A data-driven model for the prediction of stimulated reservoir volume (SRV) evolution during hydraulic fracturing

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ABSTRACT: Accurate forecasting of stimulated reservoir volume (SRV) constitutes a key step in field evaluation and optimization during hydraulic fracturing. In this work, a data-driven model is developed to take advantage of field monitored microseismicity and fracturing parameters for predicting SRV ahead of time. A voxelized method is applied to calculate SRV values using recorded microseismicity data. Fracturing parameters along with SRV history are fed into a Long Short-Term Memory (LSTM) network as inputs. This model can successfully characterize the evolution of SRV. The LSTM network has excellent prediction accuracy ($R^2 > 0.80$) at most stages while performing poorly at the initial stages. The influence of SRV history, time lag size and time window length is investigated to confirm the effectiveness of the proposed method. This study provides a new approach for unconventional reservoir hydraulic fracturing assessment using data-driven methods.

Keywords: Stimulated reservoir volume, Hydraulic fracturing, Data-driven model, Long short-term memory network.

1 INTRODUCTION

Multi-stage hydraulic fracturing technology is widely used in unconventional reservoir development. High-pressure fluid is injected into the subsurface to crack rocks and create permeable flow channels. Stimulated Reservoir Volume (SRV), defined as the extent of the rock volume stimulated by the fluid injections, is an important indicator in well completion optimization and fracturing design (Fisher et al. 2004). However, accurate estimation of SRV during hydraulic fracturing has been a long-standing challenge.

Physics-based models can be built for the simulation of hydraulic fracturing and predicting SRV. Nevertheless, these models are usually based on some simplified assumptions and fail to reproduce the conditions of in-situ reservoirs (e.g., fracture distribution, reservoir heterogeneity). Besides, physics-based methods require time-consuming simulation processes and careful model calibration, which means they are unable to take full advantage of field monitored data and make real-time predictions. Data-driven models are emerging approaches to address these issues and have been widely used in engineering prediction with real-time data. After training on massive data, these models can make fast predictions of expected parameters based on field observations. This makes them highly applicable in field evaluation and decision making.

In this paper, a data-driven model is proposed to predict the dynamic evolution of SRV based on field monitored data. This paper proceeds as follows. Raw data preprocessing and its methods are described in Section 2. The results of the proposed model are presented in Section 3, along with further discussions. A brief summary and some suggestions for future research are concluded in Section 4.

2 METHODS

The resulted SRV during fracturing process can be inferred from Micro-Seismic Events (MSEs) recorded by nearby geophone arrays. Various methods have been applied to estimate the area influenced by hydraulic fracturing based on MSE cloud size (Liu et al. 2022). Motivated by the causality between fracturing treatment and generated MSEs, this work proposes a data-driven model to predict SRV based on field observations. Field monitored fracturing parameters (e.g., surface pressure, injection rate, proppant concentration, etc.) and MSE records (e.g., location, origin time, magnitude, etc.) are collected from three hydraulic fracturing horizontal wells (denoted as H5-4, H5-5, H5-6) in Sichuan Basin, China. These data include 71 fracturing stages in total. The SRV calculation method and the deep learning model will be described as follows.

2.1 SRV calculation method

A spatiotemporal density-based clustering algorithm called ST-DBSCAN (Birant & Kut 2007) is firstly employed to exclude some ‘dry’ MSEs. These dry events are defined as the events isolated from most MSEs near the hydraulic fractures (which are referred to as ‘wet’ events). Accounting for the dry events in the SRV calculation will cause an overestimation of SRV (Maxwell et al. 2015). The voxelized method (Liu et al. 2022) is applied to calculate SRV with MSE records (Figure 1). The three-dimensional space is discretized into homogeneous and non-overlapping voxels. The size of each voxel is 15m×15m×15m. The discretized voxels are indexed by an index matrix. The binary tree algorithm named K-Dimensional Tree (also called as KD-Tree) is then used to efficiently search the number of MSEs in each voxel. A voxel is regarded as active and stimulated if the number of MSEs exceeds a threshold. SRV is acquired by accumulating all the active voxels in space. In this work, a voxel is assumed to be active as long as there is at least one MSE in it. Using different voxel sizes or thresholds will change the result of the calculated SRV (Liu et al. 2022). After comparisons of different voxel sizes and thresholds, these two parameters chosen in this work lead to a reasonable SRV magnitude.

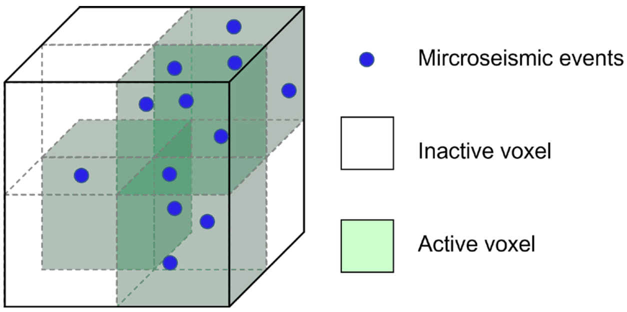


Figure 1. Illustration of the voxelized method, modified from Liu et al. (2022).

Note that SRV is calculated continuously during each fracturing stage. It means that a 1-minute expanding time window starting at the beginning of each stage is used to calculate SRV from MSEs. Every stage is treated as an individual fracturing process, so the MSEs of the previous stage are not included in the SRV calculation of the current stage. A stage-by-stage SRV evolution curve is obtained, and is used as the predicting label.

2.2 Prediction model

The input features include five operational recorded parameters: surface pressure, injection rate, proppant concentration, total injected volume and total proppant mass. They are monitored and recorded every second in the field. These time-series data are downsampled from seconds to minutes. The stage number is added as a time-independent feature to account for the model of hydraulic fracturing order. The history of SRV is considered as an additional input feature. All the feature variables are normalized by a min-max scaling. In order to enlarge the dataset and to predict the SRV value at a future moment, a 10-minute sliding time window is applied. The 7 feature variables in one 10-minute sliding time window are used as one sample (Figure 2). This makes the samples reach up to 11,994. In this work, the label (i.e., the SRV) with 15-min time lag is predicted. For example, the features recorded from the 1st to the 10th minute are used to predict the label at the 25th minute. Note that input sequences and their corresponding labels are generated on each fracturing stage separately. The training/validation/testing sets are divided on a stage basis as well. Three stages are randomly selected in each horizontal well as the validation set. The first, middle and last stages of each well are selected as the testing set. And the rest stages are included in the training set.

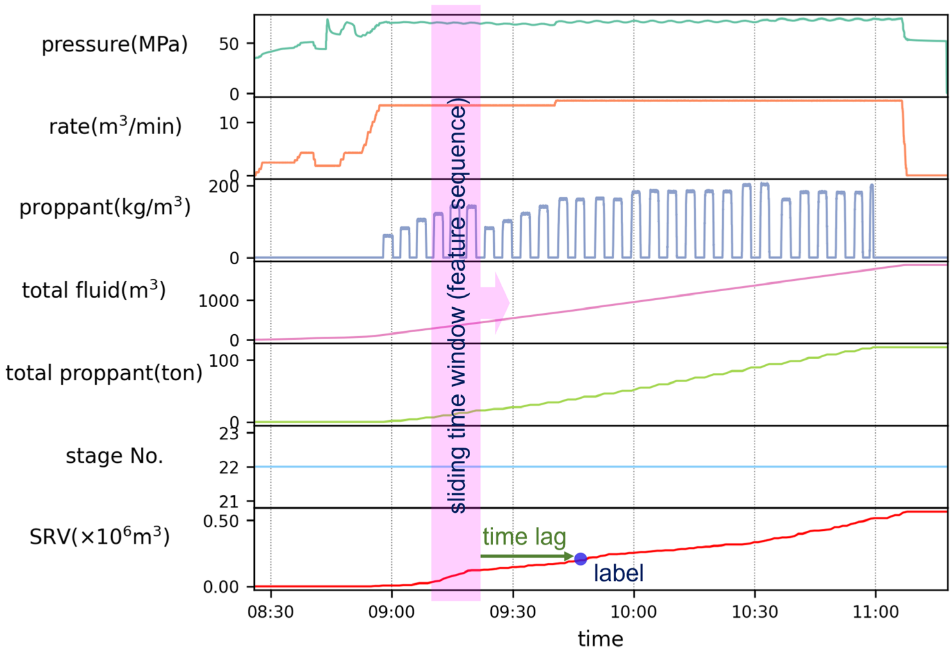


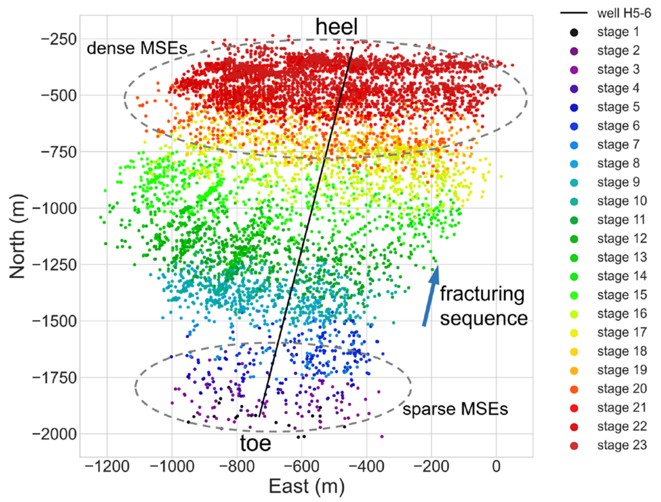
Figure 2. Features and label at stage 11 of H5-6. The sliding time window operation is visualized by the violet box. The dark green arrow indicates the time lag. The label value is marked by the blue dot.

The Long Short-Term Memory (LSTM) network (Hochreiter & Schmidhuber 1997) is used in this work as the prediction model. The LSTM network is an advanced type of recurrent neural network (RNN) which are widely used to tackle sequence data. A typical layer of LSTM network incorporates 'gate operations' to control the flow of input information, which overcomes gradient vanishing or exploding of vanilla RNN. Two layers of LSTM network are applied to extract information in the input feature sequences. The last hidden state of LSTM network is then fed into two layers of fully connected neural network with ReLU activation function. The final output of the proposed network is the SRV value at a specific time lag.

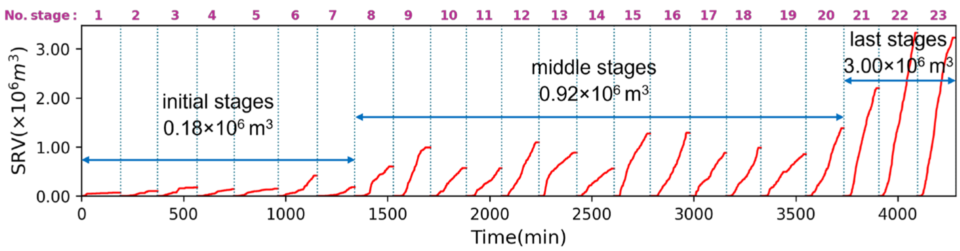
The mean-squared error is chosen as the loss function to calculate training errors. The adaptive moment estimation (ADAM) method with learning rate of 0.001 is applied to optimize network parameters. In addition, the batch size is 30 and the training epoch is 50. The proposed network is implemented in the open-source deep learning library PyTorch. The model performance is evaluated based on R^2 and rooted mean square error (RMSE).

3 RESULTS AND DISCUSSION

Figure 3a shows the MSEs distribution of horizontal well H5-6. Hydraulic fracturing treatment starts from stage 1 at 'toe' position and proceeds to stage 23 at 'heel' position. There exists sparse MSEs at initial fracturing stages, while plentiful MSEs occur in last stages. The SRV of each stage are computed from the MSE cloud size recorded in the process of hydraulic fracturing. A stage-by-stage SRV evolution curve is obtained based on the voxelized method. Figure 3b shows the evolution of SRV at different stages of horizontal well H5-6. Data from different stages are merged into a continuous time base and divided by the dashed lines to better visualize different patterns. In general, the initial fracturing stages (e.g., stage 1-7) have relatively flat SRV curves and small final SRV values (about 0.18×10^6 m^3). Stages at the middle of the horizontal well (e.g., stage 8-20) share roughly normal dynamic patterns, with average ultimate SRV values around 0.92×10^6 m^3. It is noteworthy that the curves of stage 21-23 are exceptionally steep, whose final values reach up to 3.00×10^6 m^3. Similar SRV evolution pattern can also be observed in other 2 wells. There might be two reasons contributing to the variations in SRV of different stages. First, in-situ rock of the initial stages tends to be undisturbed and less cracked before fracturing treatment, thus making it difficult to be stimulated compared with the following stages. Second, due to the decrease of stress anisotropy by the stress shadow effect, hydraulic fractures at subsequent stages tend to generate more complex and branching networks (Feng et al. 2023). These dynamics of SRV, though complex enough, can be predicted by our proposed data-driven model and will be presented as follows.



(a)



(b)

Figure 3. (a) MSEs distribution of well H5-6. The black line denotes the well trajectory. One MSE is represented by one dot, which is distinguished by different colors corresponding to stages; (b) SRV evolution curve of well H5-6.

Figure 4 shows the prediction results on test stages. There is a good agreement between the predicted SRV curves and the true ones except the curves of the first stages. R^2 of middle and last stages are all above 0.80. It is shown that the proposed model is able to make decent predictions based on the history observations of fracturing parameters and MSEs records in most cases. However, the model fails to keep track of the evolution of SRV of initial stages. On the one hand, due to the sparse MSEs occurring at initial stages, SRV curves have abnormal patterns compared to the subsequent stages. On the other hand, the small SRV values of initial stages leads to the small training errors when these data are used for training. Thus, the model learns less information at initial stages. The performance at initial stages can be improved if more samples are obtained to train the model.

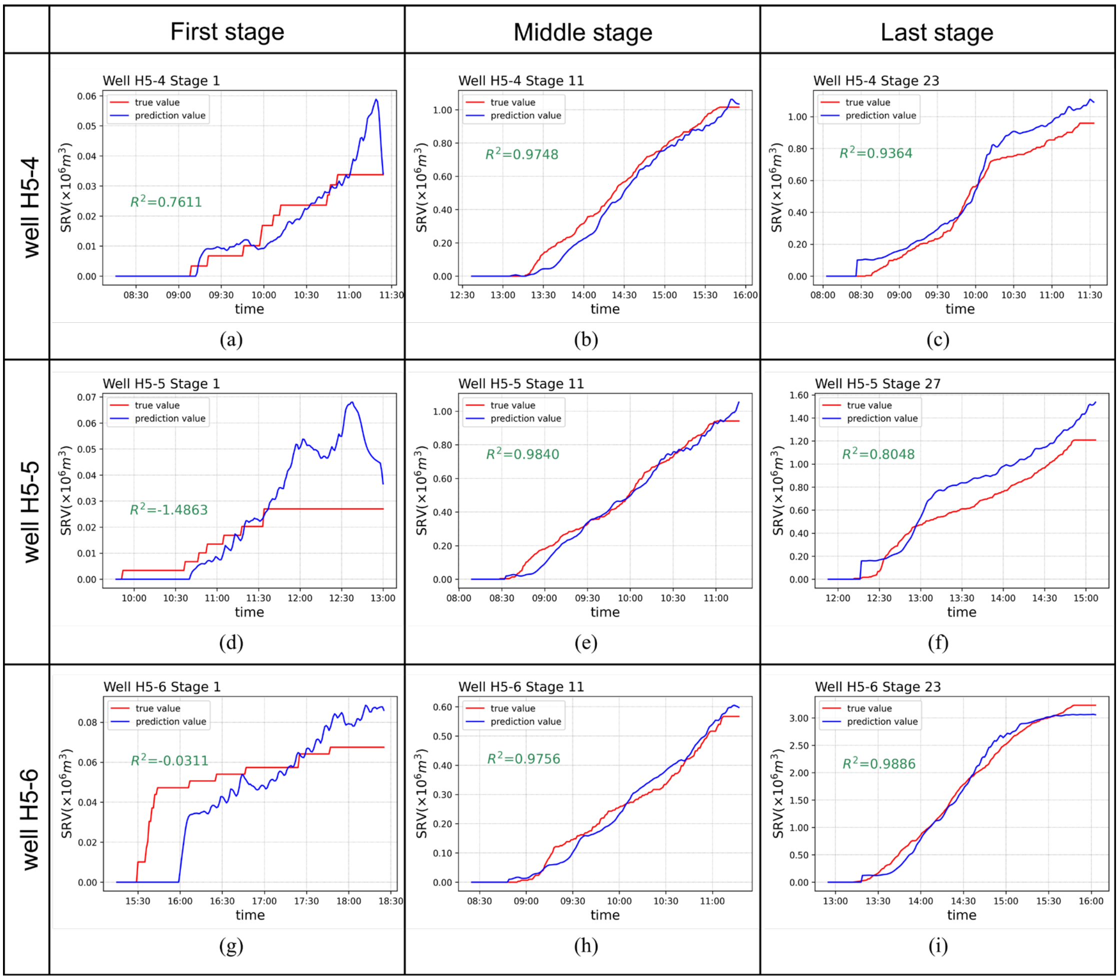
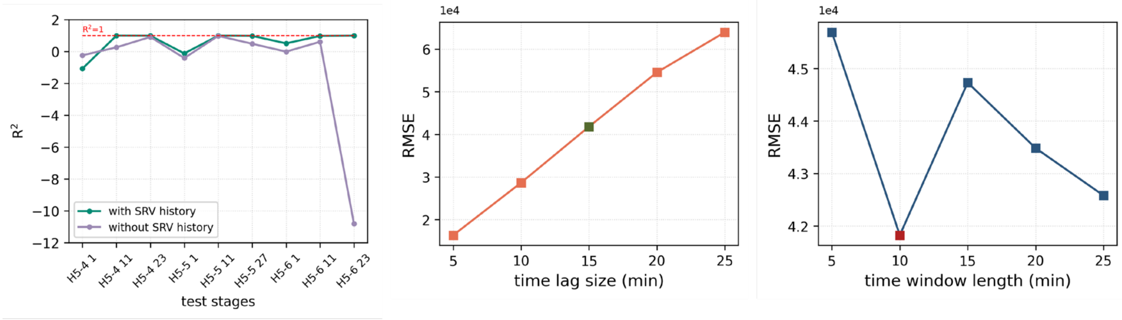


Figure 4. Predicted (blue lines) vs. true (red lines) SRV curves on test set.

It should be noted that the features include the history of SRV evolution. When this model is applied in field, in order to obtain SRV histories, MSEs still need to be monitored and interpreted timely. However, thanks to the fast development of machine learning technologies in geoscience, real-time source location of MSEs is currently feasible. A recent work by Chen et al (2022) reported an efficient (e.g., within 1 s) microseismic source localization method based on a random forest model. In addition, if the past information of SRV is not used as the model inputs, results show that this will largely reduce the prediction accuracy (Figure 5a). The mismatch at stage 23 in well H5-6 indicates that the model is unable to predict the exceptionally large SRV values if history data are not provided.

It is noteworthy that this work can predict the SRV ahead of time. The performance of this model lies in the determined time lag size and time window length. There is a tradeoff relationship between these two parameters and prediction accuracy. As shown in Figure 5b and 5c, the influence of time lag size and time window length on model performance is evaluated based on RMSE. It can be inferred from Figure 5b that a larger time lag size degrades the performance of the model in that it is more difficult for the model to predict the SRV far away from now. A 15-minute time lag is proposed in this work as it meets the requirements of field application without losing much prediction accuracy.

Figure 5c confirms the rationality of choosing the past 10 minutes' information as inputs (i.e., the length of the time window is 10 minutes) since it produces the most accurate prediction.



(a) (b) (c)

Figure 5. (a) Influence of SRV history on model R^2 of test stages; Influence of (b) time lag size and (c) time window length on model RMSE.

4 CONCLUSIONS

This study presents a data-driven model for the prediction of SRV at a future moment during multi-stage hydraulic fracturing. A voxelize method is applied to calculate SRV values based on field monitored MSEs. The LSTM network is leveraged to extract information in sequence data including fracturing parameters and SRV history. The evolution of SRV varies in different stages but is well captured by the proposed model except the initial stages. The influence of the SRV history, the time lag size and the sliding time window length on model performance is investigated. The proposed model with a 10-minute sliding window and a 15-minute time lag produces the best performance.

To further improve the accuracy and generalization of this model, more field data are needed. More importantly, geological features should be considered in order to reflect the in-situ conditions. It is worth mentioning that this model can be further used for field evaluation and decision making, which will be the focus of future research. A comprehensive workflow including real-time prediction of SRV through microseismicity and fracturing parameters optimization needs to be developed in future studies.

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