# Enhancing Sweet Spot Analysis with Machine Learning and the Ability to Predict Unconventional Well Performance

*Author information – Ilia Chaikine and Jeff Aldrich*

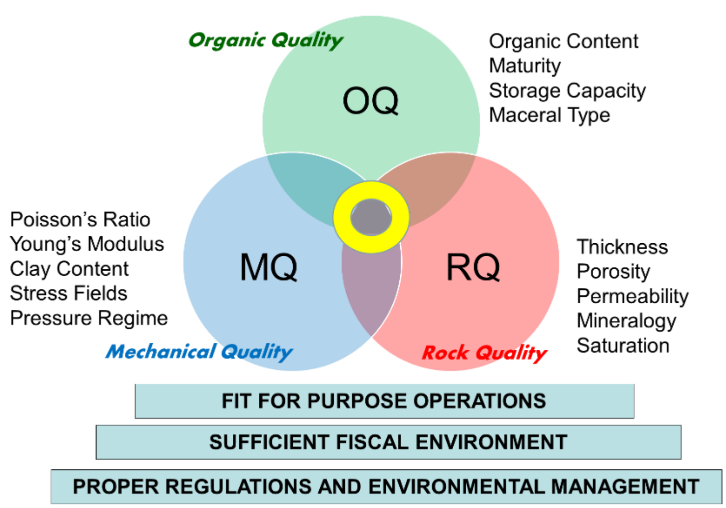
*Affiliation – Sproule*

## Summary

The authors will demonstrate how sweet spot analysis can be enhanced with advanced machine learning techniques, specifically in predicting the cumulative production profiles in multistage hydraulically fractured wells.

## Theory / Method / Workflow

The term "Sweet Spot" is often used to describe the area of a play, or a license, that will produce the highest rate of return under the currently employed technology. The optimum area for field development in unconventional fields can be defined as the intersection of three geological quality factors: Organic Quality (OQ), Rock Quality (RQ) and Mechanical Quality (MQ) each comprising key characteristics as shown in the figure below.




These geological factors help identify the sweet spots and arguably have the greatest influence on production performance. Finding a sweet spot, however, does not guarantee profitability since operational factors such as completion design, drilling order and production maintenance play a critical role in developing a successful unconventional play.

The study presented uses a machine learning algorithm with data from 74 horizontal wells located in the Montney formation in Canada, to predict the 5-year cumulative production profiles of newly drilled wells. The input data is split into three groups of variables defined at the stage level:

- geological properties of the formation – specifically the mechanical rock properties.
- completion design of each stage, - the tailored completion program
- parent-child well interactions.

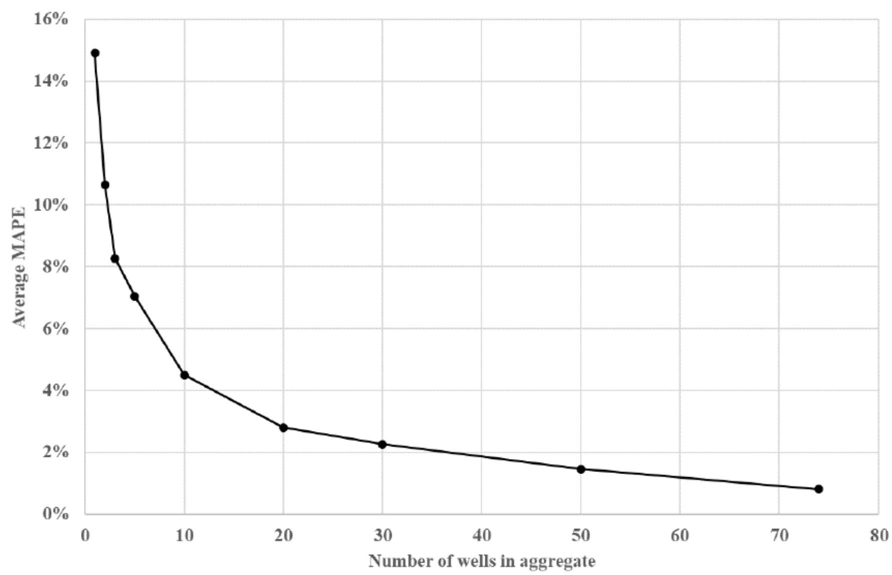
An artificial neural network was trained to find patterns in the data and make predictions of the 5-year cumulative recoveries of each of the new wells.

## Results, Observations, Conclusions

The results show that machine learning can be used to enhance the usefulness of sweet spot analysis by linking the production performance at the well head to a broad range of input parameters, both geological and operational, at every stage along a horizontal wellbore.

Using only the geological mechanical variables as inputs resulted in the average prediction error of 16.57%. Using only completion variables as inputs, such as the combination of total proppant, fluid, $CO_2$ injected, and the type of fluid used, resulted in an error rate of 19.21%. The prediction accuracy of the model using only completion variables was worse than using only the rock mechanical models which suggests that the rock mechanics surrounding a well have a greater effect on production than the stimulation design.

The lowest error rate of 14.9% was achieved using a combination of rock mechanics, completion variables and parent child interactions. Adding more stimulation variables to the input such as total fluid, $CO_2$ injected, or type of fluid used did not improve the accuracy of the model. An additional outcome of this study was that the model error rate dropped when production of multiple wells was aggregated. If all 74 wells were aggregated the average error dropped to 0.8%. This effect is shown in the figure below, the reduction in error is due to the network underpredicting some wells and overpredicting others. When these differences are added they begin to cancel each other out.




The presentation also shows some examples of how the trained model can be used for identifying optimal future well placements and completion parameters that lead to the best outcome.

## Novel/Additive Information

This presentation shows that sweet spot analysis can be enhanced with machine learning to predict the production performance of future well locations. Furthermore, most modern horizontal wells have many fracture stages and the model shown in this study is able to read data at a stage level which enhances the accuracy of predictions over input variables averaged along the entire wellbore.

The outcome of the study provides a tool for the placement and completion design of future horizontal wells in fields with existing development since it provides the ability to run multiple development scenarios without having to spend capital.

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