Bridging Data and Physics: A Hybrid Approach for Unconventional Well Forecasting

Integrating Deep Learning and Physics-Based Models for Robust Production Predictions

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Background

Challenges in Unconventional Well Forecasting

Introduction to Unconventional Reservoirs:
- Overview of hydraulically fractured unconventional reservoirs.
- Complex flow and transport processes in tight formations with intricate fracture networks.

Challenges in Forecasting Unconventional Wells:
- Existing simulation methods may introduce errors.
- Difficulty in accurately representing flow behavior and physical processes.

Current Approaches and Limitations:
- Use of conventional simulation models despite limitations.
- Data-driven analytics offer predictive models but have limitations in generalization and domain constraints.

Motivation for a Hybrid Approach:
- Rapid development phase of unconventional resources necessitates new modeling methods.
- Need to combine strengths of data-driven methods and physics-based models.
- Importance of accurate production forecasting for reserves estimation and decision-making.

Introduction

Research Focus:

- Prediction and diagnostics for unconventional well production.
- Essential for reserves estimation, optimization, and decision-making.

Proposed Solution:

- Physics-guided deep learning predictive model.
- Integrates completion, formation, and fluid properties for accurate forecasts.

Key Features:

- Accounts for prediction errors and uncertainties.
- Multi-task learning for robust forecasts and diagnostics.
- Tested using field data from Bakken Shale Play, North Dakota.

Objectives of the Presentation:

- Explore challenges in unconventional well forecasting.
- Introduce the proposed hybrid predictive model.
- Highlight its advantages and contributions to the field.

Previous Studies

Background: Reservoir engineering traditionally relies on mathematical models for well performance forecasting.

Limitations: Conventional methods struggle with the complexities of unconventional formations, hindering accurate predictions.

ANNs have been applied in petroleum engineering for various tasks including reservoir history matching, log interpretations, production prediction, fracture characterization, and production optimization.

Data-Driven Analytics: Recent advancements in machine learning offer promise for uncovering patterns in unconventional reservoir data.

Recent Advancements: Studies have explored techniques like random forest regression and deep neural networks for improved prediction accuracy.

Integration Approach: This research aims to bridge physics-based models with data-driven analytics to develop a hybrid predictive model for robust unconventional well forecasting.

Proposed Predictive Model

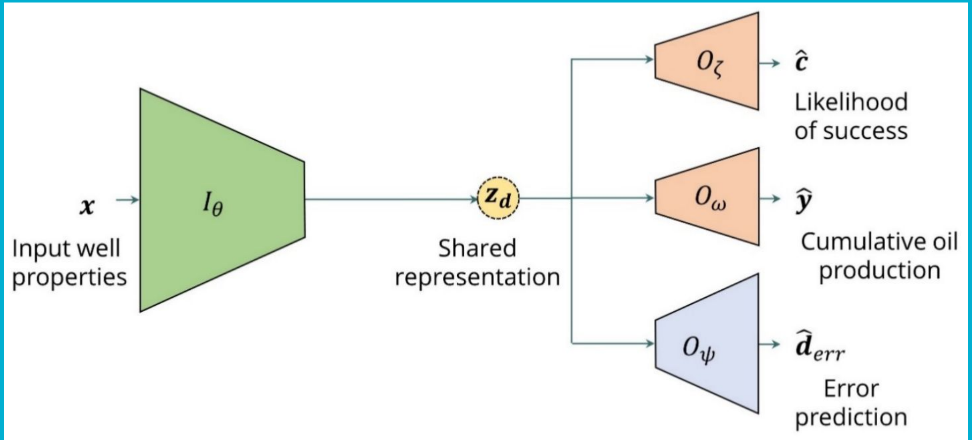
Overview

Model Overview:

- Our proposed predictive model combines physics-guided principles with deep learning techniques.
- It aims to forecast production profiles of unconventional wells using completion, formation, and fluid properties as inputs.

Key Components:

- The model comprises multiple components, including a shared feature representation layer and fully connected layers.
- Input parameters are fed into the model to generate predictions for simulation errors, cumulative oil production, and performance class labels.



$$\mathcal{L}(\theta, \mathcal{D}) = \sum_{i=1}^{N} \left(\lambda_1 \cdot \mathcal{L}_1(\theta, \mathcal{D}_i) + \lambda_2 \cdot \mathcal{L}_2(\theta, \mathcal{D}_i) + \lambda_3 \cdot \mathcal{L}_3(\theta, \mathcal{D}_i)\right)$$

Where:

- $L(\theta,D)$ represents the multi-task loss function.
- θ denotes the model parameters.
- D represents the training dataset.
- N is the number of samples in the dataset.
- λ_1, λ_2, λ_3 are weights for each task.
- L_1, L_2, L_3 are individual loss functions for each task.
- L_1 corresponds to the loss function for simulation error prediction.
- L_2 corresponds to the loss function for cumulative oil production prediction.
- L_3 corresponds to the loss function for performance class label prediction.

Multi-task Loss Function

Methodology

Technique:

- The model employs a deep convolutional neural network architecture.
- Components include one-dimensional convolution operations and leaky-ReLU activation functions.
- Multi-task learning is utilized to simultaneously predict various metrics, enhancing generalization and robustness.

Implementation:

- Implemented using the Keras deep learning library in Python.
- Loss functions include mean squared error for regression tasks and categorical cross-entropy for classification.
- Optimization involves minimizing a multi-task loss function to handle multiple related tasks efficiently.

Results

Data Collection & Input Parameters

- Bakken field data, including well properties and production responses, were obtained from the North Dakota Department of Mineral Resources website.
- Input well properties included various parameters such as perforation interval length, proppant volume, treatment pressure, and gamma-ray readings.

Models & Performance

Simulation and Prediction Model:

- Simulated production responses were obtained using a physics-based reservoir simulator.
- The predictive model was trained using Equation 1 and applied to predict simulation errors and production responses.

Prediction Performance:

- Normalized scatter plots demonstrated good prediction performance of the model on both training and test datasets.
- Small prediction root mean square error (RMSE) for the testing dataset indicated the model's effectiveness and generalization capability for unseen data points.

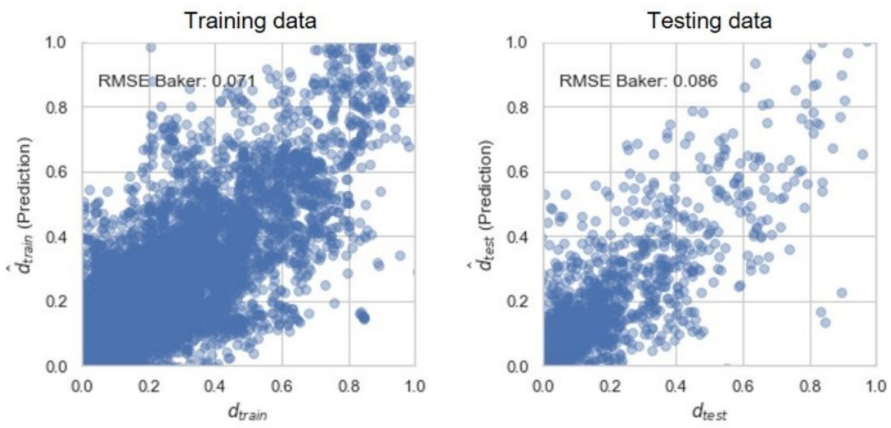


Figure 2. Scatter plot of data match of a predictive model for simulation error.

Illustrative Cases

- Discrepancies between simulated responses and field observations were accounted for by correcting simulation errors, resulting in improved agreement between predicted and reference profiles.
- Predictive model leverages the power of deep learning to account for systematic prediction inaccuracies due to incomplete knowledge about the reservoir model and the underlying flow processes.

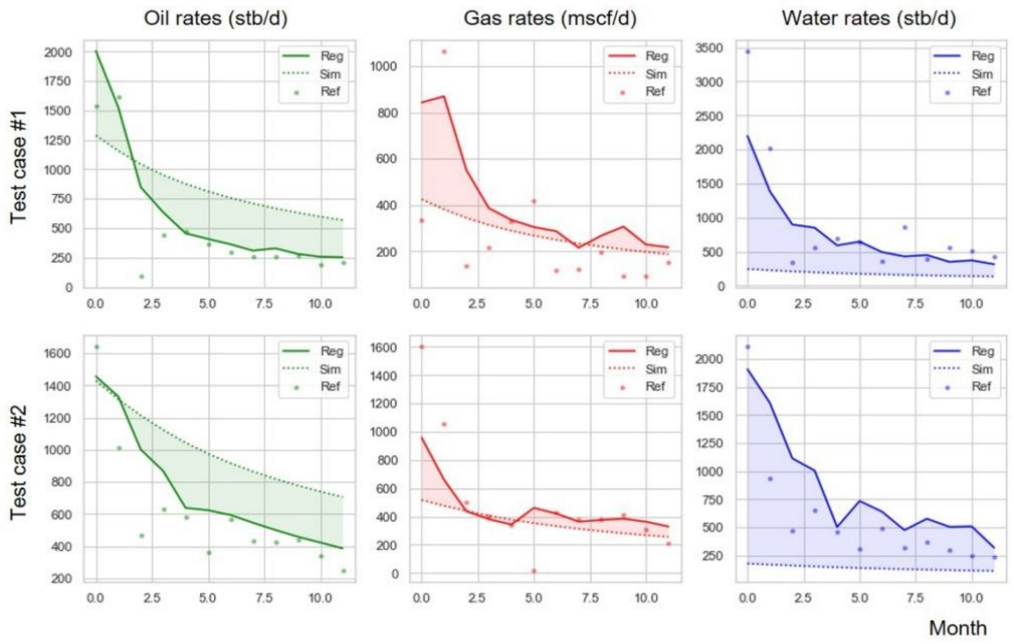


Figure 3. Match of restored profiles from a predictive model for simulation error.

Classification & Regression Tasks

- The shared representation layer provided information for predicting cumulative oil production and performance class labels.
- Confusion matrices showed approximately 95% accuracy for classifying wells as low, mid, or high performing.
- Scatter plots demonstrated effective prediction of cumulative oil production, indicating the model's generalization ability for unseen data points.

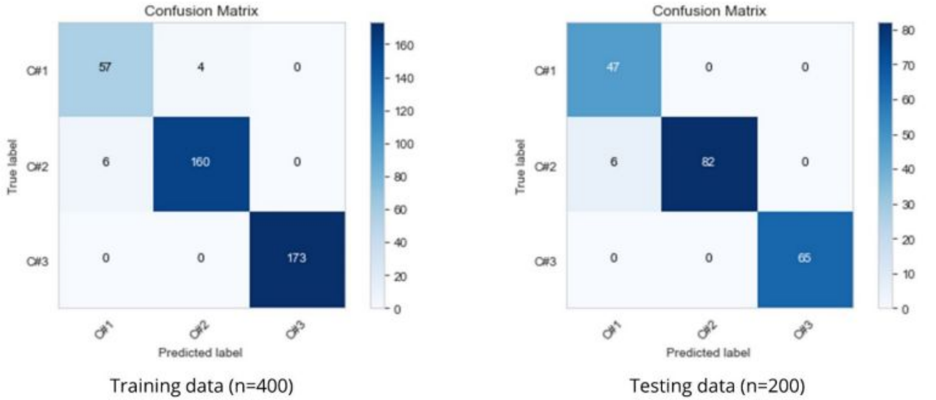


Figure 4. Confusion matrix for the training and testing dataset.

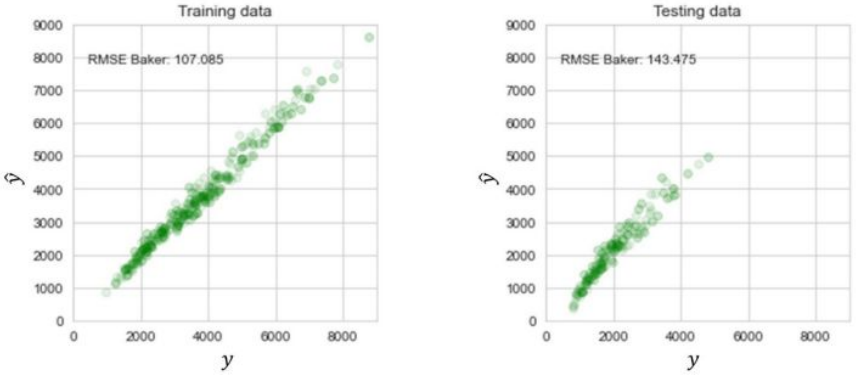


Figure 5. Scatter plots of predicted cumulative oil production versus reference for the training/test dataset.

Discussions & Conclusions

Discussion

Current State and Future Needs:

- Flow simulation models for unconventional reservoirs with complex fracture networks require further fundamental research to better represent flow and transport processes.
- The rapid development of unconventional resources necessitates new methods of modeling well performance.

Strengths of Proposed Predictive Model:

- The proposed model combines the strengths of data-driven and physics-based methods.
- Data-driven models capture complex hidden patterns, while physics-based models provide causal predictions.
- The deep learning predictive model learns discrepancies between simulated and observed production data to enhance simulation-based predictions.

Performance Comparison

Multi-Task Learning Approach:

- Enables simultaneous prediction of multiple success metrics using shared feature space.
- Outperforms single-task learning, enhancing prediction performance and generalization.

Hybrid Modeling Approach:

- Integrates physics-based and deep learning models to improve data-driven model extrapolation.
- Preliminary results indicate robust production forecasts and performance diagnostics for unconventional wells.

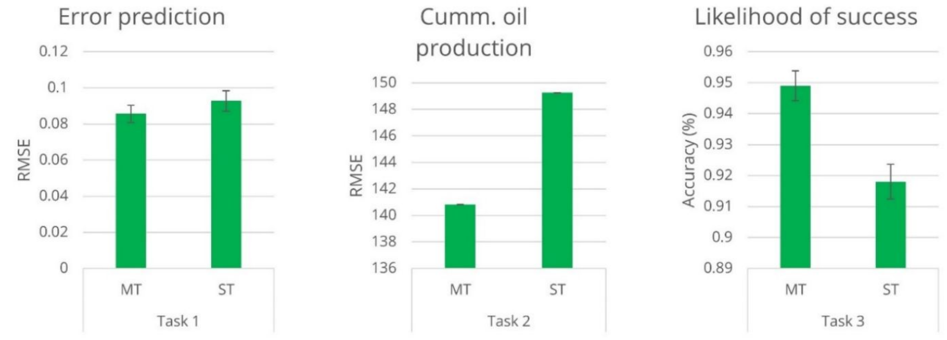


Figure 6. Performance comparison between multi-task (MT) and single-task (ST) learning for each task.

Future Work

- Further validation and refinement of the hybrid predictive model.
- Investigation into additional applications and scenarios.

Key Takeaways:

- Our research presents a novel approach for forecasting unconventional well performance.
- Integration of physics-based and data-driven techniques enhances prediction accuracy and robustness.
- Future efforts aim to expand the model's applicability and explore new avenues for optimization in unconventional reservoir engineering.

Which approach did the predictive model combine to enhance its capabilities?

A) Statistical analysis and machine learning
B) Physics-based and data-driven methods
C) Qualitative and quantitative research
D) Experimental and observational techniques

B

Physics-based and data-driven methods

THANK YOU