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Title: Science-informed Machine Learning to Increase Recovery Efficiency in Unconventional Reservoirs

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Science-informed Machine Learning to Increase Recovery Efficiency in Unconventional Reservoirs

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Summary

Production of hydrocarbons from fractured, unconventional reservoirs is inherently inefficient. But machine learning offers a pathway both to increasing recovery efficiency at a site and to improving forecasts of production, thereby improving the economics of operations in unconventional reservoirs.

Los Alamos—in partnership with DOE, NETL, and WVU—has been developing a science-informed workflow and platform for optimizing pressure-drawdown at a site, which will allow an operator to make reservoir-management decisions that optimize recovery in consideration of future production. This work relies on a hybridization of physics-based prediction and machine learning, whereby accurate synthetic data (in combination with available site data) can enable the application of machine learning methods for rapid forecasting and optimization. The physics-based prediction is built upon experimental and theoretical work to determine transport characteristics in shale at various scales, with an emphasis on materials from MSEEL-I; this fundamental shale R&D was conducted in partnership with DOE, NETL, and several other national labs.

This work has resulted from a coordinated leveraging of developments across several projects within DOE FE-30, along with internal investments from Los Alamos via LDRD.

The development has utilized data from the MSEEL–I site for calibration and demonstration; however, the workflow and platform are readily extendable to operations at other sites, plays, and basins. This machine-learning method can aid operators to improve both recovery efficiency and competitiveness; to this end, future work would quantify processes for other plays/basins and integrate production details with economics.

Rationale

Unconventional reservoirs are governed by a set of physical processes that differ from those that dominate conventional reservoirs: whereas the latter are dominated by porous flow that can be described adequately by Darcy's law, the former are dominated by flow in fractures and in tight matrix. Consequently, the strategies and tools honed over decades for conventional reservoirs do not transfer readily to unconventional reservoirs, inhibiting the ability to optimize reservoir management and, hence, to maximize recovery. This is compounded by a general acceptance that unconventional reservoirs have poor recovery efficiencies.

Nevertheless, it is also generally recognized that unconventional reservoirs exhibit a range in recovery characteristics and that this variability relates in part to operational decisions during both stimulation and, importantly, production. This latter highlights the potential for optimized reservoir management as strategy to increase both recovery and recovery efficiency, which is particularly important for the competitiveness of operations in unconventional reservoirs (Fig. 1).

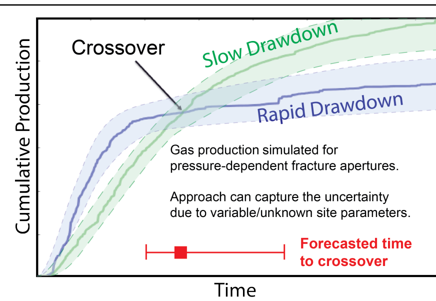

Figure 1. Simulated production for different drawdown scenarios at the same site. Operational decisions can shift between higher early returns or higher cumulative recovery. Machine-learning can help to optimize site decisions in light of projected gas future prices.

Science-informed Machine-learning for Shale

Recent developments in machine learning have transformed the efficiency of many types of processes, but they have lagged behind in impacting subsurface operations, particularly for unconventional reservoirs. This lag ties largely to limitations in appropriate and sufficient subsurface data on these systems. Fracture networks impart a higher degree of site-specificity in reservoir properties relative to conventional reservoirs, and the properties are often less well defined.

Machine learning requires a large volume of data with well-defined characteristics (termed "features"). Yet, site specificity limits the transferability of data from one site to another, and many of the datasets are not broadly available (i.e., proprietary). Hence, application of machine learning *with site data only* is limited.

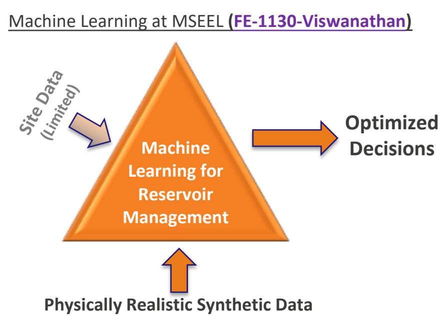

Figure 2. Schematic of the strategy to use synthetic data in combination with available site data to enable machine learning algorithms for optimizing production decisions at a site. Los Alamos has been developing a prototype platform focused on optimizing pressure drawdown in wells at a site to maximize recovery.

Synthetic data have the potential to enable machine learning at a site, provided the synthetic data are accurate. Specifically, the synthetic data must embody the physical processes that control the system, and they must represent physically realistic characteristics that could exist in the subsurface at the site (Fig. 2).

Recent advances—by Los Alamos and other research organizations—have significantly evolved our understanding of what controls the transport of hydrocarbons at the pore/matrix scale and in fractures. Figure 3 shows the comprehensive research effort within FE-30 that has elucidated key factors controlling transport of hydrocarbons in shale from pore- to reservoir-scale. Los Alamos has developed an open-source,

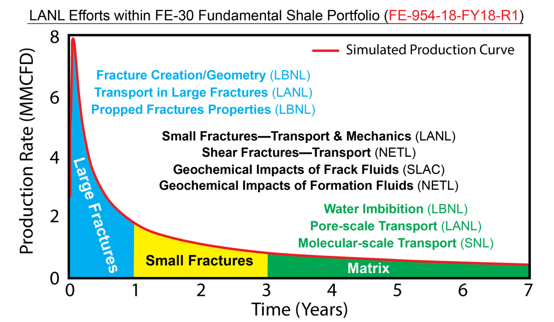

Figure 3. Overview of the FE-30 research effort on hydrocarbon production in shale. Various factors dominate at different times during the production cycle. This work has developed the fundamental understanding needed to predict transport from matrix to well.

physics-based reservoir simulator (*dfnWorks*) that incorporates these processes in a mathematically accurate grid for discrete fracture-networks (DFNs).

We can now confidently (& accurately) simulate many of the physical processes that determine hydrocarbon transport in shales. *dfnWorks* treats the production from a reservoir as resulting from a combination of fracture flow at multiple scales and matrix flow into the fractures (Fig. 4).

Simulations must incorporate relevant site characteristics to ensure the synthetic data reflect physically realistic conditions. Recent advances by the FE-30 multi-Lab consortium have elucidated transport mechanisms in fractures and matrix (Fig. 3). In addition, Los Alamos has used samples from MSEEL-I to determine appropriate site-specific transport parameters for MSEEL-I, and West Virginia University has collected extensive data at MSEEL-I to characterize site conditions such as fracture density and orientation.

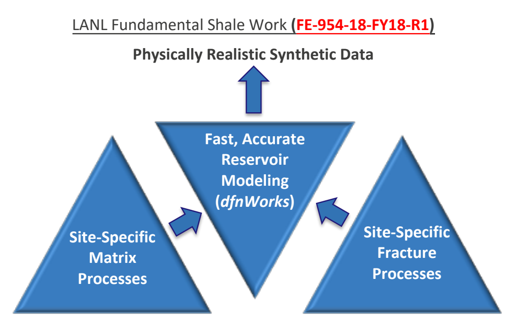

Figure 4. Schematic of the strategy to use synthetic data in combination with available site data to enable machine learning algorithms for optimizing production decisions at a site. Los Alamos has been developing a prototype platform focused on optimizing pressure drawdown in wells at a site to maximize recovery.

Beyond being accurate, the synthetic data must also be generated rapidly. Why? Machine learning algorithms need data that span all combinations of site characteristics and operational decisions that could exist at the site. Although the processes can be simulated, they depend on the specific properties of the reservoir. Even in data-rich cases (like MSEEL-I), many properties (parameters) remain poorly known or poorly constrained—therefore, they must be treated stochastically. The combination of stochastic site characteristics results in a wide range of discrete scenarios that must be simulated accurately (and quickly!) to generate sufficient data to train the machine-learning algorithm.

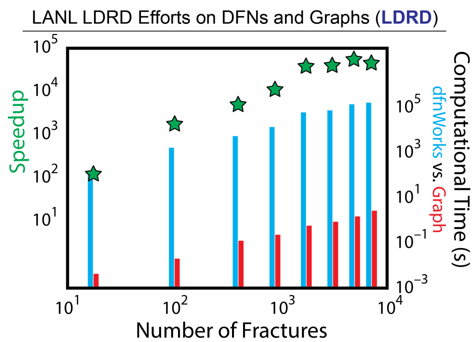

Figure 5. Comparison of computational speed for full-physics dfnWorks and the graph-based models trained from a suite of runs produced by dfnWorks. For large numbers of fractures, the graph-based models can be ~30,000× faster.

Los Alamos has integrated *dfnWorks* with graph-based models to achieve both accuracy and speed. This combination allows accurate simulation of transport of hydrocarbons at speeds >10^4× over conventional, full-physics methods (Fig. 5). The speed of simulations makes it practical to simulate large number of parameter-combinations for a site, thereby creating a library of physically realistic scenarios that can be used to train a machine learning algorithm.

Los Alamos is developing science-informed machine-learning to predict production details for different drawdown options. By using graph-based models, a comprehensive set of synthetic data can be generated for combinations of possible site characteristics and for different drawdown strategies in each well, thereby creating a physically realistic library that can be used to train a machine-learning algorithm (Fig. 6). Once trained, the algorithm can rapidly forecast future production details, such as cumulative production, distribution of remaining hydrocarbon in place, etc. The approach is being developed/tested at the MSEEL-I field test site, in partnership with West Virginia University. **Using the approach, an operator can optimize site decisions to increase recovery efficiency or to improve the economics of the operation.**

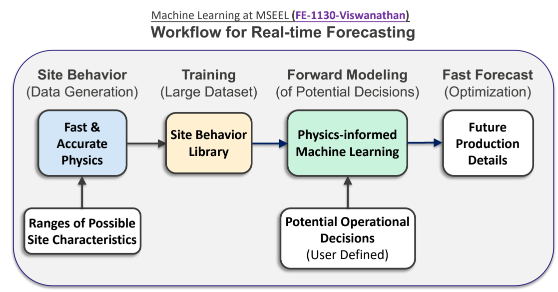

Figure 6. ML-based forecasting of pressure-drawdown effects will allow an operator to evaluate different drawdown strategies in real-time, thereby optimizing reservoir management at the site. The workflow is being developed/tested at the MSEEL-I field test site.

Extending to Other Plays & Basins

The science-informed machine learning approach above can be readily extended to various unconventional operations. The computational platforms embody the relevant physical processes that control the production behavior in fractured shales; hence, by incorporating parameters for specific plays and basins, they can be used to generate the behavior-libraries needed to train the ML-based algorithm. *Parameters necessary for specific plays/basins could be determined by extending the matrix- and fracture-scale characterization methods developed in FE-30's Fundamental Shale Portfolio to samples from prototypical sites.*

By coupling the forecasts of future production details with economic data—such as forecasts of hydrocarbon markets—site operations in unconventional reservoirs can be optimized for both recovery efficiency and economic competitiveness.

Building Science-informed Machine Learning across Multiple Projects/Sponsors

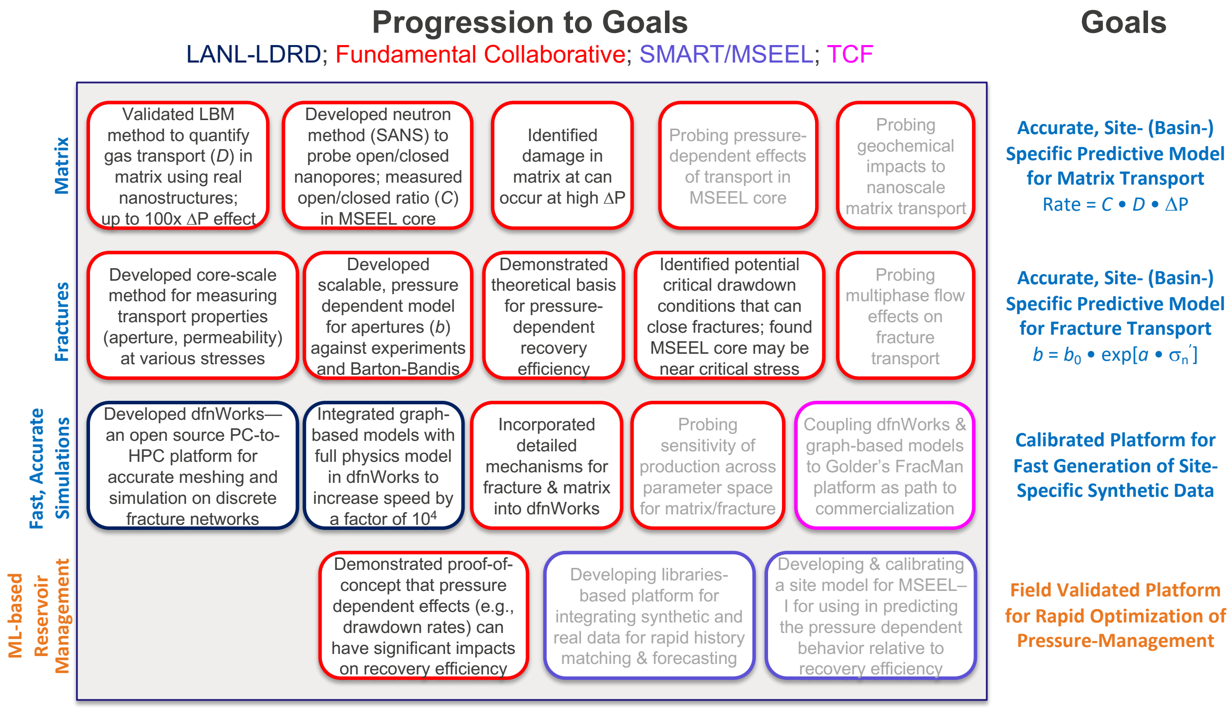

Figure 7. Schematic diagram showing R&D pieces needed to develop the science base and toolsets for science-informed machine learning to support hydrocarbon recovery operation in a fractured shale. Completed work is show by black lettering; work yet-to-be-done is shown as gray. Box outlines are colored by the projects for which the work was done (table below). Each row maps to a triangle in Figs. 2 & 3. The matrix and fracture rows show R&D needed to develop accurate descriptions of hydrocarbon transport; matrix is represented by a pressure-dependent diffusion model, whereas fractures are represented by a derivative of the Barton-Bandis relationship for aperture–stress responses. Third row shows R&D needed for a reservoir-scale platform for fast, accurate simulations, incorporating matrix and fracture flow. Fourth row shows R&D needed to develop and test a science-informed machine learning platform for optimizing pressure-drawdown decisions (MSEEL-I).

Project	Box Color (Fig. 7)	Sponsor	Purpose
FE-954-18-FY18_R1—Mechanistic Approach to Analyzing and Improving Unconventional Hydrocarbon Production	**Red**	FE-30	• Predictive models for transport in matrix & fractures • Incorporate matrix/fracture models into dfnWorks simulation platform • Proof-of-concept on pressure-drawdown and production
LDRD	**Dark Blue**	LANL	• Simulation suite for discrete fracture networks (dfnWorks) • Hydrid DFN and graph models
FE-1130-Viswanathan—Real-Time Forecasting & Data-to-Knowledge in a Fractured Reservoir	**Purple**	FE-30	• Machine learning platform for pressure-management at MSEEL-I
FracMan—Translating Geological Fracture Characterizations for …	**Magenta**	TCF (FE-30)	• Commercialization of *dfnWorks* as part of Golder's *FracMan* suite