

Deep learning using FCT-network for petrophysical property estimation from seismic-angle-stacks: 3D application to the Troll Field, North-Sea

Introduction

Hydrocarbon exploration and field development are highly dependent on reliable prediction of reservoir properties from seismic data. These reservoir properties, such as porosity, fluid saturation, shale volume, dynamic changes of the reservoir, and quality factors, can be obtained from seismic data using inverse theory (Ahmed et al., 2022, 2023). Several inversion frameworks have been presented for this purpose (Grana, 2018; Ahmed et al., 2024), and are categorized into two groups: (1) cascaded inversion methods, and (2) simultaneous inversion methods (Bosch et al., 2010).

The procedure for predicting reservoir rock properties from partial seismic stacking data is a complex, nonlinear, ill-posed, and non-unique inverse problem. The inherently nonlinear nature of the inversion problem, together with strong lateral and vertical subsurface heterogeneity, makes it difficult to establish a unique and transferable mapping between seismic data and reservoir properties. Although some rock physics models (Ahmed et al., 2017; Hussain et al., 2017; Ahmed et al., 2018; Khalid et al., 2018) can be used to link the seismic with petrophysical properties locally at well-locations, they often do not remain valid throughout the study area. Furthermore, the limited bandwidth of seismic data introduces inherent nonuniqueness, even in the absence of noise.

Recent progress in deep learning (DL) methods has opened new opportunities for seismic inversion by enabling neural networks to learn complex and highly nonlinear relationships between seismic observations and subsurface petrophysical properties (Adler and Öktem, 2017; Ahmed et al., 2025). Among several DL methods, convolutional neural networks (CNNs) have been extensively adopted to solve challenging nonlinear inverse problems and estimating petrophysical properties (Das and Mukerji, 2020; Aleardi et al., 2022). However, despite their success, CNN-based inversion methods often suffer from high computational cost due to end-to-end or cascaded architectures, limited ability to capture long-range dependencies because of their locally defined receptive fields, and increased complexity arising from parameter coupling in multi-property estimation problems.

In the present study, we apply a supervised DL method that integrates CNN into a transformer (Ahmed et al., 2026) to predict petrophysical parameters, including porosity, water saturation, and shale volume, from well logs and seismic partial-angle stacks in the Troll field, North Sea. The network adopts an encoder–decoder architecture in which convolutional layers capture local short-range features, while transformer modules model long-range dependencies and global contextual information. The network is trained on multiple well logs that comprise porosity, water saturation, and shale volume, along with nearby seismic traces from the seismic cube and P-wave interval velocity data. These multi-scale input data act as label data. The trained DL network is then employed on a 3D volume of seismic angle stacks. The 3D seismic volume comprises 3 partial angle stacks (near, mid, and far angles). The method also predicts the uncertainty in the solution by using model ensembles and Monte Carlo dropout methods.

Method: Deep Learning Network

The DL workflow starts with the preparation of the well logs and seismic and data, including quality control, data feature selection, and their alignment through seismic-to-well ties and upscaling of well log. The systematic adjustment of the training parameters is used to optimize the performance of the model, followed by a rigorous assessment based on the accuracy of the prediction of the parameters, convergence performance, and geological consistency.

Figure 1 describes the schematic workflow of the method. Seismic angle stacks and interval velocity data are provided as input features to the network, while well-logs such as porosity, water saturation, and shale volume act as label data for network training. The encoder–decoder architecture learns representations that map seismic information to target properties such as reservoir porosity, water saturation, and shale content. The performance of the model is evaluated by comparing the estimations with labels

using a mean squared error (MSE) loss function. The lateral extent of the selected seismic traces around every well is defined by a specified radius 'R'. To maintain consistency with the well-logs, the seismic trace sequence length is tailored to fit the relevant log intervals. The resulting sequences are organized into runs, enabling capturing geological variability across different depth intervals.

The model is based on an encoder-decoder architecture that uses multi-scale features from the seis-mic angle stacks and the interval velocity input to predict subsurface petrophysical properties (Figure 1). Convolutional layers capture localized structural and spectral characteristics, while attention-based transformer components identify broader spatial relationships across traces. The decoding stage rein-states the long-range spatial resolution and converts the latent representations into continuous petro-physical parameter estimation, with every parameter being predicted separately through the training procedure. The deep learning framework is trained in a supervised network using well log data as label input. The parameters of interest are obtained using the mean squared error function (representing the difference between the estimated and actual values), minimized by a gradient-based method, such as the Nadam optimization algorithm. Following training, the network is deployed to generate spatially continuous predictions of petrophysical properties across the full seismic volume. Prediction uncertainty is quantified by combining Monte Carlo dropout, in which stochastic sampling is enabled during inference, with ensemble modeling using independently initialized networks. This strategy provides confidence estimates alongside mean predictions and is further evaluated through blind testing on unseen data to assess generalization. The analyses were performed using the proprietary EarthNET platform developed by Earth Science Analytics AS. The underlying algorithms remain the intellectual property of Earth Science Analytics AS, and elements of the methodology are subject to patent considerations. The interpretation and results presented here are the responsibility of the authors.

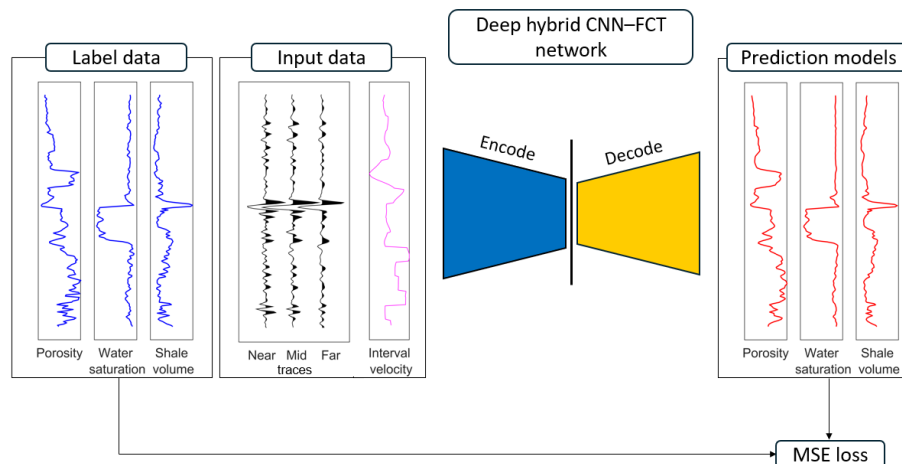


Figure 1 Conceptual diagram illustrating the workflow of the deep hybrid architecture.

Training and validation at well location

The DL method is trained and validated using well-logs of porosity, saturation, and shale volume as label data. Each log is also paired with nearby seismic traces and interval velocity to allow the network to learn the relationship between petrophysical properties and seismic responses while preserving spatial context around the well. The training process was carried out using a set of carefully selected hyperparameters to balance prediction accuracy and generalization. During training, the network uses input sequences of 128 samples with an overlapping window factor of 0.8 to improve data diversity. A batch size of 64 for up to 200 epochs is selected, with early stopping based on validation loss (patience of 75 epochs) to prevent overfitting. Data augmentation using small additive and multiplicative noise (set up to 0.05) is used to improve generalization. Furthermore, performance metrics such as R^2 , correlation coefficient, mean squared error, and mean absolute error quantify the robustness of the prediction at the well location. Figure 2a shows the predictions in one of the wells (31/2-1) used in the training along with the ground truth models. The uncertainty of the prediction is represented by the 95% confidence interval, shown

by the 2.5 and 97.5 percentiles. The predicted models show very close agreement with the ground truth models. The performance of the network model is further evaluated on a separate validation dataset consisting of blind wells not used during training, as shown in Figure 2b for well 31/2-1. In the case of blind data (well 31/2-10), although the accuracy of the prediction is reduced, the results are still reliable and accurate. This confirms the generalization ability of the model.

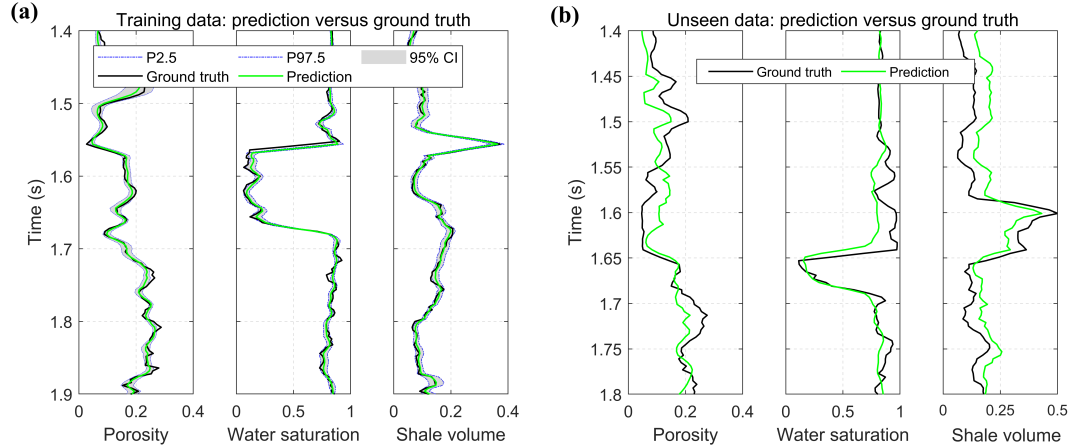


Figure 2 Ground-truth versus predicted profiles of porosity, water saturation, and shale volume at well locations: (a) Training well 31/2-1 and (b) Blind well 31/2-10 – unseen during training.

Prediction on seismic data

The trained network is then applied to a 3D seismic angle-stacked cube in the Troll field, consisting of 1,615 inlines and 2,510 crosslines. The results are generated within the reservoir interval, spanning 1440 to 1840 ms TWT. The predicted porosity, water saturation, and shale volume models at 1652 ms are shown in Figure 3. For better visualization, the Troll field polygons are drawn. We checked the accuracy of the S_w by comparing saturation maps above and below the gas-water-contact (GWC). Below GWC, the prediction is close to 100% water. Above the GWC, low S_w values are observed in the interval corresponding to the flat-spot horizon. The porosity map is checked by comparing the porosity maps at the reservoir level with those above the reservoir (sealing overburden). Concerning the shale distribution, the wells show similar shale content for reservoir and non-reservoir units. This observation is confirmed by the shale prediction.

Conclusions

A hybrid deep learning network that integrates a Convolutional Neural Network into a Fully Convolutional Transformer is applied to estimate petrophysical properties such as porosity, water saturation, and shale volume from partial angle stacks in the Troll field. Training is performed at multiple well locations, with well-log porosity, water saturation, and shale volume serving as target variables, while the corresponding nearby seismic traces and the P-wave interval velocity constitute the input features. The training subset was used to optimize the network parameters, while the validation subset was used to monitor generalization performance and prevent overfitting during training. The applications are then expanded to a 3D seismic cube, and the method produces a reliable estimate of the petrophysical properties on the training data, blind data, and seismic volume. The accuracy of the results is also verified by comparing the seismic signature with the water saturation map.

Acknowledgements

The National Center for Sustainable Subsurface Utilization of the Norwegian Continental Shelf (NCS2030) and its industry partners are acknowledged for their financial support (RCN no: 331644). The authors acknowledge the Norwegian Offshore Directorate (NOD) for providing access to well and seismic data via the Norwegian National Data Repository (NDR).

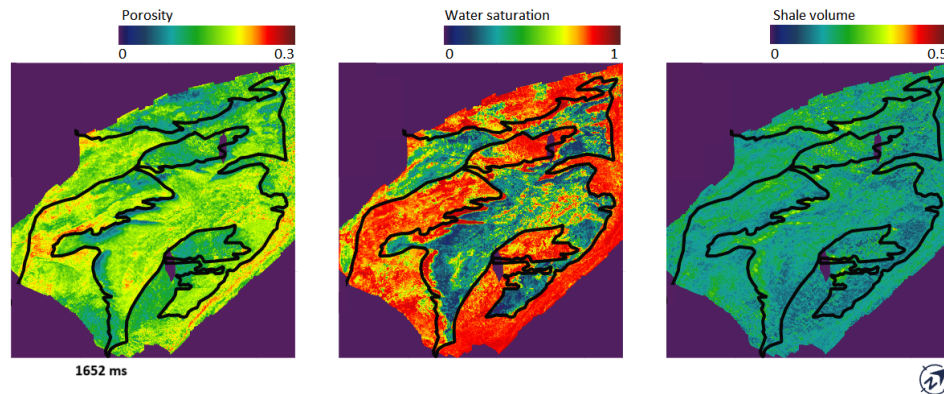


Figure 3 Estimated porosity, water saturation, and shale volume at 1652 ms TWT.

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