

Realization Generation and Ranking in Bayesian Rock Physics Inversion Using Iman-Conover Sampling: A Practical Workflow

Introduction

Seismic reservoir characterization (SRC) aims to estimate subsurface petrophysical properties such as porosity, lithology, and fluid saturation from seismic data through prestack avo and rock physics inversion workflows (Grana et al., 2021; Grana et al., 2022). Due to measurement uncertainties and the non-uniqueness of the inverse problem, stochastic Bayesian inversion approaches are commonly preferred because they enable uncertainty quantification and probabilistic reservoir characterization through posterior probability density functions (PDFs) (Liu et al., 2026). Posterior realizations are typically generated using Markov Chain Monte Carlo (MCMC) sampling algorithms; however, such approaches are often computationally expensive and may suffer from convergence and high-dimensional sampling challenges (Grana et al., 2022; Liu et al., 2026).

In this study, an alternative and computationally efficient sampling workflow is proposed for Bayesian rock physics inversion and uncertainty analysis. The method integrates Bayesian linearized rock physics inversion with the Iman-Conover sampling method to generate posterior realizations while preserving the statistical dependency structure of the reservoir properties. The resulting realizations are further utilized for uncertainty-aware reservoir characterization and realization ranking. The proposed workflow is validated using the Volve oilfield dataset from the Norwegian North Sea.

Method and theory

Bachrach (2006) was likely the pioneer among others to use joint PDF and MCMC as a sampling agent to stochastically perform rock physics inversion. Bayesian linearized rock physics inversion under Gaussian assumptions was introduced by Grana (2016), where the Taylor series expansion and Jacobian matrix are used to linearize the rock physics model and formulate the inverse problem in analytical form. Under Gaussian assumptions for the prior distribution and observational errors, the posterior probability density function (PDF) can be analytically expressed through conditional mean and covariance, enabling computationally efficient probabilistic inversion (Grana, 2016; Grana et al., 2021). In this study, Bayesian linearized rock physics inversion was applied to estimate the posterior PDF of porosity, shale volume, and water saturation from seismic inversion cubes.

Instead of conventional MCMC-based sampling approaches, the Iman-Conover method (ICM) was utilized to generate posterior realizations while preserving the statistical dependency structure between the reservoir properties (Iman and Conover, 1982). In contrast to conventional MCMC-based approaches, the proposed workflow does not require chain tuning, convergence analysis, or iterative posterior exploration, making it computationally efficient and easier to implement for large-scale reservoir studies. Under the Gaussian posterior assumption, the Iman-Conover method provides realizations that are statistically consistent with those generated through conventional multivariate Gaussian sampling. The generated realizations were subsequently ranked using net-to-gross (NTG) criteria to identify representative P(10), P(50), and P(90) reservoir scenarios.

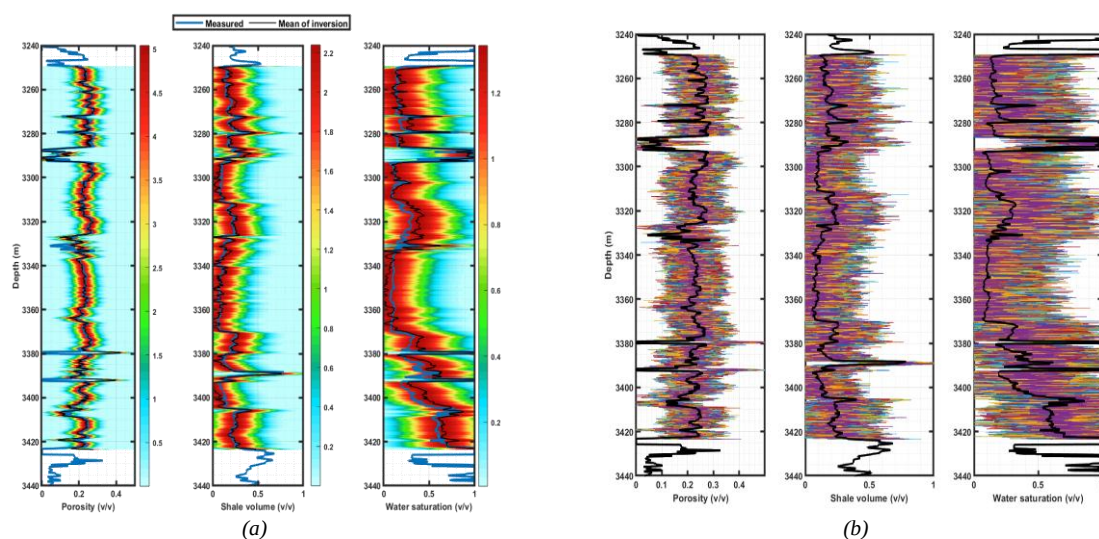
Case study – Volve oilfield

The proposed workflow was applied to the Volve oilfield, where the main reservoir corresponds to the Jurassic Hugin Formation, consisting of shallow-marine sandstones affected by regional faulting and salt tectonics. The dataset includes conventional well logs (14 wells), petrophysical interpretations, prestack seismic data, angle stacks, interpreted horizons, and velocity models. Since only a limited number of wells contained measured S-wave velocity (V_s), missing V_s logs were estimated using the

calibrated Greenberg-Castagna relationship. The simultaneous prestack inversion was performed on angle-stack seismic data (near, near-mid, mid, and far) using a three-term AVO approximation to estimate P-impedance, S-impedance, and density volumes. Blind-well validation and synthetic-to-seismic matching confirmed the reliability of the inverted elastic properties. Subsequently, empirical linear rock physics relationships between elastic properties and petrophysical parameters (porosity, shale volume, and water saturation) were calibrated using well-log data and validated on blind wells.

The calibrated models were then incorporated into Bayesian linearized rock physics inversion to estimate posterior PDF for the target reservoir properties. Figure 1(a) demonstrates good agreement between measured logs and posterior maximum estimates, while Figure 1(b) illustrates 100 realizations generated using the ICM. Posterior coverage and the posterior covariance matrices were further evaluated through crossplot density analysis (Figure 1(c)). After validating the workflow at well locations, the inversion was extended to the seismic volume, and 200 simultaneous realizations were generated over the reservoir interval. Figure 2(a) shows the comparison between measured logs and posterior maximum estimates in a blind well, demonstrating reliable inversion performance at the seismic scale. Stability analysis indicated that at least 150 realizations were sufficient for reliable uncertainty analysis. The realizations were subsequently ranked using net-to-gross (NTG) criteria based on porosity, shale volume, and water saturation cutoffs (porosity above 0.25, shale volume less than 0.3, and water saturation less than 0.3), and the resulting ranking distribution is presented in Figure 2(b). Representative P(10), P(50), and P(90) reservoir scenarios were then selected for uncertainty-aware reservoir characterization (realization number 25, 7, and 169 have been selected for P(10), P(50), and P(90), respectively). The ranked realizations for porosity, shale volume, and water saturation are shown in Figure 2(c) as cross-sections. The mean of the 200 realizations, shown in the rightmost column, represents a low-frequency average of the individual realizations.

Figure 3 presents the corresponding ranked realizations and probability maps for the Hugin reservoir. The probability maps illustrate units with more than 25% porosity, units with more than 70% shale volume, and units with less than 20% water saturation. The probability maps exhibit spatial variations that are considered geologically plausible and consistent with the structural framework of the Volve field. The northwest-dipping reservoir geometry and the concentration of well control toward the eastern part of the field may partly explain localized inconsistencies between porous and hydrocarbon-saturated regions, emphasizing the need for integrated geological interpretation of probabilistic inversion results.



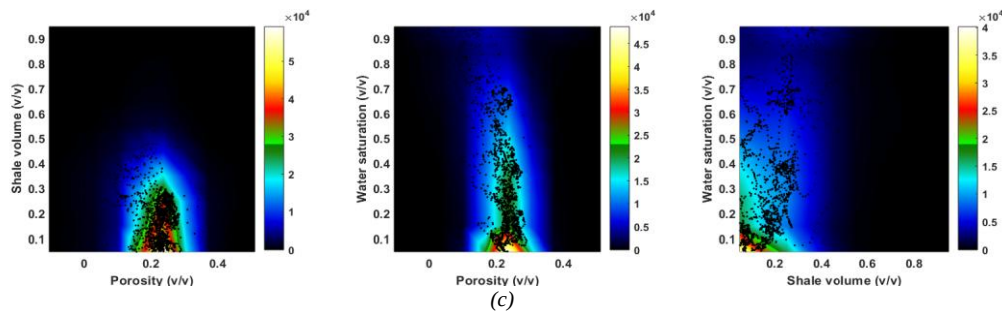


Figure 1 (a) The inverted rock physics results on a well. (b) 100 realizations sampled out of the generated posterior by ICM. (c) The density plot for assessing the posterior coverage.

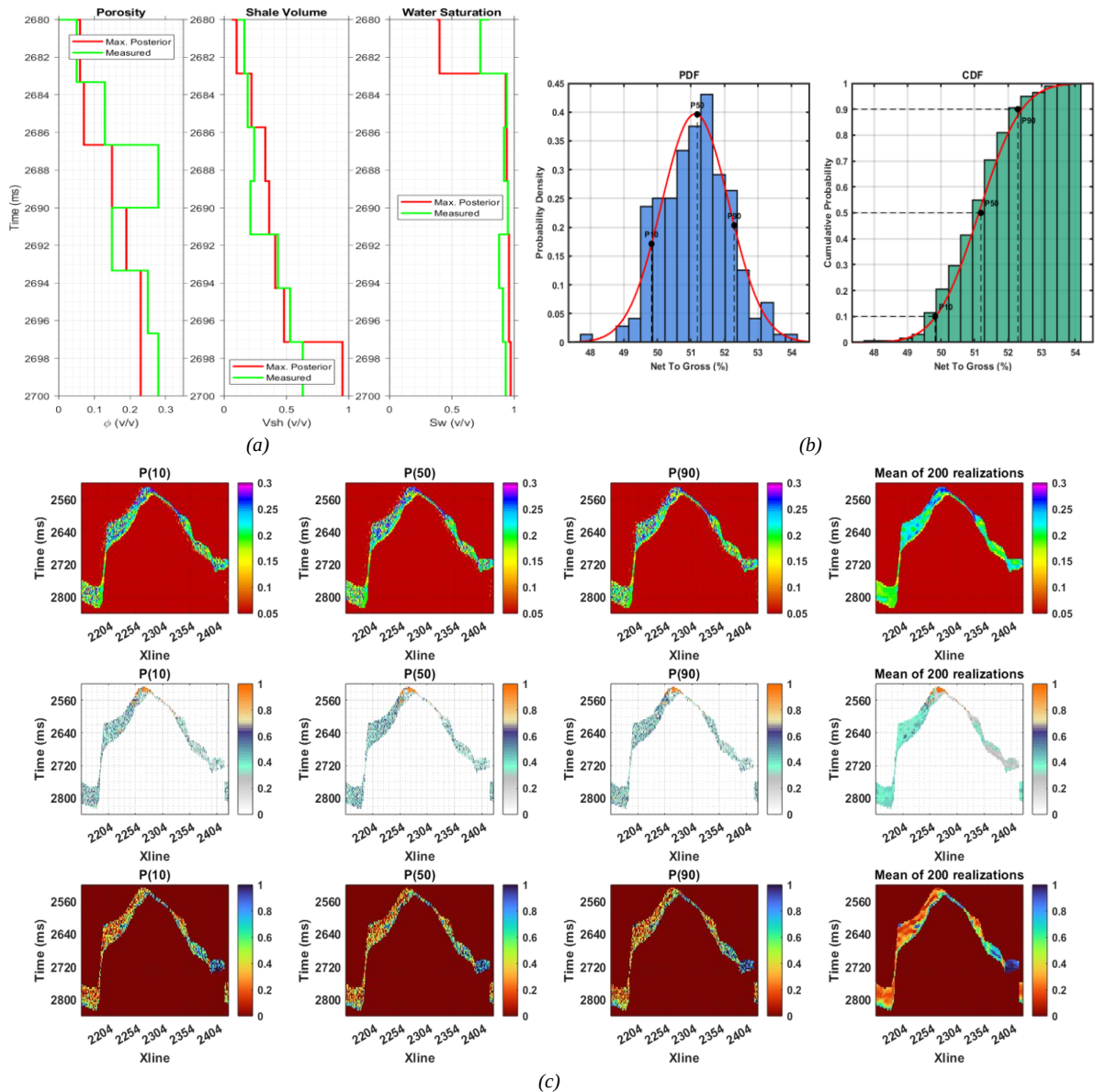


Figure 2 (a) The comparison of the inverted properties versus the real logs in a blind well after performing inversion over cubes. (b) Realizations ranking via NTG as a criterion. (c) Cross-section of the ranked realizations for porosity (first row), shale volume (second row), and water saturation (third row). The mean of 200 realizations for different properties are shown in the last column from left.

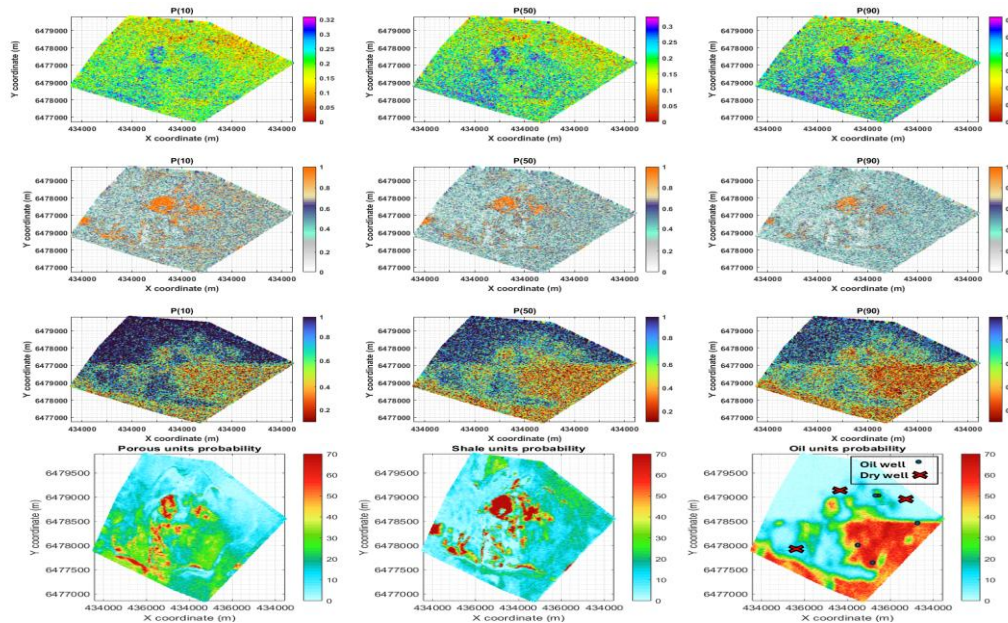


Figure 3 The maps of the ranked realizations over the Hugin reservoir (first, second, and third rows are for porosity, shale volume, and water saturation, respectively).

Conclusions

This study presents a computationally efficient workflow for uncertainty analysis by integrating Bayesian linearized inversion with the Iman-Conover sampling method. The proposed approach successfully generated posterior realizations while preserving the statistical characteristics and inter-parameter dependencies of the reservoir properties. Application to the Volve field demonstrated reliable estimation of porosity, shale volume, and water saturation, together with practical realization ranking for uncertainty-aware reservoir characterization. The workflow offers a practical alternative to conventional MCMC-based sampling approaches for large-scale stochastic inversion studies. This method can be implemented in joint-inversion (seismic and rock physics) or cascaded workflows.

Acknowledgement

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