Transformative AI Initiatives for the Upstream Unconventional Business

1 Executive Summary

Applications pertaining to the upstream unconventional business are discussed in this document. The broader theme that underpins these applications is to deliver enterprise scale, end-end AI solutions - a one-stop-shop for optimizing unconventional development cycle from planning, execution, operations to decarbonization. Furthermore, the sample cases discussed leverage industry leading AWS SageMaker capabilities to deliver integrated solutions to maximize return and minimize capital investment. Specifically, the following are discussed:

1) ***Planning***: AI powered decisioning framework for unconventional development plan optimization
2) ***Execution***: ML enabled real-time dynamic fracture design optimization
3) ***Operations***: Concurrent data driven artificial lift optimization
4) ***Decarbonization***: AI driven detection and remediation for flare reduction
5) ***Decarbonization***: Accelerating carbon sequestration through advanced seismic image processing

The applications embodies an ecosystem in which inter-disciplinary data and analysis can flow seamlessly without sacrificing overarching data privacy, governance and security.

2 Introduction

Given its distinguishing capabilities and strategic partnerships, AWS is uniquely poised to deliver state of the art, integrated and comprehensive digital solutions for the energy industry [1]. This document focuses on outlining a few potentially transformative initiatives targeting end-to-end optimization of unconventional well life cycle. Details pertaining to the applications will be expanded further.

3 Enterprise Scale Data Driven Dynamic Optimization of the Unconventional Business

3.1 AI powered structured decisioning framework for development plan optimization:

Shortcomings of existing tools to deliver robust and flexible solutions have resulted in drastic economic consequences [2]. Contrary to traditional modeling and analytical approaches, ML application is gaining momentum to deliver customized, and data driven solutions. In addition to improved predictive capabilities, ML models act as an integrating platform to address two primary development planning questions: (1) optimal number of wells to drill (2) optimal completions/frac design. The distinguishing feature is to deliver a flexible decision framework (Figure 1, Left) allowing operators to customize development plan that is resilient to market conditions. Application of smart ML driven workflow can lead to significant reduction in well count with substantial economic value [3].

3.2 AI enabled real time dynamic fracture design optimization

Currently, there are no existing automated approach for real-time optimization of fracturing operations. 'On-the-go' optimizations are limited to handful of treatment jobs as they demand extensive manual oversight. Given the volume of data and practical limitations, ML based solution appear to be a natural alternative. ML models can be trained using treatment and production surveillance. Such learned models can be used to dynamically customize hydraulic fracturing design. This in turn can help with reducing pump time/emission, maximize production, minimize completions cost and potentially minimize capital expenditure. This is a non-trivial problem with huge upside potential and relatively unexplored and provides the operator a sustained competitive advantage. Given its novelty, this use case is further elaborated in section 4.

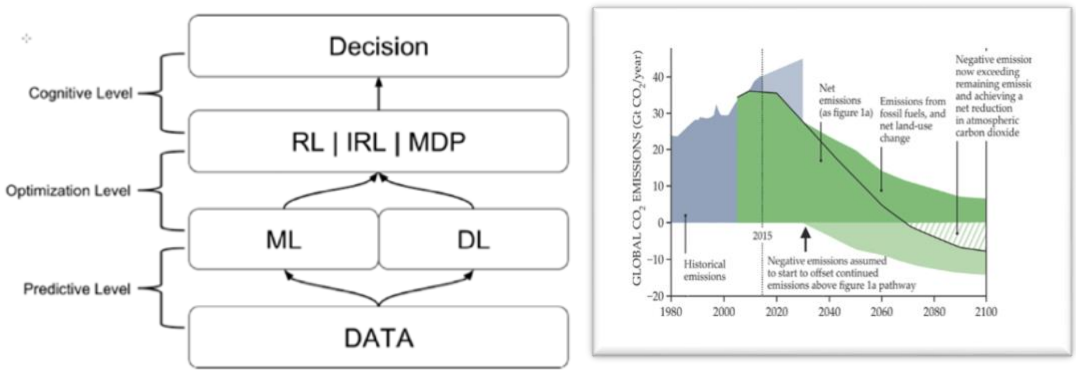

Figure 1(Left) Proposed decisioning framework using ML paradigm for optimizing development plan [4] (Right) Carbon sequestration is key to meet our global emission targets. Increasing demand for affordable solutions to reach net zero emission will pave way for ML/AI powered solutions to be at the forefront [5].

3.3 Concurrent data driven artificial lift optimization

Given the large number of wells and complex non-linear nature of subsurface production, the use of conventional techniques has become obsolete and less pragmatic [6]. On the other hand, a big-data ML-based framework can be used to integrate disparate data sources (production, compression parameters, subsurface deliverability, etc.) to optimize gas lift injection systems. It has been demonstrated that up to 15% reduction in operation cost is feasible, scale of which has never been realized using traditional approaches [6].

3.4 AI driven detection and remediation for flare reduction [7]

This is an emerging use case with extensive economic impact empowering operators to reach their 'net zero' commitments. Flaring networks represent the main over-pressure relief system of upstream facilities. Modern big data analytics framework can significantly improve security and reliability with predicting hazardous events along with prescription for mitigation actions. For instance, an AI agent could perform real-time analytics from processing petabytes of clustered and unstructured data to identify root cause events leading to dangerous overpressures within the producing system, alerting engineers with options to modify key parameters. Subsequently, it allows to maximize the asset value, granting steady operations and consequently optimum production and the lowest environmental impact.

3.5 Accelerating carbon sequestration [5] through seismic image processing using Deep Learning

AI based initiative could identify geologic seals and traps and provide operators with the competitive edge in meeting their commitment towards emission reduction (Figure 1, Left) [8]. Opportunity landscape is wide open for Smart Carbon Capture [9] and AWS SageMaker Studio [10] can be readily leveraged to deliver bleeding edge solution.

4 AI enabled real time dynamic fracture design optimization

In this section, the use case pertaining to real time optimization of multi-stage hydraulic fracturing will be discussed in detail.

4.1 Problem statement

A typical multistage fracturing involves a significant number of stages. The post-fracturing diagnostics along with production surveillance (including micro-seismic) have established that stages produce non-uniformly and only a small fraction (up to 30%) contribute to production [11]. A combination of geomechanics and fracturing design factors appear to be driving disparities from stage-stage production. Employing a single design for all stages can result in significant over-capitalization and increased emission. There is significant room for 'on-the-fly' fracturing design optimization; and the availability of large volume of data makes this problem amenable for an AI driven solution. The objective is to customize fracture design using information from prior stages, geomechanics and nearby well performance. In the next sections, ML based approach will be discussed in detail.

4.2 ML Workflow for Development Plan Optimization

The ML workflow at a high-level can be summarized as displayed in Figure 2. Problem formulation was discussed in detail in the previous section. The next step in the ML pipeline is to define the optimization metric. The metric that is typically used to optimize is the produced oil volume. Caution should be exercised while using early time production data as they are severely plagued with transient operating conditions. Late time production volumes serve as better proxy for economic value. In short, the optimization question can be re-formulated as a multivariate regression, supervised machine learning problem with the objective of maximizing production volume (i.e., minimizing differences between the actual and predicted volumes).

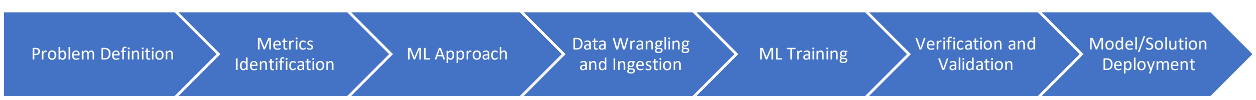

Figure 2 A quick overview of ML pipeline highlighting key steps and flow of information. It is important to recognize that this simplified version is seldom close to reality

4.3 Data Wrangling and Ingestion

A key step in any ML pipeline is data collection, munging/wrangling, and ingestion. The data set for this problem consists of geomechanics information and subsurface characterization of the rock, well performance and surveillance analysis, treatment and fracture design parameters, rates and pressures from production and geo-spatial location of well [12] and trajectory of the well. As is evident from the list, a strong synergy is required to carefully munge the multi-disciplinary dataset that can be easily consumed by ML algorithm(s). Furthermore, the data consists of categorical information, time series information, information processed from digital documents etc., that need to be carefully orchestrated to run through the ML pipeline. Building data and maintaining data management pipeline is the costliest piece of ML solution. AWS framework offers robust toolkits with deep integration with native cloud services, thereby drastically compressing the time required for data manipulation.

4.4 Solution Approach/ML Modeling

Prior to using an ML algorithm, it would be informative to reduce the number of features by performing statistical hypothesis testing. Algorithms such as Random Forest (RF) readily provides capabilities to evaluate feature importance [13] to identify critical feature set. Another useful approach is to group wells by performance using clustering algorithms such as t-SNE [14] (Figure 3, Left) to (a) extract meaningful trends (b) compare model predictability and (c) real-time data synchronization. Clustering information can be used for 'intelligent' partitioning of dataset into train-dev-test set. As far as ML algorithms are concerned, RF can serve as a reasonable starting point. With RF, features do not have to be scaled and the ensemble model typically generalizes well (with careful hyper-parameter tuning).

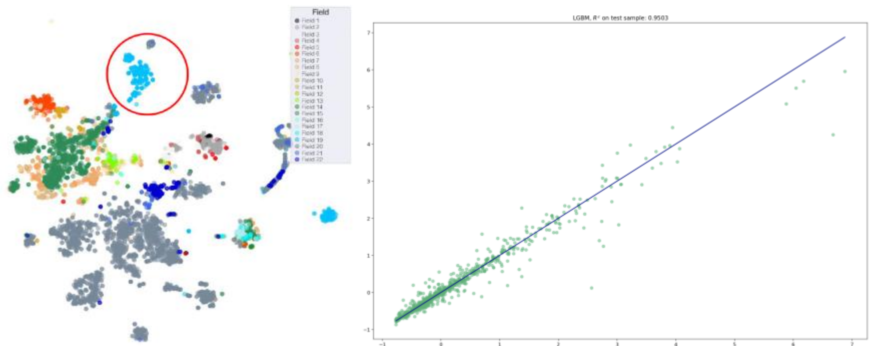

Figure 3 (Left) t-SNE for clustering wells with similar performance. EDA can help with identifying variables that are correlated and reduce feature set (Right) Model evaluation showing R^2 metric to evaluate ML model

5 Model Evaluation and Closing Remarks

Model evaluation can be performed on the training & test set showing standard accuracy metrics and charts. A RMSE > 0.8 would be acceptable (Figure 3, Right). A comprehensive discourse on model evaluation, prediction and deployment can be found in [15]. Economic metric to assess the value of the AI models can be estimated as:

$$Value = \frac{Design - Effective}{Design} * \text{number of wells}$$

Where '*Design*' is the base completions cost and '*Effective*' is the final completions cost for the well. Typical cost for standard completions is ~$3MM and a 70% savings could yield a similar performing well at ~0.9MM/well [16]. This could lead up to ~10-15% in capital savings in the unconventional value chain which is not being realized otherwise.

6 Conclusion

To conclude, several applications focused on providing end-end solutions using the AWS ecosystem were discussed. A thin thread framework for building and testing a real time dynamic fracture design optimization along with its economic metric was discussed. It is believed that the framework will be the first ever AI driven application and delivers the operator a competitive advantage with up to 15% capital savings for the unconventional value chain. The AWS ecosystem for the unconventional applications discussed in this article extends naturally to offshore and deep-water applications (with little to no modification).

7 Appendix

7.1 Distribution Restrictions

The author of the document reserves the right to restrict the use and distribution of the document beyond its intended use.

7.2 Bibliography

[1] A. E. Resources. [Online]. Available: https://aws.amazon.com/energy/resources/?energy-blog.sort-by=item.additionalFields.createdDate&energy-blog.sort-order=desc.

[2] W. S. Journal, "A Fracking Experiment Fails to Pump as Predicted - Encana's cube project suggests output problems occur if oil wells are drilled too close together," [Online]. Available: https://www.wsj.com/articles/a-fracking-experiment-fails-to-pump-as-predicted-11562232601.

[3] BHC3AI, "Field Development Optimization," [Online]. Available: https://bakerhughesc3.ai/capabilities/field-development-optimization/.

[4] N. e. a. Tamimi, "An Artificial Intelligence Decision Support System for Unconventional Field Development Design," in *Proceedings of the 7th Unconventional Resources Technology Conference*, 2019.

[5] D. Kramer, "Negative carbon dioxide emissions," *Physics Today,* vol. 73, no. 1, 2020.

[6] "Enterprise AI for Well Intervention Planning," [Online]. Available: https://bakerhughesc3.ai/customers/enterprise-ai-for-well-intervention-planning/.

[7] M. Giuliani, G. Camarda, M. Montini, L. Cadei, A. Bianco, A. Shokry, P. Baraldi and E. Zio, "Flaring Events Prediction and Prevention through Advanced Big Data Analytics and Machine Learning Algorithms," in *Offshore Mediterranean Conference and Exhibition, Ravenna, Italy, March 2019*, 2019.

[8] I. Watson, "Climate change: IBM boosts materials discovery to improve carbon capture, separation and storage," [Online]. Available: https://research.ibm.com/blog/carbon-capture-separation-storage.

[9] M. M. B. S. A. H. MohammadRahimi, "Toward smart carbon capture with machine learning," *Cell Reports Physical Science,* vol. 1 , no. 4, 2021.

[10] A. S. M. Studio. [Online]. Available: https://aws.amazon.com/energy/solutions/?nc=sn&loc=2&dn=1.

[11] A. M. A. O. A. V. E. B. E. S. G. P. R.F. Mutalova, "Machine learning on field data for hydraulic fracturing design optimization," *Journal of Petroleum Science & Engineering. Special Issue: Petroleum Data Science,* 2019.

[12] O. LLP, "Measuring the Impact of Well Spacing with Novel Geospatial Technique," [Online]. Available: https://www.jdsupra.com/legalnews/measuring-the-impact-of-well-spacing-81285/.

[13] Scikit-Learn, "Feature importances with a forest of trees," [Online]. Available: https://scikit-learn.org/stable/auto_examples/ensemble/plot_forest_importances.html.

[14] Scikit-Learn, "sklearn.manifold.TSNE¶," [Online]. Available: https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html.

[15] Uber, "Meet Michelangelo: Uber's Machine Learning Platform," [Online]. Available: https://eng.uber.com/michelangelo-machine-learning-platform/.

[16] J. Energy, "Completions Cost Estimate," [Online]. Available: https://www.jwnenergy.com/article/2016/7/20/here-are-five-main-costs-frac-job-us/.

[17] C3AI, "BHC3AI," [Online]. Available: https://bakerhughesc3.ai/bhc3-ai-suite/.

[18] C3AI, "OAI Partnership," [Online]. Available: https://c3.ai/shell-c3-ai-baker-hughes-and-microsoft-launch-the-open-ai-energy-initiative-an-ecosystem-of-ai-solutions-to-help-transform-the-energy-industry/.

[19] C3AI, "C3AI Shell Renewed Partnership," [Online]. Available: https://c3.ai/c3-ai-and-shell-extend-strategic-collaboration-to-reshape-global-energy-and-resource-industries-with-enterprise-ai/.

[20] BHC3AI, "Build, deploy, and operate Enterprise AI applications," [Online]. Available: https://bakerhughesc3.ai/bhc3-ai-suite/bhc3-ai-integrated-development-studio/bhc3-ai-ml-studio/.

[21] J. C. e. al., "Inter-well interference and well spacing optimization for shale gas reservoirs," *Journal of Natural Gas Geoscience,* vol. 6, no. 5, 2021.