URTeC: 2902641

A Fiber-optic Assisted Multilayer Perceptron Reservoir Production Modeling: A Machine Learning Approach in Prediction of Gas Production from the Marcellus Shale

Payam Kavousi Ghahfarokhi*[1], Timothy Carr[1], Shuvajit Bhattacharya[2], Justin Elliott [1], Alireza Shahkarami [3]; Keithan Martin[1]:1. West Virginia University, 2. University of Alaska Anchorage, 3. Saint Francis University.

 DOI 10.15530/urtec-2018-2902641

This paper was prepared for presentation at the Unconventional Resources Technology Conference held in Houston, Texas, USA, 23-25 July 2018.

Abstract

This study utilized the recorded data of a distributed temperature sensing (DTS) and distributed acoustic sensing (DAS) fiber-optic system from a gas producing horizontal well in the Marcellus Shale, in Northern West Virginia. A predictive data-driven model was developed to understand the well's performance and forecast the gas production using DTS data and daily flowing time as dynamic inputs, from May 2016 to May 2018. We used 1320 DTS measurements along the lateral of the well MIP-3H for each day and upscaled to a stage scale by an averaging method. A multi-layer perceptron neural network (MLPNN) was trained with stage-based daily DTS data, and daily flowing time to predict gas production for the next day. We carried out a sensitivity analysis by removing each stage DTS attribute from the input dataset to identify the most influential stages in predicting gas production. The sensitivity analysis (SA) shows that several stages carry higher weights in predicting gas production, while several stages have less impact on prediction accuracy. In contrast to DTS, DAS data was only recorded during hydraulic fracturing of the well. DAS energy variance attribute, which could be inversely related to stage stimulation efficiency, was computed for each stage and compared with the results of the neural network SA. Stages with higher variance in DAS energy (less efficient stimulation) have less effect on neural network accuracy. This relationship is more significant for stages that are completed with limited entry approach in zones with similar minimum horizontal stress. The results of the sensitivity analysis was also compared with flow scanner production logging data. Results suggests that DAS data is more correlated with sensitivity analysis results than production logging data.

Introduction

Well MIP-3H near Morgantown, West Virginia was studied for the prediction of the daily gas production from the Marcellus Shale through use of an artificial neural network (Figure 1). The 28-stage horizontal MIP-3H well, drilled as a part of the Marcellus Shale Energy & Environment Laboratory (MSEEL) project, has multi-scale and multi-sensor-based spatio-temporal data, such as DTS, DAS, production log from flow scanner production log, geomechanical logs, surface pressure, and surface temperature. DAS and DTS are recorded by a fiber-optic cable attached to the outer part of the production casing, and has recorded the temperature around the fiber to date. However, the DAS data (strain) is only available for the stimulation process and cannot be used as a dynamic input for reservoir modeling.

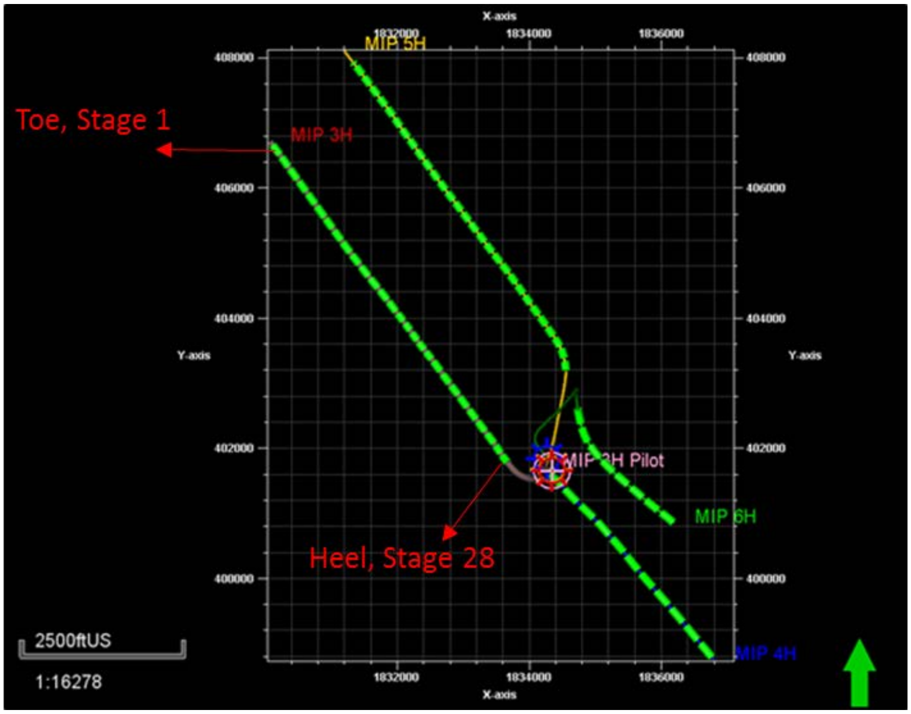

Figure 1: MSEEL project consists of 4 horizontal well in the Marcellus Shale. Well MIP-3H is the only well with the fiber-optic data

DTS has provided continuous multi-point reservoir temperature monitoring along the lateral of the MIP-3H to date. This unique dataset can be analyzed by artificial intelligence algorithms such as neural network to predict gas production from the MIP-3H. Artificial neural networks (ANN) have been of increasing popularity because of their capabilities in efficiently recognizing extremely complex patterns without making any assumptions about the data being studied (Keshavarzi et al., 2010, Zheng et al., 2014). ANNs provide a flexible way to handle regression and classification problems without explicitly stating the relationship between input and output parameters (Mishra and Datta-Gupta, 2017). Neural networks have a large range of applications as they have been used in varying fields of study. Specifically, in engineering and geology, they have been shown to have the capability to increase the performance of reservoir simulation by using enhancing sparse data (Isaiah et al., 2013). Application of artificial intelligence for unconventional oil and gas resources has also been conducted by various researchers. Mohaghegh et al., (2011) carried out data mining techniques to evaluate shale production. More recently, Anderson et al., (2016) showed the application of the machine learning in classifying hydraulic fractures in the Marcellus Shale. The reservoir production forecast has also been implemented for several unconventional Shales (Gaurav, 2017; Cao et al., 2016). However, usage of fiber-optic data as a valuable downhole dynamic input for the neural network has not been undertaken.

Fiber optic is an advanced non-invasive hydraulic fracture stimulation monitoring tool, which can record temperature and strain around the well. Fiber-optic systems works based on optical time-domain reflectometry (OTDR). A transmitter sends a light pulse into the fiber; inherent impurities in the glass core, scatter back the light toward the detector. The power and the wavelength of the backscattered light enables the detector to estimate the temperature, strain, or the vibro-acoustic on the fiber (Tanimola and Hill, 2009). DTS technology measures the “Stokes” and “Anti-Stokes” components of the backscattered spectrum (Figure 2). The “Anti-Stokes” component is sensitive to the temperature, while the Stoke component is temperature independent. Thus, a ratio of “Anti-Stokes” and “Stokes” power provides a measure of temperature (Molenaar et al., 2012). The frequency of the Brillion stokes and anti-stokes changes as a function of temperature and strain. Thus, the axial strain of the fiber can also be recorded during the hydraulic fracturing. Distributed acoustic sensing (DAS) measures the axial strain of the fiber; however, DAS data are usually available only for the stimulation time and not for subsequent reservoir production. In contrast, DTS data is more common to be recorded during the reservoir production. Unlike SEGY format DAS data, DTS data can be extracted as ASCII or CSV format without further processing.

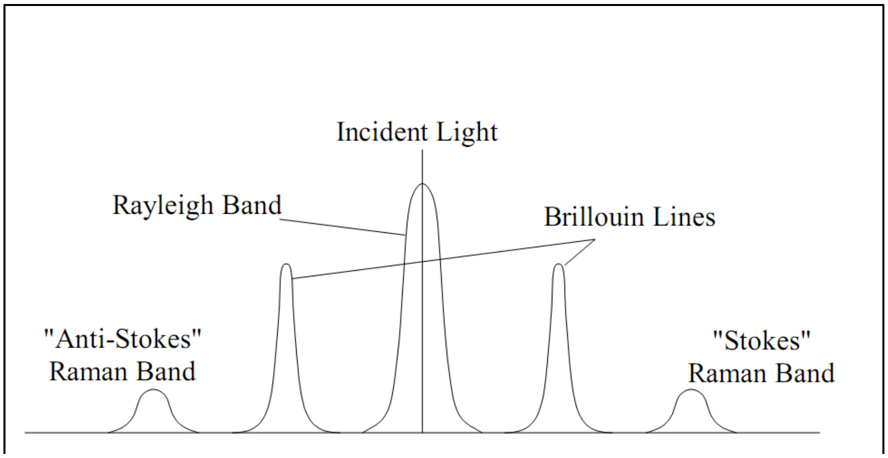

Figure 2: The backscattered light spectrum has Rayleigh Band, Brillouin bans, and Raman bands. Rayleigh and Brillouin bands are sensitive to strain while Raman bands are sensitive to the temperature around the fiber (courtesy Carnahan et al., 1999).

Discussions and Results

Ghahfarokhi et al., (2018) used the DAS and DTS data to show hydraulic connections between several stages in the MIP-3H well. The sum of DAS traces squared amplitudes can be used to calculate DAS energy attribute (Kavousi et al., 2018). The energy attribute indicates that a more uniform hydraulic fracturing was implemented for Stage 18 and Stage 17 than Stage 10 (Figure 3).

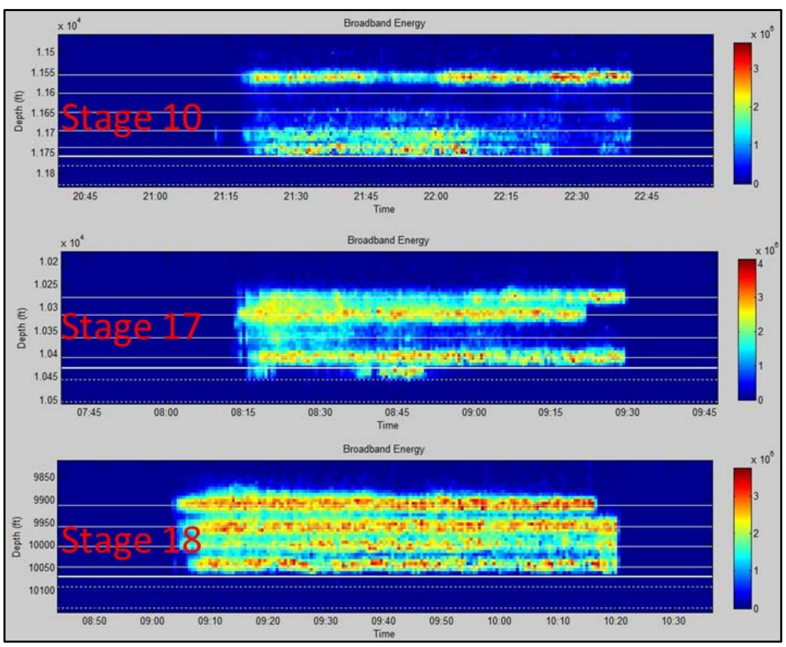

Figure 3: DAS energy attributes of three stages of the MIP-3H are shown. Note that DAS energy attribute has no unit.

The MIP-3H well in the Marcellus Shale continues to record DTS data along the lateral, to date. The raw DTS data can be visualized in a waterfall plot (Figure 4). Fiber-optic DTS system has recorded temperature at more than 1320 points with spacing of 2-3ft (0.6-0.9 m) along the lateral of the well for past two years; yielding almost 1 million DTS data points for two years. This amount of data provides the opportunity to use a neural network algorithm for predicting gas production from MIP-3H. MIP-3H gas production was constrained until late 2017, and well was producing for only several hours per day due to limited market demand. The hours of production of each day is equivalent to the daily flowing time throughout this paper. In addition to DTS, we used flowing time as an auxiliary input for neural network to predict gas production for the next day.

We upscaled the DTS measurements to stage scale by averaging the DTS data between top and bottom of each stage (Figure 5). The waterfall plot shown in Figure 5 shows that the well is cooler in the toe than the heel. Also, stages 17, 18, and 19 are consistently cooler that the adjacent stages. These results could be related to Joule-Thompson cooling effect, which occurs as natural gas expands from the higher-pressure reservoir into the lower pressure production casing.

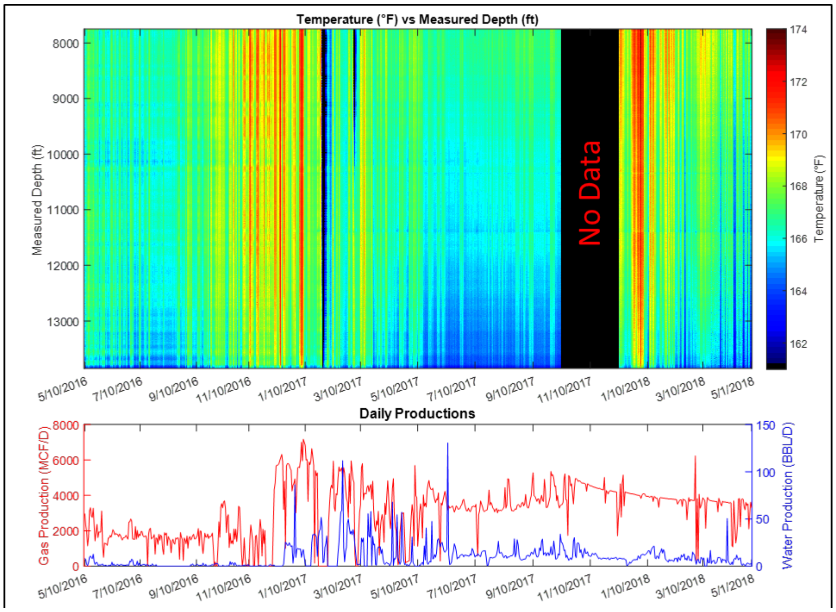

Figure 4: DTS data until May 2018 are compiled in a waterfall plot. The toe of the well is cooler than the heel of the well.

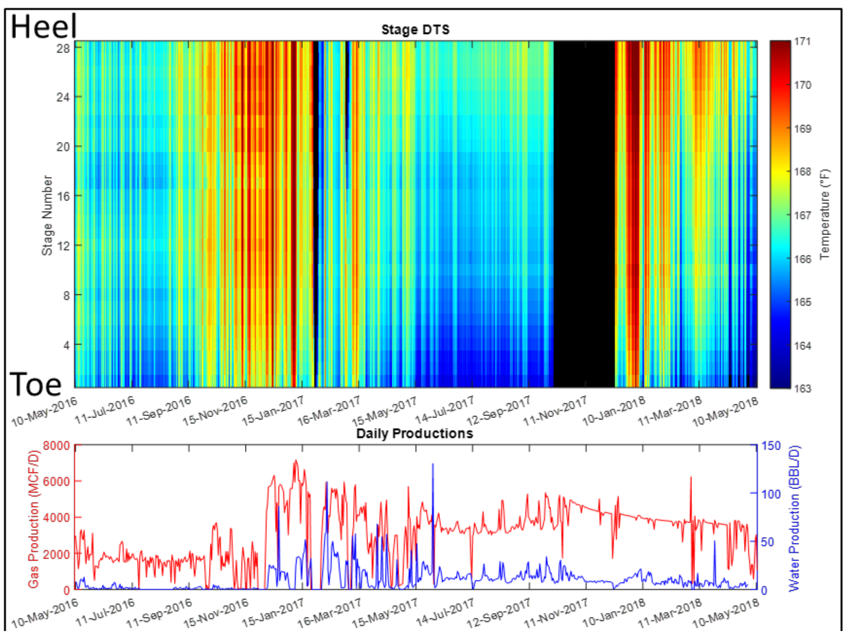

Figure 5: The DTS data in figure 4 are upscaled to the stage scale.

The upscaled DTS attribute is used as an input for a multi-layer perceptron ANN algorithm with 3 hidden layers (Figure 6). We optimized learning rate, momentum, and epoch (number of iterations) for enhanced learning of data pattern and testing it. The training, validation, and testing errors were carefully inspected to avoid ANN overfitting.

The optimal values from numerous experiment give a learning rate, momentum, and epoch as 0.05, 0.11, and 500, respectively.

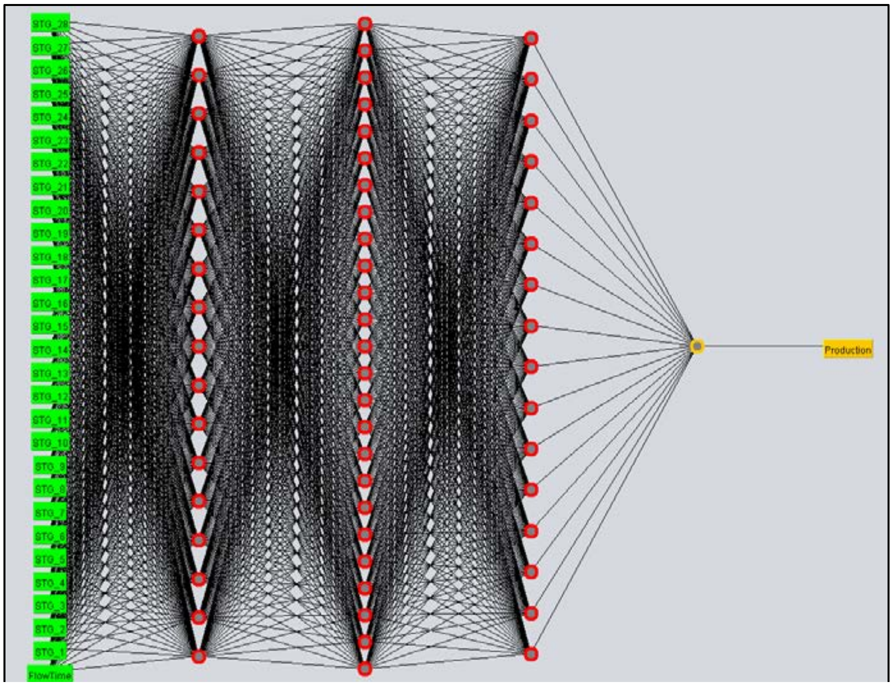

Figure 6: ANN structure with three hidden layers used for daily gas production prediction in this study. Note that input parameters are from previous days of the predicted productions.

The designed neural network uses dynamic inputs as shown in Table 1 to predict gas production of the next day. Constrained production from the well prior to late 2017 has caused the well to not show a typical declining daily production. Although the flow time input helps the neural network to learn the constraint on gas production, training is not still very accurate for sudden very high or very low productions (Figure 7). The trained neural network is then applied to 102 days of the test data (Figure 8).

Table 1: The dynamic inputs for the neural network. Note that daily gas rate is predicted from input data of its previous day.

Inputs	**Output**
Upscaled DTS (t-1) for stage 1 to 28	Gas production (t)
Flowing time (t-1)	

A neural network sensitivity analysis was then carried out by removing each input from the network and evaluating changes in the mean absolute error of the network (Figure 9). The neural network sensitivity analysis of DTS data suggests that the more influential stages such as 17, 18, 19, 20, and 28 would result in a higher mean absolute error (MAE) in network predictions if removed from the input dataset. In contrast, Stage 1 removal will decrease MAE of the neural network. Production logging was carried out on March 02, 2017 to assess the gas production share of each stage. Figure 4 and Figure 5 shows that downhole reservoir temperature is very sensitive to water and gas production and the observed stage temperature varies by time. Hence, a production log might have limited capability to be a contemporary indication of individual stage production.

We compare production log data and DAS variance attribute with the neural network sensitivity results to evaluate whether there are any relationships between these variables (Table 2). Results show that DAS variance attribute is inversely related to MAE of neural network. A smaller DAS variance for a stage could suggests a more uniform hydraulic fracturing in all clusters while a higher DAS variance implies that not all the clusters are hydraulically fractured (Figure 3). Thus, a stage with a lower DAS variance could cause a higher neural network MAE when removed from the predictions (Figure 10a). Stage 13 to 19, known as the engineered stages, are stimulated by a limited entry approach in zones with similar minimum horizontal stress. The inverse relationship between DAS variance and neural network MAE is more pronounced in engineered stages (Figure 10b). One the other hand, the production log does not show any significant relationships with neural network MAE (Figure 11a and 11b).

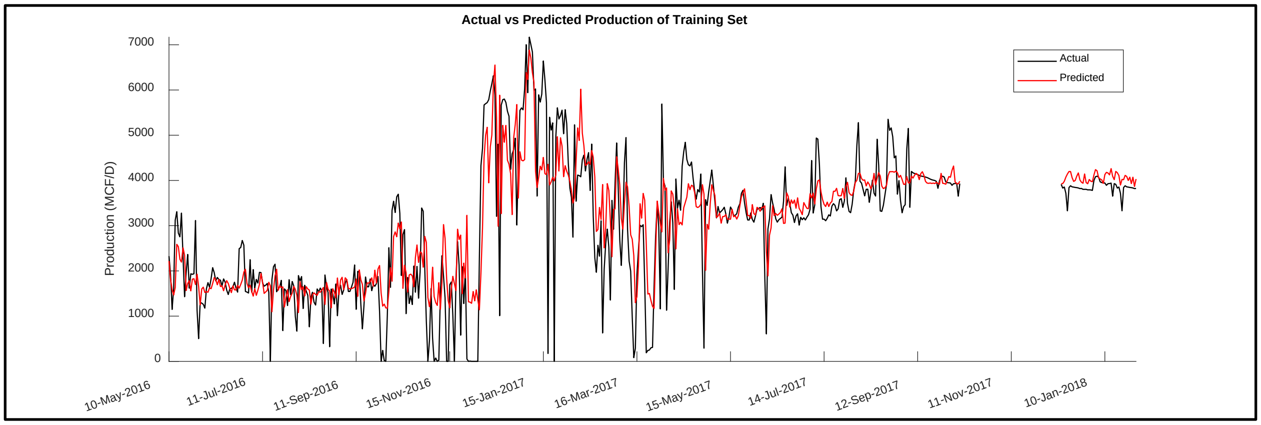

Figure 7: The network is trained for 508 days using dynamic input data.

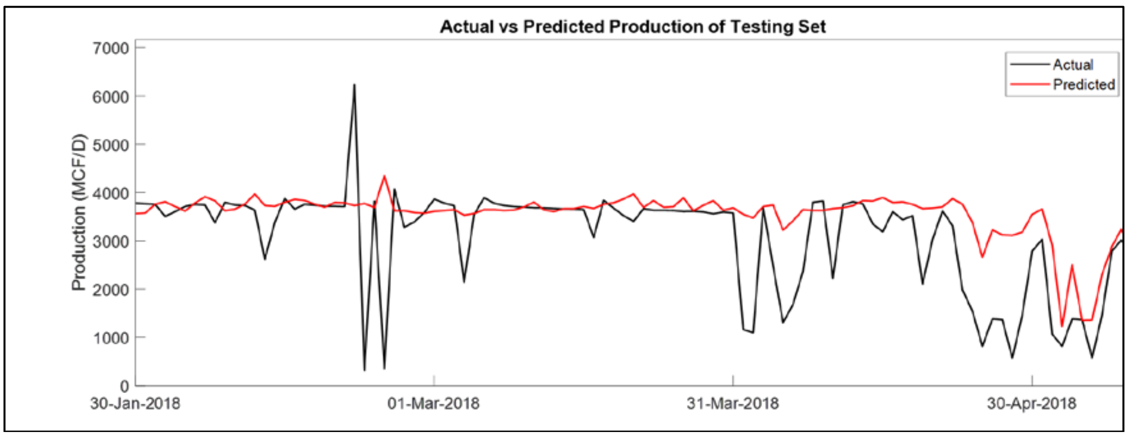

Figure 8: The test data for 102 days of the well daily gas production.

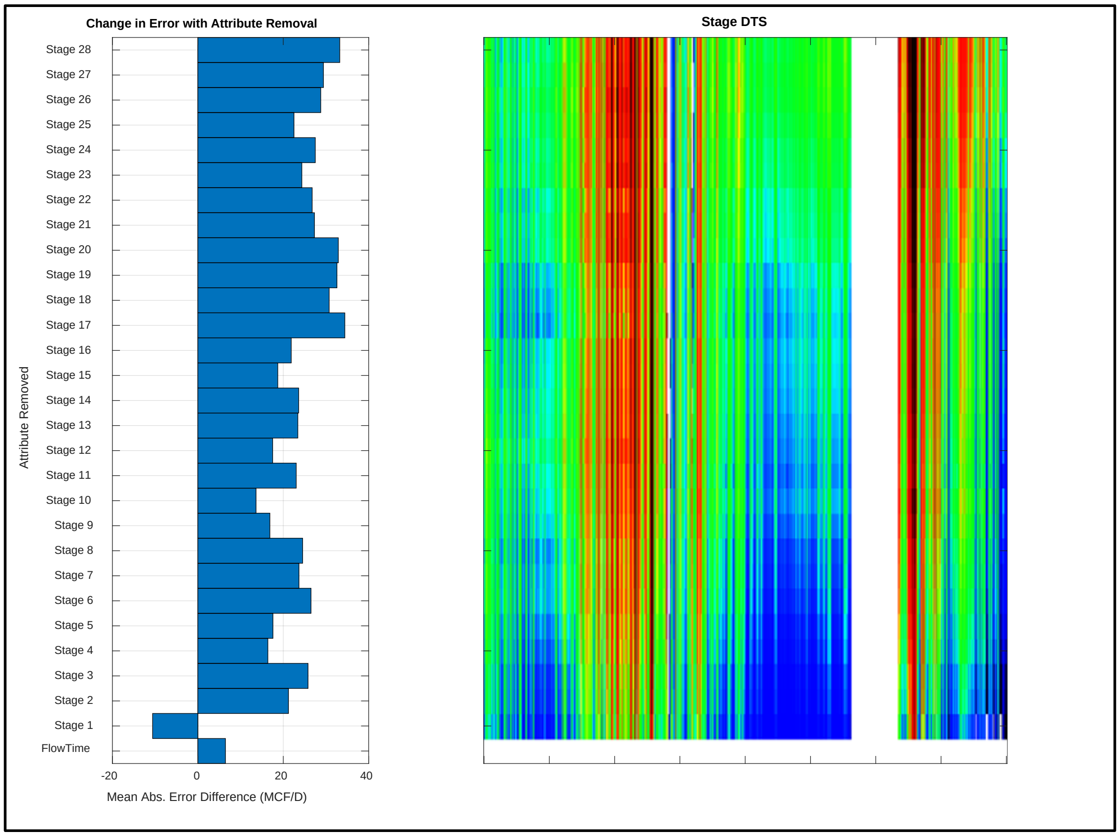

Figure 9: A sensitivity analysis for dynamic inputs suggest that casing pressure and tubing head pressure are amongst the most important factors for predicting gas production.

Table 2: The sensitivity analysis results are shown with DAS variance and production log data for all 28 stages.

Stage number	Sensitivity analysis error difference	DAS variance	Production log (MCF/d)
28	33.2344	0.084507042	50
27	29.4075	0.481690141	84
26	28.782	0.430985915	67
25	22.5155	0.346478873	158
24	27.5071	0.295774648	192
23	24.355	0.43943662	272
22	26.774	0.346478873	389
21	27.304	0.194366197	198
20	32.8965	0.566197183	99
19	32.5699	0.21971831	119
18	30.7536	0.109859155	231
17	34.4187	0.016901408	250
16	21.8756	0.38028169	378
15	18.7224	0.464788732	59
14	23.611	0.236619718	203
13	23.4141	0.185915493	268
12	17.5225	0.785915493	242
11	23.0408	0.549295775	316
10	13.6376	0.667605634	190
9	16.8706	0.228169014	167
8	24.5391	0.684507042	153
7	23.6815	0.473239437	142
6	26.5018	0.718309859	256
5	17.5871	0.709859155	310
4	16.3985	0.709859155	75
3	25.8073	0.43943662	58
2	21.2219	0.532394366	256
1	-10.5889	0.701408451	251

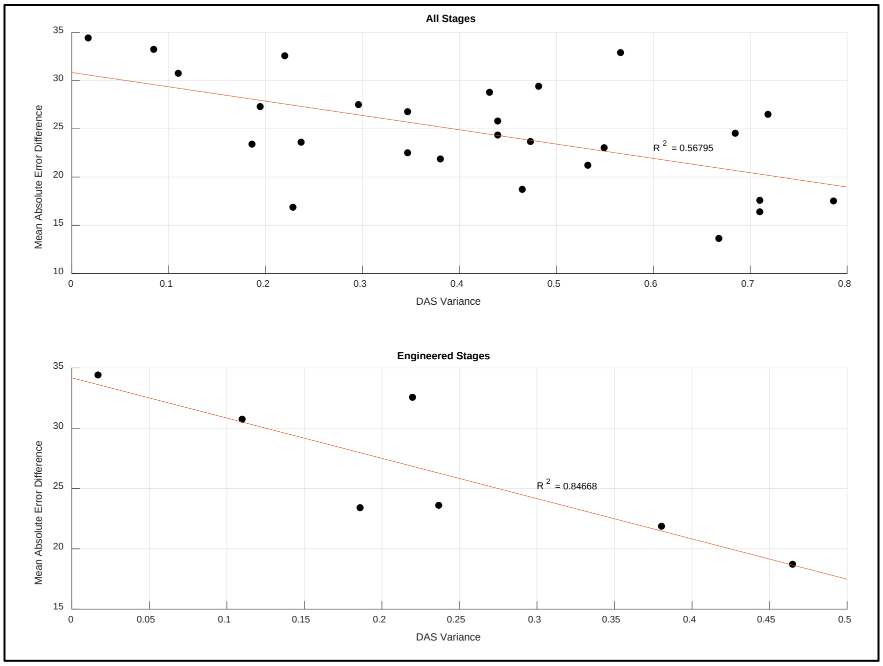

Figure 10: a) The DAS variance of each stage vs. MAE variations of the neural network if the stage is removed from the input dataset. b) The correlation for engineered stage show a significant negative relationship between DAS variance and MAE variations.

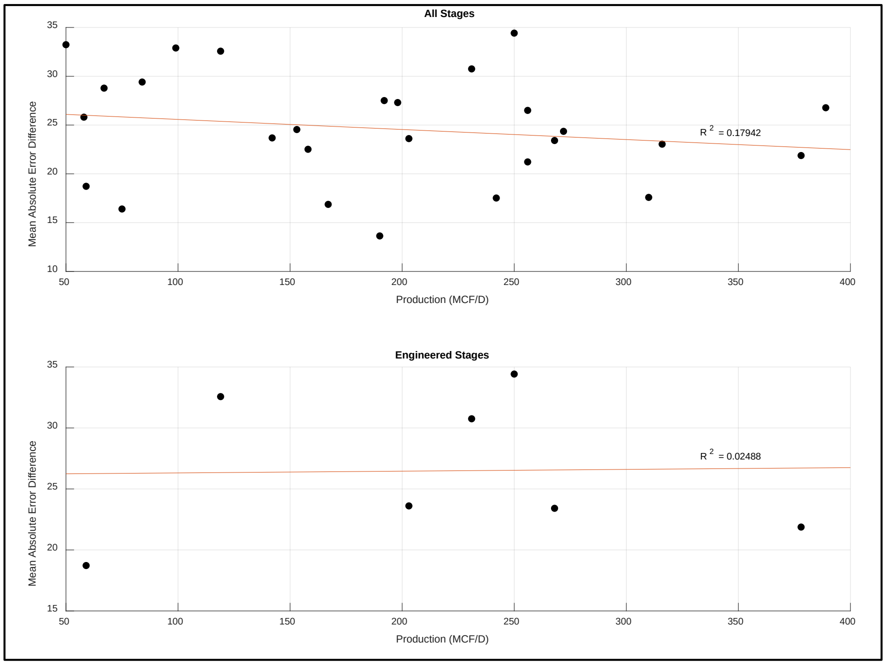

Figure 11: a) The production log data of each stage vs. MAE variations of the neural network if the stage is removed from the input dataset. b) The correlation for engineered stage does not show a significant negative relationship between production log results and MAE variations.

Conclusions

Key conclusions from this study can be summarized as following:

1. The study shows that continuous stream of fiber optic data (DTS) can be used to predict gas production of an unconventional shale reservoir.
2. Sensitivity analysis reveals the importance of several stages. A higher MAE when the stage is removed from the network suggest more importance of the removed stage.
3. DAS energy variance attribute is inversely correlated with the stage importance from the sensitivity analysis. This finding is more noticeable in engineered stages.
4. DTS data until May 2018 show that downhole temperature is dynamic parameter and fluctuate with production within any stage. A single day production logging is not a contemporary indication of stages productions.
5. Production log did not show a significant correlation with stage importance from the sensitivity analysis. This ratifies the idea that production log is a sample of production distribution in time rather than a constant share of production throughout the life of the reservoir.

Acknowledgments

This research is funded through the U.S.DOE National Energy Technology Lab part of their Marcellus Shale Energy and Environmental Laboratory (MSEEL) (DOE Award No.: DE-FE0024297). We appreciate the Northeast Natural Energy LLC. For providing data and technical support and Schlumberger for access to the fiber-optic data. We thank Machine Learning Group at the University of Waikato for providing Weka software. We also appreciate license for Mathwork MATLAB software.

References

Anderson, R.N., Xie, B., Wu, L., Kressner, A.A., Frantz Jr, J.H., Ockree, M.A., Brown, K.G., Carragher, P. and McLane, M.A., 2016. Using Machine Learning to Identify the Highest Wet Gas Producing Mix of Hydraulic Fracture Classes and Technology Improvements in the Marcellus Shale. Unconventional Resources Technology Conference (URTEC).

Cao, Q., Banerjee, R., Gupta, S., Li, J., Zhou, W. and Jeyachandra, B., 2016, June. Data driven production forecasting using machine learning. In SPE Argentina Exploration and Production of Unconventional Resources Symposium. Society of Petroleum Engineers.

Carnahan, B.D., Clanton, R.W., Koehler, K.D., Harkins, G.O. and Williams, G.R., 1999, January. Fiber Optic Temperature Monitoring Technology. In SPE Western Regional Meeting. Society of Petroleum Engineers.

Gaurav, A., 2017, September. Horizontal Shale Well EUR Determination Integrating Geology, Machine Learning, Pattern Recognition and Multivariate Statistics Focused on the Permian Basin. In SPE Liquids-Rich Basins Conference-North America. Society of Petroleum Engineers.

Ghahfarokhi, P.K., Carr, T., Song, L., Shukla, P. and Pankaj, P., 2018, January. Seismic Attributes Application for the Distributed Acoustic Sensing Data for the Marcellus Shale: New Insights to Cross-Stage Flow Communication. In SPE Hydraulic Fracturing Technology Conference and Exhibition. Society of Petroleum Engineers.

Isaiah, J., Schrader, S., Reichhardt, D. and Link, C., 2013, March. Performing Reservoir Simulation with Neural Network Enhanced Data. In SPE Digital Energy Conference. Society of Petroleum Engineers.

Kavousi, P., Carr, T., Wilson, T., Amini, S., Wilson, C., Thomas, M., MacPhail, K., Crandall, D., Carney, B.J., Costello, I. and Hewitt, J., 2017. Correlating distributed acoustic sensing (DAS) to natural fracture intensity for the Marcellus Shale. In SEG Technical Program Expanded Abstracts 2017 (pp. 5386-5390). Society of Exploration Geophysicists.

Keshavarzi, R., Jahanbakhshi, R., Nadgaran, H. and Aliyari, M., 2010, January. A Neural Network Approach for Predicting the Penetration Depth During Laser Perforation In Limestone. In 44th US Rock Mechanics Symposium and 5th US-Canada Rock Mechanics Symposium. American Rock Mechanics Association.

Mishra, S., Datta-Gupta, A., 2017. Applied Statistical Modeling and Data Analytics, Elsevier, 237.

Mohaghegh, S., D., Grujic, O., Zargari, S., et al. 2011. Modeling, History Matching, Forecasting, and Analysis of Shale-Reservoir Performance Using Artificial Intelligence. Presented at the SPE Digital Energy Conference and Exhibition, The Woodlands, Texas, USA, 19–21 April. SPE-143875-MS. https://doi.org/10.2118/143875-MS.

Molenaar, M.M., Hill, D., Webster, P., Fidan, E. and Birch, B., 2012. First downhole application of distributed acoustic sensing for hydraulic-fracturing monitoring and diagnostics. SPE Drilling & Completion, 27(01), pp.32-38.

Rickman, R., Mullen, M.J., Petre, J.E., Grieser, W.V. and Kundert, D., 2008, January. A practical use of shale petrophysics for stimulation design optimization: All shale plays are not clones of the Barnett Shale. In SPE Annual Technical Conference and Exhibition. Society of Petroleum Engineers.

Tanimola, F. and Hill, D., 2009. Distributed fibre optic sensors for pipeline protection. Journal of Natural Gas Science and Engineering, 1(4), pp.134-143.

Zheng, Z.H., Kavousi, P. and Di, H.B., 2014. Multi-attributes and neural network-based fault detection in 3D seismic interpretation. In Advanced Materials Research (Vol. 838, pp. 1497-1502). Trans Tech Publications.