Application of Machine Learning for Real-Time Prediction of Sonic Well Logs Using Surface Drilling Parameters and Gamma Ray

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Abstract /

The objective of this study is to utilize drilling parameters and gamma ray (GR) well logs to predict compressional and shear sonic logs while drilling using machine learning techniques. Surface drilling parameters and various wellbore logs of 10 horizontal gas wells were used in this study to train the machine learning model. The drilling parameters include the rate of penetration (ROP), weight on bit (WOB), drillpipe rotation (rpm), torque (TOR), standpipe pressure (SPP), and mud flow rate (gpm).

Petrophysical logs included GR, compressional wave slowness (DTCO), and shear wave slowness (DTSM). The GR and drilling parameters were used as inputs in the model, with the model output being DTCO and DTSM. The model was trained with the XGBoost algorithm (Extreme Gradient Boosting), and the prediction results on two blind wells showed an average absolute percentage error of less than 10%. Utilizing drilling parameters to predict well logs could have a significant business impact. This study demonstrates the application of machine learning for log prediction using drilling parameters in deep, long horizontal gas wells.

Introduction

To accurately determine the rock mechanical and petrophysical properties is crucial in mitigating drilling risks and optimizing well productivity. Compressional and shear sonic travel-time logs are critical rock petrophysical parameters, especially when it comes to formation evaluation and rock characterization for geophysical applications to predict rock elastic properties[1, 2]. Poor prediction of sonic log parameters may lead to the improper estimation of rock elastic parameters, resulting in severe consequences in investment decisions[3].

Compressional and shear sonic logs are available post-drilling using wireline logs that are often missing or incomplete. These detain the analysis to evaluate certain rock characteristics to determine elastic properties and in situ stresses. Due to the time and cost involved in logging, the industry benefits from using more efficient technologies to obtain compressional and shear sonic logs. Therefore, the industry relies on empirical correlations or machine learning models to estimate the values of the compressional and shear acoustic logs. Available correlations to estimate sonic travel-time vary significantly, making it universally unacceptable for log analysts to use these correlations instead of running wireline logs[4, 5].

Unlike wireline logs, surface drilling parameters are available in real-time and can be used to the industry's advantage. Measured surface drilling parameters are the most underutilized upstream data in oil and gas operations. Few studies have recently demonstrated the potential of using drilling parameters to estimate various reservoir parameters[6, 7]. The industry is gradually moving toward using machine learning-based analysis and working on replacing measured parameters with AI-based data.

Many studies reported different models such as Random Forest, artificial neural networks, and the Adaptive Neuro-Fuzzy Inference System to predict sonic log parameters. Recent studies discussed the advantages of using machine learning techniques in generating synthetic sonic logs using surface drilling parameters and machine learning techniques[8]; however, these studies were focused on shallow vertical wells[9] and short horizontal sections[10].

The objective of this study is to utilize drilling parameters and gamma ray (GR) well logs to predict sonic well logs while drilling using machine learning techniques. In this study, a total of 12 wells were used for training and testing the AI model. All the data used are for deep, long horizontal gas wells with laterals of approximately 3,000 ft in sandstone fields.

Methodology

The prediction of sonic logs, compressional, and shear travel-time logs was conducted using available surface drilling parameters and various well logs from different wells to train a machine learning model in Python. The model was first trained with multiple machine learning algorithms to best fit the predicted data with the measured data. The model with the highest accuracy was chosen for the blind prediction. The accuracy of the model was evaluated based on the mean absolute error (MAE), average absolute percentage error (AAPE), and root mean squared error (RMSE).

The first step is data processing, including cleaning, combining, and splitting the data into training data and testing data. Data processing is the most important step where corrupted or unrealistic data are removed to improve the prediction model's performance. The model contained 12 wells; 10 wells were used in training with 363,087 data points and two wells for blind testing the model's results. The algorithm was first trained using a range of surface drilling parameter data for different wells to quantify their sensitivity toward the measured sonic data. The input parameters in the model training included the rate of penetration (ROP), weight on bit (WOB), drillpipe rotation (rpm), torque (TOR), standpipe pressure (SPP), and mud flow rate (gpm). Well logs included GR, compressional wave slowness (DTCO), and shear wave slowness (DTSM). The GR and drilling parameters were used as inputs in the model, with model outputs being DTCO and DTSM.

Using 10 deep horizontal wells, the machine learning model was trained with the XGBoost algorithm (Extreme Gradient Boosting). DTCO was predicted first, and then DTSM, since only one parameter at a time can be predicted using the XGBoost algorithm. The model included seven relevant input parameters — GR and six drilling parameters — to make the prediction. The model was fine-tuned for hyperparameters and checked for robustness by training on nine wells and predicting one well before making the blind prediction for two wells for testing.

Results

The first step after cleaning the data was to use a range of surface drilling parameter data for the model's inputs and check for correlations between input parameters and output parameters. Figure 1 is a summary of different input parameters for the model with their Pearson correlation coefficients to other input parameters. Highlighted in red is the correlation between DTCO and DTSM, output parameters, surface drilling parameters, and GR. This figure clearly shows that the DTCO correlates better to the input parameters than the DTSM.

The machine learning model was trained with the XGBoost algorithm using 10 deep horizontal wells for training (Wells d1 to d10) and two horizontal wells for testing (Wells d11 and d12). The developed model was evaluated by MAE, RMSE, and AAPE across the training and testing wells. The model was checked for robustness by training on nine wells and predicting one well using the training data to check for variations across all wells before testing the two blind wells. Figures 2 to 6 illustrate the predicted sonic in red vs. actual sonic logs in blue for each of the 10 wells used in the training model.

Figures 7 and 8 show the variation of the MAE, RMSE, and AAPE for the predicted DTCO and DTSM, respectively. On average, for the 10 training wells (Wells d1 to d10), the compressional sonic log prediction was 1.748 ft in terms of RMSE, 1.312 ft in terms of MAE, and 2.358% for AAPE. On the other hand, the shear sonic log prediction was 15.797 ft in terms of RMSE, 10.397 ft in terms of MAE, and 8.298% for AAPE, on average for the 10 training wells (Wells d1 to d10).

The prediction results across the training wells suggest that predicting DTCO is more straightforward

Fig. 1 *The Pearson correlation coefficients between input and output parameters. Highlighted in red is the correlation between the DTCO and DTSM, output parameters, surface drilling parameters, and GR.*

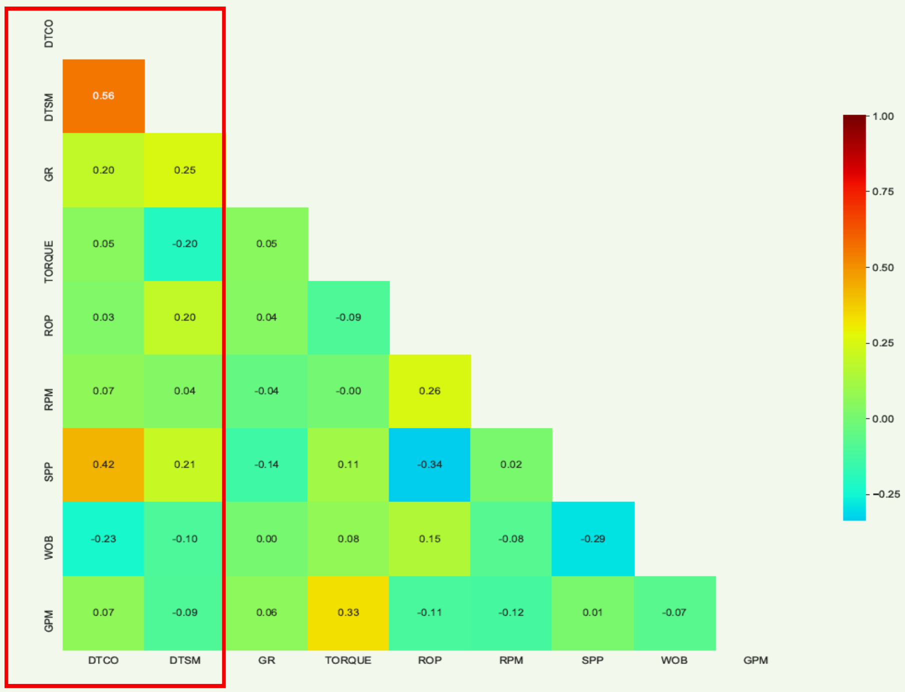


Fig. 2 *The measured and predicted (_P) sonic logs for training wells d1 (top) and d2 (bottom).*

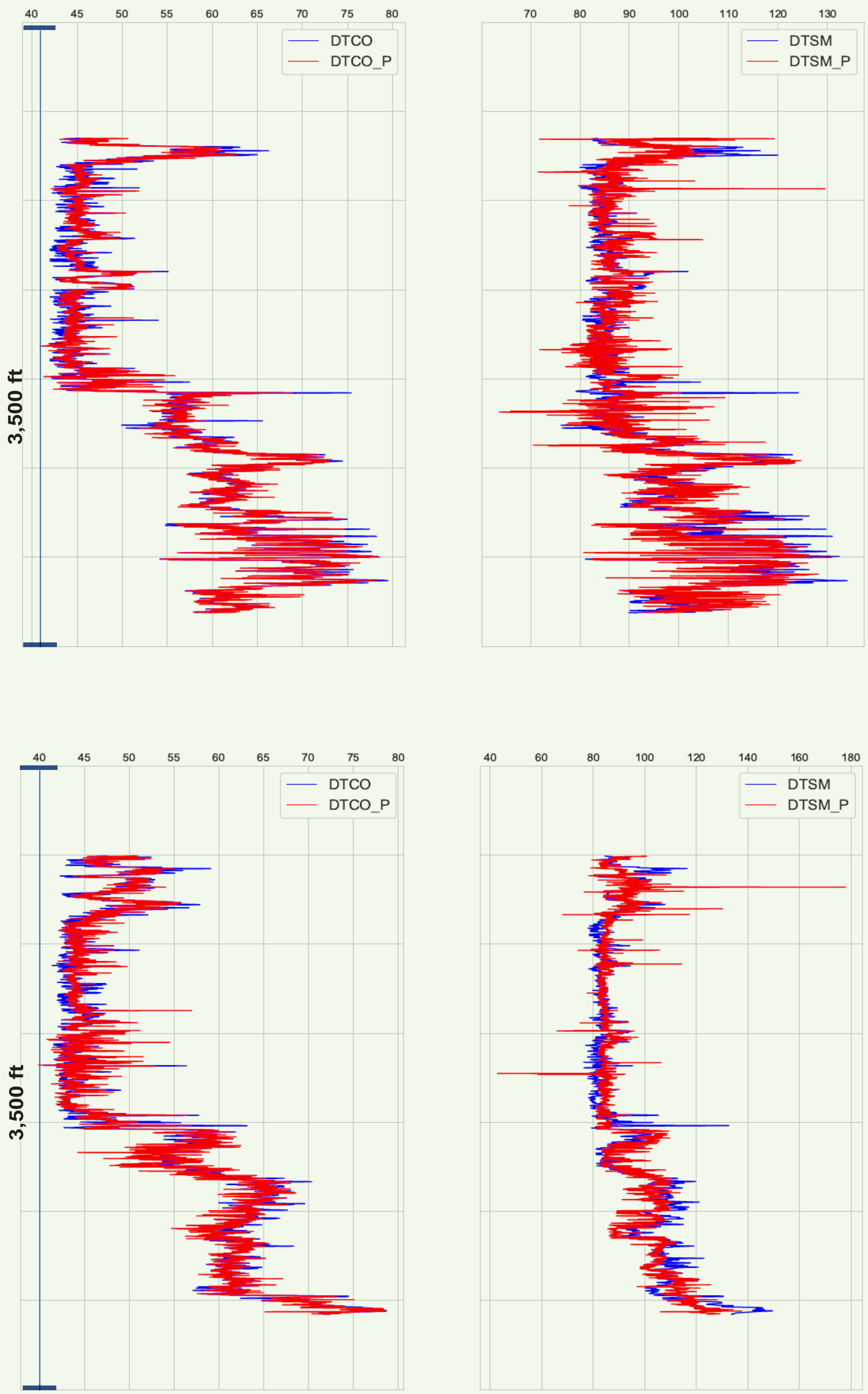


Fig. 3 The measured and predicted (_P) sonic logs for training wells d3 (top) and d4 (bottom).

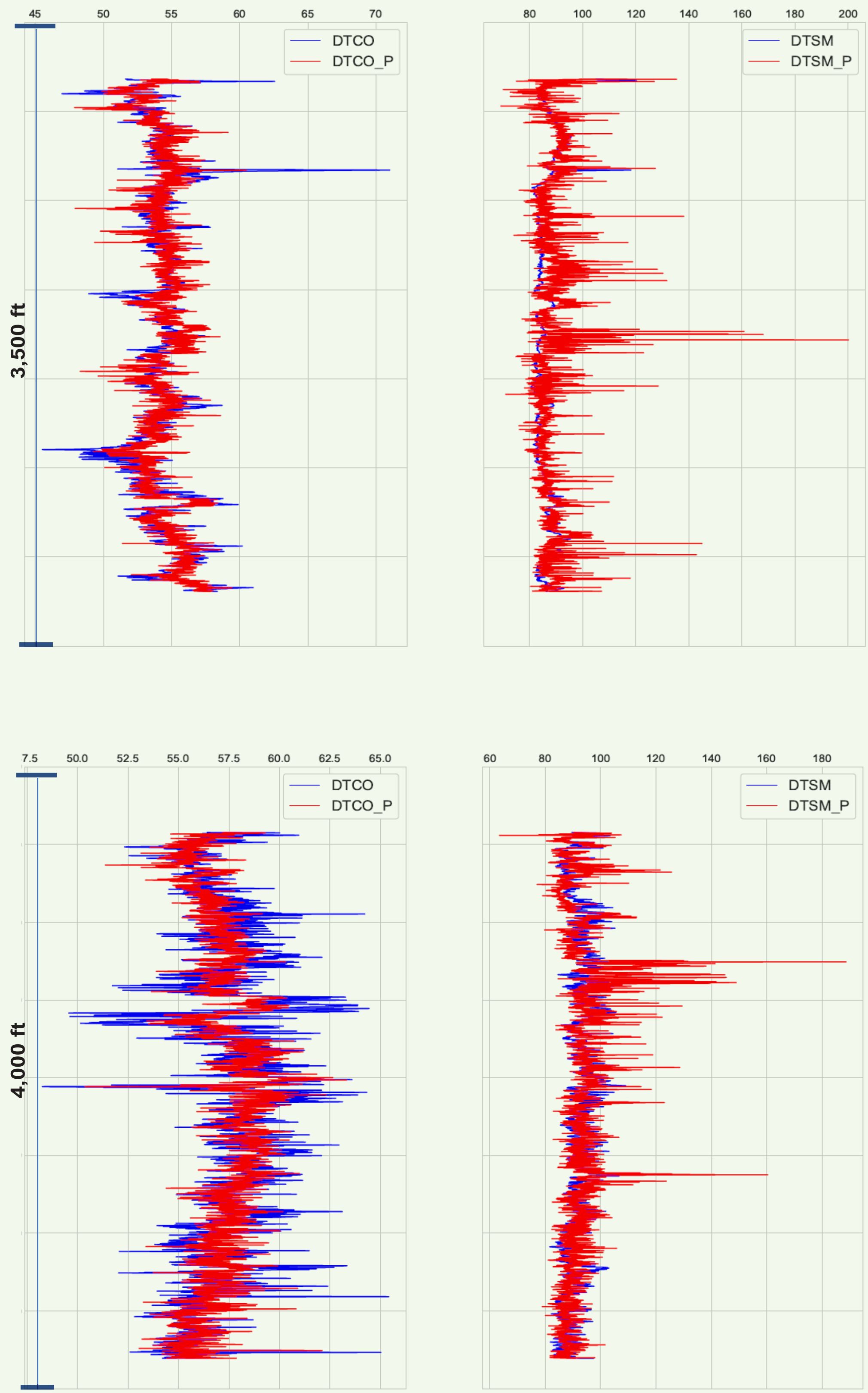


Fig. 4 The measured and predicted (_P) sonic logs for training wells d5 (top) and d6 (bottom).

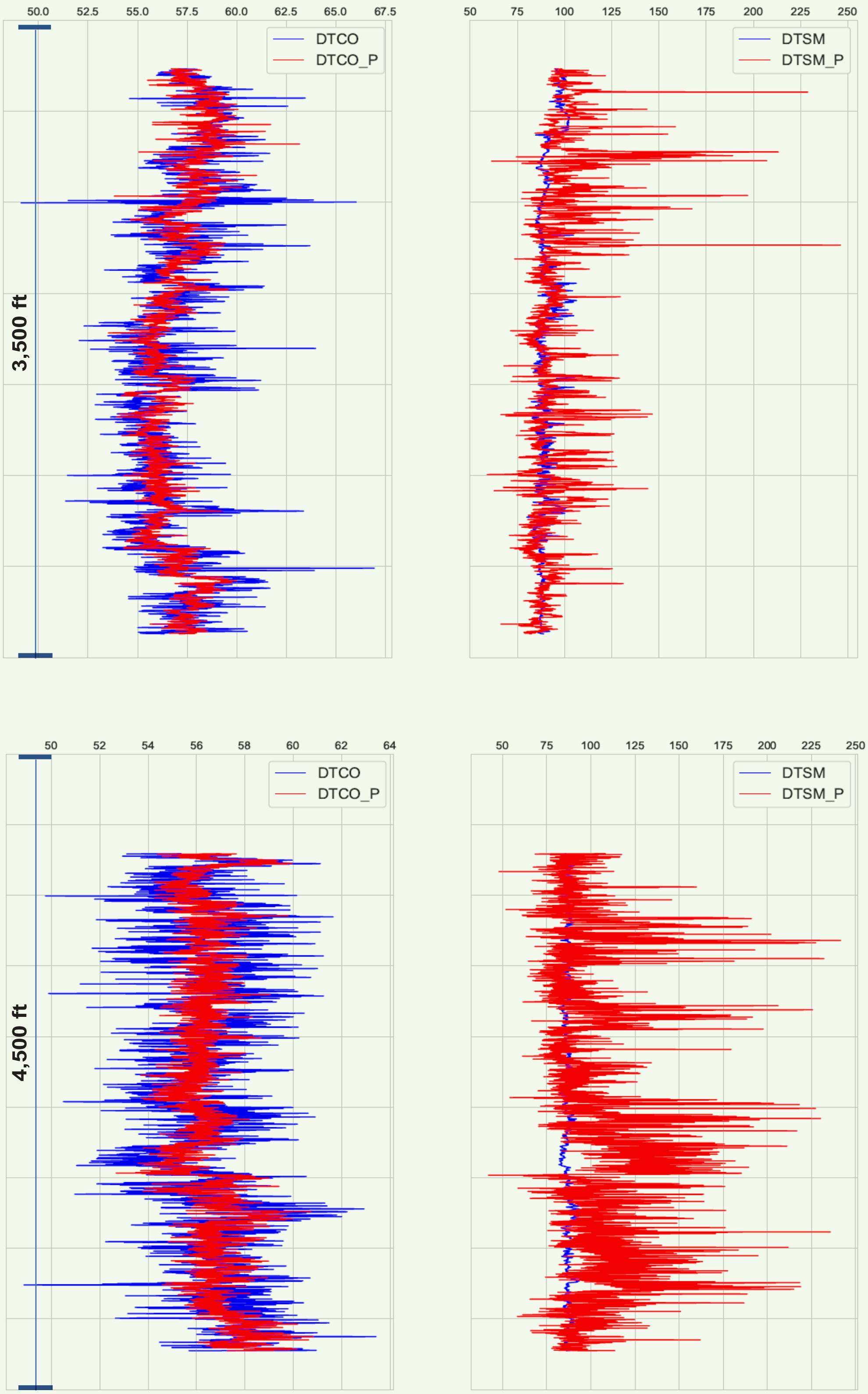


Fig. 5 The measured and predicted (_P) sonic logs for training wells d7 (top) and d8 (bottom).

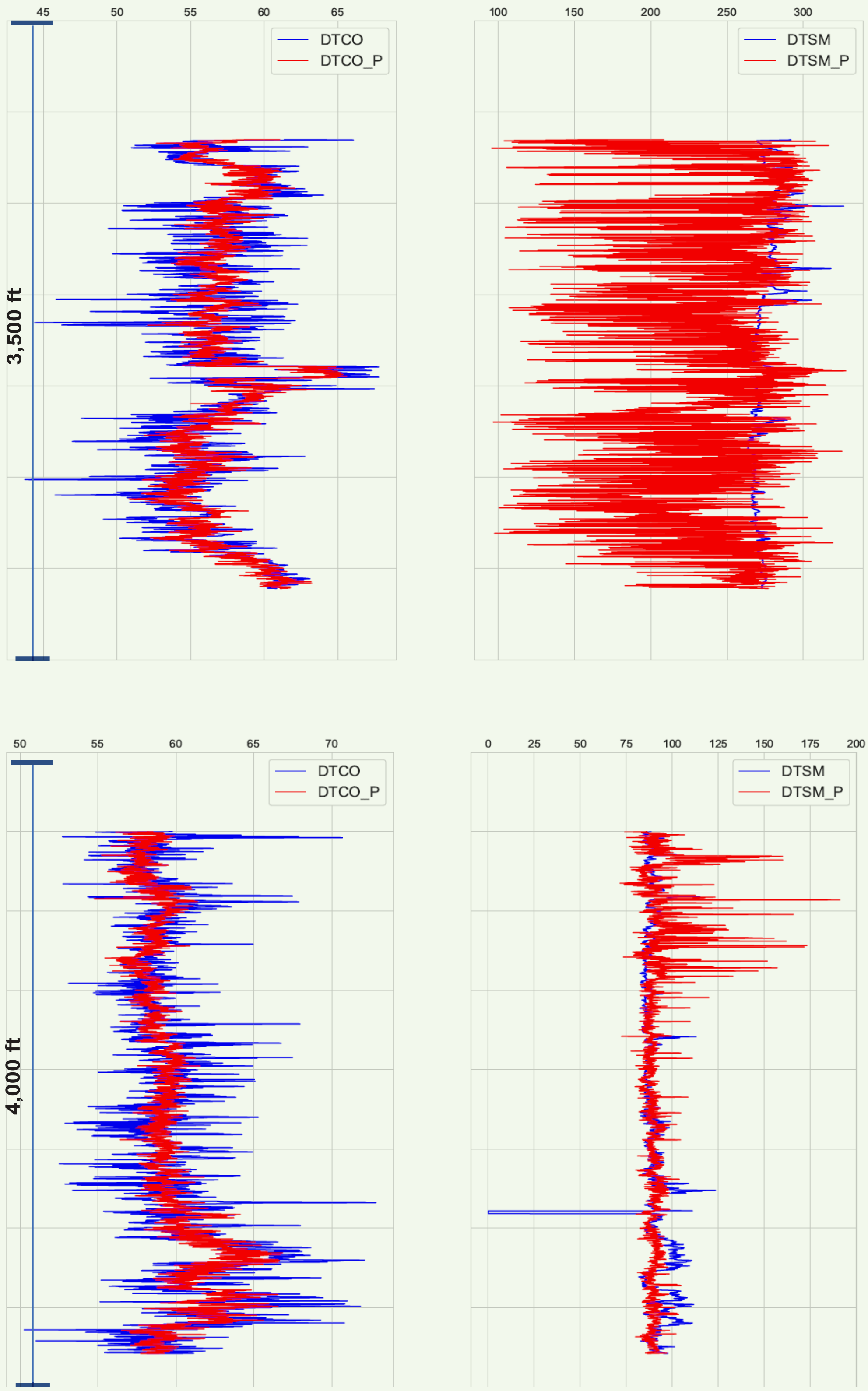


Fig. 6 *The measured and predicted (_P) sonic logs for training wells d9 (top) and d10 (bottom).*

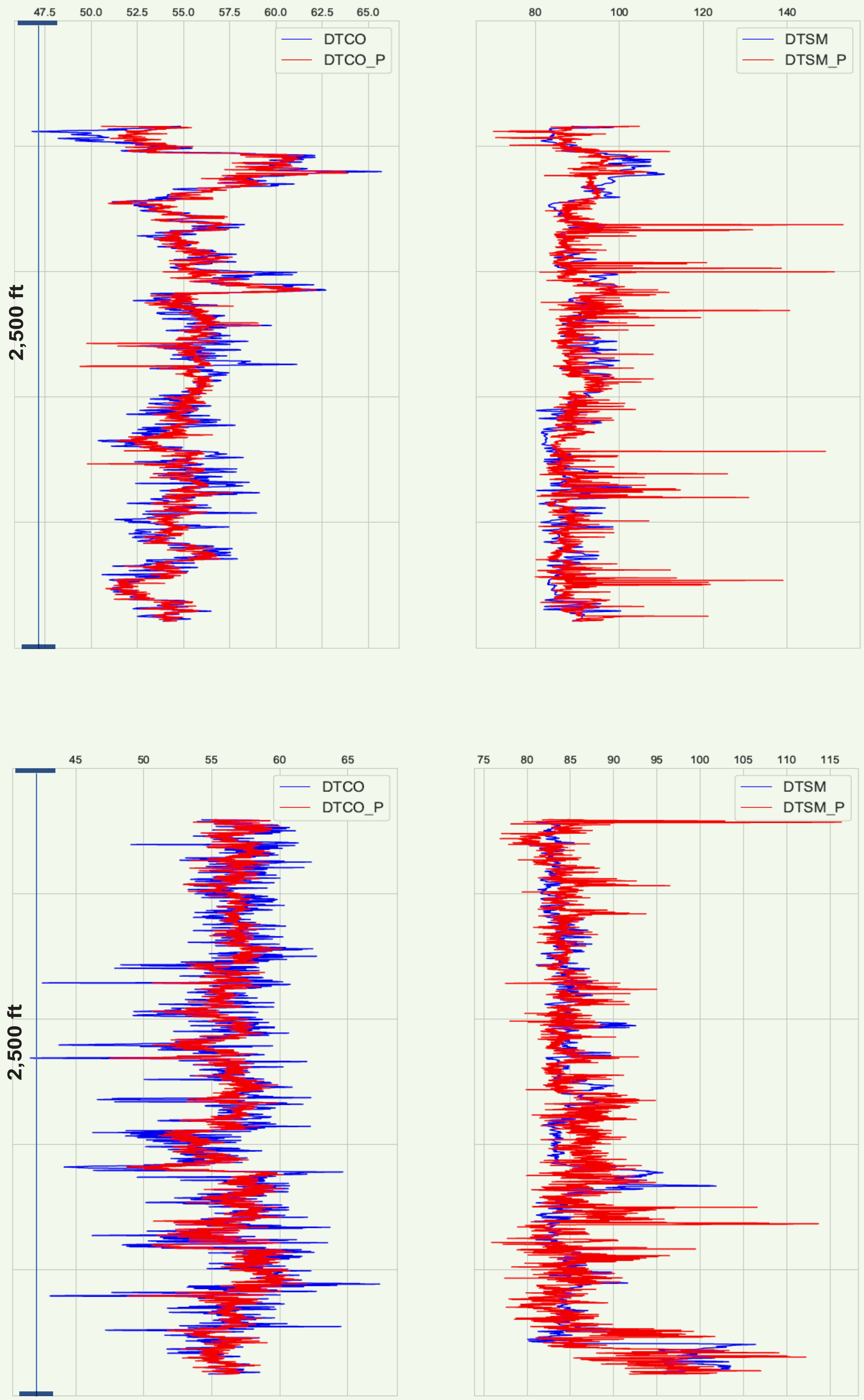
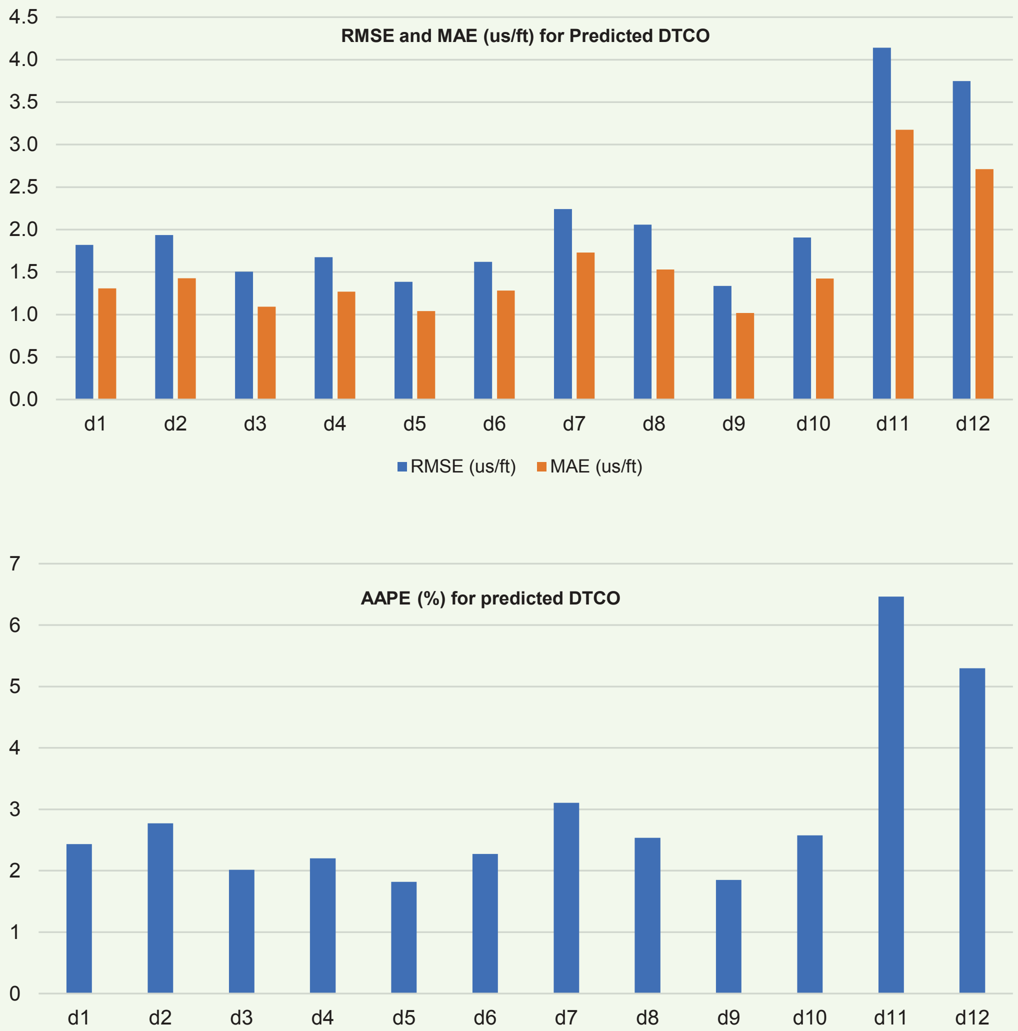


Fig. 7 The prediction error of the compressional sonic log across the training wells (Wells d1 to d10) and the testing wells (Wells d11 and d12).



than predicting DTSM. This was expected since the DTCO had a better correlation with input parameters than DTSM.

Training wells d5, d6, d7, and d8, showed the highest prediction error results for DTSM in AAPE. Among those four wells, Well-d6 had the highest AAPE of 22.6% for the predicted DTSM. The four wells were all deeper wells where the predicted values of the DTSM fluctuated significantly with either highly overestimated or highly underestimated values compared to the measured DTSM. Implementing upper and lower bounds on predicted values within the algorithm could minimize such fluctuations in predicted values.

Figures 9 and 10 show cross plots of the predicted sonic logs for blind wells d11 and d12 vs. the actual measured sonic logs, respectively. Table 1 is a summary of the error across the blind-tested wells. Figure 11 displays the GR, drilling parameters, and the measured and predicted sonic logs for the two blind wells. The testing results showed an AAPE of less than 10% for the predicted values of the DTCO and DTSM in the two blind wells.

Conclusions

Based on the data set used in this study, predicting DTCO and DTSM in deep, long horizontal gas wells appears more challenging than in shallower, vertical wells or short horizontal sections discussed in the literature. This study shows that it is possible to predict sonic logs using only GR and drilling parameters in long laterals. Utilizing drilling data with better quality could potentially improve the prediction capability.

When drilling new wells, GR and drilling parameters are almost always available. Utilizing this data to predict well logs could have a significant business impact by minimizing or eliminating the need to run logging while drilling well logs in mature fields as a cost saving measure for new planned wells.

Fig. 8 *The prediction error of the shear sonic logs across the training wells (Wells d1 to d10) and the testing wells (Wells d11 and d12).*

Fig. 9 *The predicted sonic log vs. actual sonic log of blind Well-d11.*

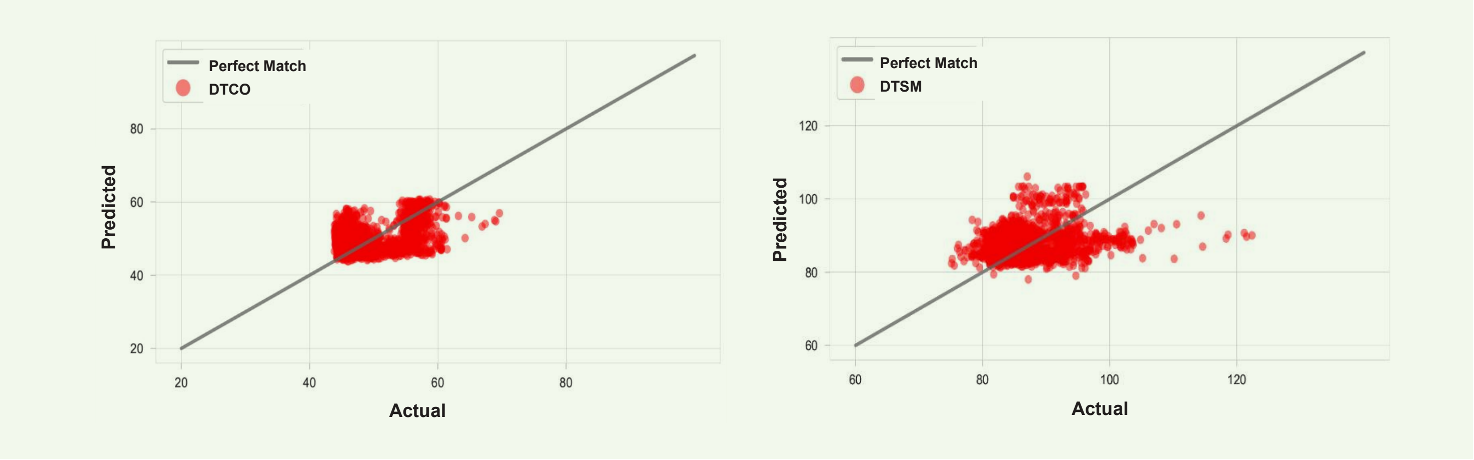


Fig. 10 The predicted sonic log vs. actual sonic log of blind Well-d12.

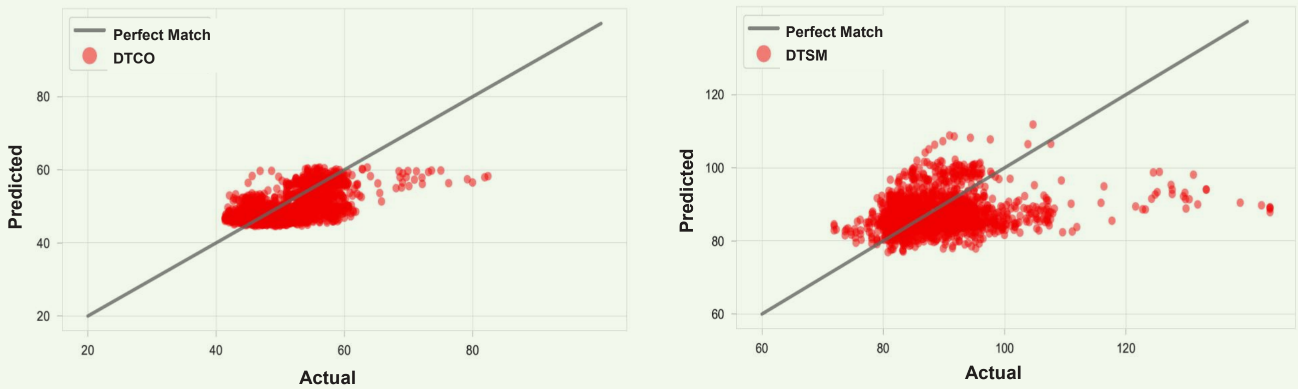


Table 1 A summary of the prediction error in the testing wells.

Prediction	Testing Well	RMSE (ft)	MAE (ft)	AAPE (%)
DTCO	d11	4.141	3.175	6.462
DTSM	d11	5.028	3.693	4.219
DTCO	d12	3.746	2.711	5.298
DTSM	d12	6.709	4.557	5.024

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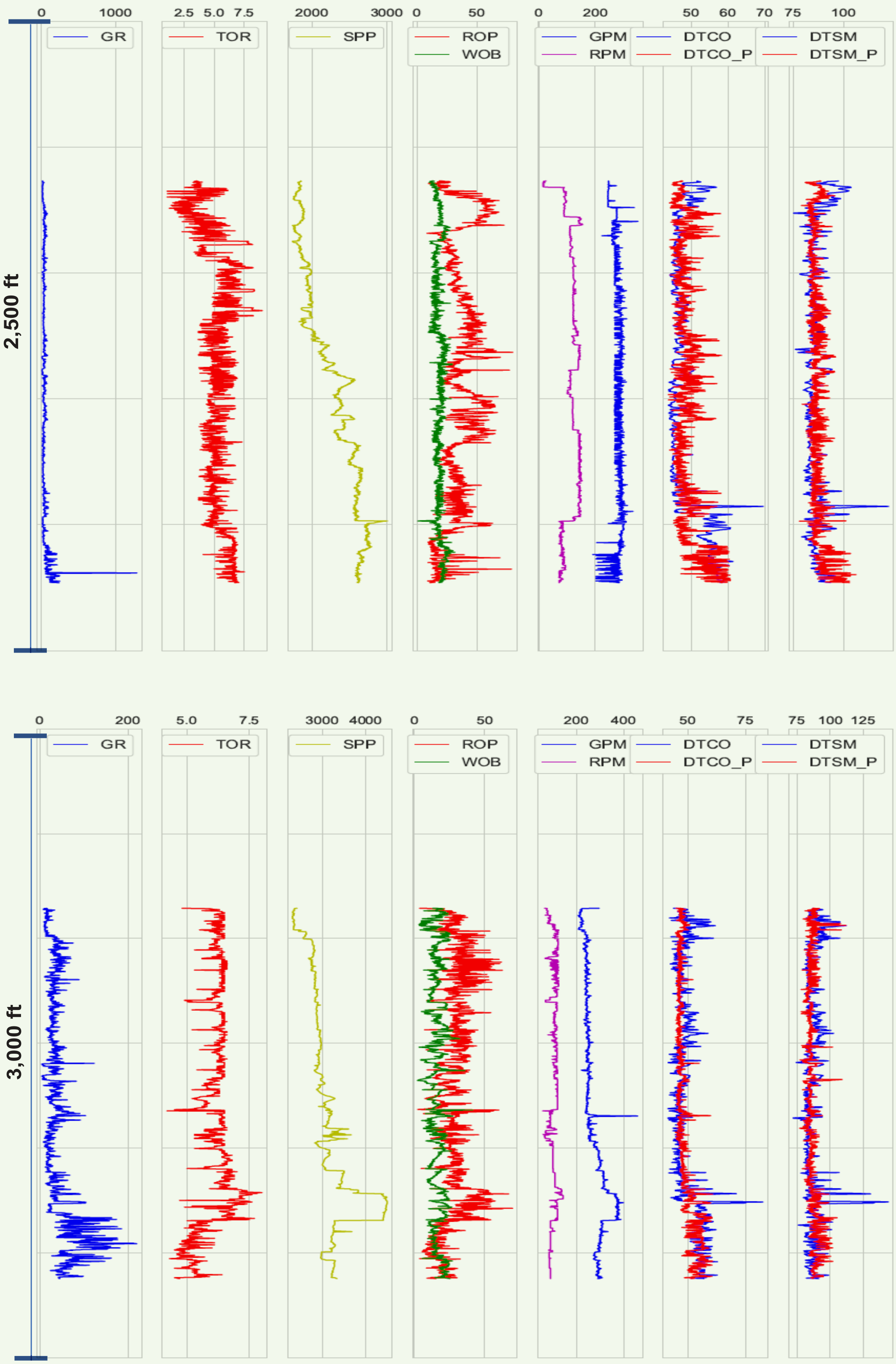
Fig. 11 *The log data for the blind prediction of Well-d11 (top) and Well-d12 (bottom). GR is in gAPI, TOR is in 1,000 lbf, SPP is in psi, ROP is in ft/h, WOB is in 1,000 lbf, gpm is mud flow rate in 1/min, rpm is drillpipe rotation in c/min, DTCO and DTCO_P are the actual and predicted compressional wave slowness, respectively, and in ft, DTSM and DTSM_P are the actual and predicted shear wave slowness in ft, respectively.*



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