Rock physics inversion for CO2 characterization at Sleipner

Hong Yan
Abstract

We combine Full-Waveform Inversion (FWI) and rock physics inversion to provide quantitative estimates of CO$_2$ saturation at Sleipner. The rock physics tool is based on uniform saturation and patchy saturation rock physics models. The patchy saturation model takes into account the attenuation at the mesoscopic scale. The uniform saturation model uses an effective fluid phase plugged into the Biot theory. The latter model will be mainly used in the Sleipner case. The rock physics inversion is implemented using an oriented Monte Carlo method (neighbourhood algorithm). We generate P-wave velocity using the FWI technology and then invert selected rock physics parameters using the rock physics inversion tool. The methodology is applied to both synthetic and real datasets. We test the feasibility of the rock physics inversion on synthetic data. We propose a method to extract the baseline frame properties using P-wave velocity combined with S-wave velocity and density. We estimate the CO$_2$ saturation using P-wave velocity model derived from 2D FWI and evaluate the associated uncertainty. We show that the CO$_2$ saturation at Sleipner can reach 90% with an uncertainty of 0.1 to 0.2. For another inline, we have a lower CO$_2$ saturation estimation because we are located 533 m away from the injection point. We estimate a Brie exponent, which is describing the distribution type, ranging between around 5 and 25, which indicates that the mixture is between patchy and uniform saturation.
Preface

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I. Table of contents

Abstract ................................................................................................................................. i
Preface .................................................................................................................................. iii
Acknowledgements ................................................................................................................ v

I. Table of contents ............................................................................................................... vii
II. List of figures .................................................................................................................... x
III. List of tables ..................................................................................................................... xvii

1 INTRODUCTION ............................................................................................................... 1

2 METHODS .......................................................................................................................... 4
  2.1 Full-Waveform Inversion (FWI) .................................................................................. 4
  2.2 Rock Physics Inversion (RPI) .................................................................................... 6
    2.2.1 Forward formulation (rock physics models) ......................................................... 6
    2.2.2 Inversion formulation ......................................................................................... 11
  2.3 Summary of the sensitivity ......................................................................................... 12
  2.4 Workflow outline ........................................................................................................ 14
    2.4.1 Baseline application ......................................................................................... 14
    2.4.2 Monitor application .......................................................................................... 14

3 SLEIPNER GEOLOGICAL SETTING AND ROCK PHYSICS PROPERTIES .......... 17

4 SLEIPNER WELL 15/9-A16 ............................................................................................ 21
  4.1 Data preparation ......................................................................................................... 21
  4.2 Estimation of frame moduli ..................................................................................... 22
5 SYNTHETIC SLEIPNER MODEL ............................................................ 23
  5.1 Data preparation and a priori rock properties .............................. 23
  5.2 Estimation of CO₂ saturation ...................................................... 27
6 FWI SYNTHETIC MODEL ................................................................. 36
  6.1 Data preparation and FWI tests ................................................. 36
  6.2 Estimation of CO₂ saturation ...................................................... 41
7 REAL DATA (INLINE 1881, VINTAGE 2008, AFTER INJECTION) .............. 49
  7.1 Data preparation ........................................................................ 49
  7.2 Estimation of CO₂ saturation ...................................................... 51
8 REAL DATA (INLINE 1838, VINTAGE 1994, BEFORE INJECTION) .......... 58
  8.1 Data preparation and a priori rock properties .............................. 58
  8.2 Estimation of frame moduli ......................................................... 59
9 REAL DATA (INLINE 1838, VINTAGE 2008, AFTER INJECTION) .............. 63
  9.1 Data preparation and a priori rock properties .............................. 64
  9.2 Estimation of CO₂ saturation ...................................................... 65
10 DISCUSSION .................................................................................. 72
11 CONCLUSIONS AND OUTLOOK .................................................... 75
  11.1 Conclusions ............................................................................. 75
  11.2 Further work ............................................................................ 75
12 REFERENCES .................................................................................. 77
APPENDIX .......................................................................................... 1
Appendix A Supplementary notes of Sleipner well 15/9-A16 ........................................ 1

Appendix B Supplementary notes of FWI synthetic model ............................................. 3

   I. FWI process on the 2D FWI synthetic model .......................................................... 3

   II. Selection of iteration number .............................................................................. 4

   III. Selection of FWI results ...................................................................................... 5

Appendix C Supplementary notes of real data (inline 1838, vintage 2008 and 1994). ........ 7

   I. Data processing procedure ..................................................................................... 7

   II. FWI tests .............................................................................................................. 10

Appendix D Grain bulk moduli and density computation for the Utsira sandstone ...... 12

Appendix E Supplementary table for the Nordland shale ............................................. 15

Appendix F Analysis tables for sensitivity test results ............................................... 16

Appendix G Publication I ............................................................................................ 19

Appendix H Publication II ............................................................................................ 25
II. List of figures

Figure 2-1. A representation of the approximate Hessian matrix $\Re\{J^T J^*\}$ by Pratt et al. (1998). .......................................................... 4

Figure 2-2. P-wave velocity variation with brine saturation for uniform saturation with various Brie exponent and patchy saturation with bubble size $a$ of 0.01 m. ................................................. 13

Figure 2-3. Panel (a) indicates the estimations of Brie exponent $e$ and brine saturation $S_w$ for uniform saturation from P-wave velocity input only. Panel (b) indicates the estimation of frame moduli for Utsira sandstone of log data from P-wave velocity only. The blue cross indicates the best model and the red cross indicates the true model. ................................................................. 16

Figure 3-1. Map of the Utsira sand reservoir thickness (Arts et al., 2004). ......................... 17

Figure 3-2: Sketch of geological model for CO$_2$ migrations (Bickle, 2009). ................. 18

Figure 4-1. From left to right: P-wave velocity, S-wave velocity, bulk density and the density log derived porosity. P-wave velocity and density responses are log data from well 15/9-A16. S-wave velocity is derived using Vernik's relation. Density porosity log is derived from bulk density log and the grain density computed from Hashin-Shtrikman bounds. The red and green dots indicate the caprock of the Nordland shale and the Utsira sandstone, respectively. ........ 21

Figure 4-2. From left to right: frame bulk and shear moduli, which are derived from the combination input of P-wave velocity, S-wave velocity and density. The black lines indicate the best estimations with the lowest misfit models. The blue lines indicate values of a set of models have misfit lower than 0.1. The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ........................................................................................................ 22

Figure 5-1. Initial 2D synthetic true model. ........................................................................ 23

Figure 5-2. Synthetic P-wave velocity model for selected region. The black line indicates the extracted vertical profile ($x = 1947$ m). ....................................................................................... 24

Figure 5-3. From left to right: P-wave velocity, S-wave velocity, bulk density, density porosity, frame bulk modulus and frame shear modulus. The red and green dots indicate the caprock of
the Nordland shale and the Utsira sandstone, respectively. The blue lines indicate the rock frame moduli (mean value with maximum misfit of 0.1) inverted using the combination input of P-wave velocity, S-wave velocity, and density. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.

Figure 5-4. From top to bottom: (a) first derivative of P-wave velocity with respect to the depth, (b) velocity model with extracted boundaries, and (c) the generated 16 layers. The vertical axis is corresponding to the row number of the matrix, while the horizontal axis is the column number of the matrix.

Figure 5-5. The derived new a priori rock properties. From top to bottom: frame bulk modulus, frame shear modulus, grain bulk modulus, porosity, grain density and permeability.

Figure 5-6. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with e = 5.

Figure 5-7. From top to bottom: estimation of CO$_2$ saturation, uncertainty of CO$_2$ saturation, estimation of Brie exponent, and uncertainty of Brie exponent using Brie rock physics model with e inverted.

Figure 5-8. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model (e = 5) with CO$_2$ properties inverted.

Figure 5-9. From top to bottom: estimation of CO$_2$ bulk modulus, uncertainty of CO$_2$ bulk modulus, estimation of CO$_2$ density, and uncertainty of CO$_2$ density using Brie rock physics model (e = 5) with CO$_2$ properties inverted.

Figure 5-10. Uniform saturation condition (true model $S_W = 85\%$): inversion of CO$_2$ density, CO$_2$ bulk modulus, CO$_2$ viscosity and brine saturation from $V_P$. The blue cross indicates the best model; red cross indicates the true model.

Figure 5-11. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with e = 1.

Figure 5-12. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with e = 3.
Figure 5-13. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with e = 40. ................................................................. 33

Figure 5-14. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using a patchy saturation with $a = 0.01$ m................................................................. 34

Figure 5-15. 1D estimation of CO$_2$ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO$_2$ saturation using different rock physics models (right panel) for $x = 1062$ m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ........................................................................................................... 34

Figure 5-16. From left to right: 1D profile of Brie exponent and other CO$_2$ properties results (CO$_2$ viscosity, CO$_2$ bulk modulus, and CO$_2$ density) inverted jointly with the CO$_2$ saturation using different rock physics models for $x = 1062$ m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty........................................................................................................... 35

Figure 6-1. Starting model of P-wave velocities before FWI ......................................................... 36

Figure 6-2. P-wave velocities after various FWI tests. ............................................................... 39

Figure 6-3. P-wave velocity for different FWI tests at $x = 1062$ m. .............................................. 40

Figure 6-4. P-wave velocity model extracted for the target region from FWI test 6. .............. 40

Figure 6-5. From left to right: P-wave velocity of FWI test 6, S-wave velocity, bulk density, density porosity, frame bulk modulus, frame shear modulus at $x = 1077$ m. The red dots indicate the Nordland caprock shale, and the green dots indicates the Utsira sandstone. The frame moduli (blue lines) are inverted using rock physics inversion for true synthetic model with plus/minus related uncertainty (dotted blue lines)........................................................................................................... 41

Figure 6-6. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with e = 5. ................................................................. 42

Figure 6-7. From top to bottom: estimation of CO$_2$ saturation, uncertainty of CO$_2$ saturation, estimation of Brie exponent, and uncertainty of Brie exponent using Brie rock physics model with Brie exponent e inverted. ........................................................................................................... 43
Figure 6-8. From top to bottom: estimation of CO₂ saturation, uncertainty of CO₂ saturation, estimation of CO₂ bulk modulus, uncertainty of CO₂ bulk modulus, estimation of CO₂ density, and uncertainty of CO₂ density using Brie rock physics model (e = 5) with other CO₂ properties inverted ........................................................................................................................................ 45

Figure 6-9. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 1 ................................................................. 46

Figure 6-10. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 3 ........................................................................ 46

Figure 6-11. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 40 ................................................................. 47

Figure 6-12. 1D estimation of CO₂ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO₂ saturation using different rock physics models (right panel) for x = 1062 m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ........................................................................................................................................ 47

Figure 6-13. From left to right: 1D profile of Brie exponent and other CO₂ properties results (CO₂ viscosity, CO₂ bulk modulus, and CO₂ density) inverted jointly with the CO₂ saturation using different rock physics models for x = 1062 m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty .................................................................................................................. 48

Figure 7-1. Seismic data after time migration from inline 1881 ................................................................. 49

Figure 7-2. P-wave velocity for 2D real data section (inline 1881, 2008 vintage, after CO₂ injection). The black square shows the selected region of interest with CO₂ saturated .................................................................................................................. 50

Figure 7-3. P-wave velocity model for target region ........................................................................................ 50

Figure 7-4. Correlation of P-wave velocity of inline 1881 real data and smoothed reservoir properties derived by log data. From left to right: P-wave velocity, grain density, density porosity, frame bulk modulus and frame shear modulus. The red dots indicate the Nordland caprock shale, and the green dots indicates the Utsira sandstone. The log data derived properties from 792 m are shifted to the depth of 762 m. The P-wave velocity profile is extracted at x = 2835 m ........................................................................................................................................... 51
Figure 7-5. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 5. ................................................................. 52

Figure 7-6. From top to bottom: estimation of CO₂ saturation, uncertainty of CO₂ saturation, estimation of Brie exponent, and uncertainty of Brie exponent e using Brie rock physics model with Brie exponent e inverted. ................................................................. 53

Figure 7-7. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 1. ................................................................. 54

Figure 7-8. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 3. ................................................................. 54

Figure 7-9. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 40. ................................................................. 55

Figure 7-10. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model (e = 5) with other CO₂ properties inverted. .................. 55

Figure 7-11. 1D estimation of CO₂ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO₂ saturation using different rock physics models (right panel) for x = 2835 m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ................................................................. 56

Figure 7-12. From left to right: 1D profile of Brie exponent and other CO₂ properties results (CO₂ viscosity, CO₂ bulk modulus, and CO₂ density) inverted jointly with the CO₂ saturation using different rock physics models for x = 2835 m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ................................................................. 57

Figure 8-1. P-wave velocity starting model for FWI. ........................................................................ 58

Figure 8-2. P-wave velocity model at last iteration of FWI using smoothing r² = 5. ...................... 58

Figure 8-3. Selected P-wave velocity model for vintage 1994 before CO₂ injection. ..................... 59

Figure 8-4. S-wave velocity model obtained from Vernik's relation. .............................................. 59
Figure 8-5. From top to bottom: estimation of frame bulk modulus $K_d$, uncertainty of frame bulk modulus $K_d$, estimation of frame shear modulus $G_d$, and uncertainty of frame shear modulus $G_d$. ................................................................. 60

Figure 8-6. From top to bottom: estimation of frame bulk modulus $K_d$, uncertainty of frame bulk modulus $K_d$, estimation of frame shear modulus $G_d$, and uncertainty of frame shear modulus $G_d$ using only P-wave velocity as input. ................................................................. 62

Figure 9-1. Seismic data after time migration for inline 1838. .................................................. 63

Figure 9-2. P-wave velocity starting model for FWI. .............................................................. 63

Figure 9-3. P-wave velocity model at last iteration of FWI using smoothing $r_2 = 5$. ............ 64

Figure 9-4. Selected P-wave velocity model for vintage 2008 (inline 1838). ......................... 64

Figure 9-5. From top to bottom: frame bulk modulus $K_d$, frame shear modulus $G_d$, porosity. 65

Figure 9-6. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 5$. ................................................................. 66

Figure 9-7. From top to bottom: estimation of CO$_2$ saturation, uncertainty of CO$_2$ saturation, estimation of Brie exponent, and uncertainty of Brie exponent using Brie rock physics model with Brie exponent $e$ inverted. ................................................................. 67

Figure 9-8. 1D estimation of CO$_2$ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO$_2$ saturation using different rock physics models (right panel) for $x = 2403$ m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ................................................................. 68

Figure 9-9. From left to right: 1D profile of Brie exponent and other CO$_2$ properties results (CO$_2$ viscosity, CO$_2$ bulk modulus, and CO$_2$ density) inverted jointly with the CO$_2$ saturation using different rock physics models for $x = 2403$ m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ............................................. 69

Figure 9-10. 1D estimation of CO$_2$ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO$_2$ saturation using different rock physics models
(right panel) for \( x = 2553 \) m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ................................................................. 69

Figure 9-11. From left to right: 1D profile of Brie exponent and other CO₂ properties results (CO₂ viscosity, CO₂ bulk modulus, and CO₂ density) inverted jointly with the CO₂ saturation using different rock physics models for \( x = 2553 \) m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ................................................. 70

Figure 9-12. 1D estimation of CO₂ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO₂ saturation using different rock physics models (right panel) for \( x = 3453 \) m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ...................................................................... 70

Figure 9-13. From left to right: 1D profile of Brie exponent and other CO₂ properties results (CO₂ viscosity, CO₂ bulk modulus, and CO₂ density) inverted jointly with the CO₂ saturation using different rock physics models for \( x = 3453 \) m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty. .................................................. 71

Figure 9-14. 1D estimation of CO₂ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO₂ saturation using different rock physics models (right panel) for \( x = 1803 \) m (outside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty. ........................................................................... 71

xvi
III. List of tables

Table 2-1: The fluid parameters corresponding to the high and low brine saturations......... 10

Table 3-1. The composite Utsira sandstone and Nordland shale properties. ....................... 19

Table 3-2. Brine and CO$_2$ fluid properties. ........................................................................ 20

Table 6-1. Different parameter settings for FWI tests. .......................................................... 37

Table 8-1. Averaged estimated frame moduli and porosity derived for baseline vintage (1994). .................................................................................................................................. 61
1 INTRODUCTION

With the increasing energy demand and consumption, the environmental protection and the mitigation of greenhouse gases have been hot topics from the last decade. Carbon dioxide is one of the most important gases to control the atmosphere temperature. The excessive emissions of the CO$_2$ have a substantial contribution to the climate change. In 2016, various countries in United Nations signed the Paris agreement on mitigation of the global warming. In this context, CO$_2$ Capture and Storage (CCS) into the subsurface is proposed as a potential mean of reducing the CO$_2$ emissions into the atmosphere and mitigating global warming. The newest annual report of 2016 (Institute, 2016) by global CCS institute shows that more than 20 large-scale CCS projects are under operation and more than 10 CCS projects will be started in the next decade.

CO$_2$ Capture and Storage requires careful monitoring to ensure the storage process and early detection of potential leakage related to geological hazards. Various geophysical techniques (including seismic and non-seismic techniques) are used prior to and during the injection process to characterize the changes in the subsurface properties. Seismic data are often recorded and several methods (for example, imaging methods like seismic migration, Full-Waveform Inversion, Amplitude Versus Offset analysis) are used to quantify the effect of CO$_2$ injection on seismic properties. In this work, we propose to study the changes of rock physics properties and quantify them during the injection of CO$_2$ at the Sleipner storage site in the North Sea.

Many empirical relations have been proposed to clarify the relation between seismic velocities and the porous rocks with respect to different parameters (clay content, porosity, and others). For example, Castagna et al. (1985) determined empirical regressions relating velocities with porosity and clay content for shaly sands of the Frio formation. Han et al. (1986) also presented a similar relation between P- and S-wave velocities based on the ultrasonic laboratory data. However, most of the empirical relations are valid only for given lithology and fluid type.

4D time-lapse seismic methods are widely considered as an important method to characterize the subsurface property changes due to CO$_2$ injection and migration. These techniques use repeated surveys to estimate changes in the reservoir and saturating fluid properties (brine, CO$_2$, gas mixtures and others). Repeated seismic surveys can be used together with other geophysical methods, such as Controlled-Source Electro Magnetic (CSEM) method, Amplitude Versus Offset (AVO) analysis, and gravity surveys. For example, Landrø (2001) introduced a time-lapse
approach based on time-shifts and AVO attributes to discriminate between pressure and saturation changes. Arts et al. (2004) applied a similar technique for CO₂ storage monitoring. They found that the presence of CO₂ has caused significant changes both in reflection coefficients and in travel time through the CO₂ plume. Arts et al. (2008) combined seismic monitoring with seabed gravimetry to help constrain the simulation of CO₂ migration. Meadows (2008) proposed a model-based approach to predict and quantify the effects of CO₂ injection for multiple reservoir properties and analyzed tuning effect including uncertainties. Since time-lapse seismic is highly dependent on the repeatability of the seismic survey, the reliability of this approach for fluid saturation changes could be discussed. White (2013) suggested an approach using time-lapse travel time differences in conjunction with log data to map the upper bound of CO₂ distribution. In this work, the pressure effects are calibrated by adopting a proper rock physics model. Bergmann and Chadwick (2015) proposed a method for volumetric estimation using time-shift analysis. They concluded that the behavior of fluid mixing could be observed in synthetic and real data application. Norman et al. (2008) studied the CO₂ saturation using time-lapse marine CSEM surveys at Sleipner. In this study, resistivity is very high due to the present of gases. This high sensitivity of resistivity change is combined with seismic data to help the study in gas saturation. Landrø and Zumberge (2017) combined the time-lapse seismic data with gravity data to address the seismic shadow zone problem and study the CO₂ saturation changes at Sleipner.

Seismic reflection Amplitude Versus Offset or Angle technology (AVO/AVA) is also widely used to characterize lithology and fluids. AVO is supposed to be more sensitive to changes in reservoir fluid than 4D time-lapse technology with the help of extra V₅ information, rather than only V₅P (Castagna et al., 1985). For example, Brown et al. (2007) proposed a workflow using AVO attributes under arbitrary fluid saturation and pressure conditions. With the help of laboratory experiments to upscale effects of small-scale heterogeneities, they concluded that AVO not only can determine the presence of CO₂, but also can track the changes in CO₂ saturation over time. However, in many cases, the CO₂ injection is associated with high-porosity high-permeability rocks, where V₅ may be difficult to obtain accurately.

During the last decades, FWI has been introduced as a powerful high-resolution method to map seismic properties of the subsurface. The method aims at searching for the best model that minimizes the misfit between observed and modelled waveforms. Tarantola (1984) first introduced
FWI and implemented in time domain. However, FWI requires solving a highly nonlinear inversion problem and important computational resources. Cycle skipping is an important issue in particular when high frequencies are considered (Virieux and Operto, 2009). The quality of the seismic data seismic data (and especially for the low frequency content of the data), and the accuracy of the starting model play a key role for avoiding convergence towards local minima. The FWI method can be formulated in the time-space or in the frequency-space domain (Virieux and Operto, 2009). Time-domain FWI always highly depend on the starting model (Mora, 1987). While frequency-domain FWI can utilize the inversion procedure from low to high frequencies to ensure converging to the global minima (Song et al., 1995). The frequency domain FWI is more flexible in data selection while the time domain method can be less expensive.

The goal of our study is to investigate how to estimate rock physics properties of the Sleipner CO2 storage pilot. To overcome the limitations of previous studies and obtain reliable reservoir properties, Dupuy et al. (2016a) described a two-step workflow with generic dynamic rock physics models. An effective fluid theory is applied to brine mixture with oil and gas. Selected poroelastic properties (rock frame and fluids properties) are estimated using an improved semi-global optimization (Neighborhood Algorithm, NA) method. In this thesis, we use a similar two-step workflow. In the previous sensitivity study (Dupuy et al., 2017; Yan, 2016), we already implemented the first step into the rock physics tool. Hereafter, we will focus on the study of this rock physics tool to different synthetic and real datasets. Combinations of FWI and rock physics inversion are used to derive CO2 saturations. We will use 2D FWI, geological knowledge, log data, and rock physics inversion to quantify CO2 distribution and evaluate its associated uncertainty. Part of this work has been published in Yan et al. (2017b) and Yan et al. (2017a).


2 METHODS

In this section, the FWI and the rock physics inversion methods are described. We consider two rock physics theories to define the poroelastic media partially saturated with brine and CO$_2$. In uniform saturation theory, we describe an effective fluid phase and then apply the extended Biot theory (Pride, 2005) to the homogenized medium. In patchy saturation theory, to study the multiphase flow induced attenuation in the porous media, we consider an extended white (White, 1975) model and use the Pride's equations (Pride et al., 2004) to obtain the effective frequency dependent moduli.

2.1 Full-Waveform Inversion (FWI)

The objective of the method is to generate a high-resolution image of the subsurface.

The FWI is proposed and first implemented in the time domain by Tarantola (1984). Pratt and Worthington (1990) give the first try in frequency domain Full-Waveform Inversion. Virieux and Operto (2009) analyse the advantages and disadvantages between time domain and frequency domain implementation. We use a similar frequency domain inversion method based on a preconditioned gradient approach as given by Pratt et al. (1998) and Romdhane and Querendez (2014). Figure 2-1 shows a representation of the approximate Hessian matrix.

![Figure 2-1. A representation of the approximate Hessian matrix $\Re \left\{ J^T J \right\}$ by Pratt et al. (1998).](image)

An approximation of the Hessian operator with only the diagonal elements is used to save computation cost. The inversion process is developed following a misfit minimization procedure.
The misfit $\delta m$ (perturbation model) and the gradient of the misfit at iteration $n$ can be formulated as:

$$
\delta m = \frac{1}{2} \| d_{\text{mod}} - d_{\text{obs}} \|^2,
$$

$$
\frac{\partial (\xi m_n)}{\partial m} = \Re \{ J^T \delta d^* \}.
$$

Where $\frac{\partial (\xi m_n)}{\partial m}$ is the gradient of the misfit at iteration $n$. $d_{\text{mod}}$ and $d_{\text{obs}}$ are the modelled and observed data, respectively. $\Re$ is the real part of a complex number. $J$ denotes the Jacobian matrix, thus $J^T$ is the transpose of the Jacobian matrix. $\delta d^*$ denotes the conjugate of the data residuals.

Therefore, the perturbation model can be defined as:

$$
\delta m_n = m_{n+1} - m_n.
$$

The gradient method can be formulated as the link between the perturbation model and data residuals, and is given as:

$$
\delta m_n = -\alpha_n \frac{\partial (\xi m_n)}{\partial m}.
$$

Where $\alpha_n$ is the step length at iteration $n$.

Proper scaling and regularization can be applied to ensure the computational stability. The approximated Hessian $H_a$ is given by:

$$
H_a = \Re \{ J^T J^* \}.
$$

If we only consider the diagonal term of the Hessian, the model that updates at iteration $n$ can be estimated as:

$$
\delta m_n = -\alpha_n (\text{diag} H_a + \lambda I)^{-1} \frac{\partial (\xi m_n)}{\partial m}.
$$

Where $\lambda$ denotes the damping parameter to ensure computational stability.
More details about this FWI method can see in Shin et al. (2001) and Pratt et al. (1998).

2.2 Rock Physics Inversion (RPI)

2.2.1 Forward formulation (rock physics models)

2.2.1.1 Uniform Saturation: effective fluid phase saturation

The widely used Gassmann equations (Gassmann, 1951) provide a way to link the saturated fluid to the bulk modulus of the rock at a low frequency. Biot (1956a) theory is combined with the Gassmann equation to account for dynamic poroelasticity. The Biot-Gassmann equations are valid under several assumptions. The Gassmann equations are valid within a low frequency limit and do not account for the chemical interaction between the grains and the fluid phases. The Biot theory is limited to homogeneous and isotropic media, which consists of only one type of grain. To be more realistic, Pride (2005) extended the Biot-Gassmann equations and involved a generalized dynamic permeability (Johnson et al., 1987). The extensive Biot-Gassmann theory can be applied to a multi-composite material saturated with a multi-fluid mixture. In addition, this approach is valid within a wide frequency range. More details on the assumptions and theory are given in Pride (2005).

The extensive Biot-Gassmann equations allow us to calculate the viscoelastic attributes for an effective fluid phase, which is referred as uniform saturation in our study. Biot (Biot, 1956a, b) demonstrate that there are three types of waves propagating in a porous fluid saturated media. They are compressional wave (P-wave), shear wave (S-wave), and an additional slow compressional wave (Biot wave or slow P-wave). The slownesses of these waves are formulated by Pride (2005) as:
\[ S_2^2(\omega) = \frac{\rho - \rho_f^2 / \rho(\omega)}{G}, \]
\[ S_3^2(\omega) = \frac{\gamma(\omega)}{2} - \frac{1}{2} \sqrt{\gamma^2(\omega) - \frac{4(\rho \rho(\omega) - \rho_f^2)}{HM - C^2}}, \]
\[ S_{\text{bio}}^2(\omega) = \frac{\gamma(\omega)}{2} + \frac{1}{2} \sqrt{\gamma^2(\omega) - \frac{4(\rho \rho(\omega) - \rho_f^2)}{HM - C^2}}. \] (6)

Where \( \rho \) and \( \rho_f \) and \( \bar{\rho}(\omega) \) are bulk density, effective fluid density, and flow resistance density.

The undrained bulk modulus \( K_U \), the Biot modulus \( C \), the shear modulus \( G \) and the fluid storage coefficient \( M \) are the mechanical moduli. The additional terms \( \gamma(\omega) \) and \( H \) are defined by:

\[ \gamma(\omega) = \frac{\rho M + \rho(\omega)H - 2\rho_f C}{HM - C^2}, \]
\[ H = K_U + \frac{4}{3} G. \] (7)

The mechanical moduli are related to the homogenized porous solid. \( K_U \), \( C \), and \( M \) are formulated as:

\[ K_U = \frac{\phi K_d + (1 - (1 + \phi)K_d / K_s)K_f}{\phi(1 + \Delta)}, \]
\[ C = \frac{(1 - K_d / K_s)K_f}{\phi(1 + \Delta)}, \]
\[ M = \frac{K_f}{\phi(1 + \Delta)}. \] (8)

Where the term \( \Delta \) is given by:

\[ \Delta = \frac{1 - \phi}{\phi} \left( 1 - \frac{K_d}{(1 - \phi)K_s} \right). \] (9)

Where porosity \( \phi \) is defined as the ratio between void and total volume in the solid matrix. \( K_d \), \( G_d \) and \( K_f \) are the frame bulk modulus, frame shear modulus and the effective fluid bulk modulus, respectively.

Thus, we can deduce the effective wave velocities and quality factors, and formulated as:
\[
V_{p,\text{Biot},S}(\omega) = \frac{1}{\text{Re}\left(S^2_{p,\text{Biot},S}(\omega)\right)},
\]
\[
Q_{p,\text{Biot},S}(\omega) = \frac{\text{Im}\left(S^2_{p,\text{Biot},S}(\omega)\right)}{\text{Re}\left(S^2_{p,\text{Biot},S}(\omega)\right)}.
\]

We consider the solid material consists of different compositions. We compute the grains bulk moduli \(K_S\) by averaging the bounds (Hashin and Shtrikman, 1963). The grain density \(\rho_S\) is computed with consideration of the compositional minerals in Utsira sandstone. Then, we use arithmetic average for the bulk density, which is given by:

\[
\rho = (1-\phi)\rho_s + \phi\rho_f.
\]

For the frame properties, Pride (2005) suggests two methods to obtained the drained frame moduli \(K_d\) and \(G_d\). He introduces the consolidation parameter \(c_s\) which allow linking the frame moduli to the solid grain moduli. This approach is valid for consolidated sandstone, which has a consolidation parameter in the range of \(2 < c_s < 20\). For unconsolidated sandstone, the Walton theory (Walton 1987) is more favourable. In the rock physics model, we considered the two approaches in the sensitivity analysis (Yan, 2016). In the application part in this paper, as the sandstone reservoir at Sleipner is unconsolidated, we do not use the \(c_s\) term but rather the separated bulk and shear moduli.

Johnson et al. (1987) proposed a frequency dependent dynamic permeability \(k(\omega)\), which correct the seismic permeability and differentiate the viscous and inertial predominant effects at low and high frequency domain (Dupuy et al., 2016). The dynamic permeability is expressed by Johnson et al. (1987):

\[
k(\omega) = \frac{k_0}{\sqrt{1 - \frac{i}{2} \frac{\omega}{\omega_c} - i \frac{\omega}{\omega_c}}}.
\]

Where \(\omega\) is the angular frequency. \(\omega_c\) is the characteristic angular frequency which is associated with the maximum attenuation. \(k_0\) is the hydraulic permeability. The characteristic angular frequency \(\omega_c\) can be formulated with the cementation factor \(m\), the effective fluid viscosity \(\eta\) and the fluid density \(\rho_f\) (Adler et al., 1992).
Biot (1956a) proposed another frequency depend property to extend the poroelasticity theory to the full frequency range. The frequency depend parameter is referred as the complex flow resistance $\tilde{\rho}(\omega)$, and is defined by:

\[
\tilde{\rho}(\omega) = \frac{i\eta}{\omega k(\omega)}.
\]

(13)

Where $i$ denotes the complex number.

We define the effective fluid phase properties for the CO$_2$ and brine mixture using different averaging methods. First, we use the empirical law (Brie et al., 1995) for the effective fluid bulk modulus $K_f$. Brie et al. (1995) proposed an empirical exponent $e$ which varies from 1 to 40 associated to different mixture trends. $S_W$ is the water (brine) saturation. $K_{CO2}$ and $K_W$ is the CO$_2$ and brine bulk moduli. The effective fluid bulk modulus $K_f$ is formulated as:

\[
K_f = (K_{CO2} - K_W)S_W^e + K_{CO2}.
\]

(14)

Carcione et al. (2006) suggest using a brie exponent equal to 5 for the brine and CO$_2$ mixture.

Teja and Rice (1981) propose an equation for the effective fluid viscosity $\eta$. Considering the CO$_2$ viscosity $\eta_{CO2}$ and brine viscosity $\eta_W$, the effective fluid viscosity $\eta$ can be formulated as:

\[
\eta = \eta_{CO2}\left(\frac{\eta_W}{\eta_{CO2}}\right)^{S_W}.
\]

(15)

The effective density $\rho_f$ is given as the arithmetic average.

\[
\rho_f = S_W\rho_W + (1 - S_W)\rho_{CO2}.
\]

(16)

Where $\rho_W$ is the brine density. $\rho_{CO2}$ is the CO$_2$ density. Hereafter, we will refer this model as the 'Brie rock physics model' and 'uniform saturation', which indicate the model using equations (14), (15) and (16). It can be uniform mixing or patchy mixing depending on the Brie exponent.

2.2.1.2 Patchy Saturation

White (1975) describes a patchy model for porous media saturated with multi-fluids. This model allows considering the pressure gradient generated by multi-fluids. Pride et al (2004)
reformulate and extend the White model using frequency dependent parameters. This allows taking into account wave induced fluid flows and associated attenuation and dispersion created by mesoscopic heterogeneities (fluid patches). In contrast to the uniform saturation, the fluids in the reservoir are not well mixed in the patchy saturation theory and the fluid-solid interactions are explicitly considered. The extended White model involves the spherical gas pocket and assumes the patch size should be much smaller than the detected wavelength. The assumptions of the extended White model are described by Pride (2005). Pride et al. (2004) point out that the extended patchy saturation has a limited range of validity for relative low and high brine saturations. Therefore, we consider the patchy model only for high brine saturation condition ($S_{w} \geq 80\%$ or similarly, $S_{CO2} \leq 20\%$ ) and low brine saturation ($S_{w} \leq 20\%$ or similarly, $S_{CO2} \geq 80\%$) in the sensitivity analysis (Yan, 2016). With the consideration of geology studies at Sleipner, the case of high brine saturation is more likely to happen at Sleipner. The fluid patch is assumed spherical and $a$ is the radius for the patch sphere. $L_i$ is a geometrical term indicating the distance with zero pressure in the brine. The contact surface $S$ between the saturated fluids and the elemental volume $V$ form another geometrical term $V/S$. Table 2-1 illustrates the parameters of the fluid properties corresponding to the high and low brine saturation conditions.

Table 2-1: The fluid parameters corresponding to the high and low brine saturations.

<table>
<thead>
<tr>
<th>Saturation Condition</th>
<th>High Water Saturation ($S_{CO2} \leq 20%$)</th>
<th>Low Water Saturation ($S_{CO2} \geq 80%$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_i^2$</td>
<td>$\frac{9a^2}{14S_{CO2}^{2/3}} \left( 1 + \frac{7S_{CO2}^{1/3}}{6} \right)$</td>
<td>$\frac{a^2}{15}$</td>
</tr>
<tr>
<td>$V/S$</td>
<td>$\left( \frac{aS_{CO2}^2}{3} \right)^2$</td>
<td>$\left( \frac{aS_w}{3} \right)^2$</td>
</tr>
<tr>
<td>$\rho_f$</td>
<td>$\rho_w$</td>
<td>$\rho_{CO2}$</td>
</tr>
<tr>
<td>$\tilde{\rho}(\omega)$</td>
<td>$\frac{\eta_w}{\omega k_0}$</td>
<td>$\frac{\eta_{CO2}}{\omega k_0}$</td>
</tr>
</tbody>
</table>
Pride et al. (2004) reformulate the Skempton modulus $B(\omega)$, the bulk undrained modulus $K_U(\omega)$, the Biot modulus $C(\omega)$, and the fluid storage coefficient $M(\omega)$, by using the stiffness coefficients $a_{ij}$ ($i,j = 1, 2, 3$) and the Biot-Willis constant $\alpha$:

$$B(\omega) = \frac{-a_{12}(a_{33} - \gamma(\omega)) + a_{13}(a_{23} + \gamma(\omega))}{(a_{22} - \gamma(\omega))(a_{33} - \gamma(\omega)) - (a_{23} + \gamma(\omega))^2},$$

$$K_U(\omega) = \left[ \frac{1}{K_d(\omega)} + B(\omega) \left( a_{12} - \frac{a_{13}(a_{23} + \gamma(\omega))}{a_{33} - \gamma(\omega)} \right) \right]^{-1},$$

$$C(\omega) = B(\omega)K_U(\omega),$$

$$M(\omega) = B(\omega) \frac{K_U(\omega)}{\alpha}.$$  \hspace{1cm} (17)

Where $\gamma(\omega)$ is the inertial transport coefficient describing the mesoscopic flow, and is given as:

$$\gamma(\omega) = \frac{S_w k_0}{\eta_w L_s^3} \sqrt{1 - \frac{i \omega}{\omega_p}},$$  \hspace{1cm} (18)

where $\omega_p$ is the transition frequency associated with a high frequency mechanism.

Using the similar equations in uniform saturation (see equations (6), (7), and (10)), we can deduce the velocities, quality factors in the patchy saturation model. More details for the patchy saturation theory are given in Dupuy and Stovas (2014). Hereafter, we will refer this model as 'patchy saturation' or 'patchy model', which is different from patchy mixing of Brie rock physics model.

### 2.2.2 Inversion formulation

The rock physics inversion process estimates the poroelastic parameters from various combination of viscoelastic attributes (P- and S-wave velocities, P- and S-wave quality factors, and density).

We assume that $\tilde{d}$, $\tilde{m}$ and $g$ represents the data vector, the model vector and the linking function for the data and model, respectively. Therefore, the forward modelling process can be described as:
\[ \tilde{d} = g(\tilde{m}). \]  

The relation function \( g \) is the rock physics model, for uniform and patchy saturation models in our study. The inverse of \( g \) cannot be computed and the system is solved by a semi-global optimization method.

We implement the inversion process by using the NA algorithm. Sambridge (1999) introduces the NA algorithm method, which is a Monte Carlo oriented method. The NA method is searching for the minimum discrepancy between the observed data \( \tilde{d}_{\text{obs}} \) and the estimated data \( g(\tilde{m}) \) from the forward modelling. The scalar misfit function \( C(m) \) can be given as a \( L_2 \) norm:

\[
C(m) = \frac{1}{2} \left[ (\tilde{d}_{\text{obs}} - g(\tilde{m}))^T (\tilde{d}_{\text{obs}} - g(\tilde{m})) \right].
\]  

The implementation of NA algorithm method has only two control parameters: the number of new models at each iteration and the resampling size of Voronoï cells. The misfit of the previous iteration decides the new sampling of Voronoï cell for the next iteration. Dupuy et al. (2016) and Sambridge (1999) provide more details of the rock physics inversion and NA algorithm, respectively.

In our sensitivity study (see (Yan, 2016)), an iteration number of 1000 and a resampling factor of 10 has been shown to be sufficient to ensure the accuracy of the results. Whereas, the iteration number is reduced for synthetic and real data applications for the computational efficiency. For the estimation of the frame moduli (Yan, 2016), the iteration number is reduced to 500 to optimize the computational process. For the CO\(_2\) saturation estimation, we reduce the iteration number to 400. This number is selected based on the misfit variation versus iteration number (see Appendix B).

### 2.3 Summary of the sensitivity

In the previous study on the sensitivity and well baseline application (Yan, 2016), we adopted a similar two-step workflow as described by Dupuy et al. (2016). We demonstrated the use of rock physics inversion for estimating CO\(_2\) properties, saturations, and rock frame properties at Sleipner CO\(_2\) storage site in the North Sea (Yan, 2016). We investigated the elastic wave velocities and quality factors for the Utsira unconsolidated sandstone containing CO\(_2\) and brine.
mixture and modeled the effect of various CO₂ saturations on viscoelastic properties. Figure 2-2 shows the P-wave velocity changes with different brine and CO₂ saturations for uniform saturation with different Brie exponents and for patchy saturation with a bubble size equal to 0.01 m.

![Figure 2-2. P-wave velocity variation with brine saturation for uniform saturation with various Brie exponent and patchy saturation with bubble size \(a\) of 0.01 m.](image)

The sensitivity tests are conducted using the extracted viscoelastic properties for uniform and patchy saturation to invert selected poroelastic parameters from various input data parametrizations. By analysis the results of the sensitivity tests, we found the following conclusions:

1) The bubble size \(a\) in patchy saturation model cannot be well estimated.
2) The critical frequency of patchy saturation is more variable compared with the one for uniform saturation model.
3) Both patchy and uniform saturation models have better estimations of CO₂ properties and brine saturation when the brine saturation is high.
4) The brine saturation (thus CO₂ saturation) can be estimated from only \(V_p\) input with more or less uncertainty. CO₂ saturation can be well estimated for low CO₂ saturation condition.
5) The additional information (quality factor of P-wave, S-wave velocity, density information) can help the estimation of CO₂ bulk modulus and reduce the uncertainty on CO₂ saturation estimates.

In a second step, we applied the rock physics inversion to the log data before CO₂ injection to estimate the rock frame properties at Sleipner. With density and S-wave velocity computed
with an empirical relation, we can derive an estimation of the drained bulk and shear moduli of the reservoir which are similar to those derived by Lindeberg (2013).

2.4 Workflow outline

In this section, we outline the basic workflow that we used for all the applications. We will explain the workflow for the baseline and monitor CO$_2$ injected application applications.

2.4.1 Baseline application

The baseline information is essential for the later estimation of CO$_2$ saturation. Based on the sensitivity analysis, we know that better estimations of the rock frame properties can be achieved by involving additional proper empirical S-wave information and density. We apply a similar procedure to estimate the rock frame properties ($K_d$, $G_d$) for fully brine-saturated baseline. We modify the baseline inversion code to handle a 2D case. For baseline information, we propose different strategies adopted for different cases. For the true synthetic model and FWI synthetic model application, we extract the baseline information using one trace with less CO$_2$ impacts and extend laterally along the layer variation carefully to obtain the associated frame properties. For the real data of inline 1881, we apply the extracted baseline information from log data. For the real data of inline 1838, we use the FWI derived baseline information.

2.4.2 Monitor application

From a practical point of view, the information of the real data is normally limited to P-wave velocity. We use FWI to generate P-wave velocity models. The initial P-wave velocity data prior to FWI would be obtained by a generated synthetic model or real dataset from seismic. Data processing is applied before the application of FWI. We select an area of the P-wave velocity model obtained from FWI. From the sensitivity analysis (Yan, 2016), we know that providing a priori properties to reduce the unknowns in the inversion process can increase the stability of inversion. Therefore, we prepare the a priori rock properties for the rock physics inversion.

To start the application study, we also modify our rock physics inversion code to be adaptable for the 2D application with given grids design. The following cases are considered:
Case 1: Estimation of fluid saturation assuming a known Brie exponent $e$ using uniform saturation model for partially saturated media.

Case 2: Estimation of fluid saturation and Brie exponent $e$ using uniform saturation model for partially saturated media.

Case 3: Estimation of fluid saturation and fluid phase properties using uniform saturation model for partially saturated media.

Case 4: Estimation of fluid saturation using patchy saturation model for partially saturated media.

Based on the sensitivity studies (Dupuy et al., 2017; Yan et al., 2017b) of the rock physics inversion tool, we found that there are always many good models with low misfit. For example, the low misfit area (pink region in Figure 2-3 (a)) shows that the trade-off between Brie exponent $e$ and brine saturation $S_W$. The best estimated model (blue cross, lowest misfit) is located at the upper part of the low misfit region (Figure 2-3 (a)). We also found that the best estimation with the minimum misfit of frame bulk modulus is located at the bound of the low misfit area (Figure 2-3 (b)). Therefore, we can expect to give a more realistic estimation when we consider average of all the low misfit models. In this sense, we select all the models with a misfit lower than a given maximum value of misfit. In addition of the mean value, we estimate the one standard deviation to give an idea of the uncertainty. It is worth noting that we also apply similar uncertainty analysis on the baseline inversion process for the estimation of reservoir frame moduli. The uncertainty in our study is an absolute value and not in percentage.
Figure 2-3. Panel (a) indicates the estimations of Brie exponent $e$ and brine saturation $S_w$ for uniform saturation from P-wave velocity input only. Panel (b) indicates the estimation of frame moduli for Utsira sandstone of log data from P-wave velocity only. The blue cross indicates the best model and the red cross indicates the true model.
3 SLEIPNER GEOLOGICAL SETTING AND ROCK PHYSICS PROPERTIES

Since 1996, the Sleipner site, known as the world’s first industrial scale CO\textsubscript{2} storage operation (Chadwick et al., 2004), is operated in the North Sea. About 1 million tons per year of CO\textsubscript{2} is separated from production and injected into the underground saline aquifer at Sleipner (Carcione et al., 2006). The CO\textsubscript{2} is injected into the Utsira Formation at a depth of 1012 m below the sea level through a deviated well (Arts et al., 2008).

The reservoir sand comprises two big depositional basins, which are lying on the North Sea Basin at depths from 550 m and 1500 m (Chadwick et al., 2000). The CO\textsubscript{2} is being injected at the part in the southern Sleipner where the thickness of the Utsira sandstone is about 300 m (Figure 3-1). The reservoir extends about 400 km from south to north, which consists of late Miocene to early Pliocene dominantly sandy unit and some shaly intra-reservoir horizons (Chadwick et al., 2000).

![Figure 3-1. Map of the Utsira sand reservoir thickness (Arts et al., 2004).](image)

Figure 3-2 shows the geological structure of the Utsira Sand, which is surrounded by the Nordland shale on the top and the Hordaland shale on the bottom. Shale layers are clearly visible on the gamma ray (GR) response with values higher than 80 API (Dupuy et al., 2017; Yan, 2016). The Utsira Formation is a highly porous, weakly consolidated, highly permeable sandstone which provides a good reservoir condition for high injection rate through only one single well (Michael et al., 2010). The intra-reservoir shale layers are very thin and can be less than 1 m
thick (Zweigel et al., 2000). The intra-reservoir shales are regarded as the low permeability barriers, which impact the CO₂ top wards migration (Chadwick et al., 2004).

Figure 3-2: Sketch of geological model for CO₂ migrations (Bickle, 2009).

The caprock shale is known as the Nordland shale, which comprises dominantly kaolinite, illite, quartz, and smectite (Gaus et al., 2005). Based on the cutting analysis, that the caprock is assumed to be a good quality seal with a low probability of leakage (Chadwick et al., 2004).

For the application of rock physics inversion, we need to determine a set of realistic a priori poroelastic properties at Sleipner. The a priori parameters are extracted based on the existing geological studies on Sleipner field. Grain moduli of the Utsira sandstone and the Nordland shale are calculated by averaging Hashin-Shtrikman bounds (Hashin and Shtrikman, 1963; Mavko et al., 2009). Effective grain density for the Utsira sandstone and the Nordland shale are computed by using volume weighted averages, the specified calculation are clarified in the sensitivity tests (Yan, 2016). The cementation parameter m is assumed to be 1 for the weakly consolidated sandstone and mudstone. The permeability for the Utsira Formation is high and ranges from $1 \times 10^{-12}$ m$^2$ to $3 \times 10^{-12}$ m$^2$ (Boait et al., 2012). We use an average permeability of $2 \times 10^{-12}$ m$^2$. Porosity of the Utsira sandstone ranges between 27% and 42% (Chadwick et al., 2004). The drained frame moduli ($K_d$ and $G_d$) of the Utsira sandstone are taken from Lindeberg (2013),
while the drained frame moduli of the Nordland shale are obtained by rock physics inversion for the fully brine saturated baseline data. The a priori properties of the Utsira sandstone and the Nordland shale properties used in our application studies are summarized in Table 3-1. The shale grain properties are applied to all the interbedded shales. In previous log data application study (Yan, 2016; Yan et al., 2017b), we use baseline information from well 15/9 - A16 before the CO₂ injection started. More details for Kₛ and ρₛ are illustrated in Appendix D and Appendix E.

Table 3-1. The composite Utsira sandstone and Nordland shale properties.

<table>
<thead>
<tr>
<th>Lithology</th>
<th>Solid Properties</th>
<th>Frame Properties</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Kₛ</td>
<td>ρₛ</td>
</tr>
<tr>
<td></td>
<td>GPa</td>
<td>kg/m³</td>
</tr>
<tr>
<td>Utsira Sandstone</td>
<td>39.29</td>
<td>2663.5</td>
</tr>
<tr>
<td>Nordland Shale</td>
<td>22.6</td>
<td>2390</td>
</tr>
</tbody>
</table>

For the a priori properties of the saturating fluids, we consider a CO₂ and brine mixture after CO₂ injection and a fully brine saturated medium before CO₂ injection. At the pressure and temperature of the reservoir, the bulk modulus of brine is 2.3 GPa (Boait et al., 2012), and the density of brine is 1030 kg/m³ (Mavko et al., 2009). Most of the CO₂ is stored in a supercritical state (Arts et al., 2008) and we use a relative high density of 700 kg/m³ for the CO₂ phase. Since the initial hydrostatic pore pressure of 8 MPa is considered (Furre et al., 2015; Furre and Eiken, 2014), the range of Kₖₒ is estimated to be 0.02 GPa - 0.075 GPa (Ghaderi and Landrø, 2009; Span and Wagner, 1996). We use value of 0.075 GPa for bulk modulus of CO₂ (Lindeberg, 2013). The viscosity property of CO₂ is discussed in many papers and depends on the temperature and pressure (Gasda et al., 2012; Singh et al., 2010). However, the effective viscosity influence on seismic velocity is minor in low frequency (Dupuy et al., 2016), and we use 6×10⁻
Pa.s for the CO₂ viscosity. The saturating fluids properties used in our application studies are summarized in Table 3-2.

**Table 3-2. Brine and CO₂ fluid properties.**

<table>
<thead>
<tr>
<th>Fluid phase</th>
<th>η</th>
<th>ρ&lt;sub&gt;f&lt;/sub&gt;</th>
<th>K&lt;sub&gt;f&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brine</td>
<td>6.90×10⁻⁴</td>
<td>1030</td>
<td>2.30</td>
</tr>
<tr>
<td>CO₂</td>
<td>6.00×10⁻⁵</td>
<td>700</td>
<td>0.075</td>
</tr>
</tbody>
</table>
4 SLEIPNER WELL 15/9-A16

In this section, we are going to apply the rock physics inversion to the baseline log data (i.e. before injection). The objective is to evaluate the uncertainty in the estimation of the rock frame moduli and to see if the estimations using the mean values are different from the model with the lowest misfit.

4.1 Data preparation

We use the same combination input data of \( V_P, V_S \) and density) for the baseline application as described by Yan (2016). The combined S-wave velocity is derived by Vernik's relation (Vernik et al., 2002). The grain density is derived from Hashin-Shtrikman bounds, and thus we derived the density porosity. We use an iteration number of 500 and a resampling size of 10. Figure 4-1 shows input information of P- and S-wave velocities, density and the density-derived porosity. The thin interbedded shale layers within the Utsira sand formation can be discriminated from the log data.

![Figure 4-1. From left to right: P-wave velocity, S-wave velocity, bulk density and the density log derived porosity. P-wave velocity and density responses are log data from well 15/9-A16. S-wave velocity is derived using Vernik's relation. Density porosity log is derived from bulk density log and the grain density computed from Hashin-Shtrikman bounds. The red and green dots indicate the caprock of the Nordland shale and the Utsira sandstone, respectively.](image-url)
4.2 Estimation of frame moduli

Figure 4-2 shows the estimations of frame bulk modulus $K_d$ and frame shear modulus $G_d$. The mean values of the extracted frame moduli are estimated with a threshold misfit of 10%. The mean estimation of the frame moduli ($K_d$, $G_d$) are similar with the one corresponding to the lowest misfit result and give a similar slight increasing trend with the increasing of depositional depth. The deviations of the frame shear modulus are slightly higher than that for the frame bulk modulus. To conclude, the difference between the mean estimation of the frame moduli ($K_d$, $G_d$) and the one corresponding to the lowest misfit result is very small.

![Figure 4-2. From left to right: frame bulk and shear moduli, which are derived from the combination input of P-wave velocity, S-wave velocity and density. The black lines indicate the best estimations with the lowest misfit models. The blue lines indicate values of a set of models have misfit lower than 0.1. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.](image)

We also try a different threshold (10 instead of 0.1). The conclusion is that the choice of the misfit threshold will not have a big impact on the mean estimation. The figures are given in Appendix A.
5 SYNTHETIC SLEIPNER MODEL

This chapter uses the synthetic Sleipner model from Traub (2008). The true synthetic model is shown in Figure 5-1. We conduct several tests to figure out various effects by different models on the estimation of CO$_2$ distribution.

![Figure 5-1. Initial 2D synthetic true model.](image)

5.1 Data preparation and a priori rock properties

In this section, we show the results using rock physics inverted rock frame information and prepare the a priori rock properties for RPI. We select a region focus on CO$_2$ saturated layers from 765m (Figure 5-2). To extract a more reliable baseline reservoir properties, we select a trace as shown in Figure 5-2. Then, we extract the frame moduli from the baseline using inputs of P-wave velocity, S-wave velocity and density. S-wave velocity and the bulk density are derived using Vernik's and Gardner's relations (Mavko et al., 2009), respectively. The Vernik’s relations for sand and shale are given by:

\[
V_s = \left(-1.267 + 0.372V_p^2 + 0.00284V_p^4\right)^{0.5} \text{ (km/s) for sandstone},
\]

\[
V_s = \left(-0.79 + 0.287V_p^2 + 0.00284V_p^4\right)^{0.5} \text{ (km/s) for shale.}
\]

The Gardner relation is given by:

\[
\rho = 1.66V_p^{0.261}.
\]

Where the bulk density $\rho$ is in unit of g/cm$^3$, the P-wave velocity $V_p$ is in km/s. The corresponding porosity is derived using the Gardner relation derived density and grain density, and can be computed by volumetric average as:
\[
\phi = \frac{(\rho_s - \rho_f)}{(\rho_s - \rho_w)}.
\]  

(23)

The deduced estimation of the frame moduli is derived using mean values of the models with misfit lower than 0.1 (Figure 5-3).

Figure 5-2. Synthetic P-wave velocity model for selected region. The black line indicates the extracted vertical profile (x = 1947 m).

Figure 5-3. From left to right: P-wave velocity, S-wave velocity, bulk density, density porosity, frame bulk modulus and frame shear modulus. The red and green dots indicate the caprock of the Nordland shale and the Utsira sandstone, respectively. The blue lines indicate the rock frame moduli (mean value with maximum misfit of 0.1) inverted using the combination input of P-wave velocity, S-wave velocity, and density. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
From the P-wave velocity model shown in Figure 5-2, we estimate the P-wave vertical gradient in order to define the boundary between shale and sand. As shown in Figure 5-4, a distinctive positive value of the first derivative is expected to be related to a lithology change from sand to shale. While a distinctive negative value of the first derivative is expected to be related to a lithology change from shale to sand. Meanwhile, we should be careful in the region with CO₂ induced reduction in velocity. Thus, we generate the 16 layers numbered with constant number from 1 to 16 (as shown in Figure 5-4).

![Figure 5-4](image)

Figure 5-4. From top to bottom: (a) first derivative of P-wave velocity with respect to the depth, (b) velocity model with extracted boundaries, and (c) the generated 16 layers. The vertical axis is corresponding to the row number of the matrix, while the horizontal axis is the column number of the matrix.

Therefore, we construct the corresponding rock frame properties using the structural model and the estimated frame moduli. We interpolate linearly for each corresponding layer based on the extracted baseline information. The procedure is repeated for all the traces. Thus, we create the a priori information of the frame properties (Figure 5-5).
Figure 5-5. The derived new a priori rock properties. From top to bottom: frame bulk modulus, frame shear modulus, grain bulk modulus, porosity, grain density and permeability.

5.2 Estimation of CO$_2$ saturation

After deriving the a priori frame properties, we use the same P-wave velocity input for the rock physic inversion. We use a central frequency of 30 Hz and a NA iteration number of 400.

Figure 5-6 shows the estimation results when we use a Brie rock physics model with a Brie exponent $e$ equal to 5 (Carcione and Picotti, 2006). The CO$_2$ saturation is high from 60% to 90% in central plume. CO$_2$ saturation is about 20% - 30% outside of the main plume. It is worth noting that the uncertainty in our estimation results is absolute value. The related uncertainty of CO$_2$ saturation is ranging from 0.15 to 0.25. This means that the saturation is known with ± 0.15 to 0.25 i.e. between 35 to 100% $S_{CO2}$. 
Figure 5-6. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 5.

Figure 5-7 shows the estimation results when we use a Brie rock physics model to invert CO₂ saturation and Brie exponent e simultaneously. The estimated CO₂ saturation is higher and the related uncertainty of CO₂ saturation is also higher. The Brie exponent e varies from 6 to 16 for CO₂ saturated layers, while for the Brie exponent can be quite high to around 35 for the CO₂ plume, suggesting uniform saturation distribution. The uncertainty of Brie exponent is around 6 – 10.
Figure 5-7. From top to bottom: estimation of CO₂ saturation, uncertainty of CO₂ saturation, estimation of Brie exponent, and uncertainty of Brie exponent using Brie rock physics model with e inverted.

Figure 5-8 and Figure 5-9 show the estimation results when we use a Brie rock physics model to invert CO₂ saturation and CO₂ properties (CO₂ bulk modulus, density, and viscosity) simultaneously. The estimated CO₂ saturation is similar with the case when CO₂ properties are defined. The estimated CO₂ bulk modulus is around 0.05 - 0.06 GPa with an uncertainty around 0.01 - 0.02 GPa for the central plume. The estimated CO₂ density is around 700 - 800 kg/m³ with an uncertainty around 30 - 50 kg/m³ for the central plume. The viscosity of CO₂ is hard to be inverted using P-wave velocity only as we concluded in the sensitivity tests. Therefore, the related figures for CO₂ viscosity in 2D are not shown here for brevity. It could be explained using the sensitivity results in Figure 5-10 (Yan, 2016). We can see that Sₚ is well estimated even when the CO₂ properties are not defined using only Vₚ. The CO₂ properties cannot be well estimated using only Vₚ as an input. There are several local minima and Kₐ cannot converge...
towards the true model. $K_{CO2}$ and $\rho_{CO2}$ can be better estimated when $V_S$ is added (Dupuy et al., 2017; Yan, 2016). Quality factor $Q_P$ is also important to reduce uncertainty. More details are provided in Yan (2016).

Figure 5-8. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model ($e = 5$) with CO$_2$ properties inverted.
Figure 5-9. From top to bottom: estimation of CO₂ bulk modulus, uncertainty of CO₂ bulk modulus, estimation of CO₂ density, and uncertainty of CO₂ density using Brie rock physics model (e = 5) with CO₂ properties inverted.

Figure 5-10. Uniform saturation condition (true model Sw = 85%): inversion of CO₂ density, CO₂ bulk modulus, CO₂ viscosity and brine saturation from Vp. The blue cross indicates the best model; red cross indicates the true model.
We also conducted the tests for fully patchy mixing with $e = 1$ (Figure 5-11) and fully uniform mixing with $e = 40$ (Figure 5-13), and the case with $e = 3$ (Figure 5-12) (Brie et al., 1995). When $e = 1$, the Brie rock physics model gives the highest estimation of CO$_2$ saturation. While the estimation using $e = 40$ is with a high uncertainty up to 0.4. This can be explained using Figure 2-2 that the P-wave velocity is less sensitive to the change of saturation when brine saturation is low. The estimation results using $e = 3$ is similar with that using $e = 5$.

![Figure 5-11. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 1$.](image-url)
Figure 5-12. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 3$.

Figure 5-13. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 40$.

Figure 5-14 shows the estimation results when we use patchy saturation model. The estimated CO$_2$ saturation is ranging from 0% to 17% with ± 0.02 to 0.035 uncertainty. Due to the limitation related to the validity range of saturation, the results are not meaningful and, therefore, we do not show this model for the later application on FWI synthetic model.

We also give a 1D view analysis at $x = 1062$ m to better visualize the estimation results. The selected trace through the main CO$_2$ plume. The estimation of CO$_2$ saturation is given in Figure 5-15 and the jointly estimated other properties are given in Figure 5-16.
Figure 5-14. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using a patchy saturation with $a = 0.01$ m.

Figure 5-15. 1D estimation of CO$_2$ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO$_2$ saturation using different rock physics models (right panel) for $x = 1062$ m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
Figure 5-16. From left to right: 1D profile of Brie exponent and other CO$_2$ properties results (CO$_2$ viscosity, CO$_2$ bulk modulus, and CO$_2$ density) inverted jointly with the CO$_2$ saturation using different rock physics models for x = 1062 m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
6 FWI SYNTHETIC MODEL

In this part of study, we apply the rock physics inversion tool on the synthetic Sleipner data using the results derived from FWI. The goal is to test and demonstrate the validity and efficiency of the proposed rock physics tool prior to the application of the real data set in 2008.

6.1 Data preparation and FWI tests

We start the FWI with a smooth starting model as shown in Figure 6-1. The warm colour region in the central is related to the layers with a low P-wave velocity ranging from 1700 m/s to 1800 m/s. This low-velocity anomaly spot is indicating the CO₂ saturated layers.

![Figure 6-1. Starting model of P-wave velocities before FWI.](image)

We run different FWI tests and generate different $V_P$ results. Figure 6-2 shows the P-wave results derived using different FWI processes. We are using a preconditioned-gradient technique jointed FWI tomographic method. We conduct the FWI process in different ways to obtain the best P-wave results. First, we detect the smoothing factor effects on the P-wave results (as shown in panel (a), (b), (c), (d) in Figure 6-2). The P-wave velocity models derived from in FWI tests 1 and 3 show the effect due to a different value of x-direction smoothing factor. The higher smoothing factor (0.8) in x-direction will slightly increase the P-wave velocity results but does not affect the discrimination of layers (as shown in panel (a), (c) in Figure 6-2). In contrast, the P-wave velocity derived in FWI tests 2 and 4 show the effect due to a different value of z-direction smoothing factor. The z-direction smoothing factor has a strong effect on the vertical resolution. An improper selection of the z-direction smoothing factor will smear the layers and geological variation in depth (as shown in panel (b), (d) in Figure 6-2). Therefore, a z-direction smoothing factor of 0.2 and a relative small z-direction smoothing factor of 0.1 are
favourable in our case. In addition, the P-wave velocity results using a FWI without smoothing show many artefacts (panel (e) in Figure 6-2). The velocity in the layers is not laterally constant in this area and cannot be distinguished from each other (panel (e) in Figure 6-2). The last FWI test (panel (f) in Figure 6-2) is designed with estimating the Hessian operator at each iteration step and with a very small damping factor for the Hessian operator ($1 \times 10^{-8}$). With this more time-consuming computation of the Hessian, the P-wave velocity is better defined and the deeper layers in the reservoir (panel (f) in Figure 6-2) are well reconstructed. The different setting parameters for different FWI tests are described in Table 6-1. More details of the FWI setting parameters are given in Appendix B.

**Table 6-1. Different parameter settings for FWI tests.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value for test 1</th>
<th>Value for test 2</th>
<th>Value for test 3</th>
<th>Value for test 4</th>
<th>Value for test 5</th>
<th>Value for test 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Damping coefficient of Hessian</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>$1.00 \times 10^{8}$</td>
</tr>
<tr>
<td>Smooth method</td>
<td>Gaussian spatial smoothing</td>
<td>Gaussian spatial smoothing</td>
<td>Gaussian spatial smoothing</td>
<td>Gaussian spatial smoothing</td>
<td>No smoothing</td>
<td>Gaussian spatial smoothing</td>
</tr>
<tr>
<td>Wavelength fraction along x</td>
<td>0.2</td>
<td>0.2</td>
<td>0.5</td>
<td>0.2</td>
<td>0</td>
<td>0.2</td>
</tr>
<tr>
<td>Wavelength fraction along z</td>
<td>0.1</td>
<td>0.8</td>
<td>0.1</td>
<td>0.5</td>
<td>0</td>
<td>0.2</td>
</tr>
<tr>
<td>Estimated Hessian at each iteration</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

We can distinguish approximately 8 CO$_2$ injected layers from the FWI derived P-wave velocity. With the considering of the higher resolution on layers saturated with CO$_2$, the full inversion
results of test 6 is used as the input for the rock physics inversion. To save the computational cost in the process of application on the rock physics inversion, we focus on a region of interest with CO$_2$ saturated. The 1D P-wave velocity profiles for selected region of different FWI tests (Figure 6-3) are extracted to illustrate the velocity variation for each FWI test.

<table>
<thead>
<tr>
<th>(a) Test 1</th>
<th>(b) Test 2</th>
<th>(c) Test 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Test 1" /></td>
<td><img src="image2" alt="Test 2" /></td>
<td><img src="image3" alt="Test 3" /></td>
</tr>
</tbody>
</table>

38
Figure 6-2. P-wave velocities after various FWI tests.
Figure 6-3. P-wave velocity for different FWI tests at x = 1062 m.

Figure 6-4 shows the selected region of FWI test 6 at depths from 765 m to 1047 m. For a priori rock physics parameters, we use true model derived frame moduli as described in previous chapter (Figure 6-5).

Figure 6-4. P-wave velocity model extracted for the target region from FWI test 6.
6.2 Estimation of CO₂ saturation

In this section, we present the estimation results using different rock physics models with a maximum misfit of 0.1 and the corresponding uncertainty. We use a central frequency of 30 Hz and a NA iteration number of 400.

Figure 6-6 shows the CO₂ saturation is ranging from 0.1 to 0.3 ± 0.1 to 0.15, i.e. between 0 and 0.45 (0 to 45% SCO₂). This is lower than that using the true synthetic model. The reason for this low CO₂ saturation estimation could be the overestimated velocity from FWI.
Figure 6-6. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 5.

Figure 6-7 shows the estimation results when we use a Brie rock physics model to invert CO₂ saturation and Brie exponent e together. The estimated CO₂ saturation ranges from 20% - 65% with an uncertainty of 0.20 to 0.36, which is higher than using e = 5. The Brie exponent e varies from 8 to 32 with an uncertainty of 5 to 16 for CO₂ saturated layers in general, which indicates the mixture is between a fully patchy mixing and uniform mixing distribution.
Figure 6-7. From top to bottom: estimation of CO$_2$ saturation, uncertainty of CO$_2$ saturation, estimation of Brie exponent, and uncertainty of Brie exponent using Brie rock physics model with Brie exponent $e$ inverted.

Figure 6-8 shows the estimation results when we use a Brie rock physics model with $e = 5$ to invert CO$_2$ saturation and other CO$_2$ properties (CO$_2$ bulk modulus, CO$_2$ density, and viscosity) simultaneously. The estimated CO$_2$ saturation are similar with that when the CO$_2$ properties are defined. The results of CO$_2$ bulk modulus and density are not as good as that for the case of true synthetic model. One possible reason is that the true synthetic model is a more favourable case with clear thin layers. The viscosity of CO$_2$ is also hard to be inverted using only P-wave velocity. The related figures for CO$_2$ viscosity in 2D are not shown here for brevity.
We also conducted the Brie rock physics model tests for fully patchy mixing with $e = 1$ (Figure 6-9) and fully uniform mixing with $e = 40$ (Figure 6-11), and the case with $e = 3$ (Figure 6-10) (Brie et al., 1995). The highest saturations for the Brie rock physics model with $e = 1$, 3 and 40 are known with 82% $\pm$ 0.2 uncertainty, 53% $\pm$ 0.2 uncertainty, and 92% $\pm$ 0.41 uncertainty, respectively. When $e = 1$, the Brie rock physics model shows the highest amount of CO$_2$. While the Brie rock physics model with $e = 40$ does not show the CO$_2$ saturated layers and has a high uncertainty up to 0.4. It could be due to the P-wave velocity is less changeable when brine saturation is ranging from 0% to 90% for the Brie rock physics model with $e = 40$ (Figure 2-2). The estimation results using $e = 3$ is similar with that using $e = 5$.

For the 2D synthetic data, we also extract the results and the input data at $x = 1062$ m, where we can observe through the injection point and the above accumulation layers of carbon dioxide. The estimation of CO$_2$ saturation is given in Figure 6-12 and the jointly estimated other properties are given in Figure 6-13.
Figure 6-9. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 1.

Figure 6-10. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 3.
Figure 6-11. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 40$.

Figure 6-12. 1D estimation of CO$_2$ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO$_2$ saturation using different rock physics models (right panel) for $x = 1062$ m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
Figure 6-13. From left to right: 1D profile of Brie exponent and other CO$_2$ properties results (CO$_2$ viscosity, CO$_2$ bulk modulus, and CO$_2$ density) inverted jointly with the CO$_2$ saturation using different rock physics models for $x = 1062$ m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
7 REAL DATA (INLINE 1881, VINTAGE 2008, AFTER INJECTION)

The data is obtained after CO$_2$ injection in 2008. This inline data is located at about 533 m away of the injection point. The seismic data after time migration of inline 1881 is given in Figure 7-1.

![Seismic data after time migration from inline 1881.](image)

**Figure 7-1.** Seismic data after time migration from inline 1881.

7.1 Data preparation

Figure 7-2 shows the P-wave velocity derived from FWI. The CO$_2$ induced low P-wave velocity region is shown with warm colour (Figure 7-2). The FWI results are discussed in Romdhane and Querendez (2014).
Figure 7-2. P-wave velocity for 2D real data section (inline 1881, 2008 vintage, after CO₂ injection). The black square shows the selected region of interest with CO₂ saturated.

In this case, we use the baseline information derived from the log data as described in Chapter 4. The 1D derived frame properties from the Well 15/9-A16 are smoothed and horizontally extended to 2D layered structure. For efficient computation, we selected a target region from the FWI model (Figure 7-3). The selected region consists of 95×401 grid points. We can see a moderate pushdown effect on P-wave velocity in the region caused by the contrast between the slow-velocity CO₂ and the surrounded high-velocity brine-saturated reservoir.

Figure 7-3. P-wave velocity model for target region.

The correlation between monitor P-wave velocity and reservoir frame properties are given by Figure 7-4. The 1D P-wave velocity profile is extracted at \( x = 2835 \) m. The log data derived frame properties are shifted form depth of 792 m - 1074 m to the depth of 762 m - 1044 m.
Figure 7-4. Correlation of P-wave velocity of inline 1881 real data and smoothed reservoir properties derived by log data. From left to right: P-wave velocity, grain density, density porosity, frame bulk modulus and frame shear modulus. The red dots indicate the Nordland caprock shale, and the green dots indicates the Utsira sandstone. The log data derived properties from 792 m are shifted to the depth of 762 m. The P-wave velocity profile is extracted at x = 2835 m.

7.2 Estimation of CO₂ saturation

We apply the rock physics tool to the selected region of inline 1881 real data. The estimation of CO₂ saturation for uniform saturation model with Brie exponent e = 5 is given in Figure 7-5. The estimations of CO₂ saturation within the sandstone layers vary in the range of 13% - 30% with a maximum misfit of 0.1. The CO₂ saturation estimates within the sandstone layers are known with ± 0.13 to 0.16 uncertainty. The higher deviation is present where the CO₂ saturation is higher.
Figure 7-5. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with $e = 5$.

The estimations of CO₂ saturation and Brie exponent are given in Figure 7-6. The estimations of CO₂ saturation within the CO₂ saturated sand layers vary in the range of 10% - 56% ± 0.12 to 0.24 uncertainty. The Brie exponent e varies from 5 to 16 with an uncertainty ranging around 6–15.
Figure 7-6. From top to bottom: estimation of CO$_2$ saturation, uncertainty of CO$_2$ saturation, estimation of Brie exponent, and uncertainty of Brie exponent $e$ using Brie rock physics model with Brie exponent $e$ inverted.

We also conduct the Brie rock physics model for cases of fully patchy mixing with $e = 1$ (Figure 7-7) and fully uniform mixing with $e = 40$ (Figure 7-9), and the case with $e = 3$ (Figure 7-8) (Brie et al., 1995). The Brie rock physics model with $e = 1$ gives the highest estimation of CO$_2$ saturation up to 62% ± 0.2 uncertainty. While the estimation of CO$_2$ saturation using $e = 40$ have a high uncertainty up to 0.4. The estimation of CO$_2$ saturation using $e = 3$ is similar with that using $e = 5$. The 2D estimation results of CO$_2$ saturation from patchy saturation model are very low and not shown here for brevity.
Figure 7-7. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 1$.

Figure 7-8. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 3$. 
Figure 7-9. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 40.

Figure 7-10 shows the estimation results when we use a Brie rock physics model (e = 5) to invert CO₂ saturation and CO₂ properties (CO₂ bulk modulus, density, and viscosity) simultaneously. The estimated CO₂ saturation is similar with the case when CO₂ properties are defined (Figure 7-5). The figures of estimation results for other CO₂ properties (CO₂ bulk modulus, density, and viscosity) are not shown here for brevity.

Figure 7-10. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model (e = 5) with other CO₂ properties inverted.

To better understand and compare the estimations of CO₂ saturation by different rock physics models, we compare the results for 1D profiles (Figure 7-11, Figure 7-12) for x = 2835 m.
Figure 7-11 shows the 1D profile of CO\textsubscript{2} saturations estimated using different rock physics models. The uniform saturation model with a smaller Brie exponent gives a higher estimation of CO\textsubscript{2} saturation. The higher Brie exponent $e$ is indicating that the fluids are mixed at the finest scale (uniform mixing). The estimation of CO\textsubscript{2} saturation is low with around 12\% for uniform saturation model with $e = 40$ within the CO\textsubscript{2} saturated zone. The high CO\textsubscript{2} saturation phenomenon is located in 7 layers at depths of approximately 810 m, 846 m, 873 m, 918 m, 942 m, 972 m and 1005 m. The difference of the estimated CO\textsubscript{2} saturation from uniform saturation using different Brie exponents is bigger for the shallower layers, which seems to be saturated with a higher CO\textsubscript{2} concentration. The estimation of CO\textsubscript{2} saturation is more consistent for the deeper deposited layers with lower CO\textsubscript{2} saturation. It could be due to the buoyancy effect controlling the CO\textsubscript{2} migration towards upper layers (with temporary boundaries created by the thin intra-shale layers). In addition, estimation of CO\textsubscript{2} saturation varies dramatically and seems higher than the other models when we use the uniform saturation to invert CO\textsubscript{2} saturation and CO\textsubscript{2} properties simultaneously. On the contrary, the patchy saturation with a bubble size $a$ equal to 0.01 m gives a lower estimation of CO\textsubscript{2} saturation. This could be due to the limit validity range.
of patchy saturation. Therefore, we do not show this model for real data application on inline 1838.

The jointly estimated CO\textsubscript{2} properties and Brie exponent are given in Figure 7-12. The higher estimation of Brie exponent (8 - 16) and the higher estimation of CO\textsubscript{2} saturation seem to have a spatial correlation. The CO\textsubscript{2} properties are difficult to inverted, while given a reasonable range of CO\textsubscript{2} properties can give a similar estimation of CO\textsubscript{2} saturation with defined range of properties. In this context, if we know the pressure and temperature in the reservoir, we can have reasonable ranges for CO\textsubscript{2} properties. For example, Alnes et al. (2011) study the CO\textsubscript{2} density variation at Sleipner using gravity data. They consider the increased temperature effects and conclude that the density variation is small (675 ± 20 kg/m\textsuperscript{3}).

![Figure 7-12](image)

Figure 7-12. From left to right: 1D profile of Brie exponent and other CO\textsubscript{2} properties results (CO\textsubscript{2} viscosity, CO\textsubscript{2} bulk modulus, and CO\textsubscript{2} density) inverted jointly with the CO\textsubscript{2} saturation using different rock physics models for x = 2835 m. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
8 REAL DATA (INLNE 1838, VINTAGE 1994, BEFORE INJECTION)

The idea for this section is to characterize the baseline frame properties before the CO\textsubscript{2} injection. The derived reservoir information will be used as input to the estimation of CO\textsubscript{2} saturation. Figure 8-1 and Figure 8-2 show the starting velocity for FWI and P-wave velocity tomography from FWI, respectively. The baseline information is based on the seismic data acquired in 1994.

Figure 8-1. P-wave velocity starting model for FWI.

Figure 8-2. P-wave velocity model at last iteration of FWI using smoothing r\textsubscript{2} = 5.

8.1 Data preparation and a priori rock properties

A target region is selected after we analysed the FWI results for the monitor data that will be described in Chapter 9. The selected P-wave velocity is given in Figure 8-3. Based on the gradient (first derivative) of the P-wave velocity with respect to depth, we can identify 10 distinct horizons and construct the lithology variations, which are later used to define the a priori rock properties.
Because S-wave velocity and bulk density are crucial for the estimation of frame properties (Dupuy et al., 2017), we build the S-wave velocity (Figure 8-4) and the bulk density by using Vernik's and Gardner's relation (Mavko et al., 2009), respectively (see equations (21), (22)). Porosity is derived using a density porosity relation (see equation (23)).

The corresponding 2D properties of permeability, cementation factor and grain density are built according to the a priori properties as given in Table 3-1. Then, based on the 2D a priori properties, we invert the bulk and shear frame moduli by combination of inputs of P- and S-wave velocities, and bulk density. The estimation result is given using the mean value of the models with misfit lower than 0.1.

### 8.2 Estimation of frame moduli

The estimation results of $K_d$ and $G_d$ (including the related uncertainty) from $V_P$, $V_S$, and density are shown in Figure 8-5.
Figure 8-5. From top to bottom: estimation of frame bulk modulus $K_d$, uncertainty of frame bulk modulus $K_d$, estimation of frame shear modulus $G_d$, and uncertainty of frame shear modulus $G_d$.

From the 2D estimation results, we average the derived frame properties for all shale and sandstone layers, respectively. Table 8-1 summarises the obtained results.
Table 8-1. Averaged estimated frame moduli and porosity derived for baseline vintage (1994).

<table>
<thead>
<tr>
<th>Lithology</th>
<th>$K_d$ (GPa)</th>
<th>$G_d$ (GPa)</th>
<th>Porosity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shale</td>
<td>4.25</td>
<td>1.67</td>
<td>24 %</td>
</tr>
<tr>
<td>Sandstone</td>
<td>3.60</td>
<td>1.42</td>
<td>38 %</td>
</tr>
</tbody>
</table>

We also tried the test to estimate $K_d$ and $G_d$ with only P-wave velocity as input (Figure 8-6). We observe higher uncertainties related to the frame moduli estimation. As the inversion system is under-determined, the frame moduli results (Figure 8-6) have a checkerboard pattern but the main trends are still visible.
Figure 8-6. From top to bottom: estimation of frame bulk modulus $K_d$, uncertainty of frame bulk modulus $K_d$, estimation of frame shear modulus $G_d$, and uncertainty of frame shear modulus $G_d$ using only P-wave velocity as input.
9  REAL DATA (INLINE 1838, VINTAGE 2008, AFTER INJECTION)

Inline 1838 is the section where the injection point is located Figure 9-1.

Figure 9-1. Seismic data after time migration for inline 1838.

Figure 9-2 shows P-wave starting model for FWI. The starting model is extracted from the seismic data acquired in 2008. Figure 9-3 shows the P-wave velocity from FWI. The extension of low P-wave velocity region is a bit larger than that for inline 1881 (Figure 7-2). More information about data processing and FWI tests can see Appendix C.

Figure 9-2. P-wave velocity starting model for FWI.
Figure 9-3. P-wave velocity model at last iteration of FWI using smoothing $r_2 = 5$.

### 9.1 Data preparation and a priori rock properties

The RPI is applied to the FWI derived P-wave velocity. We select a region corresponding to the CO$_2$ accumulation (Figure 9-4).

Figure 9-4. Selected P-wave velocity model for vintage 2008 (inline 1838).

The a priori frame properties are built (Figure 9-5) based on the structure of P-wave velocity gradient after CO$_2$ injection and based on the properties derived from the baseline before CO$_2$ injection shown in Table 8-1. The other a priori properties (grain density, grain bulk modulus, permeability and cementation factor) are built in the same way.
Figure 9-5. From top to bottom: frame bulk modulus $K_d$, frame shear modulus $G_d$, porosity.

9.2 Estimation of CO$_2$ saturation

The estimation results of CO$_2$ saturation are shown in following figures, including the related uncertainty analysis. Due to the limited range of validity of the patchy saturation model (only high or low saturations), we only show the results for the uniform saturation model.

Figure 9-6 shows the estimation of CO$_2$ saturation using $e = 5$. There are two distinct high CO$_2$ saturated layers, one at depth of around 1140 m, which could be around the injection point. Another is at depth from 900 m – 950 m, which is just below the caprock with a high amount CO$_2$ trapped. The estimations of CO$_2$ within the sandstone layer at 1140 m has CO$_2$ saturations from 30% to 40%. The CO$_2$ saturation is higher (from 30% to 75%) in the top layers. The uncertainty of the estimation for CO$_2$ saturation within the sandstone layers is around 0.15 to 0.23. In general, we observe that higher uncertainty is associated with the high CO$_2$ saturated regions.
Figure 9-6. Estimation of CO₂ saturation (top panel) and uncertainty of CO₂ saturation (bottom panel) using Brie rock physics model with e = 5.

Figure 9-7 shows the estimations of CO₂ saturation and Brie exponent. The estimations of CO₂ saturation within the sand layers vary in the range of 30% to 70%. The estimation of CO₂ saturation within sand layers is known with ± 0.15 to 0.3 uncertainty. The Brie exponent e within CO₂ saturated layers varies from 10 to 28 with an uncertainty about 6 to 16. The estimated Brie exponent is higher and more uniform than we found for inline 1881.
Figure 9-7. From top to bottom: estimation of CO₂ saturation, uncertainty of CO₂ saturation, estimation of Brie exponent, and uncertainty of Brie exponent using Brie rock physics model with Brie exponent e inverted.

The other estimation results of CO₂ saturation from uniform saturation are not shown here for brevity. To better understand the results, we select 1D vertical profiles, some crossing the CO₂ accumulations (Figure 9-8, Figure 9-9, Figure 9-10, Figure 9-11, Figure 9-12, Figure 9-13) and one vertical profile outside of the main plume (Figure 9-14).

We find that patchy mixing (e = 1) tends to give the highest estimation of CO₂ saturation (up to 90 – 100%). The uniform mixing (e = 40) seems to give peak responses for CO₂ saturation within CO₂ accumulated layers (top or near the injection points). The Brie exponent is also higher within CO₂ layers. In summary, the highest CO₂ saturation appears at the depth of around 935 m - 940 m. In addition, we found that the estimated CO₂ saturation is varying around 10% for the one vertical profile (Figure 9-14) outside of the main plume. The CO₂ properties (CO₂
viscosity, CO$_2$ bulk modulus, and CO$_2$ density) cannot be well estimated using only P-wave velocity (Figure 9-9, Figure 9-11, Figure 9-13), which is similar as our other case studies (Dupuy et al., 2017; Yan, 2016).

Figure 9-8. 1D estimation of CO$_2$ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO$_2$ saturation using different rock physics models (right panel) for x = 2403 m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
Figure 9-9. From left to right: 1D profile of Brie exponent and other CO₂ properties results (CO₂ viscosity, CO₂ bulk modulus, and CO₂ density) inverted jointly with the CO₂ saturation using different rock physics models for x = 2403 m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty.

Figure 9-10. 1D estimation of CO₂ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO₂ saturation using different rock physics models (right panel) for x = 2553 m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
Figure 9-11. From left to right: 1D profile of Brie exponent and other \( \text{CO}_2 \) properties results (\( \text{CO}_2 \) viscosity, \( \text{CO}_2 \) bulk modulus, and \( \text{CO}_2 \) density) inverted jointly with the \( \text{CO}_2 \) saturation using different rock physics models for \( x = 2553 \) m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty.

Figure 9-12. 1D estimation of \( \text{CO}_2 \) saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of \( \text{CO}_2 \) saturation using different rock physics models (right panel) for \( x = 3453 \) m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
Figure 9-13. From left to right: 1D profile of Brie exponent and other CO₂ properties results (CO₂ viscosity, CO₂ bulk modulus, and CO₂ density) inverted jointly with the CO₂ saturation using different rock physics models for x = 3453 m (inside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty.

Figure 9-14. 1D estimation of CO₂ saturation using Brie rock physics model with different Brie exponent (left panel) and 1D estimation of CO₂ saturation using different rock physics models (right panel) for x = 1803 m (outside of plume). The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
10 DISCUSSION

From all the studies, we can conclude that the uncertainties of CO$_2$ saturation are ranging around 0.1 - 0.2 for Brie rock physics model with $e = 5$ including the case with undefined CO$_2$ properties. When we invert the CO$_2$ saturation and Brie exponent simultaneously, the uncertainties of CO$_2$ saturation increase to around 0.3. Because we only have one input data (P-wave velocity), we can expect better estimation of CO$_2$ saturation when we have more information (Dupuy et al., 2016; Yan, 2016). The additional inputs will help the estimation when other parameters as Brie exponent, CO$_2$ bulk modulus are inverted jointly with CO$_2$ saturation, especially P-wave quality factor and S-wave velocity (Yan, 2016).

For the inline 1881, we show the two-step workflow as: first, estimate the frame properties from log data, and then, we estimate the CO$_2$ saturation using the log frame properties as a priori input. The baseline derived information from the log data is about 2 km away from the injection point and with a high sonic frequency, which can induce an inconsistency with the seismic monitor data of inline 1881. To minimize the uncertainty, we smooth the sonic data. While this smoothing may involve another risk in smearing out the lithology information. Instead of smoothing and extending horizontally, we might use the log data information and interpolate it based on the lithology variation. However, the created layers (as used for inline 1838) would be another source of uncertainties, which could be included in the further research work. We have a quite low estimation of CO$_2$ saturation around 20 to 60% for inline 1881, which is lower compared with some other existed studies at Sleipner (Chadwick and Noy, 2010; Savioli et al., 2017). There are several reasons for this low saturation estimation. First, the 2D section corresponding to inline 1881 is 533 m away from the injection point. Second, the FWI method tends to overestimate the velocity. For example, the P-wave velocity of the sandstone before CO$_2$ injection from log data (well 15/9-A16) ranges from 2000 – 2100 m/s while the P-wave velocity of the sandstone before CO$_2$ injection from the FWI of inline 1838 ranges from 2000 to 2200 m/s and up to 2400 m/s. This increased velocity could be due to the smearing effect and other limitations of the FWI method (Dupuy et al., 2017).

For the study performed on inline 1838 data, we change the two-step workflow as: first extract the frame moduli from FWI baseline results, and then, we estimate the CO$_2$ saturation after applying FWI to the monitor data and using the baseline information as a priori input. For the extraction of baseline information for inline 1838, the FWI results are smeared out and it is
difficult to resolve the shale sand interbedded layers. Therefore, the utilization of the extracted rock frame properties is not straightforward. In our study, we use an average value to represent the lithology variation. Including the lateral variations of the frame moduli in each layers can improve the a priori inputs. For the monitor data, the improved resolution benefited from the injected CO₂. But it is still difficult to resolve 1 m to 3 m thick shale layers. It could be due to the band-limited seismic wave, which cannot resolve the thin layers (Dejtrakulwong et al., 2010). The derived results suggest much higher CO₂ saturation for inline 1838 than that for inline 1881. The reason could be the better estimated frame properties when we using FWI data. The relation between the P-wave velocity and CO₂ saturation can also explain it. For example, the fully brine saturated case from FWI is corresponding to higher P-wave velocities. This lead to the higher estimation of CO₂ saturation for monitor data, which we think is more correct.

The estimation results in our study of CO₂ saturation within shale layers and sand layers outside of CO₂ accumulation never reach 0% CO₂ saturation. For example, the lowest CO₂ saturation we can see in the estimation of CO₂ saturation for inline 1838 is around 6%. There are several reasons for this phenomenon. First, the ‘shale’ that we see is not purely shale due to the resolution limitation of FWI. Second, the geological study shows that the sand layers in the Sleipner are interbedded with 1-3 m shale layers, which is under seismic resolution. At Sleipner, most of the CO₂ bearing layers are thin and subject to tuning effects (Arts et al., 2004b). This thin shale imbedded sequence can be also found in other CCS projects like Ketzin (Stenhouse, 2009). Therefore, we have a more homogeneous CO₂ distribution without a very high CO₂ saturation zone inside. Third, we show the mean estimation of the results instead of the model with lowest misfit. The CO₂ saturation can be 0% when we take into account the mean value with uncertainty. Some other issues and limitations in our study are listed as:

1. The uncertainties associated with the pressure effect should be discriminated from the fluid saturation change.
2. The frequency dependent fluid properties are difficult to investigate using only one frequency of 30 Hz. This may induce uncertainties induced by the frequency dispersion. For example, a higher P-wave velocity associated the same CO₂ saturation for a higher frequency.

We also compare our results with some other studies. Lumley et al. (2008) use the seismic data to monitor the CO₂ distribution as Sleipner. They conclude that the seismic tool can detect the CO₂ presentation but it is difficult to quantify the CO₂ saturation when it is larger than 10-30%.
Ravazzoli and Gómez (2014) emphasize several issues related to the feasibility of using seismic data and the influence of saturation transition zones. They suggest to use AVA to help the estimation of the state of CO₂ (Ravazzoli and Gómez, 2011). Sen et al. (2016) introduced a capillary pressure equilibrium theory in their study and they found that the CO₂ distribution at Sleipner is more uniform for high CO₂ saturation and more patch for low CO₂ saturation. In our study, we also found similar trends, i.e. that the Brie exponent is higher for CO₂ saturated layers, which is indicating a more uniform mixing phase. Ghosh et al. (2015) proposed a time-lapse method combined with a pressure-dependent differential effective medium (PDEM) theory. They conclude that the CO₂ is more patchy for the sand layers with mud layer capped and some is mixed more uniformly with brine. Zhang et al. (2014) suggested that the maximum limit of the CO₂ saturation is 89% from the relative permeability, while the CO₂ saturation from their model can reach up to around 87%. Chadwick and Noy (2010) shows an approach using history-matching simulations and 4D seismic data ad get even higher estimation of maximum CO₂ saturation of 98%. This is comparable with our application results in inline 1838, in which case the maximum CO₂ saturation can reach 90% - 93% ± 0.15 to 0.25.
11 CONCLUSIONS AND OUTLOOK

11.1 Conclusions

Our study shows a two-step workflow combining the use of a rock physics tool and the high-resolution estimations from FWI. The rock physics inversion is applied on different datasets including the synthetic data and real data for different vintages and 2D sections. We focus on the estimation of CO\textsubscript{2} saturation, considering the results derived in the sensitivity tests of this report (Yan, 2016). Some conclusions are given hereafter:

1. The application on synthetic data validates the feasibility the rock physics tool for the estimation of CO\textsubscript{2} saturation.
2. We use generic rock physics models, which may be more realistic and help to understand the mixture mechanism in the CO\textsubscript{2} storage process.
3. We provide a method to extract the baseline frame properties using P-wave velocity combined with S-wave velocity and density. We also show an approach using the P-wave velocity gradient to construct the a priori information of the reservoir.
4. We estimate the CO\textsubscript{2} saturation using only P-wave velocity from FWI. The uncertainty related to the CO\textsubscript{2} saturation estimation is usually low.
5. The extended White's model (patchy saturation) does not work well on the estimation of CO\textsubscript{2} saturation due to the validity range limited to very high or low saturations.
6. We provide a way to evaluate the uncertainty using the mean estimation including all the models with misfit lower than a certain value.
7. The uncertainty is higher for higher CO\textsubscript{2} saturations. In the case of inline 1838, we obtain high CO\textsubscript{2} saturation (up to around 90\% ± 0.15 - 0.25). We show that the undefined CO\textsubscript{2} properties is not crucial for the estimation of CO\textsubscript{2} saturation.
8. The Brie exponent is varying from 5 to 25 for the CO\textsubscript{2} saturated layers. This indicates that the brine and CO\textsubscript{2} mixture distribution is not fully patchy (e = 1) nor fully uniform (e = 40) mixing.

11.2 Further work

In our studies, we show the quantitative estimation of CO\textsubscript{2} saturation by the combination of FWI and RPI. The rock physics inversion results are dependent on the resolution of the FWI
results and are limited to acoustic approximation in our case. Using higher frequencies in FWI (if such frequency content is present in the data) and multi-parameter FWI can help to better constrain the RPI step. We expect to use FWI to estimate more information (such as P-wave quality factor and S-wave velocity) to give a better constrain on estimation of CO₂ saturation and other properties (Dupuy et al., 2017; Yan, 2016). The impact of the pressure change after CO₂ injection and the impact on the frame properties need to be considered carefully, even if the pressure effects should be limited at Sleipner. In addition, the in-situ properties of CO₂ in the reservoir can affect the CO₂ saturation results. Therefore, it can be meaningful to consider the in-situ CO₂ saturation and monitor the change of frame moduli. In addition, capillary pressure (Santos* et al., 2014) and the injected volume of CO₂ can help the understanding of the CO₂ Capture and Storage process.
12 REFERENCES


Lindeberg, E., 2013, in C. Calculation of thermodynamic properties of CO2, H2O and their mixtures also including salt with the Excel macro “CO2 Thermodynamics”., ed., Trondheim, SINTEF.


Span, R., and W. Wagner, 1996, A new equation of state for carbon dioxide covering the fluid region from the triple-point temperature to 1100 K at pressures up to 800 MPa: Journal of physical and chemical reference data, v. 25, p. 1509-1596.


In this section, we show the estimation of frame moduli with a threshold of maximum misfit equal to 0.1 (Figure A-1) and 10 (Figure A-2). We found that the mean estimations of frame properties are similar for using maximum misfit of 10 and 0.1. The discrepancy between the best estimation and the mean estimation using a misfit threshold of 10 are slightly bigger than that for the case using a misfit threshold of 0.1.

Figure A-1. Estimation results of frame bulk modulus $K_d$ (left) and frame shear modulus $G_d$ (right) inverted by the inputs of P-wave velocity, S-wave velocity derived by Vernik’s relation, and density log. The black lines correspond to the best estimation with lowest misfit. The blue lines correspond to the mean value of estimation with a maximum misfit of 0.1. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
Figure A-2. Estimation results of frame bulk modulus $K_d$ (left) and frame shear modulus $G_d$ (right) inverted by the inputs of P-wave velocity, S-wave velocity derived by Vernik's relation, and density log. The black lines correspond to the best estimation with lowest misfit. The blue lines correspond to the mean value of estimation with a maximum misfit of 10. The dotted lines correspond to the mean value of estimation plus/minus uncertainty.
Appendix B Supplementary notes of FWI synthetic model

I. FWI process on the 2D FWI synthetic model

Table B-1 shows the setting parameters for the FWI on the 2D synthetic data.

Table B-1. The parameters used in the FWI tests.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input files for FWI</td>
<td>P-wave velocity, quality factor, density</td>
</tr>
<tr>
<td>Sample number along Z direction</td>
<td>367</td>
</tr>
<tr>
<td>Sample number along X direction</td>
<td>1074</td>
</tr>
<tr>
<td>Grid size</td>
<td>3 m</td>
</tr>
<tr>
<td>pml thickness in grid points</td>
<td>2</td>
</tr>
<tr>
<td>pml coefficient</td>
<td>90</td>
</tr>
<tr>
<td>number of selected frequencies to be inverted</td>
<td>9</td>
</tr>
<tr>
<td>number of time steps</td>
<td>1250</td>
</tr>
<tr>
<td>time stepping</td>
<td>0.004 s</td>
</tr>
<tr>
<td>source wavelet file</td>
<td>fricker</td>
</tr>
<tr>
<td>maximum number of iteration per frequency</td>
<td>10</td>
</tr>
<tr>
<td>minimum velocity</td>
<td>1300</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>--------------------------</td>
<td>-------</td>
</tr>
<tr>
<td>maximum velocity</td>
<td>2600</td>
</tr>
<tr>
<td>velocity above topography</td>
<td>1200</td>
</tr>
<tr>
<td>reference velocity</td>
<td>1700</td>
</tr>
<tr>
<td>compute diagonal terms of Hessian</td>
<td>Yes</td>
</tr>
<tr>
<td>model perturbation</td>
<td>2% for optimum step length</td>
</tr>
</tbody>
</table>

## II. Selection of iteration number

The iteration number is important for the accuracy of rock physics inversion. A proper iteration number can avoid unnecessary excessive computation. We compare the misfit variation versus different iteration number and conduct different tests with iteration number from 100 up to 1000 (Figure B-1). The misfit values are tending to be stabilized when iteration number is 400 for all the rock physics models. Therefore, we decide to use an iteration number of 400 in our application of rock physics inversion.

![Misfit variation Versus Iteration number](image.png)

**Figure B-1. The misfit variation with various iteration numbers.**
III. Selection of FWI results

In this case, we use 1D derived frame properties from the Well 15/9-A16, which are smoothed and horizontally extended to 2D layered structure. We will show the rock physics inversion results using different P-wave velocity results using FWI test 1, 2 and 5. Here, we only show the results from uniform saturation with a Brie exponent $e = 5$.

Figure B- 2 shows estimation results of CO$_2$ saturation using the captured P-wave velocity model of FWI test 1 with a light smoothing along z direction. Figure B- 3 shows estimation results of CO$_2$ saturation using the captured P-wave velocity model of FWI test 2 with a strong smoothing along z direction. Figure B- 4 shows estimation results of CO$_2$ saturation using the captured P-wave velocity model of FWI test 5 with no smoothing applied. The estimation of CO$_2$ saturation from test 1 and 2 are similar (20% - 30%) within the CO$_2$ saturated layers. While CO$_2$ saturation from FWI test 5 gives higher CO$_2$ saturation and does not show the layer structure. All the estimations of CO$_2$ saturation from the tests have a similar uncertainty ranging from 0.1 to 0.15, and higher within the CO$_2$ saturated layers. In summary, the results of rock physics inversion are highly dependent on the quality of FWI results.

![Figure B- 2. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 5$ and FWI result of test 1.](image-url)
Figure B-3. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 5$ and FWI result of test 2.

Figure B-4. Estimation of CO$_2$ saturation (top panel) and uncertainty of CO$_2$ saturation (bottom panel) using Brie rock physics model with $e = 5$ and FWI result of test 5.
This section is aimed at showing the processing steps and FWI tests of inline 1838.

### I. Data processing procedure

Before the FWI, a basic processing procedure is applied using Seismic Unix on the raw data of inline 1838. We extract the data from 3D data set and try to rotate the data to a normal position in a 2D view. We outline the processing steps for inline 1838 of vintage 2008 in Table C-1, including extracting guns, muting, rotating, transformation, and trace windowing, and so on. For inline 1838 of vintage 1994, we use similar processing steps.

**Table C-1. The processing steps applied prior to FWI.**

<table>
<thead>
<tr>
<th>Step</th>
<th>Processing workflow applied to the prestack dataset of inline 1838 of year 2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Read the SEGY data</td>
</tr>
<tr>
<td>2</td>
<td>Extract the geometry information 'sx, sy, gx, gy' of the selected source No.1 and Receiver cable No.3</td>
</tr>
<tr>
<td>3</td>
<td>Mute the noises, sure as the first-arrival muting</td>
</tr>
<tr>
<td>4</td>
<td>Rotate the dataset with angle of 0.85 according the velocity cube</td>
</tr>
<tr>
<td>5</td>
<td>Translate the dataset and shift velocity cube to sy=0 and have smallest gx of data</td>
</tr>
<tr>
<td>6</td>
<td>Create the interval velocity from the RMS velocity data with the similar rotate, translation workflow</td>
</tr>
<tr>
<td>7</td>
<td>Resample the dataset (depth interval of 12.5 m) and apply the smooth factor in 3D (less smooth in the vertical direction)</td>
</tr>
<tr>
<td>8</td>
<td>Resample the sources and receivers corresponding to the velocity geometry, that the Y-axis ranges from 0 to 7 km</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>9</td>
<td>Do the amplitude corrections to the data (from 3D into 2D). Multiply the data by power of time (tpow=-2)</td>
</tr>
<tr>
<td>10</td>
<td>Apply Butterworth bandpass filtering</td>
</tr>
<tr>
<td>11</td>
<td>Top mute again to remove the filter induced noises</td>
</tr>
<tr>
<td>12</td>
<td>Scale the position unit from centimetre into meter by multiply 0.01</td>
</tr>
<tr>
<td>13</td>
<td>Offset selection with minimum offset equal to 420</td>
</tr>
<tr>
<td>14</td>
<td>Minimum to zero phase conversion</td>
</tr>
<tr>
<td>15</td>
<td>Data editing with reference to the given seismic source in the later FWI process</td>
</tr>
<tr>
<td>16</td>
<td>Create geometry profile (source depth of 6 m beneath the sea level, receiver depth of 8 m beneath the sea level)</td>
</tr>
</tbody>
</table>

The acquisition geometry of inline 1838 is given in Figure C-1. Since the 2D inline data is extracted from a 3D dataset, the previous translation and rotation process of the data help to give a better 2D view. We can see that the 2D data is well processed with only smaller than 15 m crossline offset deviation.
Figure C-1. Acquisition geometry after the processing.
II. FWI tests

To prevent a large computation cost, we cut the deeper data and clip the interested region. The sources and the receiver at the boundary of the acquisition geometry are removed to minimise the boundary effects. The lateral variation of inline 1838 for vintage 2008 is from 0 m to 6980 m. The data is later shifted with adding a 30 m air layer to investigate the multiple created by the interface of air and water.

We generated the associated same size P-wave starting model, P-wave quality factor model, and density model. We consider a small attenuation. The quality factor is assumed with a constant number of 1000. We introduced the empirical density-velocity relations to derive the density information from P-wave velocity using Gardner relation for the reservoir section (Gardner et al., 1974). In addition, we add a constant water layer density which is equal to 1000 kg/m$^3$. We know that the air density is as low as 1.3 kg/m$^3$. However, for FWI, too low density will affect the inversion results. Therefore, we add an air layer with a constant density of 100 kg/m$^3$.

Figure E-1 shows the generated density file with the water and air layers. The smoothed velocity is derived by using a function of structure smoothing. We also add a water layer with a constant velocity of 1500 m/s and a 30 m air layer with a constant velocity of 330 m/s (see Figure 9-2).

![Figure E-1. Density profile with a water layer and an air layer.](image)

The FWI process performed from low to high frequencies. We use four tests with: 3 frequencies (10.0, 10.5, 11.0 Hz), 7 frequencies (11.5, 12.0, 12.5, 13.4, 15.2, 17.1, 19.6 Hz), 5 frequencies (22.0, 23.2, 24.4, 25.7, 26.9 Hz), and 5 frequencies (28.1, 29.3, 30.5, 31.8, 33.0 Hz), respectively. We use a smoothing factor equal to 0.3 for beginning three tests and a smaller smoothing
factor equal to 0.15 for the last test to minimize the misfit. Finally, we generate the final P-wave velocity model of 2008 vintage (inline 1838) as shown in Figure E-2.

**Figure E-2. P-wave velocity model at last iteration of FWI (vintage 2008, inline 1838).**

For real data of vintage 1994, we use a similar FWI procedure to derive the baseline P-wave velocity model as shown in Figure E-3.

**Figure E-3. P-wave velocity model at last iteration of FWI (vintage 1994, inline 1838).**

The FWI results are later smoothed to smear the oscillations before rock physics inversion (Figure 8-2, Figure 9-3).
Appendix D Grain bulk moduli and density computation for the Utsira sandstone

The sandstone properties are calculated with considering mineral compositions. The bulk modulus ($K_s$) and density ($\rho_s$) of each solid grain material are considered, as illustrated Table D- 1, Table D- 2, Table D- 3.

**Table D- 1. Bulk modulus calculation illustration for the Utsira sandstone.**

<table>
<thead>
<tr>
<th>Minerals</th>
<th>$K_s$ (GPa)</th>
<th>$G_s$ (GPa)</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low bound</td>
<td>High bound</td>
<td>Low bound</td>
</tr>
<tr>
<td>Quartz</td>
<td>36.5</td>
<td>37.9</td>
<td>44</td>
</tr>
<tr>
<td>Calcite</td>
<td>63.7</td>
<td>76.8</td>
<td>28.4</td>
</tr>
<tr>
<td>Feldspar</td>
<td>37.5</td>
<td>37.5</td>
<td>15</td>
</tr>
<tr>
<td>Albite</td>
<td>75.6</td>
<td>75.6</td>
<td>25.6</td>
</tr>
<tr>
<td>Aragonite</td>
<td>44.8</td>
<td>44.8</td>
<td>38.8</td>
</tr>
<tr>
<td>Mica (muscovite)</td>
<td>42.9</td>
<td>61.5</td>
<td>22.2</td>
</tr>
<tr>
<td>Mica (biotite)</td>
<td>41.1</td>
<td>59.7</td>
<td>12.4</td>
</tr>
</tbody>
</table>

This Hashin–Shtrikman bounds are illustrated by Hashin and Shtrikman (1963). $K^{HS+}$ and $G^{HS+}$ are corresponding to the upper bound with stiffer material forms the shell. $K^{HS-}$ and $G^{HS-}$ are corresponding to the lower bound with stiffer material forms the core. We use a more general form of the Hashin–Shtrikman–Walpole bounds, which can be applied to mixtures of more than two phases and is given by:
\[ K^{HS+} = \Lambda(G_{\text{max}}), K^{HS-} = \Lambda(G_{\text{min}}) \]
\[ G^{HS+} = \Gamma(\zeta(K_{\text{max}}, G_{\text{max}})), \mu^{HS-} = \Gamma(\zeta(K_{\text{min}}, G_{\text{min}})) \]  

(D-1)

Where \( K_{\text{max}} \) and \( G_{\text{max}} \) are the maximum bulk and shear moduli of the individual constituents. \( K_{\text{min}} \) and \( G_{\text{min}} \) are the minimum bulk and shear moduli of the constituents. \( \Lambda(z), \Gamma(z) \) and \( \zeta(K, G) \) are given by:

\[
\begin{align*}
\Lambda(z) &= \left(\frac{1}{K(r) + \frac{4}{3}z}\right)^{-1} - \frac{4}{3}z, \\
\Gamma(z) &= \left(\frac{1}{G(r) + z}\right)^{-1} - z, \\
\zeta(K, G) &= \frac{G}{6}\left(\frac{9K + 8G}{K + 2G}\right).
\end{align*}
\]

Where the brackets \( \{ , \} \) indicate an average over the medium, which is the same as an average over the constituents weighted by their volume fractions.

The \( K_S \) is obtained by averaging Hashin-Shtrikman bounds, as shown in Table D-2.

**Table D-2. Ks is obtained by averaging Hashin-Shtrikman bounds.**

<table>
<thead>
<tr>
<th>( K^{\text{HS+}} ) (GPa)</th>
<th>( K^{\text{HS-}} ) (GPa)</th>
<th>( K_S ) (GPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>40.31</td>
<td>38.26</td>
<td>39.29</td>
</tr>
</tbody>
</table>
Table D-3. The grain density of each constituent in the Utsira sandstone.

<table>
<thead>
<tr>
<th>Minerals</th>
<th>$\rho_{s(i)}$ (g/cc)</th>
<th>Volume percentage (%)</th>
<th>$\rho_s$ (g/cc)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quartz</td>
<td>2.65</td>
<td>75 %</td>
<td>2.663</td>
</tr>
<tr>
<td>Calcite</td>
<td>2.71</td>
<td>3 %</td>
<td></td>
</tr>
<tr>
<td>Feldspar</td>
<td>2.62</td>
<td>13 %</td>
<td></td>
</tr>
<tr>
<td>Albite</td>
<td>2.63</td>
<td>3 %</td>
<td></td>
</tr>
<tr>
<td>Aragonite</td>
<td>2.92</td>
<td>3 %</td>
<td></td>
</tr>
<tr>
<td>Mica (muscovite)</td>
<td>2.79</td>
<td>2 %</td>
<td></td>
</tr>
<tr>
<td>Mica (biotite)</td>
<td>3.05</td>
<td>2 %</td>
<td></td>
</tr>
</tbody>
</table>

The grain density of the Utsira sandstone ($\rho_s$) is calculated by using volume-weighted density calculation method (Table D-3).
Appendix E Supplementary table for the Nordland shale

In our studies, the mineralogy of the Nordland shale in volume percentage (as shown in Table E-1) is exacted from the mineralogy in mass percentage by Gaus et al. (2005).

Table E-1. Nordland shale rock mineralogy by Gaus et al. (2005).

<table>
<thead>
<tr>
<th>Nordland shale composition</th>
<th>Mass percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plagioclase</td>
<td>12.3</td>
</tr>
<tr>
<td>Calcite</td>
<td>1.0</td>
</tr>
<tr>
<td>Quartz</td>
<td>21.5</td>
</tr>
<tr>
<td>Chlorite</td>
<td>4.1</td>
</tr>
<tr>
<td>Mica/Illite</td>
<td>24.7</td>
</tr>
<tr>
<td>Kaolinite</td>
<td>18.0</td>
</tr>
<tr>
<td>K-feldspar</td>
<td>2.1</td>
</tr>
<tr>
<td>Pyrite</td>
<td>2.8</td>
</tr>
<tr>
<td>Siderite</td>
<td>1.6</td>
</tr>
<tr>
<td>Smectite</td>
<td>8.8</td>
</tr>
<tr>
<td>Mixed layer clay</td>
<td>1.4</td>
</tr>
<tr>
<td>Total</td>
<td>98.3</td>
</tr>
</tbody>
</table>
Appendix F Analysis tables for sensitivity test results

In our sensitivity studies, the inversion estimation of fluid properties and saturation simultaneously can be concluded in the following tables. Since in geophysics, we always only obtain P-wave velocities for FWI results, we analyze the inversion tests especially for inversion from only $V_P$ at first. Then, we analyze the other parameter effect for estimation of fluid properties.

**Table F-1. Results analysis for inversion for CO$_2$ properties at $S_W = 5\%$.**

<table>
<thead>
<tr>
<th>$S_W=5%$, Patchy saturation</th>
<th>$p$</th>
<th>$K_P$</th>
<th>$S_w$</th>
<th>$n$</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>When estimated by only $V_P$</td>
<td>good</td>
<td>bad</td>
<td>very bad</td>
<td>very good</td>
<td>The best estimation of $S_w$ is from $V_P$ and $V_S$.</td>
</tr>
<tr>
<td>$p$</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>\ or +</td>
</tr>
<tr>
<td>$V_P$</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>\</td>
</tr>
<tr>
<td>$Q_D$</td>
<td>\</td>
<td>+</td>
<td>\ or +</td>
<td>\</td>
<td>\</td>
</tr>
<tr>
<td>$V_S$, $Q_S$</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>+</td>
<td>\</td>
</tr>
</tbody>
</table>

**Table F-2. Results analysis for inversion for CO$_2$ properties at $S_W = 20\%$.**

<table>
<thead>
<tr>
<th>$S_W=20%$, Patchy saturation</th>
<th>$p$</th>
<th>$K_P$</th>
<th>$S_w$</th>
<th>$n$</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>When estimated by only $V_P$</td>
<td>good</td>
<td>bad (relative error=23%)</td>
<td>bad</td>
<td>bad</td>
<td>\</td>
</tr>
<tr>
<td>$p$</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>\</td>
</tr>
<tr>
<td>$V_P$</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>\</td>
</tr>
<tr>
<td>$Q_D$</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>+</td>
<td>\</td>
</tr>
<tr>
<td>$V_S$, $Q_S$</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>+</td>
<td>\</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$S_w=20%$, Uniform saturation</th>
<th>$p$</th>
<th>$K_P$</th>
<th>$S_w$</th>
<th>$n$</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>When estimated by only $V_P$</td>
<td>good</td>
<td>bad (relative error=23%)</td>
<td>bad (relative error=37%)</td>
<td>bad</td>
<td>\</td>
</tr>
<tr>
<td>$p$</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>\</td>
</tr>
<tr>
<td>$V_P$</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>\</td>
</tr>
<tr>
<td>$Q_D$</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>+</td>
<td>\</td>
</tr>
<tr>
<td>$V_S$, $Q_S$</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>+</td>
<td>\</td>
</tr>
</tbody>
</table>
Table F-3. Results analysis for inversion for CO$_2$ properties at $S_W = 85\%$.

<table>
<thead>
<tr>
<th>$S_W=85%$, Patchy saturation</th>
<th>$\rho_P$</th>
<th>$\kappa_P$</th>
<th>$S_P$</th>
<th>$\eta_P$</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>When estimated by only $V_P$</td>
<td>good</td>
<td>bad</td>
<td>good</td>
<td>good</td>
<td></td>
</tr>
<tr>
<td>$p$</td>
<td>\ or +</td>
<td>\</td>
<td>+</td>
<td>+</td>
<td>\</td>
</tr>
<tr>
<td>$V_P$</td>
<td>\</td>
<td>\</td>
<td>+</td>
<td>\ or +</td>
<td>+</td>
</tr>
<tr>
<td>$Q_P$</td>
<td>\</td>
<td>\</td>
<td>+</td>
<td>+</td>
<td>\</td>
</tr>
<tr>
<td>$V_P, Q_P$</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>\ or +</td>
<td>+</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$S_w=85%$, Uniform saturation</th>
<th>$\rho_P$</th>
<th>$\kappa_P$</th>
<th>$S_P$</th>
<th>$\eta_P$</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>When estimated by only $V_P$</td>
<td>bad</td>
<td>very good</td>
<td>good</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p$</td>
<td>\</td>
<td>\ or +</td>
<td>+</td>
<td>\</td>
<td>+</td>
</tr>
<tr>
<td>$V_P$</td>
<td>+</td>
<td>\ or +</td>
<td>+</td>
<td>\</td>
<td>\</td>
</tr>
<tr>
<td>$Q_P$</td>
<td>+</td>
<td>\</td>
<td>\</td>
<td>\ or +</td>
<td>+</td>
</tr>
<tr>
<td>$V_P, Q_P$</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>\ or +</td>
<td>+</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>$\rho_P$</th>
<th>$\kappa_P$</th>
<th>$S_P$</th>
<th>$\eta_P$</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>bad</td>
<td>very good</td>
<td>good</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p$</td>
<td>\</td>
<td>\ or +</td>
<td>+</td>
<td>\</td>
<td>+</td>
</tr>
<tr>
<td>$V_P$</td>
<td>+</td>
<td>\ or +</td>
<td>+</td>
<td>\</td>
<td>\</td>
</tr>
<tr>
<td>$Q_P$</td>
<td>+</td>
<td>\</td>
<td>\</td>
<td>\ or +</td>
<td>+</td>
</tr>
<tr>
<td>$V_P, Q_P$</td>
<td>\</td>
<td>\</td>
<td>\</td>
<td>\ or +</td>
<td>+</td>
</tr>
</tbody>
</table>

Where:

\ is indicating that there is no obvious impact or relation.

+ is indicating a positive effect in estimation or constraining the misfit.

Good estimation is indicating the relative error < 20%.

Bad estimation is indicating the relative error > 20%.

And input groups are given as:

1. Only P-wave velocity ($V_P$);
2. P- and S-wave velocities ($V_P, V_S$);
3. P- wave velocity and density ($V_P, \rho$);
4. P- and S-wave velocities and density ($V_P, V_S, \rho$);
5. P- wave velocity and quality factor ($V_P, Q_P$);
6. P-wave velocity, quality factor, and density ($V_P, Q_P, \rho$);
7. P- and S-wave velocities and quality factors ($V_P, V_S, Q_P, Q_S$);
8. P- and S-wave velocities, quality factors, and density ($V_P, Q_P, V_S, Q_S, \rho$).
The misfit under the lower brine saturation (higher CO₂ saturation) condition is larger than that for high brine saturation (lower CO₂ saturation). We may conclude that for low brine saturation (high CO₂ saturation) it is more difficult to invert the CO₂ properties.
Appendix G Publication I

Rock Physics Inversion for CO₂ Saturation Estimation at Sleipner - Sensitivity Tests and Baseline Application
Tu P8 01

Rock Physics Inversion for CO2 Saturation Estimation at Sleipner - Sensitivity Tests and Baseline Application

H. Yan* (SINTEF Petroleum Research; NTNU), B. Dupuy (SINTEF Petroleum Research), A. Romdhane (SINTEF Petroleum Research), B. Aartsen (Norwegian University of Science & Technology)

Summary

We demonstrate the use of rock physics inversion for estimating CO2 saturation and rock frame properties at the Sleipner CO2 storage pilot in the North Sea. We investigate the relation between rock physics properties and elastic attributes for the Utstein unconsolidated sandstone. An effective fluid phase plugged into Biot theory is used together with the Brinkman theory for the calculation of effective bulk modulus. We use the estimated viscoelastic properties under different brine and CO2 distributions to invert selected poroelastic parameters from various input data parameterizations. By analysis of the sensitivity tests, we can conclude that CO2 saturation can be well estimated from only VP input, especially for high brine saturation. The quality factors of both P-wave and S-wave velocities help better estimate CO2 saturation and reduce the uncertainties. In a second part, the method is applied to well log data acquired prior to CO2 injection. The S-wave velocities are derived using empirical relations from the P-wave velocities and density and used to estimate the rock frame moduli of the Utstein sand before CO2 injection. We found that the S-wave velocities are crucial to help the estimation of frame moduli.
Introduction

Nowadays, CO₂ Capture and Storage (CCS) is acknowledged as a potential mean of reducing the CO₂ emissions into the atmosphere and therefore mitigating global warming. Understanding the relationship between seismic velocities and the porous rocks is important to characterize the changes of the subsurface properties during the CO₂ injection process. In this work, we propose a methodology to study the changes of rock physics properties during the injection of CO₂ at the Sleipner storage site in the North Sea. 4D time-lapse seismic methods can estimate the changes in reservoir and saturating fluid properties. However, most of these methods are highly dependent on the repeatability of the seismic survey (Landro, 2001, Arts et al., 2008, Arts et al., 2004). Amplitude versus offset (AVO) analysis can be more sensitive to changes in reservoir in particular when shear wave velocity information is considered (Castagna et al., 1985). Such information is however difficult to obtain accurately for most high-porosity, high-permeability rocks. To overcome the limitations of previous studies and obtain reliable reservoir properties, a two-step workflow based on a combination of Full Waveform Inversion (FWI) and rock physics inversion was developed and applied by Dupuy et al. (2016a). In this work, we focus on sensitivity tests to get accurate estimations of CO₂ saturation. We calculate seismic viscoelastic properties (density, quality factor, velocities) with rock physics forward modelling. Then, the rock physics inversion is performed under different saturation conditions. We also use the workflow to invert the drained reservoir frame properties before CO₂ injection by using well log data of the Utsira sand formation.

Rock physics model and inversion

We define effective fluid properties using Bria mixing equation for fluid bulk module (Bria et al., 1995), Teja and Rice (1981) relation for effective viscosity and weighted arithmetic average for effective fluid density. The effective fluid phase is then plugged in the extended Biot theory (Pride, 2005) to describe the poroelastic material partially saturated with brine and CO₂. The exponent of the Brie equation ranges between 1 and 40 (Brie et al., 1995). Hereafter, we use a value of 5 (Carcione et al., 2006) for CO₂ and brine mixture. From the description of microscopic properties (mineral grains, fluid phases, rock frame), the rock physics model constitutes the forward model and allows to compute viscoelastic properties. The idea in the rock physics inversion process is to extract the poroelastic parameters from seismic attributes (velocity, quality factor, density) combinations. The forward problem can be formulated as:

\[
\tilde{d} = g(\tilde{m})
\]  

Where \( \tilde{d} \), \( \tilde{m} \) and \( g \) denote the data vector, the model vector and the nonlinear relation function linking the data and model (i.e. the rock physics model), respectively. The solution of associated problem requires the use of an optimization method. In our case, the Neighborhood Algorithm (NA) described in Sambridge (1999) is used to solve the inverse problem. The method is searching for the global minimum misfit over the model domain randomly. Only two control parameters are necessary to use the NA algorithm method, which are the number of models generated in each iterations and the resampling size of Voronoi cells. The discrepancy between the observed data (viscoelastic properties derived from input data) and calculated data (viscoelastic data computed from the rock physics properties by forward modelling) is described by a misfit function following the L2 norm. After each iteration, the resampling of the model space is done according to the misfit values of each model. In our sensitivity tests, 1000 iterations are used and a resampling factor of 10 is used. In the application on baseline log data, the iteration number is reduced to 500 with regard to computation cost and time.

Sensitivity Tests

The Sleipner storage pilot is located in the North Sea. The CO₂ separated from the produced gas is stored into the Utsira Sandstone at 800 m below the sea bottom (Carcione et al., 2006). Some a priori parameters for the Utsira Fm are partly provided in Lindberg (2013), and others are extracted based on the existing papers on Sleipner field. We assume a central frequency of 30 Hz for the seismic data.
with an initial temperature of 37°C (Furre et al., 2015, Furre and Eiken, 2014) for the sensitivity tests. We obtain the seismic attributes (velocity, density, quality factor) by forward modelling. For the inversion, we use different combinations of input data. Figure 1 shows the inversion results of brine saturation $S_b$ considering low CO$_2$ saturation ($S_b = 85\%$) and high CO$_2$ saturation ($S_b = 20\%$). If only $V_p$ is provided, the estimation of $S_b$ is poor with wide low misfit area for the low brine saturation case (Figure 1 (b)). The estimation of $S_w$ is better in case of high brine saturation (Figure 1 (a)). $S_w$ is better estimated when more than only $V_p$ data is provided (Figure 1 (c), (d), (e), (f)). It can be seen that the combination of ($V_p$, $V_s$ and $\rho$) input can make the estimated best model be well matched with the true model (Figure 1 (f)). The low misfit area is better constrained when the parametrization includes quality factors (Figure 1 (d)). We conclude that the estimation of CO$_2$ saturation is correct from $V_p$ data but requires additional input if the brine saturation is low. In addition, other sensitivity tests have been carried out in less optimal cases (if the rock physics model describing is not perfectly known and if the CO$_2$ properties are not defined) and suggest that the use of additional input data, especially $V_s$ and $Q_v$ are required to get good estimation of CO$_2$ saturation.

![Figure 1](image)

**Figure 1** Estimation of brine saturation $S_b$ using input data: (a) $V_p$, (b) $S_b = 20\%$, (c) $S_w = 20\%$, (d) $S_b = 20\%$, (e) $V_p$, (f) $V_p$, $V_s$, $\rho$. Panel a is for brine saturation $S_b = 85\%$, while panels b, c, d, e and f are for brine saturation $S_b = 20\%$. The blue cross indicates the best model and the red cross indicates the true model. The color of each dot represents the misfit value for each computed model (between 0 and $1\%$ or $0.001\%$).

Rock frame properties estimation using baseline log data

To extract the baseline properties of the Utstein sand rock frame before CO$_2$ injection, we apply our rock physics model for porous medium with only one fluid phase (brine) saturating the pore space. The data were recorded at Well 159-16 before the CO$_2$ injection started. Conventional petrophysics information is provided by this well data, for instance, gamma-ray, density, porosity and compressional sonic log data. The target area in our study corresponds to the depth range 770 m-1000
The 250 m thick Utsira sandstone is surrounded by the Nordland shale at the top and the Hordaland shale at the bottom. There are several thin shale layers imbedded in the Utsira sandstone (Zweigel, 2000).

Sensitivity tests show that S-wave velocity is crucial for the frame moduli estimation (Duguy et al., 2018b). Consequently, we compute empirically S-wave sonic velocity using the empirical Vemik's relation (Marko et al., 2009). We carry out the inversion with estimation of dry frame moduli (K_x and G_z) and the inversion is applied to the whole log data. P- and S-wave velocities and density of whole log depth are shown in Figure 2 (a, b, c). The best estimated frame moduli for whole depth from (V_p, V_s, ρ) are given in Figure 2 (d, e). It is worth to mention that when only invert (K_x, G_z), the (V_p, V_s, ρ) inputs provide the most stable estimation which reveal to be consistent with the estimated values from the geological study by Lindberg (2013). In addition, the use of shear wave information is crucial for drained moduli inversion, especially for estimating the shear frame moduli. The estimation of these rock frame properties aims at forming the basis for CO₂ saturation estimation that will be done based on FWI results in a near future.

![Figure 2](image)

Figure 2. V_p, V_s and density responses from the Well 15/9-16 (left). The drained bulk and shear moduli (right), which are derived by V_p, V_s and density. V_s is derived using Vemik’s relations.

Conclusions

We demonstrate the use of rock physics inversion for estimating CO₂ saturation and rock frame properties at Sleipner CO₂ storage site in the North Sea. We model the effect of various CO₂ saturations on viscoelastic properties of the Sleipner sediments based on the effective fluid phase plugged into the Biot theory. By analysis of the sensitivity tests, we can conclude that CO₂ saturation can be well estimated from only V_p input, especially for high brine saturation condition. The quality factor of P-wave or the S-wave velocity helps for the estimation of CO₂ saturation and for reducing the uncertainties. The CO₂ saturation can be well estimated when enough input data are provided to the inversion process. Using well log data, the S-wave velocities are coupled using empirical relations with the P-wave velocities and density from well log to estimate the rock frame moduli before CO₂ injection at the Utsira sand formation.

Acknowledgements
This work has been produced with support from the uniCQue project and the BIOMASS Centre, performed under the Norwegian research program Centre for Environment-friendly Energy Research (FME). The authors acknowledge the following partners for their contributions: Gasco, Shell, Statoil, TOTAL, ENGIE and the Research Council of Norway (193816/360, 233716/E20) for their support.

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ZWEIGEL, P. 2000. Reservoir geology of the storage unit in the Sleipner CO2-injection case. Trondheim, Norway: SINTEF.
Appendix H Publication II

Rock physics inversion for CO$_2$ injection at Sleipner
Rock physics inversion for CO₂ injection at Sleipner

Hong Yan a, Bastien Dupuy b, Anouar Romdhane b, Berge Arntsen a

a Department of Petroleum Engineering and Applied Geophysics, NTNU; b SINTEF Petroleum Research

Contact email: hongy@stud.ntnu.no; bastien.dupuy@sintef.no

Introduction

Various geophysical techniques are used prior to and during the CO₂ injection process to characterize the changes in the subsurface properties. Several methods (for example, imaging and tomographic methods, amplitude versus offset analysis) are used to quantify the effect of CO₂ injection on seismic properties. In this context, the high-resolution results provided by full-wave inversion (FWI) (Virieux and Operto, 2009) can be very useful to derive rock physics properties. In our work, we use a rock physics tool with similar two-step workflow as described by Dupuy et al. (2016) to characterize selected rock physics properties of the Sleipner CO₂ storage pilot.

Methods

We use rock physics inversion based on Biot-Gassmann theory (Pride, 2005) for the Sleipner baseline well data. This extended Biot theory allows describing the porous sandstone saturated with brine (before injection) and partially saturated with brine and CO₂ (after injection). The rock physics tool allows computing viscoelastic properties from the poroelastic properties (rock and fluid phases). We use the Neighborhood Algorithm (Sambridge, 1999) to solve the inverse problem. This method is searching for the global minimum over the whole model space domain. The discrepancy between observed data (viscoelastic properties derived from input data) and calculated data (viscoelastic data computed from the rock physics properties by forward modeling) is described by a misfit function following the L2 norm.

Results

The log data from Well 15/9-16 before the CO₂ injection is used. We compute empirically S-waves sonic velocity using the empirical Vernik's relation (Mavko et al., 2009). We carry out the estimation of dry bulk and shear frame moduli (K_d and G_d) and the inversion is applied to the whole log data (Figure 1). The combination of P- and S- wave velocities and density (V_p, V_s, ρ) inputs provide the most stable estimation, which appears to be consistent with the estimated values from the geological study of Lindeberg (2013). Sensitivity tests under different CO₂ saturated conditions are performed in order to figure out how the CO₂ saturation and properties can be estimated from results provided from FWI. A priori parameters are defined based on existing studies on Sleipner. The sensitivity tests show that brine saturation S_w is better estimated when more than only P-wave velocity data is provided, but using only P-wave velocity is sufficient to get reliable results. The combination of V_p, V_s and ρ input make the
estimation more accurate. In addition, other sensitivity tests have been carried out in less optimal cases (if the rock physics model is not perfectly known and if the CO₂ properties are not defined) and suggest that the use of additional input data, especially S-wave velocity and P-wave quality factor are required to get a good estimation of CO₂ saturation.

Figure 1: Vp, Vs and density responses from the Well 15/9-16 (3 left panels). Dry bulk and shear moduli (2 right panels), which are derived by rock physics inversion.

Conclusions

We demonstrate the use of rock physics inversion for estimating CO₂ saturation and rock frame properties at Sleipner CO₂ storage site in the North Sea. We model the effect of various CO₂ saturations on viscoelastic properties of the Sleipner sediments. The CO₂ saturation can be well estimated when enough input data is provided. Using well log data, the S-wave velocities are coupled using empirical relations with the P-wave velocities and density from well log to estimate the rock frame moduli before CO₂ injection at the Utsira sand formation.

Acknowledgements

This work has been produced with support from the unICQue project and the BIGCCS Centre, performed under the Norwegian research program Centres for Environment-friendly Energy Research (FME). The authors acknowledge the following partners for their contributions: Gassco, Shell, StatOil, TOTAL, ENGIE and the Research Council of Norway (193816/S60, 235716/E20) for their support. We also thank Malcolm Sambridge for providing NA code in our study.

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