

# Machine Learning Algorithms and Reservoir Modeling



*Gjøa, North Sea Offshore Norway,  
Courtesy of Neptune Energy*

## Ranking infill wells using data conditioned reservoir models and prescriptive analytics solution

### Objective

Assess remaining reservoir volumes and identify potential infill targets

### Solution

Combine machine learning algorithms with reservoir modeling and the knowledge of the subsurface team in one streamlined process

### Outcomes

- Improved understanding of sand distribution and intra-compartment communication
- Reduced turnaround time with combined modeling solution
- Identified three infill locations which had little difference economically; however, the results suggest these should be drilled earlier than expected

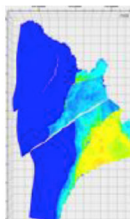
### Machine Learning in Context

Machine learning has been in use for many years in the petroleum industry, e.g. kriging and decline curve analysis. Increases in computational power have encouraged further development of algorithms. One focus has been with purely data driven algorithms in big data with production analytics, especially in unconventional plays. Another has been with model driven machine learning algorithms. This has proven to be a valuable approach since data is combined with underlying physical behavior through models. In the area of reservoir modeling and data conditioning, this application is especially useful when dealing with limited data, large uncertainty ranges and critical business decisions.

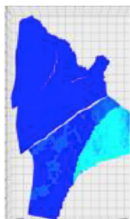
### Model Driven Algorithms

Traditionally, reservoir modeling and dynamic data conditioning have been done in a step-wise, manual or semi-automated manner, making it difficult and time consuming. With the combination of the right algorithms and repeatable modeling workflows using ResX, it was possible to automate this process while accounting for all static and dynamic data in a consistent manner across the modeling chain. Adding to this the combined expertise of the subsurface team led to an improved understanding of the field.

### Low Recovery Factor Oil



### Low Pressure Depletion

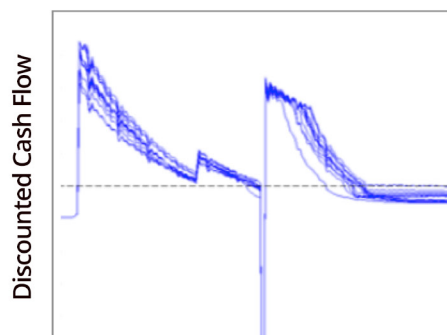


Target 1



Infill Well 1

### Infill Well 1



Prescriptive analytics solution estimated the probability of finding large connected volumes with a low recovery factor, high remaining volumes, and low pressure depletion. The probabilities were then combined to identify the target area and the infill well which was then used to run discounted cash flows.

## Solution Highlights

- 32 million uncertainty parameters were used in the model calibration process.
- The data calibration process detected when there were critical issues in the input model parameters and corrected the model parameters to reduce the mismatch, all while the static data information and the geological concept were preserved in the posterior ensemble of models.
- Using the ensemble of data conditioned reservoir models as input, the prescriptive analytics solution was applied to:
  - 1) Estimate the probability of finding large connected volume good sand (above the contact); connected volumes of remaining oil; and, connected volumes with little pressure depletion;
  - 2) Identify the intersection between these volumes where the probabilities were larger than a given threshold;
  - 3) Calculate the largest connected volumes of these intersections;
  - 4) Automatically create infill wells within the identified targets, taking physical constraints such as dogleg severity into account;
  - 5) Run predictions for the ensemble of model realizations including the new well targets and calculate the discounted cash flow for all cases.
- All infill well scenarios were economical with no significant difference; however, each case showed negative cash flow earlier than expected which suggested that the infill strategy should be accelerated for optimal NPV.