MACHINE LEARNING APPLICATION FOR COMPRESSIONAL WAVE VELOCITY LOG PREDICTION IN SLEIPNER CO2 STORAGE, OFFSHORE NORWAY

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Summary

The compressional wave velocity (Vp) log derived from the sonic log is an essential parameter in overburden, cap, and reservoir rocks characterization. However, the sonic log is often unavailable in either the whole section or most intervals of the wells, especially at shallow depths, which interval is crucial for CO2 injection site evaluation. Therefore, in this study, we implemented two machine learning algorithms, namely random forest (RF) and multi-layer perceptron (MLP), to predict the Vp log of the Nordland caprock Shale and Utsira Formation reservoir sandstone at the Sleipner CO2 storage. The training dataset was created by involving four parameters such as gamma-ray, density, deep resistivity, and depth as initial features, and a combination of gamma-ray multiplied by density was generated as an additional feature to improve the models' predictive capabilities. Prior to the models training, several pre-processing steps such as data splitting, outliers removal, and data standardization were also carried out. The results showed the MLP algorithm has better performance, and hence, it is a more generalized model for this study than the RF. This was indicated by the higher correlation and lower error the model has after being validated with hidden datasets generated from two other wells.

Machine learning application for compressional wave velocity log prediction in Sleipner CO_2 storage, offshore Norway

Introduction

In subsurface characterization, compressional wave velocity (Vp) log derived from the sonic log is widely used for reservoir property prediction (e.g., porosity, net-to.gross, etc.), evaluate caprock quality by calculating geomechanical properties (e.g., Young's Modulus, Poisson's ratio, etc.) and generate synthetic seismic . Unfortunately, due to budget control and operational issues, the sonic log is either not always available or incomplete in many wells, especially at shallow depths (Fig. 1a) like Sleipner CO_2 storage in the North Sea, offshore Norway (Fig. 1b). Therefore, the absence of the sonic log can hinder the workflow in subsurface characterization. One common solution for this problem is to predict sonic log using empirical relations (e.g., Faust, 1953; Gardner et al., 1974) or synthesizing the missing logs based on the neighboring wells which have acquired sonic log. However, these methods have uncertainties and limitations for accurately predicting the missing log. Due to the high predictive capability of machine learning (ML), ML algorithms can give a better solution. In this study, we tested two ML methods to optimize the data analysis and predict the sonic log or compressional wave velocity (Vp) log in the Sleipner CO2 storage.

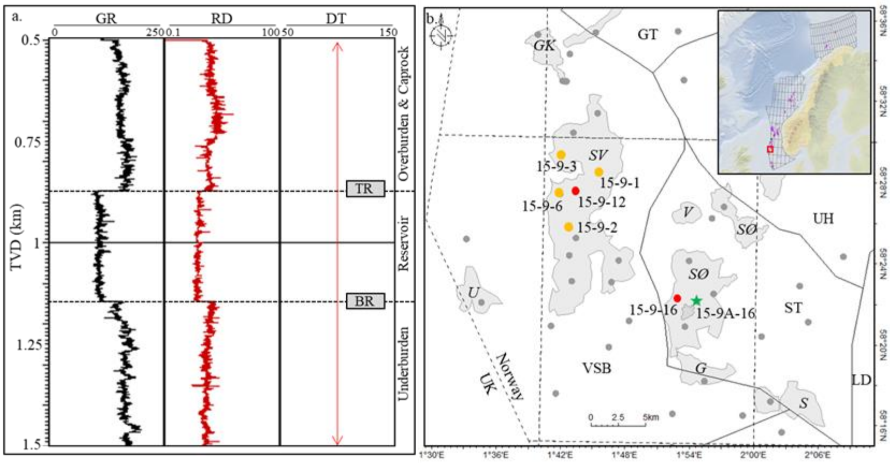

__Figure 1__ (a) The measured gamma-ray and deep resistivity of well 15_9-21S for the overburden and caprock, reservoir (TR: top reservoir, and BR: base reservoir), and underburden. However, it can be seen that the sonic log was not acquired in in those intervals. (b) The study area map representes the structural elements (VSB: Ve Sub-basin, ST: Sleipner Terrace, LT: Ling Depression, UH: Utsira High, and GT: Gudrun Terrace) and discovery fields (SV: Sleipner Vest, SØ: Sleipner Øst, U: Utgard field, G: Gungne field, S: Sigyn field, V: Volve field, and GK: Gina Krog field). Moreover, the studied wells showed in the map where yellow dots represent the training wells and red dots represent the validation wells. Additionally, the injection well in the area is marked by green star, while the rest of the exploration wells in the studied area are marked by gray dots.

The Sleipner CO_2 storage project is the first of its kind operated by Equinor since 1996. To date, a total of 24 Mt of CO_2 has been stored in the saline aquifer of the Utsira Formation Sandstone at a depth of about 1000 m that capped by the Nordland Shale (Chadwick et al., 2006). The Utsira Formation, a 200-250 m thick late Cenozoic sandstone, has been the main reservoir unit of the Sleipner CO_2 storage, while the Nordland shale acts as the primary seal of marine claystone with a thickness of around 250 m and overlain by several hundred meters of Quarternary sediments (Zweigel et al., 2004). In this study, we implemented machine learning algorithms of random forest (RF) and multi-layer perceptron (MLP) with three hidden layers and 100 neurons in each layer to estimate the Vp logs using several other logs as features such as gamma ray (GR), density (RHOB), deep resistivity (RDEP), depth, and a combination of GR multiplied by RHOB (GR×RHOB). The targeted intervals are the caprock of Nordland shale and the reservoir rock of Utsira formation of the Sleipner CCS project. A total number of 14,969 data points, which correspond to each feature, were collected from four wells to train the machine learning models. For validation purposes, the resulted models were tested on a measured dataset generated from one well within the study area.

Methodology

The general workflow is presented in Figure 2. Data sorting was the initial step in this workflow. Five wells were selected from the Sleipner Vest area, where four wells (15/9-1, 15/9-2, 15/9-3, and 15/9-6) were used for training the model while other well (15/9-12) was used for model validation. In addition, we also included one well (15/9-16) outside the clustered area, , which is located in the Sleipner Øst and near the injection well (15/9-A-16) of the Sleipner CCS project, to make a more robust validation of the models. The next process was feature selection and data splitting. Among the available logs in the wells, we selected the depth, GR, RHOB, RDEP, and generated a new parameter GR×RHOB (GR multiplied by RHOB) as features while the Vp as a target. Four wells were combined to generate a whole training dataset containing six parameters (depth, GR, RHOB, RDEP, GR×RHOB, and Vp). In addition, we also generated another dataset from wells 15/9-12 and 15/9-16, which contain only the features logs to validate the resulted models. Then, the training dataset was split into two sets: training sets (80%) and test sets (20%). Quality check was performed by removing missing values and outliers. For this purpose, we implemented Isolation Forest (Liu et al., 2008) technique to automatically detect and remove the outliers from the dataset. Finally, data standardization was done to resize the distribution of values so that the mean of the observed values is 0 and the standard deviation is 1. This is an important procedure in the pre-processing stage, especially when the input datasets are measured in different measurement units. After previous steps were successfully performed, then the training dataset was ready to be trained by the algorithms; in this case, RF and MLP algorithms were tested. In this procedure, R-squared (R^2) and root-mean-squared-error (RMSE) were used as scoring criteria to evaluate the models. Once the training process was done, the generated models were applied to the test sets. Finally, the model validation was achieved by comparing the predicted results with the measured Vp from wells 15/9-12 and 15/9-16 and computing both R^2 and RMSE to evaluate the performance and prediction accuracy.

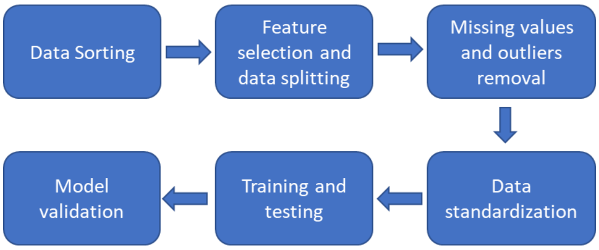

***Figure 2** Illustrated the workflow used in this study.*

Results and Discussion

This study investigated two distinct lithologies, Nordland shale caprock and Utsira reservoir sands, from the Sleipner CO_2 storage. When predicting the Vp in this dataset, it is important to select other parameters which can properly differentiate between these two formations to make good predictors. Therefore, we started this work by involving only three features, namely the gamma-ray, density, and deep resistivity, to predict the compressional wave velocity using the RF algorithm. However, the model performed relatively poorly on the test set with low R^2 and quite high RMSE, 0.631 and 0.082, respectively. The performance was worst when tested on the validation dataset from well 15/9-12, with even lower R^2 (0.423) and higher RMSE (0.065). The quality of the model performance increased as we added more features, and the best results were achieved when we included all five features in the training set. The use of depth in the dataset significantly increased the model performance. We also generated a new feature through feature engineering by multiplying the gamma-ray and density (GR×RHOB) to create a stronger predictor and finally, resulting in a much better model. All the results presented in Figure 3 are predictions generated by using all five features (depth, GR, RHOB, RDEP, and GR×RHOB).

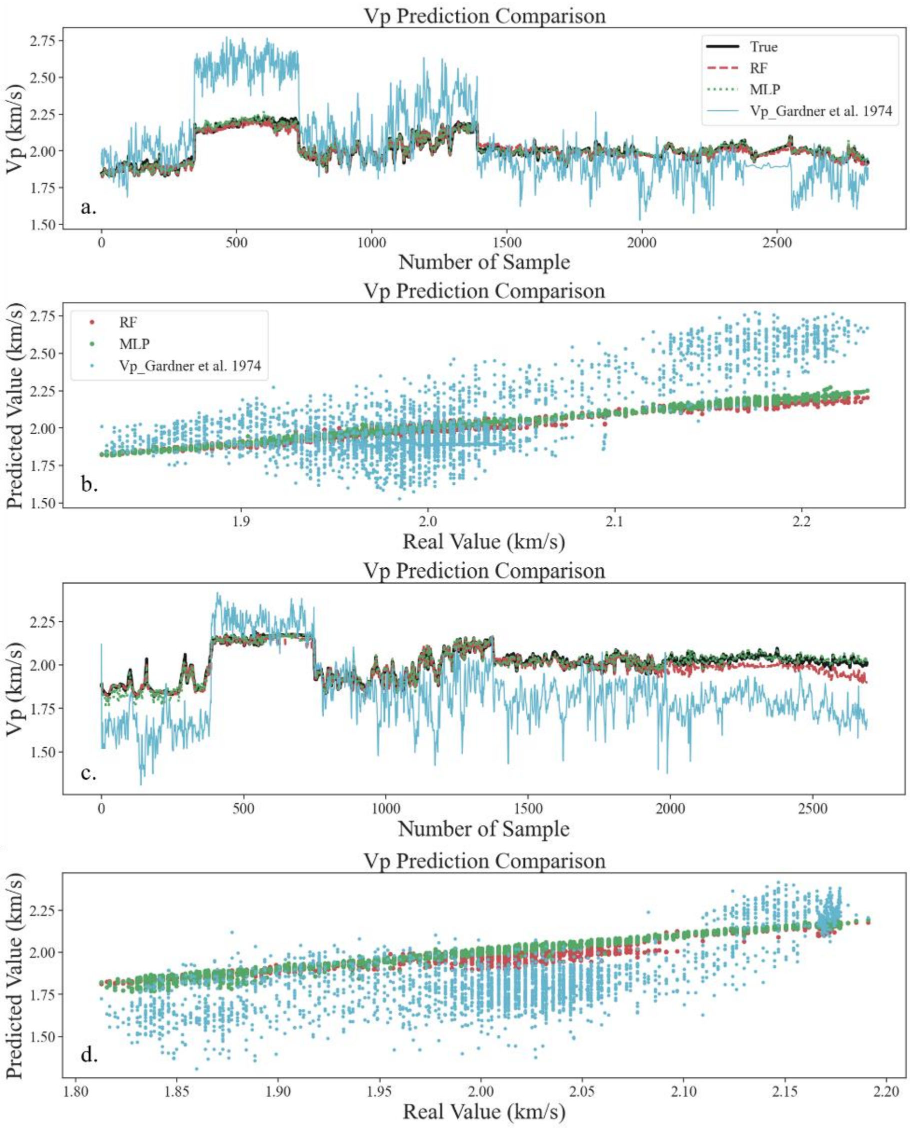

***Figure 3** Measured Vp values (solid black line) and predicted Vp values generated by random forest (dashed red line), multi-layer perceptron (dotted green line), and Gardner's equation (light blue line) plotted by the number of samples in well 15/9-12 (a) and 15/9-16 (c); and scatter plot of the predicted Vp values (random forest: red dots, multi-layer perceptron: green dots, and Gardner's equation: light blue dots) correspond to each of the measured values in well 15/9-12 (c) and 15/9-16 (d). The predictions generated from both algorithms show extremely good correlation by overlaying the measured data, however, Gardner et al. (1974) based prediction shows large discrepancies in most of the intervals compared to the measured data.*

Table 1 shows the summary of the evaluation metrics of the test and validation sets for both RF and MLP models. On the test sets, the RF exhibits a good performance, which in terms of R^2 is 0.997 and RMSE is 0.008. The MLP also performs well even though with slightly lower R^2 (0.995) and RMSE (0.009) scores. Figure 3 incorporates our predictions and comparison with real measured values on both well 15/9-12 and 15/9-16. In addition, we also included Vp calculation from density logs using Gardner's empirical equation (Gardner et al., 1974) to add more comparison to the results.

Table 1. Summary of evaluation metrics on of the test set and validation set

Dataset	R^2	RMSE
Test Set (RF)	0.997	0.008
Test Set (MLP)	0.995	0.009
Validation Set: Well 15/9-12 (RF)	0.967	0.017

Validation Set: Well 15/9-12 (MLP)	0.984	0.011
Validation Set: Well 15/9-16 (RF)	0.888	0.03
Validation Set: Well 15/9-16 (MLP)	0.974	0.014

Both machine learning models perform well on the validation dataset, either in well 15/9-12 or 15/9-16. This is indicated by how close the predicted values match with the measured ones, as shown in Figure 3. The total number of predicted Vp in well 15/9-12 is 2837 samples. As seen in Table 1, the RF model shows good performance with R^2 is 0.967 and RMSE is 0.017. However, the MLP model generated better results indicated a higher R^2 value, 0.984, and lower RMSE, 0.011. These two models also show good prediction capability when tested on the validation dataset from well 15/9-16 even though the performance indexes are relatively lower than the previous ones. The total number of predicted Vp from this well is slightly less than well 15/9-12 with 2692 samples. The R^2 of the RF model is 0.888, and the RMSE is 0.03, while the MLP shows better performance in terms of R^2 is 0.974 and RMSE is 0.014. However, the predicted Vp generated from Gardner et al. (1974) equation in both wells hardly matches the real values. From plots in Figure 3, we noticed that most of the generated Vp values are situated quite far from the real values and have significant differences compared to the measured ones, consequently leading to less accurate prediction. This is because the Gardner's equation only considers one parameter, the density, for calculating the Vp, while in the machine learning models, we considered more parameters.

Conclusions

This study successfully demonstrated the machine learning workflow to predict the compressional wave velocity (Vp) log for both the Nordland shale caprock and Utsira sandstone reservoir of Sleipner CO_2 storage by preparing datasets, training and testing regression models, and blind testing on validation datasets. According to the evaluation metrics, the MLP model outperforms the RF model by showing higher R^2 and lower RMSE values when applied on validation sets from the two wells. This also indicates that the MLP model is more generalized to be implemented in this study area. In addition, there are many other methods that can be applied to improve the models' performance and stability, such as handling the outliers with other methods, including more wells and features in the training process, and training other regression models. Splitting the datasets into two parts in terms of the lithological unit, such as shale and sand, and studying them separately could be an attempt to get even better prediction results.

Acknowledgements

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