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Machine Learning-Based Estimation of Sonic Logs in Development Wells: A Case Study from the Frade Field, Campos Basin

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The sonic travel time log (DT) plays a fundamental role in the integration of well and seismic data, being essential for accurate well-to-seismic ties and for building and calibrating reliable velocity models. These applications are critical in both exploration and development stages of hydrocarbon reservoirs. Despite its importance, the DT log is often not acquired in development wells due to operational limitations, time constraints, or budget restrictions. This common data gap can negatively impact the quality of seismic interpretation and reservoir characterization. To address this issue, this study proposes a predictive modeling approach based on machine learning to estimate the DT log using other standard logs typically available in most well logging suites. The selected input logs include density, gamma ray, neutron, and resistivity—logs that are widely acquired and hold key petrophysical and lithological information. The model implementation uses the XGBoost (Extreme Gradient Boosting) algorithm, which has gained popularity in geosciences for its high performance, efficiency, and ability to capture complex, non-linear relationships between variables. The methodology was applied to a dataset from the Frade Field, located in the Campos Basin, offshore Brazil. The field produces from Miocene-age turbidite reservoirs, which present significant heterogeneity and pose challenges for seismic interpretation and velocity modeling. The training dataset consisted of wells with complete log suites, including the DT log. The data was divided into 70% for training and 30% for validation. The model achieved excellent performance during training, with an R^2 (coefficient of determination) of 99%, and showed strong generalization during validation, with an R^2 of 83%. These metrics confirm the model's robustness and its capability to predict DT values with high reliability based on the chosen input features. To further evaluate the model's effectiveness, a blind test was conducted using a well that was entirely excluded from the training and validation phases. In this case, the model yielded an R^2 of 60%. While lower than the validation result, this outcome is still considered acceptable, particularly given the inherent heterogeneity of turbiditic deposits and the absence of localized tuning for the blind well. It also highlights the importance of geological context in predictive modeling and the potential for further refinement through regional calibration. The DT logs estimated through this approach will be utilized to generate synthetic seismograms and perform well-to-seismic ties in wells where original DT data is unavailable. Additionally, they will contribute to refining the velocity model, enhancing depth conversion accuracy and improving the quality of seismic interpretation. This methodology provides a practical, cost-effective solution for extending the utility of seismic data in reservoir development and reducing the dependence on expensive or incomplete logging campaigns. In summary, the integration of machine learning techniques—specifically XGBoost—with conventional well logs offers a powerful alternative for estimating missing DT profiles. The method delivers accurate and geologically consistent results, enabling better seismic-to-well correlation and supporting more informed reservoir decisions in complex environments such as the Miocene turbidite systems of the Frade Field.