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# Integrating Machine Learning into a Methodology for Early Detection of Wellbore Failure

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There are literally a few million boreholes in the continental US (both onshore and offshore) that include abandoned wells, production wells, and wells for underground hydrocarbon storage. Some are vulnerable to potentially catastrophic loss of seal integrity, largely owing to progressive damage of the annular cement sheath. The Deepwater Horizon oil spill and the Aliso Canyon natural gas leak have elevated wellbore integrity to national attention; new regulations have begun to address the effects of, but not causes of, well failure. It is conjectured that damage within the annular cement between host rock and well casing, engineered as the main seal between biosphere and subsurface, is one of the main leakage pathways. One approach to helping solve this problem is to utilize existing operational datasets from monitored wellbores as a testbed for developing methodologies that can screen for early detection of damage and/or failure.

There are few publicly available datasets of wellbore deformation, damage, and leakage due to geological forces. One existing group of datasets includes wellbores for several underground hydrocarbon storage facilities consisting of storage caverns built in salt domes. In these datasets, histories of wellbore casing damage have been determined from measurements taken by multi-arm calipers over many years. The operators of these facilities have observed some patterns to these deformation histories based on knowledge of the geomechanics of these salt domes, but a full explanation of these events is incomplete. This group of datasets has been selected for use in a machine-learning study to evaluate, interpret, and predict patterns of casing damage.

In our research, we explore using data science and machine learning (ML) methods to predict when a well might be approaching a state of failed seal integrity over time. We use Subject Matter Expert (SME) information as well as statistical techniques including correlation and regression analysis to define the features for our ML models. Our time series prediction considers both next time-step modeling as well as longer term time-series forecasting by utilizing random forests (RFs) and deep neural networks (DNNs) as well as recurrent neural networks (RNNs) for the predictions. The RF models allow us to perform feature importance characterization, while DNNs, specifically convolutional DNNs, facilitate utilization of spatial information including depth and volumetric data. We will utilize these models to characterize and automate the identification of factors that put wellbores at risk, so as to be used as an early detection system for failure screening that outperforms existing analysis tools.

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## Time Block Preference

Time Block C (18:00-21:00 CET)

## References

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