Oilwell Completion Regression - Literature Review

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Introduction

For centuries, oilwells have been drilled vertically and completed by perforation only. Since the invention of horizontal drilling, literature has shown that various completion parameters have a significant effect on oil production. Multiple recent sources agree that there is value in leveraging available data as input to statistacal models steeped in machine learning.(Fulks et al. 2016), (Holdaway, Laing, and others 2015), (Pankaj et al. 2018), (Subrahmanya et al. 2014) While there is some disagreement about the limitaitons and appliciablity of such models, most agree that a general data anlysis workflow is applicable. (Fulks et al. 2016),(Temizel et al. 2015),(Groulx et al. 2017), (Pankaj et al. 2018)

Body

Data Quality

In this work we compare the results of using Generalised Linear Models (OLS), Bayesian Regression (BRR), RANdom SAmple Consensus (RANSAC), Random Forests (RF), and Artificial Neural Networks (ANN), on the prediction of missing gaps in a single well.(Lopes and Jorge 2017)

The input uncertainties were primarily caused by missing data, and the available information about the input variables was used to define reasonable uncertainty ranges for the parameters. (Wang et al. 2016)

We developed real–time analytical models for detecting and classifying gross errors.(Khodabakhsh, Ari, and Bakir 2017)

However, the statistical difference is not significant, and both RFs and ANNs are computationally more expensive than the remaining regressions. (Lopes and Jorge 2017)

The major computational challenges during the surrogate construction were the sampling of a large six-dimensional parameter space, and handling the model noise. (Wang et al. 2016)

Both problems were successfully addressed using Basis Pursuit Denoising (BPDN) to calculate the PC coefficients using only 200 model samples. (Wang et al. 2016)

The present investigation suggests that the model outputs are insensitive to uncertainties in the flow rate provided it is known reasonably accurately. (Wang et al. 2016)

General Workflow

Data-driven workflows, models, and analysis can address a diverse array of business problems in the oil and gas industry. (Holdaway, Laing, and others 2015)

Parallel Coordinates plots are a good visual analysis for testing any input's impact on production performance. (Groulx et al. 2017)

The number of performance measures directly correlate with the number of patterns identified. (Groulx et al. 2017)

With enough statistical variability, the same approach finds patterns in all plays. (Groulx et al. 2017)

Parallel coordinates approach makes identification of thresholds and correlation windows easy. Which can be valuable input for other regression efforts. (Groulx et al. 2017)

The predictive proxy approach has a wide variety of applications to completion engineering and management. (Pankaj et al. 2018)

Drilling and lifting in addition to completion also benefit from faster decision making. (Pankaj et al. 2018)

This has led to the rising importance of adopting new strategies and workflows for the development of advanced analytics models.(Subrahmanya et al. 2014)

It was demonstrated that these advanced machine learning methods show considerable promise and can be integral tools in making the entire analysis procedure more interactive and productive. (Subrahmanya et al. 2014)

The workflow we presented in this paper is a systematic methodology for using and comparing machine learning methods to predict production in unconventional plays using well logs and production data from previous explorations, taking into account multiple formations. (Guevara et al. 2017)

Our experimental results show that this workflow can outperform more conventional techniques, such as kriging, in particular for the case of gas production prediction. (Guevara et al. 2017)

As future work, we would like to add to our workflow the capability of extracting and integrating features from horizontal well logs, in additional to features from vertical well logs.(Guevara et al. 2017)

The specific efficacy factors may not be directly applicable in other fields, but the framework of data analysis can be easily applied.(Luo 2018)

Each well is a geophysical experiment. (Luo 2018)

Our experiments indicate that a deep learning approach, has the potential to capture flow patterns, which may boost the classification performance. (Ezzatabadipour et al. 2017)

In this paper, we proposed an architecture to solve big data problems seen in oil refinery sensor data and implemented the architecture in private cloud utilizing open–source software.(Khodabakhsh, Ari, and Bakir 2017)

The results are applicable to oil drilling industry as well.(Khodabakhsh, Ari, and Bakir 2017)

In this paper an overview of data mining applications in oil and gas exploration was carried out. (Nikhalat-Jahromi and Jorge 2017)

Remote sensing (including satellite infrared, radar, and microwave surveying; and a serial magnetic, electromagnetic, and gravity surveying) is the most important topic in this category. (Nikhalat-Jahromi and Jorge 2017)

Although there are cases of data mining application to geobotany prospecting and geochemical exploration as well. (Nikhalat-Jahromi and Jorge 2017)

With a high prediction accuracy, this model can guide the design of production engineering project, well production optimization, and well performance analysis.(Yu et al. 2018)

Feature Importance

High proppant, high-fluid completion designs described by (Fulks et al. 2016) have shown success every basin.

degradable diversion improve cluster efficiency.(Fulks et al. 2016)

A 3 dimensional earth model determines the optimal lateral landing zone. (Fulks et al. 2016)

Large amounts of data from multiple wells as input to multivariate analysis determines the factors driving production. (Fulks et al. 2016)

In order of importance fracture half-length, proppant amount, zone coverage, and slurry volume are important for predicting production. (Temizel et al. 2015)

data analytics makes it possible to determine not only feature importance and significance, but also effect direction. (Temizel et al. 2015)

In this work, we explored the use of active learning to intelligently identify data points with the highest value of information and semi-supervised learning to combine the information from labeled and unlabeled sources in an optimal fashion. (Subrahmanya et al. 2014)

A framework of big data analytics is developed to measure the efficacy factor of fracturing fluid ingredients in terms their effectiveness on well productivity, based on FracFocus and well production databases. (Luo 2018)

As a useful demonstration, chemical ingredients that are conducive to production of wells with Marcellus shale geology are quantitatively differentiated those that negatively impact gas productivity.(Luo 2018)

The data analytics framework helps providing leads in understanding the intricate chemical and physical processes of fracturing fluids.(Luo 2018)

In this paper we proposed three types of data sets as input features and investigated the use of deep learning for the classification and prediction of two-phase flow, based on experimental data, obtained . (Ezzatabadipour et al. 2017)

We proposed six types of input features, and a corresponding architecture to precisely predict flow patterns. (Ezzatabadipour et al. 2017)

Finally, deep learning can be used to predict flow patterns using pipe characteristics, fluid properties and superficial velocities of the two-phase flows.(Ezzatabadipour et al. 2017)

We also expect to be able to add well completion parameters in the models, which we expect will be very important in terms for improving the accuracy of the production predictions.(Guevara et al. 2017)

Different techniques have been used to build models that predict and estimate various geophysical properties, by means of either regression or classification tasks including but not limited to: deterministic petrophysical modeling, using shale, matrix, and fluid properties; stochastic modeling, where an approximate curve is used as input, and the reconstructed curve is the output; and different soft-computing algorithms.(Lopes and Jorge 2017)

Two major categories of geoscientific problems, which have been the focus of data mining efforts, are studied: structural geology and reservoir property-issues. (Nikhalat-Jahromi and Jorge 2017)

After that further surveying in these places provides precise details on the subsurface formations. (Nikhalat-Jahromi and Jorge 2017)

The study quantified the impacts of uncertainties in six input parameters on the model's estimates of the trap and peel heights, and the gas mass fluxes. (Wang et al. 2016)

Comparisons with fluorescence observations, a proxy for the oil accumulation at the trap height, show the observations coinciding with the mode of the trap height PDF for the Low Uncertainty Experiment (LUE), thus suggesting that the latter range to be quite consist- ent with the fluorescence observations. (Wang et al. 2016)

It also suggests that the next priority in observation should be aimed at estimating the largest droplet size and Gas-Oil Ratio (GOR) if improvements in mass gas flux estimates are desired, whereas the priority would fall on measuring the largest droplet size and the entrainment parame- ters if improvement in trap and peel heights is desired. (Wang et al. 2016)

Simulation

Data analytics can replace fracture models built with a commercial simulators. (Temizel et al. 2015)

The approach described in Pankaj et al. (2018) creates synthetic data from first principles.

Pankaj et al. (2018) uses parametric explosion of parameters to create a model which predicts performance in unconventional reservoirs.

Engineers use a model to design completions and predict production in real-time. (Pankaj et al. 2018)

Proxy modeling indicates the optimal well completion much faster than full simulations, a matter of minutes instead of months.(Pankaj et al. 2018)

The simulation model tends to be an appropriate approach to choosing the optimum completion of the wellbore.(Bozoev and Demidova 2016)

These investigations could be further improved in future studies by carrying out more exhaustive searches for the parameters in the architectures.(Ezzatabadipour et al. 2017)

Likewise, if observations prove to be difficult or impractical, an additional compromise can be made, such as resorting to simulated data from very high-resolution numerical simulations [Fabregat et al ., 2015]. (Wang et al. 2016)

the results presented in this study reveal that in the early hydration stages of a cement slurry, the transmission of hydrostatic pressure (in a fresh cement slurry) follows Pascal's law. (Liu et al. 2018)

Model Limitations

In the absence of data proppant, fluid, and diversion are important for establishing baseline performance. (Fulks et al. 2016)

Conclusions from data driven models are specific to the model used.(Temizel et al. 2015)

Careful consideration is necessary for normalizing both performance measures and inputs. (Groulx et al. 2017)

Before discernible conclusions, patterns detected must be reviewed to refine insights. (Groulx et al. 2017)

"A calibrated model is a fundamental step to create a reliable predictive proxy." (Pankaj et al. 2018)

It points the direction to the causality - those kinds of cause-effect relationships – between ingredient and productivity straight from real-world data. (Luo 2018)

Compared with fracturing fluid lab test that still needs to be optimized in the field, the data analytics framework learns hidden connections from field data, which is the ultimate experiment, and reduces or stops the guesswork. (Luo 2018)

Analytical approaches do not take into account the interference effect. Bozoev and Demidova (2016)]

Additionally, the natural gases do not dissolve completely at the trap height under any scenario, and therefore, the next stage numerical models must be able to handle this mixture of oil and gas in order to simulate the oil fate realistically. (Wang et al. 2016)

Conclusion

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