Using Stochastic Seismic Inversion as Input for 3D Geomechanical Models
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Abstract
The dual issues of band-limited vertical resolution and nonuniqueness of deterministic inversion results has led to the development of methodologies known as geostatistical, or stochastic, inversion. In these approaches, seismic data are typically inverted directly into a high-resolution geological model. Compared to deterministic inversion, stochastic methods deliver multiple realizations that are consistent with the available well and seismic data.

The seismic inversion process is inherently nonunique, meaning that there is an unbounded number of elastic property models that fit the seismic data equally well above some threshold misfit. We explore the notion of the equally large number of possible stress states that could be interpreted from same seismic observations.

We make use of stochastic inversion results to incorporate the impact of subseismic uncertainty in seismic-driven geomechanical models. By taking multiple realizations from a prestack stochastic inversion—acoustic impedance, V_p/V_s, and density—we generate and feed a series of distributions of elastic constants into a finite element stress simulator. The multiple stress solutions allow us to account for uncertainties in the inversion results that can be ultimately captured in a suite of numerical models to predict a set of possible geomechanical states of a field. Therefore, beyond a unique geomechanical forecast for a field, we can now solve for the range of variability in geomechanically safe operational parameters within the field’s development plan.

Introduction
Deterministic seismic inversion has become a standard practice in the industry. Conventional deterministic seismic inversion results provide important information about the spatial distribution of reservoir properties between wells (see Bosch et al. 2010; Bailey et al. 2010). Together with well data, deterministic seismic inversion can be used to construct 3D geomechanical models (see Herwanger and Koutsabeloulis, 2011; Rodriguez-Herrera et al. 2013; Adachi et al. 2012; Sengupta et al. 2011). For instance, it provides a means to populate the geomechanical models with mechanical properties, which ultimately affects the response of the subsurface to the presence of loading/unloading mechanisms and guides the distribution of stress in the model.

Typically, however, deterministic seismic inversion results have limited vertical resolution compared to the scale of the well logs. In addition, the seismic inversion process is inherently nonunique, meaning that there are an infinite number of elastic property models that fit the seismic data. The output of a deterministic inversion is limited to the input seismic resolution, capturing only a bulk elastic response and with all layering details smeared over the seismic wavelength. At such a level of detail, there can be multiple combinations of layer stacks that generate the same seismic response above some threshold misfit.

As an alternative, stochastic seismic inversion generates a set of realizations that agree with the bulk seismic response and well data and that can account for uncertainties or non-uniqueness associated with the seismic inversion process. The multiple realizations can be ultimately captured in a suite of geomechanical models fed by the AVO inversion outputs, which in turn can provide insight to the range of possible responses of the reservoir under the prescribed geological conditions. The following sections will explore this idea.
Data Set

The data presented in this paper are from the Keystone field, a gas field located about 200 km offshore northwest Australia. The Jupiter-1 gas discovery in the Keystone field is within a large, north/northeast trending, wrench fault block of Triassic to Jurassic age on, or peripheral to, the Exmouth Plateau. The Jupiter-1 well intersected a number of thin gas sands in the Triassic Mungaroo formation (see Herwanger and Koutsabeloulis, 2011). The 3D seismic data presented here were acquired in 2008, and the seismic quality is considered to be good. Three angle stacks (near, mid, and far) were available together with well log data from the Jupiter-1 well. Fig. 1a shows an inline through the reservoir.

First we describe the stochastic seismic inversion workflow, the results, and the limitations using the Keystone dataset. Then we describe the workflow to construct a seismic-driven geomechanical model based on the information provided from stochastic AVO inversion in terms of acoustic impedance (AI), Vp/Vs, and density. The models constructed from a deterministic and stochastic inversion will be compared next.

Stochastic Seismic Inversion (SSI)

In geostatistical seismic inversion, prestack seismic cubes are inverted into a high-resolution 3D geological model framework. The algorithm is a stochastic simulation approach producing multiple high-resolution realizations of AI, Vp/Vs, and density that tie at the well control and are consistent with the seismic data. A geological modeling grid is used as the framework for the inversion. One benefit of this approach is that the seismic data are inverted directly into the geological modeling grid where the results are immediately at the appropriate scale for geomechanical modeling.

The stochastic seismic inversion workflow consists of the following main steps:

- Geological model building
- Well data upscaling
- Prior model building
- Variogram modeling
- Inversion to AI, Vp/Vs, and density

A geological modeling grid was built, covering the area of interest and incorporating well markers, interpreted horizons, and fault information. The grid was constructed in the time domain to honor the reservoir horizons and well markers and the stratigraphic conformance rules in the reservoir zone. It is important to design the 3D geological modeling grid at a scale that captures the geological heterogeneities of the well logs—indepent of seismic sample rate. Fig. 1b also shows the constructed grid applied in the stochastic seismic inversion.

The available well logs were upscaled into the geological modeling grid. Crossploting techniques were used to classify and estimate the different correlation modes existing between the inversion properties and such understanding was later fed into the seismic inversion engine.

![Fig. 1](image-url) — (Left, a): Seismic cross-section of the interest interval. (Right, b): 3D geological grid with the deterministic AI (prior model).
A derived deterministic AVO inversion result was used as the prior model. The approach to build the prior models could range from a constant mean and standard deviation in each layer of the model to a fully spatially variant model incorporating lateral and vertical trends. Because there was only one well available for this study, the selected approach was to use the deterministic inversion results as prior models. In areas with more well control, a different approach may be preferable.

The variogram model plays a key role in controlling the “texture” of the high-resolution details present in the inverted realizations. Experimental variograms were calculated from the upscaled well data and seismic data to characterize the vertical and horizontal variations in AI, $V_p/V_s$, and density. Spatial correlation models fitted to the experimental variograms were used as constraints in the inversion. Since we only have one well in this study, there are limitations related to the variogram analysis, and there will be uncertainties in the inversion results outside the range of the variogram. Better well control would be ideal.

The stochastic inversion was performed over the geological 3D grid shown in Fig. 1 using the described input data and data analysis. The output was multiple realizations of AI, $V_p/V_s$, and density. Fig. 2 shows an example of three different realizations of acoustic impedance, $V_p/V_s$, and density.

**Fig. 2**—Three realizations of AI and $V_p/V_s$ and Density. Leftmost column: deterministic AVO inversion results (prior model).

**Seismic-Driven Geomechanical Models**

A geomechanical model or mechanical earth model (MEM) comprises a numerical representation of the geomechanical state of a reservoir (Plumb et al. 2000; Ali et al. 2003). This includes a model for the mechanical properties of the system and the stress state (including pore pressure). It also accounts for the contribution of overburden weight and structural parameters such as preexisting faults and fractures, their stiffness, density, and orientation. Mechanical properties vary in the 3D space and account for the local variability introduced by, for instance, different geological units. Understanding the behavior of a geomechanical model under prescribed conditions ultimately allows informed decisions on planning perforations, assessing stability of boreholes, or deciding among different completion strategies.

For the construction of such a model, comprehensive field data must be collected, audited, and processed. Certain data sets can be directly recorded in the field. Some variables can be derived from known quantities, and some other pieces of the information required need to be obtained from available correlations. Measurements along wells of the relevant quantities can be directly recorded in the field. Some variables can be derived from known quantities. For the construction of such a model, comprehensive field data must be collected, audited, and processed. Certain data sets can be directly recorded in the field. Some variables can be derived from known quantities, and some other pieces of the information required need to be obtained from available correlations. Measurements along wells of the relevant quantities can be directly recorded in the field. Some variables can be derived from known quantities.

**Stochastic Mechanical Property Distributions.** For this study, we consider solely the elastic component of the subsurface geomechanical behavior. Thus, mechanical properties are given by the elastic constants, expressed in terms of Young’s modulus $E$ and Poisson’s ratio. From the AVO inversion data, the dynamic Young’s modulus and Poisson’s ratio can be readily derived:

$$E_{\text{dyn}} = \rho V_s^2 \left( 3V_p^2/V_s^2 - 4 \right) (V_p^2/V_s^2 - 1) \quad \text{...(1)}$$

$$\nu_{\text{dyn}} = 0.5( V_p^2/V_s^2 - 2 ) (V_p^2/V_s^2 - 1) \quad \text{...(2)}$$
$E_{\text{dyn}}$ and $\nu_{\text{dyn}}$ are the dynamic Young’s modulus and Poisson’s ratio, respectively. The shear wave velocity $V_s$ is computed as $V_s = AI/(\rho V_r)$, with AI being the acoustic impedance, $V_r$ the $V_p/V_s$ ratio, and $\rho$ the volumetric mass density, all derived from the seismic inversion.

For linear elastic materials, both the Young’s modulus and Poisson’s ratio are independent of stress, deformation rate, or amount of strain. For rocks, the typical case is that the dynamic moduli of rocks are greater than the static one as obtained in a quasi-static laboratory tests. Hence, for the sake of modeling the reservoir response to quasi-static changes in stresses, deformations, and pressures, an estimate of the static properties is needed. Since these cannot be directly derived from AVO inversion data alone, laboratory tests could be used to derive and apply formation-specific correlations linking the static and dynamic properties. A pragmatic approach in the absence of laboratory data would be using available correlations for the specific lithology in question. Here, it was assumed $\nu_{\text{dyn}} = \nu_{\text{stat}}$ in concordance with available published data, and for the static Young’s modulus, $E_{\text{stat}}$ was computed according to the empirical fit with the form:

$$E_{\text{stat}} = aE_{\text{dyn}}^b$$

The coefficients $a$ and $b$ were assigned from an internal propriety correlation. As an example, Figs. 3a and 3b depict a slice of the Young’s modulus in the deterministic model and from one realization of the stochastic model, respectively. In the same manner, Figs. 4a and 4b depict a comparison between the Poisson’s ratio from the deterministic and from the same realization of the stochastic inversion results. As in previous figures, it is clear the differences are introduced by the higher frequency band of the stochastic model in comparison with the smoother property distribution of the deterministic realization.

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**Fig. 3**—(Top, a) The Young’s modulus distribution derived from the deterministic seismic inversion. (Bottom, b) The Young’s modulus distribution derived from one realization of the stochastic seismic inversion. Note the higher frequency of events in the stochastic result, which is seismically equivalent to the smoother deterministic inversion.

**Fig. 4**—(Top, a) The Poisson’s ratio distribution derived from the deterministic seismic inversion. (Bottom, b) The Poisson’s ratio distribution derived from one realization of the stochastic seismic inversion. Similarly to Fig. 5, the stochastic results expand the range of variability when compared to the deterministic solution.
**In-Situ Stress State Modeling with SSI Data.** The first stage of the 3D stress analysis involves calculating stresses that represent the present-day conditions throughout the reservoir and its surroundings, with properties derived from the deterministic inversion results. The following steps involve recomputing the local high frequency stress variations with the input of new property distributions from stochastic realizations (Fig. 5). For such purposes, a finite-element geomechanical modeling engine was used to produce a 3D map of stress magnitudes and orientations that vary both laterally and vertically. The model uses the pore pressure, structure, rock mechanical properties, and far-field horizontal stresses imposed as boundary conditions in order to simulate the initial stress state of the field.

Horizontal far-field stress conditions were set as lateral boundary conditions, and, on top, the sea fluid surcharge was applied. Complying with a normal faulting regime, the gradient below the seabed of the minimum horizontal stress was 0.75 times the vertical stress gradient, and the maximum horizontal stress was set as $S_h = 1.1 S_v$. The pore pressure was assumed to be hydrostatic. In this example, the direction of the minimum horizontal stress was set to $90^\circ$ NE (i.e., it coarsely points along the normal to the main fault system in which the area of interest is embedded. In a more realistic scenario, the direction of the main stresses could be obtained from, for instance, sonic/image interpretations in the vicinity of the field.

![Fig. 5—Focused map view of four simulations of the minimum effective horizontal stress state in the east/west direction. Under same boundary conditions, the stochastic realizations introduce variability in the mechanical property model, affecting the resulting stress state required to resolve equilibration. Location A depicts the position of input well.](image1)

![Fig. 6:—Map view of (top to bottom): a) Young’s modulus distribution derived from deterministic seismic inversion. b) Young’s modulus distribution derived from one realization of the stochastic inversion. c) Fracture gradient cube map (equivalent mud density) computed from a stress simulation based on deterministic properties. d) Fracture gradient cube map (equivalent mud density) computed from a stress simulation based on the stochastic realization (b).](image2)
Assessing the Impact on Simulated Stress Results. As an application, the resulting fracture gradient was computed for the deterministic model and a set of stochastic runs. We define the fracture gradient as the minimum total principal stress. The calculation followed a two-step procedure: First, an equilibrium state of stress and strain was obtained for the deterministic geomechanical model. In a second step, the local mechanical properties \( (E_{\text{sim}}, v_{\text{sim}}) \) were recomputed using the stochastic realizations as input, and for the same deformation imposed on the deterministic model, new stress states were obtained. Fig. 6 shows a focused view of four simulations of the effective stress state in the east/west direction. Having left all additional controls equal, the stochastic realizations introduce variability in the mechanical property model that translates into a change in the stress state required to resolve an equilibration of all the forces (body + external loads) within the subsurface. It is also possible to appreciate an increase in the stress variability with increase of distance to the input well (Jupiter-1, dashed circle). This increased variability of the stress state arises from the provided variogram model, affecting the underlying drivers of rock stiffness and stress “flow-paths,” (e.g., stress will be supported by the stiffer bodies).

For the deterministic model and an example stochastic realization, Fig. 6 elaborates on the differences in stress and elastic properties of the two models at the local scale: whenever the deterministic inversion was used, fracture gradient cubes were smoother (Fig. 6c), whereas the fine-scale details of the stochastic inversion led to a more heterogeneous stress field along the model (Fig. 6d). This illustrates graphically the differences between the two approaches. A practical implication of this result can be seen in the estimation of a safe mud-weight window for drilled wells.

In Fig. 6, it is also apparent that the peaks/valleys in the stress field (rectangles A and B) were exacerbated when the stochastic property model was used. This is a direct consequence of the observed high heterogeneity over a small spatial interval, where sharp contrasts in load bearing capacity gives rise to stress transfer mechanisms across rock layers and therefore pushes the stress state into a more uneven distribution. Although the amount of stress change per change in the seismic property is not a simple relationship, it becomes evident that unaccounted seismic variability will lead to an underestimation of the range of possible stress scenarios that can be inferred. This, for example, can obfuscate low fracture gradient areas (rectangle A) and lead to apparently more optimistic drilling conditions. The same is the case of planning of hydraulic fracturing campaigns where geomechanical insight can support the optimization of completion effectiveness, in terms of being able to initiate and contain a hydraulic fracture. Some areas (rectangle B) depict higher horizontal stresses in the stochastic run (when compared to the deterministic stress state) that could be interpreted as lower required stimulation pressures in that specific region.

Summary

Geomechanical models can benefit from 3D seismic data in different ways. Firstly, seismic data is needed to interpret the structural framework used in building the geomechanical model. Seismic AVO inversion also provides a means to populate the geomechanical model in the inter well space with mechanical properties, which ultimately affect the response of the model. Stochastic inversion techniques, in principle, allow taking into account the mechanical properties of the model at a finer scale while providing some estimation of uncertainty. For this project only a single calibration well was available. In a more favorable situation, additional wells should be used to constrain the inversion process.

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References