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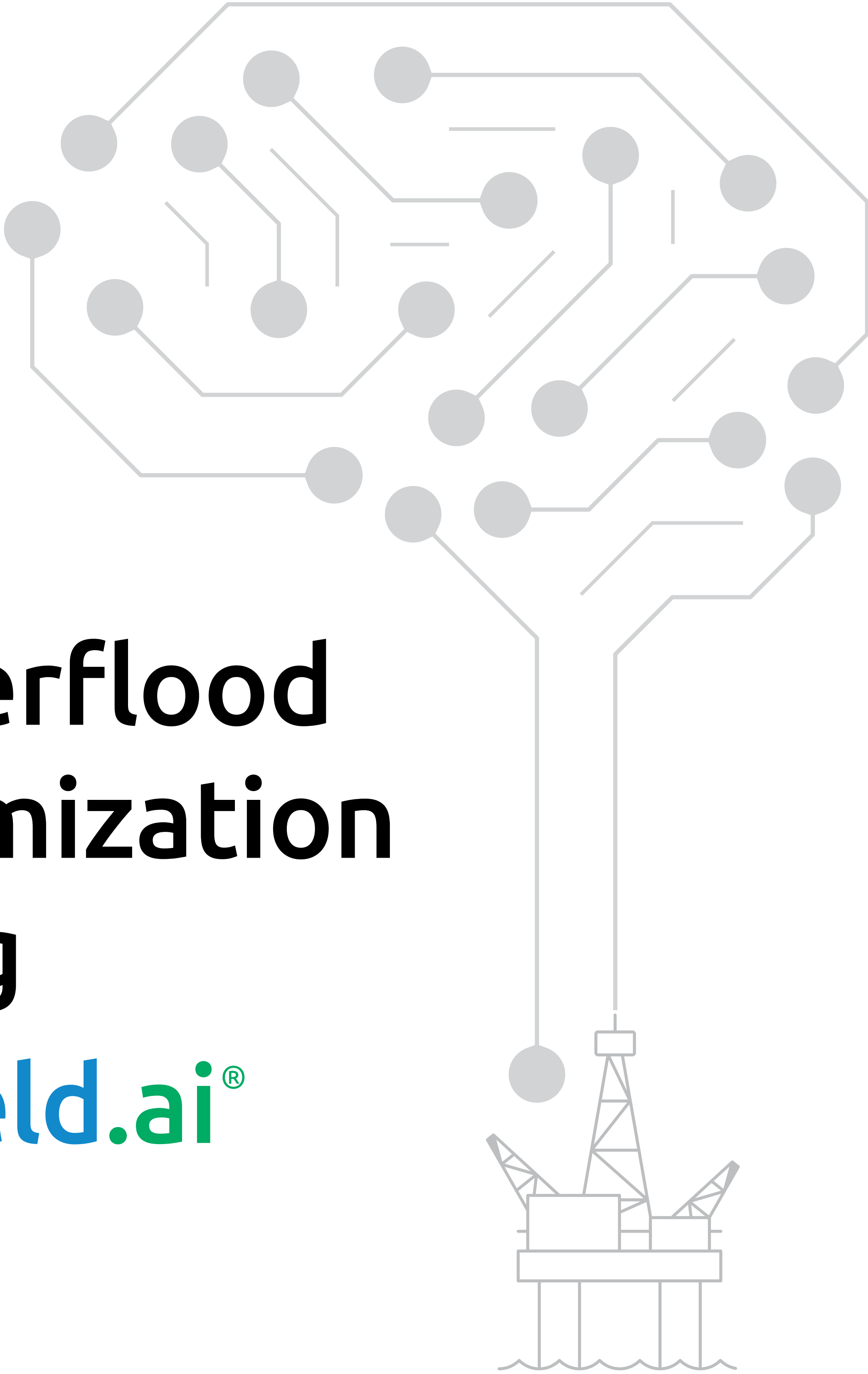


Waterflood optimization using oilfield.ai®

Contents.

Background.

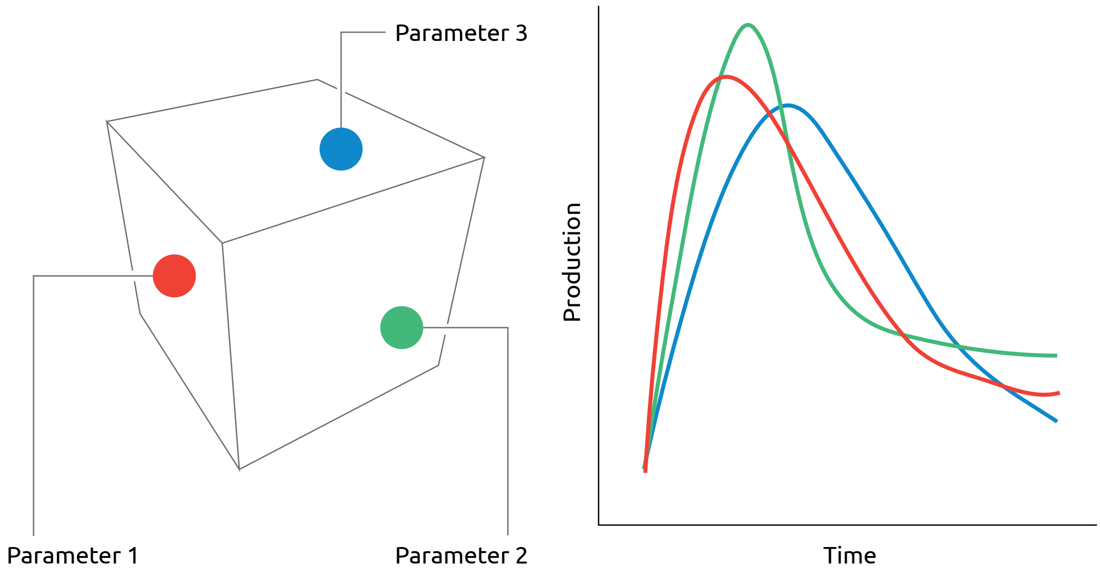
Water injection is commonly used for enhanced oil recovery across the globe. In mature fields, its performance can be boosted by modifying locations and operational conditions of wells. The optimization task entails making decisions around number of wells, positioning and spacing, configuration of completions, schedule of injection, facilities, and other technical and economic factors. In addition to many decision variables, the following two problems make waterflooding optimization a challenging issue.

Problem: numerical simulation and uncertainty.

Traditionally waterflood operational decisions are evaluated using numerical simulation software, coupled with an optimization algorithm. The steep learning curve of using a complex simulator, combined with elevated cost of evaluating hundreds of solutions suggested by the optimization routine results in prolonged project duration. This cripples the decision-making process and reduces the overall efficiency and profitability of a waterflood operation.

The large computational footprint of waterflood simulation is accompanied by various forms of uncertainty. The American Institute for Aeronautics and Astronautics (AIAA) defines uncertainty as “A potential deficiency in any phase of activity of the modeling process that is due to lack of knowledge”. In addition to lack of knowledge and incompleteness uncertainty, inaccuracy in measurements and errors in simulations impact our understanding of subsurface systems. To account for uncertainty and non-uniqueness of solutions, multiple realizations must be generated. As shown in Figure 1, this is achieved by generating carefully designed samples from input parameters and obtaining outputs for each combination of input parameters.

Figure 1: Uncertainty of production prediction arising from multiple realizations of reservoir



Solution: artificial intelligence, tamed by physics.

We use a proprietary formulation of waterflooding problem that is powered by artificial intelligence and controlled by reduced physics. This unique combination provides the most accurate solution, allowing for more pertinent secondary EOR optimization. We build a sequence of Machine Learning (ML) models for rates and pressures, each model using prediction of the previous models as features, along with geological, reservoir, completion and user defined variables. The selection of features for each model is guided by fluid flow and material balance equations.

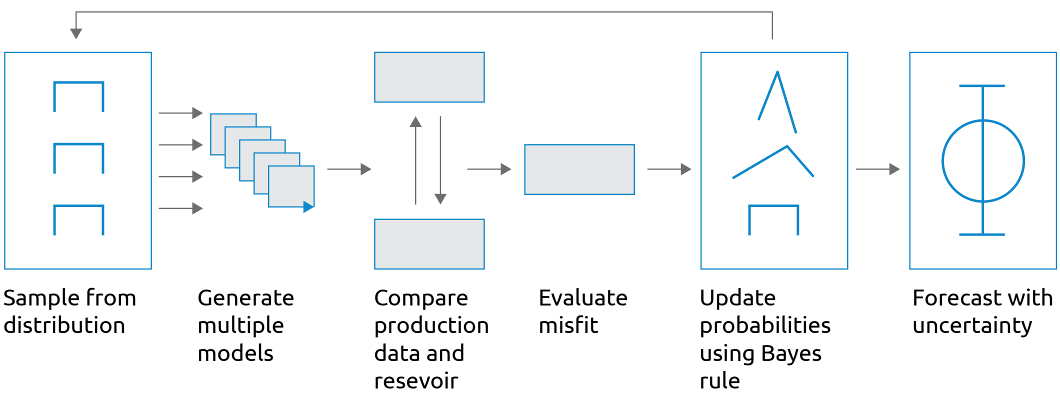
Most of the existing reduced physics models require an inversion step of using historical data of rates and pressures. These formulations are computationally fast but rely on restrictive assumptions that can be eased using ML-based approaches. Another drawback of these approaches is that if they are applied to a field with insufficient data to constrain the problem, a multiplicity of solutions may be reached. For example, if the BHP is close to constant, multiple productivity index sets may match the data from a purely numerical standpoint. We use a Bayesian framework to guide the modeling approach towards solutions that make sense from a reservoir physics perspective. Bayes' theorem is a statistical method that allows us to update our estimates of probability given an initial set of prior beliefs and some new data. The simplest version of Bayes' theorem is given below:

Equation 1

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

In essence Bayes' theorem states that given an initial prior probability for event A, P(A), we can calculate it's new posterior probability P(A|B) based on the occurrence of event B, through the conditional probability P(B|A) called the likelihood. P(A|B) describes how likely event A is given an occurrence of event B. The likelihood is a little more subtle, but a good description is to consider A as a possible scenario which influences B, which is known. The likelihood, P(B|A) therefore provides a measure of how likely A is the cause of B.

Figure 2: Bayesian uncertainty quantification framework. Christie et al. 2006

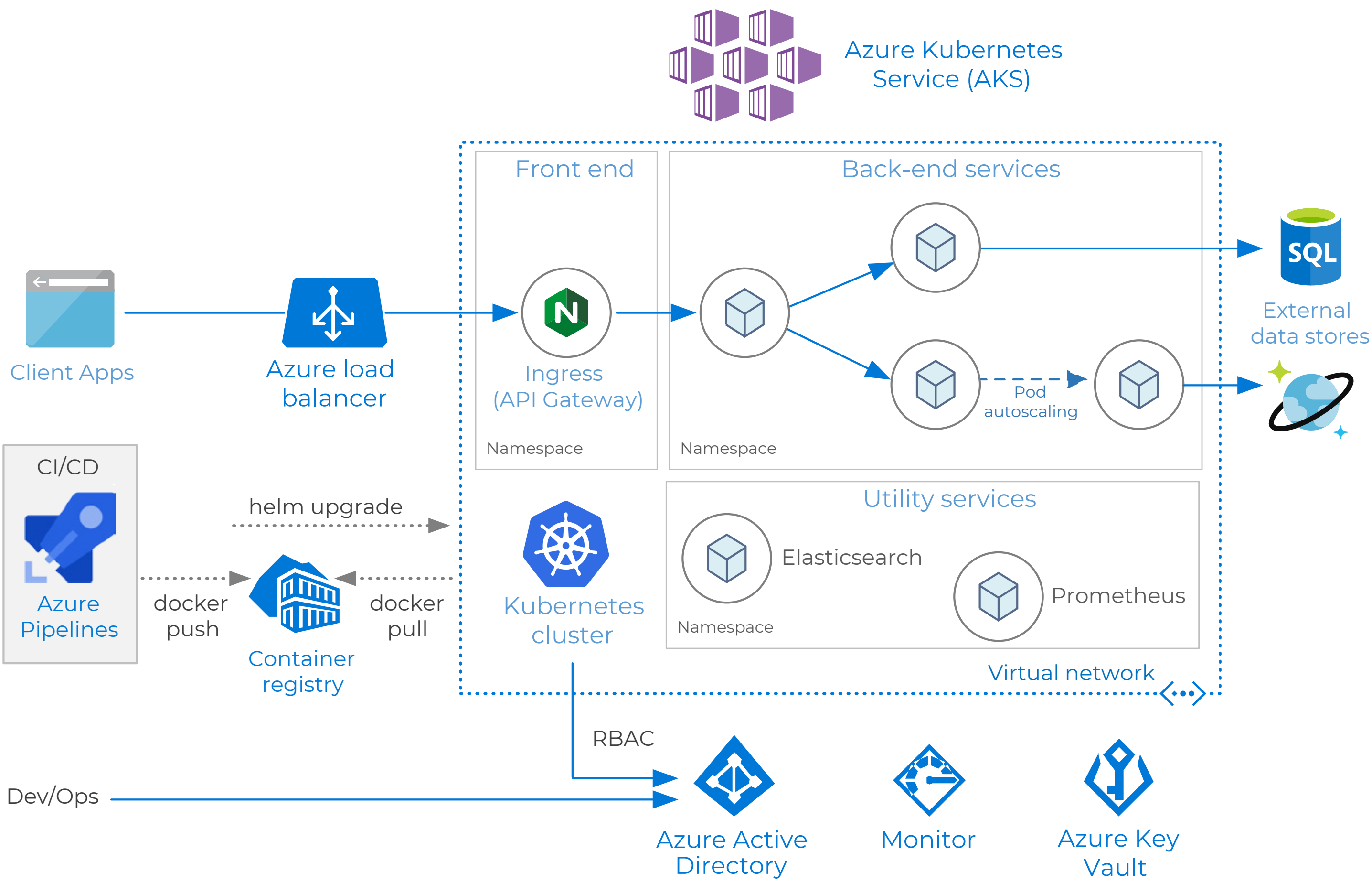


Our ultimate objective is to build a robust predictive tool is to run thousands of optimization runs to find optimal production and injection strategies. We achieve this objective by coupling our hybrid models with a multiobjective optimization workflow. This algorithm can consider multi-objective optimization (Hajizadeh et al., 2011) in order to account for different constraints and targets. For example, the algorithm will try to maximize production while considering secondary objectives such as, water supply or processing constrains.

Infrastructure.

oilfield.ai® is built on modern cloud infrastructure supported by Microsoft Azure. We use Azure Kubernetes Service (AKS), as well as Azure Batch as our scheduling and compute management infrastructure. Figure 3 shows the reference architecture and the continuous integration, continuous deployment pipeline we use to build our solutions.

Figure 3: Our reference architecture



Illustrative case study.

The Ninth SPE Comparative Solution Project (SPE9) is a challenging highly heterogeneous public benchmark case (Killough, 1995) with twenty-five randomly places producers and a single water injector.

Figure 4: The SPE9 simulation model

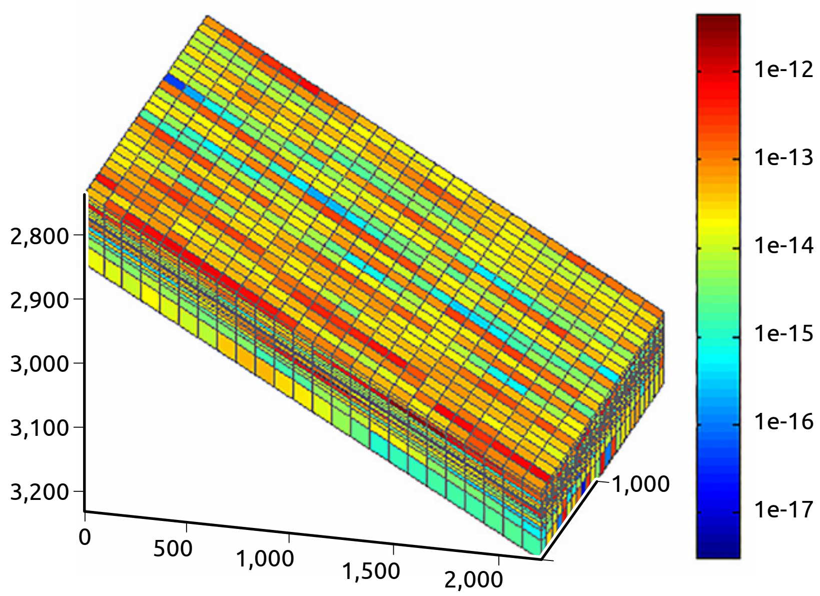


Figure shows the augmented hybrid modeling results for prediction of oil and water rates and uncertainty intervals for a well in the SPE9 model. The computational time for training and forecasting on all the wells is 7 seconds, with an R2 for the rates equal to 0.99. Figure 6 shows the cumulative water of the injector wells and the cumulative oil from the producer wells, on a Voronoi grid. The sliding bar below the map enables to display these volumes between two specific dates.

Figure 5: Rates prediction and uncertainty for well PRODU26

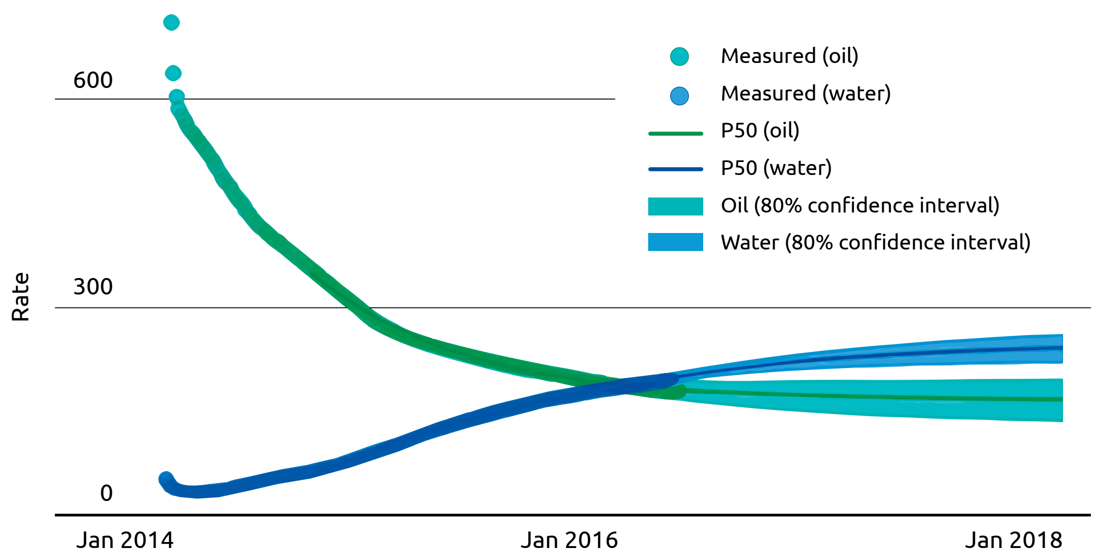
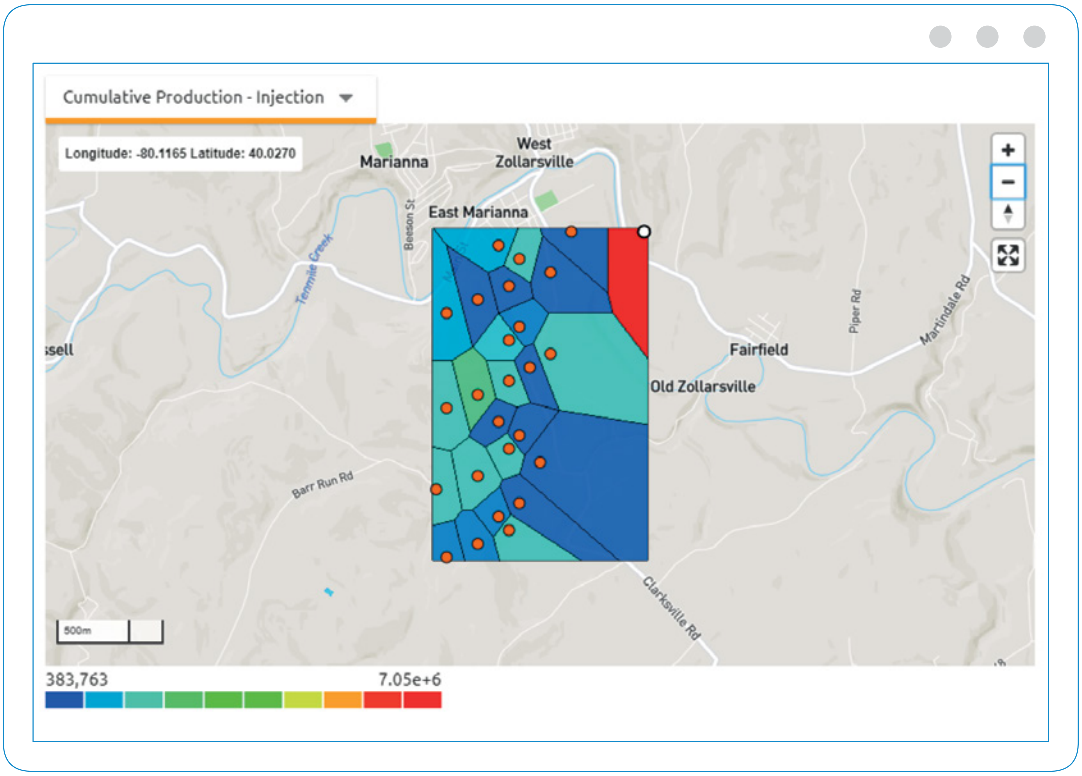
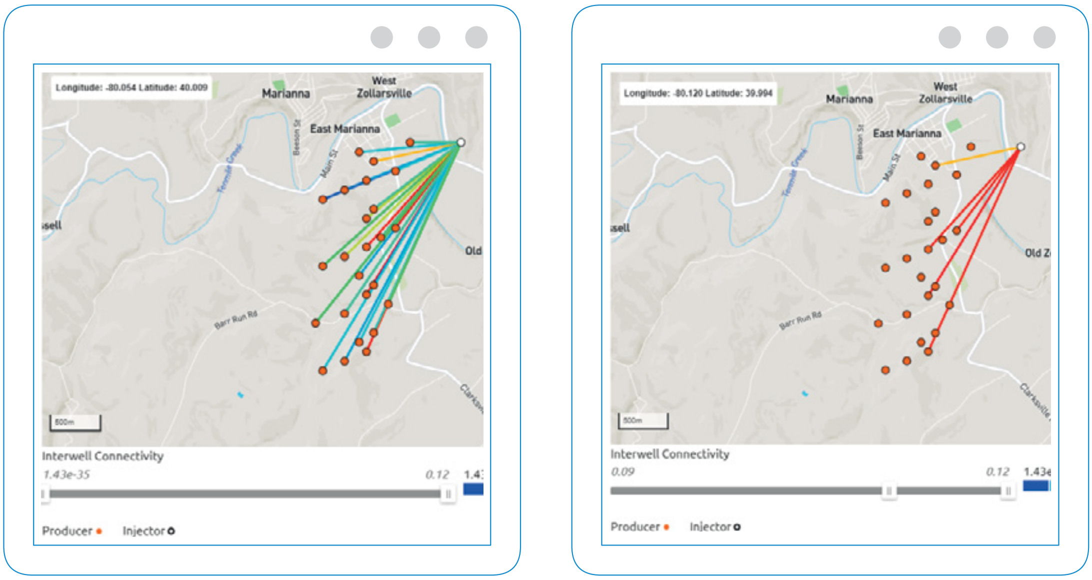


Figure 6: Cumulative water injection and oil production on a Voronoi grid



We can also look at the inter-well connections in oilfield.ai using a connection string with colors correlated to the connectivity index. By moving the sliding bar, we can see the strongest or weakest connections dynamically and in real-time.

Figure 7: Interactive visualization of inter-well connectivities



Takeaways.

Maillance offers a unique hybrid product based on machine learning and physics to optimize waterflood operations.

- *The combination of reduced physics modeling and AI enables more accurate prediction and optimization of production and injection strategies and field development planning.*
- *Our augmented hybrid runs two orders of magnitude faster than traditional numerical simulation tools. This significantly reduces the time to decision in waterflood operations.*

To learn more about our cloud-based **oilfield.ai**® product, please visit maillance.com, or send an email to software@maillance.com.

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