NTNU – Trondheim
Norwegian University of
Science and Technology

Reservoir Uncertainty Evaluation

A Producing Gas Field Case Study

Brit Elise Melhus

Petroleum Geoscience and Engineering
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Supervisor: Jon Kleppe, IPT
Co-supervisor: Knut Ingvar Nilsen, Eni Norge
Lars Rasmussen , Eni Norge

Norwegian University of Science and Technology
Department of Petroleum Engineering and Applied Geophysics

Abstract

Once a field starts to produce, new information becomes available in terms of production data and measurements. By integrating this information to a reservoir model through a history matching process, an updated uncertainty evaluation of the reservoir can be formed. In the history matching process the current reservoir simulation model will be calibrated to match the new information. This is done to be able to represent the true dynamic behavior in the reservoir, hence get reliable predictions of the future reservoir behavior. The history matching problem is a non-unique problem, meaning that it has multiple solutions. This thesis presents a case study where history matching is applied to a producing gas field, through an assisted history matching process by the use of MEPO software (Schlumberger). The aim of the study is to get an updated uncertainty evaluation of the reservoir, three years after production start. The thesis will investigate the key uncertainties associated with the dynamic reservoir behavior in the field of study. To be able to capture and mitigate the uncertainties related to reservoir parameters, the ensemble based method Markov chain Monte Carlo is used with Bayesian updating. Utilizing the Bayesian framework imply to take a probabilistic approach to uncertainty. The probabilistic theory and its application to mitigate reservoir uncertainty through a history matching process, are reviewed and further applied in the thesis.

In the study, the gas volume in place and the influence from the aquifer, in addition to the internal communication in the reservoir are considered the key uncertainties. The reservoir is divided into regions to be able to capture the uncertainty in different areas. Pore volume- and permeability multipliers for the regions are chosen as uncertain parameters in the study. The pressure in the field are matched by letting the algorithm sample the parameter values from the prior distributions for the uncertain parameters. The sensitivity simulations show the parameter influence on the bottom hole pressures in the wells and on the gas volume. The results show that the pore volume multipliers are the most influential parameters on the match. History matching is carried out in three scenarios. The ensemble of the sufficient history matches makes up the posterior distributions of the uncertain parameters. By analyzing them, it is found; presence of a possible barrier, influence from a small aquifer and a dominating parameter in terms of a pore volume multiplier. Further, the lack of convergence in the Markov chain is tested, the results did not imply lack of convergence in the sufficient scenarios, hence predictions are simulated. The field gas in place for the best matches

are found to be in the range between 6.5 and 8 GSm^3. The predictions show a total production period of 8-9 years before abandonment pressure is reached.

Even though it is important to obtain a reasonable history match, it is at least just as important with a geologically truthful simulation model to be able to obtain reliable predictions. This is why a geologist's evaluation is essential to include in the study. Discussions with a geologist lead to geological interpretations from the results in the study that should be implemented and tested in a further study. The recommendations for future work are; (1) implement the suggested faults, (2) divide the dominating region into multiple regions, and further, depending on the previous results, (3) reduce the net-to-gross parameter values in the initial model.

Sammendrag

Når et felt begynner å produsere blir ny informasjon tilgjengelig i form av produksjonsdata og målinger. Ved å integrere denne informasjon i reservoar modellen gjennom historietilpasning får man resultater som kan føre til en oppdatert usikkerhets evaluering av reservoaret. I historietilpasnings prosessen vil den nåværende reservoar simuleringsmodellen bli kalibrert til å samsvare med den nye informasjonen. Dette blir utført for å få en modell som kan representere den korrekte dynamiske oppførselen i reservoaret, og dermed gi pålitelige prognoser av fremtidig reservoaroppførsel og produksjonsforløp. Historietilpasning er et ikke-unikt problem, noe som betyr at det finnes flere løsninger på problemet. I denne oppgaven vil det bli utført historietilpasning for et produserende gassfelt, ved bruk av assistert historietilpasning som simuleres i programvaren MEPO (Schlumberger). Studien gjennomføres for å få en oppdatert usikkerhets evaluering av reservoaret, tre år etter produksjonsstart. De viktigste usikkerhetene knyttet til den dynamiske reservoaroppførselen vil bli undersøkt. For å fange opp og redusere usikkerheten knyttet til reservoarparametere, er metoden Markov chain Monte Carlo benyttet i en iterativ Bayesian oppdatering. Det å benytte et Bayesiansk rammeverk innebærer å benytte sannsynlighets teori i behandlingen av usikkerhet. Sannsynlighets teori, og hvordan den blir benyttet til å redusere og behandle reservoarusikkerhet gjennom en historietilpasnings-prosess blir gjennomgått i teoridelen i oppgaven.

I studien er gassvolumet, påvirkningen fra akviferen og kommunikasjonen i reservoaret betraktet som de viktigste usikkerhetene i reservoaret. Reservoaret er blitt delt inn i regioner for å kunne fange opp usikkerheten i forskjellige områder av reservoaret. Porevolums- og permeabilitets multiplikatorer for regionene er benyttet for å kunne representere de usikre parameterne i studien. Trykket i feltet blir historietilpasset ved å la algoritmen plukke parameterverdier fra de valgte distribusjonene for de usikre parameterne. En sensitivitets studie gir resultater som viser parameternes innflytelsen på bunnhullstrykket i brønnene og påvirkningen i gassvolumet. Resultatene viser at porevolums multiplikatorene er de mest innflytelsesrike parameterne. Det er utført tre historietilpasnings scenarier. De gode historietilpasnings simuleringene utgjør «posterior» distribusjoner av de usikre parametrene. Disse er nøye studert og analysert før følgende er funnet; tilstedeværelse av en mulig transmissibilitets barriere, påvirkning av en liten akvifer og en dominerende region i historietilpasningen. Det fantes tvil om optimeringsmetoden hadde

konvergert, og dermed om den gir riktige resultater. Det finnes ingen gode måter å teste algoritmens konvergens på, men mangelen på konvergens i Markov kjeden er testet. Resultatene antyder ikke manglende konvergens. Dermed er prognoser for fremtidig produksjon blitt simulert, basert på de gode historietilpasningene. Gassvolumet i reservoaret er funnet til å være mellom 6.5 og 8 GSm^3. Prediksjonene viser an total periode på 8-9 år før man når nedstegningstrykket.

Selv om det er viktig å få en god historietilpasning, er det minst like viktig med geologisk korrekte tolkninger og en simuleringsmodell som kan gi pålitelige prognoser. Dette er grunnen til at en geologs evaluering er viktig å ta med i studien. Etter diskusjon av resultatene sammen med en geolog er det funnet geologiske tolkninger og anbefalinger som bør implementeres og testes videre i usikkerhets evalueringen. Anbefalingene for det videre studiet er; (1) implementere de foreslåtte forkastningene, (2) dele den dominerende regionen inn i flere regioner, og videre, avhengig av resultatene av de første anbefalingene, (3) redusere net-to-gross verdiene i reservoar modellen.

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Brit Elise Melhus

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Abbreviations

AHM	Assisted History Matching
Cal	Calculated
CDF	Cumulative Density Function
Cov	Covariance
EMV	Expected Monetary Value
EnKF	Ensemble Kalman Filter
EV	Expected Value
EVPI	Expected Value of Perfect Information
FGPT	Field Gas Produced Total
GOR	Gas Oil Ratio
GWC	Gas Water Contact
HCPV	Hydrocarbon Pore Volume
HM	History Matching
LH	Latin Hypercube
MCMC	Markov Chain Monte Carlo
MEPO	Multipurpose Environment for Parallel Optimization (software)
MPERMX	Multiplier Permeability in X and Y direction
MPV	Multiplier Pore Volume
NTG	Net To Gross
OBS	Observable data
PDF	Probability Density Function
PVT	Pressure Volume Temperature
SCAL	Special Core Analysis
SD	Standard Deviation
TVDSS	Total Vertical Depth Subsea
Var	Variance

VoF Value-of-Flexibility

VoI Value-of-Information

WBHP Well Bottom Hole Pressure

Nomenclature

B_g Gas formation volume factor

°C Celsius (degrees)

C Covariance

c Compressibility

cP Centi poise

d day

f Probability density function

F Cumulative density function, Objective function

G Giga, Gas in place

Gp Cumulative produced gas

h Un-normalized density

k Permeability

m Meter, model parameter set

M Million, Mismatch parameter

mD milli Darcy

$\frac{N}{G}$ Net-to-gross ratio

p Pressure

P Probability

P10 10% quantile

P50 50% quantile

P90 90% quantile

q	Proposal distribution
Rm^3	Reservoir cubic meter
r	Hastings ratio
Sm^3	Standard cubic meter
S_g	Gas saturation
T	Temperature
u	Uniform distribution
μ_g	Viscosity of gas
V	Volume
W	Weight parameter
w	Weight,Weighting matrix
x	Variable
X	Variable, State in Markov chain
z	Z factor
α	Acceptance ratio
β	Weighting factor (degree of belief in the initial model)
μ	Expected value, Viscosity
σ	Standard Deviation
φ	Porosity

1 INTRODUCTION

1.1 Background and Objective

Uncertainty is a result of little knowledge, or lack of information related to a certain situation. The complexity in reservoirs and the variations in parameters throughout reservoirs, makes it difficult to create a clear picture of it and its properties. Hence, the uncertainty in the reservoir description is a result of subsurface complexity and limited data to describe it.

By acknowledging the uncertainties related to the description of the reservoir, quantifying and handling of uncertainty are necessary. It is difficult to know all static and dynamic properties of the reservoir, hence a perfect reservoir model is close to impossible to obtain. Reservoir simulation is important as it gives an idea of how the dynamic behavior will evolve during production scenarios in a fields' lifetime. Good predictions of future dynamic behavior will help to optimize the development and management of a field in terms of economy and recovery. To improve the model and to generate reliable predictions of future production, history matching is fundamental. History matching is known as the process of calibrating the reservoir model to match historical data.

The goal of this thesis is to make an updated uncertainty evaluation of a producing gas field, three years after production start. The thesis will investigate the key uncertainties associated with the dynamic reservoir behavior and recovery of the field. The dynamic reservoir behavior may be challenging to predict and require use of simulation programs to be evaluated. A reservoir model that previously have been used to represent the reservoir will be calibrated to the new production data, through a history matching process. The history matching problem is a non-unique problem, which means it has multiple solutions. To be able to capture and mitigate the reservoir uncertainties the ensemble based method Markov chain Monte Carlo is used in a Bayesian updating. Utilizing a Bayesian framework imply to take a probabilistic approach to uncertainty. Several authors have demonstrated that a probabilistic approaches can be beneficial in uncertainty quantification among others; McVay and Dossary (2014) and, Bickel and Bratvold (2007).

In the study MEPO software (Schlumberger) will be used to perform an assisted history match, to mitigate the uncertainties related to reservoir parameters and dynamic behavior, as well as give (expected) production forecasts. The following tasks are to be considered:

- Introduce probability theory and its application in a reservoir description context.
- Literature review of the uncertainties related to reservoir description and approaches to uncertainty.
- Present history matching theory and theory of the algorithm that will be applied.
- Apply the history matching process to the field of study.
- Discuss the results and findings.

1.2 Approach and Structure

The thesis is an uncertainty evaluation of a producing gas field. As a basic understanding of the concepts and methodology is important the thesis start with reviewing relevant theory and literature, before the field of study is presented. Further is the study carried out through; three history match scenarios, one sensitivity study and two prediction scenarios. In the end the results and findings are discussed and put in to context with each other. The thesis consists of six chapters. The following is an overview of the structure in the thesis:

- Chapter 2 introduces terms and concepts used in probability theory. Further, the probabilistic approach to handle and understand the uncertainty in the subsurface are reviewed. The last part of the chapter discuss how to create value from uncertainty.

- Chapter 3 presents the history matching theory and process, including the Bayesian formulation of updating the prior uncertainty by utilizing the algorithm Markov chain Monte Carlo.

- Chapter 4 introduces the reservoir that will be studied. The general field information, geological interpretations, and uncertainties related to the reservoir are discussed. Further is the reservoir model that will be used described in brief.

- Chapter 5 describes the implementation to, and the results of; three history match scenarios, one sensitivity study, and two prediction scenarios. There is a brief discussion of the results within the different sections describing the results, before the last section combines the results and discuss the important findings.

- Chapter 6 gives the concluding remarks from the study and recommendations for further work.

2 QUANTIFYING UNCERTAINTY

This chapter is divided in to three main subsections. The first main subsection presents the basics of probability theory, which can be used to quantify and capture uncertainties. Basic statistic principles and definitions are presented to create a basis for the further uncertainty study. The second subsection discuss how the reservoir parameters are found and how their uncertainty may be presented in probability distributions. In the study is taken a probabilistic approach as a reservoir cannot be described deterministically because of the complexity in the subsurface and limited data from measurements. The parameter values will vary throughout the reservoirs' extent which makes it difficult to give a prediction of the parameters. This is why the parameter values may be presented by probability distributions. The third main subsection discuss different approaches to uncertainty, in addition to illustrate why managing uncertainties in reservoirs can be useful in decision analysis. From a reservoir (engineers') standpoint, it is not enough that the project is economic, it is equally important to find the development and management that is optimal for the field and will give the highest economic return. Good estimates of the reservoir parameters such as hydrocarbon volume and predictions of the dynamic behavior will lead to identifications of the possible outcomes. This may again lead to more beneficial decisions. This chapter is based on the project thesis "A Literature Review of Uncertainties Related to Reservoir Parameters" (Melhus, 2014).

2.1 A Probabilistic Approach

2.1.1 Definitions

Certain words that are used in uncertainty quantification and decision analysis have different meanings within different disciplines which can lead to misunderstandings. This section will discuss and define words that are frequently used throughout the thesis.

Event, Outcome and Probability

Probability is the chance of a specific outcome taking place. The probability that describes how likely it is that an outcome will occur, is assigned by people, and should only be based on all available information and knowledge. Bratvold and Begg *(2010)* explains probability by the following statement: "*Probability is an individual's or group's assessment of uncertainty and represents a state of mind. There is no predefined probability that can be recommended for any particular uncertain situation. It always depends on the assessor's state of knowledge."* To be able to assign probabilities it is important to have a precise description of the outcome. There are certain rules that applies to assigning probabilities that always are valid. One of them are that the probabilities should range on a scale from zero to one (or 0 to 100 %). Where zero is indicating an outcome that will not happen, and one indicates an outcome that will happen with certainty. A second rule is that the sum of the probabilities of all the possible outcomes should equal to one. From this it is clear that one of the outcomes must happen.

It may be useful to distinguish an *event* from an *outcome*. An e*vent* can be looked at as the process of obtaining an observation. An example of this can be to drill a well or to shoot seismic. An o*utcome* is the specific observation or happening (of the event). For example, the drilled well can be dry or wet.

Uncertainty and Risk

It is important to distinguish between what one know about the reservoir, and the actual reservoir. The actual physical reservoir will never be exactly the same as a proposed model of the reservoir. A model is an approximation of the real reservoir by the use of available information and knowledge. It is the lack of information, or knowledge, which creates the uncertainty in the reservoir model.

Uncertainty is defined as the range of possible values, or outcomes, for an event. It is important to find every possible outcome of an event and assign a probability of occurrence to quantify uncertainty. Bratvold and Begg (2010) discuss that since the uncertainty is a consequence that comes from lack of knowledge, uncertainty is *personal*. All information need to be interpreted and put in-to context by someone. Furthermore, the assigned probability of an outcome will differ from person to person, due to its dependence on that person’s experience, assumptions, and interpretation of the available information. One could therefore argue that there does not exist any precise uncertainty for a given outcome.

Risk can be defined as the chance or probability of something happening, times the consequence of it. It is often used when the outcome of the event is undesirable. Risk in a project will be the downside probability of the possible outcomes. Examples may be outcomes where the cost is more than the revenue, or when there is no revenue at all in a project.

2.1.2 Probabilistic Method

Probability Models

For an uncertain event, a probability distribution may describe the possible outcomes and their probability of taking place. A probability distribution can be *discrete* or *continuous*. A *discrete* probability distribution is used to describe the uncertain events that only can take a fixed number of outcomes. In a discrete probability distribution, each outcome have a specific probability. An example can be rolling a dice, the event has six possible outcomes with an equal probability of occurring (one sixth). Figure 1 shows an example of a discrete probability distribution with eight different outcomes that are assigned with individual probabilities.

A *continuous* probability distribution is used to represent an uncertain event that can take any value (or outcome) over a possible range. The vertical scale of continuous probability distributions are defined as the *probability density*. Because of this, the functions are referred to as *probability density functions*, often shortened to PDF's. The probability of a parameter to be within an interval is defined by the area under the probability density function, f(x), for the defined interval. The probability, P, of the continuous variables can only be specified for the outcomes defined over an interval. Mathematically it can be shown by:

$$P(a \leq X \ \leq b) = \int_{a}^{b} f(x)\,dx \tag{1}$$

Which gives the probability of the variable X ranging in the interval from value a to b. The area under the curve represent the likelihood of a continuous random variable X, to take a value in the range from a to b. Figure 2 pictures a continuous probability distribution, where the grey shaded part in the figure shows the area under the PDF defined by the interval from a to b. The total area under the continuous probability distribution will always be equal to one. This is because any outcome must be captured by the range of the distribution by definition in Equation 2. By the definition of a continuous distribution, the probability of getting a single outcome is equal to zero. This can be shown, by integration over the same point the mathematically expression becomes zero as in Equation 3. The probability density function defined as non-negative everywhere expressed mathematically by Equation 4.

$$f(x) \geq 0 \quad \forall\, x \tag{2}$$

$$\int_{-\infty}^{\infty} f(x)\, dx = 1 \tag{3}$$

$$P(a < X \leq a) = \int_a^a f(x)\, dx = 0 \quad \text{Where } a \text{ represents any given value} \tag{4}$$

Cumulative Distributions

A Cumulative density function, CDF, represented by F(X), is another way to express probability density functions. This distribution gives the probability, P, for an uncertain outcome X to be less than or equal to a specific value. It can be described mathematically by:

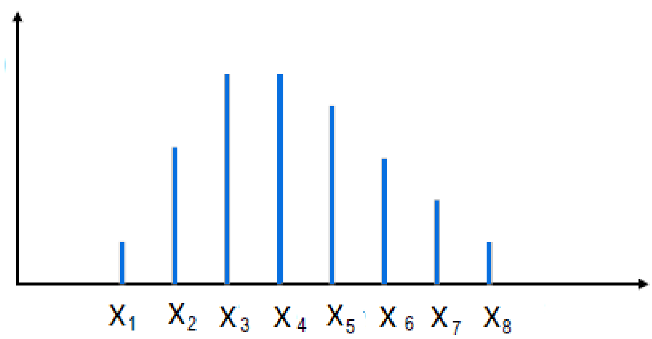


Figure 1 An example of a Discrete Probability Distribution, where the vertical axis show the probability density, and horizontal axis show the outcome.

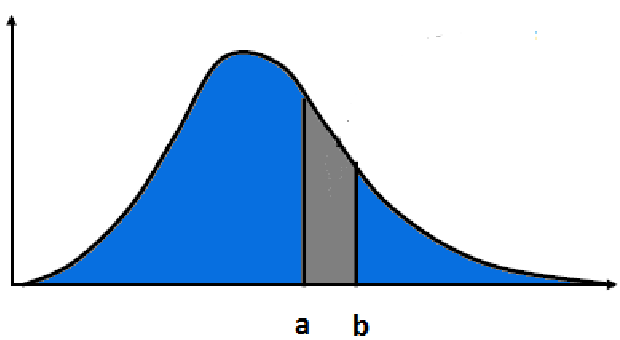


Figure 2 A Continuous Probability Distribution, where the vertical axis show the probability density, and horizontal axis show the outcome.

$$F(x) = P(X \leq x) \tag{5}$$

The cumulative distribution describes the area under the probability density function from a minimum to the given point, x. In other words, it describes the "accumulated" probability "up to x". For a continuous variable, the PDF and CDF are related by Equation 6:

$$F(x) = P(X \leq x) = \int_{-\infty}^{x} f(t)\, dt \tag{6}$$

Where “t” is used as an integrand variable. By the Fundamental Theorem of Calculus:

$$F'(x) = f(x) \tag{7}$$

Figure 3 and Figure 4 show how discrete and continuous probability density functions can be shown as cumulative density functions. In certain cases it may be more convenient to think of the CDF in terms of a probability of an outcome exceeding a value, instead of being below it, this is termed as a reverse, survival or exceedance CDF (Bratvold and Begg, 2010).

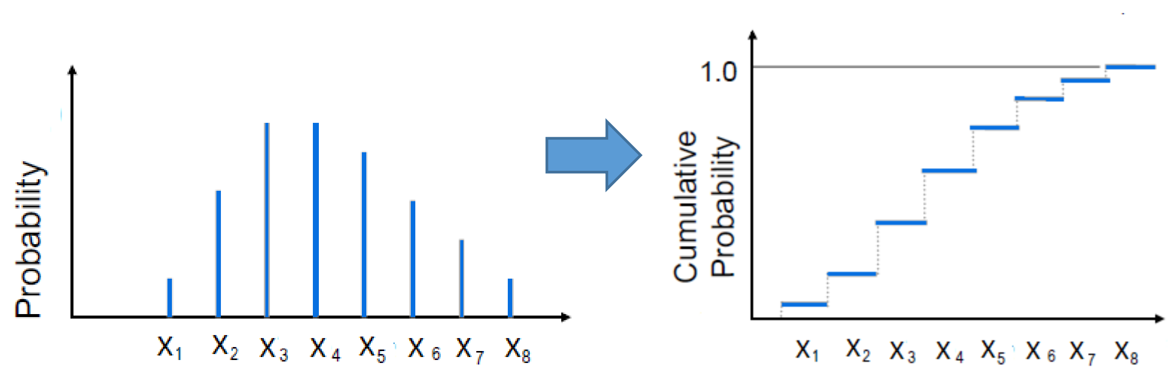


Figure 3 A discrete probability density function transformed to a cumulative density function.

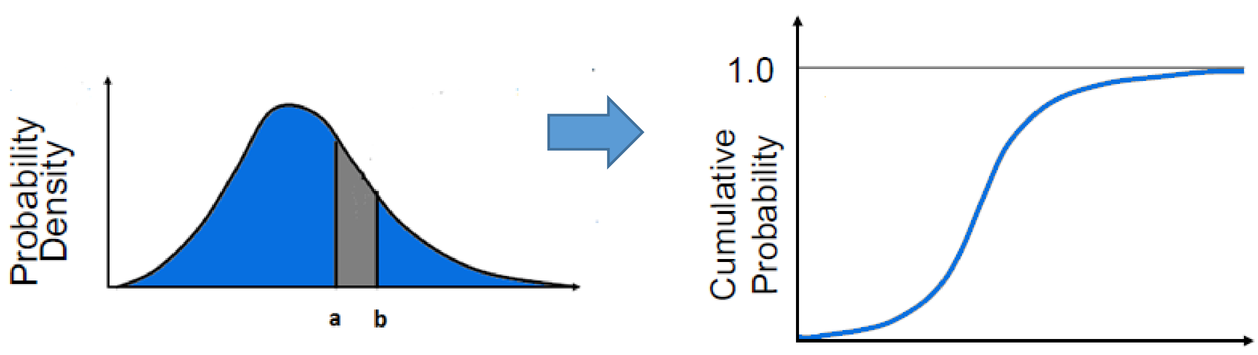


Figure 4 A continuous probability density function transformed to a cumulative density function.

Expected Value, Standard Deviation and Covariance

Expected value, EV, and standard deviation, SD, are useful parameters that are frequently used to describe probability distributions. In addition can covariance describe the relation between variables. In the petroleum industry, EV is often noted as EMV, which is shortened for expected monetary value. Their meaning are the same and the notation EV and expected value will be used further in this thesis.

The expected value, which also is referred to as the average or mean, can be considered as a measure of the center in a probability distribution. The EV is found by multiplying each of the possible outcomes with the likelihood of the occurrence of the individual outcome, and summing the values. In other words, the expected value is the sum of the probability-weighted outcomes (Bratvold and Begg, 2010). For discrete distributions, EV can be found mathematically by:

$$\begin{aligned} E[X] &= x_1P(X = x_1) + x_2P(X = x_2) + \cdots + x_nP(X = x_n) \\ &= \sum_{i=1}^{n} x_iP(X = x_i) \end{aligned} \tag{8}$$

For continuous distributions, EV is found by integrating the continuous probability density function, f(x) as showed by Equation 9:

$$E[X] = \int_{-\infty}^{\infty} x f_X(x)dx \tag{9}$$

As the expected value does not provide any information about the variation in a distribution, it is common to use the parameters *variance* and *standard deviation* to describe the variability of a distribution. The variance is the squared deviations around the expected value. (Bratvold and Begg, 2010). For a discrete PDF, the variance can be described mathematically as:

$$Var[(X)] = E[(X - \mu)^2] = \sum_{i=1}^{n} p_i\,(x_i - \mu)^2 \tag{10}$$

The symbol μ is commonly used in mathematical expressions for the expected value. For a continuous PDF the variance is described mathematically by Equation 11:

$$Var[(X)] = \int_{-\infty}^{\infty} (x - \mu)^2 f(x)dx \tag{11}$$

The variance is a number that is difficult to relate to when discussing uncertainty, as the dimension of the variance is the square of the dimension of the original variable. Standard deviation are therefore much used in describing the dispersion of the values in distribution functions (Bratvold and Begg, 2010). The standard deviation is defined as the square root of the variance:

$$\sigma(X) = \sqrt{Var(X)} \tag{12}$$

Figure 5 show PDFs with different standard deviations; zero, small and large that all have the same EV.

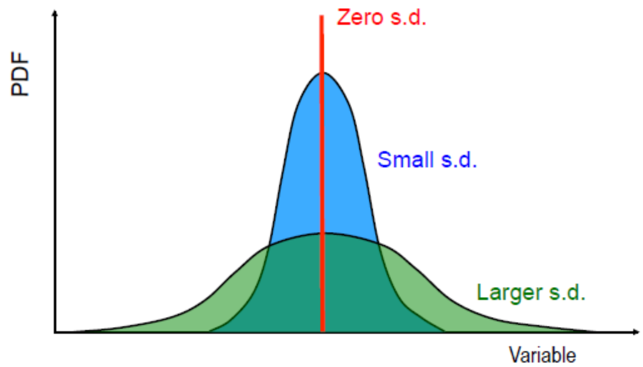


Figure 5 Variable standard deviation -Zero/Small/Large (Bratvold, 2014).

Covariance describe how two random variables are related. If the variables move in the same direction they are positively related. When the variables move in opposite directions they are inversely related. The inverse- and positive relations are often referred to as correlations, ranging from -1 to 1, respectively, where 1 represents perfect correlation. The covariance of the variables X and Y is defined by:

$$Cov(X,Y) = E[(X - E[X])(Y - E[Y])] \tag{13}$$

In the cases where both the variables, X and Y takes a value that both are greater, or smaller than their respective means, the covariance take a positive value.

Probability Definitions

In probability theory it is important to distinguish between mode, median and mean outcomes or values. *Mode* or *most likely* is the peak in a probability distribution, which is the most likely value. *Median* is the point in a probability distribution where the area under the curve is equal on both sides. This will equal the value of 50 percent also written as P_{50}. The *mean* or *average* is equal to the expected value. It is important to note that these values, mode, median and mean will be overlap for a symmetric probability distribution, for unsymmetrical distributions they will differ (Bratvold and Begg, 2010). Figure 6 show, an unsymmetrical distribution where mode, median and mean are found at different frequencies.

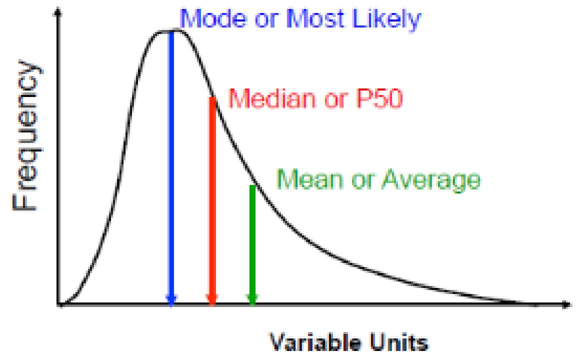


Figure 6 Log normal distribution with the points Mode, Median and Mean (Bratvold, 2014).

Marginal-, joint- and conditional probabilities are common probability terms. They are defined as follows:

Marginal probability, also referred to as total probability, is defined as the probability of an outcome, irrespective of any other outcomes. The marginal probability of outcome A is noted as:

$$P(A) \tag{14}$$

Joint probability is defined as the probability of two outcomes (A and B) happening together, and is commonly notes as:

$$P(A \cap B) \tag{15}$$

Conditional probability describes how the probability is changed by the occurrence of another outcome. The conditional probability of A happening by the occurrence of B, are noted by:

$$P(A|B) \tag{16}$$

Probability Density Functions

The probability density functions has a certain distribution which can be defined by its properties, typically expected value and standard deviation. The Gaussian distribution, also called normal distribution, is one of the most common probability distributions (Begum, 2009). A *Gaussian function* is the probability function of the normal distribution, it can be expressed mathematically by:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(x-\mu_x)^2}{2\sigma^2}\right) \tag{17}$$

The Gaussian function is characteristic by its bell shape and symmetry around its mean value. Other commonly used probability distributions in the oil and gas industry and their corresponding properties can be seen in Figure 7.

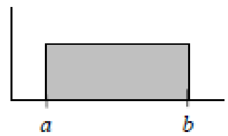
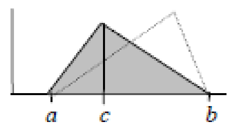
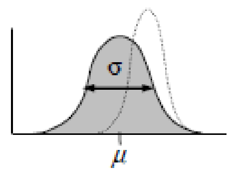
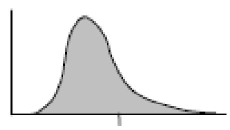
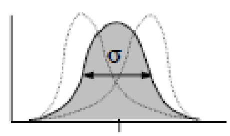
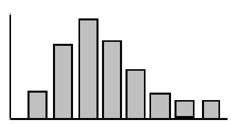
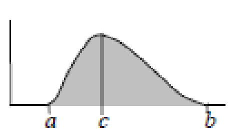
Name	Shape(s)	Mean & Variance
Uniform *(a,b)* Minimum, *a* Maximum, *b*		$\mu = (a+b)/2$ $\sigma^2 = (a-b)^2/12$
Triangular *(a,c,b)* Minimum, *a* Most Likely, *c* Maximum, *b*		$\mu = (a+b+c)/3$ $\sigma^2 = a(a-c)+c(c-a)+b(b-a)/18$ $\equiv \mu^2/2 - (ab+bc+ac)/6$
Normal (μ,σ^2) Mean, μ Variance, σ^2		$\mu =$ *as specified* $\sigma^2 =$ *as specified*
Log Normal Mean, μ Variance, σ^2		$\mu =$ *as specified* $\sigma^2 =$ *as specified*
Beta *(a,b)* Shape parameter, *a* Shape parameter, *b* (The Beta can take on a wide variety of shapes depending on the relationship between *a* and *b*.)		$\mu = a/(a+b)$ $\sigma^2 = ab/[(a+b)^2(a+b+1)]$
Binomial *(n,c)* Chance of Success, *c* Number of tries, *n*		$\mu = nc$ $\sigma^2 = nc(1-c)$
Pert *(a,c,b)* *(a variant of the Beta)* Minimum, *a* Most Likely, *c* Maximum, *b*		$\mu = (a+4c+b)/6$ $\sigma^2 = (\mu-a)(b-\mu)/7$

Figure 7 Commonly used probability distributions and their corresponding properties, in the oil and gas industry (Bratvold and Begg, 2010).

2.1.3 Practical use of Cumulative Probability Distributions

There are two approaches of constructing a cumulative density function, CDF, depending on if the cumulative probability is given in terms of $P(X \le a)$, which gives the probability for an uncertain outcome X to be less than or equal to a specific value, or by plotting 1- $P(X \le a)$. The first approach describes the probability of an uncertain outcome to be less than or equal to a specific value. This can be described as “at most” probabilities, the cumulative distribution starts at zero and sums up to one. Figure 8 illustrate this approach. The second approach, describes the probability of an uncertain outcome that is greater than a specific value, it yields the “at least” probabilities. This CDF will start at one and decrease to zero al illustrated in Figure 9. The second approach can be described as a more optimistic way of presenting the probability of outcomes, as it is presenting “at least” probabilities instead of “at most”. This can have a certain psychological effect, and may the reason why it widely used in the oil and gas industry.

Certain probability percentiles are commonly referred to when describing parameter distributions or computed values such as volumes and reserves. Probability percentiles are often used to provide estimates that are described to be pessimistic, optimistic or most likely. P_{50} represents the most likely outcome, based on the probability of the value of occurring. P_{10} and P_{90} represents the 10 % and 90 % percentiles which are defined depending on the CDF approach used.

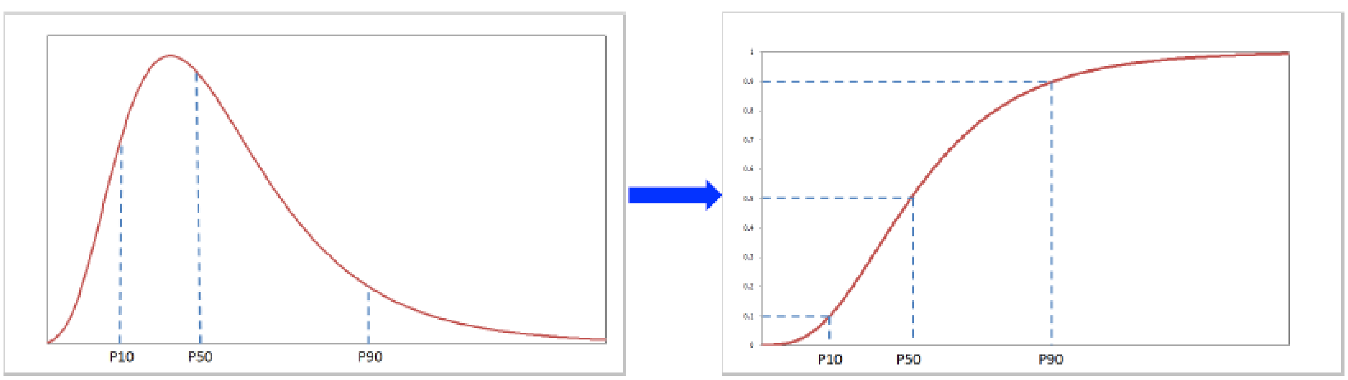


Figure 8 The CDF represents the probability of getting a value or less, and correspondingly “at most” percentiles (Bratvold, 2014).

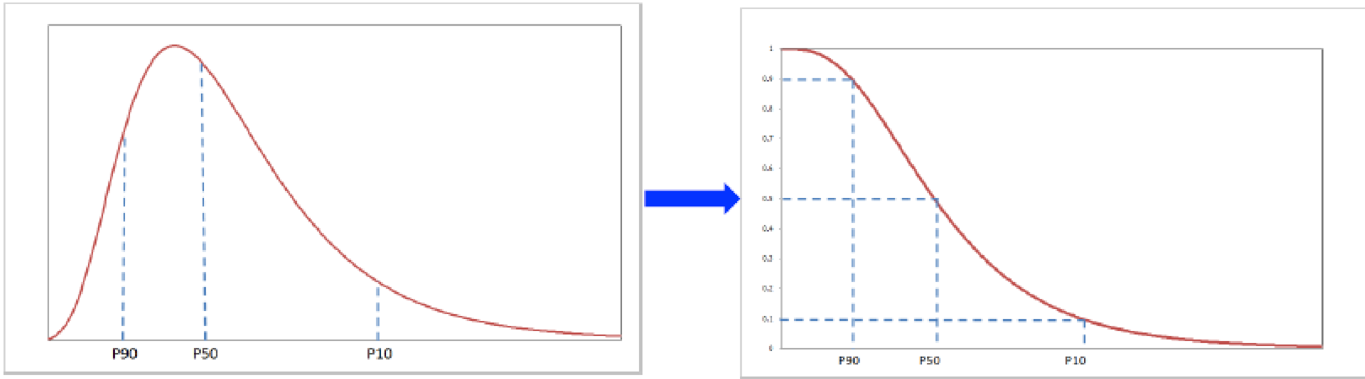


Figure 9 The CDF represents the probability of getting a certain value greater than, and correspondingly "at least" percentiles (Bratvold, 2014).

2.2 Uncertainties in Reservoir Parameters

2.2.1 Key Uncertainties in Reservoir Parameters

Ma (2011) states that there is no uncertainty in a reservoir, it is the limited data to describe the reservoir that leads to uncertainty, hence uncertainty only exists in our understanding and description of it. This means that there is only one way the real reservoir is composed, consequently uncertainty in description of the reservoir may be seen as lack of knowledge about it. A reservoir was once geologically deposited, during the burial process multiple forces acted upon it and caused mechanical and chemical changes to the geological formation. The deposition environment and the natural changes to the formation in the subsurface are the main reasons why a reservoir deposit is quite complex. Limited data, interpretations of the measurements, upscaling and inaccuracy in the measurements leads to uncertainty in reservoir description. The complexity in a reservoir leads to variation of several parameters throughout the reservoir. It can be a challenge to measure this variation correctly, and local measurements may not capture the real variations. The normal procedure of gathering information about the parameters in addition to the uncertainty in the data measurements will be presented in brief detail in this section.

The structural trap and the fluid contacts, which define the boundaries of the reservoir, make up the structural framework of a reservoir. The structural framework includes faults and surfaces which can be detected by seismic data- and interpretations. In recent years, recently developed seismic surveys can provide data about rock types and give porosity estimates. Though, there are several uncertainties linked to seismic, Ringrose and Bentley (2015) states several incidents where possible faults within and around the structural framework that are difficult to detect and may lead to the wrong assumptions from trusting the seismic.

- Faults tend to be missing in areas of poor seismic quality.
- Seismic noise makes it difficult to identify fault intersections.
- Faults may be interpreted on seismic noise.
- Horizon interpretations may be extended down fault planes.

Within the structural framework different lithologies and facies will lead to internal layering and differences. Identification of the reservoir deposit environment may lead to a better understanding of the stratigraphic trends. Though, it is necessary to go through with multiple measurements to get as much information as possible from different sources about the reservoir parameters. Rock and fluid parameters can be found by either direct or indirect measurements. *Direct measurements* are typically laboratory measurements using core samples from the reservoir. *Indirect measurements* can be petrophysical logs, well testing and seismic mapping. The area the measurements cover varies from very small areas for cores to larger areas from seismic. Core samples, logs and well tests provides information of the parameters near the measurement pint the reservoir. This means that the properties such as stratigraphy, lithology, facies, net-to-gross, porosity, permeability and PVT properties can be determined at certain points in the reservoir, namely where wells are drilled. Elsewhere, one will have to predict the trends by interpolate interpretations from seismic and well data information. To get a full reservoir description the parameters will have to be up-scaled. *Upscaling* of a parameter refers to applying the results from fine scale observations or measurements to a larger scale. Upscaling may be the biggest uncertainty concern in the reservoir description, as parameter values are assigned to unexplored areas.

Core analysis will usually give accurate descriptions of fluid and rock parameters, as they are part of the reservoir. The fluid properties are commonly found in laboratory experiments. Many methods are developed and used to get an accurate description of the fluid properties. There will still be some inaccuracy in the laboratory experiments that leads to uncertainty in the estimates. With regard to uncertainties in the fluid properties, it is important to notice that the *Lee-Gonzales gas viscosity correlation* which, according to Whitson and Brulé (2000), is used by most PVT laboratories when reporting gas viscosities, can lead to an error up to 20 % for rich gas condensates. The largest concern about core analysis, typically concerning rock parameters, is that the measurement of the parameters are very locally and any upscaling of these values introduces a great deal of uncertainty (Skogen, 2014). Core samples does not yield any information about the surrounding rocks. Nevertheless, core analysis can be used to calibrate petrophysical logs.

Petrophysical log data acquire typically parameters such as; porosity, water saturation, permeability, fluids contacts, N/G and mineral content (e.g. clay content). The well logging tools detect response signals from their measurements, e.g. gamma ray, sonic, resistivity, neutron, density and image logs to mention a few well known log measurements. New and better measurement tools constantly evolve with technology. When investigating uncertainties, one important factor is that the reservoir parameters of interest are not measured directly by well-logging tools. The parameters have to be derived through processes, including data-, processing, interpretation, and calibration. This is done to reduce any systematic errors caused by borehole effects, tool interference, resolution differences, depth shifts and other acquisition interferences, in addition to perform a consistent analyze between wells. Each of these steps involves uncertainties which lead to the resultant petrophysical data will have uncertainty and limitations in the data accuracy (Moore et al., 2011). As already stated parameters will vary throughout the reservoir, hence measurements will give a spatial variance of the measured values. The log data measurements are limited to relatively small parts of the reservoir, even though the measurements capture the variation within wells they may not capture other variations in the measured properties throughout the reservoir. Identification of the good reservoir rock areas, and the clay or shaley parts of the reservoir is important as it affects the net-to-gross value. This property will typically have a high uncertainty in early field developments (Ma, 2011).

A well test can provide estimates about the product of the permeability and the thickness of the reservoir. A well test will get the response from a larger volume of the reservoir than the other well data.

In the subsurface, many parameters vary throughout the reservoir as discussed. Petrophysical logs and core samples from the reservoir will give local variations in the parameters, and may detect different lithologies and facies, it is therefore common to create histograms which shows the *variability* in the detected data for a certain area or facies. The histograms shows the variation in the specific properties as the reservoir has natural variety, there is no probability involved. Nevertheless when several measurements are made, and variation is plotted the different data measurements should be used in combination with other available information, interpretations and knowledge to assess an appropriate probability distribution of the parameters in a given region. It is important to take into account the uncertainty of the upscaling of the parameters as the real trends throughout the reservoir may not be captured by a few wells.

2.2.2 Combining Reservoir Parameters and Probability Distributions

As this section will discuss further, and Ma (2011) writes: *Uncertainties will always exist in reservoir characterization, and probabilistic methods provide viable tools for uncertainty analysis and quantification*. A probability distribution should give a complete picture of an unknown event as it describes the outline for the possible outcomes. Probability distributions are used capture and communicate the uncertainty in the parameters, where the most frequent or probable outcomes yields a higher probability density relative to the other possible outcomes. The probability distributions for a particular parameter or function of them will take certain forms related based on what is found to be the appropriate probability distribution for the parameter uncertainty. It is important to capture all possible outcomes for the parameters with respect to the information already available and represent it in the probability distribution. When more information about the reservoir is collected and taken into consideration in the uncertainty assessment, the number of possible outcomes should decrease, hence the prior probability density function will be transformed to a posterior probability density function.

The resulting probability distribution for combined uncertain parameters (e.g. the function that describes pore volume), will take a particular form based on the relationship between the uncertainties in the applicable parameters. When the uncertain parameters are added, the resulting distribution often tends to be a normal distribution, likewise, when the uncertain parameters are multiplied the resulting curve it tends to be log-normally distributed (Bratvold and Begg, 2010).

McVay and Dossary (2014) discuss if a "true" probability distribution exists. They find that an appropriate way of defining a "true" probability distribution as *the resulting distribution, from unlimited resources applied to existing data*. However, the "true" probability distribution may not be the same for different companies or individuals. As discussed by several authors, uncertainty is personal, and is a result of different knowledge, expertise, and assessment processes (Bratvold and Begg, 2010). Hence, different companies can have different "true" distributions. Common for the "true" distributions is that they should be perfectly calibrated. This means that for similar evaluation cases the frequency of realized outcomes should correspond with the assigned probability for those outcomes. This implies that an outcome with P50 should happen 50 % of the time and similar with the other assigned probabilities (McVay and Dossary, 2014).

It can be important to understand what the probability distribution of the parameters will be used to in further analysis, and how any wrong assessments may affect the results. One way to investigate this is to do sensitivity analysis to find which parameters that have the largest impact on the resulting distribution. Sensitivity analysis can indicate how sensitive the results are with respect to small changes in the input parameters.

2.3 Creating Value from Uncertainty

2.3.1 Approaches to Uncertainty

The ability to handle reservoir uncertainty is a very important factor which will, to a large extent, determine the economic feasibility of a field development. All measurements and information gathered from a reservoir is the foundation in any field development and management project. The goal is that the development and management is optimal for the particular field in the most economically feasible way. Before making a decision concerning the field development, a better understanding of the uncertainty may lead to a change in the decision one would otherwise do. Bratvold and Begg (2010) consider this the main reason to assess uncertainty, and further that any decision should be changed in such a way that it creates value to the project.

In field development and operations the early investment phases contains a higher level of uncertainty. Figure 10 illustrates how uncertainty decreases as a function of decisions that are taken in a field development project during different investment phases. The exploration phase contains the highest level of uncertainty as seismic is often the only data available at this time. By collecting information from further sources such as; appraisal drilling, logging, well testing, reservoir simulation studies, price studies and so on, the information will reduce the uncertainty to acceptable levels for field development evaluations (Simpson et al., 2000). After the field development phase, most of the decisions with high uncertainty in the outcomes are made, however there are still multiple uncertainties related to the future reservoir behavior and production.

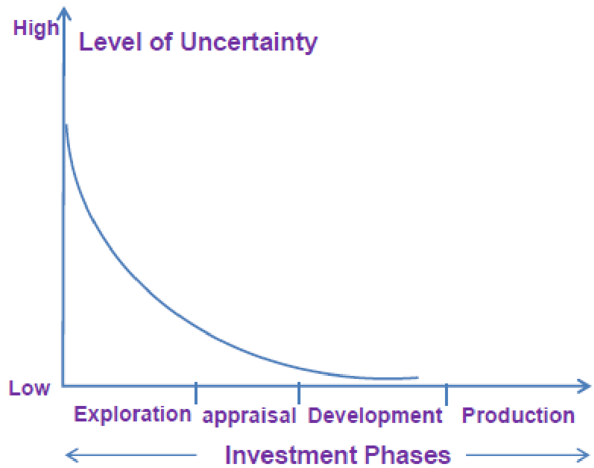


Figure 10 Level of uncertainty related to decision making development during the investment phases (Behrenbruch, 2014).

There are several ways to approach uncertainty in projects where decisions need to be taken. The following are common approaches:

1. Ignore uncertainty.
2. Reduce uncertainty by gathering information.
3. Develop a flexible response to uncertainty.

The first attitude, to ignore uncertainty, is historically common in the petroleum industry. Also in reservoir modelling, it is often the case that reservoir modelling is used to hide uncertainty rather than illustrate it (Ringrose and Bentley, 2015). This approach will in the long run result in that projects are making less value than possible (Bratvold and Begg, 2010).

The second approach, which is to reduce uncertainty by gathering information, may lead to decisions are made with better chances for a good outcome. There are multiple ways of reducing uncertainty by gathering information, some of them are listed below.

- Logging surveys
- Appraisal drilling
- Core samples
- Seismic study
- Well test analyses
- Reservoir simulation studies (e.g. history matching)

- Analyze trends in similar fields
- Implement new technology to “old” fields

The goal of doing these analyses and tests is to reduce the economic risk in a development, but to go through with the analyses and tests are costly. To quantify uncertainty should not be an end to itself, as reducing uncertainty is not the final objective. The goal should be to make a good decision in form of evaluating a development (Bickel and Bratvold, 2007). The handling and understanding of the uncertainties proves to be important to make better decisions related to field development and operations (Ma, 2011), (Bratvold and Begg, 2010). To decide if the information gathering is worth its cost a method called Value-of-Information, VoI, can be applied. It is a consistent and auditable criterion in decision making (Demirmen, 2001).

The third approach, which is to develop a flexible response to uncertainty, can be used to reduce any negative aspect such as the risk or “down sides” of uncertainty. On the other hand, it can also give room for positive outcomes of uncertainty by capture an upside. The flexibility of a field can be in form of the following:

- Prepare room for extra injection wells in a case where the field needs extra pressure support.
- Make room for extra production wells in case the reserves are higher than expected or a well becomes damaged.
- Arrange facilities suited for higher production rates.
- Use equipment with possibilities for modifications to meet changes in the production, which gives room for flexibility.

The flexibility is designed to reduce risk or to capture an opportunity. To determine if the flexibility is worth its cost, one can carry out an analysis called Value-of-Flexibility, VoF.

2.3.2 VoI and VoF

VoI and VoF analyses are useful evaluations that finds if reducing uncertainty, respond to uncertainty or a combination of these gives the highest value to a project.

VoI will give an answer to if the cost of gathering information will be worth the potential reduction in the uncertainty. The procedure to calculate VoI is to look at the scenarios of a project with or without the extra information.

First, one need to find the expected value of the project, a “base case”, EV_1. Then one can find the expected value of the project with any specific additional information, EV_2. By subtracting EV_1 from EV_2 the value of information can be found.

$$VOI = EV_2 - EV_1 \tag{18}$$

The decision criterion says that if VoI has a higher value than the cost of the gathering of information, the action to get the additional information should be carried out. For a case where the additional information is useful in multiple decision evaluations, EV_2 should then be the sum of the expected values for each of the decisions it influences. Sometimes it may be difficult to predict the expected value for a project, especially with additional information taken into consideration. Therefore the following framework is a quick evaluation can be used to decide if a VoI analysis is worth performing. By collecting any new information and the decision determination remains the same as without the information, the new information has zero expected value, hence a VoI of zero, which is the lower bound. On the other extreme, is a case where the gathered information is 100 % reliable, and once collecting the information the outcome of the decision will be clear. Thus, once knowing the outcome, it is possible to choose the optimal decision with confidence. Information that is 100 % reliable is called perfect information, and in decision making it can be very useful to compute the *expected value of perfect information*, EVPI. EVPI represents the highest price any decision maker should be willing to pay for any information to reduce the outcomes of an uncertain event (Bratvold and Begg, 2010). If the cost of any information gathering exceeds the EVPI value, it is no point in to investigate the proposal further as the EVPI represents the value of perfect information.

VoI analysis does not take into account the potential value of using flexibility to manage the uncertainty. As mentioned flexibility may reduce risk or capture opportunities, and it can be interesting to evaluate VoF to find if the benefit of flexibility is superior to its cost. Begg et al. (2002) have found several circumstances where flexibility may be beneficial:

- When it is impossible to reduce uncertainty.
- When it is cheaper than collecting information.
- When managing residual uncertainty, after already collected information.
- When flexibility will create additional value.

VoF increases with higher uncertainty and greater capability to respond to it. VoF will in general be well suited for events that are unlikely to happen but will have a high consequence when occurring. It is important to note that by adding flexibility to the field development it builds an opportunity to create value. VoF gives room for creative thinking by investigating the possibilities where the goal is to find a solution which will maximize the value.

When making decisions based on the expected value it is important to understand that the EV is used as an indication of the best opportunities for the project. For any single investment case, it is unlikely that the EV will be the actual outcome value. However, a consistent use of EV as a decision criterion has showed to be the most profitable (Bratvold and Begg, 2010). It might be that the extra cost for acquiring information or installing flexibility will not pay off for a project, even though it is the best choice in the long run from a company's standpoint. To handle the uncertainty in the best possible way, it is necessary to reduce the uncertainty to the extent it makes economic sense, and then plan for remaining consequences or risk by creating a flexible framework.

2.3.3 Relevant Approach: Reduce Uncertainty by History Matching

As described in Chapter 1, the goal of the thesis is to reduce uncertainty in a specific field by going through with a history match study. The next chapter will introduce and discuss history matching. The last decades a large amount of work and time have been spent on history match studies. At the time of study, a quick search on *onepetro* searching for "History" AND "Matching" returns 11 317 results. On *google scholar* the search word "History Matching" returns 14 900 results. Figure 11 indicates a growing interest in research about history matching through the last decade.

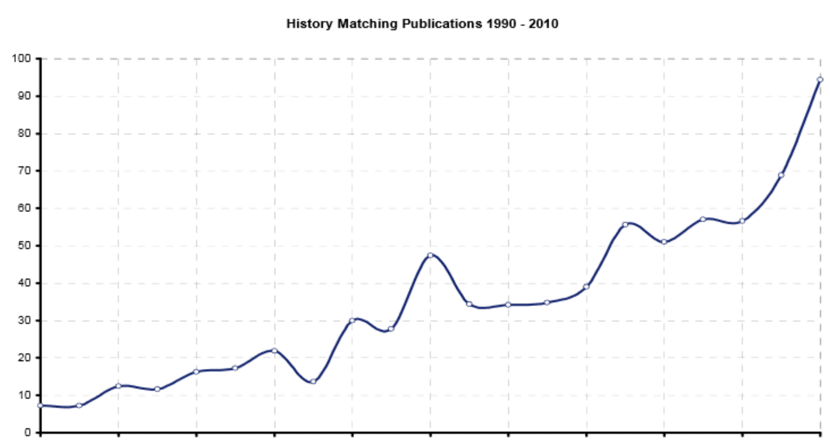


Figure 11 The approximately amount of papers published on history matching between 1990 and 2010 (Rwechungura et al., 2011).

From discussions earlier in this chapter, one can imply that the history match itself is of no value unless the information from the study can be used in a decision context. Such a decision can be related to: the drilling of extra wells (producers or injectors), well locations, and other field or recovery decisions. By performing a history match in a situation where decisions are not existent or planned, the only advantage is to reduce the uncertainty in the volume estimates and predictions. This action by itself does not add any value as the project profitability will stay the same as the hydrocarbon volumes does not (physically) change with assigned probabilities. However it might be desirable to go through with the history match study, as uncertainty reduction might add flexibility for the company and shareholders, where accurate predictions of reserves is necessary in order to support other projects (Reitan, 2012).

The increased accuracy of the model (a result of history matching, see chapter 3) comes with the price of going through with the history match and the cost of gaining the information. In a history match study the expenses will be the cost be from gaining the data measurements, the time invested in the history match study and the software and licenses that are used. By improving the history matching process, the cost of the study will decrease. Assisted history matching (further discussed in Section 3.3) is a step in this direction.

The reliability of the new information is an important factor to consider. As the next chapter will discuss, history matching is a complex inverse problem, with a non-unique solution. Measurements done in the subsurface, and the mathematically model that describes the reservoir is with few exceptions imperfect representations of the real world. However, this does not mean that imperfect information is not as useful as perfect information as the VoI is only dependent on a change in decision.

3 HISTORY MATCHING: APPLICATION OF MCMC

Reservoir simulation is important as it gives an indication of how the dynamic behavior will evolve during a fields' lifetime. Good predictions of future dynamic behavior will help to optimize the development and management of a field in terms of profitability and recovery. It is difficult to know all static and dynamic properties of the reservoir, hence a perfect reservoir model is close to impossible to create. To improve the model and to generate reliable predictions of the future production, "History Matching" (HM) is fundamental, as it is used to calibrate the reservoir model to match historical data. This chapter will discuss the history matching process and uncertainty reduction. After going through the basics the history matching process, the Bayesian framework is presented. The Bayesian framework is a statistically formulation which through an objective function can combine the predefined uncertain parameters in the reservoir model (prior uncertainty), with the new information in form of historical data, to get an updated uncertainty picture (posterior uncertainty). The application of the Bayesian framework require an optimization algorithm to be able to update the uncertainty picture. The optimizing algorithm Markov Chain Monte Carlo (MCMC) is presented and discussed as it will be used in further application. Finally, the chapter gives an overview of the possible errors induced in a history match study.

3.1 History Matching in General

History matching is defined as the act of adjusting a reservoir model until it closely reproduces the past behavior of the physical reservoir (SchlumbergerGlossary, 2015). Once a field starts to produce, new data that describes the past reservoir behavior is available in form of; observed production rates, measured gas-oil-ratio (GOR) and pressures among others. The measured field data is taken into consideration trough a history match study. A history match is mainly carried out to be able to obtain reliable predictions of future reservoir behavior, this is done by improve the geological- and reservoir models. In general, the aim of history matching is to match observed data with calculated data from the model (Dadashpour, 2009). By doing this the reservoir model is conditioned to match the historical data. History matching is an important factor that can act as a decision basis for further development and management of petroleum reservoirs.

3.2 Inverse Modeling

A mathematical model is constructed in the modelling of static and dynamic parameters to represent a reservoir system. *Static* parameters are defined as parameters that are not related to the fluid flow and movement, which typically represents parameters related to geology, geophysics and petrophysics. *Dynamic* parameters include parameters related to fluid flow, movement and transmissibility. Mathematical models are based on fundamental physical laws in order to predict the behavior of a physical system with a sensible accuracy (Dadashpour, 2009). Dynamic reservoir behavior can be very complex as it consists of different physical effects. The more detailed the mathematical model is, the slower will a computer be able to calculate the solutions. The mathematical model required in this thesis is a reservoir simulator which describes the fluid flow and dynamic behavior in the reservoir. A reservoir simulator is a computer program which use numerical solution techniques to solve reservoir flow problems. In the model the number of grid cells will to a large extent determine the amount of calculations required. The simulator is based on relevant physical laws that are combined to a system of differential equations and matrices, typical physical laws that are combined are the following (Dadashpour, 2009) :

- Mass conservation law
- Darcy's law
- Equation of state
- The capillary pressure and relative permeability relationships

The model may be used in forward modeling or inverse modeling. To illustrate this let F represent the mathematical equations, and a set of known model parameters denoted as *m*. Further, let OBS describes the observed data. Then the following equation can describe the forward problem:

$$F(m) = OBS \tag{19}$$

The predicted observable data is found by running a numerical reservoir simulator that calculate a solution by numerical approximation by a set of partial differential equations (Mohsen, 2011). By changing the model input parameters in the parameter set *m*, different solutions will be found. The numerical simulator for a forward problem can also be used as a "process investigator" in an inverse problem, where the observable data are known, and the reservoir parameter values are of interest. History matching may be used to investigate and give better estimates of uncertain parameters in a reservoir model by solving an inverse problem. An inverse problem exists when the dependent variable is the best known aspect of a system and the independent variable must be determined (Dadashpour, 2009). In an inverse problem such as history matching, the observed data in form of production rates, pressures etc. are known, and the static and dynamic parameters in the reservoir system are varied. The procedure of solving the inverse problem is to start with initial guesses of the parameters and after a certain amount of iterations the best fit between the observed and calculated data are obtained.

Note that the forward model has a unique solution for a given set of parameters. The inverse problem has a non-unique solution as the inverse problem may have several different combinations of the parameter values that give the same solution. Figure 12 illustrates the process of forward modeling and inverse modeling.

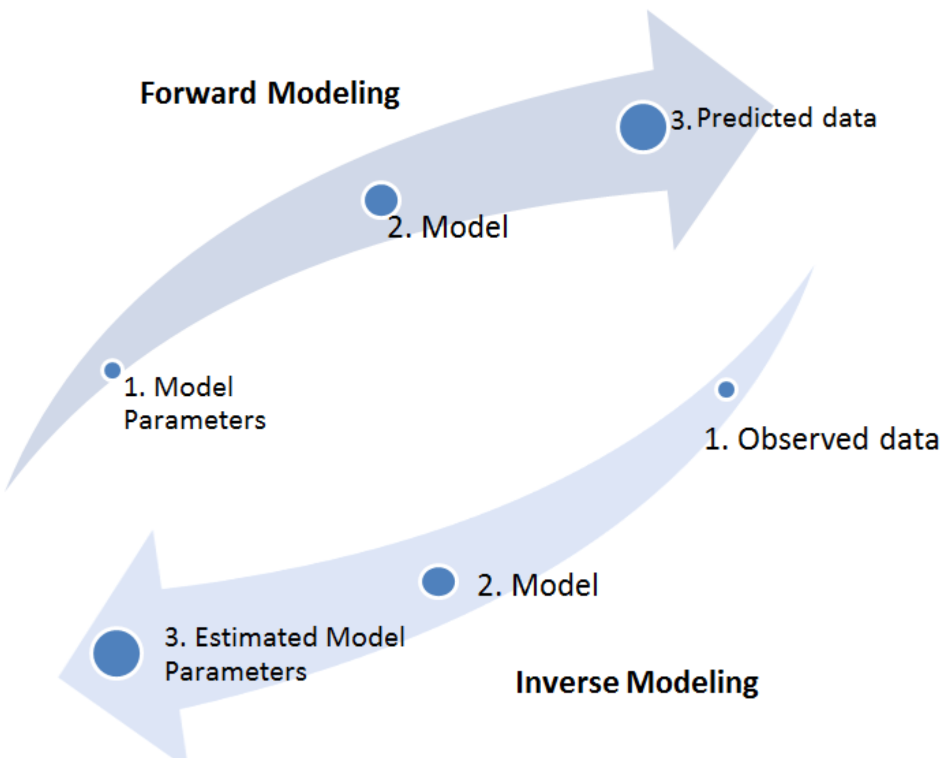


Figure 12 Process of Forward Modeling and Inverse modeling.

3.3 Manually and Assisted History Matching

History matching can be performed “manually” or “assisted”. The latter is a method which is more used in the later years, and will be performed in this thesis.

Manual history matching is also called traditional history matching and considers a deterministic reservoir model. Manual history matching is basically an update of the model by manually varying different reservoir parameters, such as; permeability, porosity, fluid contacts and so on. One or a few parameters are changed at a time to keep track of which parameters are influencing the calculated results. By trial and error parameters are changed in order to improve the match between the observed data and the model results. The goal is to find which parameters that have the largest influence on the match, and to find the parameter values that give an acceptable match. A simple sensitivity analysis of chosen parameters is often the objective with a manual history match. The manual history match is commonly updated in two steps, one pressure match and one saturation match (Rwechungura et al., 2011). As described, a history match is an inverse problem which are non-unique due to the fact that multiple solutions can be found. The quality of a manual history match will to a large extent depend on the engineers’ that are performing the history match, earlier experience, knowledge of the field, and the time dedicated to the study. For a field associated with many uncertainties there are a great flexibility to which parameters to update, for such a case manual history matching is not an optimal technique. On the basis of the above descriptions manual history matching is in general associated with many uncertainties and is today typically used as a guide or a starting point for an assisted history match (Mohsen, 2011).

Assisted history matching (AHM), sometimes referred to as automatic history matching, is used to make multiple of the manual tasks done automatically, in order to make the procedure of history matching less time consuming. The most important tasks that are automated are; the simulation runs, the comparison of observed data to the simulated data, modifications to the model based on the matching results and the basis establishment for future predictions. In assisted history matching it is necessary to apply optimization algorithms to mathematically describe and iteratively minimize the mismatch between the observed data and the simulated data. The updating procedure is done by updating predefined uncertain parameters in the reservoir model. The amount of deviation, or mismatch, between the observed data and the simulated data is represented by the objective function (further discussed in the next section). The uncertainty in the parameters to be changed in a reservoir model is often defined by the user in form of probability density functions, in addition correlation between parameters may be added. It is important to recognize that the subjectivity from the user plays a major role in defining the parameter uncertainties. In an assisted history matching problem it is important that the following are properly defined:

- A reservoir model (forward model) which describe the physics of the system in the best possible way from available information.
- An objective function which represents the mismatch between observed and calculated data.
- An optimization algorithm which provides the values of the uncertain parameters that minimizes the objective function, hence gives the best representation of the physical system when taking observed data into consideration.

To solve the inverse problem by assisted history matching, the following algorithm can be applied (Dadashpour, 2009) :

1. Make an initial guess of the uncertain parameters, based on available information.
2. Simulate the model response.
3. Calculate the objective function.
4. Parameters are updated by minimizing of the objective function (by the use of an algorithm).
5. If the mismatch expressed by the objective function is not sufficient or correct return to step 2.

Assisted history matching speed up the history matching process, and gives much quicker convergence to minimal mismatch between the model performance and the observed data than by performing manual history matching. In addition will the study from an assisted history match provide room for uncertainty analysis, which is not captured by manually history matching.

3.4 The Objective Function

The objective function is defined as the amount of discrepancy, or mismatch, between the observed data and the simulated response from the reservoir model for a given set of parameters. One may say that the objective function evaluates how well a model reproduces the observed data from a field. The least square formula, the weighted least square formula and the generalized least square formula are well known methods used for calculating the objective function.

Last-Square formula:

$$F\ (m) = (d_{obs} - d_{cal}(m))^T\ (d_{obs} - d_{cal}(m)) \qquad (20)$$

Weighted Last-Square Formula:

$$F(m) = (d_{obs} - d_{cal}(m))^T\ w(d_{obs} - d_{cal(m)}) \qquad (21)$$

Generalized Last-Square Formula:

$$\begin{aligned} F(m) = \frac{1}{2}(1-\beta)\{(d_{obs} - d_{cal}(m))^T C_d^{-1}\ (d_{obs} - d_{cal}(m))\} \\ + \frac{1}{2}\beta\{(m - m_{prior})^T C_m^{-1}\ (m - m_{prior})\} \end{aligned} \qquad (22)$$

Where d_{obs} represents the observed data, $d_{cal}(m)$ represents the calculated data predicted by the forward model. m represents a set of model parameters e.g. m = (k, phi, N/G, Sg,….). w is a diagonal matrix which contains individual weighting coefficients for each measurement. The weighting is assigned on the basis of number of data points in a set and the degree of uncertainty associated with the individual measurement. In the Generalized Last-Square Formula covariance as regularization is included. The first term represents the data mismatch (the discrepancy between the calculated and the observed data) weighted by the inverse of the covariance of noise in the data C_d^{-1}. The second term represents the model mismatch deviation from the prior model parameters, where the deviation is measured by the covariance of the model parameters, C_m. β is a weighting factor that represents the degree of belief in the initial model.

When correlation effects between measurements data are not considered, as in the case when they are assumed to be independent, the covariance matrix C_i reduces to a diagonal matrix which include the variance of the measurement errors, σ^2. The Objective function is then simplified and can be written as:

$$F(m) = \sum_i \frac{w_i}{N_i} \sum_j^{N_i} w_i^j\ (\frac{d_{cal}^j(m) - d_{obs}^j}{\sigma_i})^2 \qquad (23)$$

Where weight w_i can be used to favor certain wells or datatypes and w_i^j can be used to emphasize data in specific intervals. i represents an objective element, i.e. production and pressure data for specific wells. j references a specific measurement time step, where an observed value exists. N_i represents the number of objective elements, and N_i represents number of measurement times in each response parameter. The minimization of the objective function is often defined as the sum of squared errors between observed values and calculated results.

3.5 OPTIMIZATION METHODS

Optimization can be formulated as the act, or methodology, of finding the maximum or minimum of a function iteratively. In assisted history matching the aim of an optimization algorithm is to minimize the objective function. This is done by iteratively changing the model parameter set till an optimum solution is found, namely the minimization of the objective function, this can be expressed by the following expression:

$$F^{Optimum} = Min(F(k, \varphi, GWC, Sg \dots)) \tag{24}$$

There are multiple different algorithms and methods for optimization (or minimization). The optimization can either be applied with a deterministic or stochastic approach. A deterministic approach require calculations of Jacobian or Hessian gradient matrices to find a solution. While stochastic approaches does not require the use of gradients. Generally, the algorithms are classified as gradient based methods and non-gradient based methods, depending on whether the methods use the gradient of an objective function in the optimization process. The gradient of the objective function can be defined as:

$$\nabla F = \left(\frac{\partial F}{\partial \vec{\alpha}}\right)^T \tag{25}$$

The most common gradient based algorithms that are the following; The steepest descent, Gauss-Newton, Lovenberg-Marquardt, Singular Value Decomposition, and Conjugate Gradient. In practice, the algorithms are run until $||F|| < \varepsilon$, where ε is a small positive number which represents the acceptable mismatch error (Dadashpour, 2009). There are some disadvantages by using gradient-based methods:

- There is a possibility of converging to a local minimum in the objective function. (While it is desirable to converge to the global minimum).
- The algorithm provide a single solution, even though multiple solutions are possible. Hence the methods will not present a basis for estimating parameter uncertainties.
- The gradient calculation requires long computing time.
- If it is noise in the observed data measurements it needs to be filtered out.
- Functions to be minimized can be difficult or impossible to differentiate.

Non-gradient methods are the alternative to gradient-based, they do not require information about the gradient (hence the name). They are relatively simple to implement. Non-gradient based methods can be divided into different categories: Direct Search-Methods, Proxy-Based Methods and Ensemble-Based Methods.

Direct Search Methods are iteration based and consist of Search-and-Test-Algorithms which of some have local- and some have global search properties. Common Direct Search Methods are: Evolutionary Algorithms, Genetic Algorithm, Hooke-Jeeves, General Pattern Search and Mesh Adaptive Direct Search.

Proxy-Based Methods generates proxy models that substitutes any response derived from a full field simulator. It is a function which replicates the simulation model output for selected input parameters (Azad and Chalaturnyk, 2013). In a proxy model, the most common underlying algorithms are kriging, polynomial interpolation or regression. There are challenges related to the creating of high quality proxy models as they are related to the quality of the input data set. In addition it is time consuming to create the proxies. With increasing complexity and numbers of uncertain parameters the proxy methodology is not recommended (Azad and Chalaturnyk, 2013).

The propagation of uncertainties from history to prediction is commonly investigated by the use of ensemble-based approaches or a combination between ensemble-based and proxy-based approaches. This is done by generating posterior distributions of the reservoir uncertainties as a basis for estimating prediction forecasts (Schulze-Riegert et al., 2013). Known Ensemble Based Methods are Markov chain Monte Carlo (MCMC) and Ensemble Kalman filter (EnKF). EnKF is a technique which is based on both the original Kalman Filter and sequential Monte Carlo method. An ensemble of realizations is employed to represent multiple models, the technique assimilates the observed data and update the models simultaneously, in each update the mean and variance is reported. The mean represents the most probable model and the variance is a measure of the uncertainty. EnKF generates multiple history matched models and allows the user to characterize the uncertainty in reservoir description and future performance (Emerick and Reynolds, 2010). The theoretical formulation of the EnKF includes assumptions of system linearity and that the uncertainties can be described by the use of Gaussian probability distributions. On the basis of this, the use of standard EnKF to reservoir models can give poor characterization of the uncertainty. Nevertheless, multiple algorithms are based on the standard EnKF and are much used in history matching. As the MCMC method will be used further in the case study, the Bayesian framework and the MCMC method will be described more in detail in the following section.

3.6 Markov Chain Monte Carlo in a Bayesian Framework

MCMC is in general Monte Carlo integration using Markov chains. The MCMC method is based on random walk and will produce a sequence of models from the model space through a Bayesian update. The *Markov chain* characteristic is that when generating a new model, it is conditional on the previous model, and *only* this. The basics when using MCMC in history matching is to begin with a reservoir model which have prior defined distributions for the uncertain parameters. During the MCMC optimization the uncertainty is continuously updated, and will in the end yield the stationary posterior distributions that describe the updated uncertainty, and can further be used to calculate the predictions.

3.6.1 Bayesian Formulation

Bayesian framework is a statistically formulation which involve statistical methods that assign prior probabilities to parameters (or events) based on best guesses from limited information, before collecting new information, and by applying Bayes' theorem[1], revise the prior probabilities to obtain posterior probabilities.

The Bayesian formulation defines the relationship between the prior probability, the posterior probability and the likelihood. The posterior probabilities of the different parameters can be

[1] Bayes' theorem is named after Thomas Bayes (1702-1761), who was an English minister and mathematician. An early attempt to establish what today is referred to as Bayes theorem was done in his work "Essay Toward Solving a Problem in the Doctrine of Chance". BRATVOLD, R. B. & BEGG, S. 2010. *Making good decisions,* Richardson, TX, Society of Petroleum Engineers.

estimated after conditioning the prior data to the likelihood. Bayes' theorem is fundamental in Exploration and Production phase's uncertainty analysis and history matching as it can be used to capture prediction uncertainties, which is one of the main goals of history matching. In a history matching context the prior probabilities are updated by maximizing the likelihood (minimizing the objective function) in several sets of models constructed by combinations of prior parameters. The likelihood represents the probability of that the data in the model matches the observed data. In other words, it represents the degree of match between the observed behavior and the model behavior. Prior probability distributions, which represents the reservoir uncertainties should consist of all possible descriptions of the reservoir uncertainties from a geological perspective and based on available data. The prior probabilities will change with new data that becomes available when starting up production from a field (or further appraisal). The posterior probabilities which are gained from Bayes' theorem will lead to mitigation of the uncertainty in the parameter distributions and can be used to update the reservoir model which will lead to better understanding of the prediction uncertainties.

Bayes' theorem can be written as:

$$P(m, d_{obs}) = P\ (m|d_{obs})P(d_{obs}) = \ P\ (d_{obs}|m)P(m) \tag{26}$$

Dividing by $P(m)$ and rearranging, yields the following:

$$P\ (m|d_{obs}) = \frac{P\ (d_{obs}|m)\ P(d_{obs})}{P(m)} \tag{27}$$

In Bayesian probability theory and history matching the variable m represents the uncertain parameters, $P(m)$ represents the prior probability distribution of the uncertain parameters and d_{obs} represents the observed data. Further, the updated probability, $P\ (m|d_{obs})$, is termed the posterior probability, and $P\ (d_{obs}|m)$ represents the likelihood and describe the probability of making the observation, or matching the observed data. From Bayes' theorem the posterior probability is the updated probability found by considering the new information.

The mathematical description of a probability distribution for model parameters under the condition of measurement data is derived from Bayes' statistics (Schulze-Riegert et al., 2013). When the history matching problem is framed in a context where the model variables are represented by prior probability distributions, a likelihood function for the model variables given the prior data and the computation of posterior probability distributions and generating samples from the posterior PDF’s are of interest, Markov chain Monte Carlo methods are well suited for the problem (Oliver and Chen, 2011). The posterior probability left side in Equation 27 can be computed numerically by MCMC integration by combining the prior information with observed information, right side equation 27. The MCMC in a Bayesian framework is in general formulated in terms of probability distributions. Due to its Bayesian interpretations the objective functions defined in Section 3.4 are often used as objective functions in MCMC simulations. MCMC approach is as mentioned in Section 3.5 a known ensemble based optimization technique and will be further explained in the following sections.

3.6.2 Monte Carlo

When a deterministic model is turned into a probabilistic model it is in general referred to as a *stochastic* model. *Monte Carlo* Simulation is a stochastic technique, which is used to combine multiple uncertainties to calculate any expected outcomes. The method randomly picks samples from the for uncertain variables probability distributions, multiple times, and by forming sample averages the method approximates the expected output. More frequently samples are generated for the more probable variables. Predefined PDF’s for parameter uncertainties are used as inputs, the Monte Carlo model combines the input uncertainties to a calculated output, by and hence a distribution of possible outcomes for the output variable is generated. A concern about the use of Monte Carlo sampling is that the low probability areas, typically in the end of the distributions, may not be sufficient sampled if they are fairly flat. One solution to this can be to use stratified sampling, where the distribution is split in to a number of equal probability intervals. Each interval is then sampled randomly. One method that employs this is Latin Hypercube (LH) sampling, which commonly is used for screening and uncertainty quantification.

Latin Hypercube sampling consider the parameter distribution when picking parameter values for the parameter sets in the experiments. The parameter distribution is divided into equally large compartments, further will Latin Hypercube pick randomly from each interval and more probable parameter values are picked more frequently. The numbers of intervals to sample is divided into the same number as iterations required, and each interval is only used once. Figure 13 shows a typically Gaussian distribution for a parameter distribution (red curve) and the Latin Hypercube sampling of the parameter values form equally large compartments (blue).

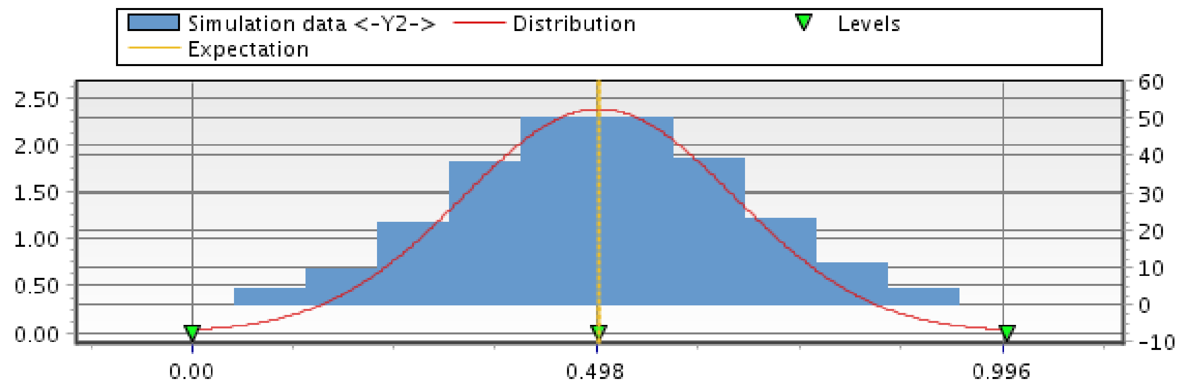


Figure 13 The Latin Hypercube sampling method applied to a typical Gaussian parameter distribution.

3.6.3 Markov Chain

Suppose a series of random variables: $\{X_{0,} X_{1,} X_{2,} \dots \dots X_{n,}\}$, that for each iteration (or time step), *n*, the next state, X_{n+1} has a conditional probability distribution which only is dependent on the current state of the chain X_n. Mathematically this can be expressed by the following:

$$P(X_{n+1} \mid X_n, X_{n-1}, \dots, X_{1,} X_{0,}) = P(X_{n+1} \mid X_n) \tag{28}$$

The expression in Equation 28 show that for a given state X_n the next state, X_{n+1} does not depend on the history of the chain, but only on the current step, this series or sequence is called a *Markov chain*. P(.|.) is called the *transition kernel* of the chain. Due to regularity conditions the chain will eventually "forget" its initial state $P(.\mid X_0)$, and will gradually converge to a unique stationary distribution that will not be dependent on time or the initial variable set (Gilks, 1996). A stationary distribution is a distribution that persists forever once it is reached. In a Markov chain it is possible to have several stationary distributions. A finite Markov chain does always have at least one stationary distribution (Zhang and Srinivasan, 2003).

3.6.4 The Metropolis-Hastings Sampler

Markov chain Monte Carlo picks samples from the distributions by running a cleverly constructed Markov chain for a long time. For every iteration a criterion will decide whether to replace the current model with the proposed model. The criterion can be constructed several ways, nonetheless all of them are based on the general framework of Metropolis and Hastings, including Gibbs sampler (Geyer, 2011). The Metropolis-Hastings method evaluates the proposed models and then accept or reject them as the next model. The Metropolis-Hastings finds an "acceptance ratio" for the proposed parameter values to the current parameter set in the model, and then evaluates the probability of acceptance. The Metropolis-Hastings method has a notable property, which is that the proposal distribution q, is arbitrary (Geyer, 2011), and means that the distribution may be un-normalized. Say that the distribution (the desired probability distribution of the MCMC sampler) has an un-normalized density h. h is a positive constant times a probability density which represents the prior value times the likelihood for the specific state (Geyer, 2011). At each iteration step the next state *j* is proposed based on the current state *i*. The proposal probability matrix is denoted q (j | i) (Zhang and Srinivasan, 2003). Calculating the Hasting ratio, also called the acceptance ratio:

$$r(i,j) = \frac{h(j)q(i \mid j)}{h(i)q(j \mid i)} \tag{29}$$

A criterion is defined that decide if to accept or reject the proposed transition from state *i* to state *j (*Zhang and Srinivasan, 2003*)*. If the new step is accepted, the chain moves to state *j*. If it is rejected the chain remains in state *i*. The probability of acceptance is given by:

$$\alpha(i,j) = \min(1, r(i,j)) \tag{30}$$

The next iteration X_{n+1} equals *j*, with a probability of α and remains equal to *i* with a probability of 1- α. When having a calculated value for α, a random number from a uniform distribution from 0 to 1 is generated, noted as u. If u > α reject the proposed model, and continue with the current, if α > u, accept the proposed model and continue with this. By this constraint, a proposed model that gives a better fit to the observed data than the current model will always be accepted, hence the current model will be replaced. If the proposed model gives a worse fit to the observed data it is accepted with a probability which is proportional to the ratio, r (i, j) which basically represents the ratio of the likelihoods of the new and old models.

Gibbs sampler is a distinct case of Metropolis-Hastings, where the acceptance probability is 1, the iterations are always accepted. In order for Gibbs elementary to be useful, it must be combined with other updates (Geyer, 2011).

A fully review of the MCMC algorithm can be found in the book, *Markov chain Monte Carlo in practice* (Gilks, 1996).

3.6.5 Application of MCMC in MEPO

The software MEPO[2], which is further described in Section 5.1.1, is used in the execution of the case study in this thesis. In MEPO, the Ensemble Based Method, MCMC, is used in combination with integrated proxy building, where the proxies are used as support material. By the software the MCMC method may be applied in two modes: optimization for history matching and sampling for predictions. Both methods are applying MCMC in combination with proxy modelling. This section will cover the procedure of applying MCMC and the basic theory applied in the software.

Introducing Proxy Modeling

A proxy model attempts to mimic the reservoir simulation model, based on existing simulation data. Proxies act as a simulator model but are using simple equations, allowing a large number of simulations to run within a short time period (SPT Group, 2014). A proxy can be created by interpolation techniques that are used to transform the individual reservoir models into proxy models that contain information of all relationships from input parameters and output space (Zangl et al., 2006). A proxy model is typically built by the use of a proxy generation algorithm such as kriging, regression or other interpolation techniques. In an iterative refinement process, such as MCMC, optimal sets of simulation experiments for improved history matched cases are sampled and proxy models that represent key responses from the full field simulator can be generated. A good proxy model should represent the observed variations by using as little information as possible. Proxy models can be useful in multiple areas:

- They may be used as a response surface model to identify the most influential uncertainty parameters on chosen responses, viewed in Figure 14. By doing this they are able to calculate approximate responses from the reservoir model very quickly.
- A proxy can be used to optimize responses e.g. total production (Zangl et al., 2006).
- They can be used to cover the uncertainty spread in predictions from an approximation to the posterior distributions (Zangl et al., 2006).

Figure 14 illustrates a response surface model that approximates a number of data points as a function of three given uncertainty parameters.

[2] MEPO (Schlumberger), Multipurpose Environment for Parallel Optimization.

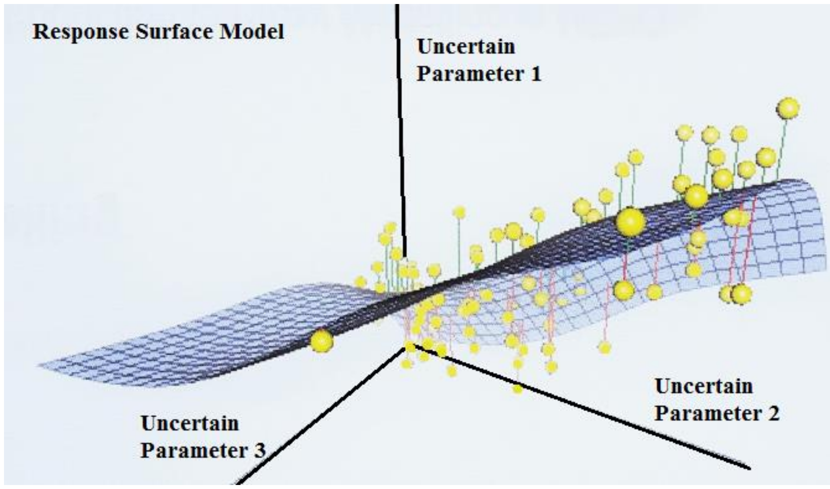


Figure 14 An example of a response surface model.

The History Matching Procedure

By doing an assisted history match study by the use of an MCMC approach a certain procedure need to be followed. Figure 15 shows the process included in an assisted history matching study. The steps in the procedure are the following:

1. Sampling from prior distribution.
2. Launching multiple realizations.
3. Calculating the model discrepancy to history data.
4. Generate posterior distributions.
5. Optimization method repeat the process to improve the history match.
6. Predictions are run.

As seen from Figure 15 the first step in the procedure, is to sample from the prior distributions, as mentioned these can have any probability distributions. Then multiple model realizations are calculated (by a proxy) before the accepted sample sets are used in full field simulations. In the third step, the model response from these experiments is compared to history data to evaluate the mismatch. Posterior distributions are updated (4) as the procedure is repeated (5). When stationary posterior distributions are generated, predictions can be run (6) by sampling from the posterior distributions.

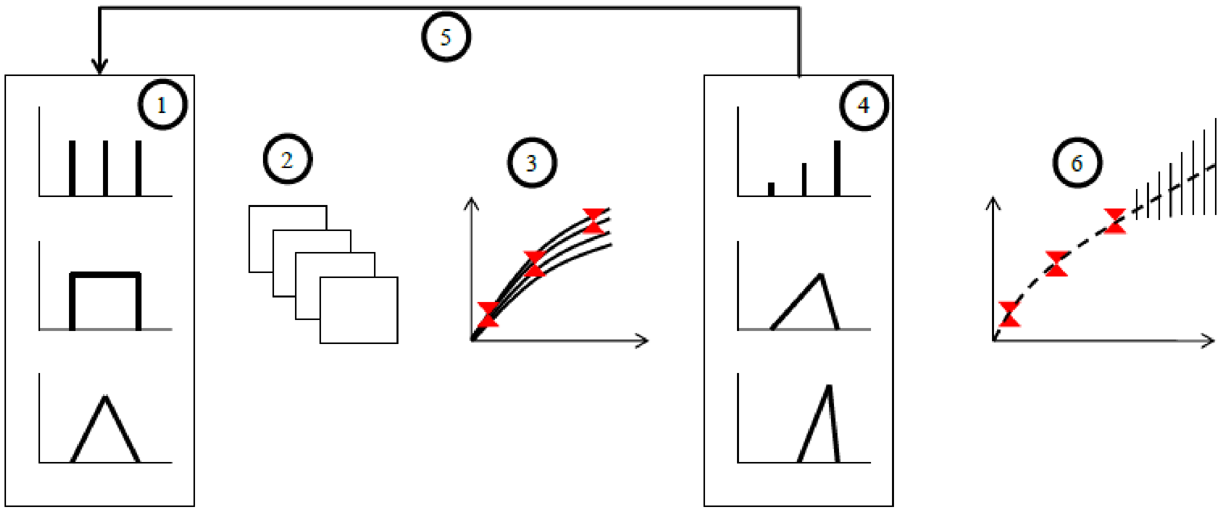


Figure 15 Process in an assisted history matching case (Schulze-Riegert et al., 2013).

MCMC Optimization for History Matching

As the process of the sampling algorithms require numerous of function evaluations and calculations to explore the full probability distributions, it will be unfeasible to use full field simulations for all samples. This is solved by building proxy (response surface) models that embody information of all uncertain parameters and responses represented by the objective function. In the MCMC optimization workflow the *global* objective function is used, which means that all objective response parameters are considered. When the numbers of response parameters and match points (further explained in Section 5.1.1) becomes large, it is essential with *automatic* proxy modelling techniques.

After the burn-in period and several iterations of gradually improvements in the Markov chain, the chain will contain optimal sets of values for the uncertain parameters, this ensemble of accepted values makes up the posterior distributions and are included in the proxy model (Gallagher et al., 2009). Note that a proxy model is made after each chain iteration, this means that the quality of the proxy will gradually improve as the chain is getting closer to its stationary state.

When in optimization mode the MCMC experiment generator produces a number of experiments by sampling from the proposal distributions. The best experiments of the Markov chain are automatically picked as the current parameter sets. In the optimization workflow (it is recommended that) each chain delivers *one* best candidate. The best candidate from each chain are added to the experiment list to go through a full field simulation. By doing this the best candidate will improve the proxy for the next loop of chain evaluations. Before going to the next chain step, the new sample sets need to be generated, this is done by an evaluation based on Metropolis-Hastings method explained in Section 3.6.4. To be thorough, the evaluation used in MEPO is described in the following section.

The chain moves from a sample set m^i to a new sample set m^{i+1}, by drawing new samples from the proposal distribution. By definition the update in the Markov chain depends only on the previous realization. This leads to the following expression:

$$m^{i+1} = m^i + \delta \tag{31}$$

Where δ represents the change in the parameter set. The new samples need to be accepted by the test, based on Metropolis-Hastings method, to be used further as a new sample set. MEPO uses the following test to sample new experiments (Schulze-Riegert, 2015):

$$\alpha = \frac{P\left(m^{i+1}\middle|d\right)}{P\left(m^{i}\middle|d\right)} \begin{cases} \alpha \geq 1 \; accept & \\ \alpha < 1 & \begin{cases} accept \; if \; \alpha > rnd(0,1) \\ reject \end{cases} \end{cases} \tag{32}$$

Equation 32 shows the procedure of how new candidates are picked. A proxy model is used to calculate the global mismatch value for each sample set, this is included in the probability $P\left(m^{i+1}\middle|d\right)$. $P(m|d)$ represents the probability of matching the observed data with the chosen samples in the candidate set *m*. *i* represents the iteration or time step. Based on the conditional probabilities new samples are picked for the next experiments. If the new sample set has an equal or better probability of matching the observed data $(\alpha \geq 1)$, it will be accepted forthwith. If the new samples have a lower probability of matching $(\alpha < 1)$ it can be accepted only if the threshold, $\alpha,$ is higher than a random number the program picks between 0 and 1. By using this regulation, MCMC can explore sample sets as well as having a higher probability of getting a good match. Note that every time a proposed model set is rejected, it is added a copy of the current model set to the ensemble. The best model set at the end of the simulation will represent the next m^i value. This process is continuously updating the posterior distribution. Figure 17 show how a probability distribution is updated by applying the MCMC algorithm that iteratively improves the history match in Figure 16. The green probability distribution in Figure 17 represents the prior distribution which leads to the highest uncertainty in estimating the reservoir response seen in Figure 16. As the MCMC algorithm conditions the model to the observed data (black line in Figure

16), the prior probability distribution gradually transforms to a posterior distribution, hence the uncertainty decreases in the reservoir response. In the MCMC optimization process the history match is gradually improved and the parameter uncertainty decreased.

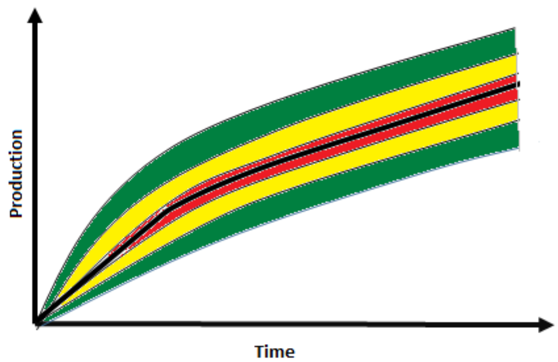


Figure 16 Iterative process of approximating the observed data (black curve).

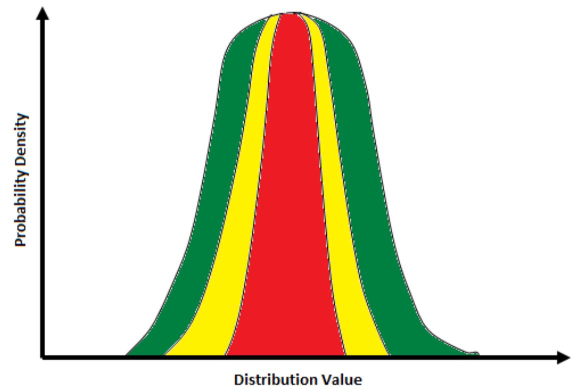


Figure 17 The Prior distribution (green) iteratively transforms to the posterior distribution (red distribution).

MCMC Sampling for Predictions

After obtaining a sufficient history match, prediction forecasts can be run. In MEPO the MCMC sampling method is applied for prediction simulations. MCMC sampling is similar to the MCMC optimizing method, the difference is that the sampling is done by is using a unique proxy that are made in the history matching process (often the last one from the last chain). MCMC sampling generates experiments from the posterior distributions given by the proxy to explore the prediction uncertainties. In a MCMC sampling only one Markov chain is run as one proxy is chosen.

Sometimes it may be more interesting to run the predictions from the whole range of history matched models, rather than sampling from the posterior distributions (Gallagher et al., 2009). This can for instance be for a case for the models that contain the most likely uncertain parameter values. This can be accomplished by first filtrating the experiments which gives a sufficient history match and then run predictions for the experiments with given parameter sets.

3.6.6 Markov Chain Monte Carlo in Practice

As described in brief, the basic scheme of MCMC is to draw arbitrary samples from the prior distributions. By the Markov chain update, after a sufficient number of iterations, the sample pick behave as if drawn from the posterior distributions. When this is the case, the MCMC algorithm has *converged* (Ferrero and Gallagher, 2002). It is difficult to determine if and when the MCMC has converged to the true posterior distribution. In practice there are only rules of thumbs, such as sufficient burn-in-time, and simulation runs that are relied on to assume convergence. This means that there are a possibility of gaining a posterior distribution representing the uncertainty which may differ from the true uncertainty. If the probability distributions have not converged it may lead to suboptimal predictions. However, studies show that the by applying MCMC correctly the method is in most cases reliable (Salakhutdinov and Mnih, 2008).

The construction of the MCMC algorithm requires certain predefined values, typically: number of chains, start values in the prior distributions, and the burn in time. The importance of these predefined values are discussed and tested multiple times by literature. Some conclusions and discussions from research are taken into consideration in the case study and are presented below.

Number of Chains

The recommendations of number of chains have been fairly inconsistent in literature. Some research suggest many short chains, while others are debating several long chains to one very long chain (Gilks, 1996). According to Gilks (1996) it has been generally agreed that running several short chains is misguided, and the debate between several long chains and one very long chain is set to continue. Adrian E. Raftery and Steven M. Lewis (1992) have showed that one long run is not always good enough, if the starting values are poorly chosen, the simulation of one single chain may not reach convergence. Comparison between chains cannot prove convergence. Nevertheless can comparison between chains that seemingly have converged, reveal differences if there chains not have approached their stationary state (Gilks, 1996).

Starting Values

It is important to know if the starting values should be chosen carefully and time should be spent on finding the right starting values. Gilks (1996) have found that rapidly mixing chains quickly will find its way from poorly chosen starting values. For slow mixing chains it may be more important to carefully choose starting values. Raftery and Lewis (1992) have calculated the importance of starting values to be small, given that there is launched a realistically large number of iterations and more than one chain.

Burn in time

It is important that the chains run long enough so they are not dependent on the initial sample. To ensure this, the initial period of sampling, which is known as the burn-in time, need to be set to an appropriate time. If extreme starting values are avoided, it is recommended to set the burn in time between 1% and 2% of the simulation run time (Gilks, 1996).

3.6.7 Advantages and Disadvantages by using MCMC

All optimization algorithms have individual advantages and disadvantages. These can be beneficial to recognize before application. The most important advantages and disadvantages of the MCMC method are the following:

- The main disadvantage of MCMC method it that it may require several iterations to converge to the correct distributions, which lead to the method can be time consuming.
- In addition it may be difficult to identify when it has converged.
- A great advantage of using MCMC, is that it permits a huge amount of model flexibility.
- Another advantage of the MCMC approach is that it in combination with Bayesian framework, it enables analysis of all desirable uncertain parameters, or functions of them. (O'Neill, 2002).

3.7 Errors in the History Matching Process

In the process of constructing a mathematically model, including uncertain parameters that describe the physical reservoir, use a numerical simulator to simulate the reservoir behavior, apply the theory of an inverse problem including the construction of an objective function and finally apply an optimization algorithm by a optimization program, several errors may occur. The most essential causes to the errors are mentioned here.

Reservoir Model

In a mathematical model relevant physical laws and flow equations are combined to a system of differential equations that are used to describe the physical system mathematically. Several assumptions are done to be able to make the mathematical model. The reservoir model is a computer model that uses numerical solution techniques to solve reservoir flow problems. The model is divided in to a grid system and the equations are solved numerically. The model errors is to a certain degree dependent on the choice of numerical simulator, i.e., mass balance or streamline, finite element or finite difference (Saleri, 1993). Finite-difference methods are numerical methods that are used to solve the differential equations. These will give approximates of the solutions of the flow equations, which means that the procedure automatically introduces errors in the computations. The mathematical models are simplified as that the more detailed the mathematical model is, the slower will a computer calculate the solutions.

Model Input Parameters

When introducing real numbers to the mathematical model, further errors may be introduced. The reservoir model is in general divided into a grid system, where each grid block is homogeneous. Every grid cell in the model need to contain multiple specified parameters for it to be representable of the real system. To get an accurate reservoir model, numerous parameters need to be close to the real values to give a good representation of the actual reservoir system. This can be very challenging with little information of the reservoir. When applying specific parameter values to the reservoir model, it is important to take into consideration the spatial variance and measurements errors. To get the most accurate model of the reservoir, all data measurements need to be used in relation to each other. Well log data should be calibrated to, and integrated with other measurements, such data from cores, pressures, and well flow tests, when this data is available and appropriate (Moore et al., 2011). In addition, impermeable barriers interpreted from seismic should be integrated and tested. As it is expensive to gather information, limited measurements will lead to upscaling of the parameters to be able to represent the whole reservoir. Upscaling can cause major errors, as interpolations of parameters often are based on (personal) interpretations. A fine grid can help to give an approximation to the heterogeneities in a reservoir. Each single cell has a set of assigned properties, hence is homogeneous. Large grid blocks (used to reduce simulation time) will lead to loss of local information when assigning cell properties.

Data Quality

Data from measurement tools have in many cases a known uncertainty, it is important that the data measured is calibrated correctly according to this. The measured data need to be treated consistently in such a way that limits the errors. If the input data to a reservoir study is wrong, the results from the study will be wrong. Production data smoothing can be an important step in reducing observable deviations (Begum, 2009).

Optimization Program and Algorithm

The optimization software may induce errors either through computational tasks or user mistakes. The algorithm applied trough the software may induce incorrect results, e.g. the MCMC method may require several iterations to converge to the correct distribution, if it has not had the time to converge to the correct distribution, the results will not be correct.

Uncertain Parameters in the History Match

In an uncertainty study, the most uncertain parameters in the model are studied closely, and possible values and combinations of these should be tested to get an updated uncertainty picture. Sensitivity studies may help the user to find the most uncertain parameters. In a history matching process, most of the parameters are fixed. Only a limited numbers of parameters are varied, these should represent the most uncertain parameters. If these parameters are not chosen correctly hence does not represent the largest uncertainties in the reservoir, the study will not give the correct results.

4 CASE STUDY

This chapter introduces the reservoir that will be studied. General field information are presented in addition to the geological interpretations of the reservoir deposition environment. The key uncertainties in the reservoir are presented and discussed. Further, is the reservoir model that will be used in this study introduced. This chapter is based on information given by confidential documents and personal communication provided by the company the author is in collaboration with (Eni Norge, 2015).

4.1 General Field Information

The case study concerns a relatively small field that produces from a gas condensate reservoir. The reservoir which consists of Cretaceous sands, and is located at a depth where the structural top is at 2750 m TVDSS (true vertical depth subsea) and the gas-water contact is at 2843 m TVDSS. The reservoir formation have a variation in thickness from 5 to 20 m. A cross section graphic of the reservoir is shown in Figure 18, as viewed the reservoir is tilted. The important reservoir properties are showed in Table 1.

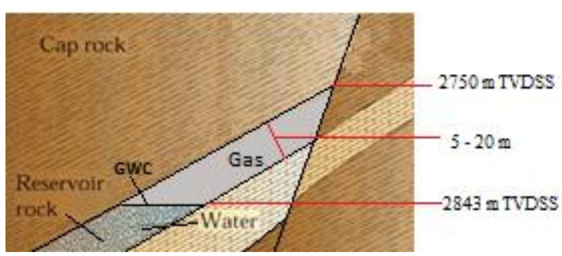


Figure 18 This graphic visualizes the cross section of the tilted reservoir.

Table 1 Reservoir properties.

Tres [°C]	101
Pres [Bar]	374.4
GOR [Sm^3/Sm^3]	11 524
Dew Point [Bar]	373.5
Bg [Rm^3/Sm^3]	0.00353
Average NTG	0.70
Average PHI	0.23
Average k [mD]	200
Sg	0.1
µg [cP]	0.029
Gas Specific Gravity (air=1)	0.68

The field is produced by natural depletion by gas expansion. There are two producing wells, Well A and Well B, due to flow assurance issues only one well produce at the time. This allows the non-producing well to observe the pressure in the reservoir. The buildup pressures, that are measured while a well is shut-in, are important as the reservoir response is reflected. At the time of study the field has been operative for just over three years. Approximately half a year after the production startup, the wells were shut-in for a year due to technical concerns. After this shut-in period the producers have been producing sequentially. At the time of study around 2.3 GSm^3 gas has been produced. Figure 19 shows the bottom hole pressure in the wells and the production rate over the time of production.

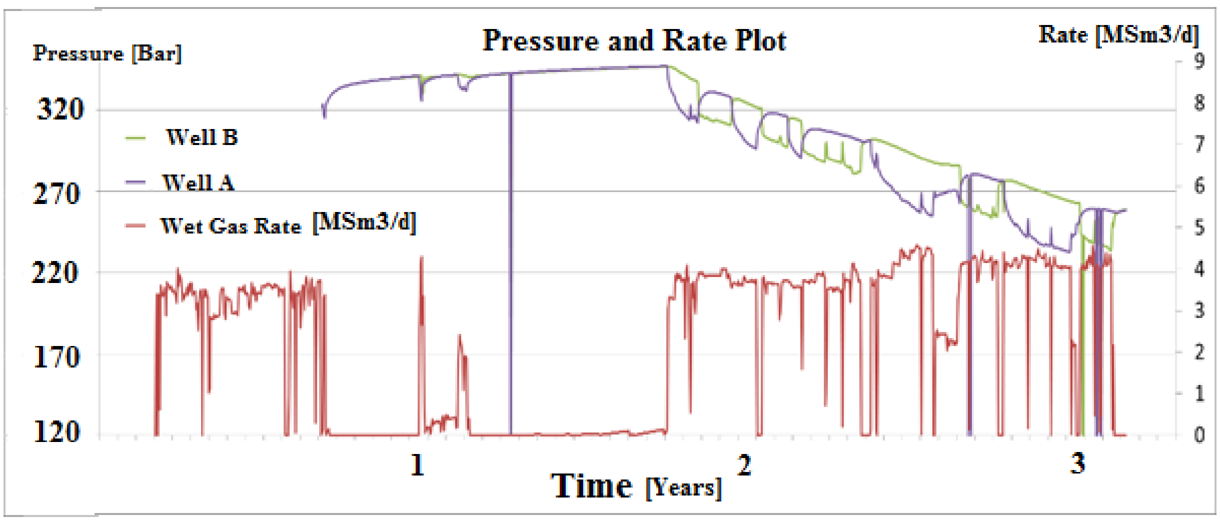


Figure 19 Field Pressure and Rate Plot.

At time of the development phase the field gas in place (FGIP) were estimated to be between 10-17 GSm^3, with a most likely value of 15 GSm^3. By taking the production information into consideration in an uncertainty study, the uncertainty spread of the volume estimates may change. To better quantify the uncertainty will in many cases improve a decision making process. In this case study further information of the reservoir uncertainties may help deciding a few decisions that need to be considered in the near future. They are as follows:

- Drill a third well.

  A potential third well was discussed at field development time.

- Continue production for a longer period, hence pay for equipment upgrade or infrastructure.

After production for a certain time period, it might be necessary with upgrade of certain equipment or infrastructure, hence it need to be determined if it is economically feasible to do these changes to continue production.

- Update the predicted volume in place distribution.

4.2 Deposition Environment and Reservoir Geology

The reservoir trap is formed by a Cretaceous dome structure above a Jurassic horst block. The reservoir is deposited in what can be described as an intra-slope turbidite basin. A turbidite deposit is a sedimentary deposit formed by a turbidity current (Dictionary.com, 2002). Usually will these deposits consist of sequential sediment layers, where the bottom layers contain the coarsest gains, and the upper layers contain the finer grain. The turbidite deposit system is imaged by amplitude and coherency maps from 3D seismic illustrated in Figure 20. The high amplitude areas are showed as red, orange and yellow (by decreasing amplitude) on the map, before the amplitudes are showed as green, light blue and then dark blue with respect to decreasing amplitudes. By taking well data into consideration it is found that the system mainly consists of a unit with a fining-upward stacking pattern where channel-fill and channel-lobe transition facies are overlain by lobe deposits. Sediments have hit the structural high and deposited to what became an area with thin fine sands on the structural heightening and a thicker central zone with coarser sands. In the areas close to the fault, flow interference with the syndepositional high lead to sudden deceleration and rapid sedimentation, generating sand liquefaction and large clay clasts (Eni Norge, 2015).

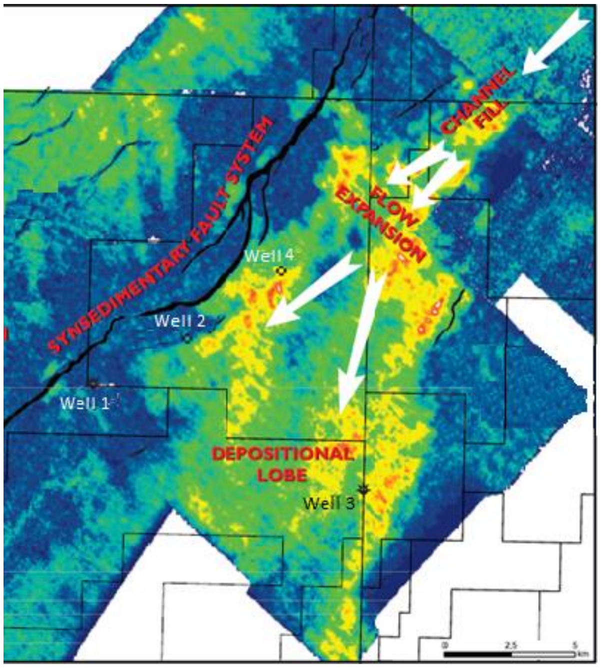


Figure 20 The amplitude map shows the geological environment and interpreted system. North is up and south is down . (Eni Norge, 2015).

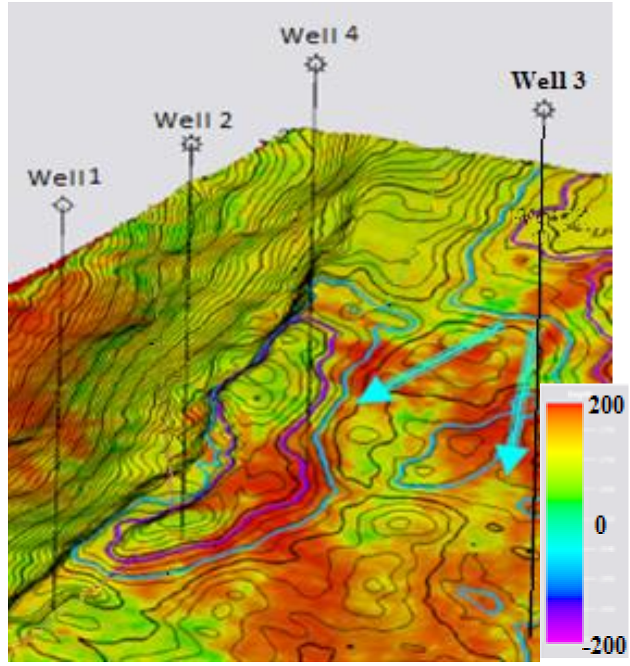


Figure 21 The outlined reservoir and the wells 1-4 in the amplitude map (Eni Norge, 2015).

The reservoir, outlined in Figure 21, extends approximately 9 kilometers from the south (-west) to the north (-east). It has an average width of around 3 kilometers. In the field area a total of six wells have been drilled, including the two producers. The placement of the four first wells can be seen in Figure 21. The southernmost well "Well 1" was drilled below the contact prior to the discovery well being drilled. The field was first discovered by the discovery well "Well 2" which was penetrated the gas-condensate sands. A dry well, "Well 3", located in a different structure east, was drilled after the discovery. The last well to be drilled before development was "Well 4", which also penetrated the saturated reservoir. After deciding to develop the field, two production wells were drilled, "Well A" and "Well B". Figure 22 shows the wells penetrating the gas reservoir; the discovery well "Well 2", the appraisal well "Well 4" and the two production wells (and their pilots) "Well A" and "Well B". The distance between the production wells are approximately 2.7 kilometers.

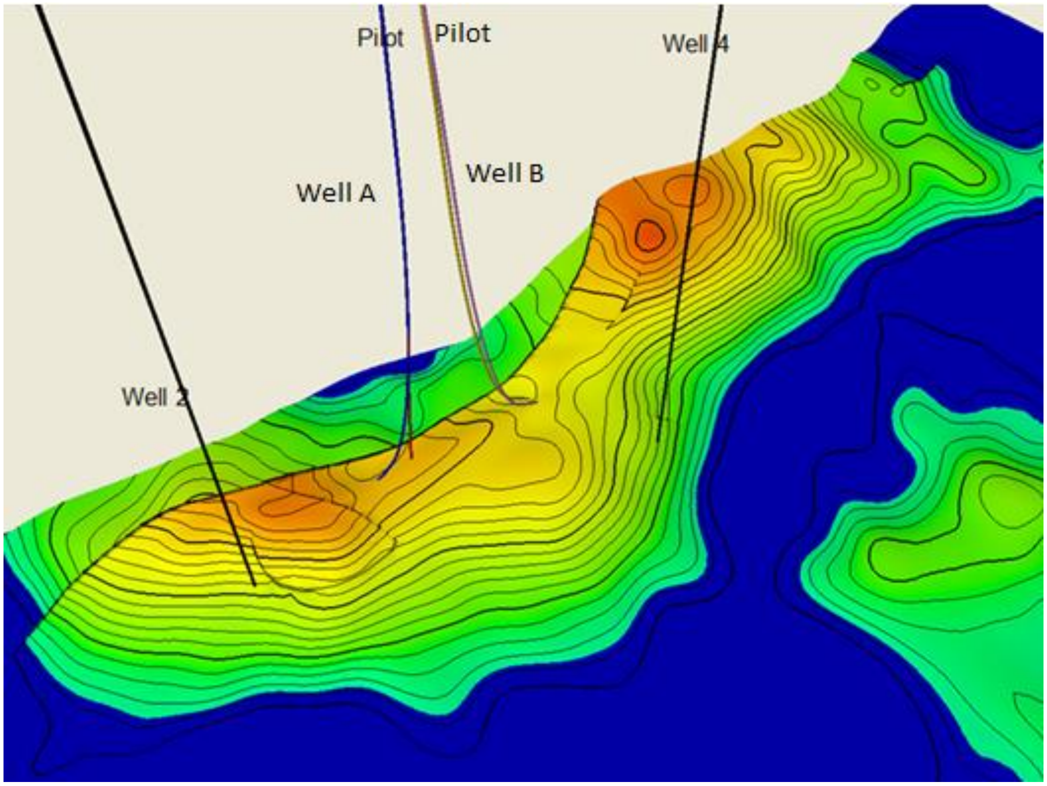


Figure 22 The reservoir with drilled wells and GWC (Eni Norge, 2015).

The wells confirmed the geologists, sedimentologists and geophysicists interpretations from the seismic amplitude map. Based on this it was seen a correlation between the seismic amplitude frequency and the reservoir thickness and facies quality. From well logs and amplitude map four different facies were identified and categorized:

- Log facies 1: Clean sandstone, high quality. This is the best reservoir facies, and consists of very high to high quality sandstone.
- Log facies 2: Sandstone with residual structures, high to medium quality. Reservoir facies consisting of massive sandstone which is locally and reasonably well sorted, the facies contains water escape structures.
- Log facies 3: Sandstone that is poor sorted and laminated, medium to low quality. Minor reservoir facies, the sandstone is locally laminated with increasing amount of silty layers.
- Log facies 4: Laminated fine sandstone, siltstone and mudstone, low quality sandstone. This is a low quality facies, none reservoir facies as only locally massive mudstone is present.

Figure 23 show a picture of the cores from the four different facies. Figure 24 shows the percentage of the different sandstone facies in the drilled wells.

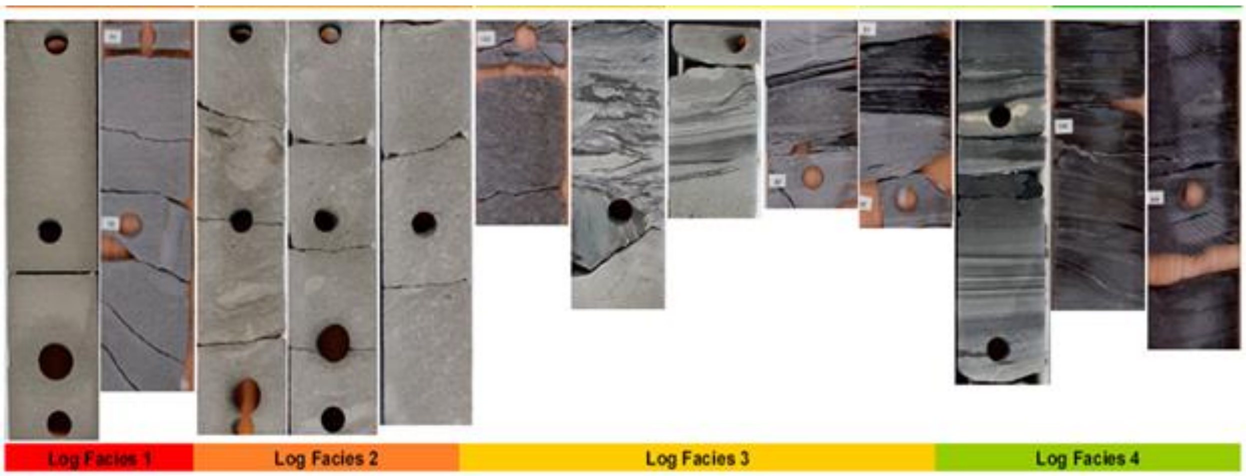


Figure 23 Cores of the different facies (Eni Norge, 2015).

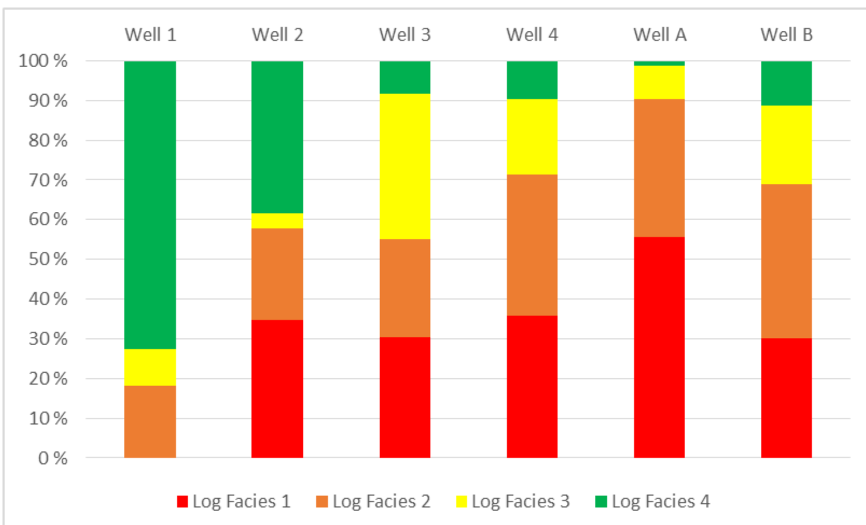


Figure 24 The percent of the different facies in each well.

It has been done thorough work with probability modelling of facies distributions based on amplitude maps and well data. In addition it has been created parameter distribution maps for porosity and permeability based on the facies quality. Further, bodies' dimensions and structure analysis were carried out before these were used as a basis of the geological reservoir model.

4.3 Key Reservoir Uncertainties

The uncertain parameters to consider is decided based on earlier uncertainty and sensitivity studies including a manual history match. They are as follows:

1. Drainage volume (pore volume).
2. Effects from an aquifer.
3. Internal communication.

Drainage Volume

Volume in place is the most important uncertain factor as it to a large extent determine the profitability of the field. Earlier studies indicate a volume in place between 10 to 15 GSm^3. The gas volume is also important to find as it is desirable to get an estimate for how long the field can continue to produce.

The author did an individual uncertainty study for the field in the project thesis carried out autumn 2014. By the use of given information from PDO time and Monte Carlo simulations the author found a P50 value of the volume to be 11.76 GSm^3.

Effects from an Aquifer

Another uncertain factor is the aquifer, there are uncertainties related to the size and contribution from the aquifer. Before production, it is difficult to know the dynamic response from the reservoir, hence determine the effects from an aquifer. The hydrocarbon accumulation in a reservoir is often hydraulically connected (in pressure communication) with the water surrounding it, which is called an *aquifer*. The inflow of water to the reservoir as the pressure declines due to depletion is called water drive or water influx. The effect from an aquifer depends mainly on the aquifer permeability, aquifer size, initial reservoir pressure and water and rock compressibility (Bruns et al., 1965).

A good connection between the aquifer and the hydrocarbon-filled reservoir is caused by a high permeability in the layer connecting them, and it means that fluids easily can flow between the contacts. By depletion, the pressure near the wells will decrease faster than in the rest of the reservoir, and fluids will start to flow towards the lower pressure zones. An aquifer in good connection with the reservoir will start to expand into the reservoir region, by fast response of inflow of water the reservoir pressure will to a large extent be maintained. If the connectivity between the aquifer and the reservoir is limited, it will take a longer time for the aquifer to react upon the depleted reservoir. A pressure decline in the reservoir will indicate limited connection. For very low aquifer permeabilities, (less than 1 mD) the reservoir behavior can be described as a constant volume reservoir, because inflow of water is so limited that the reservoir behaves independent of the aquifer (Fevang, 1995). (Melhus, 2014).

The aquifer contribution can be correlated to the uncertainty in volume in place as discussed further in next section.

Internal Communication

There are uncertainties related to internal transmissibility features, due to possible continuous shale layers or other sub seismic features. Though evidence of reservoir barriers are limited, seismic may not capture the true picture of the subsurface as there is a chance it is not detecting faults. Shale layers which are dividing the reservoir zone are observed in Well A, the horizontal well have perforations over and under the shale layers. This can be a factor that potentially can complicate the pressure relief when producing. Shale layers are not observed near Well B, this implies that the layers are not continuous over a longer distance. Discontinuities in the reservoir may reduce the pressure communication hence give a delayed pressure response in the field. If there are gaseous areas bounded by faults, the gas may be may be trapped. Then the reserves that are not in contact with the gas volume surrounding the wells, will not affect the pressure measurements.

4.3.1 Indications of Gas Volume from Material Balance p/z-Plots

An interpolation of the straight line p/z vs cumulative produced gas plot, has traditionally been used to estimate the original gas in place for depletion-drive gas reservoirs (Elahmady and Wattenbarger, 2007). A reservoir depleted only by gas expansion will in general give a straight line curve, this volumetric behavior is commonly used to quantify the in place volume. If a reservoir is affected by an aquifer, it is expected that the p/z curve in the plot will deviate from the straight line by certain trends. Figure 25 show the typically p/z curve behavior of different aquifer strengths ranging from weak to very strong in gas reservoirs. In general, a gas reservoir with water influx will have a lower ultimate recovery. A certain amount of the gas is trapped behind the water, and will be unrecoverable after a water breakthrough. According to Fevang (1995) the trapped saturation is dependent on rock properties, initial water saturation and is correlated to the trapping constant C_t. (Further information of Ct can be found in in (Ringrose and Bentley, 2015)) (Melhus, 2014). The recovery for a gas reservoir with no connection to an aquifer, namely, a volumetric gas reservoir, is commonly over 80 %. Even though it is expected to get a curved line in a reservoir influenced by an aquifer, Elahmady and Wattenbarger (2007) have found that for a gas reservoir with water influx in transient phase (unsteady state) and producing under a certain rate schedule (not a constant rate) the p/z curve can still be plotted as a straight line on a p/z-plot masking the existence of the aquifer. This will cause significant overestimation in gas reserves.

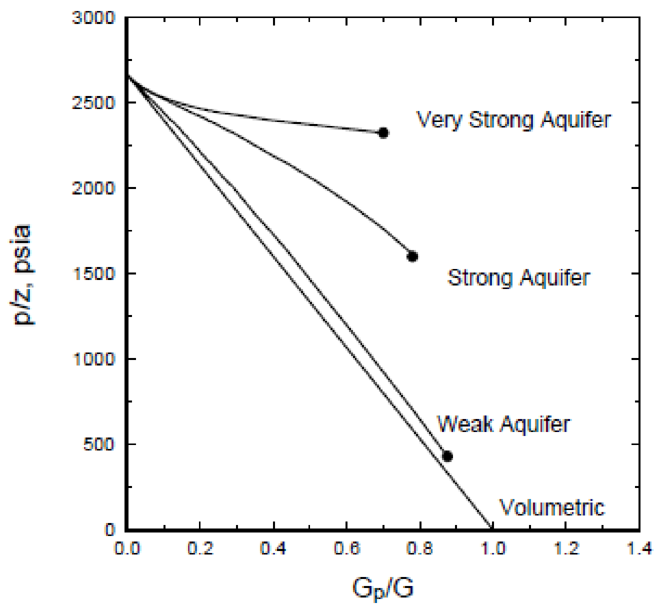


Figure 25 Effects of water influx on a p/z curve (Fevang, 1995).

Figure 26 shows the straight line p/z curve (blue) that is expected for a reservoir depleted only by gas expansion, and the deviated trend (the black dots) from the p/z curve that is expected if the reservoir is influenced by an aquifer. Figure 27 show the misleading straight line that may occur for wells with special rate schedules and will mask the existence of an aquifer. G represents the real volume, G’ represents the wronged volume.

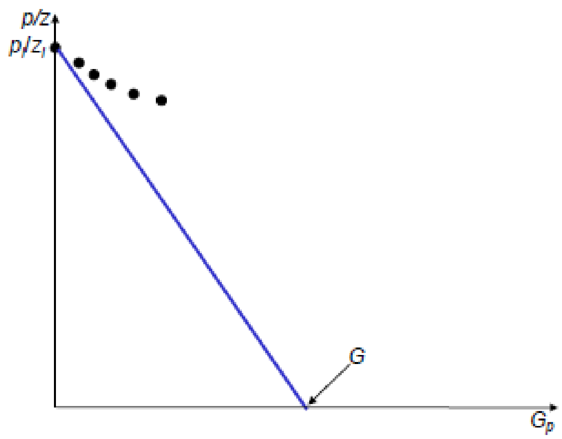


Figure 26 Typically expected behavior when influenced by an aquifer (Elahmady and Wattenbarger, 2007).

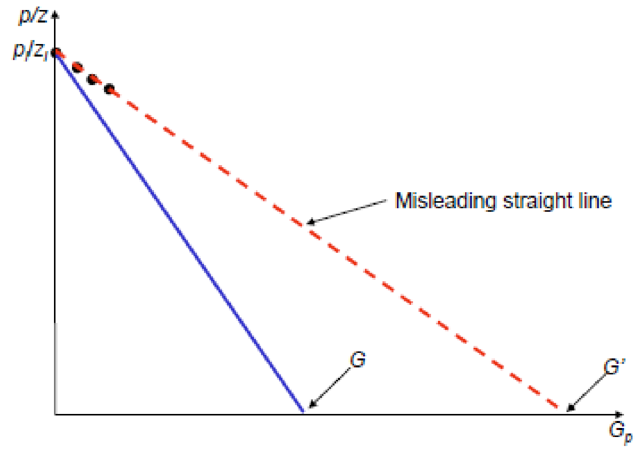


Figure 27 Misleading straight line behavior when influenced by an aquifer (Elahmady and Wattenbarger, 2007).

This means that for a case where the reservoir producing with a special rate schedule and it is uncertain if the reservoir is influenced by an aquifer or just depleted by gas expansion, a straight line plot can be misleading in quantifying the original gas in place volume. Early curvature behavior can in the cases where the reservoir is affected by the water influx, be more reliable in volume predictions. In Figure 28 it can be observed reliable early curvature behavior, by the points before the point *M*, where the misleading effects starts showing. In most cases the early time behavior is not observed, due to it is not conventional with such early pressure measurements (Elahmady and Wattenbarger, 2007).

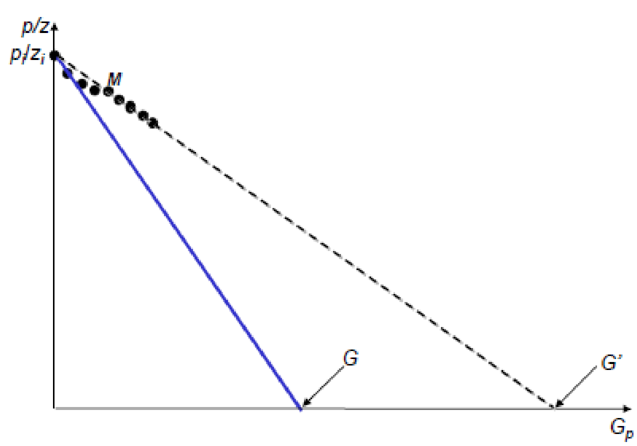


Figure 28 Early curvature and following misleading line when aquifer affects the measurements (Elahmady and Wattenbarger, 2007).

Case Study Observations

In the case study both the volume and the influence from an aquifer are major uncertain factors. In general, a minimum of 10 to 20 % of the in-place volume must have been produced before there is sufficient data to identify a trend and reliably extrapolate to the original in-place volume through material balance. At the time of study the field has produced approximately 2.3 GSm^3, which from the time of development estimates should range between 15 and 23 % of the in-place volume. As the produced volume should be sufficient, a p/z-plot has been made for the production time and can be seen in Figure 30.

As the producers are producing in sequence, the individual wells may or may not go under what Elahmady and Wattenbarger (2007) describes as a "certain rate schedule". On the basis of this the p/z plot should be carefully used as it may give misleading results. As the producers are producing one at the time, and one is always acting like an observer, continuous pressure data are measured. This might lead to an opportunity of capturing responses from the early time period not affected by a potential aquifer.

After analyzing the p/z plot in Figure 30 carefully, especially the early behavior, measured after the long shut in period of one year, showed in Figure 31, two extrapolated curves have been drawn as seen in the plot, p/z and p/z'. The first linear curve, p/z', is plotted to only take into consideration the early reservoir response, assuming that the pressure in the early period (of measurements) are not affected by an aquifer which is captured by the later responses. This scenario represent a case where the volume is in a lower range than predicted. The p/z' curve extrapolates to a gas in place volume to be around 6.7 GSm^3. The second curve, p/z t is made to consider the later reservoir response, the plotting of this curve is done assuming no influence from the aquifer. This interpolation indicate a gas in place volume to be approximately 10 GSm^3. An assumption is required for the interpretation to be valid. The long shut-in of the wells of approximately one year should be able to cause the reservoir pressure to stabilize at a new initial state. Figure 29 shows how the interpretation can be valid. There is no data of the early production period before the long shut in. The blue curve represent how thought measurements of the earliest field behavior may have been. The red curve shows that after the long shut-in the reservoir has reached a stabilized pressure, possibly close to the reservoirs initial pressure, that again might reveal the unaffected early period, before any misleading behavior occurs. Both curves show how only the early behavior represents the actual field gas in place.

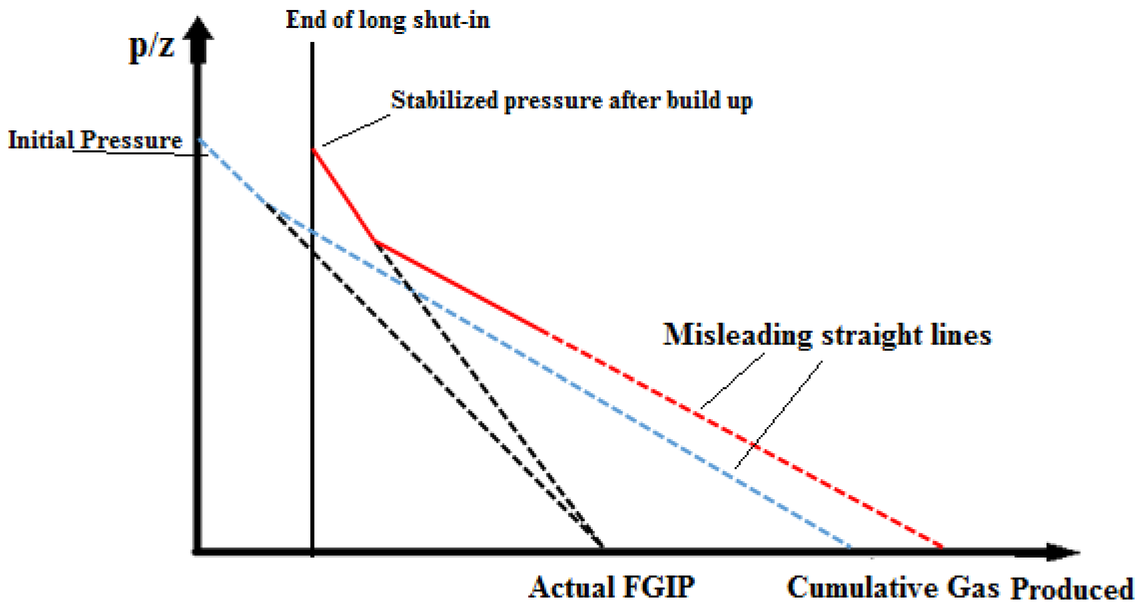


Figure 29 The p/z interpretation of initial state stabilizing after one year of shut-in wells.

As mentioned earlier, the wells produce sequentially, this is an important factor that allows for analyzing of the early period after the shut-in. In the early period after shut-in Well A is producing, and Well B acts as an observer and maps the early pressure response from the field. As seen in Figure 30, the p/z curve indicates a gas volume to be around 10 GSm^3 with a cumulative production of almost 8 GSm^3. The p/z' curve indicates a gas volume to be around 6.5 GSm^3 and cumulative production to be slightly over 5.1 G Sm^3.

Other literature argue about and doubts the reliability of the p/z plots to give a valid representation of the volume in place. Some state that the problem with the interpretation is that the pressure at the end of the buildup is not representative of the average pressure for the drainage area of the well (Ross, 2014). Payne (1996) states that a straight-line p/z decline cannot be used to conclude that the reservoir behaves like a tank, and that the p/z curve may or may not point to the true gas in place.

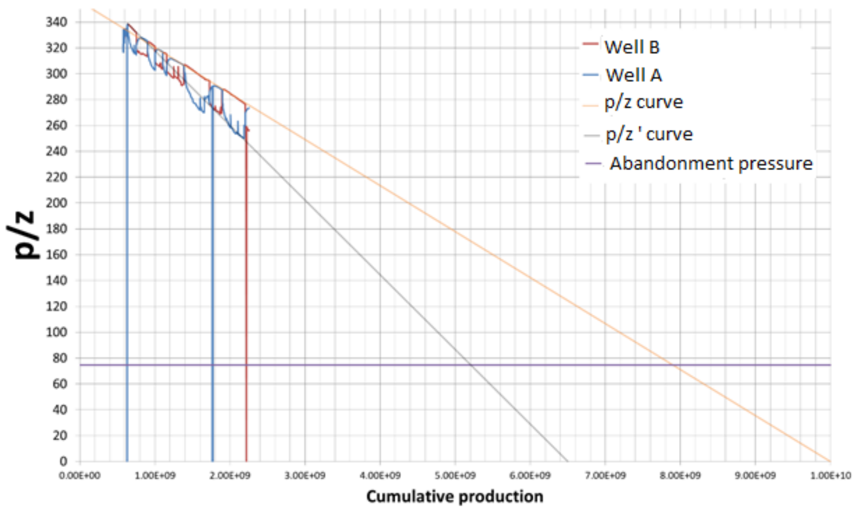


Figure 30 p/z plot after producing approximately 2.3 GSm^3, including two extrapolated curves.

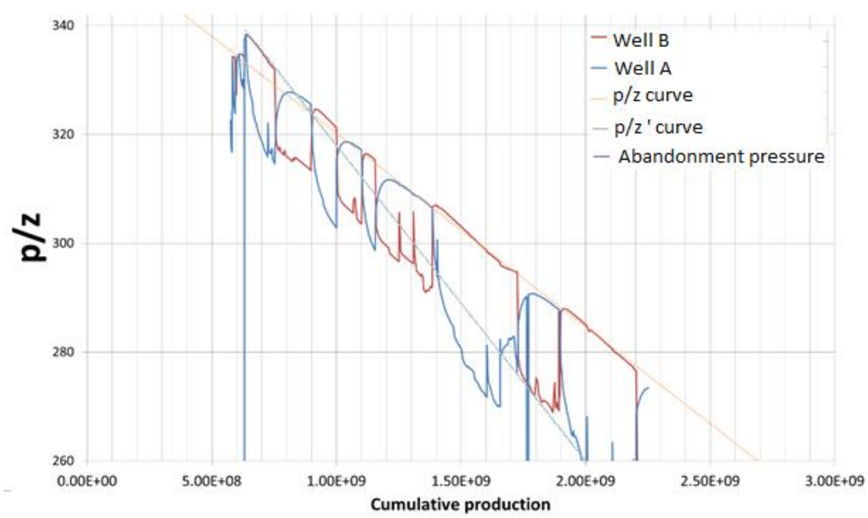


Figure 31 p/z plot which shows the early field behavior.

Remarks

- An aquifer influence will normally increase the pressure in the reservoir by water influx. Therefore the early period not affected by the reservoir will show a steeper pressure decline trend.
- In the case study, the historical data from the early period the p/z curve does not seem to increase similar to the trend viewed in Figure 28, but a more rapid decrease in pressure from the early period is observed.
- The later period trend shows a gentler pressure decline than the early period.

4.4 Reservoir Model

4.4.1 The Base Case Reservoir Simulation Model

The base case model is the simulation model that represent the reservoir before any production information is introduced. By the use of history matching the model will be calibrated by changing the most uncertain properties. The reservoir simulation model is modelled in Eclipse 100. Eclipse 100 is a fully-implicit, three phase black oil simulator, and is using a finite volume method to solve material and energy equations. The base case reservoir model is designed based on earlier studies and includes information in from of:

- Static data.
- Dynamic well test data.
- PVT studies.
- SCAL: Relative permeability and J-function.

The reservoir model has grid dimensions of 109x203x16 cells, which makes the total number of grid cells 354 032 of which 231940 cells are active. The lateral dimension of each cell in the reservoir area is approximately 100 x 100 meters. The reservoir is divided into 16 layers in the z-direction. As the hydrocarbon zone has a thickness variation from 5 to 20 meters the vertical resolution of a cell is defined according to the thickness. Each cell in the model has individually assigned properties, assigned by facies. There is correlation between the properties; permeability, porosity and saturation in the different facies. The grid cells properties are based on a static geological model from Petrel (2009.2 software). The following are implemented in the model:

- Faults

    In the simulation model there are implemented faults that were observed on seismic. There is one major sealing fault which bounds the reservoir extending from north towards north south. In addition there are some minor sealing faults in the reservoir, where the most important and largest is a fault south for Well A. Sensitivity studies have showed that the sealing faults have negligible impact on the dynamic behavior in the reservoir.

- J-Function

  The gas water capillary pressure is calculated by Eclipse by using the J-function curve and the keyword JFUNC.

- Wells

  Two horizontal production wells are integrated in the reservoir model.

4.4.2 Regions

The reservoir model is divided into regions to be able to express the parameter uncertainties in the different parts of the reservoir. The boundaries and the extending of the regions are decided based in the seismic interpretation of the amplitude map. In the low amplitude the reservoir thickness and the facies quality are in general lower than in the high amplitude areas. The regions are constructed in Petrel, and imported to Eclipse. A total of 6 regions are defined, these can be seen in Figure 32. The average assigned properties in each of the regions in the base case model can be seen in Table 2. The following gives an overview of the regions:

- Region 1 (blue) and 6 (red) are mainly low amplitude areas. The properties in Table 2 show that the average N/G, average porosity and average permeability is lower than the other regions, this implies lower quality of the reservoir properties in these regions.
- Region 2 (light blue) represents a transition zone between the low amplitude and the high amplitude areas. An idea about having a transition zone is that it can be used as a flow barrier between the zones.
- Region 3 (purple) represents the medium to high amplitudes and represents the main reservoir area which is of high reservoir quality. The two producers are located in this region.
- Region 4 (light pink) represents a near well area, the region is located around Well B. The reason to have a region around Well B is to evaluate the flow around and between the wells. Note that this instead could have been implemented by specific well adjustments for the well.
- Region 5 (pink) represents an aquifer surrounding the reservoir. As the presence of an aquifer is rather uncertain, the region is created to be able to determine the influence caused by an aquifer.

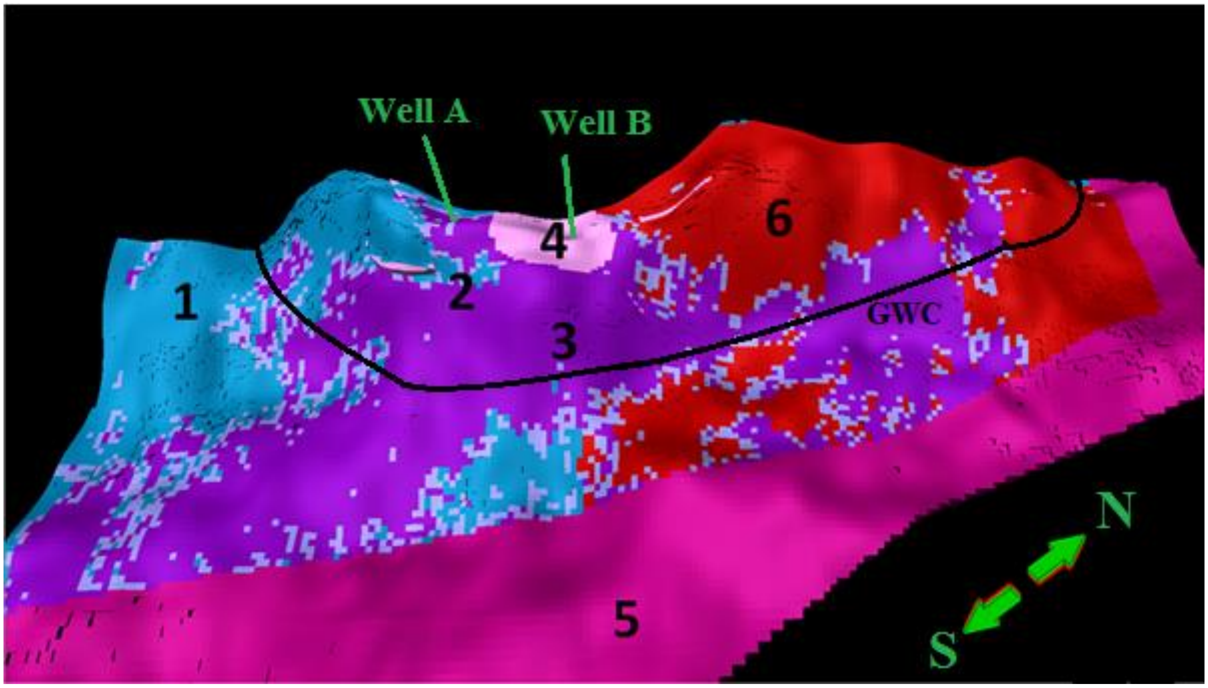


Figure 32 The reservoir model and the defined regions 1-6.

Table 2 Average parameter properties in the reservoir model.

Average	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
Porosity	0.19	0.19	0.21	0.19	0.19	0.15
Permeability XY[mD]	165	169	191	155	157	126
N/G	0.74	0.91	0.97	0.92	0.92	0.76

Dividing the model into regions allows the user to assign different uncertainty ranges and distributions for the parameters for each region. As the regions are mainly divided according to the response from the amplitude map, as it is believed that the response from the amplitude map is consistent with the reservoir parameters. It is important to remember that in the base case model, each cell has assigned properties. A multiplier for a region will take into account the differences in the individual cells.

The regions may also be important as certain parts of the reservoir are better explored than other parts. By dividing the reservoir into regions the PDF's for the uncertain parameters can have, a limited range for the more explored parts, that contains relatively less uncertainty, and a wider range for the unexplored parts of the reservoir. By applying the regions in the uncertainty study the user can easily change the properties in the cells in one region independent of the other regions.

The use of regions in this study is a simplification, the thought is use the regions to explore the influence from each region, and find the most influential parameters. The results from the study will have be communicated back to the geologists to discuss if the combined results of the regions are realistic based on the geological knowledge of the field.

5 RESULTS AND DISCUSSION

This chapter presents the implementation to the software, in addition to the results obtained from the uncertainty study of the field presented in the previous chapter. The ensemble based method MCMC is applied in a history matching process (as viewed in Figure 15), the method yields an updated uncertainty picture of the parameters. Analyzing the results is important to be able to evaluate the reliability of the updated uncertainty. History matching is emphasized as the main focus is on capturing and mitigate the uncertainty in the reservoir by the historical data taken into consideration. In addition is a brief sensitivity study carried out to find the influence from the different parameters that are used in the study. Further predictions are simulated to find the future behavior and the production time. Some results are discussed during the different scenarios, before the Section 5.5 summarizes and discuss the results in relation to each other.

5.1 MEPO Introduction

MEPO (Schlumberger), Multipurpose Environment for Parallel Optimization tool, is the software used in this study. MEPO is a flexible framework for assisted history matching and is based on an input reservoir model. To perform a HM study certain steps need to be followed. Uncertain input parameters need to be defined by the user, in addition, field history data to be matched will have to be introduced. Different optimization techniques can be utilized to minimize the objective function through multiple simulation runs to find the solutions that best matches the history data. When the user is satisfied with the matching results, the parameter uncertainties can be reviewed and analyzed. Further predictions can be simulated based on the history matching results.

Workflow in MEPO

To be able to work in MEPO, the user have to create a *project*, this is a file that contain information about the multiple *cycles*, where in each created cycle one can import data, decide sampling/optimizing algorithms, run simulations, and review the results. A project will typically contain several cycles, where the cycles may have different cycle objectives, such as history matching, sensitivity and forecasting. Depending on the choice of cycle objective the following need to be defined by the user: input variables, variable ranges and distributions, response parameters such as mismatch parameters or watch parameters, simulation algorithm, number of simulation runs and so on. Since the further study will mainly focus on history matching and prediction, only these procedures are explained in further detail.

5.2 History Matching

5.2.1 MEPO Implementation – History Matching

The procedure carried out to prepare the history match runs are explained as follows. The base case model in an Eclipse data file is uploaded to the project, this is done in the *input parameters* panel. When the data file is added to MEPO, the user is able to view and make changes to it. Parameters in the data file can be selected by the user and made *Design Parameters* in the *Input Parameters* option. The *Design Parameters* represent the uncertain parameters in the reservoir model, and will be represented probabilistically. The user can manually apply a range, start value and distribution for each of the Design Parameters to represent the uncertainty. The number of uncertain parameters will impact the simulation time. Thus it can be necessary in the cases with many uncertainties to identify which parameters that have large impact on the results, and which that have little or no impact and can be excluded. This can be done through sensitivity analysis where the goal is to determine the most influencing parameters. In this study the uncertain parameters are decided based on earlier sensitivity studies, hence a selection process is not necessary.

5.2.1.1 Input Parameters

In general are the input parameters defined based on prior knowledge that comes from geological information and the understanding of the reservoir. The uncertain parameters to consider in this study is already decided based on earlier sensitivity studies including a manual history match. As the volume in place, water influx and internal communication are the largest uncertainties, the input parameters should be able to capture this uncertainty. As the simulation time increases with the number of input parameters, a limited amount of input parameters have been created to capture the uncertainty that is present. In this case study two kinds of input parameters have been considered uncertain parameters: pore volume multipliers and permeability multipliers.

The pore volume multipliers represent the uncertainty in the parameters defining the pore volume. Pore volume multipliers for the different regions (previously defined in Section 4.4.2) have been implemented to the data file by the use of the keyword MULTREGP. A total of four pore volume multipliers are defined:

- MPV1- multiplier for the pore volume in region 1.
- MPV3- multiplier for the pore volume in region 3 and 4.
- MPV5- multiplier for the pore volume in region 5.
- MPV6- multiplier for the pore volume in region 6.

Pore volume multipliers will only affect at the actual volume calculated in each cell of the reservoir model. The parameters concerning the volume will when combined (in the pore volume calculation) have to give the same answer as the volume presented by the application of the multiplier. The use of a pore volume multiplier will not capture the individual parameter uncertainty. The multipliers can only be used as an indication of the pore volume range for a certain region. Further individual parameter uncertainties will have to be discussed with a geologist depending on the results.

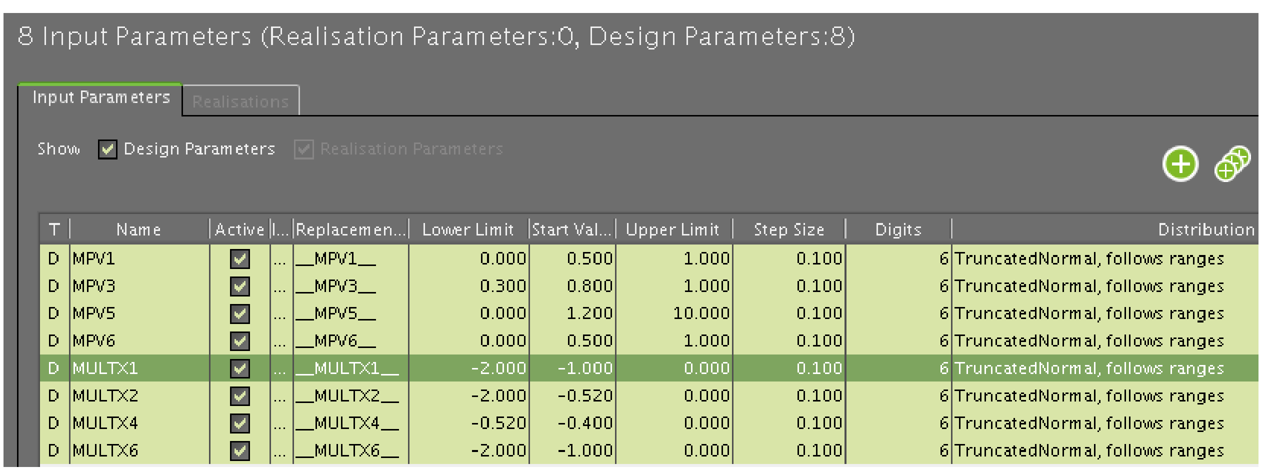
The second input parameters are permeability multipliers, which represent the transmissibility of fluids in the different regions. Permeability multipliers are implemented by the keywords MULTX and MULTY, and represent the permeability in the X- and Y-direction, namely the horizontal permeability. The multiplier are applied for region 1, 2, 4 and 6 with the keyword MULTIREG. In MEPO they are defined as:

- MULTX1- multiplier for horizontal permeability in region 1.
- MULTX2- multiplier for horizontal permeability in region 2.
- MULTX4- multiplier for horizontal permeability in region 4.
- MULTX6- multiplier for horizontal permeability in region 6.

It is important to understand that the multipliers on the pore volume and the permeability may yield the same result as by only using one or the other. A pore volume multiplier controls the actual volume that can be produced, the permeability multiplier will keep the volume in the base model but will affect the flow in the reservoir and to the wells. Applying both multipliers to the most uncertain parts of the reservoir gives MEPO greater flexibility. This is the case for region 1 and 6 where both multipliers are applied. Region 2 does not have an assigned pore volume multiplier as the few cells in region 2 would not give a considerable impact on the result. The region is mainly made to be able to influence the flow between the regions.

Input Ranges and Distributions

The chosen input parameters, which all are multipliers, should represent and capture the true uncertainty of the specified region. As described before, some regions contain more uncertainty than other parts that are better explored. It is desirable that the ranges and distributions of the input parameters reflect this. The ranges that are assigned as prior distributions are mainly ranging from a lower limit, zero, to an upper limit of one which represents the value in the base case model. The reason that the multipliers are assigned by this range is that earlier studies imply that the properties in the base case reservoir model may be *"too good"* to get a sufficient history match. The permeability multipliers ranges are implemented as log values, the actual multiplier value these represent (that will be applied to the reservoir parameters in the model) can be seen in Table 3. Figure 33 shows the *Uncertainty Parameter Panel* and gives an overview of the input parameters and ranges. Region 3 has a lower boundary of 0.3 as it is the most explored region, where the values to a larger extent are based on observed data. The permeability multiplier for region 4 has the same limited lower value of 0.3, as region 4 is included in the same area. As discussed, the purpose of region 4 is mainly to regulate the inflow to Well B and the flow between the wells, hence has a specified permeability multiplier. The pore volume in region 4 is included in the MPV3 parameter. The aquifer is a key uncertainty and for the region to act like an aquifer a larger pore volume range need to be applied, the range for region 5 is set to range from 0 to 10. Start values should, based on literature, not have much to say, they are chosen based on what is believed to be a most likely value.



T	Name	Active	I...	Replacemen...	Lower Limit	Start Val...	Upper Limit	Step Size	Digits	Distribution
D	MPV1	✓	...	__MPV1__	0.000	0.500	1.000	0.100	6	TruncatedNormal, follows ranges
D	MPV3	✓	...	__MPV3__	0.300	0.800	1.000	0.100	6	TruncatedNormal, follows ranges
D	MPV5	✓	...	__MPV5__	0.000	1.200	10.000	0.100	6	TruncatedNormal, follows ranges
D	MPV6	✓	...	__MPV6__	0.000	0.500	1.000	0.100	6	TruncatedNormal, follows ranges
D	MULTX1	✓	...	__MULTX1__	-2.000	-1.000	0.000	0.100	6	TruncatedNormal, follows ranges
D	MULTX2	✓	...	__MULTX2__	-2.000	-0.520	0.000	0.100	6	TruncatedNormal, follows ranges
D	MULTX4	✓	...	__MULTX4__	-0.520	-0.400	0.000	0.100	6	TruncatedNormal, follows ranges
D	MULTX6	✓	...	__MULTX6__	-2.000	-1.000	0.000	0.100	6	TruncatedNormal, follows ranges

Figure 33 The Uncertain Parameter Panel showing the 8 input parameters.

Table 3 Permeability multiplier values.

	Log(x) Low	Log(x) Start Value	Log(x) Upper	Low	Start Value	Upper
MULTX1	-2.00	-1.00	0.00	0.01	0.10	1.00
MULTX2	-2.00	-0.52	0.00	0.01	0.30	1.00
MULTX4	-0.52	-0.40	0.00	0.30	0.40	1.00
MULTX6	-2.00	-1.00	0.00	0.01	0.10	1.00

The distributions are used in the Monte Carlo and Latin Hypercube sampling process and are chosen to be truncated normal for all uncertain parameters. By using truncated normal distributions the expected value does not necessarily need to be the midpoint in the assigned distribution range. The start value acts like the most likely point. The input distributions for the different input parameters can be seen in Figures 34-41.

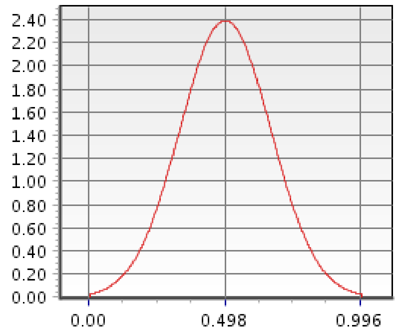


Figure 34 MPV1.

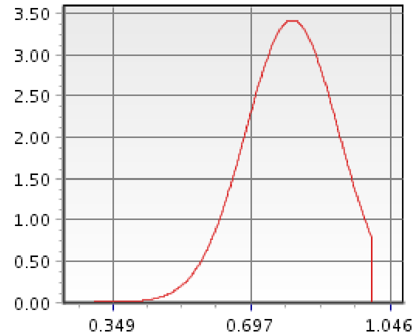


Figure 35 MPV3.

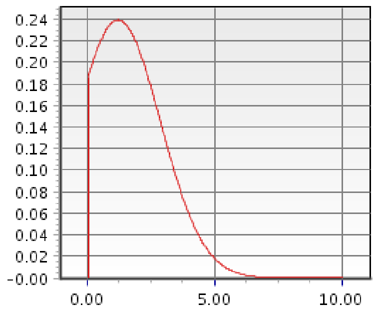


Figure 36 MPV5.

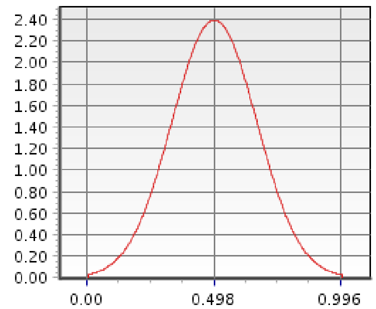


Figure 37 MPV6.

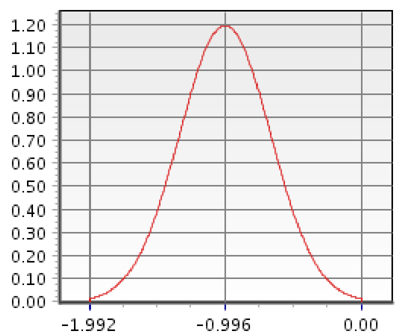


Figure 38 MULTX1.

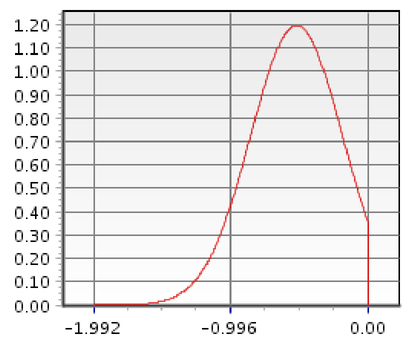


Figure 39 MULTX2.

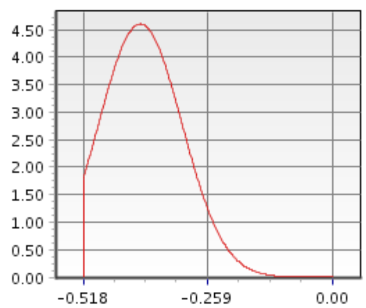


Figure 40 MULTX4.

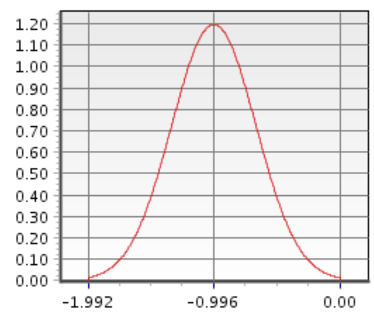


Figure 41 MULTX6.

5.2.1.2 Response Parameters

In the *Response Parameter Panel* the user defines the key parameters of interest that are directly related to the simulation data. In the response parameter panel data history to be matched is added typically from the files .SMSPEC and .UNSMRY that contain production history and model output information of the base case model. Field history to match is defined as *mismatch parameters*, and the useful results to acquire as an output after the simulation may be added as *watch parameters*. Important parts of the history data can be emphasized by applying weighting terms in the mismatch parameters.

The measured pressures from Well A and Well B are historical data that will be matched. A total of four mismatch parameters are created. Two for each well, as build up periods and flowing periods are considered in different mismatch parameters. The mismatch parameters can be evaluated as series (*match series*), where all data is matched, or as points (*match points*), where the user manually picks the points of interest to match. In this study the latter is used as it gives more control of the data points matched in addition to favor the simulation time. The mismatch parameters that are added are M1 and M2 that are empathizing only the buildup pressures in respectively Well A and Well B. In addition to M3 and M4 which empathizes the flowing periods respectively in Well A and Well B.

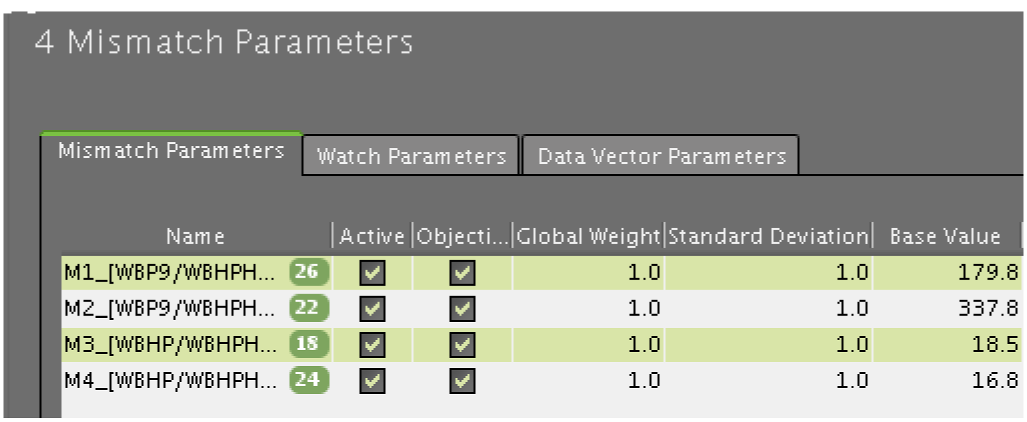


Figure 42 The Response Parameter Panel viewing the Mismatch Parameters.

The response parameter panel in Figure 42 shows the four mismatch parameters that are chosen as inputs to the response modelling process. For the response parameters it is possible to select "active" and "objective". By selecting *active* means that the specified parameter should be calculated. *Objective* means that the parameter is taken into consideration when calculating the objective function. As it is desirable to view the history match cases and to include the pressures in the objective function, both are ticked *on*. A Global Weight of 1 is used for all mismatch parameters, which means that all mismatch parameters are evaluated with equal importance in the objective function. A Standard Deviation of 1 is applied, by this it is assumed that there is no measurement errors in the historical data that are used. The Base Value represents the base case mismatch for the individual mismatch parameter which is given by summation of the mismatch for the match points. The total global value will be the sum of these including any assigned weighting.

Weighting Strategy

Equation 23 in Section 3.4 shows the objective function with weighting properties. The optimization algorithm will focus on minimizing the objective function. When a mismatch parameter or a mismatch point is multiplied by the individually assigned weight the objective function get a higher discrepancy at the point and will focus on minimizing the discrepancy where it is highest. The weighting applied to certain wells or datatypes is called the global weight. Nevertheless, as the Well A and Well B are equally important the global weight of 1 is assigned. It is also possible to apply weighting to emphasize data in specific intervals considered as important periods. This is done by assigning weight to the individual mismatch points. As the buildup periods will provide the reservoir response it is desirable with main emphases on the buildup periods in the mismatch parameters. On the basis of this, additional weighting are applied for buildup periods only. As the base case model does not match the response in the most recent time very well, it is applied increasing weighting with time. Weights that are applied to the mismatch points are ranging from 1 to 8. Each buildup period has at least three match points to capture the curvature. To match the important last point in the buildup this has been given the highest weight. The weighting has been applied by trial and error (e.g. if discrepancy is observed at important parts in the buildup that are desirable to match better, additional weighting are applied).

The mismatch parameters M1-M4 are explained and viewed in the Figures 42 - 45. In the figures the green curve represents the base case model response with the initial parameter values and the black line represents the historical data. The red dots are the chosen match points to be included in the objective function. The mismatch parameters are described as follows:

M1: Mismatch parameter for Well A, where only the buildup pressures are empathized with match points. A total of 26 match points are added, where there are at least 3 points on each buildup period that captures the curvature. Weighting are applied in accordance with the weighting strategy. M1 is showed in Figure 43.

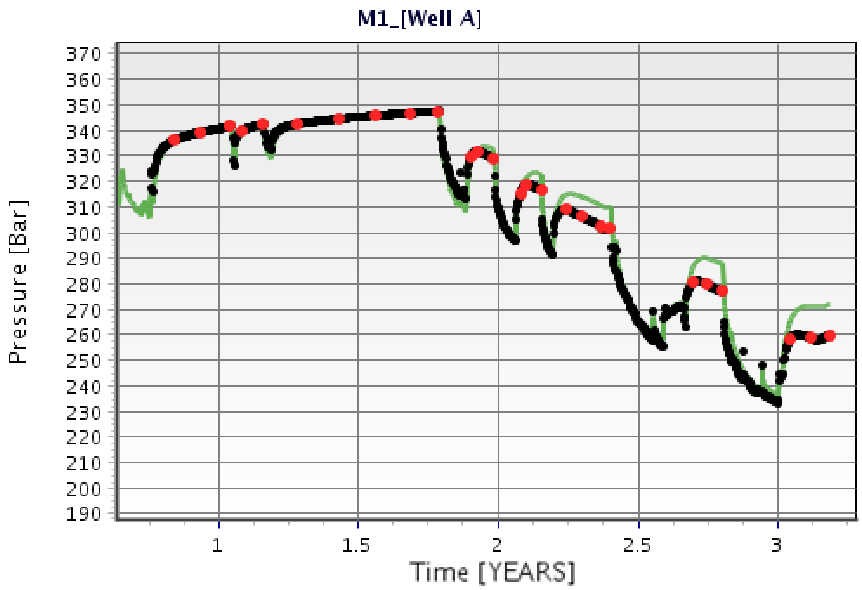


Figure 43 M1:The red dots show the chosen match points for the buildup periods in Well A.

M2: Mismatch parameter for Well B, where only the buildup pressures are empathized. A total of 22 match points are added. Weighting strategy are applied. M2 is showed in Figure 44.

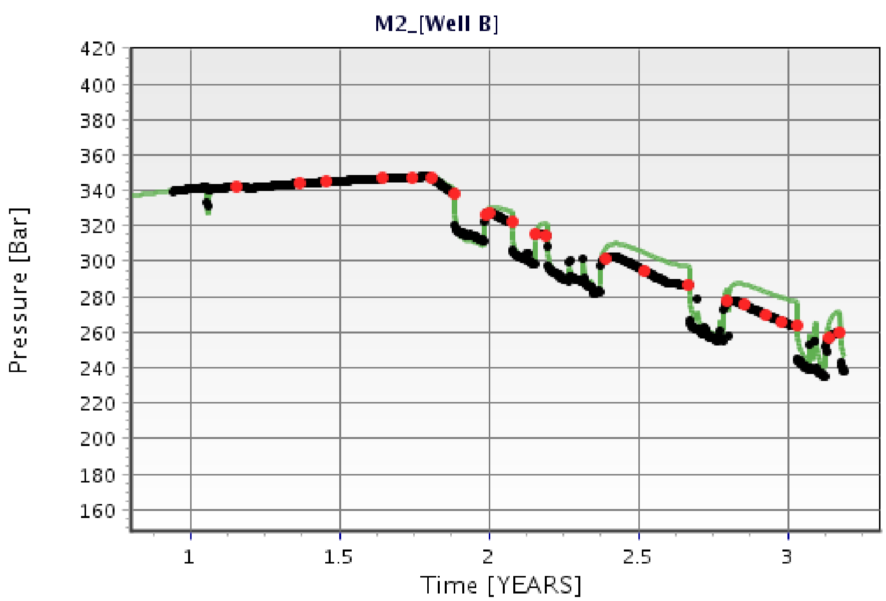


Figure 44 M2: The red dots show the chosen match points for the buildup periods in Well B.

M3: Mismatch parameter for Well A, where only flowing (drawdown) pressures are empathized with match points. A total of 18 match points are added. No additional weighting are applied, which means that each match point has a standard weight of 1. M3 is showed in Figure 45.

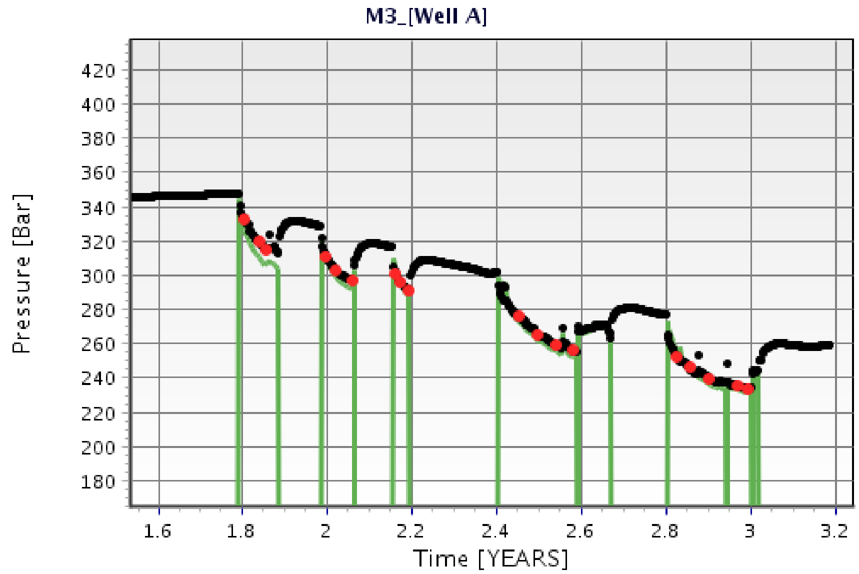


Figure 45 M3: The red dots shows the chosen match points for the flowing periods in Well A.

M4: Mismatch parameter for Well B where only the flowing (drawdown) pressures are empathized with match points, showed in Figure 46. A total of 24 match points are added. No additional weighting are applied, thus each point have a standard weight of 1.

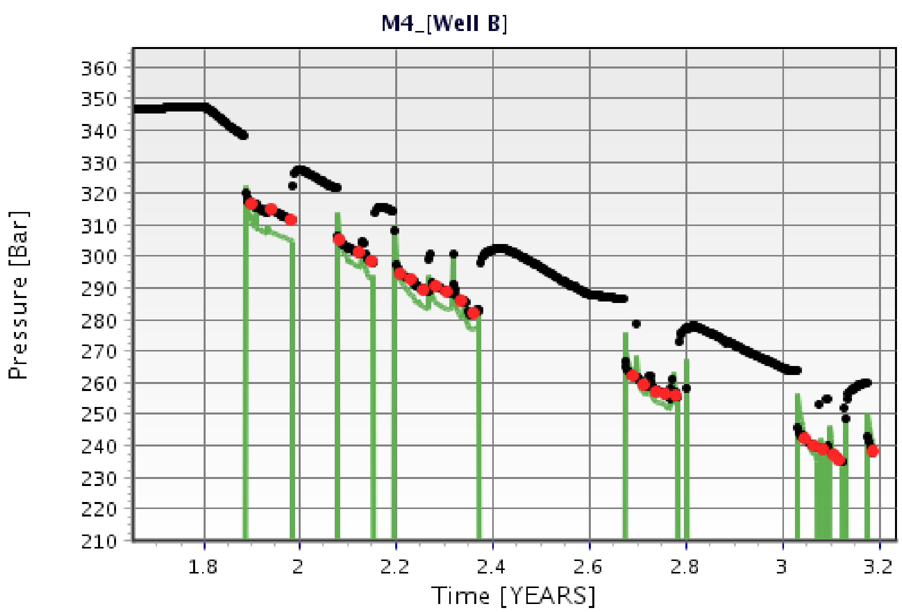


Figure 46 M4: The red dots shows the chosen match points for the flowing periods in Well B.

Watch Parameters

The variables included in the summary file from the base case model, which are uploaded in the response parameter panel, are possible to choose as watch parameters. Figure 47 show the watch parameters in the Response Parameter Panel. The watch parameters are not included in the matching process and in the objective function, thus they are not marked as objective. The following watch parameters are added:

- W1: FGIP, the field gas in place. The parameter will show gas in place at production start, and how the FGIP decreases with production time. The starting point of this watch parameter is of great interest.
- W2: Well bottom hole pressure for Well A.
- W3: Well bottom hole pressure for Well B.
- W4: Time Vector. To include a watch parameter of the TIME vector makes it easy to find how many days the simulation has run, and if the simulation has run through the history period.

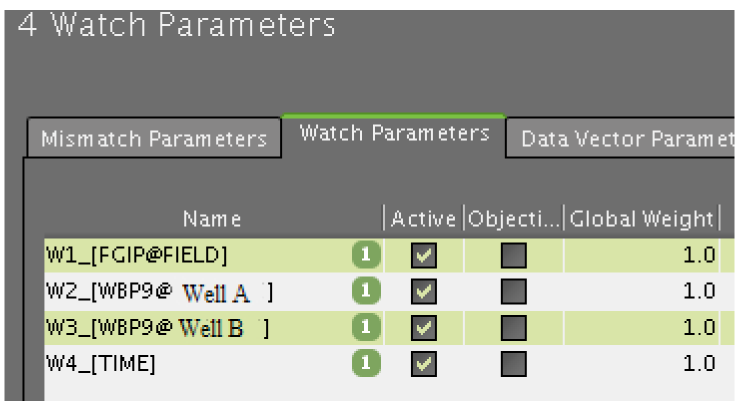


Figure 47 The Response Parameter Panel viewing the Watch Parameters.

5.2.1.3 Simulation Control Centre

In the Simulation Control Centre panel the user decide which algorithm that should be applied in the process of minimizing the objective function. The optimization direction is set to *minimize* as the global objective function should be minimized to get a match. Sampling methods that will be used in the history matching process are:

- Latin Hypercube, this sampling method is used as initial screening by scanning the search space.
- MCMC optimization algorithm, which will minimize the objective function. The method is based on the results from the screening method.

Both methods require the maximum number of simulations to be specified by the user. By the use of MCMC optimization method, certain additional specifications need to be defined by the user, they are as follows:

- Number of samples.
- Burn in time.
- Proxy building method.
- Proxy training set size.
- Number of chains (which in practice means number of experiments in each chain).

In general, for history matching cycles in this study the number of samples are set to 1, the burn in time set to 1000, proxy building method set to Regression-Automatic, the proxy training set size is set to 200 and the number of chains are varied. As this is the recommended procedure (SPT Group, 2014). The number of simulations has been varied both for the screening and for the MCMC optimization. A procedure of starting simple and adding complexity and number of simulations has been followed. By "staring simple and adding complexity" means that a first attempt should be run with few simulations to see if everything is working properly, and to verify if the set-up can give a good match. The second attempt will be a long simulation, which will give proper results that can be used in further analysis. This procedure is put into practice to save simulation time.

Advanced Task Manager Panel

Before running the simulation the user will have to set up the workflow that MEPO will perform for each simulation, this is done in the Advanced Task Manager Panel. The workflow set up used for the study is shown in Figure 48. Each of the workflow tasks are explained in brief below (SPT Group, 2014) :

- Create directory

  Within the cycle folder for the project a directory is created for each experiment, this is where the simulations will be run.

- Pre-processor

  Pre-processing is typically used to prepare a simulation run. MEPO will make a copy of the input files and modify the values of the defined input parameters.

- Eclipse Simulation

  The Eclipse Simulation task is used to launch Schlumberger's Eclipse simulator. A queuing system can be applied which will allow MEPO to use available Eclipse licenses and not occupy them when the licenses is needed elsewhere. This is applied in the study.

- Post-processor

  A post processor typically reads the results of the simulation run. It extracts the response parameter values from the simulation results. In addition will the post-processor calculate the global value for each experiment.

- Save results

  The save results task saves important files produced by the simulator. For the study the files *.SMSPEC,*.UNSMRY and *.OBI are saved. The archived files are used by MEPO for data analysis and plotting.

- Remove directory

  The remove directory task will remove the folder containing the simulation data. In the beginning of a project, or if errors occurs when launching the simulations, it may be helpful to keep the directory to be able to check the certain files in the directory. E.g. the print file may contain more information about the errors that occurs than what the MEPO log window shows.

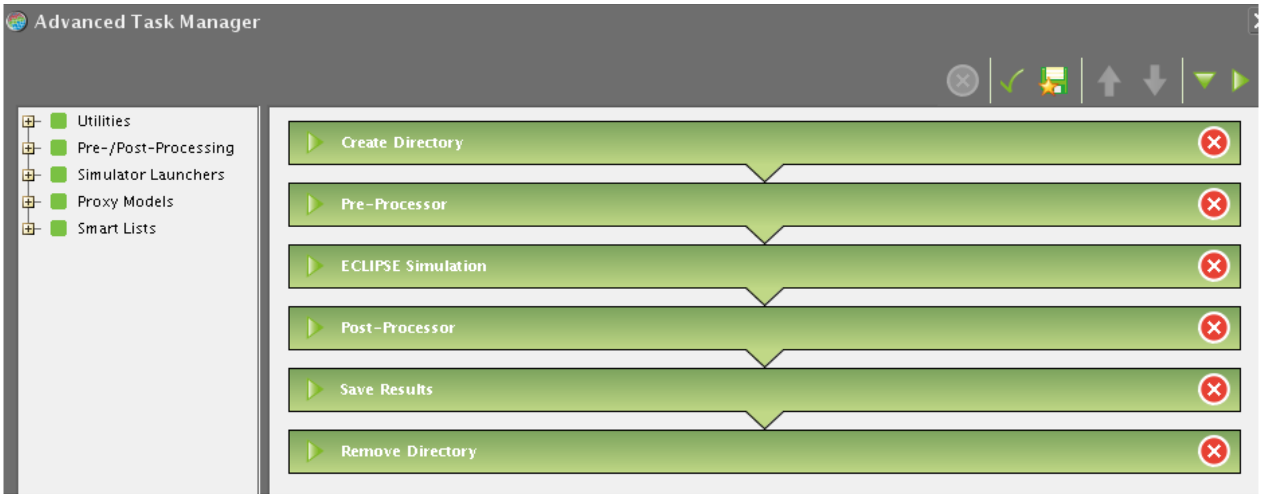


Figure 48 The Simulation Workflow in the Advanced Task Manager Panel.

A maximum simulation time for each experiment is set to 7200 seconds, from the start of launching the experiment. This is done to get more efficient simulations by the use of sequential MCMC iterations. The time is set based on the model and complexity in the cycle. Most of the simulations are finished within a good margin to the maximum time set. The maximum simulation time is set as sometimes a few experiments are taking a very long time to finish, these will slow down the process of going to the next step in the chain. By having a time limit the possibility of a few unfinished simulations should be taken into consideration when deciding the number of experiments in each chain.

The Simulation Analysis Panel and the Global Value

The Simulation Analysis Panel allows the user to select specific history matches and view the results in multiple different plots, in addition the user can view the sampled parameter values for the experiments from the prior distribution. The user may filter out simulation runs and analyze the desired experiments. In addition the user can view the frequency of the parameter samples in posterior distributions. When analyzing the results the *Global Value* is useful. The global value represents the *final* value calculated by the objective function, which is the sum of all the objective points in each response parameter as showed in the expression bellow.

$$Global\ Value = \sum_{i}^{N} Partial\ Objective\ Value_i \tag{33}$$

Where N is the number of response parameters set to objective. Each response parameter has an objective value that is calculated individually by the objective function which includes the defined match points and assigned weights. The global value is calculated for each experiment after a simulation. For simulations done in different cycles but with identical weighting and mismatch parameters the global values can be compared and used to evaluate the history match scenarios. The global value describes how well a model reproduces the historical data. The objective function used in this study will provide values that, by dividing the global value by the total number of match points, will give the average mismatch value for each match point.

Figure 49 summarizes the workflow that will be used for the HM simulation cases in MEPO in a flowchart. The specified numbers of experiments are typically numbers for a final study (with "added complexity").

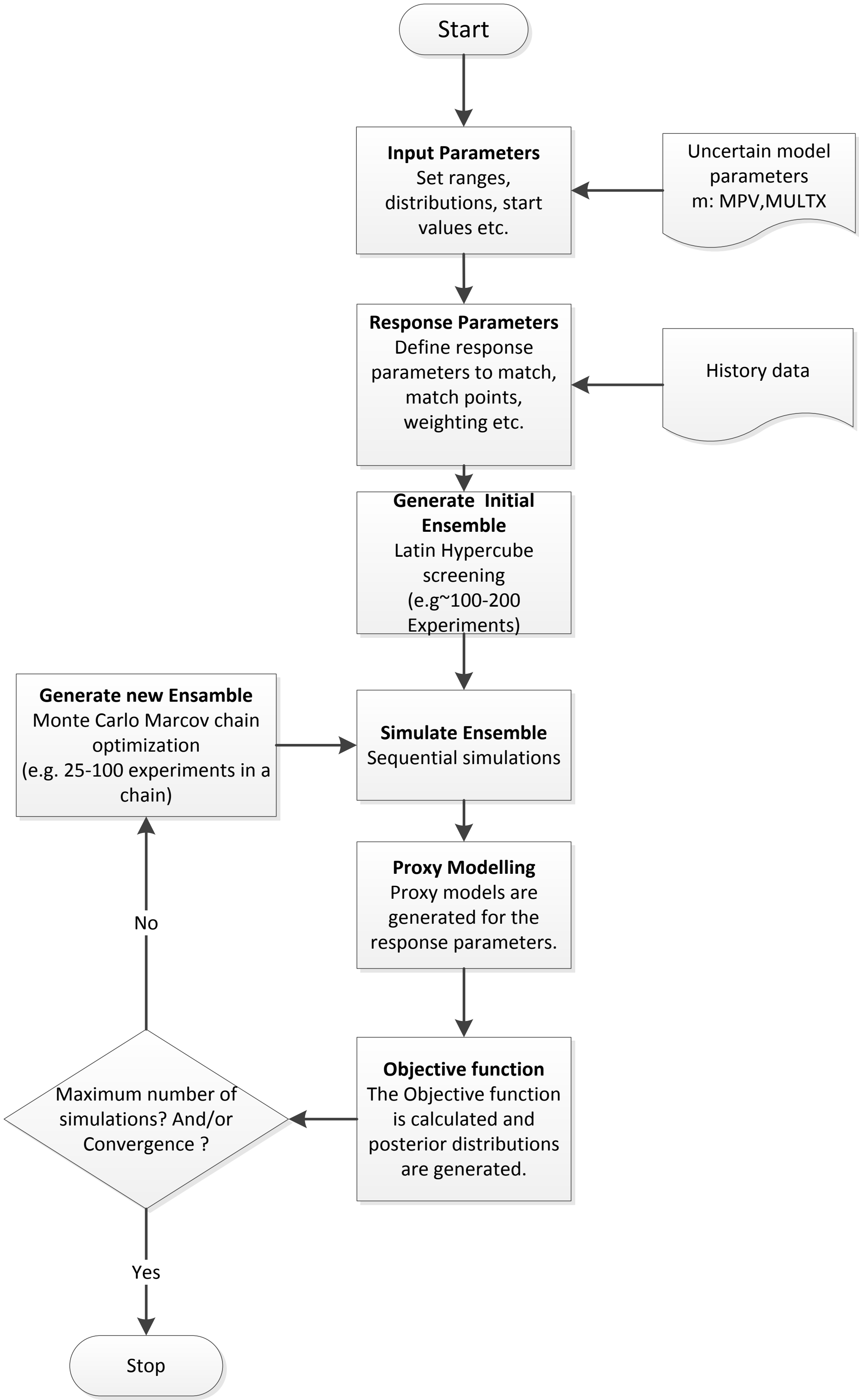


Figure 49 Flowchart of the workflow that will be used for a history matching simulation case in MEPO.

5.2.2 History Matching - Scenario 1

It is desirable to determine if it is possible to get a sufficient history match without applying any changes to region 3. This will be examined in this scenario. Region 3 is the most explored region, thus should contain the least uncertainty. The grid cells in region 3 in the reservoir model has been assigned the properties based on observed data from the drilled wells, and further has the properties been up scaled throughout the high amplitude area defined as region 3. The high amplitude areas are interpreted to be areas of high quality facies. By keeping the parameters defined in the base case model for region 3, only the defined uncertainty in the surrounding regions will be taken into consideration to get a history match. This is done to evaluate and get a picture of the uncertainty in the surrounding regions and to test if the assigned parameter values in region 3 can match the reservoir response.

The following changes and regulations are done in the history match cycle:

- In the input parameter panel the design parameter, MPV 3, is made inactive.
- Note that the input parameter MULTX4 (the permeability multiplier surrounding Well B in region 3) is active but that the uncertainty range is limited compared to the other permeability multipliers as viewed in Figure 33.
- An initial sample period by the use of Latin Hypercube is set to 100 experiments.
- The number of simulations in MCMC has been set to maximum 200 and it is chosen to launch 10 experiments in each chain.

If the simulations gives a sufficient history match longer chains will be run to get reliable results and more likely convergence in the posterior distributions.

The plot in Figure 50 shows the global value calculated for each of the simulated experiments. In the plot, the x-axis displays the number of the experiments in the order that they are launched, while the y-axis shows the calculated global value from the objective function (from Equation 23 in Section 3.4) for each experiment. The first 100 experiment simulations contain parameter value sets that are picked by the Latin Hypercube method, where the goal is to scan the search space. Note that there is no minimization of the objective function in the LH simulations, hence the experiments yields high global values. After the screening period, MCMC is applied and includes the minimization process. As discussed, the MCMC algorithm is continuously trying to minimize the objective function by picking the right input parameter values for the experiments, this process improves the history match. Figure 51 shows the improvement in the global value by the MCMC optimization simulations. It is observed that in the MCMC process the global value is minimized until it reaches a minimum global value of approximately 550. The global values for the experiments in seven chains (with ten experiments in each chain) can be seen in the figure, it is observed limited improvements in the last chains before the simulations were stopped.

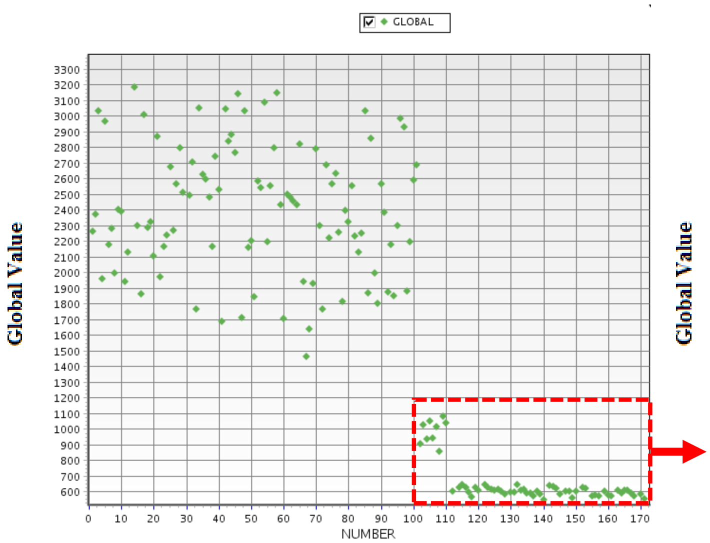


Figure 50 Global values are plotted for all the simulations in Scenario 1.

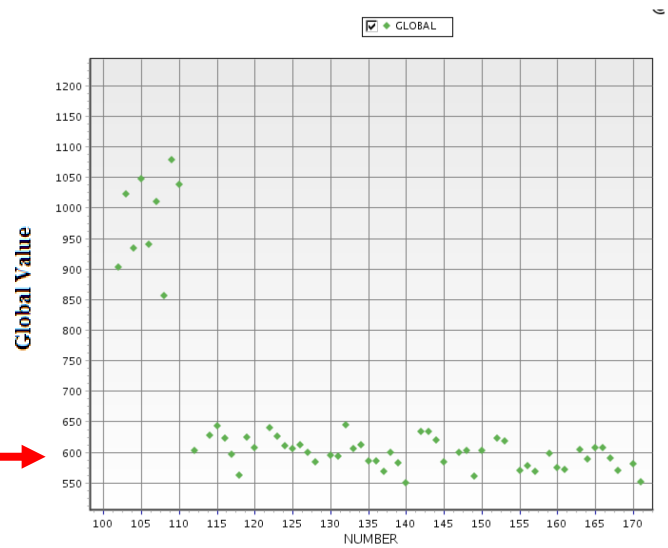


Figure 51 Global values plotted for the MCMC simulations in Scenario 1.

As global value is the summation of the discrepancy between the calculated pressure and the observed pressure for all the match points in the response parameters, the global value is a direct reflection of the pressure match. The global value plots did give an indication of the pressure matches by the global value ranging around 550-600. Figure 52 and Figure 53 shows the plotted pressure matches for all experiments for Well A and B respectively, including the LH experiments. In the figures are the black curve representing the historical data, and the colored curves representing the reservoir model response from the different experiments. This format will be the same for all further pressure match figures. It can be observed that the experiments does not match the historical data very well, especially after the second year of production. From the plotted experiments it seems like it is not possible to get a good match with the chosen input parameters and distributions.

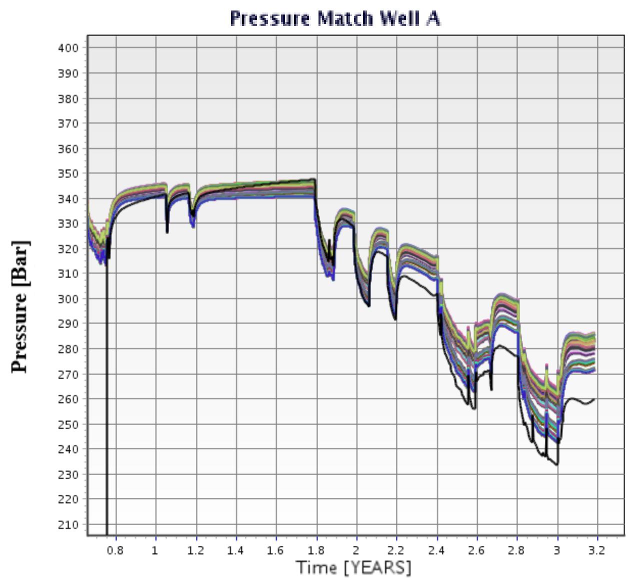


Figure 52 Pressure Match for all experiments for Well A.

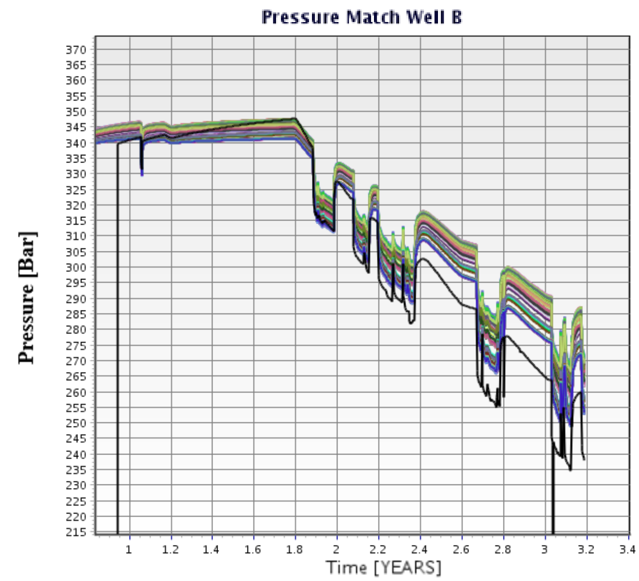


Figure 53 Pressure Match for all experiments for Well B.

As Figure 51 shows, the best MCMC simulations matches have a global value ranging between 650 and 550. These experiments will give the pressure matches with least discrepancy in the pressure match. As the best matches will be the matches that represents the reservoir behavior best, only these will be examined more closely. The pressure matches that have a global value lower than 600 has been chosen as the “best matches”. Figure 54 and Figure 55 show the best pressure matches for Well A and Well B, respectively. The chosen “best matches” are in total 26 experiment simulations, where the lowest global value is 548.9. For both Well A and Well B the model response is lower than the observed data until approximately two years after production, approaching the second year of production the match looks good for a short period of time. After this period the simulated model response gives a higher pressure than the measured pressure for both wells, it seems like the mismatch is increasing with time.

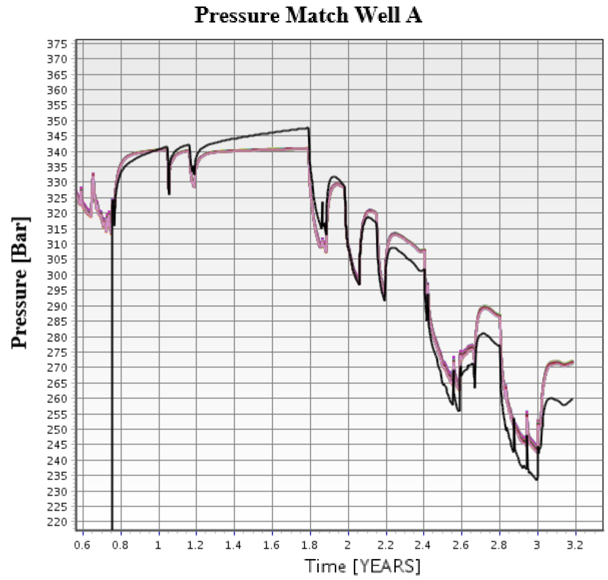


Figure 54 The best Pressure Matches for Well A.

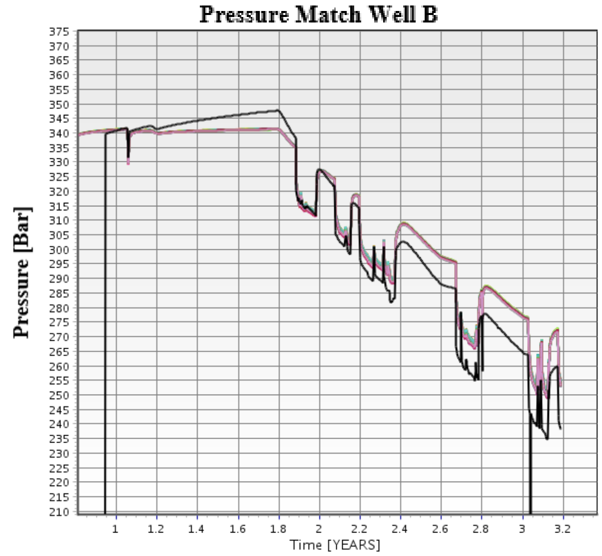


Figure 55 The best Pressure Matches for Well B.

As the model responses and the observed data are not in agreement with each other the volume result is unlikely to represent the true value in the field. Nevertheless, the volume and posterior distributions from the simulations are presented in the following figures as they may be interesting in further discussions and analysis. The field gas in place for the best matches are displayed in Figure 56. The plot shows that the FGIP (before production start) is ranging between 11.1 GSm^3 and 11.2 GSm^3.

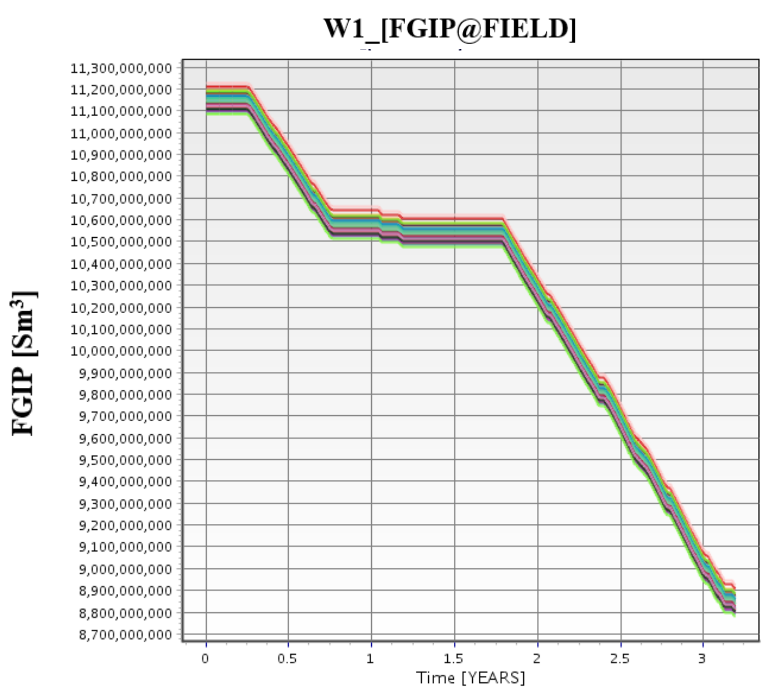


Figure 56 FGIP for the best matches in Scenario 1.

Figure 57-62 show the posterior distributions (in blue compartments) compared to the prior distributions (red line) for the 26 best matches. Where the x-axis represents the multiplier value for the uncertain parameter, and the y-axis represents the frequency of the chosen values in the considered experiment ensemble. The posterior distributions illustrates the sampling of the parameter values for the best matches. It seems like the aquifer is the only parameter that can have a high multiplier in the chosen matches. The pore volume- and permeability- multipliers are reduced towards the lower part of the prior distributions. This may illustrate that the MCMC algorithm is not working properly because the match most likely is outside the initial prior distribution range. An enlargement in the distribution range may in cases like this be useful to improve the match. As the posterior distributions of the parameters are sampled in the lower range, and close to the limit of 0, it is physical impossible to reduce the prior limit further (permeability and pore volume cannot be negative). Region 3 which is the main reservoir area with good facies, are not taken into consideration as an uncertain parameter in the match, this may have led to the need to condition the available uncertain parameters to reach their physical limits to compensate for the lack of possible adjustments in region 3.

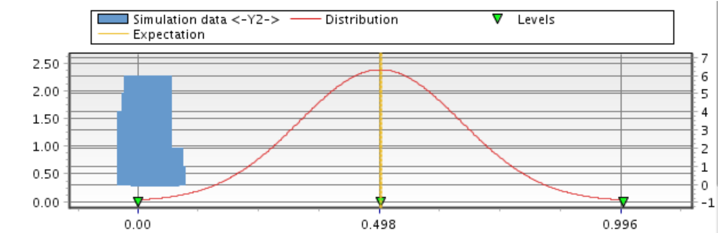


Figure 57 Prior and Posterior distribution MPV1.

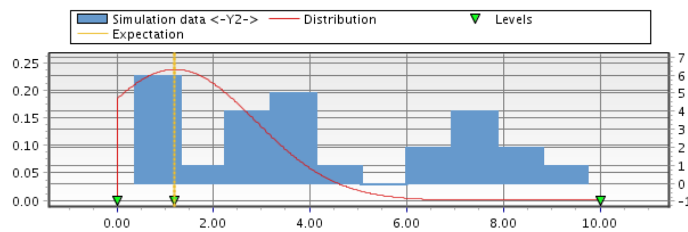


Figure 58 Prior and Posterior distribution MPV5.

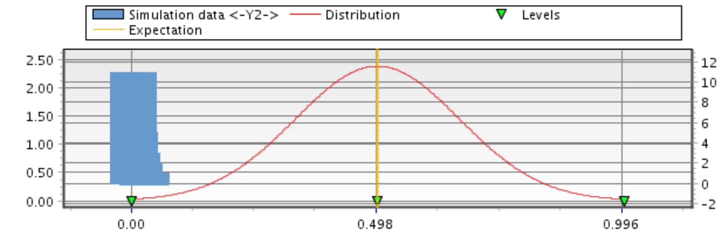


Figure 59 Prior and Posterior distribution MPV6.

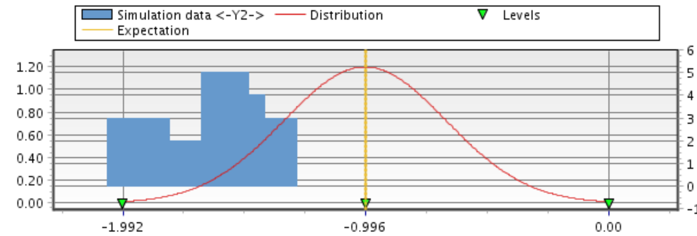


Figure 60 Prior and Posterior distribution MULTX1.

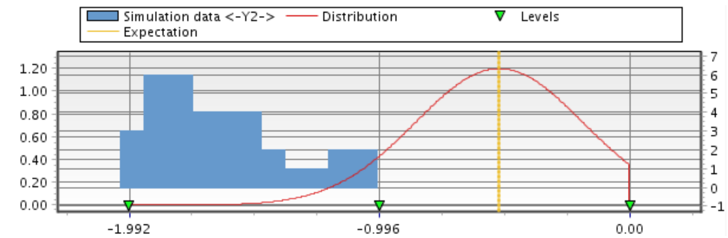


Figure 61 Prior and Posterior distribution MULTX2.

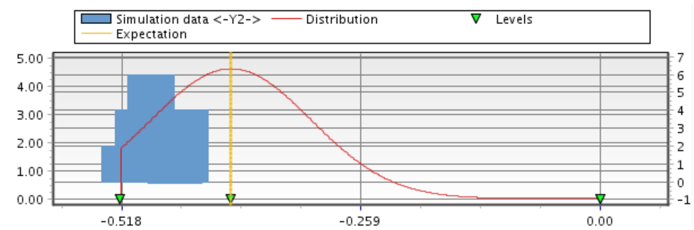


Figure 62 Prior and Posterior distribution MULTX4.

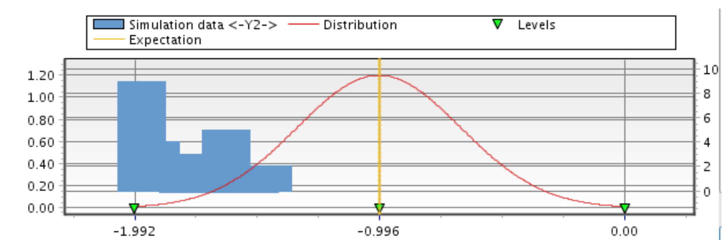


Figure 63 Prior and Posterior distribution MULTX6.

Remarks based on Scenario 1

It is found that the best history matches are not sufficient as they do not capture the later reservoir response in the match. Based on this there is no need to go through with a longer simulation and further predictions. By the registration of the posterior distributions sampling of low values for the input variables it was decided to add an uncertain parameter to region 3 in form of a pore volume multiplier. This is done in hope of getting a better match, as the current base case model is not able to match the historical data.

5.2.3 History Matching - Scenario 2

As the concluding remark from Scenario 1 were to take into account the pore volume multiplier for region 3 as an uncertainty in the reservoir model, MPV3 is added in this scenario. Region 3 is the most explored region and represents the high amplitude area on the seismic that are interpreted to reflect the best reservoir properties, the good reservoir properties were confirmed by the wells. Based on this, the uncertainty spread is not as large as the other regions, hence it is desirable to limit the reduction of the parameter values. This is done by setting the lower limit of the uncertainty range to 0.3. The input parameters are chosen to be as shown in Figure 33, where MPV3 is set active. After a good first simulation attempt with the specified input parameters, a longer simulation was run and will be reviewed here as Scenario 2.

The following changes and regulations are done in the history match cycle:

- An initial sample period by the use of Latin Hypercube is set to 250 simulations, as it should be sufficient to thoroughly scan the search space.
- MCMC has been set to maximum 600 simulations and 50 experiments should be launched in each chain step.

Figure 64 shows the number of the launched experiments and their respective global value. After a long screening period it is observed that the MCMC quickly reaches a low global value. Figure 65 show that after approximately the third step in the Markov chain, the global value has reached a constant low value where all further experiments have a global value under 50. The simulations are stopped after 550 experiment simulations when there is insignificant improvements in the global value in the chain.

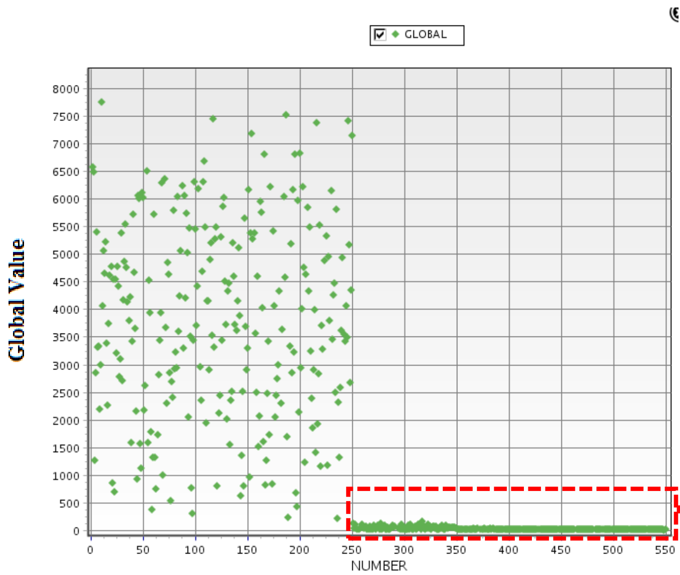


Figure 64 Global values for the simulations in Scenario 2.

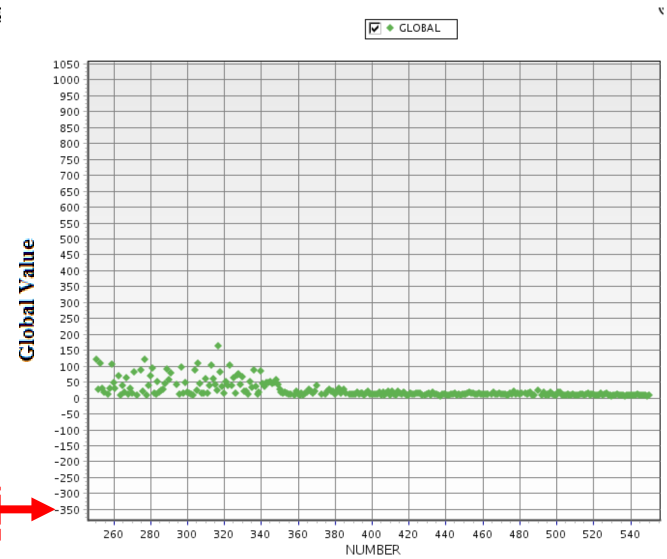


Figure 65 Global values for the MCMC simulations in Scenario 2.

Before choosing the best matches based on the global value, the pressure matches and FGIP estimates for all the experiments will be reviewed. It may be interesting to see what results the reservoir model gives for the whole defined range of the input parameters that is explored in the Latin Hypercube simulations. Figure 66 and Figure 67 show the pressure response in Well A and B respectively for all simulated experiments.

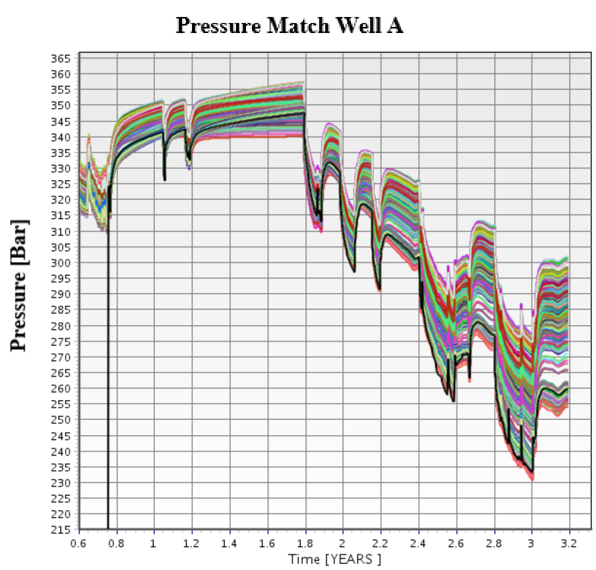


Figure 66 Pressure matches for all simulated experiments in Scenario 2 for Well A.

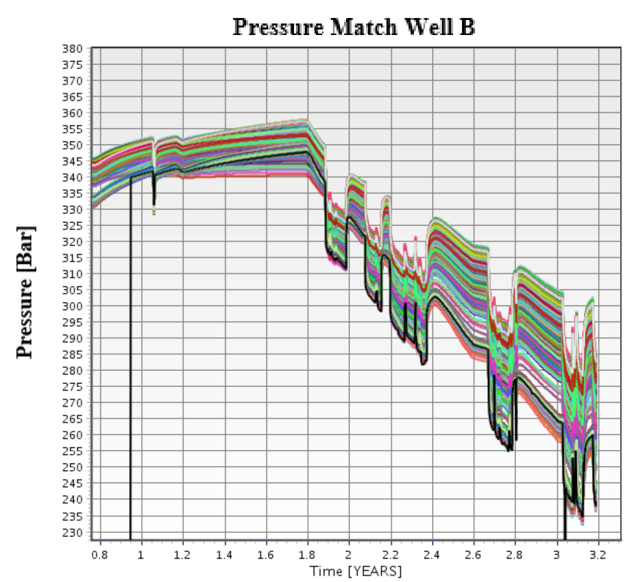


Figure 67 Pressure matches for all simulated experiments in Scenario 2 for Well B.

The pressure matches show that by sampling from the prior distributions, most of the model results yields a higher pressure response than the observed pressure. It seems like the curvature of the observed pressure is adapted to the experiments for most of the production period, the exception may be the long build up period from the first year of production to the beginning of the second year, where the curvature may be a bit different for some of the visible matches. Note that when viewing 550 matches, multiple of them overlays and the best curvature matches may not be easy to spot from the plots showed.

The field gas in place for all experiments can be seen in Figure 68. The prior distributions yields FGIP values ranging from 6 GSm^3 to 13.5 GSm^3. This means that no matter which values are picked from the input distributions, the FGIP will be within this range for all experiments. Table 4 show the percentiles for the 250 Latin Hypercube experiments that are only based on the prior probability distributions.

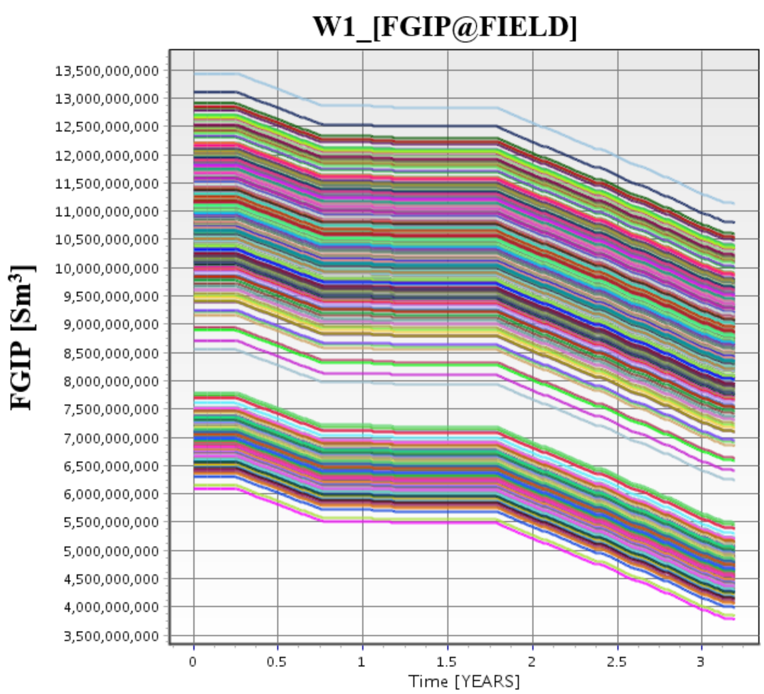


Figure 68 FGIP for all experiments in Scenario 2.

Table 4 Latin Hypercube FGIP Percentiles for Scenario 2.

		FGIP [GSm3]		Uncertainty range
Latin Hypercube	P10	P50	P90	P10-P90
Scenario 2	9.92	11.14	12.29	19 %

To be able to find the matches that can represent the historical data and the mitigated uncertainty in the reservoir, the non-representable matches have to be filtered out. From Figure 65 it seems like the MCMC has reached convergence at a global value under 50. Figure 69 and Figure 71 show the pressure match in Well A and Well B respectively, for the matched experiment with a global value under 50. Figure 70 and Figure 72 show a close-up of the pressure match for the last year of history data. In the buildup periods it seems like the experiments matches the observed data well, with approximately +- 4 bars for the last build up sections.

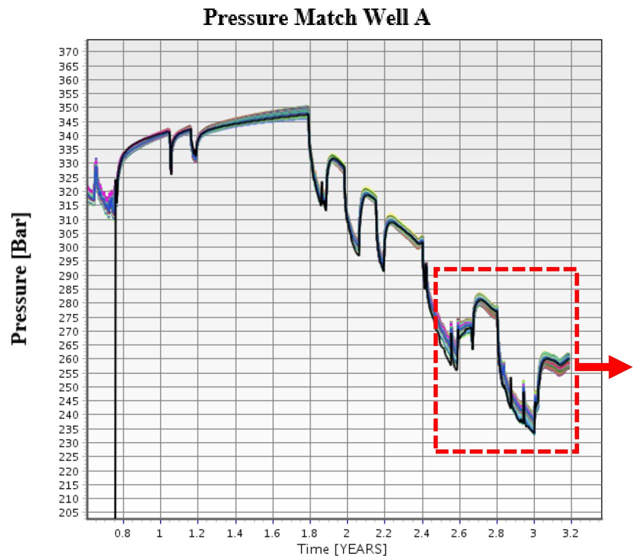


Figure 69 Pressure match for Well A for the matches with a global value under 50.

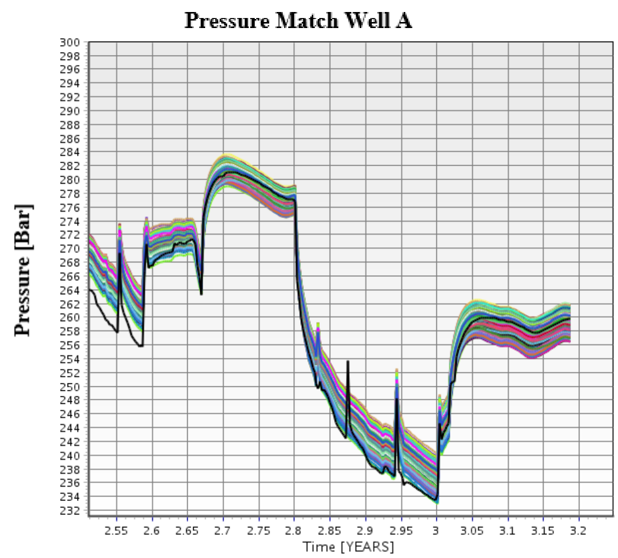


Figure 70 Close-up of the pressure match for Well A for the matches with a global value under 50.

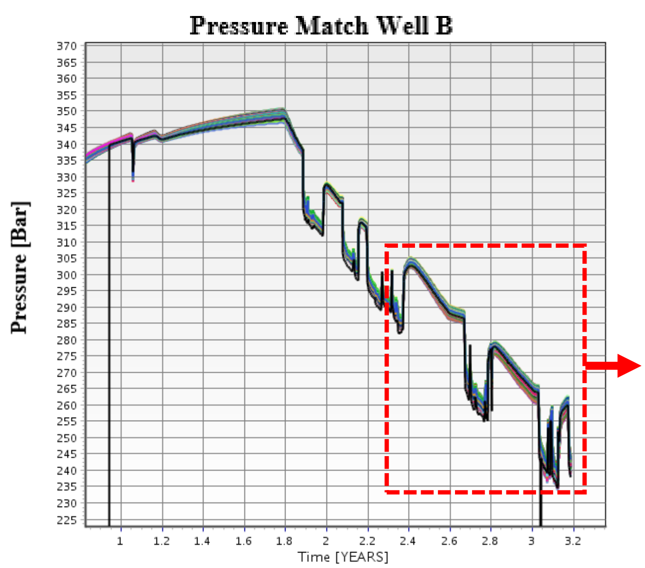


Figure 71 Pressure match for Well B for the matches with a global value under 50.

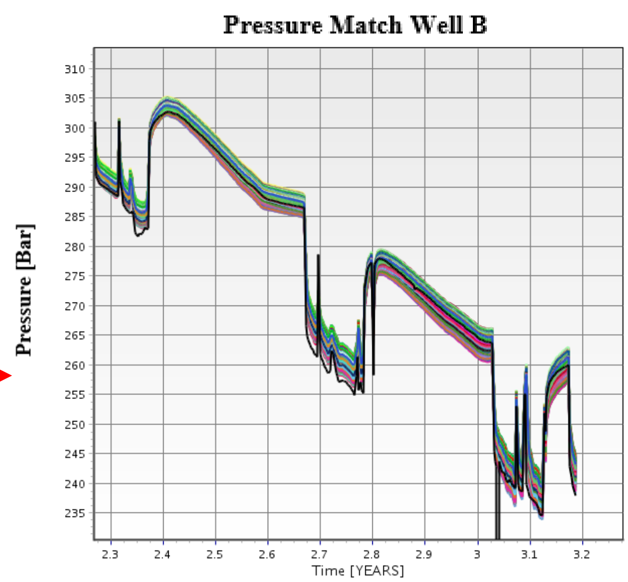


Figure 72 Close-up of the pressure match for Well B for the matches with a global value under 50.

The field gas in place percentiles for the MCMC experiments with different cutoffs on the global value is presented in Table 5. By filtering on a high global value matches with a larger discrepancy from the observed data are taken into consideration. In most cases by allowing a higher mismatch, a higher uncertainty will be taken into consideration in the results. Table 5 show how the global value cutoff changes the percentiles of the estimated FGIP. The percentiles for the higher global value are to a certain degree capturing more uncertainty. The results stay within a volume change of + - 4 % within each percentile.

Table 5 FGIP percentiles for different filtering on the global value.

Filter on		FGIP [GSm^3]		Uncertainty range
Global Value:	P10	P50	P90	P10-P90
8	6.95	7.23	7.41	6 %
10	6.95	7.2	7.44	7 %
15	6.92	7.16	7.43	7 %
20	6.92	7.14	7.43	7 %
50	6.84	7.12	7.41	8 %
All MCMC	6.70	7.09	7.40	9 %

Further, the experiments represented by a maximum global value of 10 is chosen as the "best matches" as most of the experiments from last chain contain global values under this value. There are approximately 80 simulated experiments in total with a global value under 10, where the lowest global value is found to be 6.16. The pressure match for the best matches for Well A and Well B can be seen in Figure 73 and Figure 75 respectively. For both wells the pressure match looks very good. The close-up views in the plots in Figure 74 and Figure 76, show that the buildup pressures are matched better than the flowing periods, this is a result of the weighting of the important build up periods.

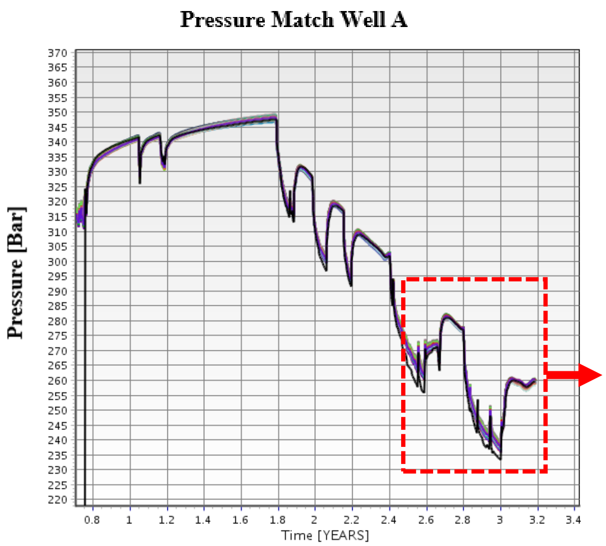


Figure 73 Pressure match for the best matches in Well A.

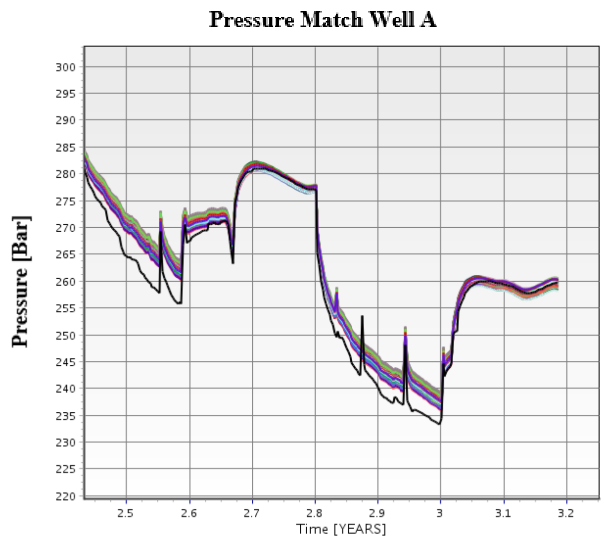


Figure 74 Close-up of the pressure matches for the last year in Well A.

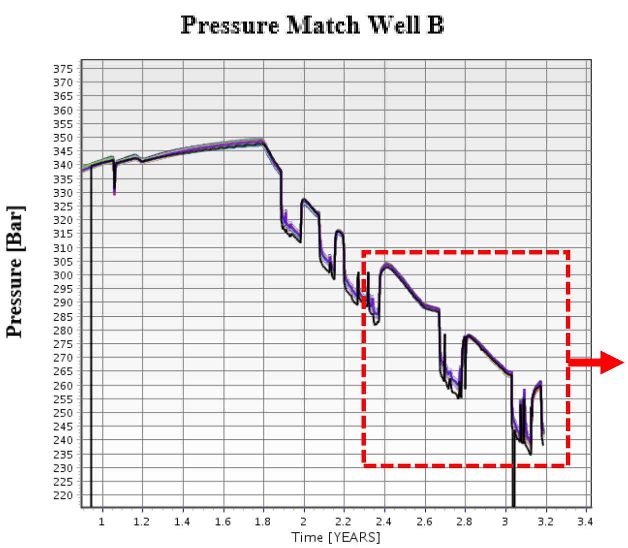


Figure 75 Pressure match for the best matches in Well B.

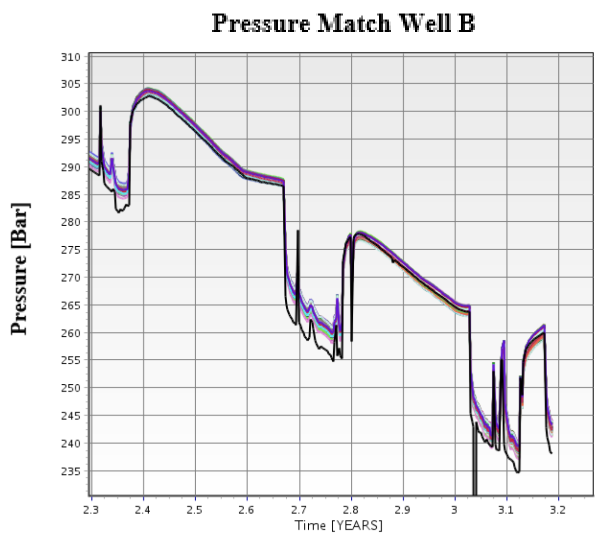


Figure 76 Close-up of the pressure matches for the last year in Well B.

The field gas in place for the best matches is showed in Figure 77. The FGIP mainly ranges from 6.85 GSm^3 to 7.5 GSm^3 in addition to a few experiments that calculates the FGIP to be 7.8 GSm^3.

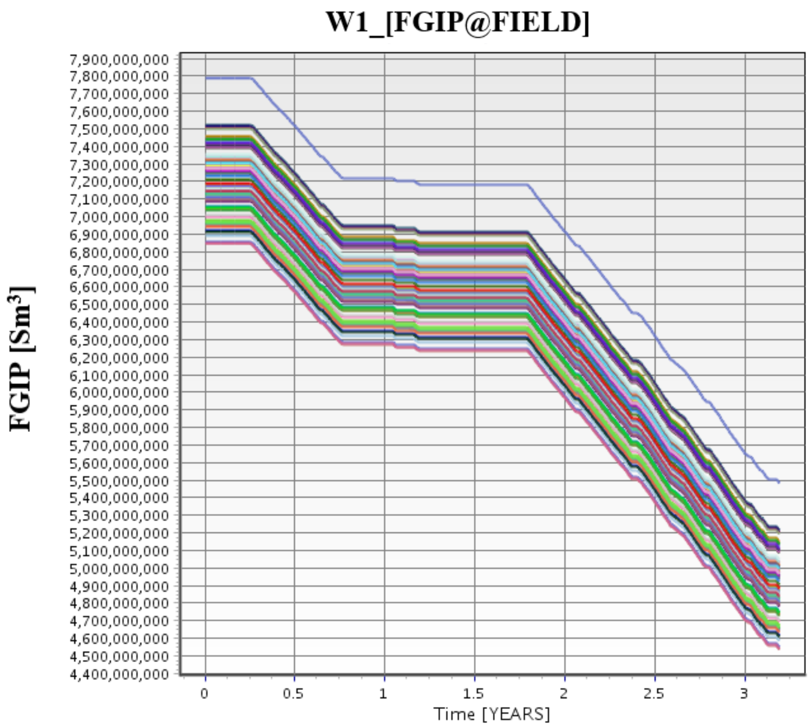


Figure 77 FGIP for the 80 best matches in Scenario 2.

When comparing the pressure match and the FGIP of the good matches to the matches from the screening period it is observed that by filtering out the experiments that gives high discrepancy in the pressure match, also the high volume estimates are gone. Only the lowest FGIP estimates remains after the filtering. From this it can be found that the high pressure matches in Figure 66 and Figure 67 represented the high FGIP in Figure 68. The percentiles for the matches with a global value of 10 is showed in Table 5.

The posterior distributions will show the updated uncertainty in the parameters that represent the uncertainty picture for the best matched experiments. The posterior distributions for the best matches are showed in Figure 78-84. These will be discussed further in Section 5.5. As the distributions are based on the 80 best matches, there are some uncertainties related to if they have reached their stationary state. This may be desirable to test.

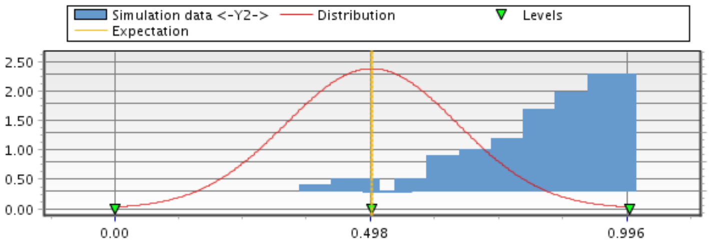


Figure 78 Prior and posterior distributions MPV1.

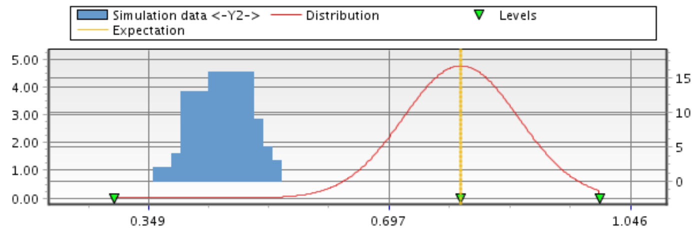


Figure 79 Prior and posterior distributions MPV3.

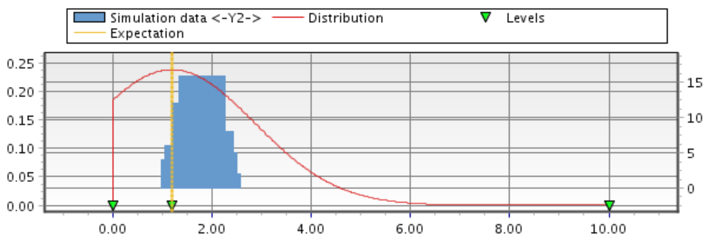


Figure 80 Prior and posterior distributions MPV5.

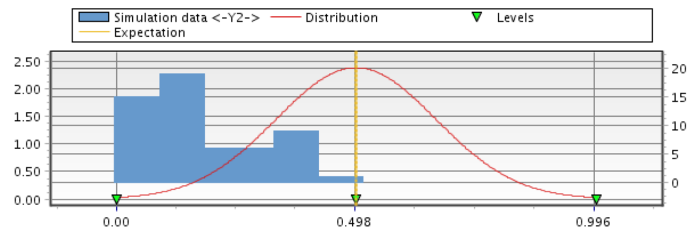


Figure 81 Prior and posterior distributions MPV6.

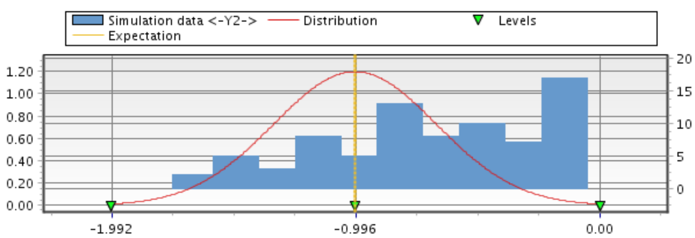


Figure 82 Prior and posterior distributions MULTX1.

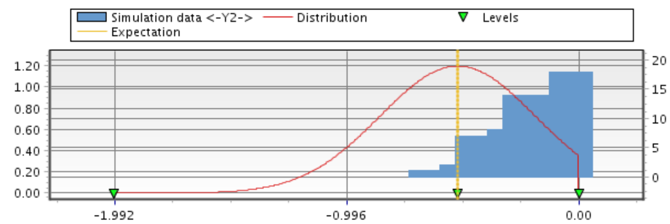


Figure 83 Prior and posterior distributions MULTX2.

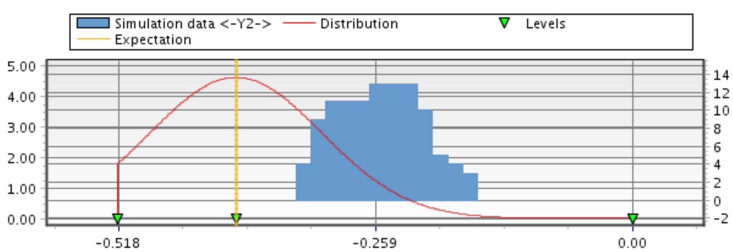


Figure 84 Prior and posterior distributions MULTX4.

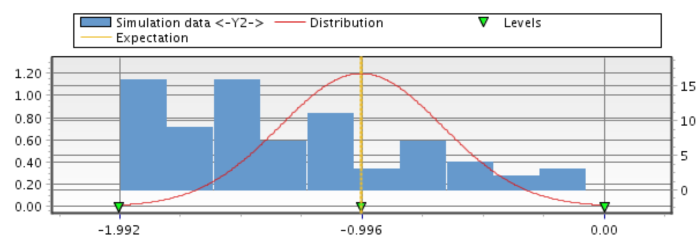


Figure 85 Prior and posterior distributions MULTX6.

Remarks Scenario 2

The history match is found to be sufficient, but as the posterior distributions for further analysis are of interest it is desirable to find if it is possible that they have converged to their stationary distribution. The posterior distributions should represent the uncertainty in the reservoir and yield a complete uncertainty picture. From this scenario there is still doubts about whether the uncertainty range is represented properly.

5.2.4 History Matching - Scenario 3: Investigating Convergence

After viewing the resulting posterior distributions in Scenario 2, it was decided that it was desirable to find if the MCMC has been running long enough for the posterior distributions to reach convergence. This is difficult to determine as discussed in Section 3.6.1. It is made an attempt, at least, to find if the distributions *not* have reached convergence. This is done by keeping the same set-up as in Scenario 2 with approximately twice as many simulation runs.

After the simulations have been run in a new cycle, it is found that the number of sufficient matches has increased significantly. By choosing the experiments with a global value under 10 (to be consistent with Scenario 2), there are approximately 550 matches, compared to 80 in Scenario 2. The lowest global value is found to be 5.88. By choosing the same upper limit of the global values in Scenario 2 it is assumed that the posterior distributions should be the same if they have converged.

The pressure matches for Well A and Well B can be seen in Figure 86 and Figure 88 with a close-up of the last time period in Figure 87 and Figure 89. They look similar to the matches in Scenario 2, but there are multiple times additional experiments overlaying.

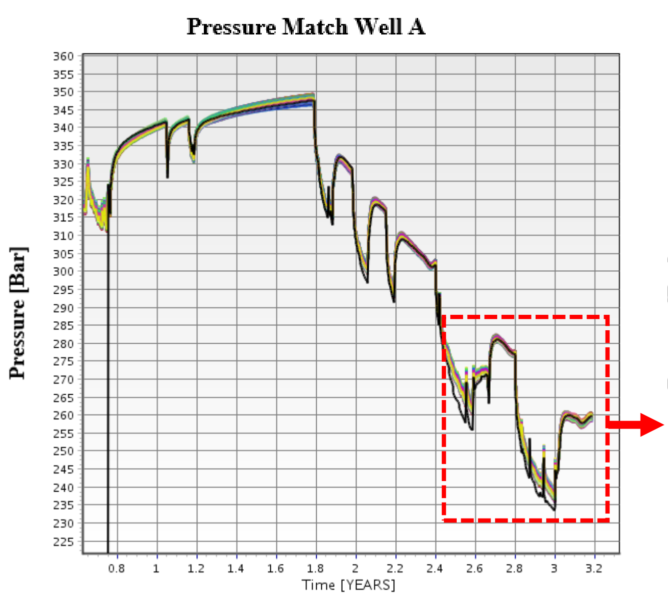


Figure 86 Pressure Match Well A.

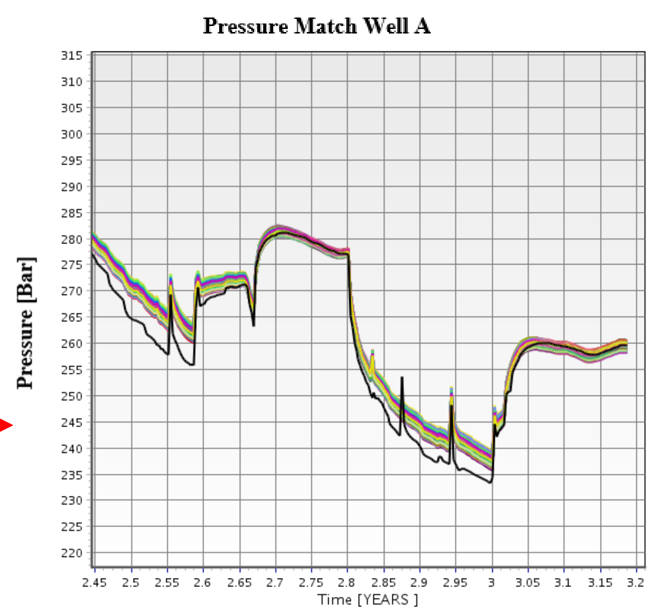


Figure 87 Pressure Match Well A.

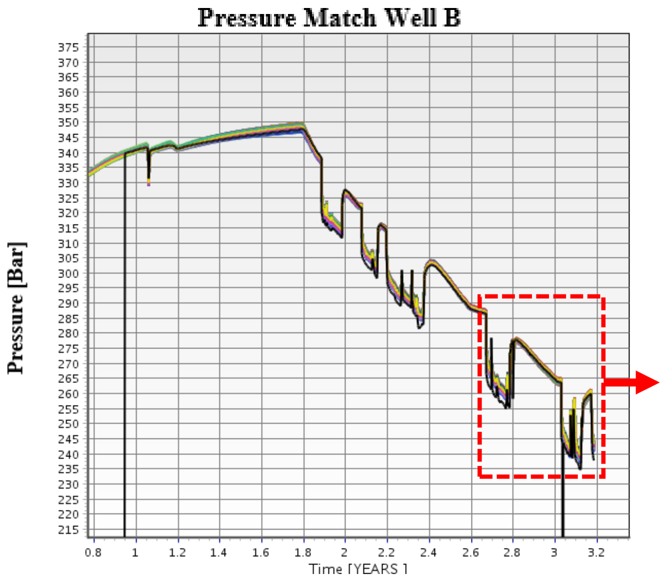


Figure 88 Pressure Match Well B.

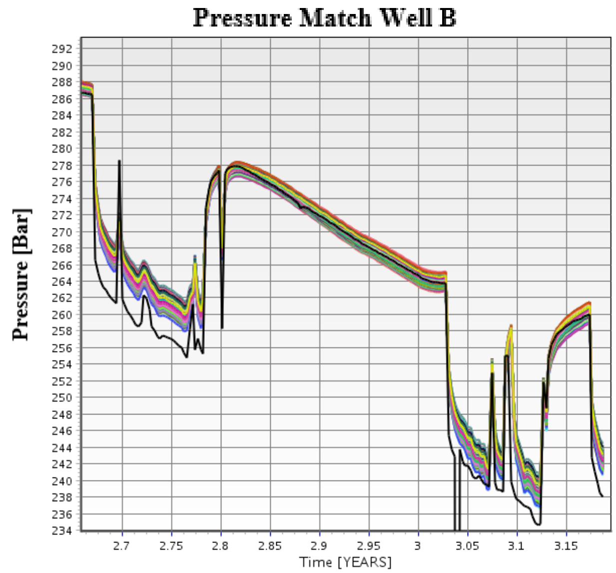


Figure 89 Pressure Match Well B.

The field gas in place for the 550 best matches can be seen in Figure 90. By comparing the plot to Figure 77, it is observed that the 550 cases gives a more complete picture than the 80 experiments in Scenario 2 as all gaps are filled. The upper and lower boundaries are observed to be approximately the same.

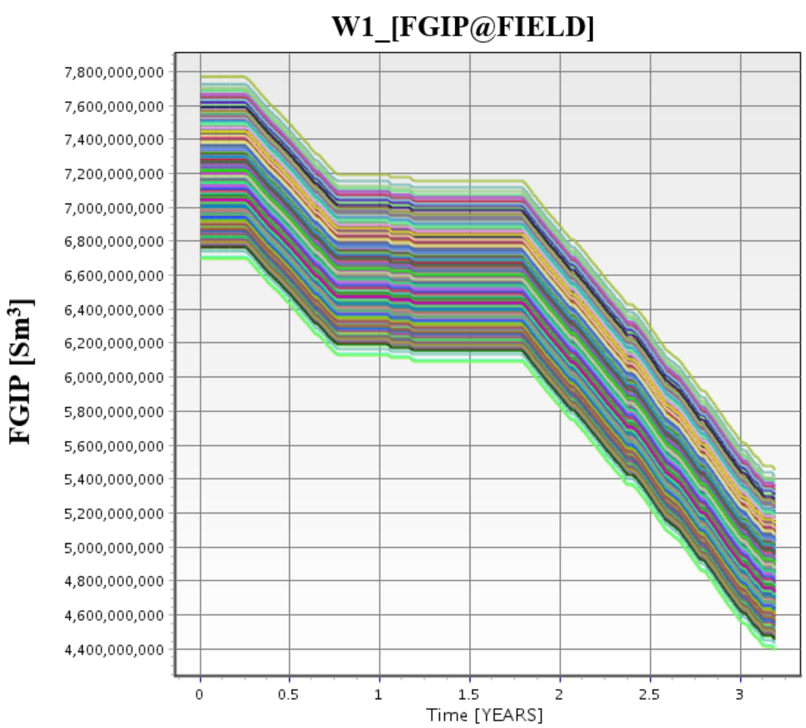


Figure 90 FGIP for the 550 sufficient matches.

Table 6 show the FGIP percentiles; P10, P50 and P90, for filtering on different global values. It is observed very little change in the percentiles. This is mainly because the majority of the matches contain a low global value hence is dominating a certain uncertainty interval on the FGIP. As described approximately 550 matches have a global value under 10, this is exceeding half of all the MCMC experiments in the cycle. As there are high frequency of the matches giving a certain volume, the experiments with a higher global value, that may have different volume estimates, does not influence the percentiles as much as they would in a scenario with fewer experiments.

Table 6 FGIP for different global values.

Filter on		FGIP [GSm^3]		Uncertainty range
Global Value:	P10	P50	P90	P10-P90
8	6.94	7.15	7.38	6 %
10	6.92	7.17	7.4	6 %
15	6.91	7.17	7.43	7 %
20	6.91	7.17	7.43	7 %
50	6.91	7.17	7.43	7 %
All MCMC	6.9	7.17	7.43	7 %

The posterior distributions for the experiments with a global value under 10 are shown in Figure 91-97. Comparing the posterior distributions from the two cycles it is observed that they are reasonable comparable as there are not much differences in the distributions.

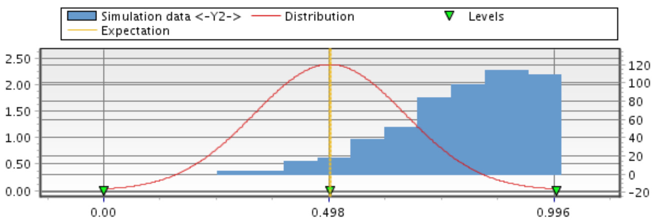


Figure 91 Prior and posterior distributions MPV1.

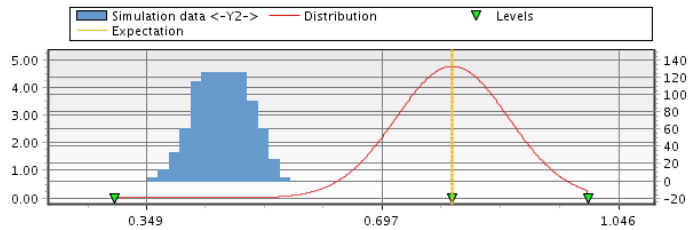


Figure 92 Prior and posterior distributions MPV3.

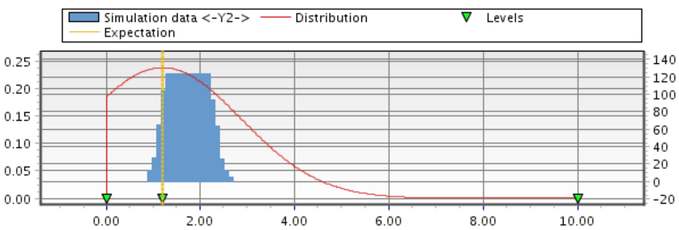


Figure 93 Prior and posterior distributions MPV5.

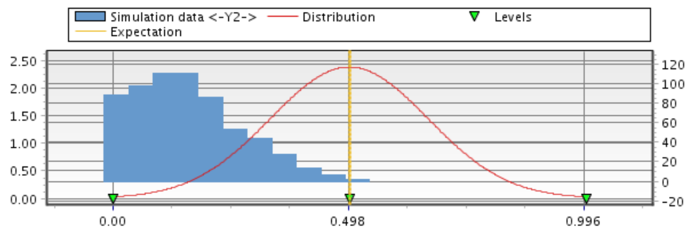


Figure 94 Prior and posterior distributions MPV6.

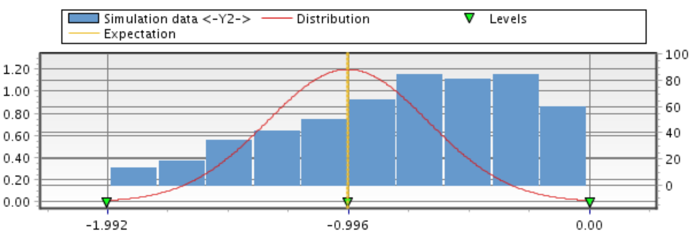


Figure 95 Prior and posterior distributions MULTX1.

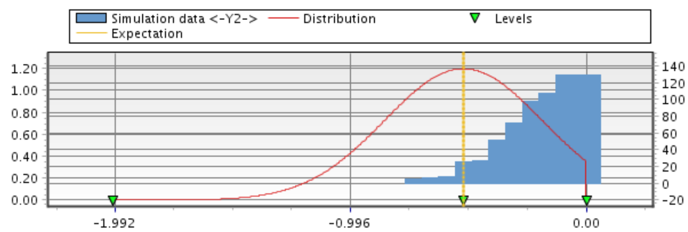


Figure 96 Prior and posterior distributions MULTX2.

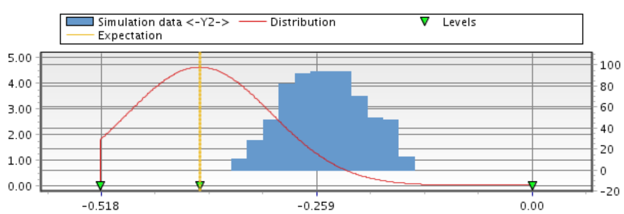


Figure 97 Prior and posterior distributions MULTX4.

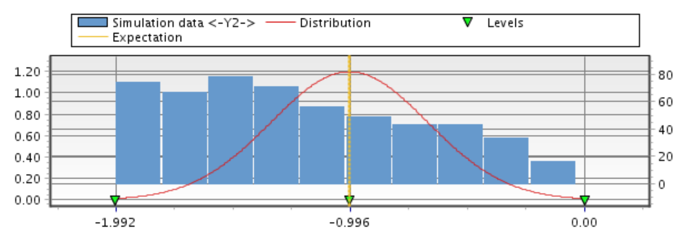


Figure 98 Prior and posterior distributions MULTX6.

Remarks Scenario 3

The long simulation of MCMC yields a large increase of the experiments with low global values, hence a good history matches. Compared to Scenario 2 the long simulations yields a fuller picture of the FGIP. The posterior distributions seem to cover the same range and are to a large extent similar to the ones in Scenario 2.

From this it seems like the "best" experiments in Scenario 2 captures the same uncertainty as Scenario 3, in particular in terms of the parameter uncertainty represented by the posterior distributions. The longer simulation in this scenario verifies the posterior distributions in Scenario

2, however this is not a proof on convergence. Nevertheless, literature have found that if the chain did not reach convergence, it is likely that this could be found by comparing the results from a simulation as in this scenario.

What is to discuss further is if the uncertainty picture from the posterior distributions are able represent the uncertainty in the reservoir, and what interpretations to be tested further.

5.3 Sensitivity

A sensitivity simulation has been carried out to be able to find how the input parameters, defined by their prior uncertainty range, will influence the pressure match. In addition it is of great interest to find the influence of the different pore volume parameters on the gas in place.

The method one-variable-at-a-time (OVAT) has been utilized for the sensitivity study of the prior parameter distributions. The OVAT method is fairly simple. The method does only calculate the states for the endpoint values, for each of the parameter distributions, by varying one value at a time and keeping the other parameter values constant at their chosen start values. By applying this method the number of states tested, and experiments that are launched are two times the number of input parameters plus one. Where the last experiment is calculated by keeping all the parameter values at their start points. The same sensitivity results have been confirmed by the experimental design method; Plackett-Burman (Plackett and Burman, 1946), as the method yields the same results as OVAT method.

Figure 99 and Figure 100 presents the results from the sensitivity study in tornado charts with descending parameters based on their influence on the pressure calculated by the reservoir model. The parameter influence on the pressure in Well A is shown by Figure 99. The parameter influence on the pressure in Well B is presented in Figure 100. From the tornado chart it is found that by picking the lowest boundary value from the MPV3 distribution, the pressure reduction is around 20 % in both wells. (Note that this is by holding the other values constant at their start values). The MPV6 lower boundary can decrease the pressure by around 7 %, MPV5 by approximately 5 %, MPV1 by 2.5 %, and the permeability multipliers with under 2 %. The total pressure reduction or increase in an experiment is reflected by the sum of the influence of the parameter values that are in the parameter set for the experiment.

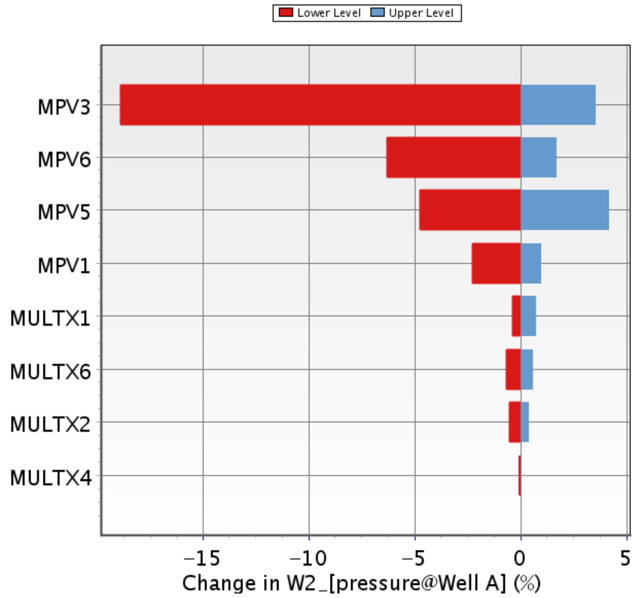


Figure 99 Tornado chart showing pressure match influence for different input parameters, Well A.

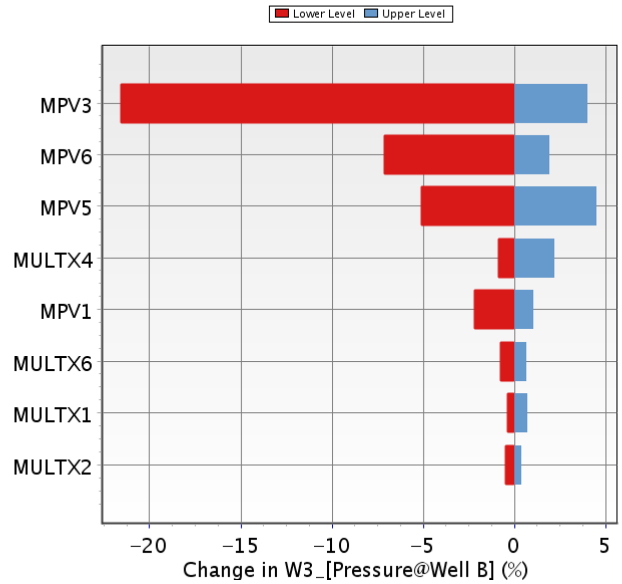


Figure 100 Tornado chart showing pressure match influence for different input parameters, Well B.

Figure 101 shows the parameter influence on the field gas in place. MPV3 is dominating with the input parameter range are able to decrease the gas pore volume by over 40 % and increase it by almost 20 % from its starting point. MPV6 can adjust the pore volume by around 13 % in either direction and MPV 1 can adjust it by around 5 %. Region 5 does only contain water, hence there are no pore volume that can contribute in the FGIP volume.

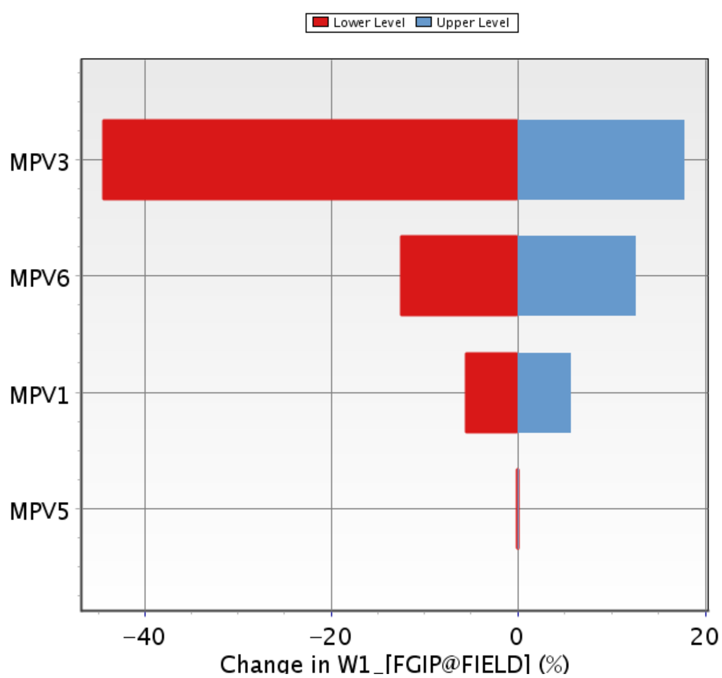


Figure 101 Tornado chart showing the pore volume multiplier sensitivity for the FGIP.

5.4 Predictions

When a history match is sufficient the next step is to simulate how the results gained from the HM will affect the future production. In the history matching process performed in the previous sections, the prior distributions are transformed to posterior distributions. The posterior distributions should represent the mitigated uncertainty after conditioning the model to the historical data. The posterior distributions may be used to explore the possible responses in the future production. As Section 3.6.5 discuss, the MCMC sampling method should give a picture of the uncertainty spread in the predictions by independent sampling from the posterior distributions, which further are used to simulate future reservoir responses. This f will address the procedure of setting up a prediction cycle in MEPO, before the MCMC Sampling method is applied.

5.4.1 MEPO Implementation - Prediction Cycle

As the predictions need to be simulated in separate cycles from the history match cycles, the first step is to copy the HM cycle which gives a sufficient HM to a new cycle. The new cycle objective is changed to *history conditioned forecasting* (which will recommend the prediction methods in the simulation control center panel). Further changes to the cycle are described in the following sections.

Input Parameter Panel

As the predictions are run for a certain future time period this period need to be defined in the simulation runs. This is done by modifying the schedule section in the data file to include production in the future for the desired time period. The production rates for given time periods are implemented in the data file in the input parameter panel, where planned downtime also are taken into consideration. Instead of implementing the sequential production, both wells are producing half of the required production rate. The schedule section is modified to cover a total time period of 19 years after production startup. This means that each simulation will predict responses for this time period.

Response Parameters Panel

Any new response parameters of interest may be added to the list created in the history match cycle. In the prediction cycle the total field gas produced is of interest, hence is added as a watch parameter, W1 FOPT. The cycle now have five watch parameters in the Response Parameter Panel as viewed in Figure 102.

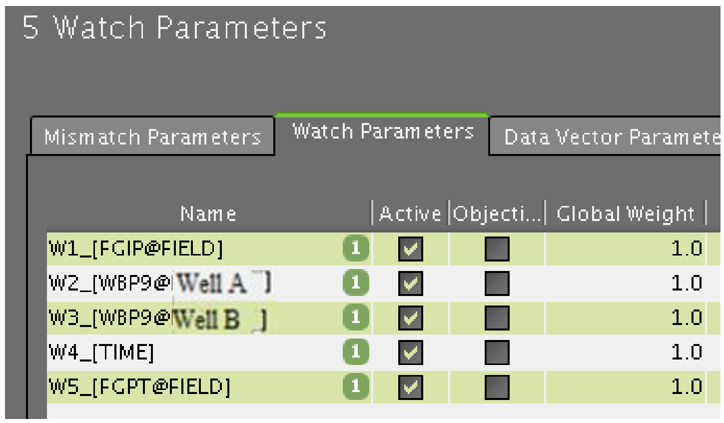


Figure 102 Watch Parameters for the prediction cycle.

Simulation Control Center

In the Simulation Control Center the MCMC Sampling method is added. This method will sample from the posterior distributions by using the selected proxy model (often the last proxy) from the history match cycle. As mentioned in Section 3.6, after each Markov chain iteration a proxy model is created and saved in the proxy parameter panel. As the MCMC leads to an iterative refinement process the proxy models gradually improved and becomes of higher quality. Based on this, the last proxy is often chosen as the proxy to use in the MCMC Sampling method for predictions.

In the MCMC sampling task panel the user needs to define the number of experiments, the specific proxy to use from the copied history match cycle, the number of chains and the burn in time as shown in Figure 103 and Figure 104. The last proxy from the history match cycle is chosen, number of chains are chosen to be 1 as one proxy is added, and the burn-in set to be 1000.

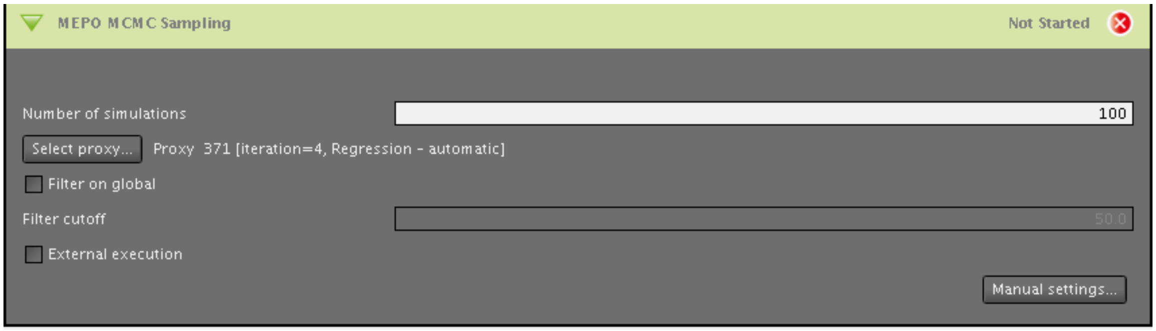


Figure 103 MCMC Sampling task panel.

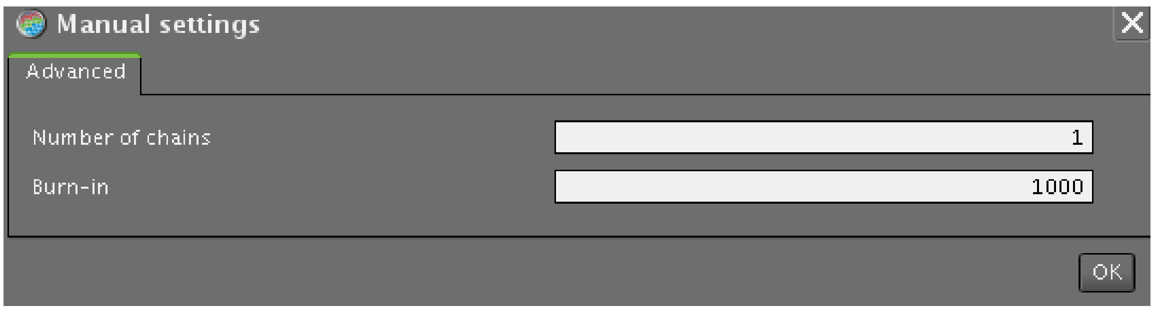


Figure 104 Manual settings panel in the MCMC Sampling task.

These are the changes applied to history match cycle to be able to run the predictions in a new prediction cycle. Settings not mentioned in this section including the workflow, remains the same as in the history match cycle.

5.4.2 Prediction - Scenario 1

As multiple of the history matches in HM Scenario 3 are sufficient, this scenario cycle is chosen for further prediction simulations. The cycle set up is done as described in Section 5.4.1. In the further specification in the MCMC simulation task, the number of simulations is defined to be 100, and the last proxy from the last iteration in the HM in Scenario 3 is chosen as the proxy model as seen in Figure 103.

After running the MCMC sampling simulations it was observed that the global value would increase to large values for multiple experiments. This act is unexpected as the global value calculation include the same objectives as the history match cycle, hence the global value should be in the same range as the experiments in the last iteration which makes up the proxy. The highest global value of all the experiments that make up the proxy if found to be 23. As the chosen proxy contains the posterior distributions created by the experiments it is expected that the further experiments in MCMC sampling are given parameter values from these, thus will give a similar global value and match in the period that is history matched. However after the MCMC Sampling simulations the global values are ranging between 7 and 2967, which means that the history matched period is not history matched anymore for most of the experiments. When viewing the pressure prediction plot, multiple experiments shows a large mismatch in the history matched period, as presented in Figure 105 and Figure 106.

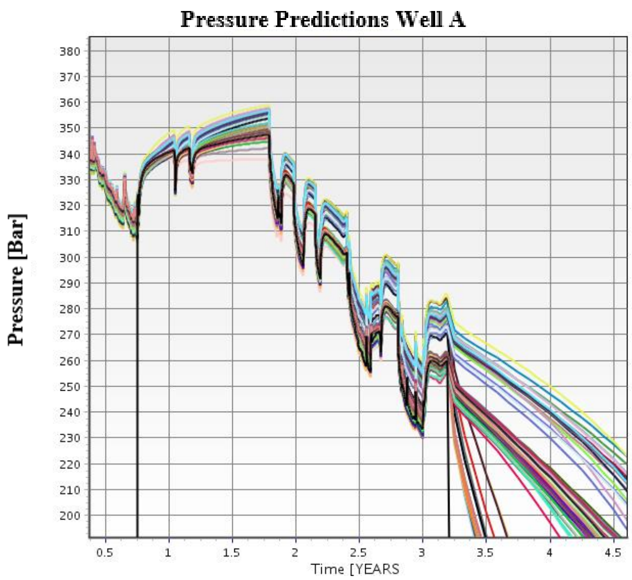


Figure 105 Pressure Prediction plot Well A for all simulations from MCMC Sampling.

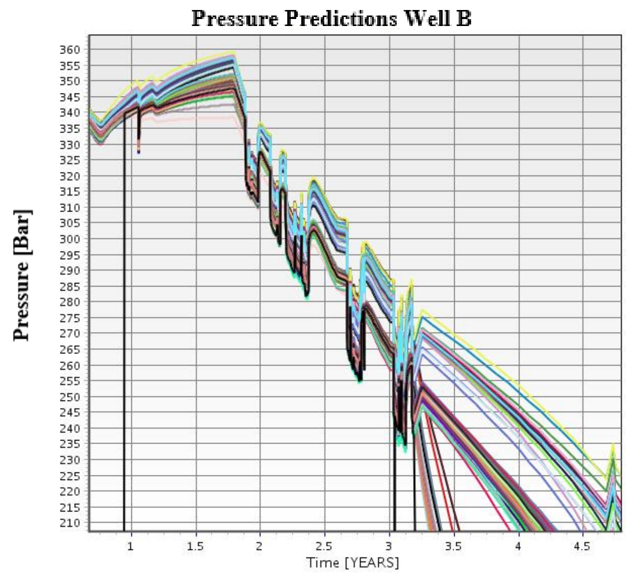


Figure 106 Pressure Prediction plot Well B for all simulations from MCMC Sampling.

From the results it appears like the MCMC sampling method are not taking the posterior distributions that should be integrated in the proxy into consideration. Multiple attempts were tested by using the “Filter on Global” in the MCMC Sampling panel. As the “Filter on Global” did not seem to influence in the resulting matches, the experiments were filtered on the global value in the simulation analysis panel.

The matches with a global value lower than 50 where chosen to use in further analysis as reasonable matches were obtained. Approximately 50 experiments contain a global value lower than 50. Figure 107 and Figure 109 show the pressure predictions obtained from the chosen experiments. The history matched period is showed in Figure 108 and Figure 110, it is observed that the match is not as good as the original match presented in Scenario 3, this is also reflected by the global value.

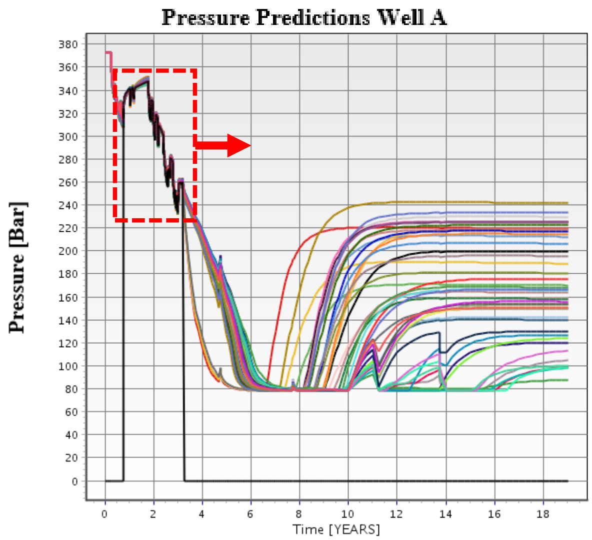


Figure 107 Pressure Predictions Well A.

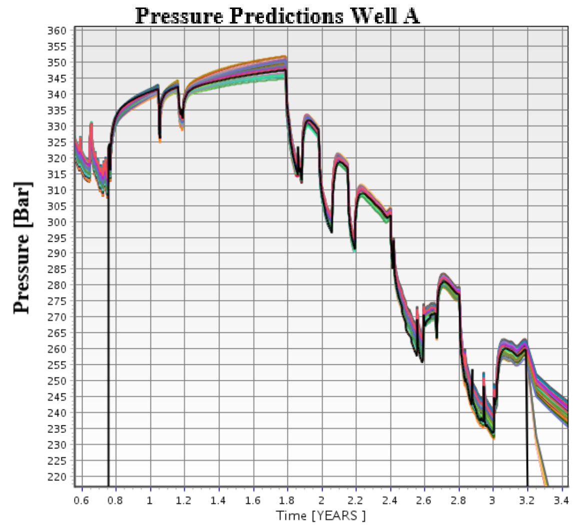


Figure 108 The period of history data in the Pressure Predictions plot for Well A.

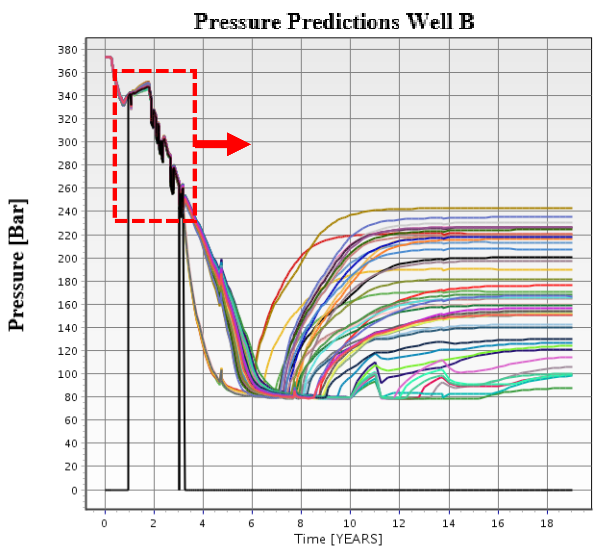


Figure 109 Pressure Predictions Well B.

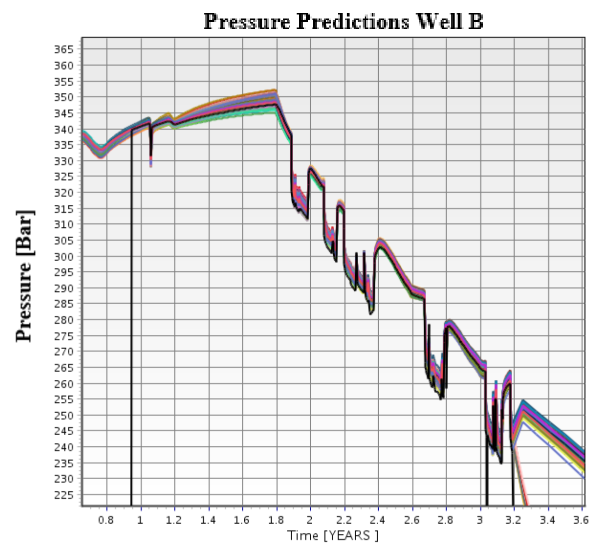


Figure 110 The period of history data in the Pressure Predictions plot for Well B.

The pressure prediction plots shows a rapid decrease in the pressures in both wells until approximately 6 years of production. This is the time the reservoir is allowed to produce at plateau rate. After this the figures show a slowly decrease until almost 8 years of production, this period represents a reduction of the rate to compensate for reduced pressure, and is termed the tail production. Production is stopped when a well is watered out or the abandonment pressure is reached. The minimum tubing head pressure is 65 bar, this will lead to abandonment pressure in the bottom hole (the when including the pressure drop) is around 80 bar. After reaching the abandonment pressure, the wells are shut-in, hence the plots show a buildup period for the rest of the prediction time. There are observed a large spread in how the buildup pressure are acting. The highest build up pressures represent a model that is influenced by an aquifer. While the experiments with little buildup represents models with little or no aquifer influence. When the buildups are leveling off the reservoir pressure is stabilized.

Figure 111 show that total field gas produced for the experiments. The FGPT is observed to be ranging between 5 GSm^3 and 6.5 GSm^3.

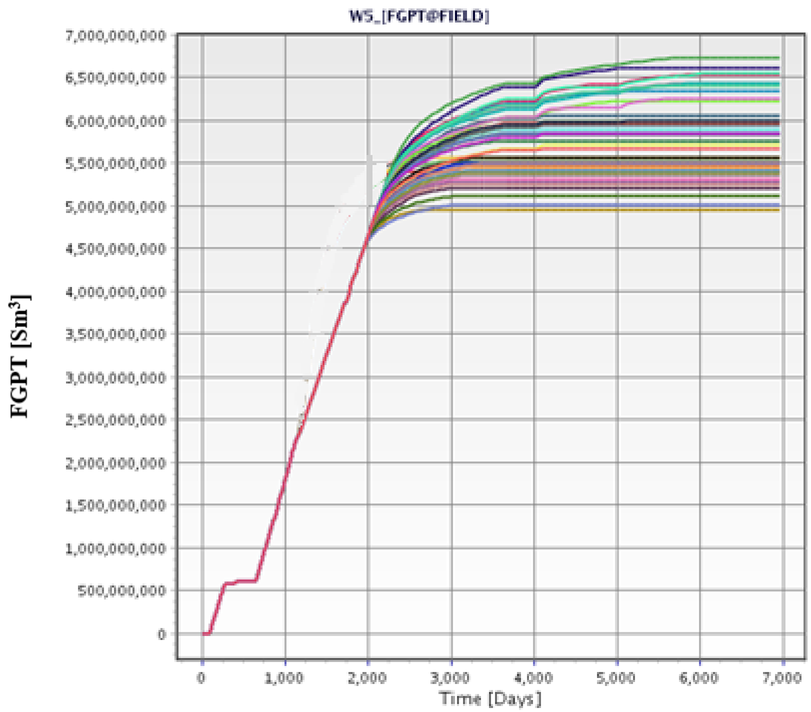
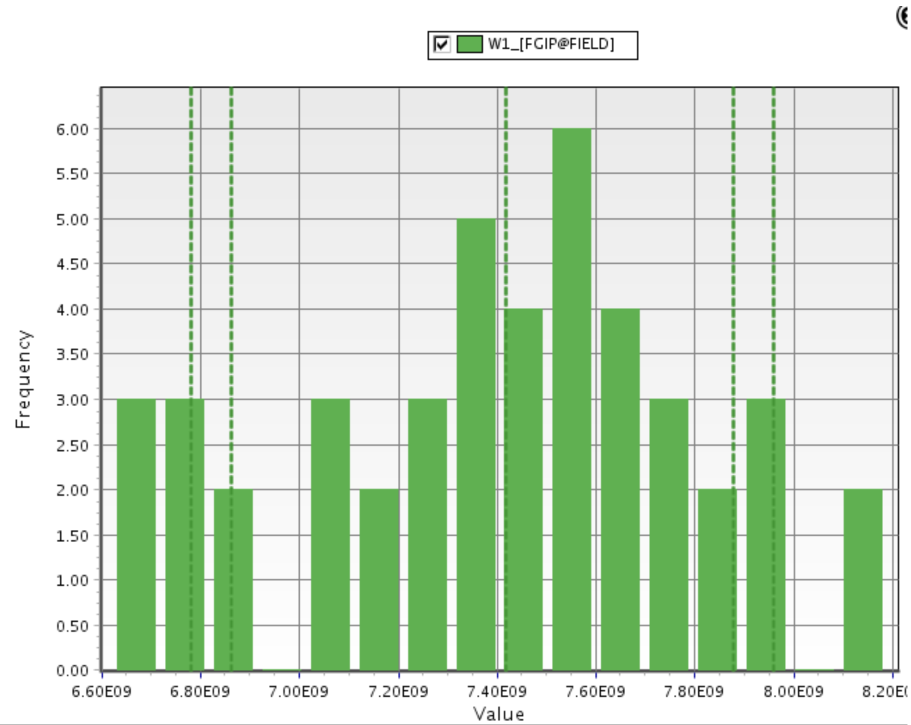


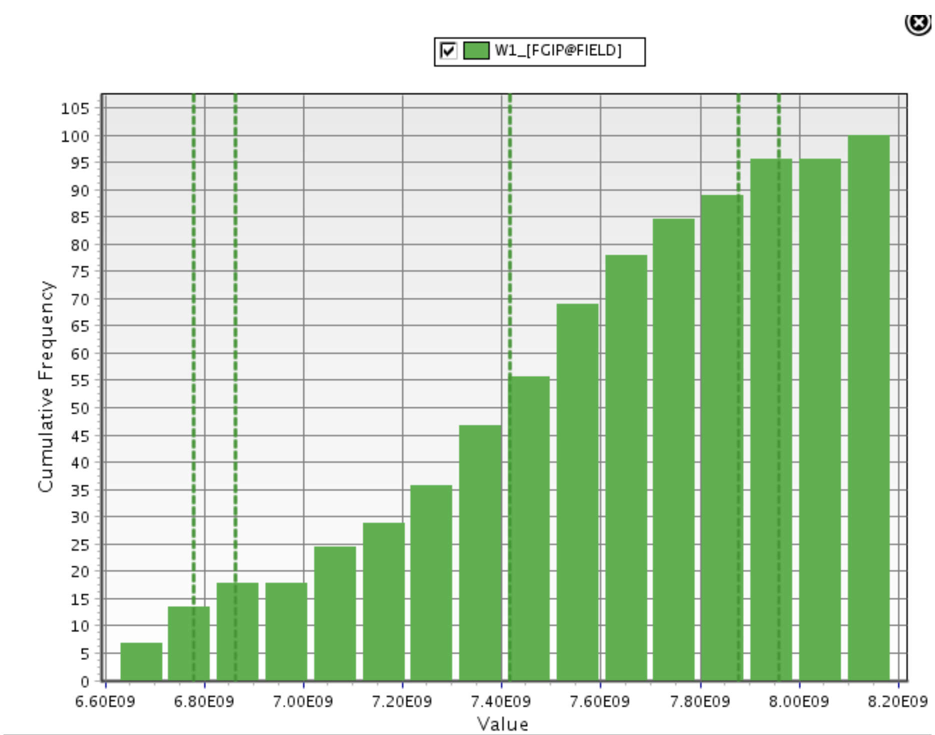
Figure 111 Total field gas produced for Prediction Scenario 1.

Figure 112 shows the FGIP distribution, for the 50 chosen experiments. The y-axis show how many experiments that yields the resulting value showed by the x-axis in the unit Sm^3. Figure 113 shows the cumulative probability density, where the y-axis gives the probability ranging from 0 to 100 % of the FGIP to be less than or equal to the values on the x-axis. The percentiles of the field gas in place are found from the plots and are shown below the figures. According to the results P10 is found to be 6.78 GSm^3, P50 is 7.42 GSm^3 and P90 is 7.96 GSm^3.



Series Name	P10	P15	P50	P85	P90
W1_[FGIP@FIELD]	6.779E09	6.862E09	7.417E09	7.878E09	7.958E09

Figure 112 FGIP density distribution for Prediction Scenario 1.



Series Name	P10	P15	P50	P85	P90
W1_[FGIP@FIELD]	6.779E09	6.862E09	7.417E09	7.878E09	7.958E09

Figure 113 FGIP cumulative density distribution for Prediction Scenario 1.

Remarks Prediction Scenario 1

As the results from the MCMC Sampling were a bit unexpected, the author contacted MEPO costumer support to discuss the MCMC sampling results. It was confirmed that the MCMC Sampling method in MEPO at the date of usage were affected by a bug, and it did not sample properly from the posterior distributions in the proxy (MEPO, 2015). A different procedure to estimate the predictions should be performed to avoid the deficiency in the MCMC sampling and compare the results with.

5.4.3 Prediction - Scenario 2

A second prediction approach is carried out as the MCMC sampling contains some sampling errors. The approach involves to use the best matches from the history matching cycle and further simulate predictions for the same sets of parameter values. This is done by exporting the best matches in the HM cycle in an .EDM file and further import the .EDM file to the prediction cycle.

The experiments to export are chosen from the longest history match simulation described in Scenario 3. The experiments with a global value under 8 is chosen as the experiments for running the predictions, as these provide the best matches. There are 174 experiments that contain a global value under 8. By choosing these experiments it is assumed that a better match is more likely to reflect the true reservoir behavior.

After the setup of a prediction cycle as described in Section 5.4.1, the 174 experiments are exported from the HM cycle and imported to a new prediction cycle in an .EDM file. By importing these files into a prediction cycle, the experiments still contain the specific parameter value sets from the HM cycle. Once the .EDM file is imported to the prediction cycle, the experiments appear in the simulation analysis panel, after reassuring that all the chosen experiments are imported, they are selected and *rerun*. Further the results are reviewed.

The pressure predictions for Well A and Well B are viewed in Figure 114 and Figure 116 respectively. As expected the experiments are matching the observed data, this can be observed from Figure 115 and Figure 117. It is observed that the pressure is decreasing rapidly until approximately 6 years of production. Then, there is a period of slow decline in the pressure (tail production) until approximately 8 years for Well B and around 9 years for Well A. After this period the pressure has reached the abandonment pressure and the wells are shut-in, hence the pressure in the wells starts a buildup.

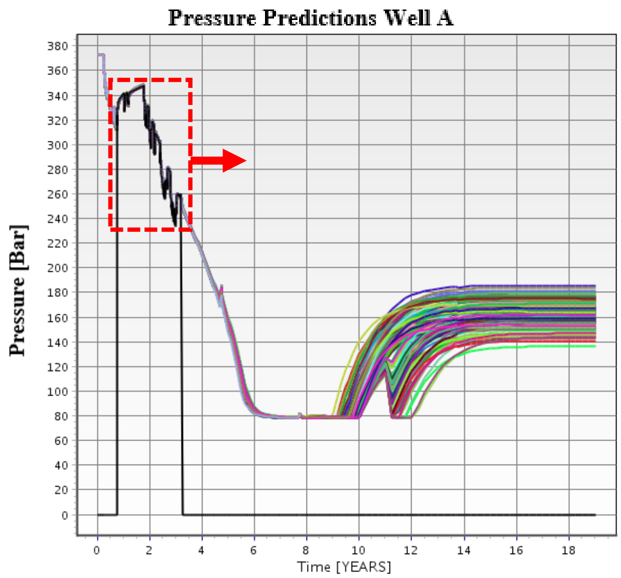


Figure 114 Pressure Predictions Well A.

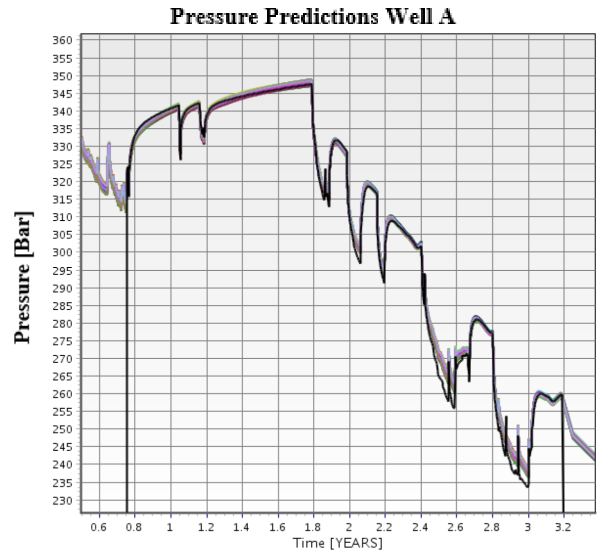


Figure 115 Pressure Predictions for the history matched period in Well A.

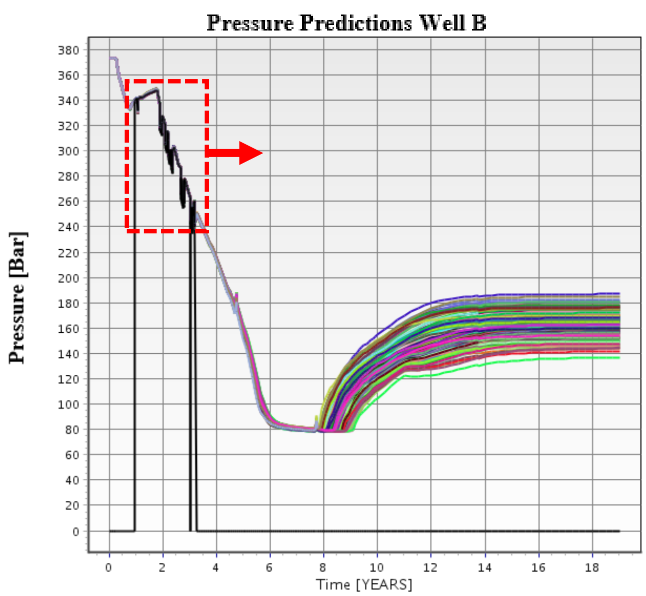


Figure 116 Pressure Predictions Well B.

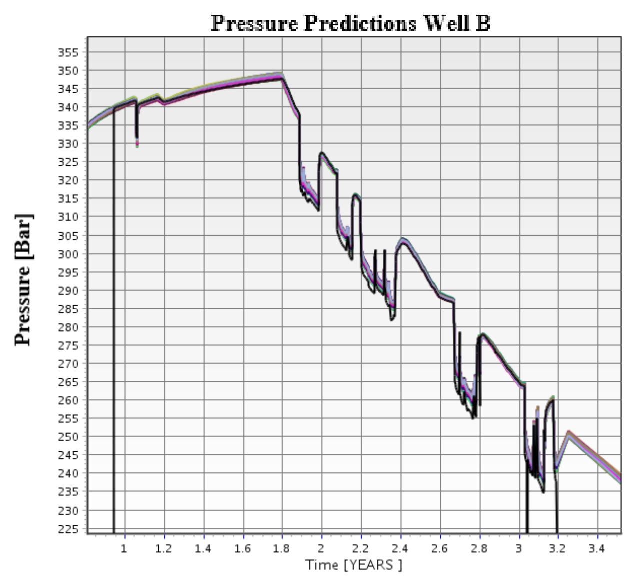


Figure 117 Pressure Predictions for the history matched period in Well B.

Figure 118 shows the predicted total field gas produced from production start till shut-in. It is observed that the FGPT are ranging between 5.3 GSm^3 and 5.9 GSm^3, compared to Prediction Scenario 2 the range is smaller.

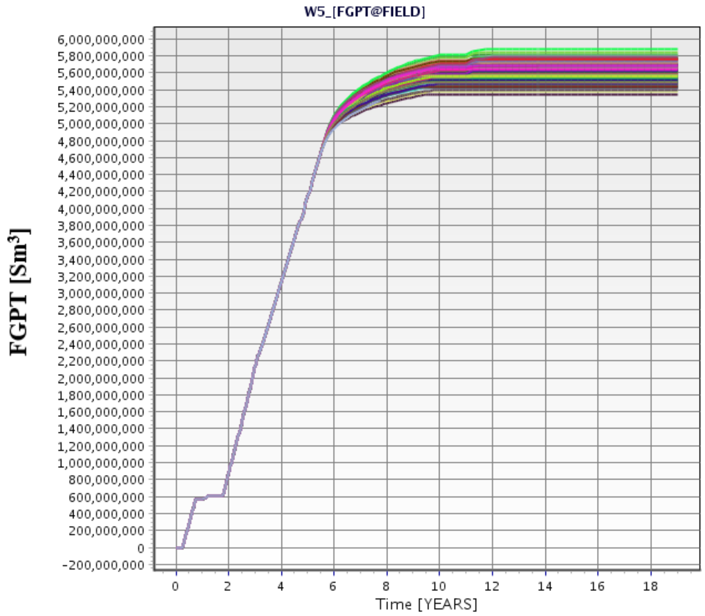
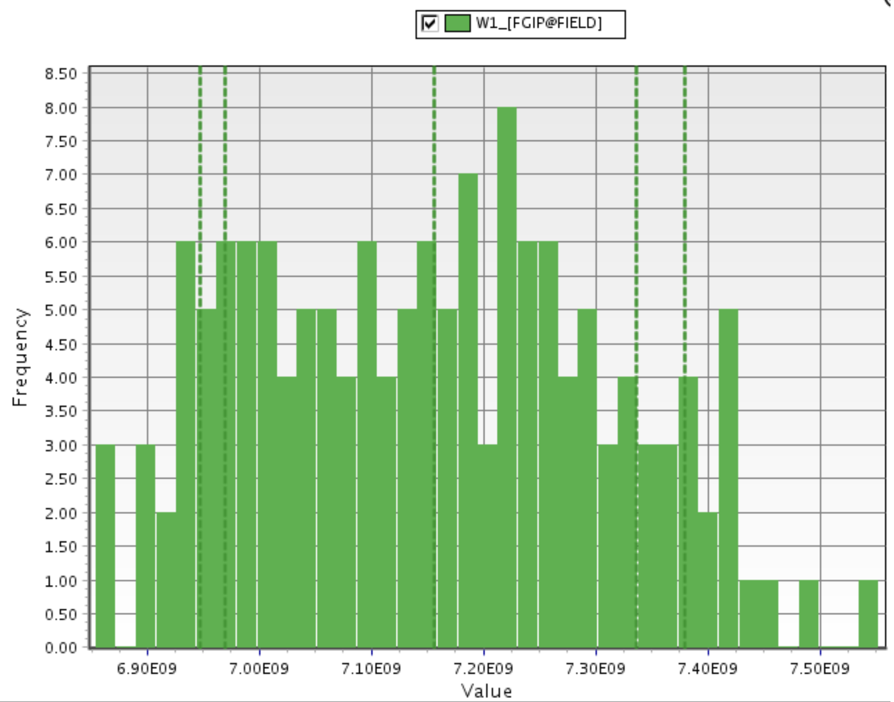


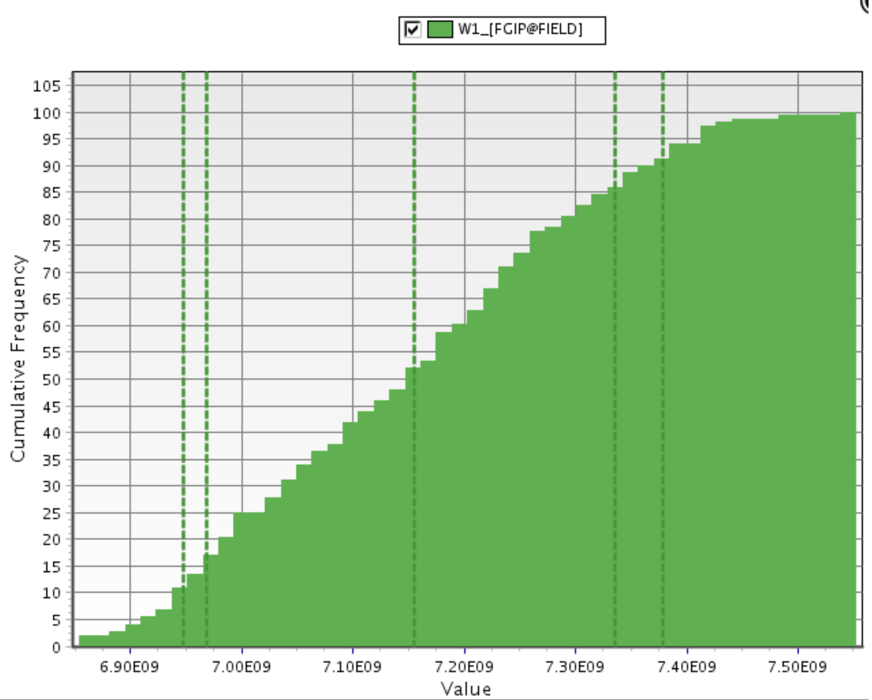
Figure 118 FGPT for the experiments in Prediction Scenario 2.

Figure 119 show the field gas in place distribution for the 174 experiments. Figure 120 show the cumulative distribution og the FGIP for the experiments. According to the results P10 is found to be 6.95 GSm^3, P50 is 7.2 GSm^3 and P90 is 7.38 GSm^3.



Series Name	P10	P15	P50	P85	P90
W1_[FGIP@FIELD]	6.947E09	6.969E09	7.155E09	7.335E09	7.378E09

Figure 119 Distribution of the FGIP.



Series Name	P10	P15	P50	P85	P90
W1_[FGIP@FIELD]	6.947E09	6.969E09	7.155E09	7.335E09	7.378E09

Figure 120 Cumulative distribution of FGIP.

Remarks Prediction Scenario 2

An approach like this were not originally planned as the number of simulation runs required to maintain a good uncertainty quantification by selecting individual models are very high. By not being able to include sufficient experiments that cover the spread in the posterior distributions may lead to multiple uncertain cases are left out.

5.5 Further Discussion

Evaluation of the History Match Scenarios and Sensitivity

During this study, three history matching scenarios have been carried out. First, by HM Scenario 1, it was tested if it is possible to get a sufficient history match by excluding MPV3 as an uncertain parameter. This was done as it was believed that region 3 contains the most certain parameter values, and the uncertainty in the other regions would be better explored by holding region 3 constant at its base case parameter values. The results did not give a sufficient match and the posterior distributions of the uncertain parameters were reduced to a minimum for the best (yet insufficient) matches, except from the aquifer that were sampled from the whole prior distribution range. The best matches were not true reflections of the reservoir behavior, as the results showed an increasingly mismatch with time. Based on this is was concluded that the pore volume multiplier for region 3 needed to be considered to get a match. Multiple attempts were launched by running short simulations where the MPV3 reduction was very limited, these attempts were not showed in the result section as they were a part of a try and fail procedure. In some of the attempts the ranges of the other uncertain parameter distributions were limited to the lower part of the range, similar to the posterior distributions from Scenario 1, but neither these simulations gave a sufficient history match. A sufficient history match was first obtained by letting MPV 3 range between 0.3 and 1. Based on this a longer simulation were run where other input parameter distributions were kept as in Scenario 1, and the MPV3 were included with the range that could give a sufficient match, this simulation is presented by HM Scenario 2.

As the Latin Hypercube method screens the search space, the pressure range obtained by the full Latin Hypercube sampling represents the pressure of the fully explored prior distributions of all input parameters. This means that by applying Latin Hypercube any possible match should be within the proposed range. If the observed pressure is outside the Latin Hypercube simulations range (as in Scenario 1) the input parameters or their distributions need to be adjusted to be able to obtain a sufficient history match. From Figure 66 and Figure 67 in HM Scenario 2, it was found that by the assigned ranges of the uncertain parameters (viewed in Figure 33) the response pressures from the model are in general too high to give a sufficient match for most of the experiments, only a limited amount of experiments are close to the historical pressure. This may be an indication of that some of the parameters in the model are "over predicted". By the correct assigned probability distributions that represent a high uncertainty there should be approximately as many experiments under as over the observed data, as the observed data should be assigned as a "most likely" value. The prior uncertainty ranges are ranging from 0 to 1, which is the base case value. Typically should a reservoir model represent a most likely case, hence should the start values be around the initial values in the model, and the range consider the downside and the upside if it is believed the base case model is the most likely model. The prior uncertainty distributions that are constructed based on earlier sensitivity studies, suggest that the base case model is an upside model. This may imply that the downside has not been properly considered by early interpretations of the reservoir parameters.

After applying the MCMC algorithm in Scenario 2, there were obtained enough sufficient matches to get a picture of the posterior distributions. The experiments with a global value under 10 were chosen as the sufficient matches that should make up the posterior distributions, this was approximately 80 experiments. By choosing the sufficient matches based on the lowest global value, it was assumed that best matches would be the most representative of the reservoir behavior. A higher global value would include a higher number of sufficient matches and allows for larger mismatch in the pressure match, hence the posterior distributions would have been a bit wider, as illustrated by Figure 16 and Figure 17. Table 5 shows the FGIP and the increased uncertainty by a higher global value in HM Scenario 2. It is observed that the uncertainty range within P10-P90 does not change very much by choosing a higher global value. This is a result of the many Latin Hypercube experiments launched before the MCMC simulations. By launching multiple LH experiments, the MCMC are able to quickly find good matches. In Table 5 it seems like the uncertainty in the lower range of the FGIP is increasing with a higher global value. This may imply that the downside is better captured by a higher global value.

When using the posterior distributions to describe and evaluate the uncertainty in the reservoir, it is important that the posterior distributions have converged to their stationary distributions. It is believed that when the global value is fairly constant for multiple chain iterations the chain has converged and the stationary posterior distributions are obtained. This is an assumption as convergence is difficult to prove as discussed in Chapter 3. It is made an attempt to determine, at least, if the distributions *not* have reached convergence by HM Scenario 3. The results from Scenario 3 show that by a twice as long simulation as in Scenario 2, the number of sufficient history matches with global value under 10 have increased from 80 to 550 experiments. When the Markov chain has converged the samples are picked from the same parameter range, defined as the stationary posterior distribution. The results show that the FGIP estimates and posterior distributions for the two scenarios to a large extent are covering the same uncertainty range. The longer simulation give a fuller picture of the FGIP and posterior distributions, however as the uncertainty range is approximately the same. From this there is found no lack of convergence.

To find each of the input parameters influence on the pressure match and on the FGIP a sensitivity study was carried out. The sensitivity plots in Figure 99 and Figure 100 show how influential the prior parameter range is to the calculated pressure by the reservoir model. By taking into consideration the information from the pressure sensitivity plots, with the Latin Hypercube experiments that are illustrated in Figure 66 and Figure 67, it is found that sampling of low values in region 3 is necessary to get a pressure match. This is because the observed pressure measurement located in the lower range for all the experiments and only MPV3 are able to decrease the pressure to the necessary extent. The MPV3 sampling is confirmed by the posterior distribution shown in Figure 79. Figure 101 shows that by picking the low parameter values from MPV3 the gas volume is reduced significantly from the start point values. Which again results in the FGIP in the lower range of the experiments in Figure 68. From the sensitivity study it is found that it is necessary to pick low parameter values for MPV3 to be able to get a match with parameter values from the defined input distributions. It is also found that influence on the match from the permeability multipliers are limited. When studying the sensitivity plots it is easier to understand the sampling from the prior distributions, and the forming of the posterior distributions.

Geological Discussion

Even though it is important to obtain a reasonable history match, it is at least just as important with a geologically truthful model to be able to get reliable predictions. This is why a geologist's evaluation is essential to include in the study. The base case reservoir model and the initial grid cell values are based on earlier uncertainty studies and interpretations of the amplitude map. The average values of these in the different regions are presented in Table 2. As presented in Chapter 4, the drilled wells confirmed the good facies and the properties that were interpreted from the amplitude map. In the study the parameter uncertainty are represented by the posterior distributions. The interpretations of the posterior distributions found from Scenario 2, and confirmed by Scenario 3, take certain forms that may indicate certain features. The posterior distributions need to be in conformity with each other and other geological knowledge to be a good representation of the real reservoir. First is an interpretation of the forms of the posterior distributions presented in the following points then is a geologist involved to evaluate the interpretations. The distributions can be viewed in Figures 91-98.

- Loosely conditioned distributions:

  MULTX1 and MULTX6 seem to be loosely conditioned by the historical data, as about the whole prior distribution range (red curve) is presented by the posterior distribution (blue). The different values from the parameter range are able to result in sufficient matches, this imply that the parameters have a limited influence on the history match. This is also confirmed by the sensitivity.

- Distinct conditioned distributions:

  MPV3, MPV5 and MULTX4 seem to have distinct conditioned distributions. The posterior distributions seem to take the form of normal distributions, similar to the prior distributions. MPV3 is observed to be in the low portion of the prior probability distribution, which may lead to the interpretation of a reduction in the pore volume in region 3. The posterior distribution sampling of MULTX4 seem to be in the middle of the predefined range, the permeability multiplier leads to a reduction of the permeability in region 4 (hence reduces the inflow to Well B). The MPV5 seem to consist of samples located around the starting value. The distribution implies a slightly increase in the aquifer, represented by region 5, from the base case model.

- Upper bound distributions:

  In the MULTX2 posterior distribution the sampling are in the upper range and seem to contain sampling around the base case values. The region was added to be able to adjust the flow between the regions. This may indicate that there is no limited flow between the regions, or that the multiplier does not act it was intended to do.

- Lower bound (and upper bound) distributions for the low amplitude areas:

  It is notable that the MPV1 and MPV 6 posterior distributions, that both represents the low amplitude areas, are resulting in such different posterior distributions. MPV1 consist of values that are chosen in the upper half of the predefined range, while MPV6 consists sampling from the lower half of the range. The picking of low values for region 6 may be an indication of the presence of a possible transmissibility barrier in the field, or the difference may imply different quality of the reservoir properties in the regions.

The interpretation of the posterior distributions and other results of the study have further been discussed with a geologist, which has good knowledge of the reservoir. The following were discussed:

- As the study show from the posterior distribution MPV6, the picking of low values may indicate a possible barrier. This should be tested by implementing one or two faults in the reservoir model. The geologist recommend two possible fault locations. A possible scenario is that the fault already implemented in region 6, could be extending into region 3. A second approach is to implement a fault that limit the flow from the northern part of the reservoir, this means that region 6 and the northern part of region 3 are sealed off and are not in contact with the gas that are being depleted.
- From the sensitivity study it is found that MPV3 is dominating both the pressure match and the FGIP, by dividing the region into multiple regions may lead to better uncertainty quantification. The northern part should be a separate region. To further divide the region to a southern and middle part is also recommended by the geologist.

- The sampling of high values in MPV1 and the lower values in the MPV3 distribution, are most likely not correct assignment of the geological parameter values. The MPV3 represents the high quality reservoir sands hence should contain higher MPV parameter values. It may be believed that since the MPV3 is dominating in the history match the uncertainty in MPV1 is not examined correctly by the method applied. In the new implementation it might be necessary to have a higher lower boundary for MPV3 to get the correct results of the other uncertain parameters.
- The posterior distributions for the aquifer represented by MPV5 consists of values ranging between 1 and 3, which means that the water implemented in the base case model should be multiplied by a factor as represented from the MPV5 posterior distribution. The results show a rather small aquifer influence. In the sensitivity study it is found that the pressure in the wells could be affected by approximately +-5 % by the assigned input range of the aquifer in the time period of historical data. The Geologist thinks this may be a true reflection of the aquifer in the study.

The geologist thinks that the structural probability is the most uncertain property, and that the implementation of faults may be the correct implementation to start a further study. The reliability of the parameter values based on the amplitude map seems to be higher as it is confirmed by the drilled wells.

By applying the suggested implementations, new results will be able to confirm or disprove the interpretations, and by this give a better understanding of the reservoir. After the suggested scenarios are run and new posterior distributions are found, the parameter values assigned based on the amplitude map need to be carefully evaluated in hindsight of the study together with a geologist. There is a chance that the upscaling of the properties from the wells may have led to layers have gotten better properties than they actual have. If the pore volume multipliers are in the lower range after testing the new scenarios, the net-to-gross of the reservoir is the first thing the geologist would adjust in the reservoir model (approximately 10 % decrease to start with), as it is the most uncertain parameter the reservoir turbudite system.

To summarize, the following scenarios should be implemented and evaluated:

- Add one or two transmissibility barriers, in form of impermeable faults dividing the wells from the northern part of the field. There may be present barriers not detected by seismic.

- Dividing region 3 to two or three regions (north, south and mid). This can be useful for better uncertainty quantification.
- Give MPV in region 3 an increased lower boundary so that MPV in region 1 most likely will be adjusted to have lower parameter values than region 3.
- Adjust the net-to-gross in the geological model further indications of lower pore volumes by the multipliers.

Field Gas in Place

At the time of development the FGIP was estimated to be between 10 and 17 GSm^3. Before further study of the geologically evaluations it is difficult to say if the volume found from the sufficient matches in Scenario 2 and 3 can represent the actual reservoir volume. The results from this study show a lower FGIP than what was expected before the field development, the study estimates an approximately range from 6.5 to 8 GSm^3. The calculated in place volume is to a large extent dependent of the sampling of the MPV3 parameter values. Which is intuitive as region 3 covers most of the gas saturated reservoir, in addition to that region 3 is given the best reservoir properties in the base case model based on the interpretations from the amplitude map and well data. By testing the suggested implementations for the geologist the sampling might be different, hence yield a different FGIP.

Another way of predicting the gas in place volume is the material balance p/z plot. There are clearly a lot of uncertainties related to the use of the plot according to literature, however it can be taken into consideration when discussing the aquifer influence on the results from the study. After analyzing at the p/z plot two responses from the plot curves were considered. In the plot in Figure 30 the p/z curve indicated an initial gas volume to be around 10 GSm^3, while the p/z' curve indicates a gas volume to be around 6.5 GSm^3. The first scenario assumes a reservoir only affected by natural gas expansion as the depletion strategy. The second approach takes into account only the early period that possibly is unaffected by water drive effects or other effects. Note that there is a possibility that the early period is affected by other effects e.g. transient coning behavior which does not result in a true FGIP assignment. The results of the study show a small aquifer influence, and a volume estimated to be in between 6.5 to 8 GSm^3, which falls within the two p/z plot scenarios.

One important factor to mention is to consider if the buildup responses from the observation well is influenced by the other producing well. If this is the case, the pressures in the p/z plot can indicate a lower volume in place than the actual volume in place. The reservoir simulation model will take this into consideration in the dynamic behavior calculations.

Evaluation of the Prediction Scenarios

In Prediction Scenario 1, MCMC Sampling method were applied. The main reason to apply MCMC Sampling algorithm in combination with a proxy is to be able use the stationary posterior distributions as a representation of the uncertainty in the field, which further represent the uncertainties in the predictions. The posterior distributions represent the possible parameter values (from the prior distribution range) that can give a sufficient match. In Prediction Scenario 1, a total of 100 predictions were run based on a proxy model. The chosen proxy model that is based on the last iteration of the MCMC in the history match cycle, as it is the most likely to have reached convergence in the posterior distributions. After the MCMC sampling were applied, it was found that the method did not work properly due to software bugs. The experiments that were used in further analyses were only the experiments with a global value under 50, as they gave a sufficient match in the period of history data.

In Prediction Scenario 2, multiple sufficient history match experiments were transferred to a prediction cycle. The best matches are considered the most true to the actual reservoir behavior as they better matches the observed data. A maximum global value was set to 8. A total of 174 experiments were then chosen, as in an approach like this the number of simulation runs required to maintain a good uncertainty quantification by selecting individual models are very high.

While the global value for the 174 experiments in Prediction Scenario 2 is under 8. The global value for the best 50 experiments in Prediction Scenario 1 is under 50. Table 7 show the P10, P50 and P90 FGIP percentiles from the two Scenarios. It can be observed that a higher global value gives a larger spread in the FGIP uncertainty estimates. In the FGIP estimates is seems like Scenario 1 covers a larger uncertainty spread in the volume estimates than Scenario 2.

Table 7 Percentiles for the FGIP for Prediction Scenario 1 and 2.

		FGIP [GSm^3]		Uncertainty Range
	P10	P50	P90	P10-P90
Prediction Scenario 1	6.78	7.42	7.96	15 %
Prediction Scenario 2	6.95	7.2	7.38	6 %

The uncertainty coverage of the scenarios can also be observed by the buildup periods, as the pressure build up reflects the reservoir response. The experiments in Prediction Scenario 1 are viewed in Figure 107 and Figure 109. From the figures it can be found that they seem to show a large spread in the buildup period, hence contain a large uncertainty in the reservoir response. This may reflect the uncertainty of the influence from an aquifer. As a strong aquifer tends to yield a higher reservoir pressure after depletion. The buildup pressures for the experiments in Prediction Scenario 2 in Figure 114 and Figure 116 seem to be following the same trends and does not show as large uncertainty spread as Prediction Scenario 1.

In a production scenario it is important to find how long the field can produce. For Prediction Scenario 1 the total production time is found to be varying between 7 and 10 years for both wells. For Production Scenario 2, Well A is found to produce approximately for 9 to 10 years, and Well B is found to be producing for approximately 8 to 9 years.

Both of the methods in the scenarios seem to have some weaknesses associated with them. It is doubts about whether Prediction Scenario 2 are able to fully cover the uncertainty in the reservoir. Prediction Scenario 2 is based on the best pressure matches from the history match cycle. The number of experiments in a prediction cycle should be sufficient to cover the realistic combinations of the distribution values, hence capture the uncertainty. A total of 174 experiments are chosen, as they all matches the historical pressure well. The parameter sets for the chosen experiments creates their own posterior distributions, these should be able cover the true uncertainty spread. As the Prediction Scenario 1 is affected by a bug in the applied algorithm, the results might not be reliable even though the non-sufficient matches are filtered out.

For a similar case it might be a good idea to run both the MCMC Sampling and in addition transport the best matches in an EDM file to be able to compare the uncertainty spread represented by the proxy with the best matches.

Creating Value from Uncertainty

One of the main reasons to make quantify and analyze the uncertainty is to enhance decision analysis. The increased accuracy of the model and the results comes with the price of going through with the history match and the cost of gaining the information. Hence, the need of mitigation of uncertainties in a reservoir should depend on the cost of the gained information. In this case study the expenses are; the cost of gaining the pressure measurements, the time invested in the history match study and the software/licenses that are used. As mentioned, further history matching scenarios should be run to explore other the scenarios suggested by the geologist, before a final updated uncertainty evaluation is found. The results from this study show a lower FGIP than what was expected before development. Further scenarios should be run before assuming this is the right FGIP for the field. However should the further scenarios results appear similar to the results in the study, the following decisions may be taken based on this information.

- A decision whether to trill a third well may be decided. To decide to go through with the extra well there should be a very high probability of trapped gas volumes that are not in contact with the producing wells.
- Another decision concerns if it is desirable to upgrade certain equipment or infrastructure. Reliable predictions for the probable results from the further scenarios will be able to determine such a decision.
- The results from the study might lead to adjustments of expected production volumes. To know the most likely outcomes of the project by itself does not result in any decision changes. However this can lead to greater flexibility in terms of being able to invest in other projects.

6 CONCLUSIONS

This section will summarize the most important findings from the case study, before recommendations for future work based on experience and results are given.

6.1 Results

Good understanding of the reservoir, as well as geological knowledge of the parameters, are essential in an assisted history match study. As stated in the introduction of this thesis, the main objective of this thesis were to make an updated uncertainty evaluation of a producing gas field by integrating production data. A probabilistic approach is applied in addressing the reservoir uncertainties. Prior distributions are used as a starting point, which by combining static and dynamic uncertainties should cover the uncertainty domain in the reservoir. MEPO, an assisted history matching tool, was used to obtain multiple history matches by the use of MCMC optimization algorithm. Key takeaways from the research are listed below.

- ❖ The sensitivity analysis of the predefined uncertainties provided results showing the key uncertainties that have significant effect on the pressure match are mainly the pore volume multipliers, representing the parameters that makes up the pore volume. Referring to the regions defined in Section 4.4.2; the pore volume in region 3 has the highest influence on the match, followed by the pore volume in region 6, the influx from the aquifer (region 5), the pore volume multiplier in region 1 and permeability multiplier around Well B. The permeability multipliers in regions 1, 6 and 2 have a limited influence on the pressure match.
- ❖ By exploring the search space of the prior uncertainty, using Latin Hypercube, it is found that most of the experiments results in a higher pressure than the historical pressure. Hence, the results show that the base case model need to be adjusted by reducing multiple parameter values to match the historical data.
- ❖ Three history matching scenarios were constructed, where Scenario 2 and Scenario 3 gave sufficient history matches. In Scenario 3, over 1100 simulations were run to evaluate the range of reservoir uncertainties, and checking for lack of convergence in the Markov chain. The results implied no lack of convergence in the Markov chain.

- The posterior distributions obtained for the sufficient matches provided a basis of interpretations. The interpretations are; a possible barrier which restrict the flow from the northern part of the reservoir to the wells, a small influence from the aquifer, the loosely conditioned distributions of the permeability multipliers imply that they have limited influence on the history match and the distinct distribution for the influence dominating region might cause the less influential parameter distributions to be biased.
- Even though it is important to obtain a reasonable history match, it is at least just as important with a geologically truthful interpretations and simulation model to be able to get reliable predictions. This is why a geologist's evaluation is essential to include in the study. Based on the geological discussions, the recommendations for future work are; (1) implement the suggested faults, (2) divide the dominating region into multiple regions, and further, depending on the previous results, (3) reduce the net-to-gross in the initial model.
- Two prediction scenarios were simulated. A FGIP between 6.5 and 8 GSm^3 were predicted by the sufficient history matches. The predictions show a total production period of 8-9 years before abandonment pressure is reached.
- For a similar case it might be a good idea to run both the MCMC Sampling and in addition transport the best matches in an EDM file, to be able to compare the uncertainty spread represented by the proxy with the best matches.

6.2 Recommendations

Software User Recommendations

The following are a few recommendations for any MEPO Software user, which will perform a history match study by the use of MCMC optimization and MCMC sampling.

- (1) Run sensitivities on the input parameters. A sensitivity analysis of multiple parameters is a good way to determine the uncertain parameters used further in the study. When the uncertain parameters are determined and the uncertainty ranges are chosen, the analysis will provide information of how influential the uncertain prior parameters are on the history data and the volume in place.

  (2) Run Latin Hypercube to find if the observed data measurements are within the search space of the uncertain parameters. Compare the sensitivity plots with the Latin Hypercube results.

  (3) Further proceed with MCMC simulations if the Latin Hypercube and sensitivity study show that it is possible to get a sufficient match with the most uncertain parameters.
- Start simple and add complexity, to save total simulation time.
- By increasing the number of Latin Hypercube experiments it is observed quicker convergence of the global value.
- Allow MEPO to launch multiple simulations simultaneously (the number of experiments in a chain is the optimal number of simulations to run simultaneously. To avoid occupations of licenses add a queuing system, this allows MEPO to only use available licenses at all times. (Eclipse MR allows MEPO to only use one license while simulating and would be a good alternative).
- Set a maximum simulation time for the experiments simulations. The maximum time is the time from the individual simulation start to the simulation end of an experiment. The maximum time need to be assigned individually for the case as it is dependent on the model and the set up. By predefining a maximum time threshold, the MCMC iteration will be a more efficient process, as the next step on a chain is dependent on the current. By setting a maximum time MCMC is allowed to continue to the next step with the finished simulations.
- At the time of usage, MCMC Sampling contains a bug which may affect the results gained in Prediction Scenario 2. While using MCMC Sampling for predictions, be sure to check

the pressure match for the period with observed data, and filter on the good matches. A recommendation can be to always import the best matches as an .EDM file for prediction to check if the MCMC sampling yields a similar result.

Case Study Recommendations

The following scenarios should be implemented and evaluated in a further study of the field:

- Add one or two transmissibility barriers, in form of impermeable faults separating the wells from the northern part of the field. The geologist thinks that there may be present barriers not detected by seismic causing the results in the study.
- Dividing region 3 into two or three regions (north, south and mid). This can be useful for better uncertainty quantification.
- Give the pore volume multiplier in region 3 an increased lower boundary so that the pore volume multiplier in region 1 will be adjusted to contain lower parameter values than region 3. Which should be correct according to information from the field.
- Adjust the net-to-gross if further indications of lower MPV posterior distributions.

Further Research Suggestions

- Explore the number of experiments in a chain iteration and the number of chains that that are most beneficial to use in the MCMC algorithm to reach convergence.
- Compare EnKF and MCMC algorithms.
- As the geological model is made in Petrel using the history matching optimization program in to Petrel would be an interesting comparison to MEPO.
- There are doubts whether a dominating uncertain parameter may lead to biased posterior distributions of the less influential parameters by application of the MCMC. This may be tested in further research.

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