An indirect method of fracturing pressure interpretation based on data-driven workflows

Lei Hou[1], Derek Elsworth[2], Xiaoyu Wang[3]

1 The University of Warwick; 2 The Pennsylvania State University; 3 ETH Zurich

Introduction

Hydraulic fracturing, injecting water-based fluid under high pressure into subsurface formations, is still the prevalent technique to stimulate hydrocarbon production from unconventional reserves. Fracturing pressure remains one of the most important observations that carry valuable information regarding the proppant transport and formation properties. Nolte et al. (1988) and Wang et al. (2019) interpreted the shut-in pressure based on the instant shut-in pressure, closure pressure, and fluid efficiency (G-function-based analysis) to characterize the resulting fracture networks. Congruent with recent developments in data analysis techniques, machine learning (ML) algorithms are introduced to analyze the fracturing pressure of the entire injection process. Ben et al. (2020) and Shen et al. (2020) examined the variation in fracturing pressure with time, attempting to predict fracturing pressure and deconvolve pressure-related events based on machine learning algorithms. Yu et al. (2020) used a deep learning algorithm to understand patterns of pressure time histories and detect sand screen-out events.

Previous efforts of direct pressure interpretation are inspiring, yet it remains difficult to extract useful information as the fracturing pressure is controlled by multiple factors, including geological characteristics, hydraulic variations, fracture propagation, and human interventions. We, therefore, propose an indirect pressure-interpretation method (pressure used as output) compared with the traditional way of processing the pressure directly (pressure used as input). We perform this interpretation based on workflows that highlight one theory (dual-element hypothesis) and three assembled methods (numerical models, ML algorithms, and error analyses). The dual-element hypothesis summarizes the inputs of the algorithm into injection and formation features, by which the control variate method is applied to evaluate injection safety or formation evaluation, separately. Numerical models are employed to extract the injection and formation features. The ML algorithms execute the pressure prediction. Error analyses then evaluate the contribution of these features to pressure predictions. Then, numerical models used for feature extractions are promoted or optimized based on the error analyses, ultimately improving the numerical characterization of injection safety and formation evaluation.

One of the advantages of our method is its compatibility. By integrating different numerical models, it is possible to investigate more detailed features and greater fidelity of fracturing pressure. We present two successful case studies to highlight the promising and broad applications of our method: 1) discovering new insights into the evolution of proppant “dunes" under an alternate injection schedule, and 2) optimizing the brittleness index for formation evaluation. Another superior feature is that the method yields a fundamental understanding of process (e.g. new numerical models) immediately from field data. This study may be extended for broader application to the engineering and geological responses of hydraulic fracturing.

Methodology

We propose a dual-element hypothesis to summarize the factors controlling fracturing pressure into injection and formation elements. Numerical models are applied to extract injection and formation features from original data for the training of the ML algorithm. Different algorithms are employed and trained by extracted and original features to predict the fracturing pressure. Errors between predictions and field measurements are analyzed to refine the numerical models, thus improving injection safety and formation evaluation.

The field data used in this study are collected from shale gas wells in the Sichuan Basin, China. The field collections consist of hydraulic (pump rate, wellhead pressure, fluid viscosity, proppant concentration, etc.) and geological (well depth, principle horizontal stresses, pore pressure, logging data, etc.) characteristics and observations. Neighbouring wells are selected for training and prediction to limit the impact of geological uncertainties that increase with spatial distance. For instance, we use the data from one well for algorithm training and apply the data from its neighbour for predictions.

The data processing workflow is shown in Fig. 1. The workflow (Fig. 1 a) highlights one theory (dual-element hypothesis) and three assembled methods (numerical models, ML algorithms, and error analysis). The extracted features include the accumulated height of the proppant (H_1 in case 1) and the brittleness index (BI in case 2). The injection and formation features are examined separately with slightly different forms of the workflow. In Fig. 1 (b), the same field data are processed twice with different proppant accumulation features (H_1) to estimate the proppant transport state in the subsurface fractures. In Fig. 1 (c), the injection features (Q – pump rate; fluid type; C – proppant concentration; D_p – averaged proppant diameter) are used as control variables. The contributions of different BIs are optimized based on the predictions of different algorithms (MLR – Multiple Linear Regression; SVR – Support Vector Regression; ANN – Artificial Neural Network).

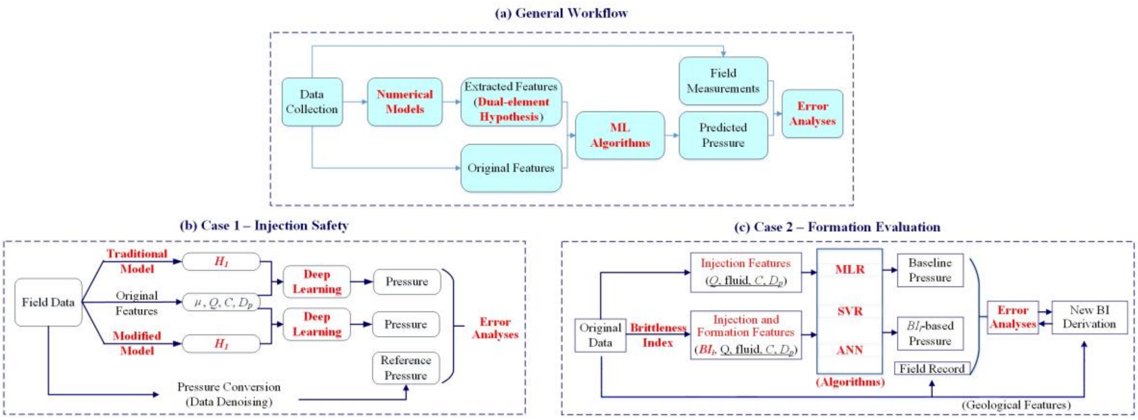

Figure 1 *Data processing workflow to interpret the fracturing pressure indirectly. (a) General workflow, (b) Specific workflow for Case 1, and (c) Specific workflow for Case 2.*

Case 1 – Proppant dune evolution by alternating injection schedules

An alternating injection schedule (injecting proppant-laden slurry then pure fluid, alternately) is widely used for shale gas fracturing to improve proppant transport in low-viscosity fluid (slickwater). The proppant dune that develops within the subsurface fracture may deform and change geometry (Fig. 2 b), differing from that under a non-alternating injection schedule (Fig. 2 a) – the mechanisms controlling this have been not fully explored through laboratory, analysis and field investigations. We test and demonstrate the effect of the formation of a proppant ridge on fracturing operations by analyzing the pressure evolution: 1) Two workflow streams are executed based on the same original data source, attempting to minimize the effect of the geological features. The algorithm is trained based on both traditional and modified models (Fig. 1 b) to compare the performances of the models; 2) the original wellhead pressure is converted into a downhole pressure to eliminate the influences of variations in hydrostatic pressure and friction; 3) a three-layer GRU (Gated Recurrent Unit) is established for pressure prediction, as illustrated in Hou et al. (2022); 4) neighbouring wells from the same well-pad are used in pairs for training and prediction, respectively (one of the neighbouring wells is used for training and the other is used for prediction).

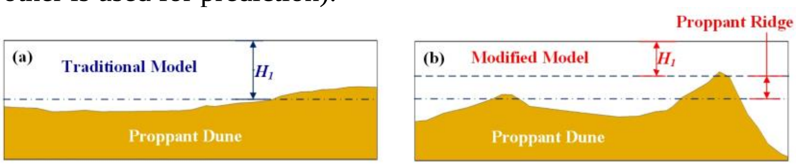

Figure 2 *Schematic of proppant forming a dune in subsurface vertical fractures. (a) Ideal equilibrium state of the proppant dune and the flowing region (H_1); (b) Transition state of the proppant dune and proppant ridge from using alternating injection and showing the liquid-only flowing region (H_1).*

Overall, the modified model considerably improves the accuracy of the predicted pressure (Fig. 3). The deviations between predictions and observations significantly decrease for all cases at early and late periods of proppant injection. The fracture is considered initially present but with an undeveloped volume in the early period and this volume progressively fills with time with the proppant ridge being easier to generate. The apparent improvements under those two conditions demonstrate the existence of the proppant ridge (under field conditions) and its significance. The commonly-used volume of the sweeping fluid (equal to the wellbore volume) in the alternate injection schedule is an empirical and approximate estimation that considers only the proppant transport in the wellbore. The sweeping volume should be optimized not only to clean the proppant from the wellbore, but also to control the growth of the proppant ridge in the fracture. Therefore, injection safety can be improved by optimizing an alternate schedule based on the pump rate, the development of the proppant ridge and controlling the flowing region (H_1), among other variables.

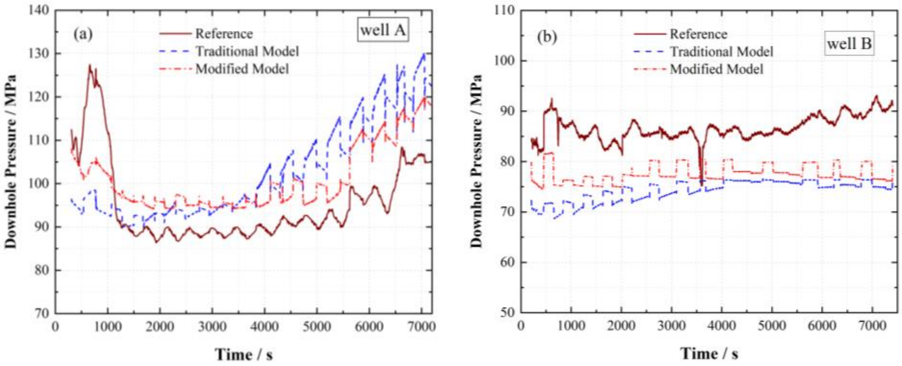

Figure 3 *Error analyses of downhole pressure based on data from (a) Well A and (b) Well B. The solid red curve is the reference pressure converted from field records. The blue and red dashed curves are the GRU predictions based on the traditional and modified models, respectively.*

Case 2 – Optimization for the brittleness index

The brittleness index (BI) is one of the most representative formation properties, commonly applied in mining (e.g. rock cutting) and petroleum engineering (e.g. drilling and fracturing). Traditional BIs characterize the formation properties based on mineral components, logging data and rock-mechanical tests. By collecting data from shale gas fracturing wells, we predict the operation pressure based on different BI calculations, attempting to optimize for the index by the relative error improvement compared with the Baseline values (Fig. 1 c). Six traditional BIs are tested, based on three classic ML workflows, attempting to restrict potential interferences induced by the performance of the algorithm. We use 68 stages of fracturing operations (at minute-level) to train the algorithm and eight more stages (from the same wells, neighbouring wells and far-distant wells) for prediction. The predicted RMSEs (root mean squared errors) based on the prediction stages are averaged for the analyses.

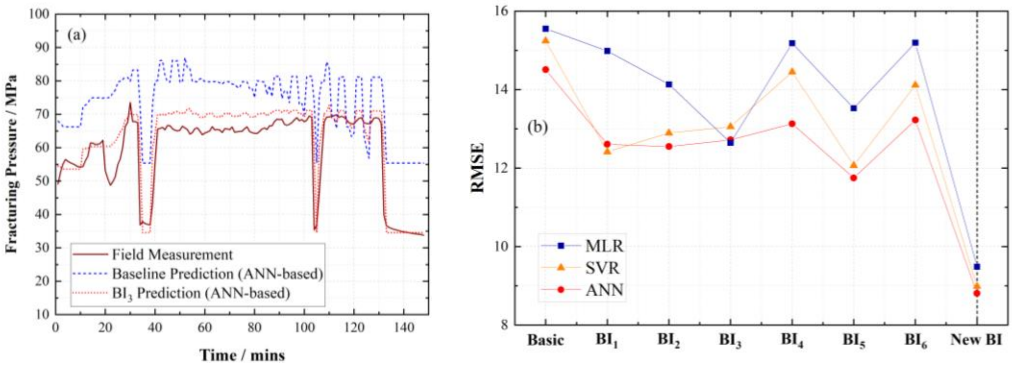

Figure 4 *Fracturing pressure prediction and interpretation based on BI. (a) Example of the predicted and measured pressures, and (b) Error analysis based on different BIs and algorithms.*

The predicted pressures are presented in Fig. 4 (a) using BI_3 and ANN algorithm as an example. Generally, the derivations between field measurements and predictions are significantly improved by introducing the BI. The comparison is repeated using the seven remaining fracturing stages, five BIs and two algorithms. The averaged errors are shown in Fig. 4 (b). A new BI (Eq. 1) is derived using a backward elimination strategy, considering the normalized BI_1 (mineral-component-based), BI_3 (logging-data-based) and BI_5 (elastic-based), together with the ratio of principal horizontal stresses. The error is approximately halved based on the new BI compared with those based on traditional BIs, as shown in Fig. 4 (b). The differences in RMSEs produced by various algorithms are also compressed based on the new BI (Fig. 4 b). The new BI provides a more reliable option for formation evaluation, thus improving the recognition of the target formation.

$$BI_{New} = \frac{(BI_{1n} + BI_{3n} + BI_{5n})}{3} \times \frac{Stress_{\min}}{Stress_{\max}} \tag{1}$$

Conclusions

A new data-driven workflow is proposed combining one theory (dual-element hypothesis) and three assembled methods (numerical models, ML algorithms, and error analyses). Fracturing pressure is interpreted indirectly based on the workflow by analyzing the correlation between numerical models and pressure predictions. The new method uses analyses at field scales to produce more confidence in the results. By integrating different numerical models, the new method is compatible with broader applications to engineering and geological responses to hydraulic fracturing.

Two cases are presented to illustrate applications of the new workflow for injection safety and formation evaluation. By predicting pressure time histories and analyzing errors, the development of a proppant ridge (induced by an alternating liquid-then-slurry injection schedule) and its effect on fracturing injection are revealed. The volume of the sweeping fluid in the schedule should be optimized to control the growth of the proppant ridge in the fractures for enhancing injection safety. In the second case, a new brittleness index is derived based on optimization. The prediction errors are approximately halved, when compared with traditional BIs, thus providing a more reliable option for evaluating the formation brittleness.

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