Machine learning applied to hydraulic fracturing data for microseismic prediction

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Summary

Hydraulic fracturing (HF) is an essential technology for the development of low-permeability, unconventional hydrocarbon resources (King, 2010). During a HF treatment injection parameters such as pressure, injection rate, and proppant concentration, are continuously monitored and properly time-sampled to assure the effectiveness of the fracture plan. To optimize the reservoir engineering of the stimulation, microseismic monitoring has become an important tool used to infer key aspects of the complexity and geometry of hydraulic fractures. Linking the injection monitoring data with the microseismic event pattern allows for the understanding of specific fracture expressions corresponding to clear-cut injection characteristics that can be optimized to improve well performance. This study introduces a machine learning workflow to predict the radial distance of the microseismic events from the injection source. We apply a set of regression algorithms to a dataset from an open-hole well stimulation near Rimbey Alberta to illustrate the methodology.

Theory

Microseismicity during hydraulic fracturing

Hydraulic fracturing, a technique that involves the pumping of high-pressure fluids and proppant to fracture the rock, has become one of the main methods used in unconventional hydrocarbon reservoirs to enhance permeability and increase the volume of stimulated rock. This process provides information about the fracture growth and proppant placement but fails on predicting details of the fracture dimensions and complexity. To optimize the fracturing treatment, and map the fracture geometry, microseismic monitoring has been widely used in recent years (Warpinski, 2013). During hydraulic fracturing, the location of the shear slippages relative to the injection source can be used to approximate fracture dimensions. Microseismic mapping provides an estimate of the fracture azimuth, height, length, and complexity. These are important parameters used by engineers to optimize the completion strategy and increase production rate (Cipolla 2012, Fisher 2004).

To understand the spatial and temporal evolution of induced microseismic clouds due to the tensile opening and propagation of a hydraulic fracture, a model of material balance for an incompressible treatment fluid like water is commonly used. The volume of fluid injected during hydraulic fracturing is the sum of the volume lost through leak-off and the volume used to create the fracture. This mass conservation equation is defined as (Economides, 2000)

$$Q_i t = V_l + V_f, \qquad (1)$$

where Q_i is the total injection rate and t is the pumping time of the treatment. The terms V_l and V_f refer to the volume leaked to the formation and the fracture volume respectively. Their values depend on the geometry of the fracture's cross-section. For a PKN fracture model (Perkins et al., 1961), and using Carter's (1957) model of fluid loss, the fracture half-length as a function of time is given by

$$L(t) = \frac{Q_i t}{\left(4hC_L\sqrt{2t} + 2hw\right)}. \tag{2}$$

Where L is the fracture half-length (assuming a symmetrical bi-wing hydraulic fracture), h is the height of the fracture, w is the width, and C_L is the fluid-loss coefficient. Equation (2) remains valid in the case of a propagating hydraulic fracture. However, in situations when the bottom hole pressure created by the injection of fluid is smaller than the absolute value of the minimum principal compressive stress (e.g. during the subsequent times after reaching the instantaneous shut-in pressure), microseismicity is mainly controlled by a linear process of relaxation of stress and pore pressure at the injection source (Shapiro, 2015). Thus, in the absence of any dominant hydraulic fracture, equation (2) can be replaced by the triggering front equation (Shapiro et al., 2002).

$$L(t) = \sqrt{4\pi Dt}, \tag{3}$$

where D is the hydraulic diffusivity. To sum up, equations (2) and (3) serve as an approximation of the fracture dimensions as a function of injection time during a HF treatment.

Machine learning

Machine learning is an automated process that extracts patterns from data and uses the experience to improve performance (Mohri et al., 2018). In supervised learning, the model receives a set of labeled data (i.e. training set) and then makes predictions on unseen data (i.e. testing set). In this paper we use an ensemble of supervised learning, regression algorithms, to link the injection monitoring curves and the microseismicity for the prediction of the radial distance of microseismic events. The purpose of regression is to predict as closely as possible the real-value label of the point considered. The performance of the prediction depends on the magnitude of the difference between the real and predicted value (residuals), usually defined by an error function. Thus, a good regression model is quantified by the combination of weights that produce the minimum error.

The main advantage of using ensemble learning is a reduction of variance and bias that allows the model to make more accurate predictions in the test set (Zhou, 2012). In this work we use 2 regression algorithms to build the ensemble regressor. The Random Forest (RF) regression consists of a large number of randomly sampled regression trees built by the recursive partition of a random sample with replacement (i.e. a bootstrap sample) known as the root node, into subgroups called nodes, and down to the terminal nodes. In this process, each partition is done based on specified splitting parameters and the final prediction, once reaching a stopping criterion, is the average value of the appropriate terminal node (Breiman, 2001). In the end, the overall prediction of the RF is the average of predictions from all trees. Additionally, we utilize the Ridge Regression (RR) algorithm, also known as linear least square's regression with l2 regularization. The RR minimizes the following objective function (Hoerl et al., 2000).

$$\hat{\beta} = \left[X^T X + \lambda I\right]^{-1} X^T Y, \tag{4}$$

where $\hat{\beta}$ is a vector that contains the regression coefficients, X is a matrix made from the independent variable, Y is a vector containing elements of the dependent variable, I is the identity matrix, and λ is the penalty coefficient that determines how much regularization is applied.

Data and method

We employ data from a six-stage hydraulic fracture operation done in the Rock Creek Formation at the West Pembina field in Alberta, Canada. The last stage of the treatment is analyzed, comprising 2800 seconds of continuous injection monitoring data and a catalog of 615 microseismic events recorded simultaneously with the stage treatment. First, we calculate the radial distance from the hypocenter of the microseismic events to the port of stage 6. We define the input parameters for the ML model from the injection monitoring curves. For this work, we use the time-series data of treating pressure, injection rate, and proppant concentration. To evaluate the performance of the model, we split the whole dataset into training and test sets. We select the first 2000 seconds of data as the training set and use the remaining 800 seconds of the data to validate our model.

To create a model that captures the dynamic behavior of the hydraulic fracture, we derive statistical features using moving time windows with 94% overlap applied to the input time-series data. For a window size of 10 minutes, we extract 33 statistical features (11 per input time-series). We calculate features like mean, standard deviation, kurtosis, and quantiles. These are common statistical measures used in time-series analysis to understand the central tendency and variability of the data. We then label each training example x_i as the maximum radial distance of the microseismic events within the time window y_i, calculated from the time-series data of the maximum event distance per minute. The machine learning dataset d is as follows

$$d = (x_i, y_i)_{i=1 \ldots n}\,, \tag{5}$$

where n is the total number of training examples. Figure 1 shows the radial distance of the microseismic events in the spatial domain, the input time-series used to extract the statistical features, and the radius vs time ($r - t$) plot of the microseismic events in the training set. To train the model, we first standarized the training and test sets by removing the mean and scaling to unit variance. Then, we used the ridge regression and random forest regression algorithms from Pedregosa et al., (2011) to create the ensemble learning model. To avoid overfitting, we use k-fold Cross Validation to split our training dataset into k=5 number of subsets, called folds. We then fit the model 5 times, each time training the data on 4 of the folds and evaluating on the remaining fold, the validation set. We quantify the accuracy of the prediction using the mean absolute error (MAE) regression loss evaluated on the validation set.

Results

We train the random forest and ridge regression models on the training set and obtain an average MAE over the 5 folds of 2.79 and 2.89 respectively. Then, we ensembled the models using a weighted average and assigned a weighting factor of 0.1 for the RF model and 0.9 for ridge regression. Figure 2 shows the labels and predicted radial distance of the microseismic events from each regression model and the ensemble in the test set. While the RF model was not able to predict the increase in radial distance at the end of the stage, the RR model did a pretty good job with a slight overestimation of the radial distance. Finally, the ensemble model achieves a MAE = 3.13 in data that it has never seen during training. The accuracy is remarkable considering that our model does not use past or future information to make a prediction and is based solely on statistical features extracted from the input features on the rolling time windows.

Conclusions

We introduced a new method to predict the radial distance of the microseismic events in the upcoming minutes of a HF operation using machine learning. For that, we use an ensemble regression model on real hydraulic fracturing and microseismic monitoring data recorded at the West Pembina Field in Alberta, Canada. The results prove that, at least for a single stage, our ML approach can predict with high accuracy the evolution of the radial distance of microseismicity over time using only statistical features extracted from the injection monitoring curves. Our analysis corroborates the importance of integrating the injection history with microseismic mapping to create a better approximation of fracture dimensions. To conclude, we determined that a careful setup of the input parameters allows the ML model to correlate the distance of the microseismic events to the injection monitoring data.

Acknowledgements

The authors would like to thank the sponsors of the Microseismic Industry Consortium for financial support. Special thanks to Pedregosa et al., (2011) for the open-source Scikit-learn library.

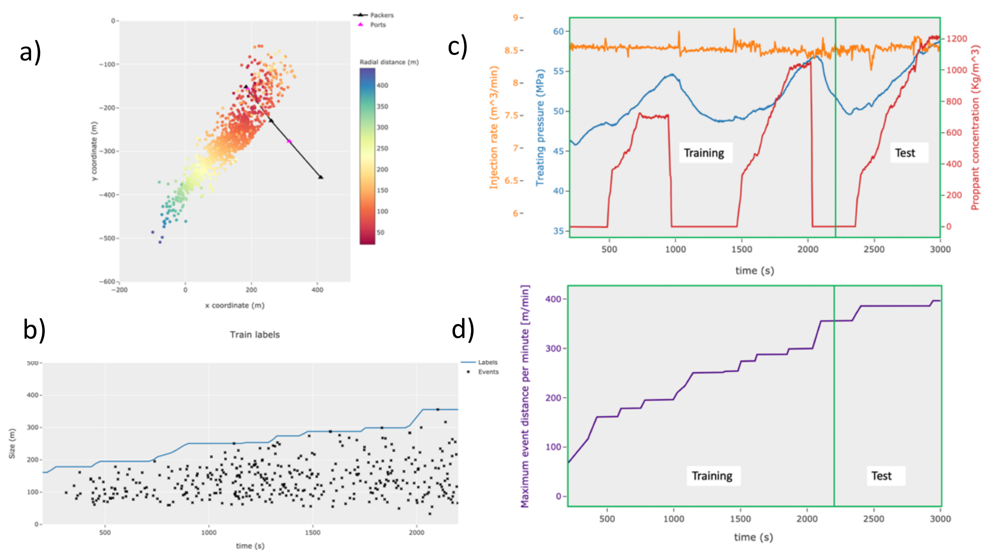

Figure 1: (a) Microseismic events colored by radial distance from the injection point of stage 6. (b) Radius vs time $r - t$ plot of the events on the training set. The blue curve shows the target label. (c) Injection monitoring curves showing the training and test sets. (d) average moment magnitude per minute and maximum radial distance of events per minute.

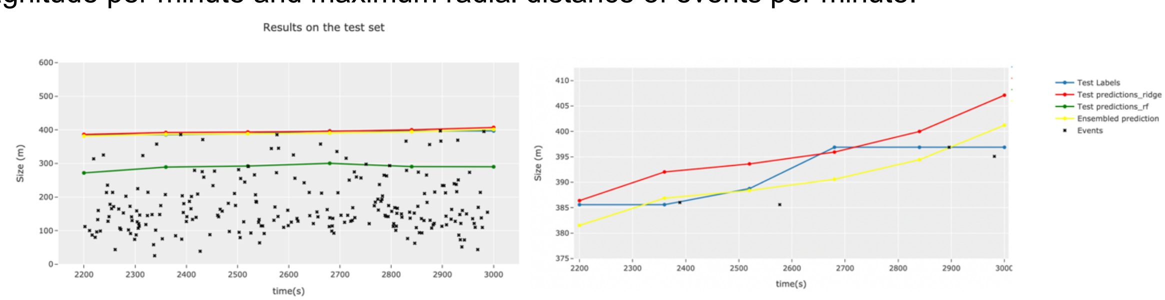

Figure 2: (a) Test labels (blue curve) and predictions on the test set. The green curve shows the RF prediction, red curve is the RR prediction, and the yellow curve is the ensemble result.

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