Data-driven rock physics analysis of North Sea tertiary reservoir sands
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\textbf{ABSTRACT}
We have demonstrated an approach for data-driven rock physics analysis, where we first do facies classification using elastic well log data from several wells, followed by facies-constrained regression analysis to establish local rock physics relations for the prediction of $V_P$ and $V_S$ from geological input parameters. We have applied this approach to a multi-well log data set (53 wells, 40 of which had reliable/useful data) from the greater Alvheim area. We show how we can derive very robust local empirical rock physics relations for the prediction of P-wave and S-wave velocities as well as densities, for given combinations of porosity and clay volume. These locally derived empirical relations are recommended instead of universal rock physics models, even when the latter are locally calibrated. Using elastic facies with geological characteristics (cemented versus unconsolidated; normally compacted versus injectites; homogeneous versus heterogeneous) helps to improve the predictability of the regression models. The local rock physics relations that we obtain can furthermore be used to create training data for AVO classification.

\textbf{Key words:} Borehole geophysics, Rock physics, Reservoir geophysics.

\textbf{INTRODUCTION}
Palaeocene sandstones in the North Sea are prolific hydrocarbon reservoirs that normally can be detected from amplitude versus offset (AVO) analysis (e.g. Avseth \textit{et al.} 2008; Avseth and Lehoki 2016). Reliable AVO analysis depends on a good rock physics understanding of the caprock shales and reservoir sandstones. Contact theory models (Dvorkin and Nur 1996) are known to be suitable for the rock physics characterization of North Sea Palaeocene sandstones (e.g. Avseth 2000). However, these models need to be parameterized with input parameters that are often not well known by practitioners. In areas with abundant well log data, local rock physics relations can be extracted from the data, using multiple linear regression (MLR) analysis (cf. Han \textit{et al.} 1986), where input parameters are normally well known by interpreters. In this study, we investigated data from 40 wells in a region of the North Sea (see Fig. 1) and extracted local rock physics relationships from the data constrained by facies classification.

The main goal of this study was to improve the understanding of various geological processes/parameters that control elastic properties of reservoir sandstones and shales in the Alvheim area, as well as to generate site-specific, empirical rock physics models for sands and shales. The study was divided into three steps:

1. Data preparation, quality control (QC) and sorting,
2. Data screening and rock physics diagnostics,
3. Data classification and multiple linear regressions for various formations and/or facies.

In step 1, we gathered well log data and sorted these in categories depending on data quality and availability of key logs. Key logs include sonic P-wave and S-wave, density and gamma ray. Measured shear wave log data were often lacking, but predicted (LFP) logs were sometimes at disposal. If available, petrophysical (CPI) logs, including total porosity, shale volume and saturation logs, were also utilized. Other relevant logs or data that were used include temperature, calliper, resistivity and neutron porosity. We performed an
extensive QC on log data from 53 wells (all wells currently released by Norwegian Petroleum Directorate; see NPD 2019) in the greater Alvheim area (shown in Fig. 1) and found that 40 had a good quality logs. Thirteen out of 40 wells had very good quality well log data as well as measured $V_S$ logs. We refer to this subset of wells as ‘green’, that is, wells with excellent quality measurements. The remaining 27 wells had moderate quality and/or missing key logs, but the data could still be used in our analysis.

In step 2, we screened all the well log data and searched for statistical trends in the data. We focused on porosity–velocity trends, but also looked at rock physics depth trends. This step is important to understand the expected facies classes in the area of interest, and we used elastic bounds to filter away data that are physically unreliable. In particular, we investigated the effect of depositional trends (sorting, clay volume and heterogeneity) and diagenesis (burial history and cement volume) on rock physics properties. We focused on the sandy and shaly intervals of Eocene and Palaeocene age, comprising the following formations/members: Frigg, Sele, Hermod, Lista, Heimdal and Ty.

In step 3, we first performed facies classification (i.e. facies with characteristic elastic properties) followed by MLR-s, where input parameters were either shale volume and porosity or shale volume and burial depth. Elastic logs could then be predicted empirically from these input parameters, constrained by predefined facies.

The results from this study can be utilized to predict elastic properties for various geological scenarios, and to create pseudo-logs in the studied area. This has the potential to be used in AVO feasibility studies, for improved understanding of expected AVO signatures in the area. There is also a future potential to include results from this study in machine learning algorithms in order to conduct data-driven AVO inversion/classification (cf. Lehocki et al. 2020).

METHODOLOGY

The first step was the cleaning and sorting of the well log data. The initial data set consisted of 53 wells (Fig. 1), out of which 40 were used after a thorough quality control. The main reasons for data rejection included washout effects revealed by calliper anomalies, gaps in, or complete lack of some of the essential log data (sonic and/or density logs), and poor or erroneous petrophysical logs (e.g. unrealistic total porosity values). Hydrocarbon zones were investigated in detail for potential mud-filtrate invasion effects using resistivity logs and calibrated rock physics templates (Avseth et al. 2003; Ødegaard and Avseth 2004). Data were then sorted into stratigraphic intervals, and key log data used in the analysis included P-wave velocity, S-wave velocity (measured in 13 ‘green’ wells), bulk density, gamma-ray, temperature, volume of clay, total porosity and saturation logs.

The second step was to do rock physics screening of the data. Elastic bounds were used to investigate if data comply with physics. In Fig. 2 we show some useful rock physics models for high-porosity sands and sandstones (Avseth et al. 2000) that can be used to quantify geologic trends and rock texture.
Figure 2 Rock physics diagnostic models used in this study, applicable for high-porosity, poorly to moderately consolidated sandstones (Avseth et al. 2000).

Figure 3 shows well log data from 13 ‘green’ wells within the Palaeocene target zone, including sandstone data for all formations before (left subplot) and after filtering (right). Before filtering there are still noisy scatters of data outside physical bounds for quartz-rich clean sandstones (lower bound = friable sand model at 20 MPa effective pressure; upper bound = increasing cement model; see Avseth et al. 2010 for more details). Some zero porosities represent errors in petrophysical data. High-porosity anomalies are either washout effects not corrected for or gas-filled sand stringers not corrected for in fluid substitution. Calcite stringers tend to plot above the stiff sandstone bound, whereas shaly sandstones and shales will plot below the soft bound. After filtering with respect to clay content (including only $V_{clay} = 0–0.3$) and removing noisy porosity data and velocity outliers, we have a much cleaner scatter of sandstone data (right subplot). Still some sands are plotting below the lower bound likely due to effective stress being lower than 20 MPa, which is assumed in the model. Also, we see some sandstones plotting above the stiff bound, likely representing mineral compositions that are effectively stiffer than pure quartz (e.g. calcite).

After cleaning and sorting of data, we screened them in rock physics crossplot domains. We created a scatterplot of $V_P$ versus porosity and temperature versus $V_P$ (Fig. 4), where temperature gradients were taken from metadata (available information in The Norwegian Petroleum Directorate) or from petrophysically estimated temperature curves, if available. From the left subplot of Fig. 4 we see that the temperature gradients in the wells have a large spread, which is likely reflecting the uncertainty in temperature gradient more than natural variability. The values range from 17°C/km to 38°C/km, with a peak at around 32°C/km. We assume that the higher gradients are more plausible, as these are often recorded in more recent wells. It is a known fact that temperature measurements in old wells (early 1970s) were affected by time delay and cooling of borehole by drilling mud. Nevertheless, we observe a clear trend and correlation between velocities and temperatures. This is expected since quartz cementation of quartz-rich sands is controlled by time and temperature (Walderhaug 1996) and is known to initiate between 60 and 80°C (Bjørlykke 2015). In Fig. 4, we plot 1D (subplot a) and 2D (c) normalized kernel density estimates (NKDEs) of the probability density functions (PDFs) of temperature gradient ($T_{grad}$) and P-wave velocity–temperature ($V_P–T$), respectively. Botev et al. (2010) and Lehocki et al. (2015) motivate the use of KDE techniques for reconstruction of the underlying PDFs: they are robust, flexible, data-driven, 1D, 2D or higher dimensional PDF estimation techniques. The normalization of KDE-s to a maximum value of 1 is not a necessary step, but is done to make the comparison
of plots simpler/easier (e.g. in Fig. 6). In Fig. 4(c), a velocity jump at around 60°C is observed, where velocities are seen to exceed ca. 3.0 km/s. A rule of thumb is that when $V_p$ exceeds 3.0 km/s in sandstones, they are cemented (Avseth and Dræge 2011). A cluster of data with $V_p > 3.0$ km/s and temperatures of around 55°C is also easy to spot. However, this could be related to wrong temperature data already mentioned. It could also be related to early diagenesis that sometimes occurs with amorphous silica (Opal A $\rightarrow$ Opal CT), which can be associated with diagenesis of tuffaceous rocks. Calcite cement is also known to occur even at low temperatures.

Figure 5 shows the 2D NKDE of $V_p$ versus porosity for all Palaeocene sandstones considered (Frigg, Hermod, Heimdal and Ty) in 13 of the ‘green’ category wells in the studied area. As can be seen, most of the data fall within the elastic bounds of clean sandstones and are following a clear diagenetic trend. However, some of the data fall outside. These can either be heterolithics, calcite spikes or noisy data points.

By exploring formations one by one (Fig. 6), we can observe more detailed patterns and trends in the sandstone data. The Frigg Formation (Fm) of Eocene age seems to consist mostly of unconsolidated sands (falling closer to the lower bound), with some clear sorting trends. The range of P-wave velocities is ca. [2.2–3.0] km/s, whereas porosities vary from 0.25 to 0.4. The Hermod Fm sandstones show very high porosities, but data are still located closer to the upper bound, with P-wave velocities in the range of [2.5–3.2] km/s and porosities ranging from 0.28 to 0.38. Heimdal...
Fm sandstones are stiffer with more intermediate porosities (0.2–0.3) and velocities mainly spanning the [3.0–3.8] km/s interval. Finally, Ty Fm sandstones have fewer data, but clearly these are even stiffer than the Heimdal Fm sandstones, with $V_p$ mainly in the range of [3.6–4.1] km/s. In summary, we observe depth-dependent trends caused by increasing quartz cementation from one formation to the other. However, we also observe sorting and/or packing trends within each sandstone formation.

Investigating depth trends (Fig. 7), it is obvious that the sandstone data included in the analysis follow a characteristic pattern. Porosity decreases linearly with a clear gradient. P-wave velocities are nicely explained by the Dvorkin-Nur contact cement model plotted in function of depth below the depth corresponding with temperatures higher than 70°C, where we assume the porosity reduction is caused by contact cement. This was also documented by Avseth et al. (2009) and Lehocki and Avseth (2010). A few data in the shallower region manifest that the mechanical compaction domain can be predicted with Hertz-Mindlin contact theory (cf. Avseth et al. 2003). The spread in the data (variability) at a given depth is likely associated with sorting, clay content and/or grain size variations. In particular, we see that the shear wave velocities tend to plot below the clean sandstone model. The effect of just a little bit of clay is much larger on shear wave velocities than on P-wave velocities. One very interesting observation in Fig. 7 is that there are high-porosity anomalies in the depth range of around [2100–2300] m TVD RKB (True Vertical Depth measured from Rotary Kelly Bushing). This is

Figure 5 Probabilistic crossplot of P-wave velocity versus porosity for all sandstone formations in Palaeocene with data from 13 ‘green’ category wells. All the sandstone data fall nicely between the elastic bounds. Subpopulations are plotted below the lower bound, representing unconsolidated shallow sands and shaly sands, respectively.

Figure 6 Probabilistic crossplots of $V_p$ versus porosity for different sandstone formations. Note the increasing velocities and decreasing porosities with increasingly older/deeper formations (Frigg, Hermod, Heimdal and Ty, respectively).
Rock physics analysis of North Sea tertiary reservoir sands

possibly associated with undercompacted, high-porosity sandstones of mostly Frigg and Hermod formations representing injectites that have been remobilized after deposition. Note that these can still be cemented since they are buried (or have been buried) at temperatures high enough to set off the cementation process (i.e. \(T > \text{ca. 70°C}\)).

Next, we looked into the \(\frac{V_P}{V_S}\) versus acoustic impedance crossplot. Figure 8 shows the 2D NKDE of brine-saturated sandstone data from the ‘green’ wells that have the measured \(V_S\) logs available (see Fig. 1). Data plot nicely between the template models representing unconsolidated sands (at 20 MPa effective stress) and increasing cement model, respectively. This plot demonstrates the validity of modelled rock physics templates that have been utilized in the Alvheim area in previous studies (e.g. Avseth et al. 2009; Rimstad et al. 2012).

We also investigated properties and trends of shale data. Both Sele and Lista Fm shales were of interest, as these are caprocks of Hermod Fm sandstones and Heimdal Fm sandstones, respectively. Figure 9 shows the porosity–\(V_P\) crossplots of Sele Fm shales and Lista Fm shales, respectively. The majority of data in the Sele Fm falls close to the modelled smectite-shale model (green dashed line in Fig. 9; see Avseth et al. 2005 for more details about the model). For the Lista Fm, however, a significant portion of the data plots on top of,
Figure 9 Probabilistic plots of shale rock properties from 40 wells in the Alvheim area. The Sele Fm (left) mainly plots along a smectite-shale model (shale model explained in Avseth et al. 2005). The Lista Fm shales (right) show a larger spread, with tails along the illite shale model.

Figure 10 Shale depth trends for Sele and Lista Fm-s. The Dræge shale model is superimposed, and we can clearly see the smectite-to-illite transition in the Lista Fm. For the Sele Fm, most of the data are still in the smectite-rich range.

or even above, the modelled illite shale model (blue line in Fig. 9). The transition from smectite-rich shales to illite-rich shales is even more evident in the depth trends shown in Fig. 10. For Lista Fm shales, we clearly see an en echelon pattern over a transition zone from smectite-rich to illite-rich shales. The superimposed model is taken from Avseth et al. (2008) where shale depth trends were modelled using the Dræge et al. (2006) shale model and compared with data from the Alvheim field. The Dræge model is an inclusion-based model where anisotropy is also accounted for (Fig. 10). The smectite-to-illite transition is known to happen in marine shales at around [60–80]°C, and for the Sele Fm data, we observe mostly smectite-rich shales. According to the model, this is because the smectite-to-illite transition has not occurred, as opposed to what we see in the lower parts of the Lista Fm shales. Quartz is a by-product of the smectite-to-illite diagenetic alteration, and microcrystalline quartz can cement and stiffen the shale (Thyberg et al. 2009). Hence, we also include a stiff (modified upper bound Hashin-Shtrikman) trend from the shale models to the quartz mineral point in Fig. 9. We do not observe a data trend following the quartz cementation line in Fig. 9, but in Fig. 10 we see some spikes of high velocities that could be quartz-cemented silty layers sourced from this diagenetic process.

### FACIES CLASSIFICATION

In order to reduce uncertainties and ambiguities in regression analysis, we first performed a facies classification of well log data, where each facies class will have a characteristic set of velocities and densities (i.e. total porosity for a given mineralogy). The facies should also be clearly explained in terms of geologic characteristics and cover all possible geological scenarios for the target depth (cf. Avseth and Mukerji 2002). We concentrated on sandstone facies with different texture, diagenesis and degree of heterogeneity. At the end, we defined five different sandstone facies, as shown in Fig. 11.

The various facies include:

1. Undercompacted, yet cemented sandstones which are often found in the Hermod Fm. These are likely injectite facies, where early overpressure has prevented mechanical compaction, and high porosities have been preserved until quartz cementation has started. They can typically have porosities in the range of [0.35–0.4], even at 2 km burial depth.

2. Normally compacted, unconsolidated, well-sorted clean sands. These are often soft, still uncemented sands, and
Elastic facies definitions for Eocene and Palaeocene sandstone facies in the Alvheim area.

1. Undercompacted, yet cemented. Typical in Hermod Fm. Likely injectites.
2. Normally compacted, unconsolidated, well sorted clean sands.
3. Cemented, clean, well sorted sst.
4. Well cemented and/or well packed sst.
5. Heterolithic sandstones (shaly sst).

Porosities are likely in the range of ca. [0.3–0.35]. They are commonly found in the Frigg Fm, part of Hermod, or even upper parts of Heimdal Fm in some wells where cementation has not yet started, or has been delayed due to some geological factors (e.g. clay coating, early migration of oil and oil-wetted grains).

3. Cemented, clean, well-sorted sandstones. These are often found in Heimdal Fm or even parts of Hermod Fm. They are normally compacted and slightly cemented. Porosities are normally in the range of ca. [0.25–0.35].

4. Well-cemented and/or well-packed sandstones. These are typically the deeper parts of Heimdal, or the Ty Fm sandstones, with porosities in the range of ca. [0.15–0.25]. Cement volumes are significant, as the sandstones have been buried way below the critical temperature for onset of quartz cementation (>70°C).

5. Heterolithic/shaly sandstones. They are normally more poorly sorted and/or with more shaly components, either as pore-filling clays and/or as laminations. The porosities tend to be lower than for clean sandstones, but velocities can be higher than for clean, unconsolidated sands and lower than for clean cemented sandstones. These facies are often abandonment facies on the top of Heimdal Fm submarine fan systems, or overbank/levee facies in more channelized systems of Hermod and Frigg formations.

Facies classification has been performed on the various sandstone intervals for the wells available, using the Mahalanobis distance method (Mahalanobis 1936). This is a linear or quadratic discriminant analysis method and it can be defined as follows:

\[ D = \sqrt{(x - \mu)^T C^{-1} (x - \mu)}. \]  

Here, \( x \) is the sample feature vector (measured attribute), \( \mu \) is the vector of the attribute means for different categories or facies classes, and \( C \) is the training data covariance matrix. The Mahalanobis distance can be interpreted as the usual Euclidian distance scaled by the covariance. This is done in order to decorrelate and normalize the components of the feature vector. Instead of using all the data as training data, we actually use only the means and the covariances of the training data during the classification; hence, we talk about training ellipses instead of training data below. The underlying assumption is that the input features follow Gaussian distribution. So, a given set of measured attributes \( x \) (e.g. well log velocity and porosity) would be classified as the facies to which it is the 'nearest' in terms of the Mahalanobis distance. If covariances are different for different classes, as in our case, we are dealing with quadratic discriminant surfaces. Prior probabilities can be added as an extra term, \( \ln[P(\text{class})] \) to the right side of equation (1) if these are assumed to be different for different classes (Avseth et al. 2005). Both linear and quadratic discriminant classifiers are simple classifiers that can produce very good results compared with more advanced classifier methods (e.g. Bayesian classifiers and neural network methods; see Avseth and Mukerji 2002). Even better performance may be achieved by generalizations of linear discriminant analysis, such as flexible discriminant analysis and mixture discriminant analysis, as described by Hastie et al. (2001). It is important to make a note here that our goal is not to obtain a "perfect" facies classification, but to group data into major clusters or categories that will make the linear regression analysis more robust.

Figure 12 shows the classification results using predefined training ellipses for the various wells that include the
Figure 12 Facies classification results for Hermod Fm. Note that data falling below soft bound in crossplot to the left are not included in the classification.

Hermod Fm. The figure includes a porosity-$V_p$ crossplot (left) and a pie chart map (right) where the proportions of various facies are indicated for each well. The size of the pies is proportional to the thickness of the sandstone interval. The pie chart maps are useful to assess the distribution of elastic facies geographically in the studied area. These maps can be compared with seismic amplitude maps and can aid in the interpretation of seismic facies. Note that for Hermod Fm, several of the wells have large portions of facies 1, which is the injectite facies.

Figure 13 Facies classification results for Heimdal Fm.

Facies classification results for Heimdal Fm are shown in Fig. 13. Here we see that for most of the wells, facies 3 and 4 are predominantly present. However, in well 25/4-11, there is a significant portion of Facies 1 (injectites). Focusing on the upper 10-m interval (Fig. 14), we see that both 25/4-11 and 25/1-2 in the northern area of the map have more than 50% injectite facies. This is interesting information extracted from the elastic facies analysis when considering the fact that well 25/4-11 was drilled based on a soft anomaly that was believed to be hydrocarbon-filled Heimdal Fm.
sandstones, but turned out to be a high-porosity water-filled sandstone.

We can superimpose the pie chart for the upper 10-m Heimdal interval on top of a seismic attribute map (i.e. frequency decomposition colour blending, where brighter colours correlate with the presence of reservoir sands) extracted for Top Heimdal Formation (Fig. 15). Here we see that the wells falling along the main feeder channel system in the Alvheim area have normally compacted and cemented sandstone facies. Injectite and heterolithic facies seem to be located outside the main feeder channels. There are probably both diagenetic and depositional variations affecting the map view in Fig. 15, and there may be competing effects of maximum burial depth and depositional sub-environment giving a rather complex distribution. However, the most typical Heimdal Fm sandstones seem to be located along the main fairways that we observe from the seismic attribute map.

We can also investigate the facies classification results on the well log data. An example is shown in Fig. 16, for well 24/9-3. In this well, Frigg, Hermod and Heimdal Fm-s are penetrated. It is easy to see that there is a depth trend in the facies classification, with mostly unconsolidated sands in the Frigg Fm, predominantly injectite facies in the Hermod Fm, and a gradual change from mostly facies 3 to facies 4 in the Heimdal Fm.

A more sophisticated facies classification using more log data and higher dimension machine learning algorithms could have been undertaken in this study (cf. Hall 2016).

However, as mentioned above, the goal here is to show that grouping data into only a few geologically distinct facies has a strong impact on the regression analysis, as will be documented below. Also, it has been shown that porosity–velocity crossplots contain a lot of information about both
diagenetic and depositional trends in sandstone data (cf. Avseth et al. 2010), so we do not really need to apply higher dimensions for this purpose. This is also time saving with respect to QC of input well log data and facies classification results.

**REGRESSION ANALYSIS**

Finally, we performed multiple linear regressions on the available (and cleaned/sorted) data. After a thorough analysis, we found it most useful to perform regressions of elastic properties per facies, with porosity and clay volume as ‘predictors’.

Figure 16  Facies classification in well 24/9-3.

Figure 17  Facies-constrained regression planes of elastic properties. Regression predictors include porosity and clay volume. Porosity can be replaced by burial depth; this will better capture depth dependencies in the regression, and no interaction is expected with clay volume.
Figure 18 Calculation results using porosity and clay volume as predictors to estimate density, $V_p$ and $V_s$; example from well 24/6-2. Calculation is only performed in the sandy intervals, that is, $V_{sh} < 0.5$. Note the improved prediction results when honouring formation and facies (subplots IIIa–IIIe), which is also quantitatively captured in a smaller RMSE number for all elastic parameters (e.g. RMSE[$V_p$] decreases from 0.21 km/s in Ic to 0.11 km/s in IIIc). Key to other abbreviations: FS N, ‘No Facies Separation’ of training data; FS Y, ‘Yes Facies Separation’ of training data in multilinear regression.
Porosity and clay volume are not completely independent variables; hence, we included the interaction term ($\beta_3$ in Eq. 2) which mathematically captures the interdependence between these two parameters. The regression equation takes the following form:

\[ Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 (X_1 X_2) + \varepsilon, \]  

(2)

where $Y$ is the predicted variable ($V_P$ or $V_S$), $X_1$ and $X_2$ are the predictors, $\alpha$ and $\beta$ are regression coefficients, and $\varepsilon$ is the error term. The regression planes for different facies are shown in Fig. 17. Note that the derived coefficients are only applicable to the area of study and are considered confidential information. The main objective of this study is to show the methodology and document the improved prediction results when the regressions are constrained by predefined facies categories.

The regression results, together with the goodnesses of fits, are shown in (all three) subplots (b) and (c) in Fig. 18. We first ran regression for all sandstone data (i.e. we did not separate sandstone formations; Fig. 18a(Ia–Ie)), without honouring the facies classification. The goodness of fit for each elastic parameter is quantified by calculating the root-mean-square error (RMSE), which is a standard measure of difference between predicted and observed values (logs). The prediction results for velocities (coloured logs in subplots with elastic properties; Fig. 18a(Ic)) are quite good (e.g. RMSE[$V_P$] = 0.21 km/s), except in the shallower part (grey logs are measured log data), while the prediction results for density (Fig. 18a(Ib)) are excellent (RMSE[\rho] = 0.01 g/cm$^3$). When we constrained the regression analysis by facies (still without separation of sandstone formations; Fig. 18b(IIa–IIe)), we obtained even better match in the velocity predictions (middle subplots), which is clearly captured by the decrease of RMSE (e.g. RMSE[$V_P$] = 0.12 km/s in Fig. 18b(IIc)). Finally, if we perform regression per formation (in the case of lowermost subplots (IIa–IIIe) in Fig. 18(c), this means fit to Heimdal data from all the useful wells) and honour facies, we obtain even better velocity predictions (RMSE[$V_P$] = 0.11 km/s). The predicted logs show some erratic pattern when facies are honoured as we flip between different facies. Hence, for optimal velocity predictions, both input logs, but also the predicted logs should be smoothed/despiked.

CONCLUSIONS

We completed a detailed rock physics analysis of 53 wells in the greater Alvheim area, North Sea. We demonstrated an approach for data-driven rock physics analysis, where we first performed facies classification using elastic well log data from several wells, followed by facies-constrained multiple linear regression analysis to establish local rock physics relations for prediction of $V_P$ and $V_S$ from geological input parameters. The locally derived rock physics relations will presumably give better prediction results than using more universal rock physics models, even when the latter are locally calibrated. However, if there is a need to extrapolate away from well control, traditional rock physics models should be utilized.

The multiple linear regressions provide us with local empirical relationships between elastic ($V_P$, $V_S$ and density) and geological parameters (volume of clay, porosity/burial depth). Interactions between clay volume and porosity can optionally be implemented in the regression analysis, as pore-filling clay may affect the porosities at a given depth. However, if clay is laminated, it will not necessarily affect the porosities much. The facies classification helps to constrain the regressions and gives improved velocity predictions.

The resulting local rock physics relations from this study can be used as input to create training data for AVO classification. Furthermore, pseudo-wells/training data can be generated from the obtained regression models. These training data can then be used in a machine learning algorithm for the AVO classification of lithology and fluids in the Alvheim area.

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DATA AVAILABILITY STATEMENT

All well log data used in this study are currently released by Norwegian Petroleum Directorate and available for members of Diskos (The Norwegian National Data Repository for Petroleum data: www.npd.no/en/diskos). Petrophysical (CPI) logs used in this study were provided by AkerBP and are considered proprietary.

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