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aFDP-Accelerated Field Development Plan

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Abstract

The process of field development planning represents a grade of complexity due to required integration between multiple domains, many scenarios evaluation and limited time frame. With the aim to accelerate this task, an agile methodology is proposed to integrate workflows and technology to fast-track the multiple scenarios evaluation based on subsurface uncertainty and economic evaluation.

The proposed methodology is based on identifying reservoir zones with higher potential to produce hydrocarbons (Al-Khazraji et al 2015) creating an integrated workflow combined with machine learning techniques which allows to generate automated target screening considering the uncertainty regarding to modelling (Static and dynamic), thus, evaluating the multiple development scenarios with hundreds of well possibilities to define the best number of wells, well trajectory, well orientation and lateral length. This initial stage allows to evaluate technically and economically each development scenario using as selection criteria economic indicators such as Net Present Value (NPV). Also, thanks to monte-carlo sampling method is possible to estimate an efficiency frontier of project (Tonnsen et al 2008)

Once the bests development scenarios are carefully chosen, further simulations were made to assess uncertainty. As result of integrated analysis, reservoir understanding and multiple scenario evaluation, the main outcome of the methodology is a "well ranking" associated to a rate of success value which allows to select well location with lowest risk associated.

As application example, results showed that only 50% of the initially proposed wells delivered above the economic threshold criterion and a similar recovery compared to reference field development plan. Base on those new locations were recommended to minimize the CAPEX honoring the target set.

Introduction

As mentioned in many studies, well targets identification is one of the more complex tasks into processes to create field development plans and normally it is performed manually for each simulation case. The scenario success is directly proportional to the definition of well locations because the appropriate locations would yield maximum sweep efficiency and recovery. However, the difficulty to perform this task is extremely high and could increase if a proper workflow is not implemented. This activity requires tens, hundreds, or thousands of repetitions to test the full spectrum of possible solutions with a lot of options to locate, complete and schedule the wells, consuming a lot of time from both the human resources and hardware/software viewpoints.

Reservoir quality index (RQI) is one of the methodologies used to help the PetroTechnical experts to found targets but there are a lot of RQIs formulas according to specific types of fields/reservoirs. That is why is crucial that we can identified the main well productivity drivers, to be able to develop an appropriate equation that fits with the reservoir reality

This methodology based on an integrated and automated workflow allows sampling any uncertainty variable such as: Petrophysical variables, natural fracture properties, structural features, horizontal length, wells spacing, wells orientation and well trajectory type (horizontal or vertical), and running case ensembles with the well targets identified and calculating economic variables, for instance: Net present value (NPV), Return of investment (ROI), which allows the team evaluate the strategies performance to support the decision making process, but even better it is a flexible workflow that can be adapted to any condition of reservoir characteristics or economical constrains reducing the duration to generate FDP under uncertainty for brown or green field from months to weeks or days

Methodology and Data

This digital solution has been applied in several fields in different consulting projects with great results in term of execution timeframe, uncertainty quantification, optimization and boosting the decision-making process. Figure 1 describes eight steps of the methodology where every step is integrated with the next one for a better understanding of subsurface uncertainty.

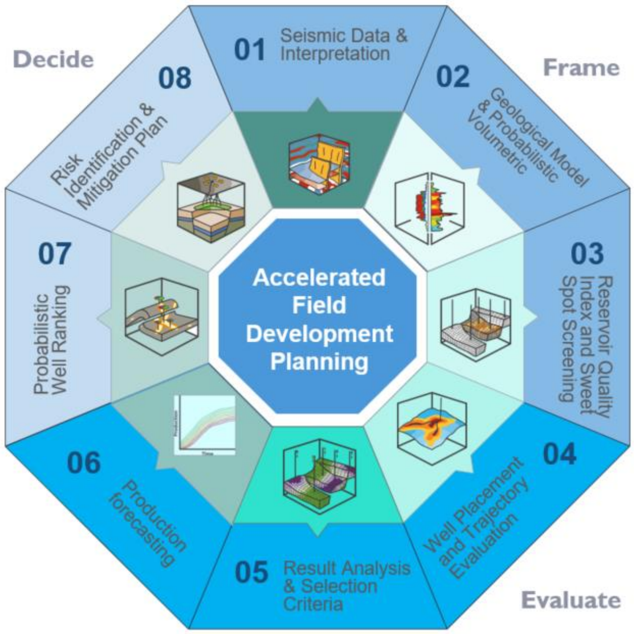

Figure 1. Accelerated Field Development Plan Methodology Scheme

Seismic Data & Interpretation

Conventional reservoir characterization begins with comprehension of seismic data available of the region where horizons are interpreted, and the reservoir structure is delimited. At this initial stages of structural modelling, seismic resolution has associated uncertainty. Therefore, first step in the methodology is to include variation or possible outcome from more than one interpretation. Figure 2 illustrates top, middle, and bottom limits and their range of variation used in the process. This allows to capture one of many key uncertainties during the evaluation process of well position. The automatization of the methodology gives the opportunity of measure the impact on production forecast and economic potential of the asset.

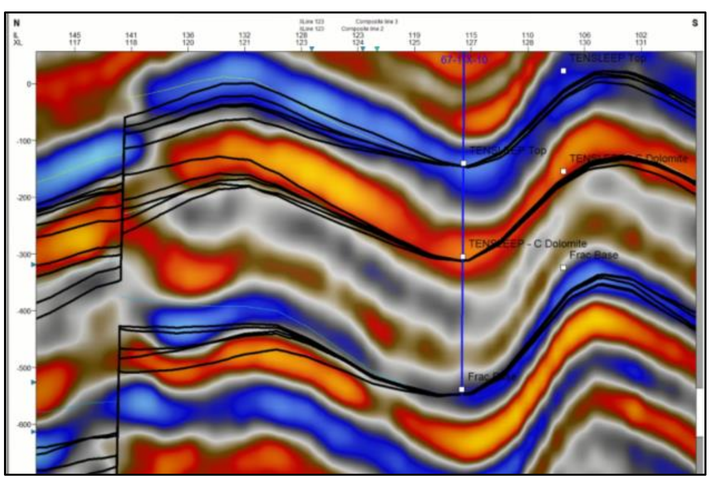

Figure 2. Seismic interpretation ensembles

Geological model & Probabilistic Volumetric

A probabilistic approach is a common practice for estimation of original oil in place (OOIP). The multiple realizations of static models were connected to simulation models, associated uncertainties such as porosity, permeability, oil-water contact and structure where considered. Figure 3 exemplifies normal distribution of volumetric calculation.

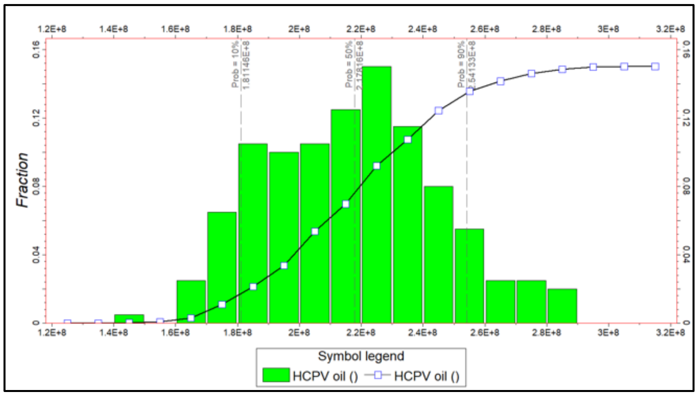

Figure 3. Probabilistic calculation for OOIP.

For carbonate reservoirs, a discrete fracture network changes have been included to the automated workflow. For instance, fracture aperture (a), sigma (σ), fracture intensity where also evaluated.

Reservoir Quality Index and Sweet spot screening

As part of methodology, Reservoir Quality Index technique (Al-Khazraji et al 2015) has been implemented in many reservoirs to identify reservoir potential zones with higher opportunity to maximize oil recovery, however this is a general equation that resume all the production drivers in 3 global indexes which is not always the best way.

This method was defined as follow:

Equation (1)…………………………………………………………………………………………… $\mathrm{RQI} = \sqrt[3]{\mathrm{ISO} * \mathrm{IHCVP} * \mathrm{IKH}}$

RQI = Reservoir Quality Index
ISO = Oil saturation index
IHCVP = Hydrocarbon volume index
IKH = Flow capacity index

To overcome this issue, workflows in an industry software platform (Schlumberger 2020) with a Machine learning algorithm are used considering the historical performance of the existing wells in the field to obtain the main drives (Productivity= f (ISO, HCVP, KH, P, OWC…. n)) in the field that would lead to have a performer producer well. Then, that information is incorporated in the main automated workflow to find the zones that still has remaining oil to produce, ensuring that the wells proposed in the forecast will have a good probability to achieve the objectives.

In the Figure 6 there is digram that represets the details of the uncertainty workflow, as is shown, the uncertainty study starts with a mached cases in case of brownfield, for hystory matching process there are several options availables in the platform (Schlumberger 2020). as evolutive algorithms with machine learning techniques also. Automated workflows for model calibartion have been created adapted for each reservoir situation, in the Figure 4 there is a digram to define an influence region (voronoi regions) for making selfadpated changes in the connectivity fracture network in order to match de water production.

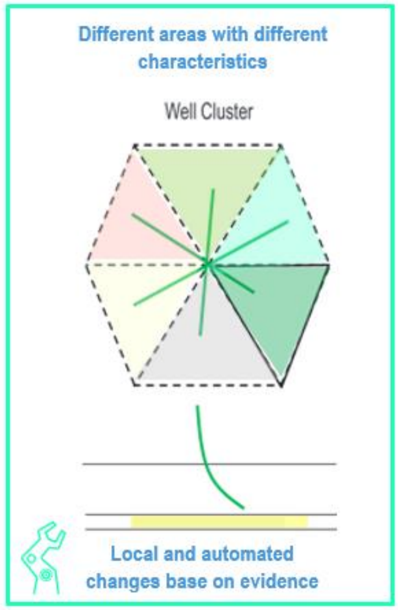

Figure 4. Voronoi regions to perform changes in the discrete fracture network

There is another technology available as digital capabilities in Cloud (Schlumberger 2020). This is a plug-in for history matching that uses an advanced machine learning algorithm called Ensemble Smoother –Multiple Data Assimilation (ES-MDA) (Alexandre Emerick et al 2012). This algorithm operates like algorithm that predicts the weather, assimilating the real data multiple times and making changes in the uncertainty parameters generating hundreds of cases for each iteration or assimilation process. This technology delivers an ensemble matched solution representing subsurface uncertainty that supports the risk assessment and investment decisions in the forecast scenarios

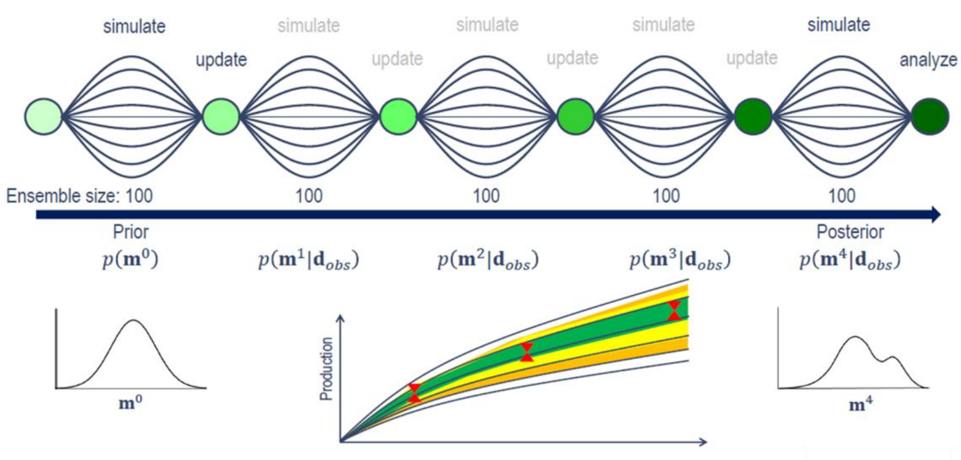

Figure 5. Ensemble Smoother –Multiple Data Assimilation ES-MDA

Once the uncertainty parametes are defined the RQI formula is determined using the history production data and the infered posible drivers for the history productivity, these drivers depend of the nature of the reservoir .Then, a supervised neural net is computed for these inputs and the correlation and factor weigths between them are obtained, then, if the weights are important enough their are kept to define the final equation, which is going to be used with the current reservoir conditions for the target screening in the next step of the workflow

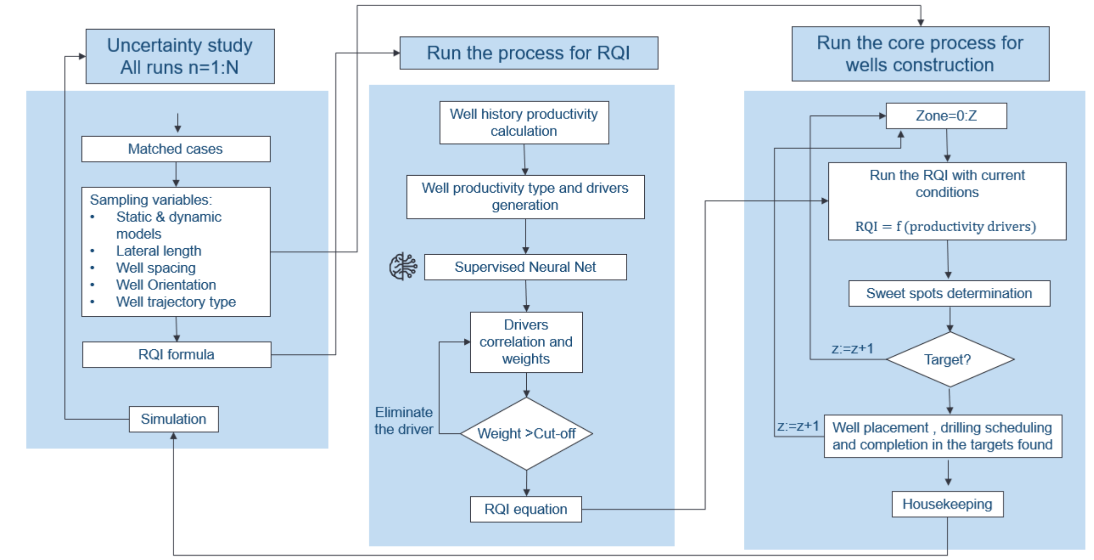

Figure 6. Flow diagram for aFDP

Well placement and trajectory evaluation

This is one of the most important stages in the methodology attributable to the well spacing, rig resources and automatic completion which controls the total well number for each iteration. Software automatization and integration allows to combine RQI with well positioning tools easily switch between vertical, deviated, and horizontal wells to compare multiple FDP concepts. It is possible to evaluate also waterflooding projects, creating well patterns that can be optimized using pattern flow management (PFM) available in the numerical simulator used. In the Figure 7 are 3 examples of the wells that could be part of different 3 FDP strategies

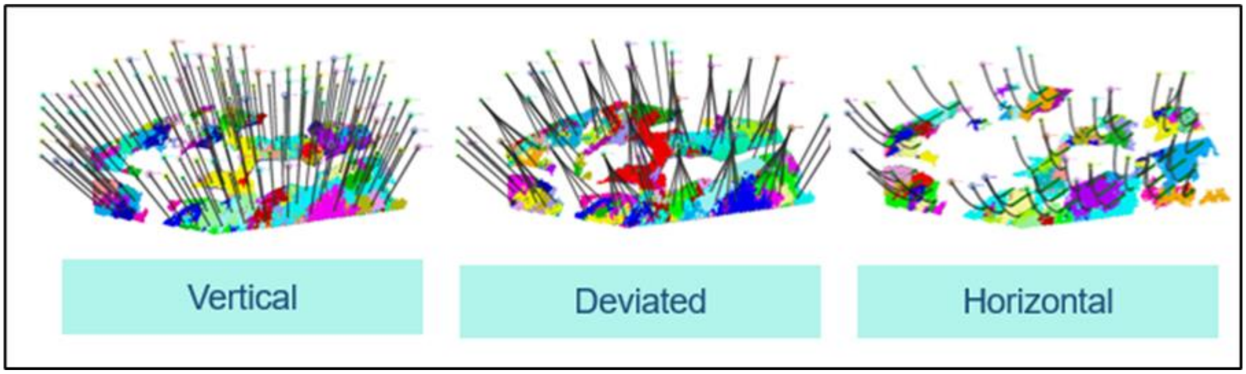

Figure 7. Well placement options for aFDP.

Results and discussions

In one of the projects working with a naturally fracture reservoir, 8 productivity drivers were identified for this field and after computing the neural net the weight for each one was obtained. Those drivers with an impact greater than 10 % were kept for building the final equation (green drivers in the Table 1. Drivers Correlation)

Table 1. Drivers Correlation coming from neural net

Driver	Correlation with a Performer Well	Partial contribution	Posterior Correlation	Posterior partial contribution
ISO_m_1	0.2295	14.9	0.2295	16.7
IHCVP_m_1	0.1292	8.4		0.0
IKH_m_1	0.0319	2.1		0.0
IOWC_1	0.2906	18.9	0.2906	21.1
PI_m_1	0.2893	18.8	0.2893	21.0
Sigma_m_1	0.2234	14.5	0.2234	16.2
IHCVP_F_1	0.1776	11.6	0.1776	12.9
IKH_F_1	0.1653	10.8	0.1653	12.0

The final equation that will lead the target screening in this reservoir is bellow

Equation (2)………………………………………. $RQI= (0.167 * ISO_{matrix} + 0.211 * \mathrm{IOWC} + 0.21 * P_{matrix} + 0.162 * Sigma + 0.129 * IHCVP_{fracture} + 0.12 * Kh_{fracture})$

RQI = Reservoir Quality Index
ISO = Oil saturation index
IHCVP = Hydrocarbon volume index
IKh = Flow capacity index
IOWC = Free Water Level index

Once the equation is obtained a RQI was computed for the historical conditions to be able to create a cross plot to define the minimum RQI value that provide a good chance of success in the proposed wells in the FDP. In the Figure 1 it is shown the trend of cumulative oil with the RQI for the current wells in the field, the results were clustering using Kmeans algorithm, it is clear that as higher RQI as higher cumulative oil, however the objective is to find the minimum value that the best wells had, in this case values greater that 0.4 will ensure wells with high oil production cumulative

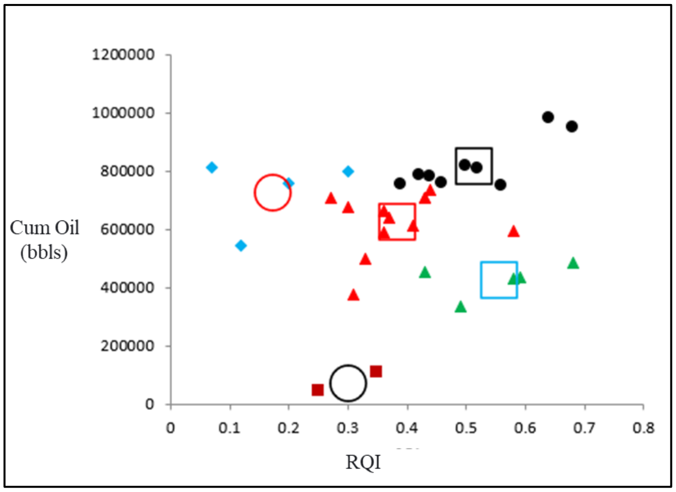

Figure 8. Clusters of Cumulative oil vs RQI

The next step is to use this information for sweet spot screening and construct the wells in those targets, then hundreds of cases are generated that deliver a value cumulative oil and the economic indicators

Result analysis & Selection criteria
Multiple scenarios can be executed in a few hours under uncertainty which allow to use different selection criteria for each case with a particular feature or constrain. In Figure 9 and Figure 10, oil production cumulative and oil rate for the case ensemble are showed, later these values together with economic parameters is used to calculate NPV for all the evaluated scenarios and using a statistical approach P10, P50 and P90 are calculated and compared with the same percentiles for oil cumulative (Figure 11)

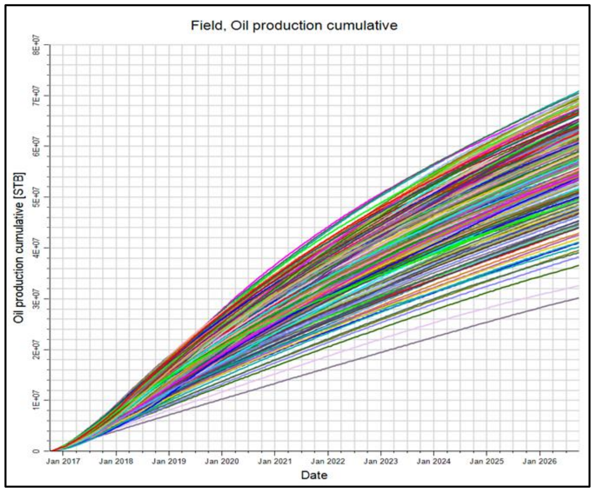

Figure 9. Oil production cumulative for the ensemble of cases

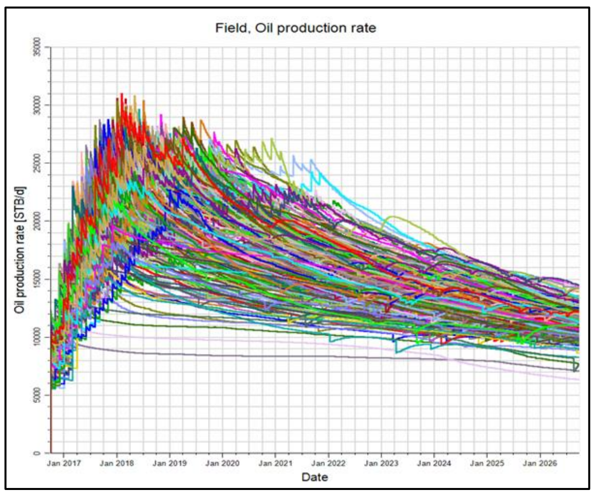

Figure 10 Oil rate for the ensemble of cases

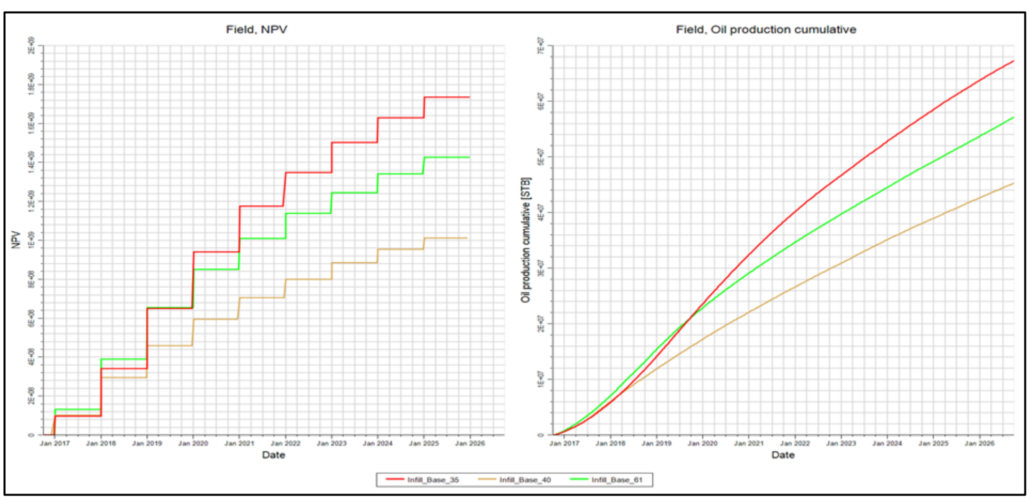

Figure 11. Comparison of NPV and Oil cumulative for P10, P50 and P90

An additional way to compare results and select the best cases is through complementary economic indicators (i.e., return of investment) and using frontiers of efficient (Figure 12), in this case 2 methods were used: first with a cross chart between Net Present Value and Return of Investment and another one with Oil Production Cumulative against Return of Investment. Here it is important to highlight that all these graphs and methods could be modified, based on operator or field particularities, adapting the workflow quite simple. With this kind of plots, we can determine the optimal well spacing or number of wells, also if the waterflooding is a profitable option, in general what case allow to yield the maximum recovery (Figure 14) or to select that case that delivers the high cumulative or ROI within a designed budget for CAPEX (Figure 15)

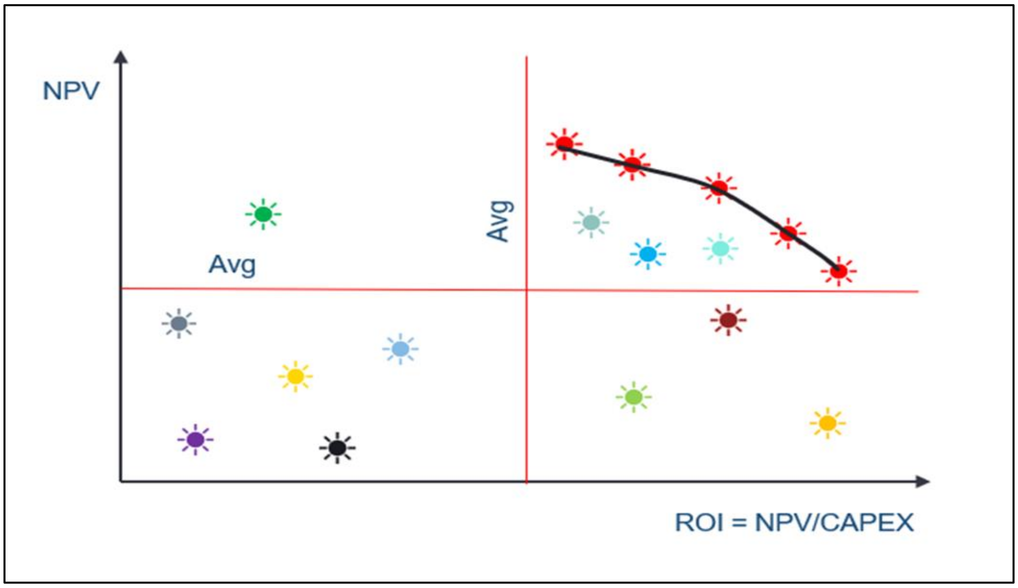

Figure 12. Comparison of NPV and Oil cumulative for P10, P50 and P90

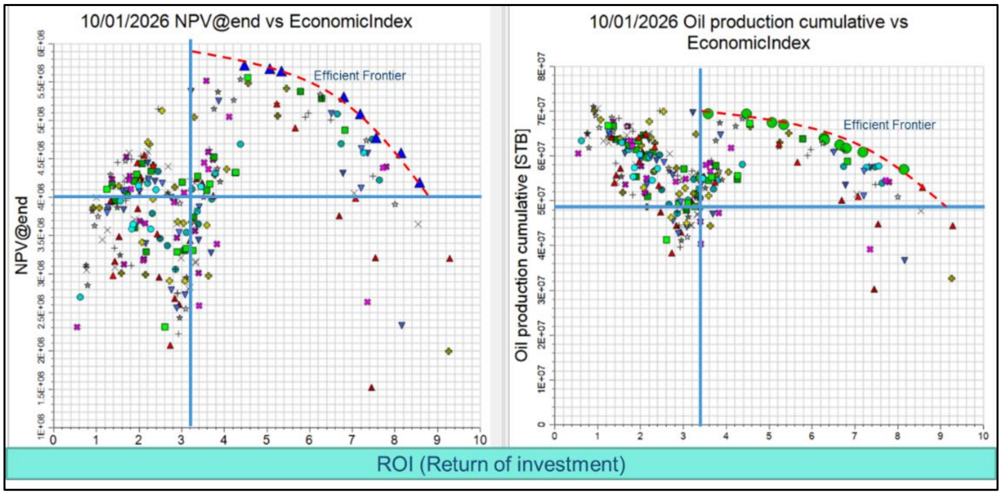

Figure 13. NPV vs ROI Comparison of NPV and Oil cumulative for P10, P50, P90

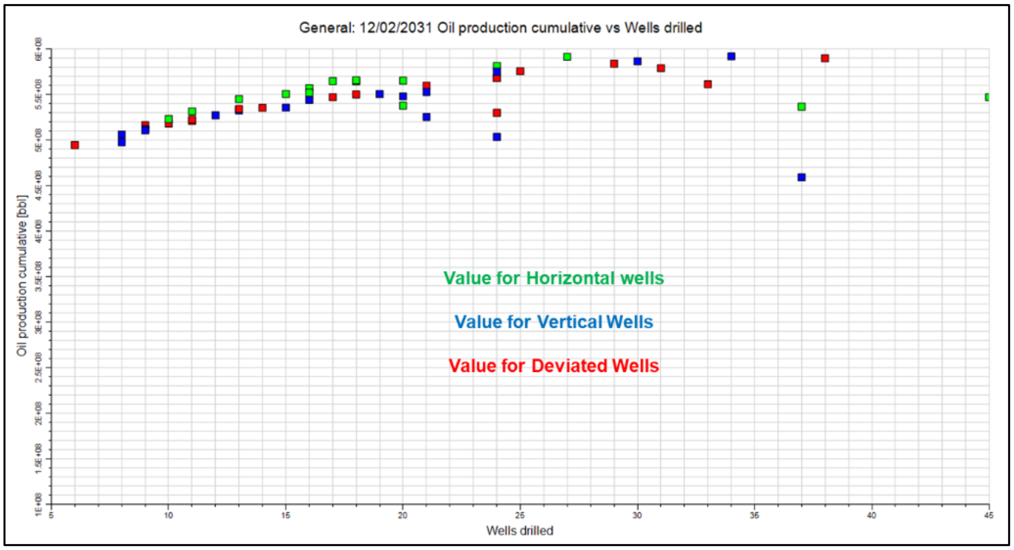

Figure 14. Cumulative oil vs Wells dilled

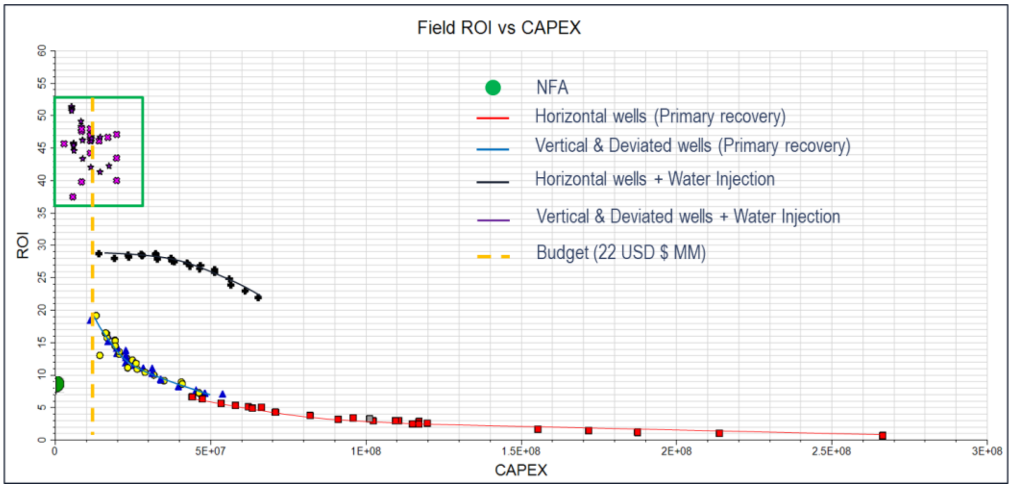

Figure 15. Comparing FDP strategies

Production forecasting

From previous results, each selected scenario could be submitted to sensitivity and uncertainty analysis with the purpose of analyze other uncertainty variables in more detail and the subsequent probabilistic well ranking. For this study an uncertainty analysis was performed for each percentile previously determined which allows later well ranking for each percentile covering the entire uncertainty present. the results of ensemble of cases are showed in the Figure 16, Figure 17 and Figure 18

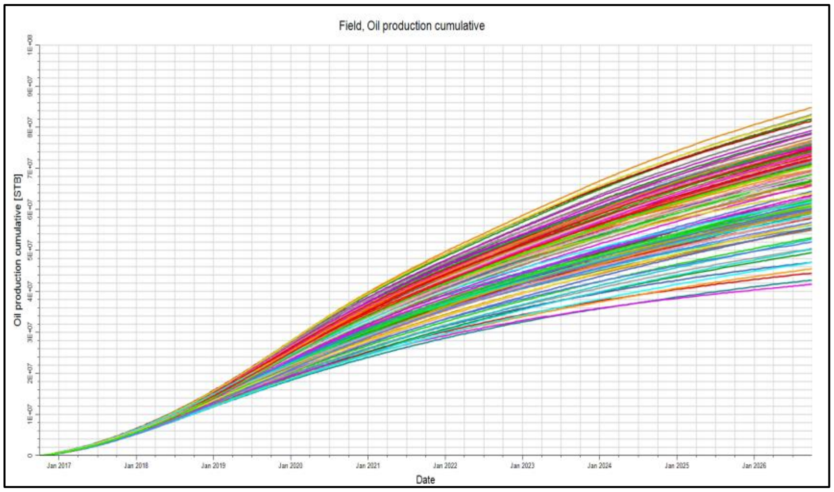

Figure 16. Ensemble of cases from uncertainty for case P10

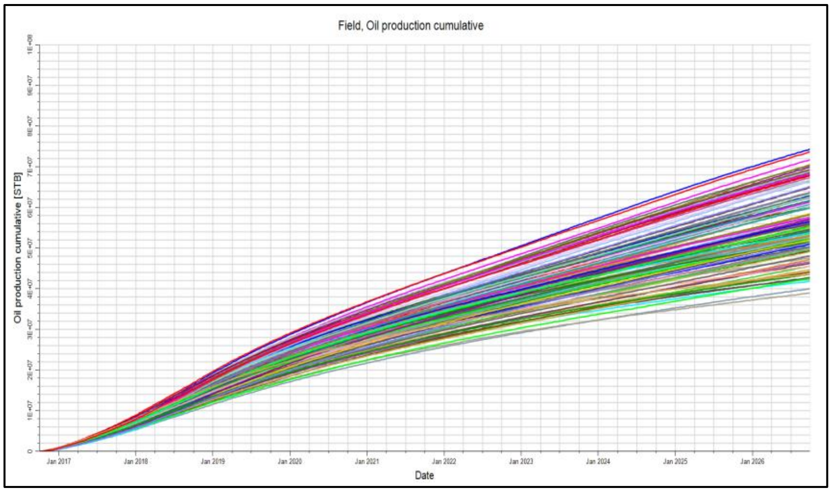

Figure 17. Ensemble of cases from uncertainty for P50

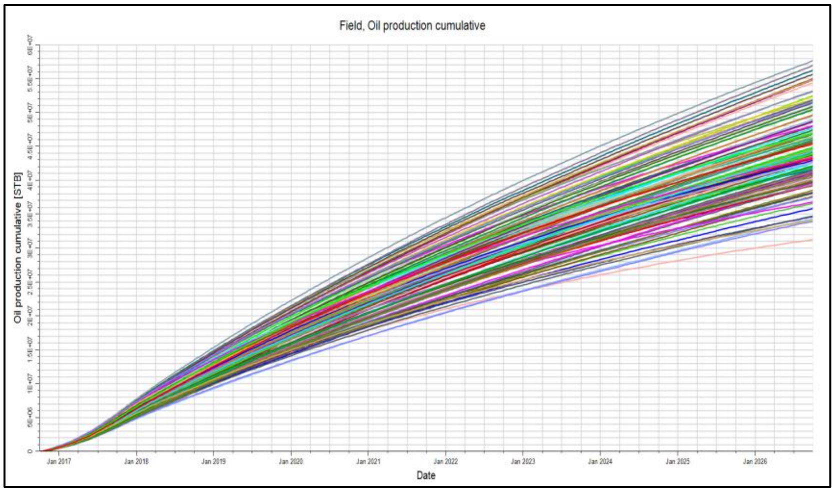

Figure 18. Ensemble of cases from uncertainty for P90

Probabilistic well ranking

As part of the final stages, all wells for each percentile or ensemble of cases could be ranked based on the selected success criteria. For this study the success criteria were the well economic demand (Schulze-Riegert et al. 2020) considering the probability of success. Figure 19 shows the probability of success for all wells in the ensemble of cases generated from P50, the NPV and NP for Well P02 (Figure 20) and probability of success for well P02 in the cases ensemble from P50, which has a probability of success of 38% and is below of the minimum acceptable for this evaluation (60%), Figure 21.

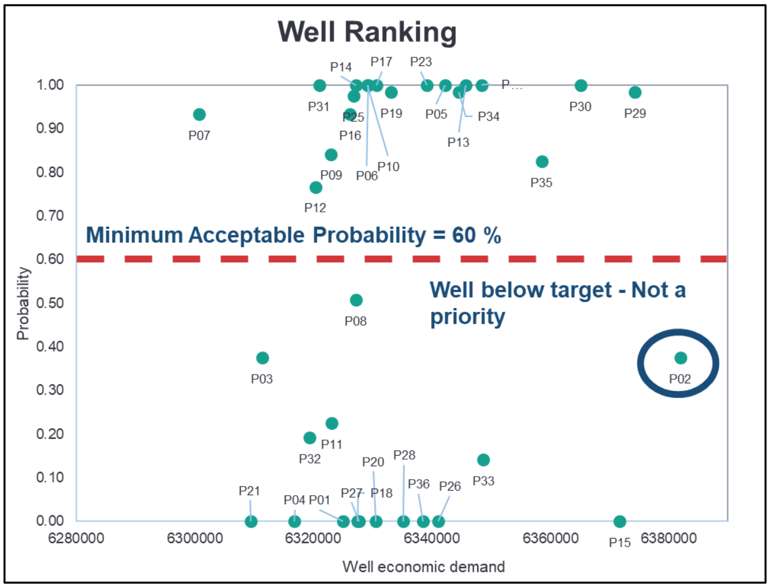

Figure 19. probability of success for all wells in the Ensemble of cases from P50

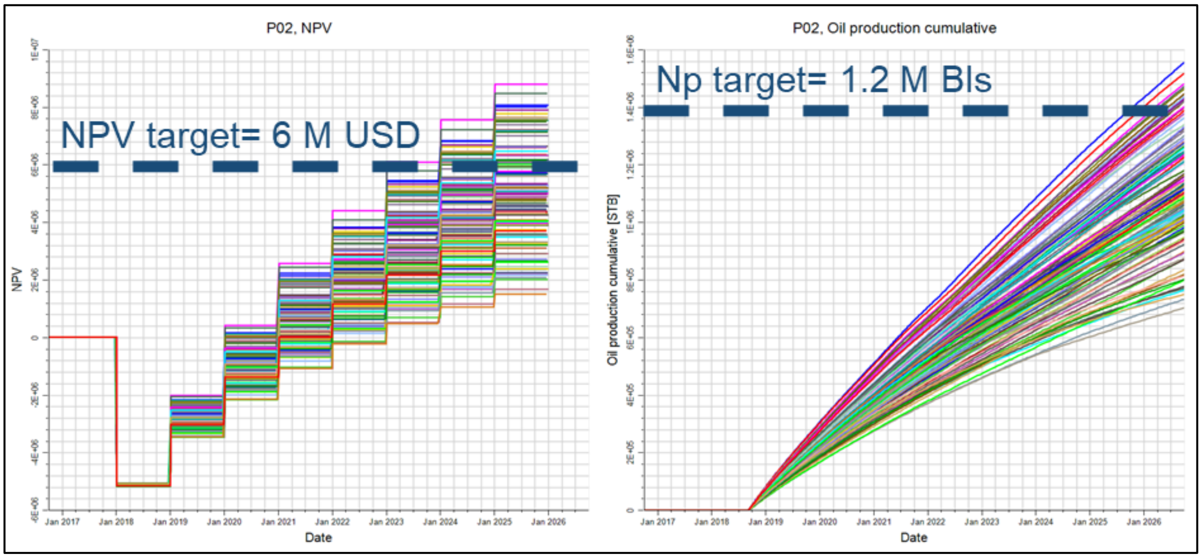

Figure 20. NPV and NP for Well P02 in the ensemble of cases

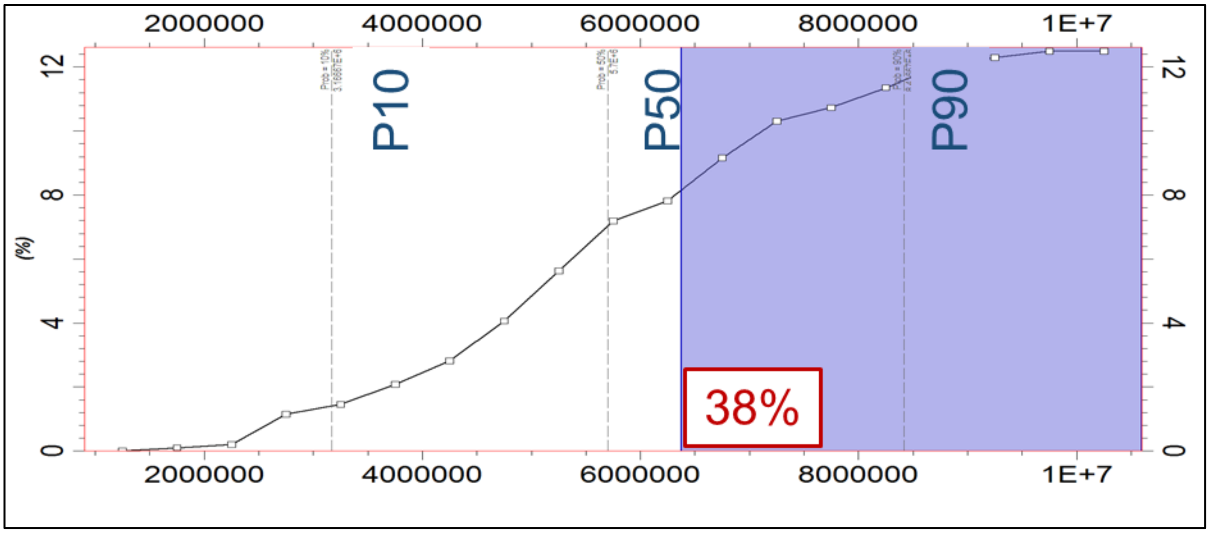

Figure 21. Probability of success for well P02 in the Ensemble of cases from P50

Risk identification, mitigation plan and reporting
The last step of this methodology is a risk mitigation plan supported by the results of sensitivity analysis previously performed and the customized reporting. The main idea of the mitigation plan is to invest only where is necessary. So that data acquisition strategy will be led by those variables with more impact, in this case those parameters are the aquifer, oil water contact, API gravity, initial pressure and relative permeabilities curves (Figure 22) and based on that the acquisition plan comprises MDT/RFT. Fluid samples and PVT analysis, core sampling and SCAL.

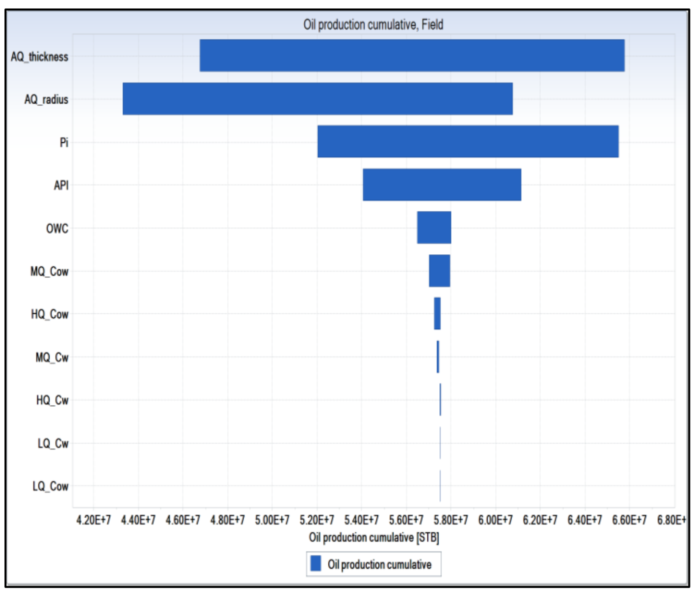

Figure 22. Tornado plot and variables in the Ensemble of cases from P50

Conclusions

We have presented a methodology for evaluation of multiple field development scenarios that can be done in reduced timeframe thanks to automatization of workflows. The focus of this paper is a flexible and integrated workflow comprising:

- Geological Model and Probabilistic Volumetric
- Reservoir Quality evaluation through dynamic modelling using digital capabilities
- Well Placement and trajectory evaluation
- Probabilistic well ranking and risk identification

This methodology allows to quantify subsurface uncertainty and support business decision with hundreds of executions through a probabilistic approach. The integration with economic indicators (ROI and NPV) strengthens selection of best field development plan concept consuming less than 20% of the regular execution time
As application example, results showed that only 50% of the initially proposed wells delivered above the economic threshold criterion and a similar recovery compared to reference field development plan. Base on those new locations were recommended to minimize the CAPEX honoring the target set.

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