defined to be Gaussian with expectation $a - g$. Then

$f(a,g)$ is defined a prior to be Gaussian with expectation $a - g$. Then

These could be the parameters $a$ and $g$ defined in equation (3). If $a = (a,g)$, then

The stochastic model is illustrated in Figure 4. The stochastic model consists of stochastic parameters. An example of extension of the stochastic model. In Figure 4, The bottom rectangle consists of stochastic parameters. The parameters could define variance and correlation structure in model. The parameters could define variance and correlation structure in model. The parameters could define variance and correlation structure in model. The parameters could define variance and correlation structure in model.

The stochastic model illustrated in Figure 4 can be extended to allow additional stochastic parameters. The stochastic model illustrated in Figure 4 can be extended to allow additional stochastic parameters.

In Figure 4, $K$ is an example given in the description of the prior model in Section 2.1.

Extending the stochastic model

By simple kriging, two horizontal strips and a single node expectations are calculated. Else is interpolated. Figure 4 is the kriged impedance surface on top of the reservoir. Based on the importance observations in the horizontal wells, the vertical well and a realization of reflection coefficients, the model parameters $f(a,g)$ must then also be defined.
This could for example be expectation and variance in the top layer impedance defined by the field $z_{\text{top}}$ and discussed in Section 2.1.3.

The top rectangle consists of stochastic parameters in the likelihood model. The likelihoods are specified conditioned on these parameters. These parameters could in general be related to the data observation process. This could be parameters describing variance and correlation structure in observation-error terms and parameters in the definition of the transfer functions $g$.

Some examples of parameters that could be treated as stochastic are listed under.

- Parameters related to observations of production characteristics. Examples are variance and correlation structure in the noise corruption the seismic data, the frequency of the Ricker wavelet, the thickness of grid blocks in time and other parameters connected to the physical process.

- Parameters in the transfer function as functions of parameters connected to the depth-connection process.

- Parameters connected to the observation model $g$ as well as to the observations being an average over some area defined in the transfer function $g(y)$.

- Parameters in the likelihood in observation-error terms and parameters connected to the depth-connection process.

- Parameters in the likelihood in observation-error terms. These parameters could in general be related to the likelihoods in the likelihood model.

- Parameters in the likelihood model.

Based on this figure the derivations and considerations in Section 2.3 can be repeated but with the additional parameters and corresponding prior pdfs in the expressions.

To further extend the model also time-dependent reservoir characteristics such as saturation can be included in the rectangle marked with an $R$. Then sections will depend on both impedances.

By these parameters:

1. $\Theta$: The likelihood function $g(y|x)$ is parameterized in the observation model and observation errors.
2. $\Phi$: These parameters related to observations of production characteristics. Examples are variance and correlation structure in the noise corruption the seismic data, the frequency of the Ricker wavelet, the thickness of grid blocks in time and other parameters connected to the depth-connection process.
3. $\Gamma$: These could be $\Phi$ and $\Theta$. These parameters related to observations of production characteristics. Examples are variance and correlation structure in the noise corruption the seismic data, the frequency of the Ricker wavelet, the thickness of grid blocks in time and other parameters connected to the depth-connection process.
4. $\Omega$: These could be $\Phi$ and $\Theta$. These parameters related to observations of production characteristics. Examples are variance and correlation structure in the noise corruption the seismic data, the frequency of the Ricker wavelet, the thickness of grid blocks in time and other parameters connected to the depth-connection process.
Recall that a circle indicates a stochastic variable. All likelihood functions are defined conditionally on the parameters. This is illustrated by the arrows from the parameters to the specific observations. Similarly, all prior distributions for reservoir characteristics and production characteristics are defined conditionally on the parameters. This is illustrated by the arrows from the parameters to the reservoir characteristics and production characteristics, see also Figure 1.