# Machine learning approach for vertical permeability prediction and permeability anisotropy of Hugin sandstone formation: Data driven model (Volve field)

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## Abstract

Permeability is one of the most important petrophysical properties of a reservoir that needs to be measured or estimated for oil and gas field development. In particular, permeability anisotropy helps to understand the contrast between the vertical and horizontal flow of fluid in the reservoir and helps in planning development wells for exploitation of the reservoir.
This study is carried out for prediction of vertical permeability using machine learning approach and analysis the nature of anisotropy of Hugin formation (Volve field). The top to bottom measured depth interval of the formation is about 100 m at a depth of 3820 m reference at rotary Kelly bushing (RKB) of interested well. 619 samples of well logs and 96 samples of core data of same well are used for making data driven model. The best model among different models is used for prediction with the accuracy correlation coefficient ($R^2$) of 0.83 on validation data set. Core data is used to validate it further.

## Introduction

During the development phase of a field, reservoir permeability anisotropy plays a major role in reservoir simulation studies. It also helps in optimizing the injector and producer wells at the time of secondary and enhanced oil recovery for the best field operations (Sinan *et al*., 2020; Al-Obaidi and Khalaf, 2017). Permeability anisotropy is also linked to rock mechanical anisotropy which is used by the petrophysicists to analyze borehole stability problems during drilling operations (Asaka and Holt, 2021).

Depending upon the directions, there are two types of permeabilities that are generally discussed in the literature (Zagrebelnyy *et al*., 2017; Aliouane *et al.*, 2012). Vertical permeability (Kv) is perpendicular whereas horizontal permeability (Kh) is parallel to the bedding plane. The ratio (Kv/Kh) is an important parameter which represents the contrast between horizontal and vertical planes within the subsurface formation.

Empirical relationships are often used to estimate permeabilities from various combinations of well logs. However, with the recent success of machine learning (ML) algorithms in various areas including oil and gas industry, an attempt is made to predict permeability with machine learning approach. We have used five different ML algorithms to train the model with available core data of well '15_9-19 A' of Volve field. The well logs of the same well are prepared as blind test data for the best ML trained model for prediction of Kv. The well logs attribute Kh is soft data which is estimated by multi variable regression analysis for Volve field (Solfjell and Lehne, 2006). Data pre-processing plays a crucial role in building a usable ML data driven model. It involves different techniques which are implemented in a sequential approach based on the target to achieve. A number of experiments are done to find the best techniques for data cleaning, logs smoothing, feature correlation, normalization, and removal of outliers.

## Methodology

Two different approaches of supervised machine learning algorithms are used: shallow learning models and tree-based models including ensemble models for training the data. The shallow models are multi linear regression (MLR) & artificial neural network (ANN). The tree-based regression models are based on decision tree (DT), gradient boosting regression (GB) and random forest (RF). A complex and hybrid model with many parameters may not be necessary and there are chances of overfitting for this low dimension regression problem.

The wireline logs measured, and derived properties are used as log attributes, namely, porosity (PHIF), water saturation (SW), volume of shale (VSH), bulk volume water (BVW), and horizontal permeability (Kh), hydraulic mean radius (HMR). All these attributes are independent features of ML models and functions of Kv. However, the dependent attribute, i.e., target, is core data Kv. The HMR is a new feature derived from domain knowledge and feature engineering concept. In this approach the ML model is trained by considering core data Kv as target and the corresponding well logs attributes as inputs from the pre-processing of well logs. The data processing can be intensive and time-consuming, and it takes 40% to 60 % of the total work time needed for training of the dataset.

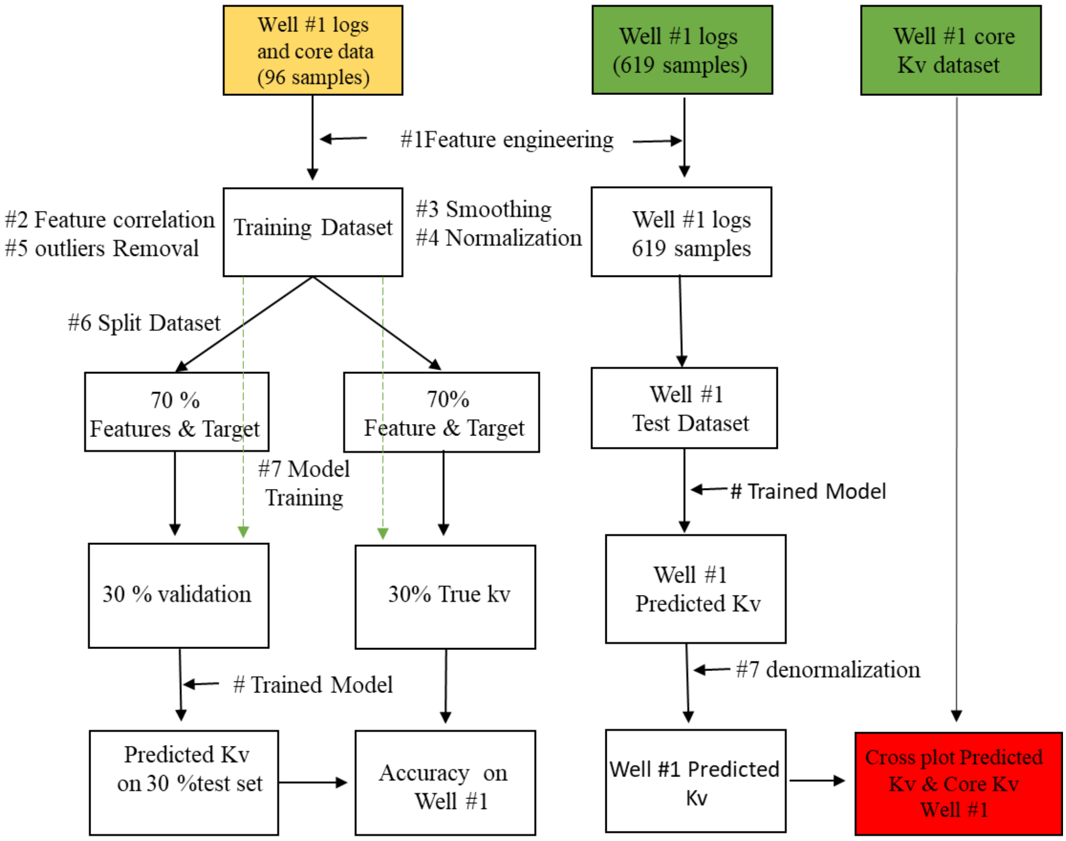


Figure 1: The schematic diagram showing workflow of data processing, model training from well logs and core data, model validation, and prediction on blind test data of well #1 logs.

## Results

Performances of all ML models have been evaluated based on three metric scores, namely, coefficient of correlation ($R^2$), mean squared error (MSE), and mean absolute error (MAE). Random Forest (RF) outperformed among all ML models.

The correlation coefficient ($R^2$) for RF model is 0.87 on validation data set and MSE is 0.12. In case of the shallow model, MLR performs better than ANN for which $R^2$ and MSE are 0.73 and 0.24, respectively. Finally, the best ML model is used for prediction of Kv for well #1. The predicted Kv log is validated by plotting the core data along with it.

Table 1: Prediction performance of models is evaluated using the metrics. The table shows the performance of all models on 30% of validation dataset.

| Metric On test/validation dataset | MLR | ANN | DT | GB | RF |
|---|---|---|---|---|---|
| $R^2$ | 0.73 | 0.21 | 0.69 | 0.83 | 0.87 |
| MSE | 0.24 | 0.73 | 0.28 | 0.15 | 0.12 |
| MAE | 0.36 | 0.69 | 0.4 | 0.3 | 0.24 |

The ratio Kv/Kh is used to represent the reservoir anisotropy. Typically, $Log_{10}$(Kv/Kh) is calculated to show if the reservoir is vertically anisotropic (the value is positive). In Figure 2, the value of $Log_{10}$(Kv/Kh) has been plotted with depth for visualization and identification of anisotropic zones within Hugin formation.

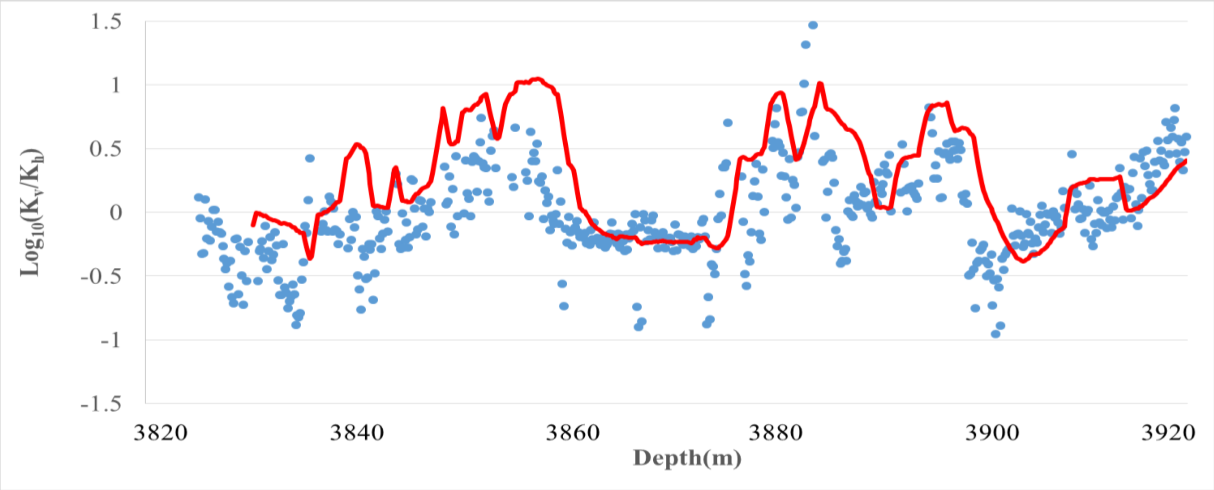


Figure 2: A plot of moving average of $Log_{10}$(Kv/Kh) ratio vs depth for Hugin sandstone formation over a depth range of 100 meters, to know whether vertical permeability anisotropy varies systematically with depth.

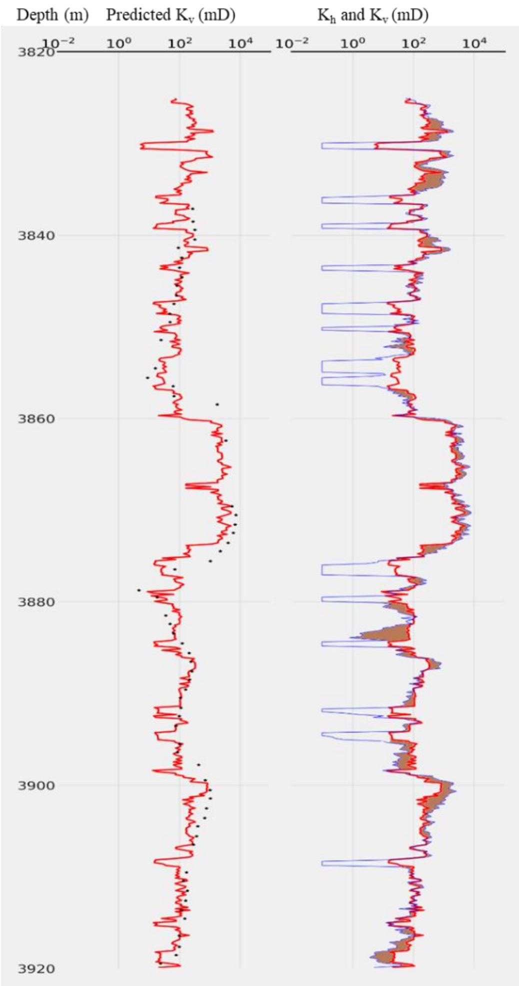


Figure 3: Track 1, red well log curve is the predicted Kv along with core data plotted and cross plot of vertical and horizontal permeability on Track 2 is showing vertical anisotropy near well bore zone.

## Conclusions

The ensemble random forest ML model exhibits good prediction over the shallow learning model. However, shallow multi linear regression model performance was also fair and produced a good model among all the models for the prediction of $K_v$. The RF model was successfully tested on blind test data and validated with available field core data of the same well. The Hugin sandstone formation near well bore was a bit vertically anisotropic and can be considered as moderately anisotropic.

## Acknowledgement

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## References

Al-Obaidi, S.H. and Khalaf, F.H., 2017, The Effect of Anisotropy in Formation Permeability on the Efficiency of Cyclic Water Flooding, International Journal of Scientific & Technology Research, volume 6, issue 11, 223-226.

Aliouane L., Ouadfeul SA., Djarfour N., and Boudella A., 2012, Petrophysical Parameters Estimation from Well-Logs Data Using Multilayer Perceptron and Radial Basis Function Neural Networks. In: Huang T., Zeng Z., Li C., Leung C.S. (eds) Neural Information Processing. ICONIP 2012. Lecture Notes in Computer Science, vol 7667. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-34500-5_86

Asaka, M., and Holt, R.M., 2021, Anisotropic Wellbore Stability Analysis: Impact on Failure Prediction. Rock Mech Rock Eng 54, 583–605. https://doi.org/10.1007/s00603-020-02283-0

Sinan, S., Glover, P.W.J. and Lorinczi, P., 2020, Modelling the Impact of Anisotropy on Hydrocarbon Production in Heterogeneous Reservoirs. Transp Porous Med 133, 413–436. https://doi.org/10.1007/s11242-020-01430-z

Solfjell, E., and Lehne, K. A., 2006, *Sleipner Øst and Volve Model 2006 Hugin and Skagerrak Formation Petrophysical Evaluation*. 1–64.

Zagrebelnyy, E. V., Glushcenko, N. A., Martynov, M. E., Tsiklakov, A. M., Blinov, V. A., Weinheber, P., Karpekin, Y. A., Ezersky, D. M., and Y. S. Bugakova.2017, Permeability Anisotropy in the Thinly-Bedded Pokurskaya Formation from Advanced Wireline Logs and Formation Testers. Paper presented at the SPE Russian Petroleum Technology Conference, Moscow, Russia, October 2017. doi: https://doi.org/10.2118/187760-MS