Exploring Reservoir within Hugin Formation in Theta Vest Structure using 4-D Seismic and Machine Learning Approach

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Abstract. This paper aims to identify the oil distribution using 4-D seismic below a complex 3-D surface in Hugin Formation using machine learning and geobody detection. The exploration well 15/9-19-SR, drilled to the Theta Vest structure, was based on the interpretation of reprocessed ST8215R 3-D seismic survey data from 1991 in the Sleipner area, encountered oil in the Jurassic Hugin Formation. The drills stem test showed outstanding production capacities through time, with low water cut and low GOR. 4-D seismic has all the traditional benefits of 3-D seismic. A significant additional potential benefit is that fluid-flow processes can be directly imaged. The 4-D seismic analysis was conducted in 2012 to repeat the 3-D seismic surveys and analyze images in time-lapse mode to monitor time-varying fluid-flow processes during reservoir production. A comprehensive study of the structure and the discovery has been performed and is reported. The DNN method to predict facies far away from existing production wells by using facies log well to supervise seismic inversion created by the Seismic Color Inversion method. It can detect some oil pockets distribution and risk the well planning and the right candidate for new proposed wells.

1. Introduction
The Theta Vest structure is dome-shaped to trap oil. The structure has a well-defined spill point to the east and is a base case believed to be filled down to this point. However, several faults cutting the structure's crest could be sealing the hydrocarbon accumulation off from spilling eastwards. The hydrocarbon discovery of exploration well 15/9-19-SR has been evaluated using 3-D seismic data taken in 1991 with comprehensive analyzes have been carried out, such as seismic interpretation, structural model, petrophysical evaluation, DST test, and geochemical analysis [1]. Finally, a resource analysis of the discovery and associated prospects has been performed. The exploration well 15/9-19-SR is located on the Theta Vest structure in the Sleipner Øst area (Figure 1). Well planning on the Theta Vest structure was based on the interpretation of reprocessed ST8215R 3-D survey data from 1991. The Top Hugin Formation horizon has been mapped after the well was drilled. With the limited resolution of the seismic data and a weak reflector, the horizon has been challenging to interpret consistently.
In a single 3-D seismic survey, seismic waves are generated by sources (dynamite, airguns, and various sources.) at or near the subsurface. These source waves reflect subsurface seismic impedance contrasts: rock and fluid compressibility, shear modulus, and bulk density. They are recorded as they arrive back at the subsurface. The recorded waves form the classic wiggle traces where high positive amplitude portions are often filled in on a black and white image to enhance visual contrast and show lateral continuity. A wave-equation imaging algorithm is applied to the recorded reflection data to create 3-D seismic images of the reservoir rock and fluid property (seismic impedance) contrasts. 4-D seismic reservoir monitoring is the process of repeating 3-D seismic surveys over a reservoir in time-lapse mode to look for differences caused by the production [2]. The potential exists for dramatic benefits to reservoir management because it is the first technique that may directly image dynamic reservoir processes such as monitoring fluid movement, pressure build-up, and heat flow in a reservoir in a true volumetric sense. In these reservoirs, production causes subsurface deformations and changes in seismic velocity. These changes in the overburden can be monitored and interpreted. Optimal interpretation of this data enables enhancement, well placement, production and injection operations, production history matching, and reservoir simulations by defining reservoir fluid-flow characteristics to improve flow models.

4-D seismic has all the traditional benefits of 3-D seismic, plus a significant additional potential benefit that fluid-flow processes can be directly imaged. It involves repeating the 3-D seismic surveys and analyzing images in time-lapse mode to monitor time-varying fluid-flow processes during reservoir production [3]. In the first order, seismic images are sensitive to spatial contrasts in two distinct types of reservoir properties: 1) non-time-varying static geology properties such as lithology, porosity, shale content, and 2) time-varying dynamic fluid-flow properties such as fluid saturation, pore pressure, and temperature. A 3-D seismic survey is representing a single snapshot in time. It is impossible to distinguish an oil-water contact from a horizontal depositional boundary in a single seismic image. However, with 4-D seismic surveys, examining the difference between time-lapse 3-D seismic images allows the non-time-varying geologic contributions to cancel, resulting in a direct image of the time-varying changes caused by reservoir fluid flow. For example, an oil-water contact may move with time in a series of time-lapse seismic images, whereas a depositional boundary should not.

The 4-D time-lapse seismic technique has the potential to image in a large volume encompassing many wellbores, changes in fluid saturation, pore pressure, and temperature during production. It can provide more robust and reliable volumetric constraints between wells than those developed by interpolating borehole properties [4]. This technique allows observing the dynamic processes in and around the reservoir to help place wells more effectively, increasing development and production success.
Some successful 4-D case examples have been acquired at reservoirs containing high porous clastic rocks. Examples of such fields are Draugen and Gannet [5], Gullfaks ([6], Troll [7], Schiehallion [8], Foinhaven, Norne ([9], and Heidrun [10]. Like the Ekofisk [11] and Valhall [12] fields in the Southern North Sea, some significant chalk fields have reported good 4-D results.

The seismic impedance can help compute each reservoir model grid cell through a large but highly parallelizable cell-by-cell inverse problem easily integrated into the reservoir property updating workflow [13], [14]. One of the seismic impedance methods is seismic colored inversion. It is a post-stack inversion technique that transforms seismic data into layered rock properties [15]. Seismic colored inversion performs significantly better than traditional inversion methods like model-based inversion, band-limited inversion methods, fast, easy to use, less expensive, robust, and suitable for application to 3-D datasets [16]. It is a process where the acoustic impedance spectra derived from log data are used to compute the operator's spectrum [17]. Other inversion methods are time-consuming, expensive, and are not performed routinely by the interpreter.

Before its expanded use, the introduction of facies definition is described as a distinctive rock formed under a particular process or environment [18]. Thus, the response of well logs could vary in terms of rock changing through measurement and applied with electrofacies.

Seismic facies automated classification processes are a proven technology. It plays an increasingly vital role in seismic stratigraphy interpretation and reservoir characterization workflows. Due to advances in seismic acquisition, processing, and imaging, geoscientists now have access to high-definition subsurface images; Well characterization was collaborated with seismic attributes and distributed using Democratic Neural Network Association Methods (DNNA). DNNA performs facies inversion based on lithology and seismic data and is a robust alternative to conventional approaches. It comprises different neural networks, having various activation functions but trained with the same labeled dataset. The workflow for DNNA is consists of two training phases. The first training phase performs learning using a set of training samples issued from seismic attributes or amplitudes and facies distribution measured along well boreholes to provides a suite of independently predicted responses. The second training phase is to perform using two kinds of data: soft data and hard data. Soft data are data labeled by the democratic system, which contain lower weights value in training. Hard data are from well data that contain large-amplitude weights value—the DNNA method to reduce the training bias associated with each network. DNNA uses cross-validation and bootstrap error values. They are considerably lowered on synthetic and real datasets to perform facies inversion based on lithology and seismic attributes [20].

2. Data and Methods
The dataset is provided by Equinor, a Norwegian multinational energy company. The data is from the Volve Field in the North Sea. Data used in this research are grouped into two kinds of data: 3-D and 4-D data. The 3-D data and 4-D data are divided into two seismic amplitudes, 3-D and 4-D seismic amplitude data. Four wells (15/9-19-SR, 15/9-F-15-C, 15/9-F-1, and 15/9-F-5) were used to analyze the Hugin Formation is Callovian in age, probably of Late Callovian. The 15/9-19-SR well proved oil in Jurassic sandstones of the Hugin Formation. The 18 meters thick Hugin Formation was filled with hydrocarbons to its base at 2882.0 m MSL TD and reached in Triassic sediments at 3110.3 m MSL. The Hugin Formation's petrophysical analysis in the 15/9-19 SR well results in a mean net/gross of 0.924, the porosity of 22.6%, the permeability of 2913.2 mD, and water saturation of 11.0%. The sandstones are interpreted to be deposited in a high-energy marine environment, possibly a mouth bar setting. The reservoir interval consists of highly variable fine to coarse-grained, well to poorly sorted, subarkosic arenite sandstones with good to excellent reservoir properties. The underlying Skagerrak Formation is entirely tight due to extensive kaolinite and dolomite cementation. Within the Sleipner Øst area, the Jurassic and Triassic reservoir distribution are complicated. Based on lithofacies in 15/9-19-SR well, it can be applied to other wells such as 15/9-F-15-C, 15/9-F-1, and 15/9-F-5, as shown in Figure 2.
Secondary data resulted from field samples, field geological structures measurements, and tops of geological age markers using paleontology samples from well reports to control geological interpretation and reconstruction. Horizon and fault interpreted on 3-D and 4-D post-stack-final-psdm seismic processed in 26-11-2011 and 30-03-2012, respectively, as shown in Figure 3.

Before making any interpretation and processes the seismic, the first well tie needs to be computed based on the seismic section from West to East direction for some wells data. Figure 4 below for Inline 10135 and 15/9-19-SR well data, one of the well tie results.
Figure 4. Seismic section of 4-D and 3-D at Well Marker of Top Hugin.

2.1. 3-D and 4-D seismic color inversion

Seismic colored inversion is used because it is easy to use, less expensive, and suitable for a field without any gathers seismic. It is applied to the 3-D and 4-D post-stack seismic data to estimate petrophysical parameters by using the same parameters to process wells and seismic data to generate an impedance seismic, as shown in Figure 5. For the inversion to be as accurate as possible, the 3-D seismic volume ideally would be multiple free, zero-offset, migrated, and (preferably) zero-phased. The seismic wavelet is extracted from the data via a matching filter between the operator derived from the impedance log and the seismic trace at the well location. The operator is derived in the following steps: First, the acoustic impedance is calculated and plotted against frequency for the wells in the seismic section. Second, a curve line is fit to the amplitude spectrum of the acoustic impedance to represent the impedance spectrum in the subsurface in the log scale. Third, the average seismic spectrum is calculated from the seismic traces closed to the wells. These two spectra are used to calculate the operator spectrum, transforming the seismic spectrum into the average impedance spectrum. Fourth, the final spectrum is combined to create the operator in the time domain.

Figure 5. 3-D and 4-D Seismic color inversion
The entire seismic data is inverted into impedance volume with a correlation factor is estimated at 0.35. Low impedance values are estimated between 2550ms - 2590ms time intervals, which are interpreted as Hugin Formation oil sand, as shown in Figure 6. After seismic color inversion is calculated, we post the result and overlay it with the seismic amplitude shown in Figure 6.

![Image of seismic data](image)

**Figure 6.** Seismic Section of 3-D and 4-D of Seismic Color Inversion

The purpose of overlay seismic color inversion with seismic amplitude is to see the impedance differences and determine their lithologies contents on the zone of interest. From Figure 6, we can see the yellow color below the blue color is a low impedance value indicated as oil sand or a good reservoir in the formation.

2.2. *Seismic facies automated classification*

Seismic color inversion derived from post-stack seismic and log data is typically used to predict reservoirs' lithology and fluid content. Well-analysis is considered reliable when describing the reservoir; however, well data are generally too sparse of a data set to describe a prospect adequately. So, we applied a neural network application through the use of DNNA to infer facies defined at wells data. The probabilistic approach of DNNA combines all seismic-related information to build facies probability cubes. This paper proposed a new method for DNNA analysis using Seismic 3-D and Seismic 4-D of their Color Seismic Inversion and has been evaluated to achieve the best prediction. We focus on the reservoir zone between the top and 100 ms below the Hugin formation base to run DNNA facies classification. The result of DNNA is a facies volume between the interval time-lapse of 4-D and 3D seismic, and the facies predicted can be extracted along the borehole, as shown in Figure 7.
3. Results and discussion

The lithofacies and seismic inversion data at the well location represent the training dataset used as input to the DNNA process (Figure 7). On the data input tracks, there is a lithofacies log and then another that may be extracted or upscaled to eliminate thin layers to give more homogeneity to the vertical distribution of the facies. Track number five corresponds to the seismic traces, each associated with a different attribute, extracted along the well 15/9-19 SR.

Once that process has been run, the intermediate stage is to validate the quality of the operator by visualizing the reconstruction results at the wells (Figure 7). The eighth track is the reconstructed lithofacies log curve. In this context, “reconstructed” is defined as the predicted lithofacies curve that results from applying the neural network model at the well location using only seismic data as input. Therefore, it is a best-case scenario for the reconstruction of lithofacies using this method. Finally, the maximum probability curve for each of the created classes of the reconstructed lithofacies curve is on the far right side.

Machine Learning with DNNA algorithm can produce the facies volume with the prediction number of bootstrap sets: 100, Bootstrap (training) error: 0.165361 and Bootstrap classification rate: 78.8264 % also the Matthews correlation coefficient (all wells): 0.912. The facies classification volume can be extracted along the well path, as shown in Figure 8. below, to blind test the well.
The blind test well as predicted 0.912, produced high accuracy at well positions. Furthermore, for facies distribution, we can extract the facies volume on top of the Hugin Formation, see in Figure 9, as shown below.

The fuchsia color is the Hugin Formation's oil sand, showing some interesting geological-stratigraphy features inside the Hugin formation interval. Geobody detection can detect and create surfaces for bodies of facies five, as shown in Figure 10. Furthermore, by looking at the picture above, some places need to be considered candidates for the following proposed wells.
Figure 10. Geobody detection of Hugin Formation (left) and Wells that penetrated geobody (right).

Geobody detection inside the Hugin formation interval can help us to determine the lateral distribution of facies 5. Furthermore, we found some geobodies penetrating existing wells, and the blind test wells confirmed them.

4. Conclusion
DNNA analysis using 3-D and 4-D seismic data using facies log and color seismic inversion is discussed in the above section. The analyses showed that the seismic colored inversion method and 3-D and 4-D seismic supervised by facies logs provide consistent facies volume output. In addition, the methods estimated the reservoir distribution within the reservoir zone with the Mathew correlation 0.912, which confirmed hydrocarbon distribution that needs to be considered to reduce the risk and for the following proposed wells. Moreover, it can be done ineffectively to achieve the best accuracy of predictions compared to the traditional way. Furthermore, it helps to optimize the production in Hugin Formation within the Theta Vest Structure.

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