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Physics-Based Artificial Intelligence combined with Agile Reservoir Modelling Improved the Opportunity Identification in A Mature Gas Condensate Field

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Abstract

Two adjacent offshore gas-condensate reservoirs were analyzed. One reservoir has been produced for a long time with associated pressure depletion and aquifer sweep with the reduction of depth of the gas-water contact. The second reservoir has also undergone some pressure depletion; however, its gas-water contact remains at its initial depth. This seeming contradiction impedes the development of this unproduced reservoir. A simple physics model of spill-fill is proposed to account for these observations. This model is fully tested by a cloud-based artificial intelligent (AI) approach to explore the full range of parameters consistent with this physics model. Machine learning/ artificial intelligent (ML-AI) is also used to probe whether other distinct models can yield the same set of observations. This paper demonstrates a liberated workflow to calculate the recommended parameters that achieve the minimum mismatch score. The workflow is executed through a cloud platform offering compute elasticity to expedite the field history matching workflow. It is composed of three main steps. The first step is data loading, where simulation results and parameters are extracted from the submitted ensemble(s). The second step involves data preparation and cleaning. Wells devoid of data are removed, and scaled metrics are created to calculate the mismatch score. Simulation ID then groups the data to get a field-level aggregation. The aggregated and cleaned simulation results are merged with the parameters list to create the input dataset for the final step where several machine-learning (ML) models are trained and evaluated in parallel. The data is split into training and testing datasets. The target variable is the mismatch score, as the models are trying to predict the mismatch for a given set of parameters. Supervised learning regression algorithms were used. The best-performing ones were found to be random forests and gradient-boosted trees. After fine-tuning the ML models and evaluating them based on their coefficient of determination (R2 score), the best-fitting model is used to calculate the optimized parameters. This happens iteratively by generating a new series of parameters within a range and using the ML model to predict the mismatch for each until the lowest mismatch is found. The parameters resulting in the minimum mismatch are the recommended parameters.

The cloud-based Agile reservoir modeling approach enriched with AI algorithms enabled the generation of multiple realizations that match 30 years of historical production and pressure profiles, capturing many possible combinations of uncertain geological parameters and concepts. In addition, several forecast scenarios for 3 new appraisal wells were optimized based on the ensemble of history-matched models minimizing the risk of drilling dry wells. Besides going through the work process and results, this paper highlights the method's practical effectiveness and common issues in a real-world application.

Introduction

Reservoir simulation is required to aid in the decision-making for high-impact projects. It is a culmination of geophysical, geological, petrophysical, and engineering assessments of sparse, uncertain, and expensive data. History matching is a process of elevating trust in numerical models as they are calibrated to mimic the behavior of the real-life asset. Traditional history matching relies on direct parameter assignment based on flat files used as input to the reservoir simulator. This enables a convenient method for the perturbation of uncertain parameters and their value assignments during the history-matching process. Given the nature of the input files, the scope for uncertainty parameters is limited to the original petrophysical properties, their derived simulation properties in a specified group of grid blocks, and is occasionally extended to include fluid and multiphase flow properties. However, there are key influential model-building steps prior to reservoir simulation related to data interpretation. These steps control not only the values of petrophysical properties but also their spatial correlation, cross-correlation, and variability. The limitation in the scope for parameterization adds bias to the model calibration process, hence negatively impacting its outcome.

In an era where ML/AI algorithms are shaping data interpretation methods, key modeling decisions can be revisited to realize the maximum value of subsurface data. However, a framework is required whereby these important model-building steps are captured in history matching to eliminate bias and ensure the geological consistency of the subsurface model during and after history matching. This paper demonstrates a liberated workflow to calculate the recommended parameters that achieve the minimum mismatch score.

This workflow is implemented on a simulation model built for a mature gas condensate field in the Mediterranean of Egypt. The field comprises three Anticlines with a spill-fill Petroleum system, where most of the wells are in one of the Anticlines. In contrast, the other Anticlines have few wells and are candidates for appraisal. Moreover, there is high uncertainty in the sand distribution and reservoir properties, spill points depth, depletion, and observing an explained phenomenon of a sustainable gas-water contact in the new Anticline even after 30 years of production from the old Anticline. This uncertainty in the understanding of the relation between the two Anticlines makes the selection of the drilling locations a challenge. To Assess remaining reservoir volumes and identify potential infill targets, we used the ML to study all the uncertainties combinations in a full-loop approach, from static to dynamic model and generate multiple representations that honor the geological understanding.
The cloud-based Agile reservoir modeling approach enriched with ML/AI algorithms enabled us to generate various realizations that match 30 years of historical production and pressure profiles, capturing many possible combinations of uncertain geological parameters and concepts. In addition, several forecast scenarios for 3 new appraisal wells were optimized based on the ensemble of history-matched models minimizing the risk of drilling dry wells. In addition to going through the work process and results, this paper highlights the method's practical effectiveness and common issues in practical application.
The use of cloud-based technology had great cost savings and efficiency improvements; for example, giving the existing on-premises infrastructure would take 1-2 years to achieve the same results that were achieved in 1-2 months and cost savings of around 1 million dollars in cluster hardware purchase. Moreover, Cloud-based technology enables collaborative,

iterative working styles for integrated teams and access to scalable technologies that are developed on the cloud only.

Field Background

An Offshore Gas Condensate Field located in the Mediterranean as shown in Fig.1, the reservoir is composed of three main Consecutive Anticlines. It started production from the middle Anticline in 1986 and currently has 10 producers. Then in 2011, the left Anticline was explored with one well. In this new Anticline, it was found that the pressure was depleted but also found an unexplained phenomenon in which the water contact sustained at the same original level that was found in the producing Anticline 20 years ago, while currently, the water contact in the producing Anticline is much shallower due to production. So, this new Anticline was never produced until now, as there were concerns about whether the producing Anticline is communicated or not with the new Anticline, and if it’s communicated, will the remaining reserves be economical or not? But since production from the middle Anticline started to decline in 2015 due to water encroachment, it was essential to reconsider developing the new Anticline.

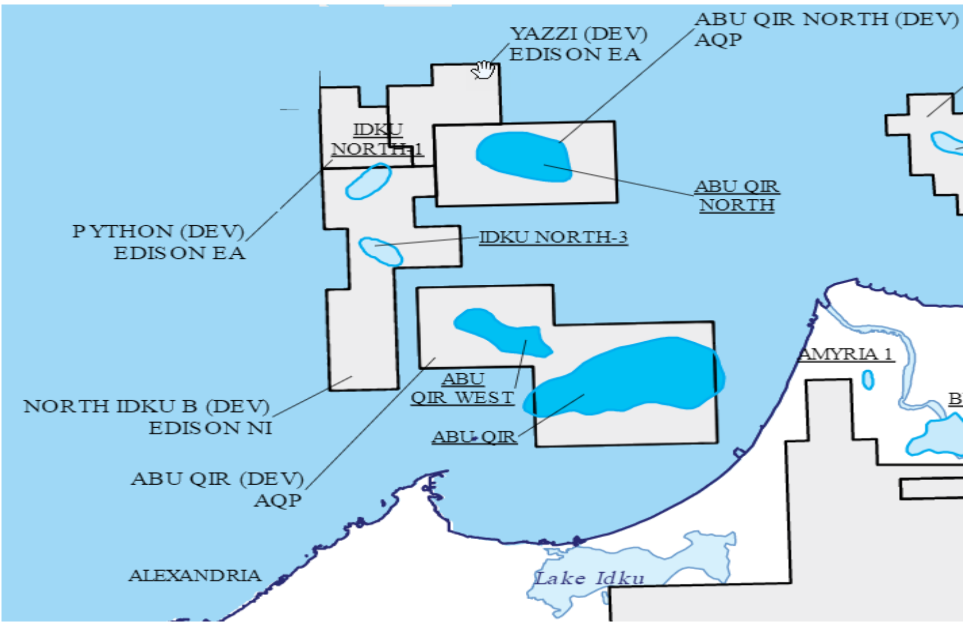

Fig 1. Abu Qir Petroleum Assets in the Mediterranean

Study Objective and Challenges

The objective of the study is to have a clear understanding of the relationship between the new Anticline and the producing Anticline, through a detailed reservoir simulation model to fully characterize the reservoir and reveal how the water contact remained sustainable in the newly explored Anticline after producing for 20 years from the middle Anticline. Then, using this model to estimate the remaining reserves in the new Anticline and study if it's economical for drilling the new wells to increase the company's production profile and finally, forecast the whole field performance for the next 10 years including the new area, for reserve booking purposes.

However, in this case, building a representative model was very challenging due to high subsurface uncertainty. From the geological modeling perspective, there was high uncertainty in the top structure of the formation and consequently, the spill point between the producing and the new Anticline was unknown, so as was the communication between them. Also, the geological depositional concept was not clear, leading to high uncertainty in facies, rock, and petrophysical spatial distributions. Then from the flow dynamics perspective, the challenge was to history match 30 years of historical data including (gas- condensate- water breakthrough- Static pressure- WHP- RFT Pressure) on a well-by-well level, and also mimicking the unexplained Sustainable water Contact in the new Anticline and the rising water contact in the producing Anticline So Traditional Modeling approach is neither be convenient nor effective in this case.

Methodology

First, let's discuss the traditional modeling approach shown in Fig.2, to differentiate our new approach later. In the beginning, the geoscience team starts by interpreting raw seismic and log data and from this comes up with an interpretation for the formation horizons, faults, and all other structural elements. This interpretation is used to build the structure of the reservoir model; then within this structure model, petrophysical properties such as facies, porosity, permeability, and saturation are populated while honoring all the dependencies between those properties. The dynamic properties and historical data are introduced to the model to simulate flow dynamics. Then, because the model is not representative at the beginning, we start tuning all the uncertain inputs manually until the model matches the historical data. After that, we suppose that the model now represents reservoir behavior, so we can utilize it to forecast field performance. The problem with this approach is that it is a sequential approach and usually takes from 12-18 months or more -depending on the complexity- due to looping between different processes, and at the same time, the realizations are very limited, just one or two models which might not capture all the possible scenarios due to subsurface uncertainty.

On the other hand, As illustrated in Fig.3 the new approach we introduced is an Artificially Intelligent and Agile Reservoir Modeling approach using a commercial cloud environment in which we build an uncertainty framework to consider all the possible uncertainties starting from seismic interpretation until flow dynamics then using the scalability and agility of the cloud, the framework is designed to simultaneously build thousands of structure models, then populate thousands of petrophysical models and finally thousands of dynamic models.

At this stage maybe none of the dynamic models are matching the history data, so we deploy an AI algorithm to learn from the thousands of the dynamic models' results and their respective geological inputs to automatically conclude Multiple combinations of the geological inputs that provide multiple representative dynamic models, to capture all the possible subsurface uncertainties and reduce the drilling risk. Finally, those multiple representative models combined will be used to provide an ensemble-based forecast for field performance and not just a single forecast relying on one single representative model. This helps de-risk drilling the new wells in the new Anticline.

This workflow took less than 1 month to generate more than 3000 realizations instead of just a single realization using the traditional approach. The workflow can be summarized in the following processes:

1- Framing the uncertain parameters and their ranges, this step includes parameters from seismic attributes to guide sand distribution maps, petrophysical properties and dynamic rock-fluid properties
2- Building a base case for the model with most likely values for each uncertain parameter
3- Utilizing a random sampling algorithm like Monte Carlo enhanced with Latin Hypercube to generate and run thousands of random simulation cases with different combinations of the uncertain parameters.
4- Liberating the simulation cases inputs and results from the simulation platform to the data science platform within the cloud.
5- Training, testing, and validating an AI algorithm to learn from the liberated thousands of simulation inputs and outputs and compare it against the actual historical data through a mismatch function.
6- Deploying the AI algorithm to run millions of combinations and scenarios of uncertain parameters and come up with the best several combinations that match the history data.
7- Predicting each of the representative models using the same operating conditions to deliver an ensemble-based type of forecast to de-risk the drilling of the new wells.

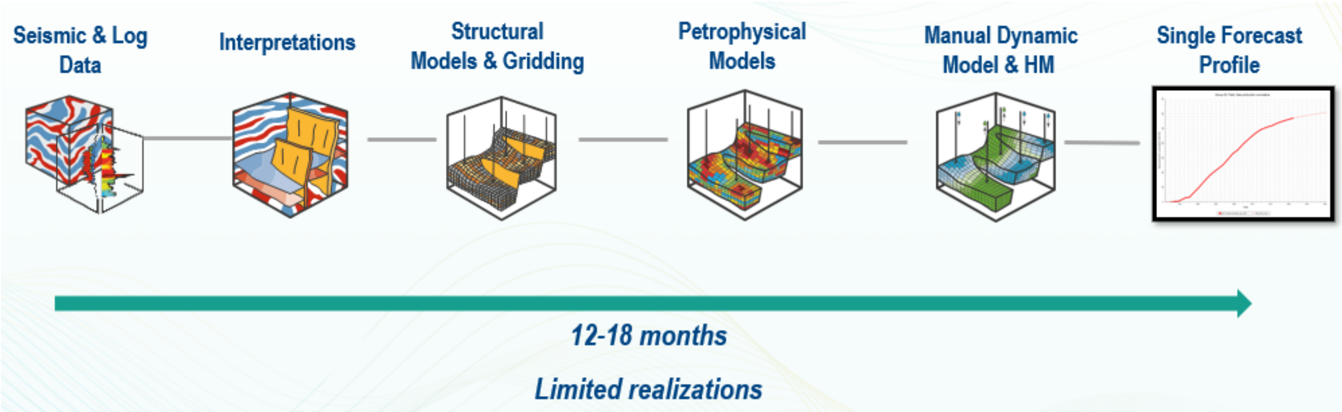

Fig 2. Traditional Reservoir Modeling & Simulation Approach

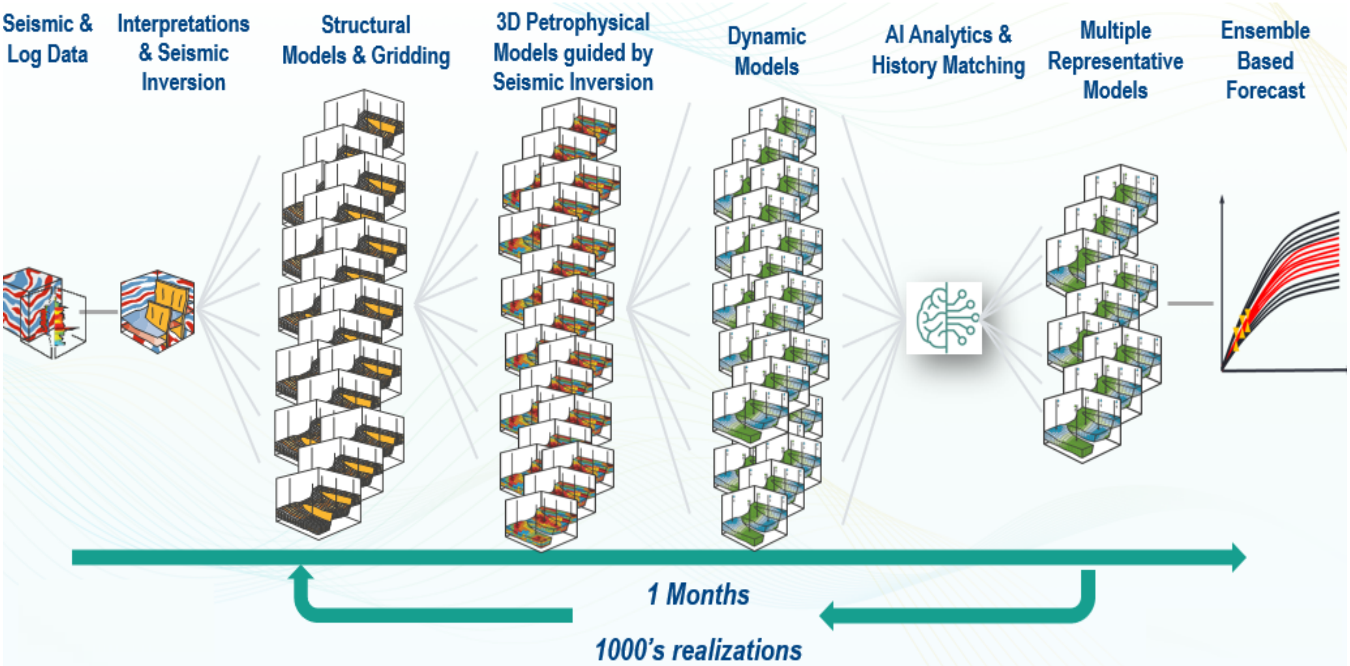

Fig 3. Agile Reservoir Modeling Approach Enriched with ML using the Cloud

ML Algorithm

First, it was important to ensure that the data coming out of the reservoir simulator was structured correctly. Each well within each case needed to have the same start date. The simulation timestep had to be set to daily. Once these settings are set, the model is put through the Agile Reservoir Modeling system.

After the Agile Reservoir Modeling system finishes its runs, API (Applications Programming Interface) calls were used to extract all the simulation cases, the parameters for each case assigned by the Monte Carlo distribution algorithm, and each case results per timestep per well. Since the simulator is the main source of information, it was imperative to ensure that any conditions, exclusions, and rules used to compare cases together were accounted for in the machine-learning solution. Rules like ignoring zeros, exclusions like removing certain unnecessary wells, and conditions such as the inclusion of measurement error values were all implemented in the data preparation stages of the ML pipeline.

Using the 30 years of actual production history and well tests, the root mean square error (RMSE) for each well in each case per timestep was calculated and aggregated. Some real-life data points didn't fall on the first of the month, so their calculations were tied to the closest simulation point. This global mismatch parameter would be the target for the regression ML algorithm to predict given the parameters used in the cases. For this project, as shown in Fig.4, random forest regression was used in order to predict the mismatch of each case. Random Forest, as an algorithm, is very efficient and doesn't consume a lot of resources when performing training, testing, and predictions. It's also more accurate than other algorithms and can deal with missing data with relative ease. It can maintain its accuracy even if there are big portions of the data that are missing.

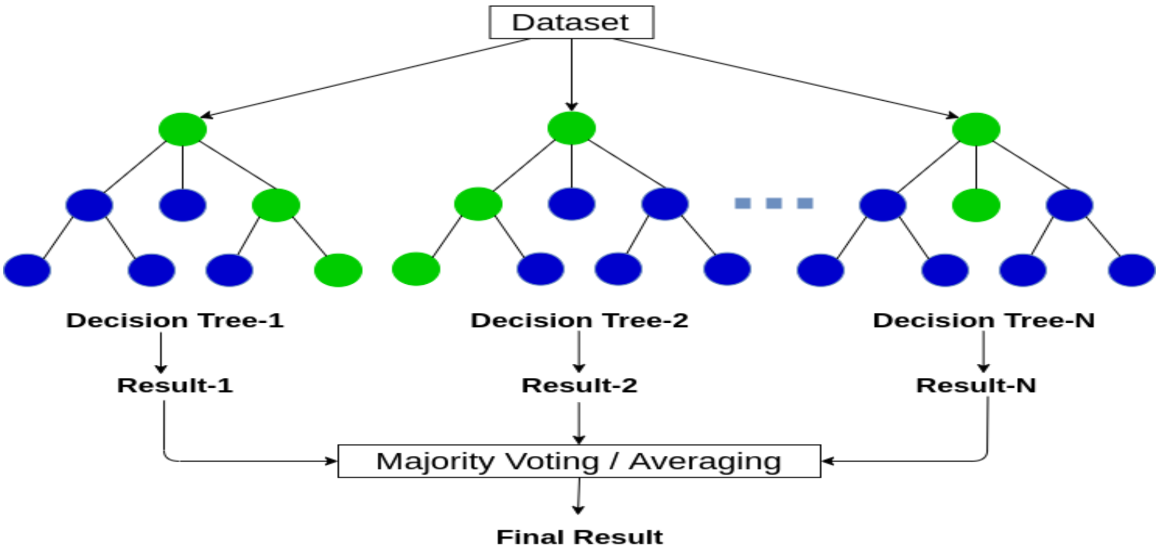

Fig 4. Small example of how Random Forest voting and aggregating results works

Random forest regression is an ensemble method, creating several weak regression trees and having them all vote on what the outcome is. Each regression tree will split the data into dense or sparse subsections of the data based on a cost function. The cost function tries to split branches into subsets with the most homogeneity, or branches groups of subsets with similar responses. The trees will continue to split until a minimum specified number of observations are found in each branch. Once each tree is created, the collected response of all the trees (the forest) is then aggregated and averaged in order to get a more accurate prediction than any individual model by itself.

After testing and training the algorithm, a new combination of parameters was given to the model for testing. The model would predict the mismatch produced by the given parameters through millions of scenarios as illustrated in Fig.5, and the best of these parameters would be tested by the reservoir simulator, guiding the reservoir engineer and improving the possibility of finding a more accurate history-matched model. This iterative process allows for fine tuning and scenario testing quickly and efficiently, removing the sequential and blind testing of the old/traditional way of doing history matching.

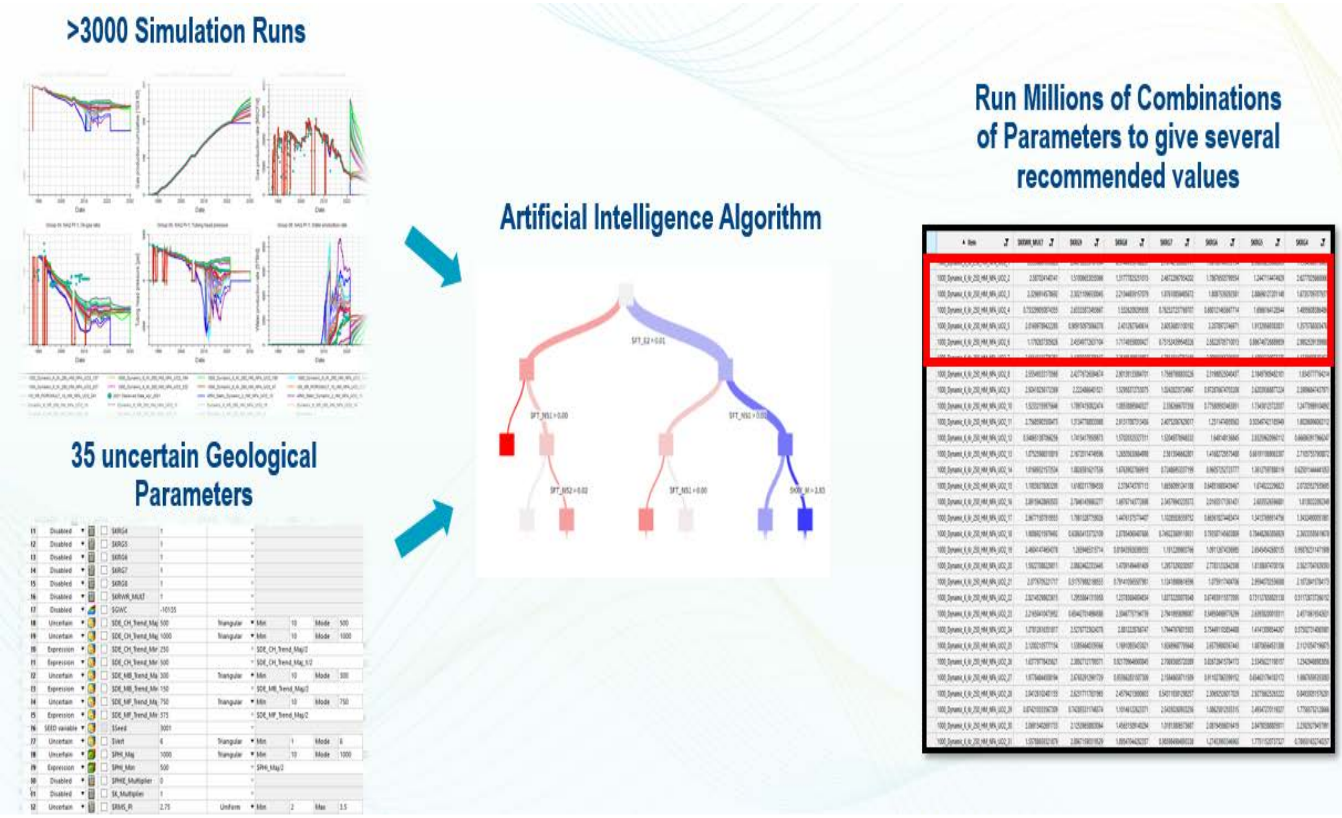

Fig 5. Illustration of the AI Role to Calibrate the Reservoir Model

Computation Requirements

For this study and having the model size, huge processing power was required to accommodate the superior parallel scalability and capability to simulate high-resolution models within an acceptable timeframe.

As the demands on IT infrastructure are rapidly increasing – and the ability of the infrastructure to adapt and respond becomes more critical. Performance is essential, and we were looking for flexible solutions that could quickly respond to dynamic usage patterns, but with a reduced financial burden. Due to the limitation of the in-house infrastructure and capital investment required to get the required hardware to deliver the study on time. The platform used in this study is entirely hosted on the cloud. This allowed the asset team to analyze a wealth of data and run up to 250 different simulation runs at the same time and consume up to 1024 cores in parallel at reduced cost, the data generated from the simulation results being pushed instantly to the data ecosystem for further analysis by the visualization tools, AI/ML based platform, all integrated into one platform/interface which allows the data science team to work in collaboration with the asset team.

Completing this study required good reservoir and model understanding, cloud-based solution for Reservoir simulation, AI, ML, and visualization business intelligence tools fully integrated into the cloud data ecosystem, and access to scalable computing capacity, this helped the project team to overcome the technical and software challenges related to in house software and hardware to run large cases without any limitations to the asset team. The cloud-based environment can complete the entire process from generating multiple geological realizations, searching for valid models by filtering the history data, predicting the forecast performance, optimizing the development plan, running the ML model, and virtualization in a very fast timeframe.

Results

The AI Algorithm recommended four different combination of uncertain parameters that generate the best four representative reservoir models matching 30 years of historical data while explaining why the water contact is sustainable in the new Anticline as will be illustrated in the next section. This proved That the ensemble of reservoir models provides a robust geological representation and understand to the field that can be trustfully used for predicting the new wells performance as shown in Fig.6.

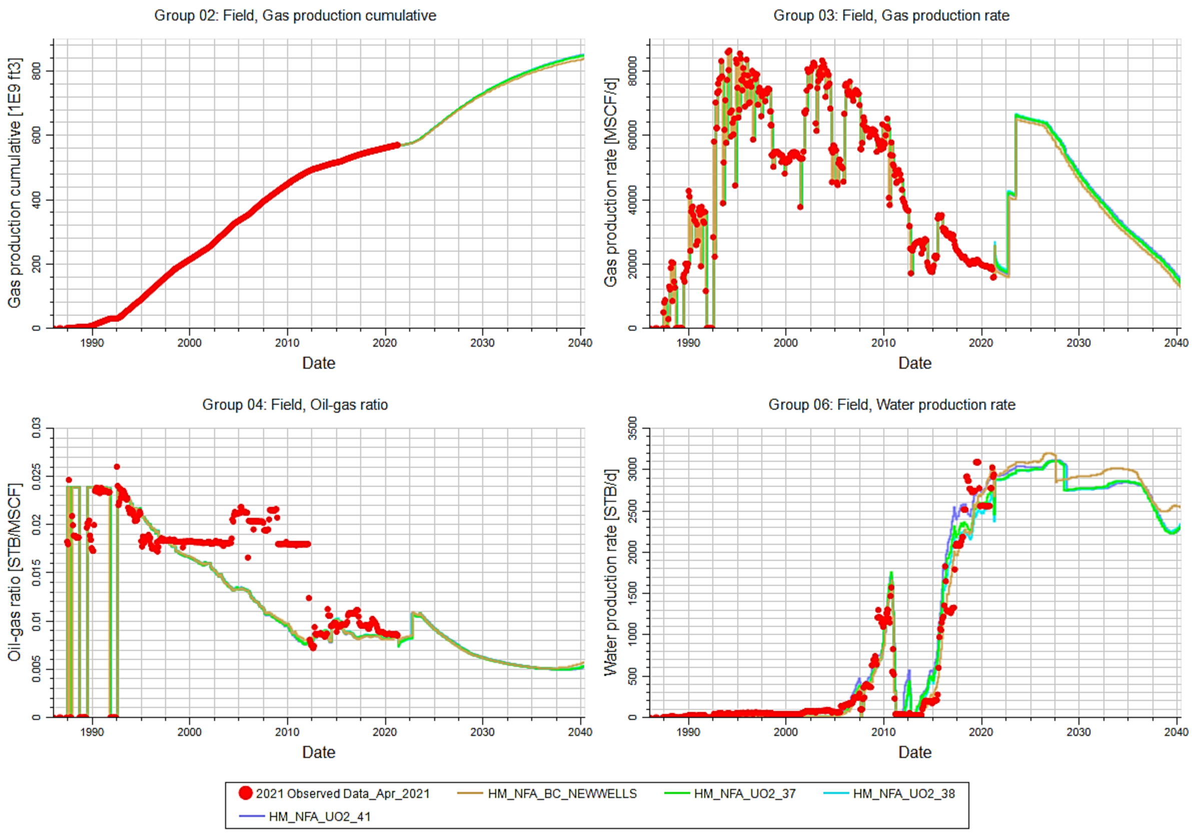

Fig 6. Four representative reservoir models that match 30 years of historical data

Conclusion and recommendations

The Agile reservoir modeling enriched with AI helped the simultaneous generation of multiple representative reservoir models and ensemble-based forecasts in a timely manner, the AI model learned from thousands of actual simulations on the field in order to recommend the values of the geological as well as flow dynamic parameters to match the historical data and from those geologically representative models the following was concluded:

First, All the representative models yielded one important feature that the spill point depth should be exactly at the original water contact level, which concluded that the hydrocarbon trap is based on a spill-fill petroleum system in other words, the water contact is controlled by the spill point depth between the Anticlines. Consequently, the new Anticline almost spilled out 20% of its gas into the producing Anticline through the saddle due to pressure depletion while keeping the water contact level exactly at the spill point depth due to the difference in gas and water compressibility as illustrated in Fig.7.

However, so far, the remaining reserves in the new Anticline are still economical to drill 2 new wells. And those new wells are expected to increase the recovery of the field by around 30%.

So, the main recommendation was to start drilling as early as possible to avoid further drainage of the reserves within the new Anticline. Based on this, the drilling campaign and the new wells will be drilled by the end of this year.

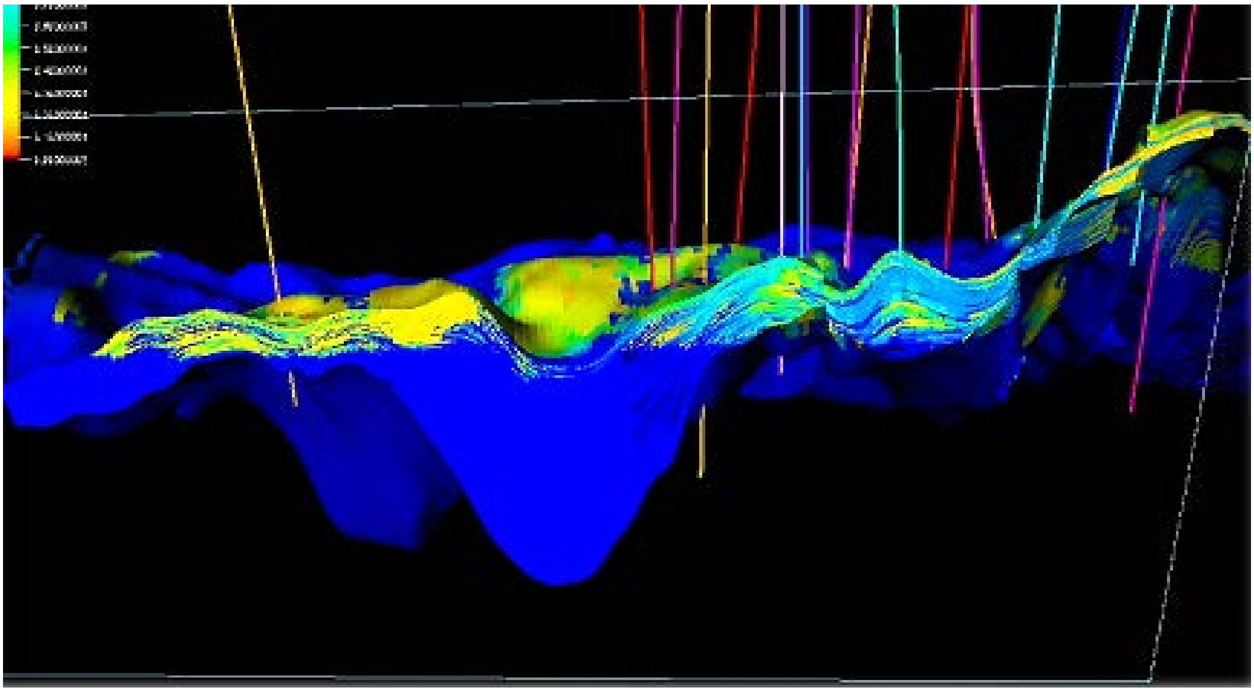

Fig 7. Sustainable Water Contact in the new Anticline while water is rising in the producing Anticline

Potential Way Forward

The current approach functions and allows the output of mismatch scores for a series of potential different scenarios. It might be worth exploring a more direct approach to predicting history-matching parameters. Restructuring the problem and employing a more complex algorithm might allow the optimization of history-matching parameters directly. Rather than defining a range and generating millions of permutations of the parameters to predict how high or low the mismatch of those parameters will be. This shall be a logical evolution to the project presented in this paper.

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