Predicting Microseismic Event Density before Drilling

David Gray[1], Dalton Hawkins[2], Renjun Wen[1], Cindy Luo[1]

[1]Geomodeling Technology Corp.

[2]SM Energy Company

Summary

There is a need to understand where microseismic events will occur before designing pads and drilling and completing wells. In this presentation we implement an Artificial Intelligence (AI) method that uses a deep-learning Neural Network (NN) to learn to predict microseismic event densities based on results of earlier microseismic surveys. The method requires training data that represents the expected magnitude range of microseismic events and attributes from surface seismic data or geomodels that represent the range of geomechanical properties of the rock. In any area covered by these attributes, this NN can estimate what the microseismic event density will be early on, before drilling any further wells. Cut offs on this prediction can be used to find a proxy estimate for Stimulated Reservoir Volume (SRV) and these can used for future pad, well, and completions designs.

Method

We can estimate microseismic event density throughout the seismic volume from existing microseismic events, say from a pilot pad or earlier work done in the field. The method is described in Wen et al. (2022) following work by Gunning (2021). These event densities are sampled to a stratigraphic grid (strata-grid), to which measured seismic or geomodel attributes can also be sampled. Then they are extracted along the wellbore in Near-Wellbore Volumes (NWV). The NWV is an area around the wellbore in which the rock properties may influence the microseismic events. A reasonable NWV for microseismic density prediction would be something like the SRV (Stimulated Reservoir Volume), or other areas around the wellbore could be used. There is one NWV for each attribute for each well used. So, if there are 10 attributes and 5 wells, there are 50 NWV's. One important attribute that we include in our NWVs, in addition to the measured attributes, is distance to the well, which is expected to have a first-order influence on microseismic density. It is automatically calculated from each point in the NWV to the center of its wellbore. All these predictor attributes are used for training a deep learning neural network to predict the microseismic event density. The asset team plays important roles in this analysis as they use their expert knowledge to review the predictor attributes that the NN has selected to ensure that they make physical sense and that they are not highly correlated to other predictors. This role is to ensure the best predictors are used in the neural network, especially in the case where they are correlated. In addition, some proportion of the training data is used for validation and blind tests. We typically use 10% for each. The validation samples are used to avoid overtraining and the blind test samples are used to ensure the final trained NN works on data not used in training. Furthermore, the results are analyzed using various QC plots including SHAP value plots (Lundberg and Lee, 2017) to understand the contribution of individual input attributes (Shapley, 1953) and ensure that the trained NN model makes sense. This is another important role for the asset team. For example, they would expect the distance to the well to have a significant influence and that influence should decline with distance. This influence should be observed in the SHAP plot for distance to well. If that expected influence is different than expected, then the asset team needs to analyze the attributes in more detail, for example checking for high correlations to other attributes, before making changes to the NN predictor attributes.

The next step is to apply this NN to wells that have microseismic data, but which were not used in the training. Once again, the knowledge of the engineers and geoscientists on the asset team provides important feedback at this stage. If the prediction is unsatisfactory, then they will assess why and make changes to the training to compensate for any observed deficiencies. They will continue to iterate the training of the NN until satisfactory results are obtained.

Upon a satisfactory realization, then the NN is applied to the rest of the data to predict likely microseismic event density away from existing well information. Since these event clouds are calibrated to the microseismic events already observed in the field, they are likely the best estimate of microseismic event density around future wells. From these estimates of microseismic event densities, SRV for the future wells can also be estimated, and that can lead to improved planning of well spacing, completions, pads, and facilities.

Results

We have applied these techniques to a few horizontal wells in the Eagle Ford shale. Key variables in the prediction include distance to well (more fractures close to the treatment well are expected), curvature (which is an expression of natural fracture intensity), shear impedance (which is the resistance of the rock to shearing), Lambda-Rho (compressibility), and a few other attributes that contribute small amounts.

Note that we have different ways of examining the importance of the key variables in our analyses. All these methods show that distance to the well is most important, but secondary variables change based on the method used to determine their importance. For example, individual correlations suggest curvature, shear impedance and Lambda-Rho are important, while Shapley values suggest Vp/Vs ratio and relative acoustic impedance is also important. These variables are also assessed for their mutual correlations. Many of the available input variables are correlated and have therefore been removed. For example, shear impedance is highly correlated to acoustic impedance, as can happen if they follow the “Mudrock Line” (Castagna et al., 1985) in this area. Therefore, our team decided to keep shear impedance over acoustic impedance because the resistance to shearing is likely more closely related to shear microseismic events that are observed in this field. In total, half the available attributes were eliminated in this way. All these methods are used by the technical experts on the asset team to appraise the optimal inputs to the NN.

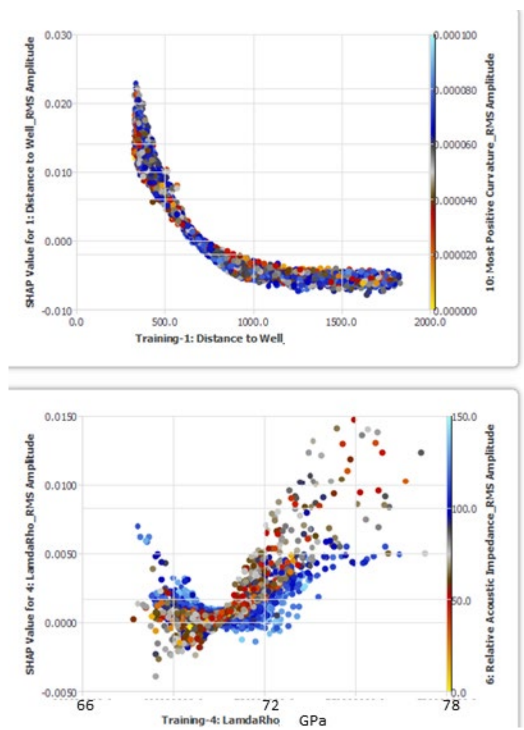

Figure 1 SHAP plots for Distance to Well (top) and Lambda-Rho (bottom)

The SHAP plots in Figure 1 show the expected fall-off of the influence on the prediction of distance to well. They also show the occasional surprise, for example, here the SHAP values for Lambda-Rho at around 70GPa are about zero and therefore have no influence on the prediction, whereas the further Lambda-Rho is from 70GPa the greater its influence on the prediction. This might be something for the technical staff to follow up on, asking the question, "Why do rocks with Lambda-Rho compressibilities near 70GPa not want to fracture as much?". Answering this question could lead to better wells in the future.

The training results have a 0.91 correlation with microseismic data that were used for training. The validation data were even better with a 0.93 correlation, and the blind test data also had a 0.91 correlation.

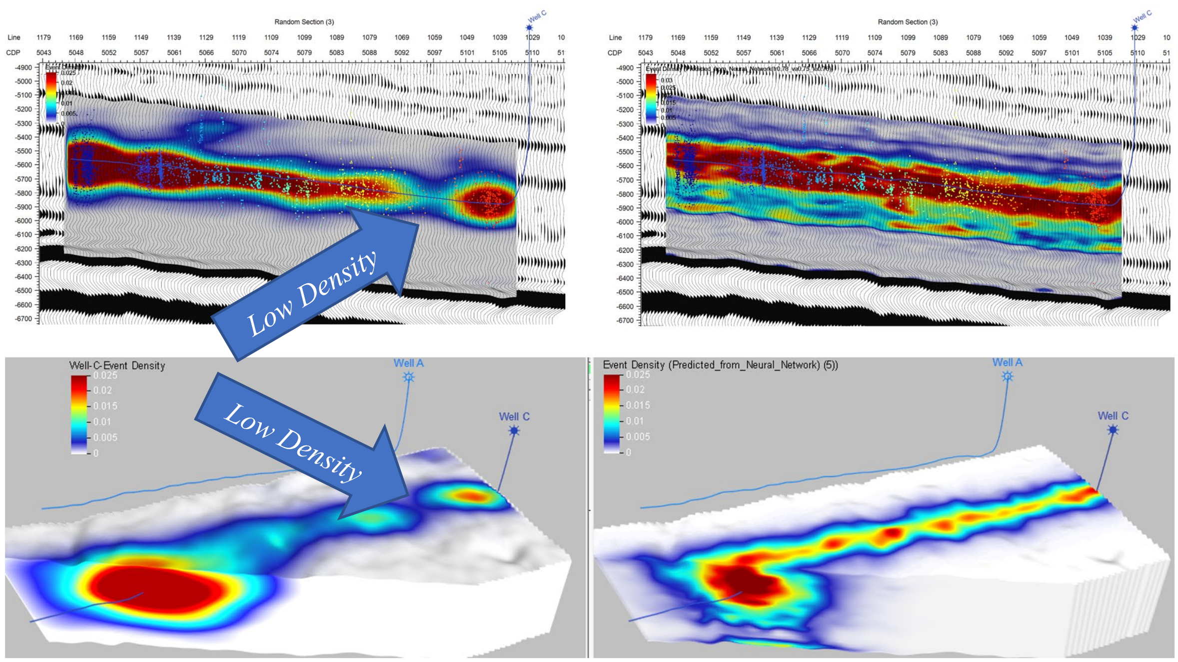

Figure 2: On the left is the measured microseismic event density during hydraulic fracturing of well C. On the right is the event density predicted by seismic attributes through our machine learning algorithm. The upper figures show the event densities over a seismic stack with individual microseismic events indicated by dots. The lower figures show a cutaway of the microseismic event densities around the level of the Well C wellbore. A zone of low microseismic density is indicated by the arrows, triggering the asset team to examine the data for indications of a fault.

Comparing the prediction to the actual event density shows that the NN effectively captures the overall trend in microseismic event density (Figure 2). There are observable differences, especially in areas where the observed event density is lower than predicted near the heel of the well (Figure 2). This prompted our technical staff to look at this area more closely. With this additional information, they observed features that might be related to a small fault in this area, which may be acting as a thief zone stealing the hydraulic fracture fluid injected nearby rather than fracturing the rock there. Further investigations of neighboring stages show microseismic events appearing in this area outside of the predicted event cloud, further strengthening the argument that there may be a small fault around this one stage.

Once the event densities around a well with microseismic measurements can be reasonably estimated from seismic attributes, then, assuming field properties don't change away from the training well(s), these seismic attributes and this NN can be used to predict microseismic event densities around other wells and future wells. Since an SRV can be estimated from the microseismic event densities around the training well, these estimated event densities can then be used to predict the SRV around future wells (Figure 3). The SRV estimates the probable drainage area of the well. So, knowing the SRV around future wells gives the team the information they need to optimally space future wells by either avoiding SRV overlap or limiting the SRV overlap between wells. This, in turn, can contribute to pad, well, and completions design.

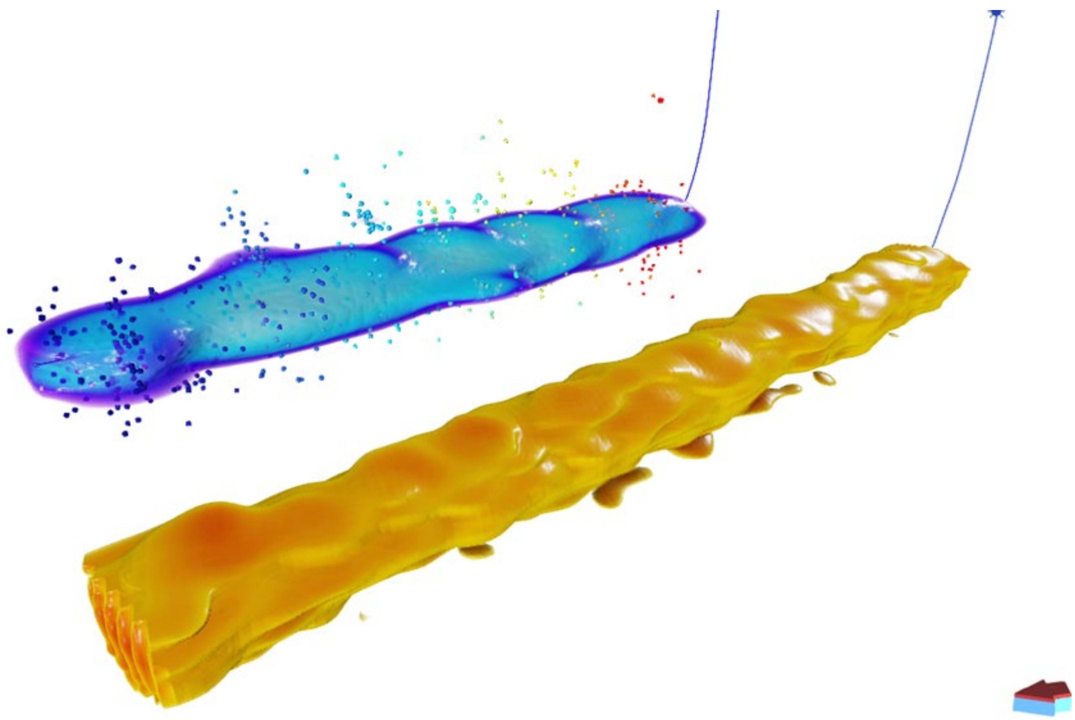

Figure 3 SRV estimated from microseismic events (blue) and SRV estimated from seismic attributes (gold) on a neighboring well by using a cutoff on the estimated microseismic event densities.

Conclusions

We have shown that a Neural Network driven by attributes available from seismic or geomodels placed in Near-Wellbore Volumes can predict microseismic event density reasonably well. Since the NN is driven by data from the field, assuming no large changes in properties across the field, then it can be assumed that microseismic event densities away from the training well(s) can also be predicted reasonably well, even before the drilling or completion of the well. Since SRV is often estimated from microseismic event density, then SRVs can be estimated for these future wells. By optimizing overlap between these SRVs, then optimal drainage of the reservoir can be engineered, optimizing spacing and completions, and minimizing frac hits.

Novel/Additive Information

Using Near-Wellbore Volumes, AI can be employed to make reasonable estimates of microseismic event density early in the life of a field. This should lead to an ability to optimize field and pad designs, well spacing, and completions while reducing frac hits as the field is developed.

Acknowledgements

We would like to thank SM Energy for permission to use the data in this presentation and their assistance with this work.

References

Castagna, J.P., Batzle, M. L., and Eastwood, R. L. [1985] Relationships between compressional-wave and shear-wave velocities in clastic silicate rocks, Geophysics, 50(4), 571-581.

Gunning, B. [2021] Predicting microseismic event density during hydraulic fracturing from surface seismic with gradient boosted trees. 2021 GeoConvention, Extended Abstracts.

Lundberg, S.M. and Lee, S.I. [2017] A Unified Approach to Interpreting Model Predictions. Proceedings of the 31st International Conference on Neural Information Processing Systems, Long Beach, 4-9 December 2017, 4768-4777.

Shapley, L. S. [1953] A value for n-person games. Contributions to the Theory of Games 2.28: 307-317.

Wen, R., Hawkins, D., and Luo C.L. [2022]. Quantitative Prediction of Microseismic Density Volumes and SRV from Surface Seismic Attributes and Completion Data. 2022 GeoConvention, Extended Abstracts.