Shiny web applications for optimization of diagnostic fracture injection test (DFIT) event detection with unsupervised learning

Author information – Lukas V. Sadownyk, Marcelo Guarido, Danial Zeinabady, Erfan Sarvaramini, Zhenzihao Zhang, Farshad Tabasinejad, Hashem Salari, Kristopher A. H. Innanen, and Christopher R. Clarkson

CREWES - University of Calgary

TOC - University of Calgary

Summary

Diagnostic Fracture Injection Tests (DFIT) are commonly used to derive key hydraulic fracture design and modeling parameters. Although this process can identify properties needed for well completion, it can also be time-intensive and impacted by human interpretation bias. This report addresses this adversity by applying unsupervised clustering methods: K-Means, DB-Scan, Hierarchical modeling, and Gaussian mixture models to identify point density variation that correlates to key parameters on a DFIT curve. An R-Studio Shiny Web App has been developed to apply these methods and supply a user-friendly platform for adjusting input variables and hyperparameters. Exploring the clustering approach emphasizes the importance of different variable combinations in addition to noise considerations when interpreting a DFIT curve with clustering methods. Principle Component Analysis (PCA) further demonstrates why clusters occur along a DFIT curve. Unsupervised clustering applied to DFIT data achieves an unbiased and quick workflow for event identification.

Theory / Method / Workflow

To ensure successful and economic development of low permeability, hydrocarbon baring organic-rich shales, a fracture stimulation design must be implemented to liberate hydrocarbons and optimize drilling programs. The process of designing and modeling a fracture program is a computationally intensive and iterative process that requires the estimation of multiple geologic and mechanical properties. These include permeability, formation pressure, fracture half-length, minimum horizontal stress (S_{hmin}), instantaneous shut-in pressure (ISIP), breakdown pressure, fracture extension pressure, reservoir permeability, and fluid content (Clarkson et al., 2012). To extract these properties, innovative technologies such as DFITs have been designed for measurement by injecting a small volume of fluids into the target formation to create a hydraulic fracture in the borehole of a well (Jung et al., 2016). These key parameters can be derived by measuring the downhole or surface pressure change over time (pressure-time series) (Figure 1). Here we will focus on current analytical methods and newly proposed machine learning methods of interpreting these curves in this study.

Figure 1 reveals that the interpretation of these key parameters directly from a pressure decline curve is non-trivial. Current methods of visualizing these hidden nonlinear property relationships involve manual interpretation of derivative curves such as G-function, Bourdet derivatives, first-order derivatives, and Agarwal time (Zanganeh et al., 2018; Liu and Ehlig-

Economides, 2018, McClure et al., 2016, Barree et al., 2009). Unfortunately, the analytical nature of these methods has the unintended result of introducing human bias and error, coupled with the time-consuming task of defining these interpretations for multiple DFIT curves that exist for large datasets. These circumstances provide an opportunity to test and evaluate the potential of machine learning methods to resolve such adversities.

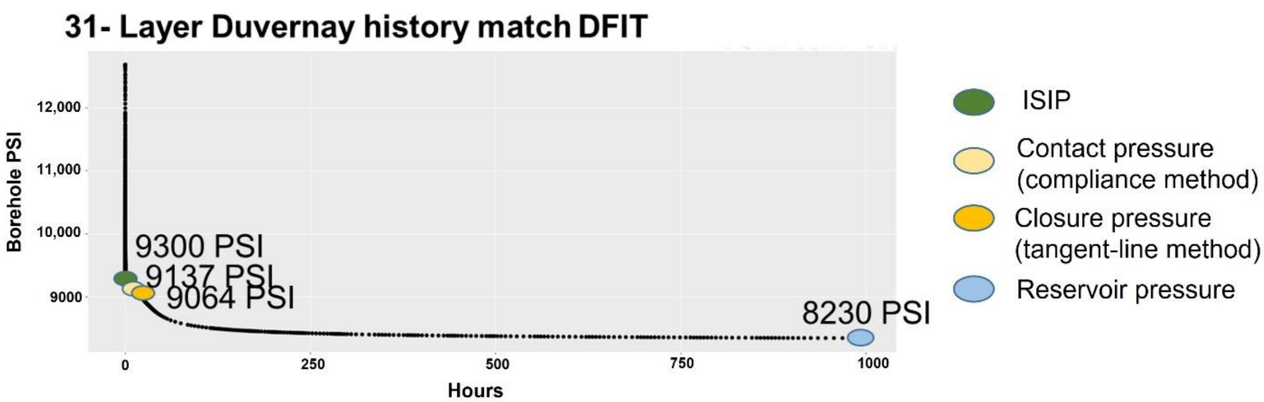

Figure 1. ResFrac® history matched pressure falloff data obtained from simulation of a DFIT performed in the 31-layer Duvernay Formation model. Interpreted events along the curve are superimposed and color-coded. Approximations of the S_{hmin} are made using both the compliance (McClure et al., 2016) and the tangent line method (Barree et al., 2009).

Despite the recent rise in machine learning applications to large datasets, little literature exists for applying these methods for DFIT curve interpretation. Instead, current studies address the interpolation of missing DFIT pseudoradial flow data using Gradient Boosting (GB) and Random Forest (RF) regression methods (Mohamed et al., 2020) and the integration of real-time well stimulation datasets (injected proppant volumes, downhole pressures, and microseismic events) to identify stimulation related events using CNN, Autoencoders (AE) and Support Vector Regression (SVR) (Shen et al., 2020; Alatrach et al., 2020; Wang and Chen, 2019). This study aims to fill this gap and develop a workflow to identify reservoir parameters ISIP; S_{hmin}; and reservoir pressure) with the aid of unsupervised clustering algorithms: K-Means, DB-Scan, Hierarchical modeling, and Gaussian mixture models. The application of this method intends to speed up interpretation times for datasets consisting of many DFIT curves and eliminate human bias. Implementation and visualization of these clustering methods are complemented by developing the CREWES DFIT Clustering App using Shiny Web Apps from R-Studio®.

Three DFIT curves were clustered using the multitude of derivative curves from DFIT data to evaluate this method. Iterations were taken to determine optimal combinations of variables, and clustering method produces boundary events that coincide with the key parameters from manual interpretation. Test DFIT curves include history matched pressure decline models generated from a "simple" 3-layer Duvernay system and a "complex" 31-layer Duvernay system. ResFrac® simulator was used to create a synthetic pump-in/shut-in response. ResFrac® is a fully coupled hydraulic fracturing, reservoir, and wellbore simulator that rigorously models the key physical process involved in DFITs. The detail of the ResFrac® conceptual model and numerical approach is described in McClure et al. (2021). Field data from a DFIT acquired in the Duvernay near Fox Creek, Alberta, Canada, is tested using the optimized hyperparameters from the model cases. Further analysis using PCA aims to explain the mathematics as to *why* the clusters appear where they do.

Results, Observations, Conclusions

The CREWES DFIT Clustering App using Shiny Web Apps from R-Studio® successfully defined key parameters along DFIT curves using its interactive features (Figure 2). Results found that a combination of all derivative curves and DB scan clustering methods work optimally for idealized models. In contrast, the Gaussian mixture model excelled in the field test.
Furthermore, the implementation of PCA reveals that changes in dimensionality and slope are the primary factors controlling cluster boundaries, displaying the 'hidden' physics of a DFIT pressure decline (Figure 3).

The CREWES DFIT Clustering App can be used to quickly interpret and reduce bias in DFIT-derived parameter estimates. Future studies will use this method to create training data for supervised learning methods for automated event identification.

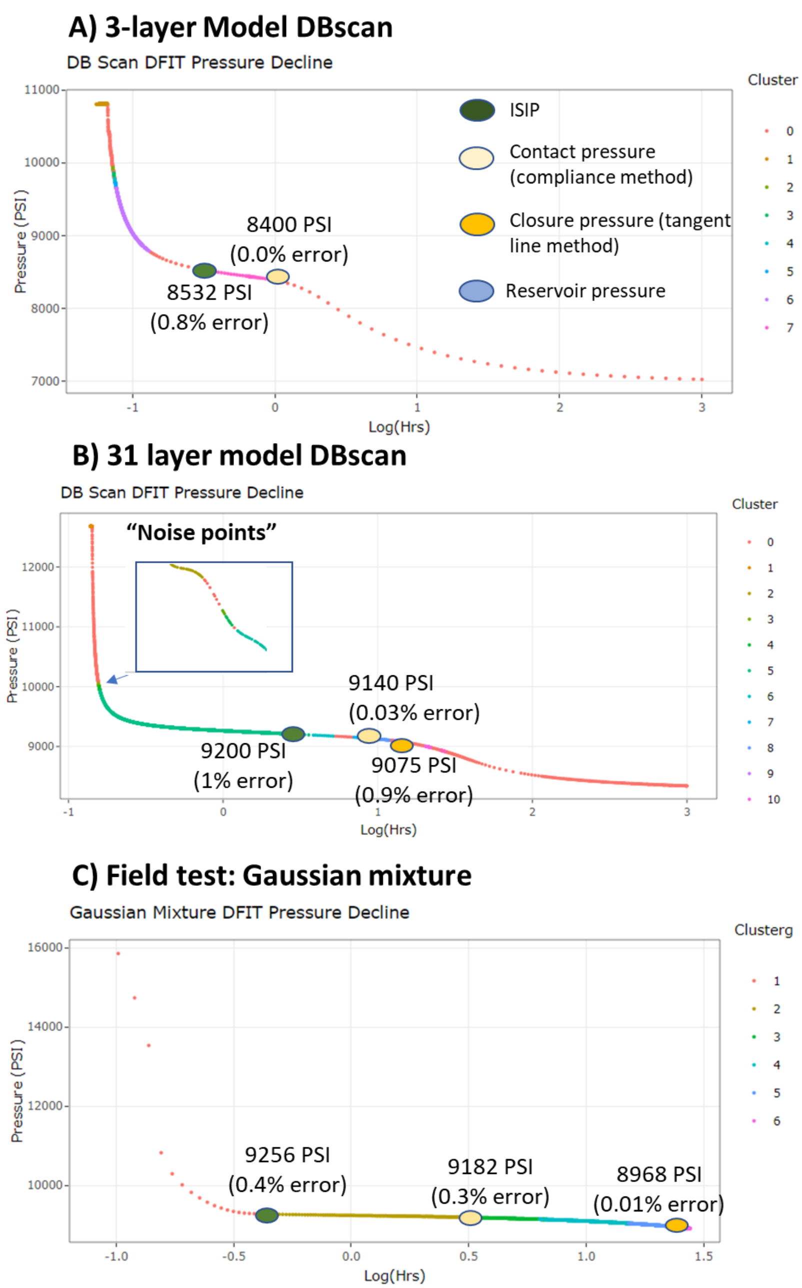

Figure 2. Results of applying optimal variable combination, hyperparameters, and clustering method to each of the three datasets in this study. Percent error is indicated on each plot to quantify the difference from actual/interpreted values.

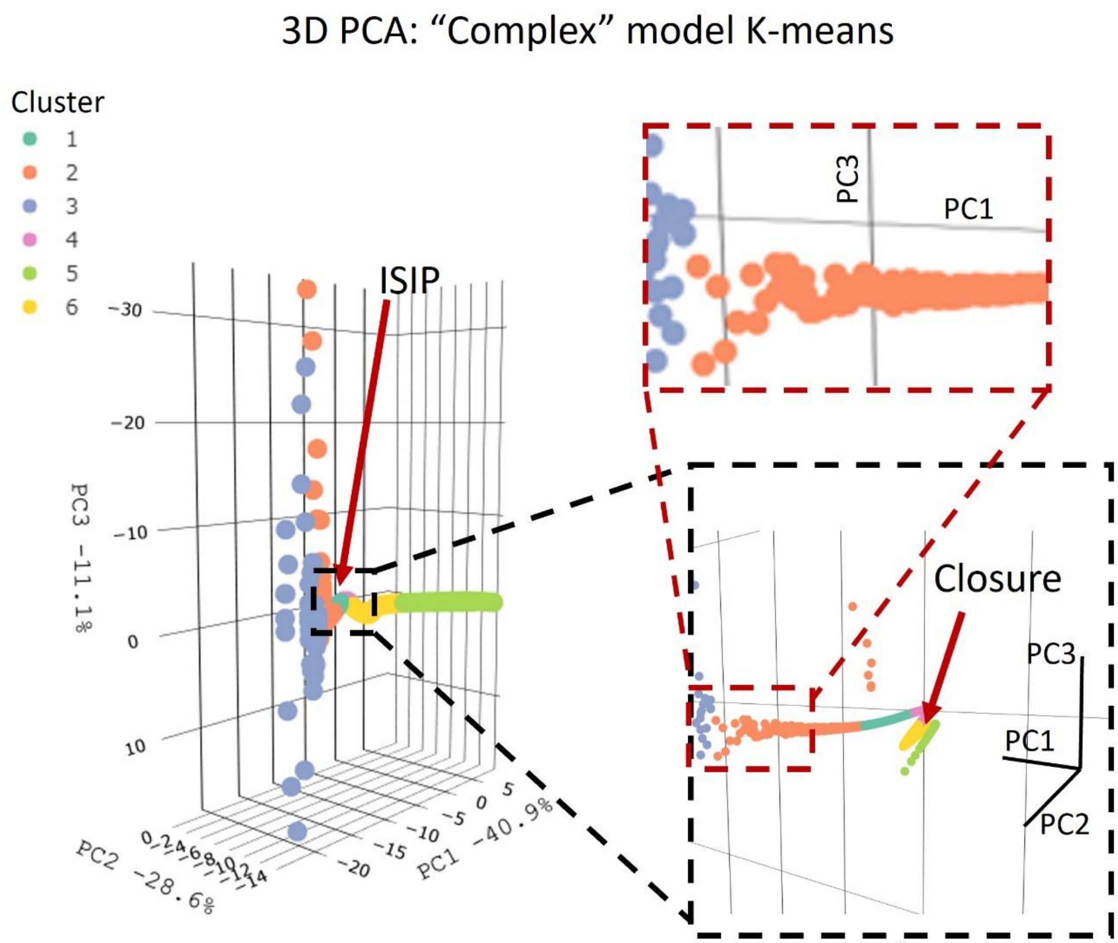

Figure 3. A three-dimensional principal component plot was used to understand the distribution of clusters created from DFIT data. Using the K-means algorithm, this case shows the "complex" DFIT model with its associated identified events. In addition, this figure includes different perspectives of the data to understand variation.

Acknowledgements

We thank the sponsors of CREWES for their continued support. This work was funded by CREWES industrial sponsors and NSERC (Natural Science and Engineering Research Council of Canada) through the grant CRDPJ 543578-19. The first author was partially supported by an NSERC Alexander Graham Bell Canada Graduate Scholarship (CGS-M) scholarship. The Canada First Research Excellence Fund funds the first, second, fifth, and seventh authors through the Global Research Initiative at the University of Calgary. The NSERC Alliance grant supports the third and sixth authors. We gratefully acknowledge Mark McClure (president of ResFrac) for providing academic licenses of ResFrac for use in this study.

References

Alatrach, Y., Mata, C., Omrani, P. S., Saputelli, L., Narayanan, R., and Hamdan, M., 2020, Prediction of well production event using machine learning algorithms: Presented at the Abu Dhabi International Petroleum Exhibition and Conference.

Barree, R. D., Barree, V. L., and Craig, D., 2009, Holistic fracture diagnostics: Consistent interpretation of prefrac injection tests using multiple analysis methods: SPE Production and Operations, 24, 396–406.

Clarkson, C. R., Jensen, J. L., and Chipperfild, S., 2012, Unconventional gas reservoir evaluation: What do we have to consider?: Journal of Natural Gas Science and Engineering, 8, 9–33. of non-ideal behavior during diagnostic fracture injection tests: Journal of Petroleum Science and Engineering, 145, 114–136.

Jung, H., Sharma, M. M., Cramer, D. D., Oakes, S., and McClure, M. W., 2016, Re-examining interpretations of non-ideal behavior during diagnostic fracture injection tests: Journal of Petroleum Science and Engineering, 145, 114–136.

Liu, G., and Ehlig-Economides, C., 2018, Practical considerations for diagnostic fracture test (DFIT) analysis: Journal of Petroleum Science and Engineering, 171, 1133–1140.

McClure, M., Kang, C., Medam, S., and Hewson, C., 2021, ResFrac technical writeup: https://arxiv.org/abs/1804.02092v9.

McClure, M. W., Jung, H., Cramer, D. D., and Sharma, M. M., 2016, The fracture-compliance method for picking closure pressure from diagnostic fracture-injection tests: SPE Journal, 04, 1321–1339.

Mohamed, M. I., Mehta, D., Salah, M., Ibrahim, M., and Ozkan, E., 2020, Advanced machine learning methods for prediction of fracture closure pressure, closure time, permeability, and time to late flow regimes from DFIT: SPE/AAPG/SEG Unconventional Resources Technology Conference.

Shen, Y., Cao, D., Ruddy, K., and Moraes, L. F. T. D., 2020, Near real-time hydraulic fracturing event recognition using deep learning methods: SPE Drill and Compl, 35, 478–489.

Venieri, M., Weir, R., McKean, S. H., Pedersen, P. K., and Eaton, D.W., 2020, Determining elastic properties of organic rich shales from core, wireline logs, and 3-d seismic: Journal of Natural Gas Science and Engineering, 84, 103,637.

Wang, S., and Chen, S., 2019, Insights to fracture stimulation design in unconventional reservoirs based on machine learning and modeling: Journal of Petroleum Science and Engineering, 174, 682–695.

Zanganeh, B., Clarkson, C. R., and Jones, J. R., 2018, Reinterpretation of flow patterns during DFITs based on dynamic fracture geometry, leakoff and afterflow: SPE Hydraulic Fracturing Technology Conference and Exhibition.