Prediction of leak-off pressure in Norwegian offshore using NPD database and deep neural network

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Introduction

Leak-off pressure (LOP) is defined as the well pressure that can create the fracture and fluid leak into the formation (Fjær et al., 2008). The LOP is important parameter to determine the upper limit of drilling mud and in-situ horizontal stress, and it is one of the common test procedure during the well drilling. In offshore Norway, there are more than 1700 exploration and 4600 development wells. This study analyzes the wellbore database to get better understanding on the stress condition in subsurface Norwegian continental shelf. The LOP were predicted using deep neural network (DNN) (Bengio, 2009) and the analyzed data.

Data analysis

This study collected around 3000 leak-off tests from 1799 Exploration wells in offshore Norway. The well data comes from the NPD factpages (NPD, 2017). Norwegian Petroleum Directorate (NPD) provides database information regarding the petroleum activities on Norwegian continental shelf through the NPD factpages. Figure 1 shows the collected leak-off test data. The figure shows that the LOP is increasing with depth. The data from the Barents Sea (i.e. blue dots) shows more variation in the profile than the Norwegian Sea and the North Sea. The collected data were correlated to the spatial and regional information. The correlation matrix (Figure 2) shows that the LOP has a strong positive correlation with the LOP depth and moderate negative relationship with the water depth.

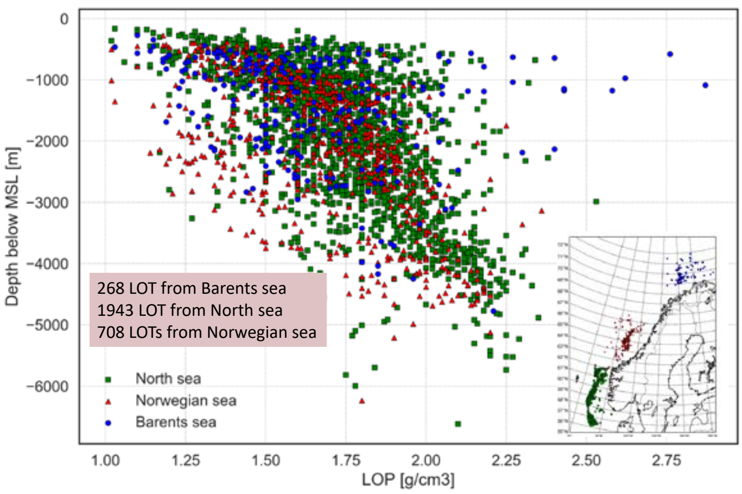

Fig. 1: Collected leak-off test data from NPD factpages (NPD, 2017).

Prediction model using DNN

The analyzed data were used to train prediction model using the deep neural network (DNN) model. The DNN model was constructed by the open source library Keras (Chollet, 2015) with a Tensor Flow, which is an open source machine learning framework by Google (Abadi et al., 2016), as a backbone. The model tested different size of hidden layers (i.e. 3, 5, 10 layers) and neurons. To avoid overfitting, early stopping algorithm was applied. 80% of data (i.e. around 2300 leak-off test data) were used for training set and the rest are used to validate the model. When the predicted data were compared to the measured data (Figure 3), the DNN model predicted LOP quite accurately. Especially, the DNN model can predict the LOP quite accurately even in shallow depth, which has large variation of the value.

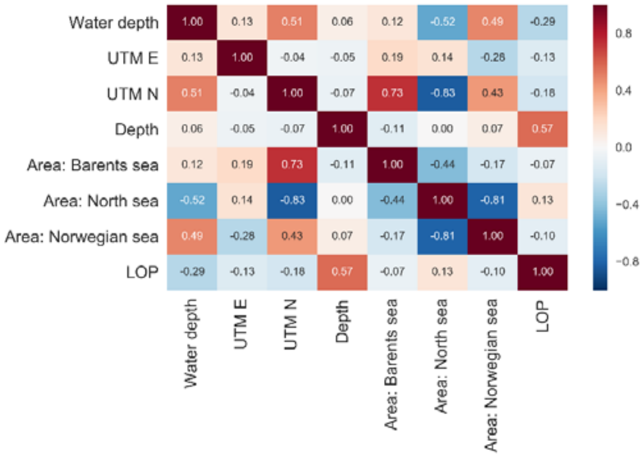

Fig. 2: Correlation matrix

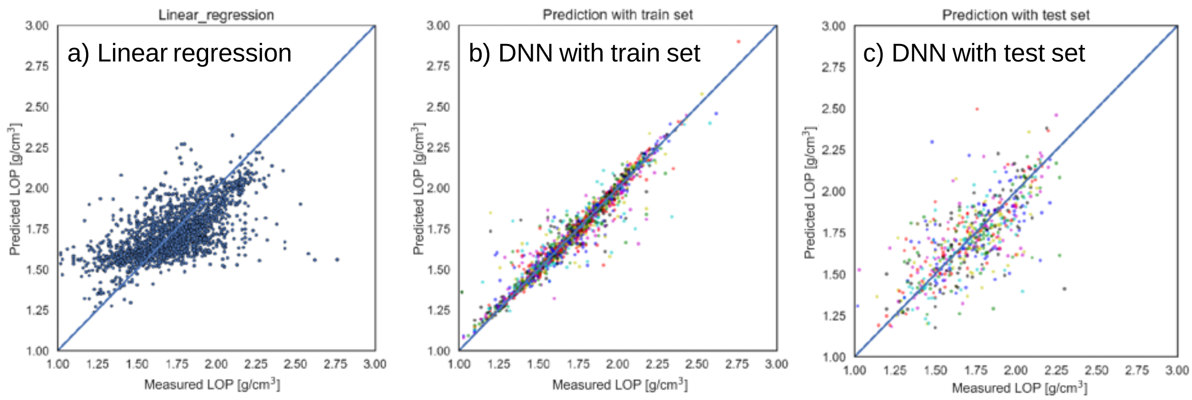

Fig. 3: Measured LOP versus predicted value using a) linear regression, b) DNN model with training set, and c) DNN model with test set. The model plotted in b) and c) used 10 hidden layers

Conclusion

The results indicate that the suggested method using DNN can be a powerful approach to predict LOP for pre-drilling studies as well as geomechanics studies, and especially for regional scale developments (e.g. large scale CO2 storage). Although this feasibility study is based on a limited amount of correlations parameters, the prediction can be enhanced through analyzing more available correlation parameters normally influencing LOP (operational factors, lithology type, geomechanical parameters from logs, pore pressure, geological history) in future study. The methodology can also be applied on other field test data, i.e. extended leak off tests (XLOT) and minifrac tests, to enhance prediction for minimum horizontal stress. However, these datasets are not available through NPD fact pages (NPD, 2017) so far. It should also be noted that quality of LOP tests and individual interpretations can vary. The variation in the quality can also add uncertainty of big database like NPD. Better way to quality control of the data should also be a part of further evaluation.

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