geoconvention
Virtual Event
September 13 - 15
2021

Geomechanically Informed Machine Learning Models Predict Trouble Stages and Casing Deformation

Joel Mazza
Fracture ID

Summary

An operator in the Midland Basin experienced several wells with casing deformation related to trouble stages during the completion. They discovered these regions of deformation while drilling out plugs post-completion. The deformations were significant enough that the drill-out assembly could not pass through the obstructions. An analysis of the stage-by-stage treatment pressure data revealed that the locations of deformation were at the same depths as stages with elevated post-job frac gradients relative to the mean. The areas of deformation were also contained within the heel half of the well. However, there was no single driver immediately found for the elevated frac gradients and not every heel-side stage with an elevated frac gradient had noticeable casing deformation. Since remediation costs and lost production were tangible concerns, the author's engineering team was tasked to build a database of all available historical data and use machine learning to train models that would predict trouble stages, casing deformation events, and identify drivers/causation parameters. Predictive models were successfully built, and several contributing factors were identified from a consolidated database consisting of the wellbore construction data, drill bit geomechanics data, and seismic data. This study demonstrates the necessity of including sub-surface data in analytical models and how the models can be applied. This body of work expands on the study presented by Romberg et. al at the 2020 SPE Annual Technical Conference and Exhibition.

Method

Complete datasets were available for 26 Midland Basin wells; 4 of those wells had casing deformation. A database was built that included stage aggregated statistical data from completions, drill bit geomechanics, wellbore surveys, and seismic models–totaling to 1,587 stages worth of data.

Criteria were established that constituted a "trouble stage" and appropriate machine learning models were then chosen. The team knew there was a connection between elevated post-job frac gradients and casing deformation, so it was determined to build a multivariate regression model supervised by the recorded pressure data. Any stage with a post-job frac gradient above 1.0 psi/ft or 22.6 kPa/m was flagged as a trouble stage. Since not all high post-job frac gradient stages resulted in casing deformation, and it was a relatively rare event, an additional trouble stage model was built to help with precision. The second trouble stage supervising feature chosen was "stage average proppant concentration" to train a multivariate classification model. Any stage with an average proppant concentration below 0.89 ppg or 106.65 kg/m^3 (and not caused by operational issues) was flagged as a trouble stage. This metric was chosen because trouble stages often had to be cut short or extended using sweeps and lower proppant concentration stages due to high treating pressures. These strategies to place the designed amount of proppant caused noticeable drops in the stage average proppant concentrations.

The frac gradient regression model scored best using a random forest algorithm determined by a root mean squared error (RMSE) metric. The classification model scored best using a boosted variant of a random forest algorithm determined by the area under the curve (AUC) metric.

Having "yes or no", or deterministic, models have their utility, however the team believed it would be useful to develop probabilistic models to provide the percent likelihood of a stage being a trouble stage. After some iteration, a stacked model approach was utilized that incorporated the deterministic models as an input to the probabilistic models (Romberg, 2020). Hyperparameter turning was performed for the models which modestly increased performance (Romberg, 2020).

Results

The post-job fracture gradient multivariate regression model performed well with a RMSE of 0.064 psi/ft or 1.45 kPa/m compared to a naïve (or mean) RMSE of 0.074 psi/ft or 1.67 kPa/m (Romberg, 2020). It should be noted the RMSE for the model should be lower than the naïve to be considered predictive. The following predictive data features were ranked in order of importance: Sh_{min} (minimum horizontal stress) gradient from drill bit geomechanics, true vertical depth (TVD) from the wellbore survey, stage distance from heel from completion reports, cumulative wellbore 3D tortuosity from the wellbore survey, most negative curvature from seismic model, similarity from seismic model, and the standard deviation of Sh_{min} gradient across the stage length from drill bit geomechanics.

The high post-job fracture gradient probabilistic (classification) model received an acceptable AUC score of 0.91 (Romberg, 2020). The high score was because there were very few false positive predictions made by the model. However, the model did not predict all instances of high fracture gradient stages which meant the model had high precision but low recall (Romberg, 2020). It is generally understood that post-job frac gradients can be affected by several factors in addition to those captured in the model such as variations in completion strategy, cement quality, plug performance, varying fracture dimensions, and intra-stage stress shadowing. Thus, the low recall was considered acceptable. The following predictive data features were ranked in order of importance: predicted post-job frac gradient from the regression (deterministic) model, similarity from seismic, and Sh_{min} gradient from drill bit geomechanics.

The low average proppant concentration classification model scored an acceptable AUC of 0.84 and had a fair true positive and fair false positive rate (Romberg, 2020). The following predictive data features were ranked in order of importance: TVD from the wellbore survey, instantaneous 3D tortuosity from the wellbore survey, average Young's Modulus (YM) from drill bit geomechanics, standard deviation of Sh_{min} gradient from drill bit geomechanics, average layering (anisotropy) from drill bit geomechanics, distance from the heel from the completion reports, standard deviation of YM from drill bit geomechanics, and average Sh_{min} gradient.

The low average proppant concentration probabilistic (classification) model scored slightly lower with an AUC of 0.75 (Romberg, 2020). The following predictive data features were ranked in order of importance: low average proppant concentration classification prediction, average layering (anisotropy) from drill bit geomechanics, average Sh_{min} from drill bit geomechanics.

Observations and Application

As presented above, all four models performed well individually for predicting their proxies for trouble stages across all wells. Of the four wells with casing deformation, three were included in the training set and one included in the test set. For the well not in the training set, the trouble stage related to casing deformation was successfully predicted to be a trouble stage by each of the probabilistic models. In other words, the stage with casing deformation had both an elevated post-job frac gradient and a low average proppant concentration and was predicted by the models to have a greater than a 50% probability of occurrence. This observation was consistent with the three wells in the training set where casing deformation stages were successfully predicted by the two probabilistic models. The authors acknowledge statistical significance is lacking in this study due to the rarity of the casing deformation events, but the results are encouraging. The models were combined into log plots for easier interpretation. An example is shown in Figure 1.

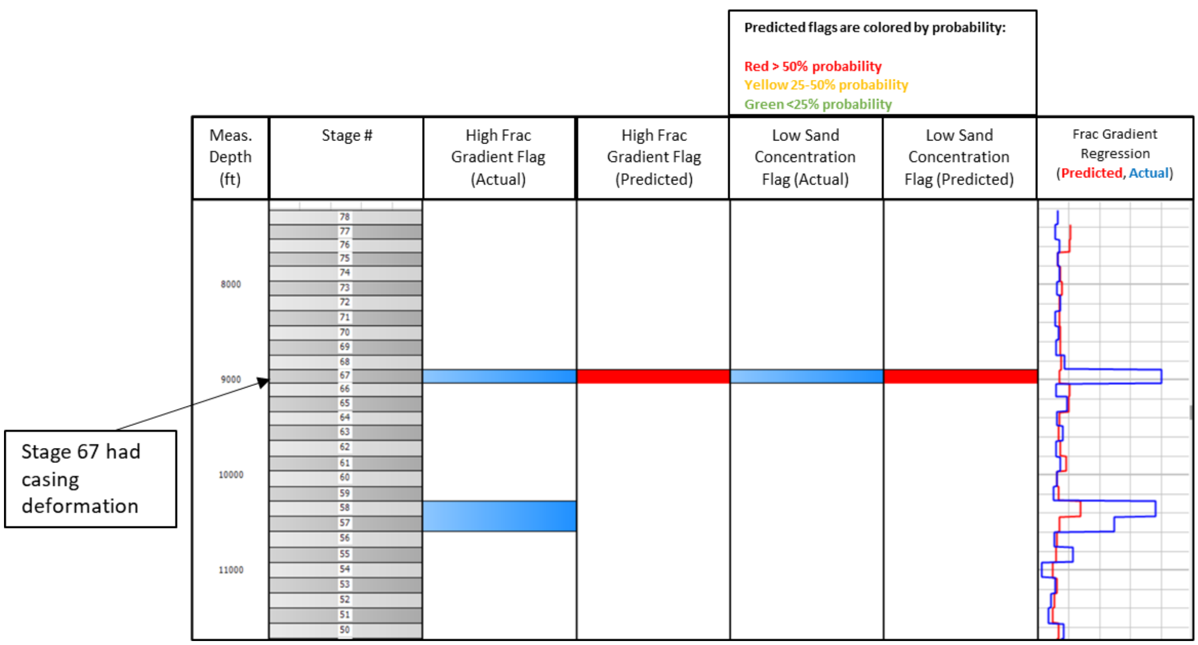

Figure 1 - Well not included in training set showing model predicted and actual (observed) trouble stages (Romberg, 2020).

An interesting observation from the well shown in Figure 1 is the post-job frac gradient regression (track furthest to the right) did not predict and elevated post-job frac gradient, but the probabilistic model still deemed it high risk (above 50%).

After discussion with the operator, the team developed a casing deformation mitigation strategy to be deployed on future wells. The strategy was as follows:

1. Continue to collect drill bit geomechanics when drilling future wells.
2. Run trouble stage models ahead of completion.
3. Highlight high-risk stages and provide prediction to the completion engineer.
4. During operations, perform step down tests on high-risk stages.

5. Determine if the pre-job frac gradient is elevated compared to the population mean as this is an additional indicator of a trouble stage with potential casing deformation.
6. On-site consultant to model bottom hole pressure and adjust the treatment program to maintain bottom hole pressure below 1.0 psi/ft.
7. If maintaining bottom hole pressure below 1.0 psi/ft cannot be achieved, terminate the stage, and move to the next.

This plan has yet to be executed due to a recent change of asset ownership.

Conclusions

The machine learning models presented in this study indicate a complex system consisting of multiple contributors plays into trouble stages that lead to casing deformation. It is clear the geomechanics play a critical role in all four models because they are not predictive when geomechanical properties are absent. Broader geologic features derived from seismic contribute as well. Other factors are either formation specific (e.g., TVD*S_{hmin} gradient = Sh_{min} or closure stress) or due to wellbore construction (wellbore tortuosity) and stage location (distance from heel).

Novel Information

As unconventional development progresses, there is an increasing need for predictive models to decrease operational costs and increase productivity. However, high-resolution subsurface data are rarely acquired and are critical components to understanding and solving problems such as casing deformation. This workflow shows that machine learning can be used and implemented to understand causal factors of complex subsurface problems.

The team hopes to apply similar workflows to predict and mitigate other subsurface-driven problems prevalent in the industry such as fracture-driven-interactions and induced seismicity.

Acknowledgements

Chris Niedz, Brian Wehner, Aaron Fisher - Tracker Resources; Eric Romberg; Alex Zhou; Colleagues at Fracture ID

References

Romberg, E., Fisher, A., Mazza, J., Niedz, C., Wehner, B., and Zhou, A. 2020. Predicting Trouble Stages with Geomechanical Measurements and Machine Learning: A Case Study on Southern Midland Basin Horizontal Completions. APE Annual Technical Conference & Exhibition, Virtual, 26-29 October. SPE-201699-MS. doi: 10.2118/201699-MS.