FIRST BREAK

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Physics-guided neural networks for predicting unconventional well performance — using Unconventional Rate Transient Analysis for smarter production data analytics

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Introduction

Geoscience modelling poses many challenges due to the limited sampling and the complexity of the phenomena that create the resulting rock and its properties. When adding to the geologic and geomechanical complexity the various possible fluid flow mechanisms that are often not fully understood, one realizes quickly how daunting geomodelling could be. As a result, oil and gas fields are often bought and sold using reserves computed with simple decline curve analysis tools. Unfortunately, these simplified production analysis tools contain no physics and do not help develop oil and gas assets which require the knowledge of 1) rock properties distribution and 2) the impact of the rock properties on the selected production mechanism. For example, if one has a naturally fractured reservoir, the presence or absence of the natural fractures and the way the wells are drilled to encounter or avoid these rock properties will determine the reserves and the future of the company developing such an asset. Very often the future of many companies is not very bright due to their lack of knowledge of the distribution of the rock properties such as natural fractures and the subsequent fluid flow resulting from drilling and fracking into these heterogeneous rock properties.

For the companies that want to prosper by intelligently developing their assets, niche companies and technologies have been used throughout the years to address all these challenges. Among these technologies we find the use of artificial intelligence and machine learning, which were introduced in the oil and gas industry in the early 1990s with successful application to petrophysics, well test analysis and reservoir modelling. Three decades later, the oil industry and its unconventional revolution is facing frequent challenges ranging from frac hits and well interferences, casing deformation and collapses, expensive cube development with meager returns on investment and many other puzzling issues with no easy solution. Suddenly, under the stress of financial constraints, the machine learning tools criticized for three decades as 'black boxes' are now becoming the preferred solution to all problems. Unfortunately, this love-hate relationship the oil industry has with data-driven approaches may hit a rough patch very soon due to its inability to recognize the limitations of the available data used in the various oil and gas challenges.

Does the data contain all the physics?

Artificial intelligence was introduced in the early 1990s to solve two types of oil and gas problems: Firstly, problems with complex and unknown physics, and secondly, problems where the physics is known but computationally intensive and does not allow for its use in an optimization process where multiple iterations are needed. An example of the first type of problem is the modelling of the distribution of natural fractures (Ouenes et al., 1995) where multiple geologic factors contribute through time in creating today a complex fracture network. In such a problem, the complex physics that starts with the deposition of the rock, followed by multiple tectonic events and finally diagenesis that cement some fractures while keeping others open, is impossible to represent in a model. The alternative solution is to use the available natural fracture data or their proxies along with the various geologic factors representing deposition, tectonic events and diagenesis to capture that complex physics. However, if the field is naturally fractured but the limited data present at the wells show no fractures, then the machine learning tools will have nothing to learn since the physics to be learnt is not captured in the available data.

In the second type of problems, artificial intelligence tools could be used to replace a computationally intensive physics model with a neural network that could provide a similar answer in a very short time. An example of such an application is to replace a fluid flow simulator through porous media by a neural network (Ouenes et al., 1994). Here again, the data generated by a physics model, such as a reservoir simulator for fluid flow, to create a neural network model or any other machine learning tool must represent all the possible physics. If a unique set of boundary conditions (for example a producer well is turned into an injector) are not simulated and provided to the neural network, then the desired physics is not captured in the data.

In unconventional reservoirs, the available data may not have the proper physics, or the physics is too complex and

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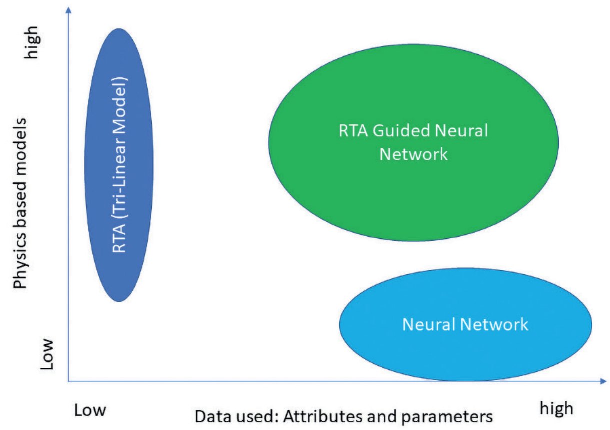

Figure 1 The x-axis measures the use of data while the y axis represents the use of physics-based models. The introduced RTA guided neural network uses the advantages of both approaches.

computationally intensive thus making it difficult to include in an optimization loop to investigate multiple completions strategies. The use of neural networks could be an ideal tool if properly used to address both problems. We introduce the use of physics-guided neural networks (Jia et al., 2019) in geoscience to provide an elegant solution to both problems.

Physics guided neural networks for unconventional reservoirs

In establishing an unconventional well where we would like to optimize the five-year EUR by adjusting its fracing parameters, the goal is to find in possible solutions of fracing parameters the best combination that will achieve the highest 5 year EUR. Unlike the current machine learning solutions applied to the same problem, in this work we introduce a different approach that leverages all the available data and physics based models. The fracking data are collected at the wells and the physics-based simulation tools are 1) full field reservoir simulation and 2) unconventional RTA represented by an asymmetric tri-linear model as described in Ouenes et al. (2017). The major difference between existing industry solutions and the one described in this article are summarized below

1. In addition to the existing fracking data, we enrich the space solution with 100 full reservoir simulations covering all possible situations operationally possible around the considered unconventional well.
2. The neural network includes in its structure, our unconventional RTA tool which allows us to incorporate some physics during the training of the neural network.

This dual use Data vs Physics is illustrated in Figure 1 where we show the key position played by the physics guided neural networks.

A simple way to achieve the ability to include in the neural network a physics-based model such as the RTA model is to change the objective function used in the neural network as shown below.

- Neural Net Objective Function =

$$\sum \tfrac{1}{2}(target - output)^2 + \gamma \sum \tfrac{1}{2}(physics - output)^2$$

Where

- Target is the EUR Estimated from the full-field finite difference simulator
- Output: EUR estimated from neural network model
- Physics: EUR estimated using the Trilinear model
- Gamma: regression parameters

The target EUR is computed by inputting the following parameters in a full-scale reservoir simulation.

- Reservoir porosity and permeability
- Asymmetric fracture geometry
- pressure-dependent permeability

Figure 2 Space solution showing the various classical neural network realizations that have satisfied both the required testing and training threshold (green dots) and those that are only able to satisfy the training requirements (red dots).

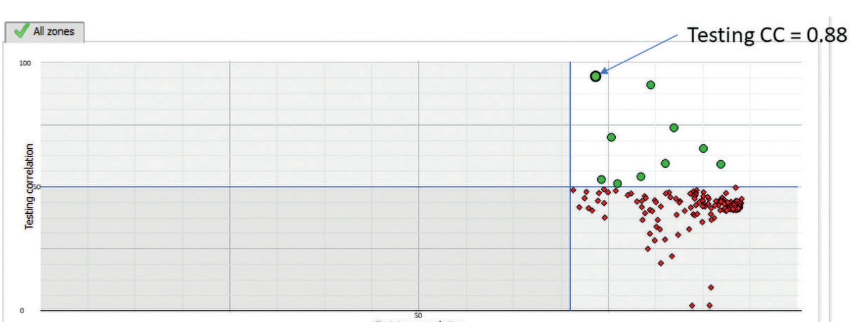

Figure 3 Space solution showing the various new physics based neural network realizations that have satisfied both the required testing and training threshold (green dots) and those that are only able to satisfy the training requirements (red dots). Notice the higher testing correlation coefficient achieved thanks to the trilinear model added to the neural network training.