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Advanced Methods for Determining the Value of Information of Surveillance Data Acquisition Using Predictive Analytics

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Abstract

In stacked reservoirs with commingled production, achieving an understanding of relative contributions of the flow units is fundamental to reservoir management, most notably for conformance management of reservoirs under water flood or enhanced oil recovery (EOR) scheme.

To that effect, the desired surveillance data usually includes: reservoir layer pressures, phase distribution profiles (through PLTs) in flow units, and monthly well test data (water cut, gas oil ratio, oil rate etc.). These measurements will form the basis of well by well flow unit production allocation; all necessary information for classical engineering analysis and reservoir simulation. The enduring challenge of value-effective reservoir management is to determine the 'adequate' frequency and selection of well and flow units data acquisition. Industry practice shows clearly that there is no consistent answer to this challenge. In the authors' opinion, this is due to the unavailability of a methodology and tools to rigorously define the Value of Information (VOI) associated with surveillance data acquisition. VOI is defined as the net present value (NPV) difference between the total production & costs outcomes with the benefit of information, and the total production & costs outcomes without this information. In some cases, the VOI can also indirectly translate to critical understanding of subsurface integrity such as unintentional communication of deeper, higher pressure gas reservoir with shallower reservoir units having a much lower fracture gradient that if left unattended could subsequently lead to subsurface blowout scenario.

In this paper, we set out to define surveillance data acquisition decisions as an optimisation problem: where is the optimum cost versus reward for a field, given allocated well

production and the usual (partial) understanding of reservoir layer absolute and relative permeability at the well, from logs and core.
We present how novel predictive analytic algorithms, coupled with multi-phase deliverability models, material balance analysis, and global optimisation search methods are integrated to assess the resulting uncertainty in layer-phase allocation, in presence of different surveillance datasets. We use a representative synthetic field simulation model to formulate reservoir outcomes.
As a precursor to a full VOI, we define an allocation uncertainty versus the data acquisition frequency, and provide general recommendations in terms of data frequency and type that can be generically used as findings.

Introduction

Understanding the Value of Information (VOI) is a common challenge for upstream in oil and gas. Despite the fact, that many Operators and National Oil & Gas Companies (NOC's and NGC's) are implementing detailed plans on appraisal drilling and surveillance data acquisition programs, the real value of gathered information in many cases is not transparent and not properly understood.
Subsurface studies are requiring a lot of information to be collected and processed, which is usually associated with significant operational costs. For green fields, classification and estimation of VOI is generally correlated with the known list of critical or missing data: about structure and geological deposition, rock properties, fluids properties and their areal and vertical distributions. It is more or less straightforward process to estimate the value of drilling an appraisal well in the new block – the relation between drilling costs versus estimated increment of potential hydrocarbon reserves increment.
For mature fields, a massive dataset of subsurface information and production data is usually available. However, the challenges are moving towards data quality and measurements interpretation, organising classified and structured storages to improve data available at any stage of asset development. Under mature field specifics, an efficient surveillance process is essential. In brownfields environment, blind data collection and measurements could lead to annual OPEX costs with almost zero value, while not collecting specific data could be the cause of wrong development decisions and cost even more. It is an infinite cycle: spending money on surveillance without clear understanding of VOI is not efficient, not spending money on truly required information could be critical. The only way to progress under such circumstances – develop a proper understanding of VOI and translate it into operational surveillance plan.
An obvious case when mature field is not covered by general subsurface data is not a part of discussion raised in this paper. Authors would like to focus on production associated data collection process, which if organised wrongly usually lead to subsurface misinterpretations and far from optimal development decisions or purely unrecoverable mistakes. Some of the key questions to be answered in this paper:

- How well test frequency affecting production data reliability?
- Commingled multi-stack reservoir development: how to improve reservoir back allocation?
- Which wells to run PLT on?
- How big is the impact due to incorrect development decision?

In this paper, authors describe innovative stochastic optimised methods to perform areal and reservoir (vertical) production allocations. These methods allow to control metering and subsurface uncertainties during production allocation process, quantify the VOI associated and assess risks with respect to development decisions to be made based on production analysis.

Study Approach

The studies discussed in this paper require a set of reference data. A synthetic dataset has been built utilising one of the industry-recognised simulators. The objectives of having a synthetic model are:

- To have a reference "correct" answer for comparison.
- To be able to limit the amount of "known" information for each particular study.
- To illustrate a wide range of field surveillance aspects within an integrated asset.

Reference Synthetic Model

Model description

A black oil model (Figure 1) was set up for a synthetic field, with a relatively simple anticline structure, with 19 wells producing from 3 productive zones – "reservoirs" with their respective OWCs in a commingled and non-commingled manner. All wells in the model are controlled by BHP (set a constant value of 1015 psia).

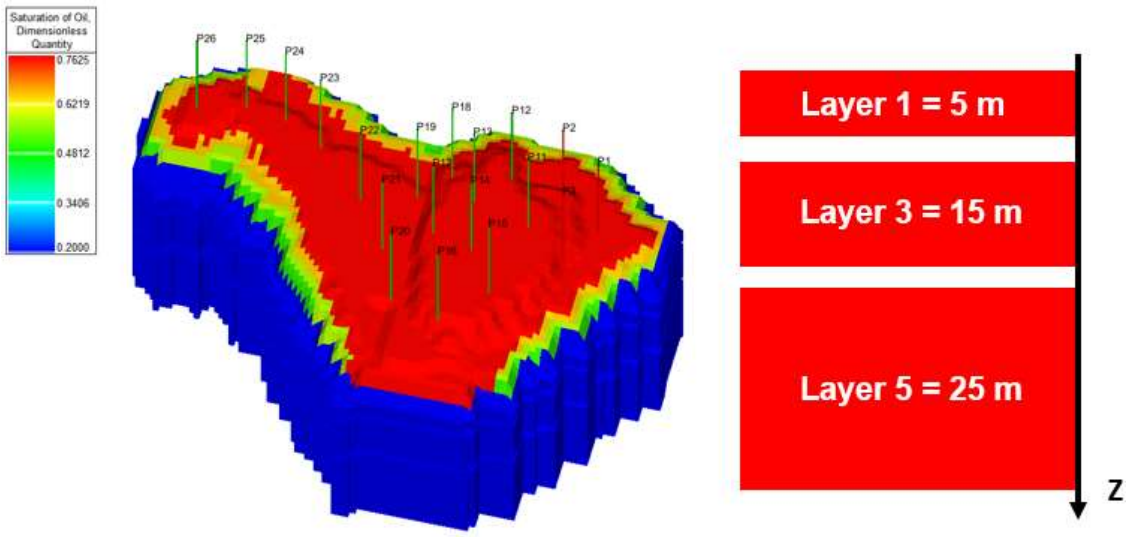

Figure 1: *Synthetic model overview.*

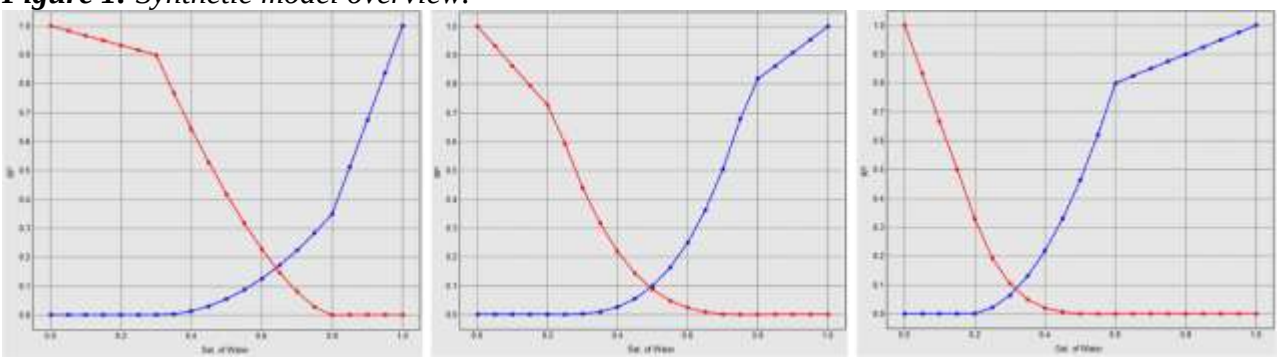

Figure 2: Relative permeability curves used layer 1 (left), layer 3 (middle), layer 5 (right).

The model was set up with 50,000 gridblocks (11,649 active gridblocks) with a cell size of 25m x 25m. All 3 reservoirs (Layers 1, 3, 5) are isolated from each other by impermeable Layers 2 and 4. Thickness of Layer 1 is 5 m, Layer 3 is 15 m and Layer 5 is 25 m. The maps of average property for each layer are shown in Figure 3.

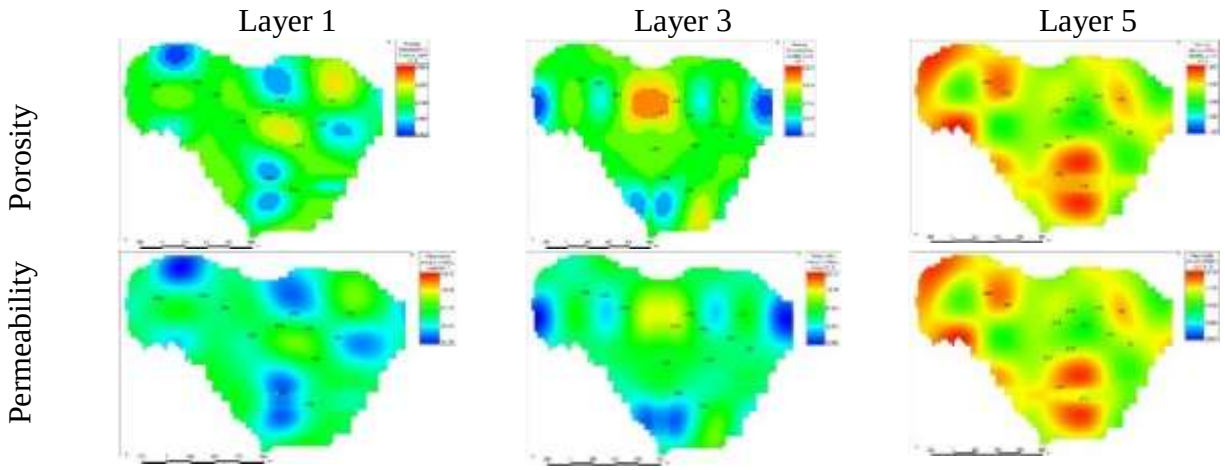

Figure 3: Synthetic model - reservoir porosity and permeability.

Average porosity of Layer 1 = 0.22, Layer 3 – 0.23, Layer 5 – 0.25. Average permeability of zones is 43 mD for Layer 1, 48 mD for Layer 3 and 113 mD for Layer 5.

Initialisation of model

The model is initialised with a hydrostatic pressure gradient. For simplicity, no capillary pressure is defined. The relative permeability curves used for all reservoirs are shown in Figure 2. Different curves were defined for each layer to demonstrate different water movement in reservoirs. The STOIIP for the field is 15.6 million m^3.

Synthetic production history

A synthetic realistic production history is developed over 20 years (Figures 4-6), with a number of events such as perforations of new intervals, drilling of new wells, and closing of wells. After 20 years of production history, the field recovery factor reaches almost 27.3%. The individual reservoirs maturation dynamics is different, so recovery factor for layers vary from around 18% to almost 52%.

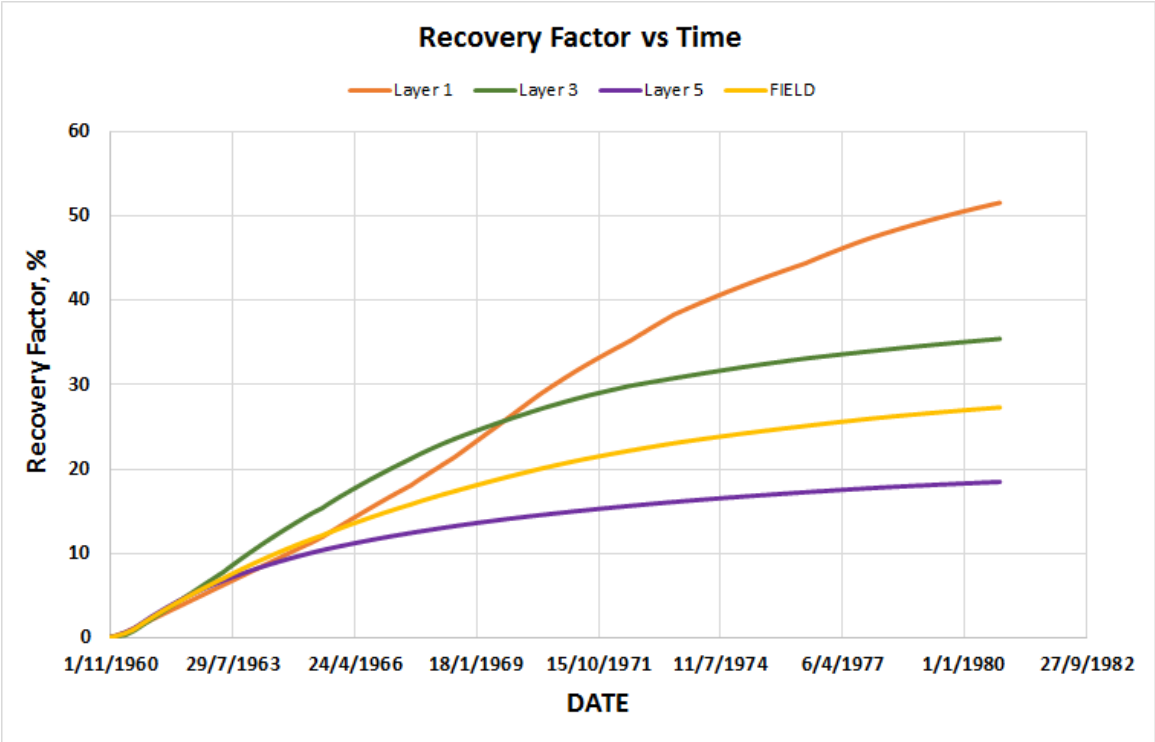

Figure 4: Field recovery factor (5 years – RF=12.5%, 10 years – RF=20.4%, 20 years – RF= 27.3%).

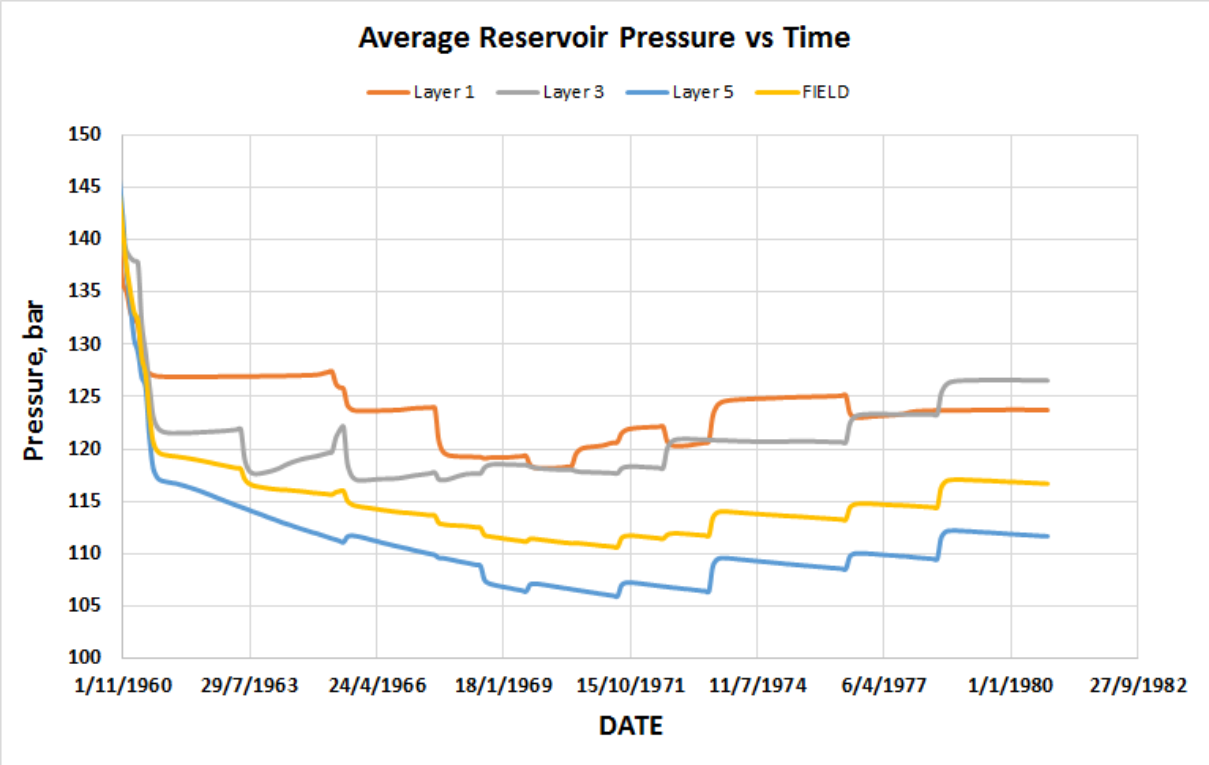

Figure 5: Field and reservoirs average reservoir pressure trend.

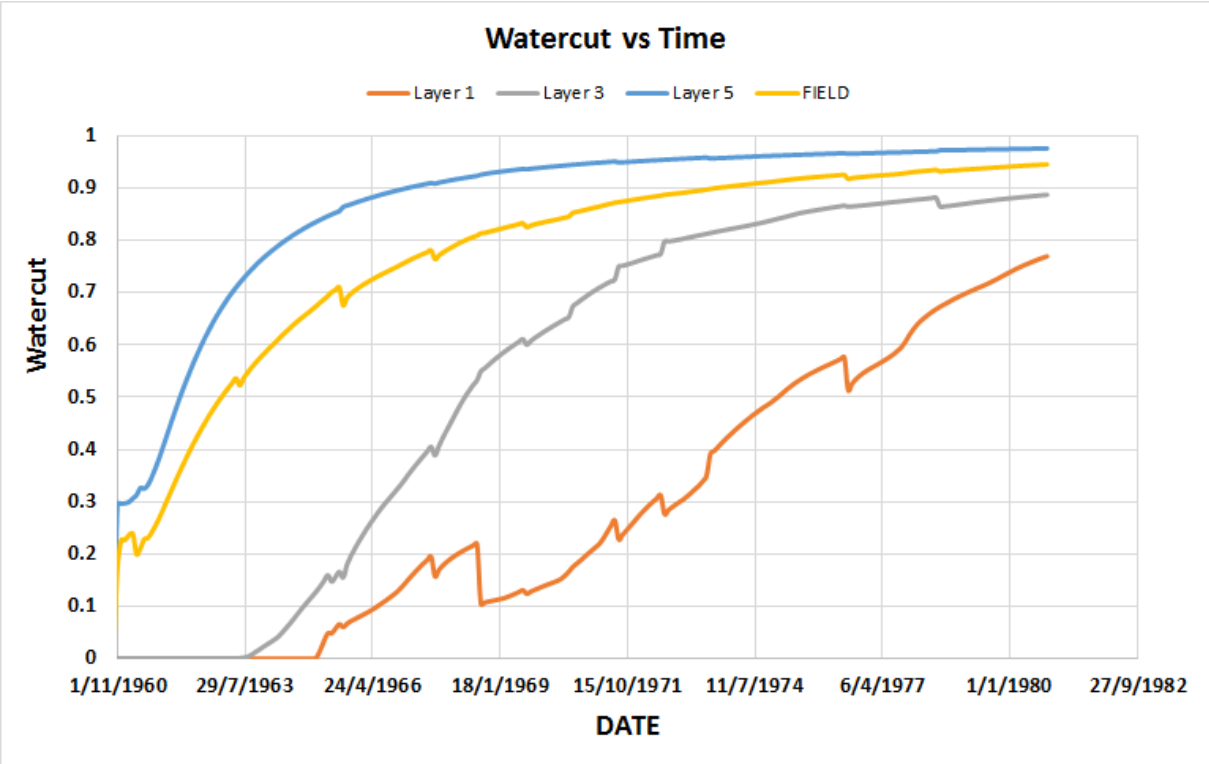

Figure 6: Field and layers watercut trend.

Aquifers are attached to each of the layers, with varying strengths, to simulate a partial pressure support. The different pressure histories in each layers were created deliberately to illustrate the impact of reservoir pressure in the allocation process using different methods.

Attention was given to also create a vertically varying watercut history, so that layers show different water ingress behaviour. As can be seen in Figure 6, the highest and fastest increase of watercut was simulated in Layer 5, whilst the water encroachment is more gradual throughout history for Layer 3 and especially Layer 1. The opening and closing of well zones were being exercised during the simulation as manifested in the occasional dips of the watercut profiles. Here, the objective is to demonstrate the problem with a single phase, deliverability-based allocation (i.e. based on K, KH or KHΔP) when watercut evolutions do not behave consistently among between commingled layers.

Quite a few wells in the model were defined as mixed producer, when production timeline includes a combination of commingled and non-commingled flow periods. Figure 7 shows an example of such producer (well P23), which is having 4 flow periods; firstly commingled production from single Layers 3 and 5, then joined by production from Layer 1, after closing Layer 5, and finally closing Layer 3 and continuing single layer production from Layer 1 until the end of history. Production allocation exercise could be challenging on this type of wells.

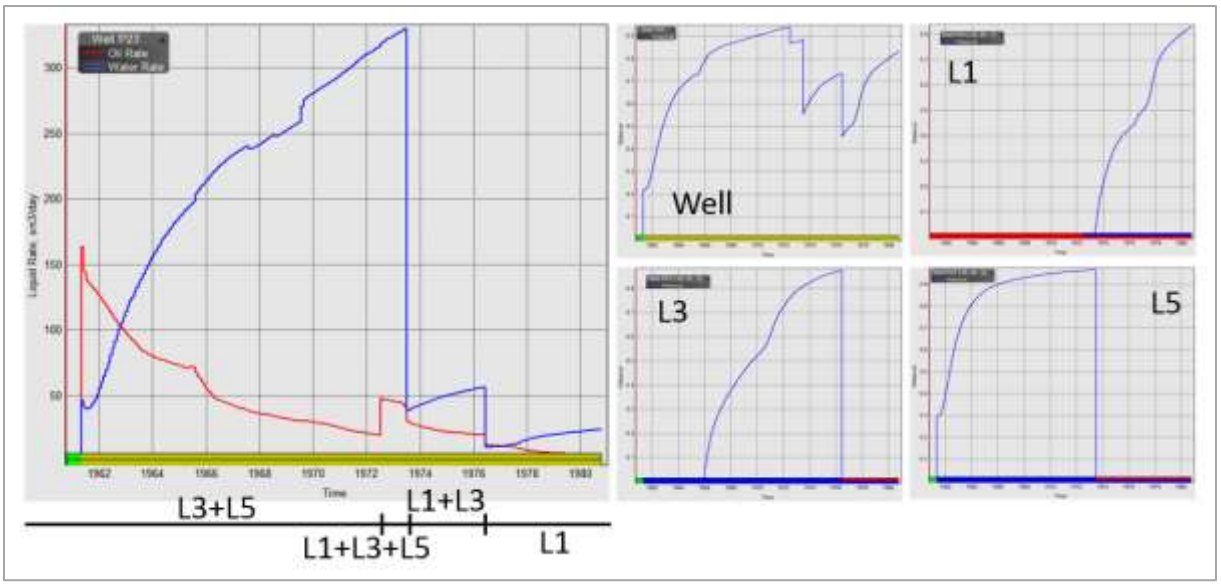

Figure 7: Well P23 with commingled/non-commingled production periods (left) and layers watercut trend (right).

Production Allocation

We are going to discuss the value of information (VOI) in application to production back allocation process with respect to:

1. Areal allocation process – from field/platform/group measurements to wells/strings
2. Vertical reservoir allocation process – from individual wells/strings to individual reservoirs/completions

Areal allocation

An areal allocation uncertainty is an important factor to be taken into account before allocating the production to reservoir level. The main objective we pursue in this areal allocation study is to illustrate how the metering facilities accuracy and frequency of the measurements could have an impact on allocated well production. We grouped the wells on the synthetic field into 3 platforms:

1. Platform A: P1, P2, P3, P11, P12, P13, P14
2. Platform B: P15, P16, P17, P18, P19, P20, P21
3. Platform C: P22, P23, P24, P25, P26

We focus on platform C and assume that platform separator measurements for all phases are known, so it is possible to back calculate the wells productions with respect to well test values. In the back allocation process we studied a few sets of cases as listed in Table 1.

Table 1: Areal allocation cases evaluated with varying metering accuracy and sampling frequency.

Case	Metering accuracy			Sampling frequency for each well/month
	Level	Liquid	Watercut	
1.1	All	0%	0%	3
1.2	All	0%	0%	1
1.3	All	0%	0%	0.5*
2.1	Well test	±10%	±10%	3
2.2	Well test	±10%	±10%	1
2.3	Well test	±10%	±10%	0.5*
3.1	Well test	±10%	±50%	3
3.2	Well test	±10%	±50%	1
3.3	Well test	±10%	±50%	0.5*
4.1	Platform	±3%	±3%	3
	Well test	±10%	±10%	
4.2	Platform	±3%	±3%	1
	Well test	±10%	±10%	
4.3	Platform	±3%	±3%	0.5*
	Well test	±10%	±10%	
5.1	Platform	±3%	±3%	3
	Well test	±10%	±50%	
5.2	Platform	±3%	±3%	1
	Well test	±10%	±50%	
5.3	Platform	±3%	±3%	0.5*
	Well test	±10%	±50%	

Note: 0.5* denotes one time per 2 months

The variation in production profiles for all these cases is depicted in Figures 8-12. It is expected that accurate measurement coupled with reasonable sampling frequency will lead to quite accurate well allocation results, while low accuracy and infrequent measurements will lead to wrong and misleading results (see Figure 8 for well P22). However, meter uncertainty could be incorporated into the back allocation process. Imbalance of volume produced (ΔQ) rather than total volume produced Q is allocated to each contributor based on their relative volume uncertainties. Moreover, meter uncertainty will construct uncertainty band for each well production profile which further could be used to constrain multi-phase production allocation model in vertical reservoir allocation process (will be discussed in the next section).

The study performed shows that in idealistic cases where all meters are accurate, there is no need for high frequency measurements. Figure 8 presents a comparison of oil, water production and water cut data measured 3 times per month (Case 1.1), once per month (Case 1.2) and once per two months (Case 1.3). All plots are similar to each other and to the real one obtained from simulation. However, in reality, this is not the case and frequency of measurements defines the accuracy of production allocation.

It can be seen on Figures 8-12 that with higher metering inaccuracy, oil and water production allocation error grows significantly. For example in Case 5.3 (Figure 12) which has platform metering accuracy of ±3% for liquid, ±3% for water cut and well test metering accuracy of ±10% for liquid, ±50% for water cut, oil and water allocated have 43% error for oil, 11% error for water, and 6% error for watercut if measured 3 times per month and 66% error for oil, 21% error for water and 10% error for water cut if measured once per 2 months.

In general, the accurate production surveillance on the platforms coupled with reasonable well test frequency will lead to quite accurate well allocation results, while low accuracy and infrequent measurements will result in the low back production allocation quality.

In the following section it is illustrated, how limited surveillance data could be efficiently coupled with vertical allocation techniques by introducing the uncertainty bands for multiphase and multi-solutions reservoir production allocation. This approach allows deploying a consistency between areal and vertical allocation process leading to a high-graded representation of Value of Information as a matter of process efficiency and development opportunities understanding with respect to optimised surveillance effort and costs.

For accurate meters:

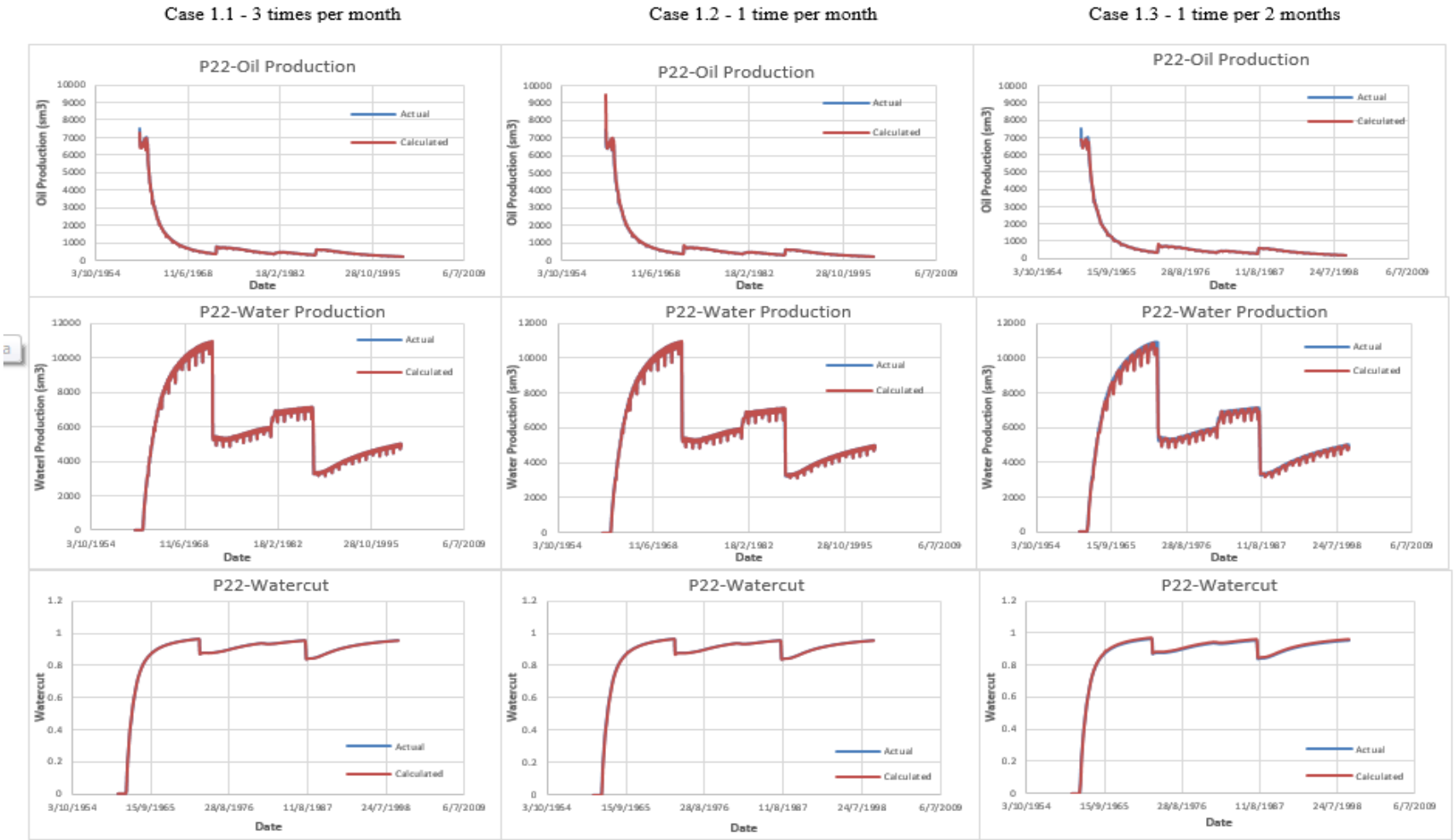

Figure 8: Areal allocation for Platform C - well P22: Accurate meters Cases 1.1 - 1.3.

For Well test with metering accuracy ±10% liquid, ±10% water cut:

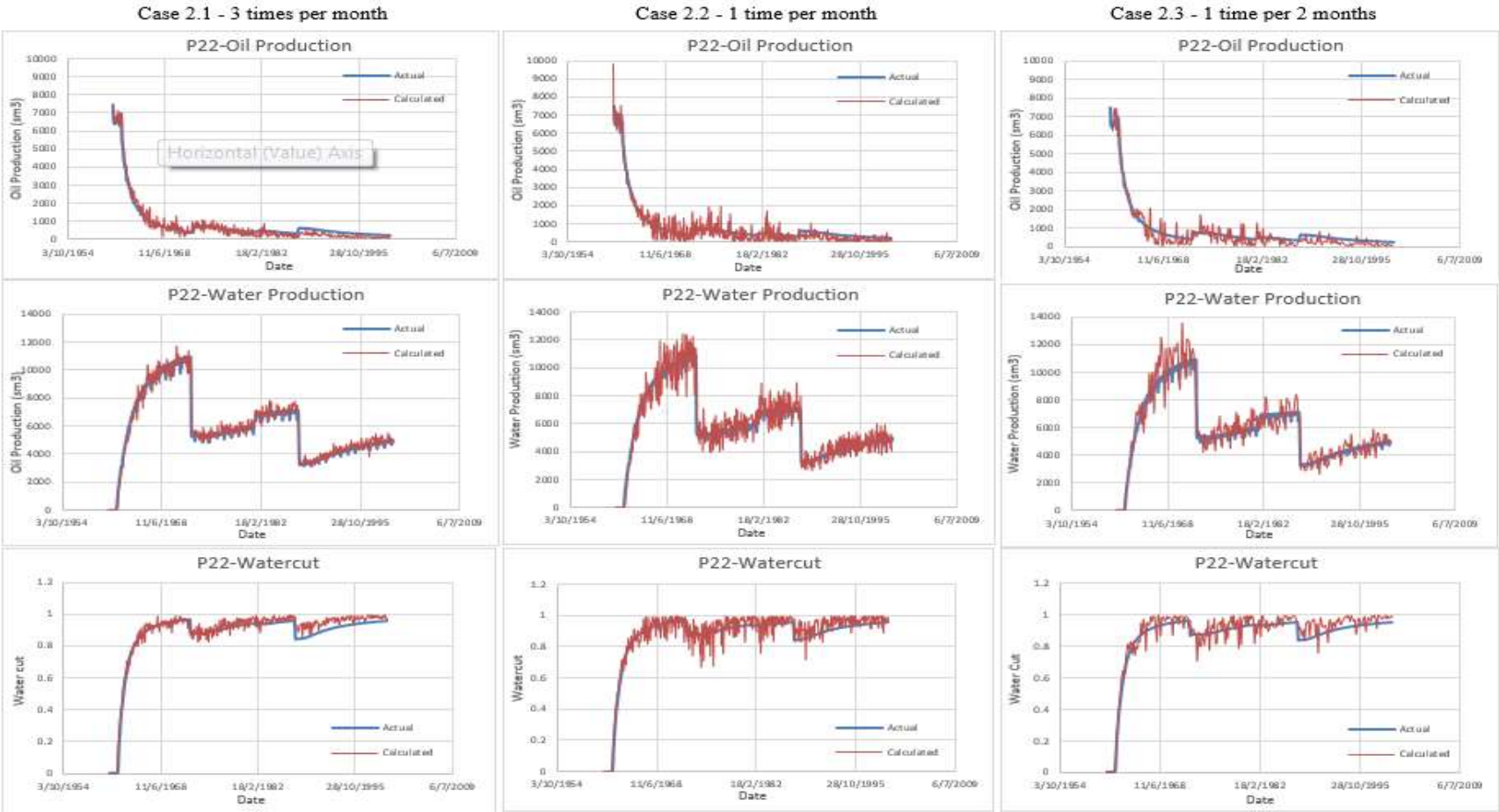

Figure 9: Areal allocation for Platform C - Well P22 with Cases 2.1 - 2.3 metering accuracy.

For well test with metering accuracy ±10% liquid, ±50% water cut:

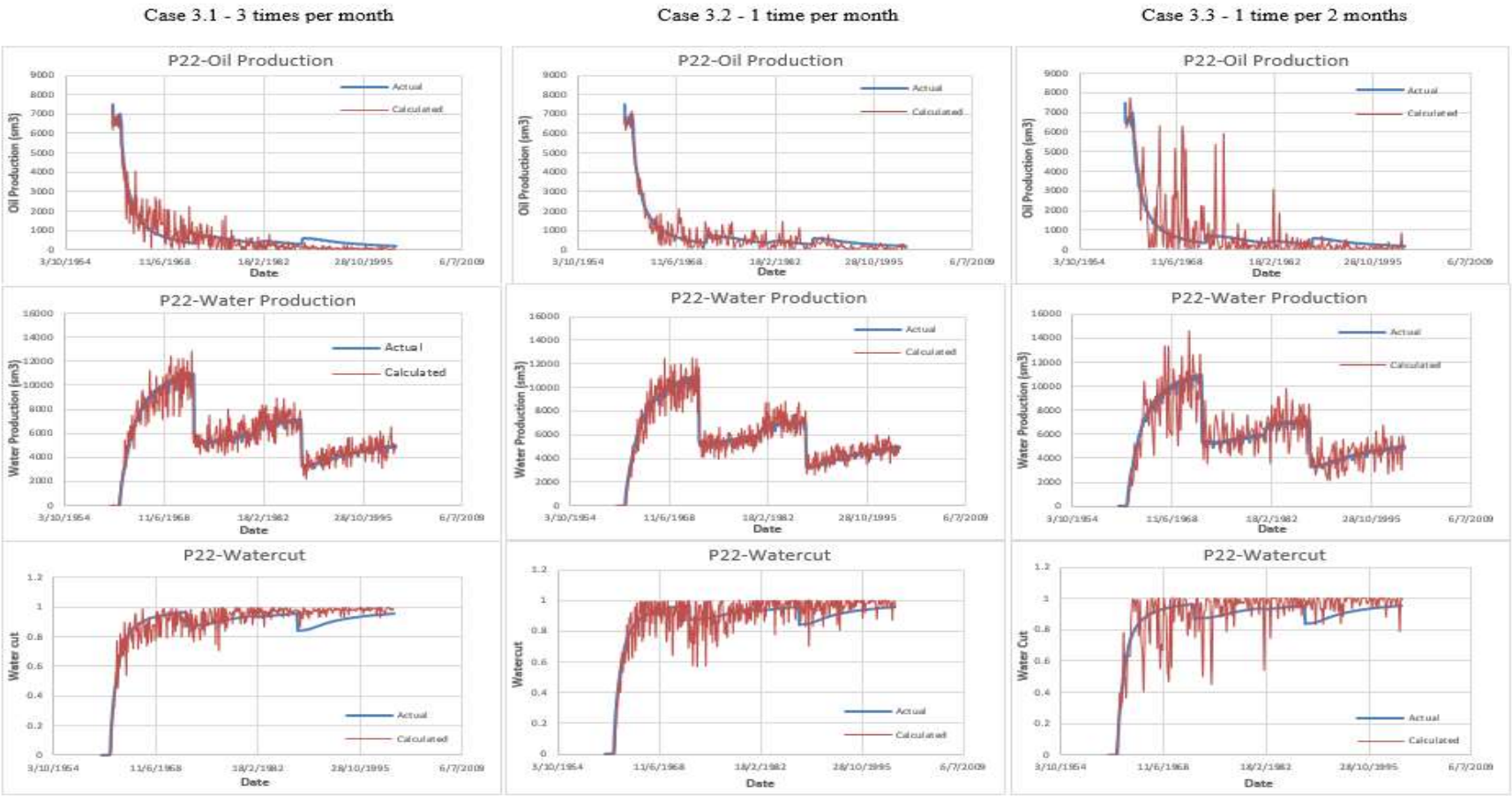

Figure 10: Areal allocation for Platform C - Well P22 with Cases 3.1 - 3.3 metering accuracy.

Platform metering accuracy ±3% liquid, ±3% water cut; well test metering accuracy ±10% liquid, ±10% water cut

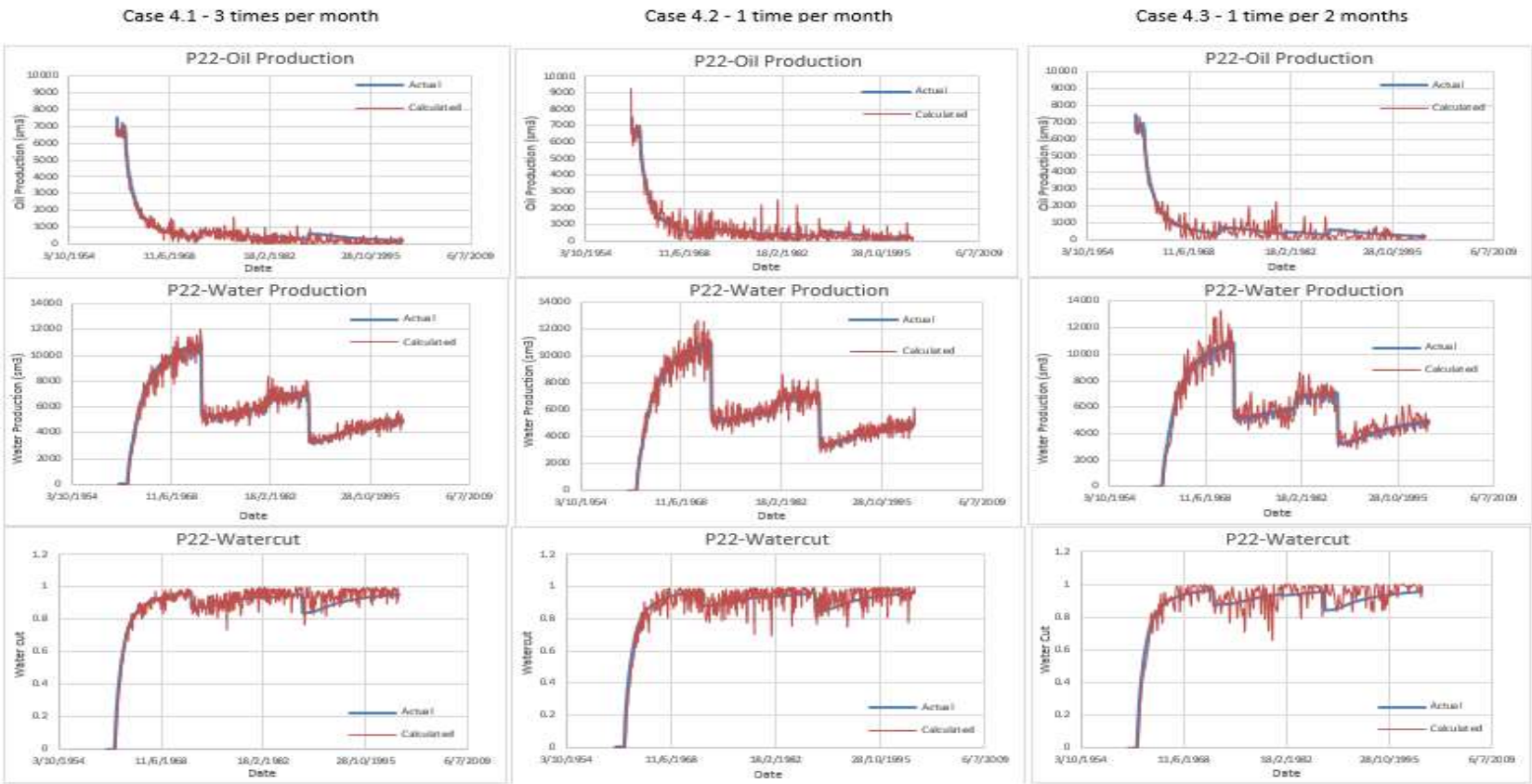

Figure 11: Areal allocation for Platform C - Well P22 with Cases 4.1 - 4.3 metering accuracy.

Platform metering accuracy ±3% liquid, ±3% water cut; well test metering accuracy ±10% liquid, ±50% water cut

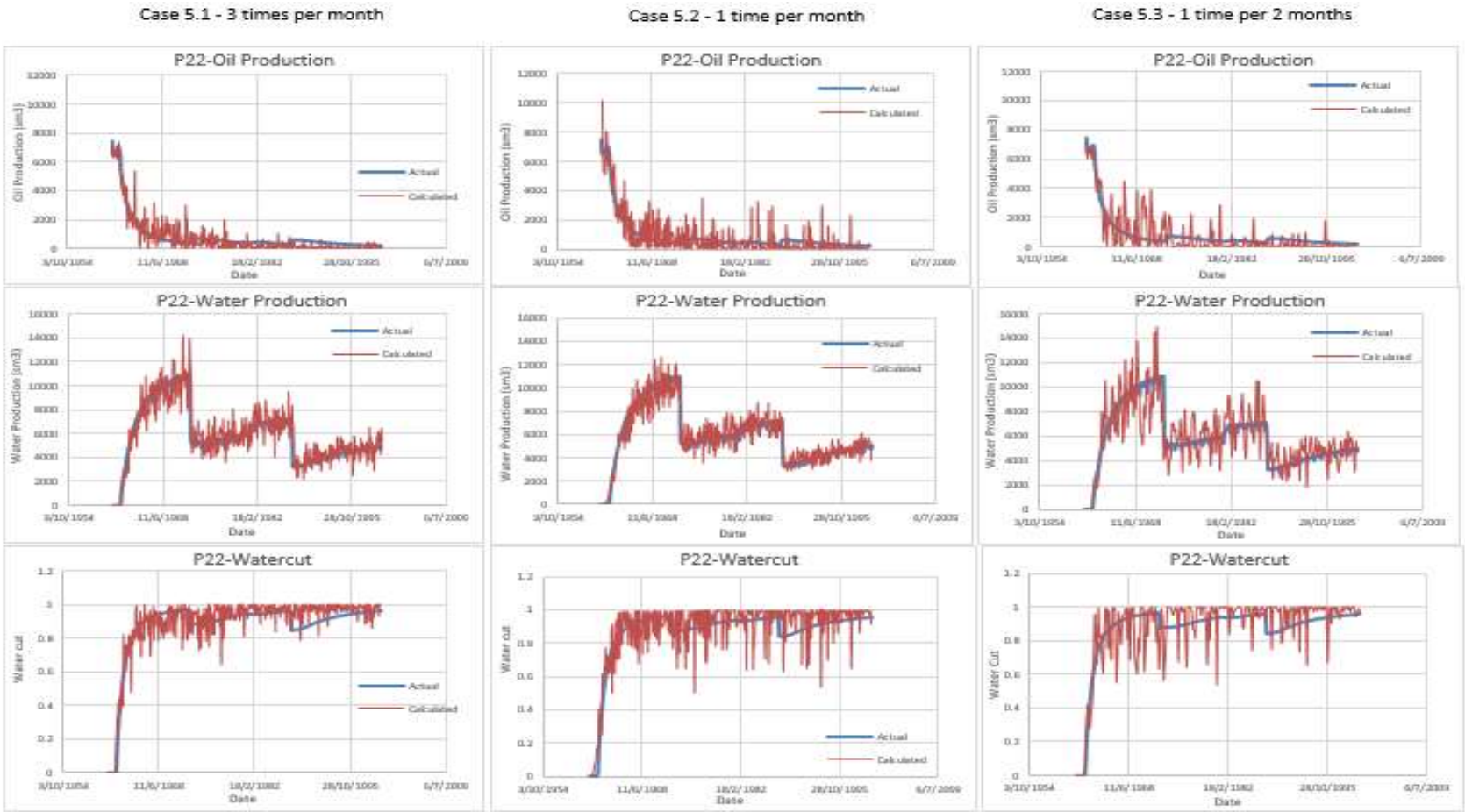

Figure 12: Areal allocation for Platform C - Well P22 with Cases 5.1 - 5.3 metering accuracy.

Reservoir vertical allocation

For a reservoir allocation exercise, we use several techniques: single-phase deterministic and multi-phase stochastic optimised methods with and without constraints. Deterministic single phase allocation (SPA) method is a widely used industrial approach for calculating the layers production split factor (AF) assuming a set of known properties from well inflow equation:

$$AF_{i,pf} = \emptyset * k_i h_i \Delta P_i \Big/ \sum_i k_i h_i \Delta P_i \qquad (1)$$

where, i - layer index, pf - fluid phase index, k_i - layer permeability, h_i - layer net pay or gross thickness, ΔP_i - pressure drop in the layer, $\emptyset$ - status of the layer (open or closed).

Practically, in most cases, only static properties are taken into account, for example, net pay thickness and permeability (so-called "KH" allocation model) due to unavailability of frequent pressure measurements. This makes the allocation factor calculations time independent between two well events. In the case of reservoir pressure data is available, it is then possible to take into account the pressure depletion trend of individual zones ("KHP" model). The gradient pressure model ("KHΔP") includes the flowing pressures and delivers better allocation factor estimation in case of non-fully stabilised well regimes. In this study, we used 4 SPA methods i.e., H, KH, KHP, and KHΔP methods.

We also applied a novel multi-phase allocation method (MPA), which couples mathematically-described watercut trends for well-layer with a global stochastic evolutionary search, thus allowing us to generate multiple allocation solutions honouring the total well production versus time. For each reservoir, a search engine will look for water-oil ratio (WOR) evolution type curve which honour well total phase productions. The objective is to compute flow rates for all phases based on minimising the error between the total measured rates and the sum of rates computed on the layer level. Once the error between those two phase rates is minimal, the solution is considered as a possible and listed down. It should be noted that zero error is unachievable due to the nature of the search and areal allocation noise. However, a compensation of imbalance could be done based on found allocation factors. Otherwise, uncertainty band could also help to constraint the range of possible solutions – those that lay inside the band would be considered as possible solutions.

The search can be improved further by constraining it with PLT data and as expected, the more PLT information available in the form of phase contribution at a given time from each layer, the more constrained the solution space becomes, and the diversity of solution reduces accordingly.

There are 3 scenarios for MPA compared: unconstrained (MPA_Unc), constrained with few PLT points per flowing period (MPA_PLTf), constrained with many PLT points (MPA_PLTm). We utilised the reference synthetic model wells productions to recreate the allocation workflow with available SPA and MPA methods.

Figures 13-16 illustrate the differences of the allocation for oil and water phases using the said methods. On the pie-chart of Figure 13, allocated oil production (left) and water production (right) between reservoirs is shown for each allocation method. Each colour represents a reservoir. The graph illustrates that if different watercut trends are observed between the reservoirs, SPA methods would produce a misleading allocation results and fully unconstraint MPA model would give results with a limited accuracy. While even few PLT points improve the quality of reservoir production allocation, thus phases distribution obtained with MPA-PLTf and MPA-PLTm models are closely matching simulated reservoir production allocation.

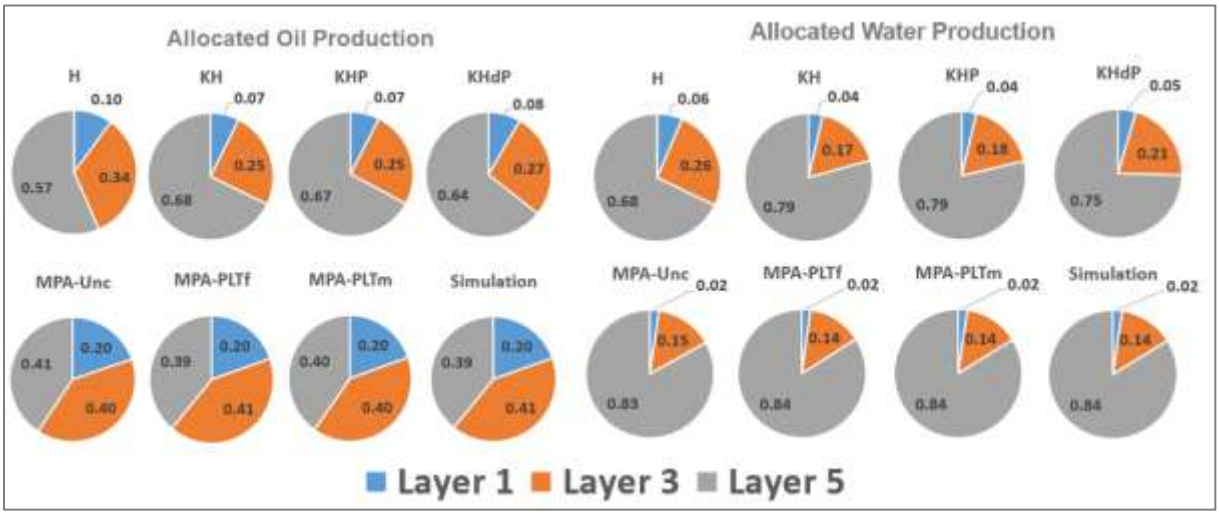

Figure 13: Allocation layers pie charts for oil (left) and water (right).

Similar to Figure 13, on Figures 14-16, a bar chart (different bars represent different allocation models with the AA-prefix refers to MPA cases) of allocated cumulative oil production is presented for each layer. Three realisations of each MPA scenario were displayed to demonstrate the uncertainty range of allocated production.

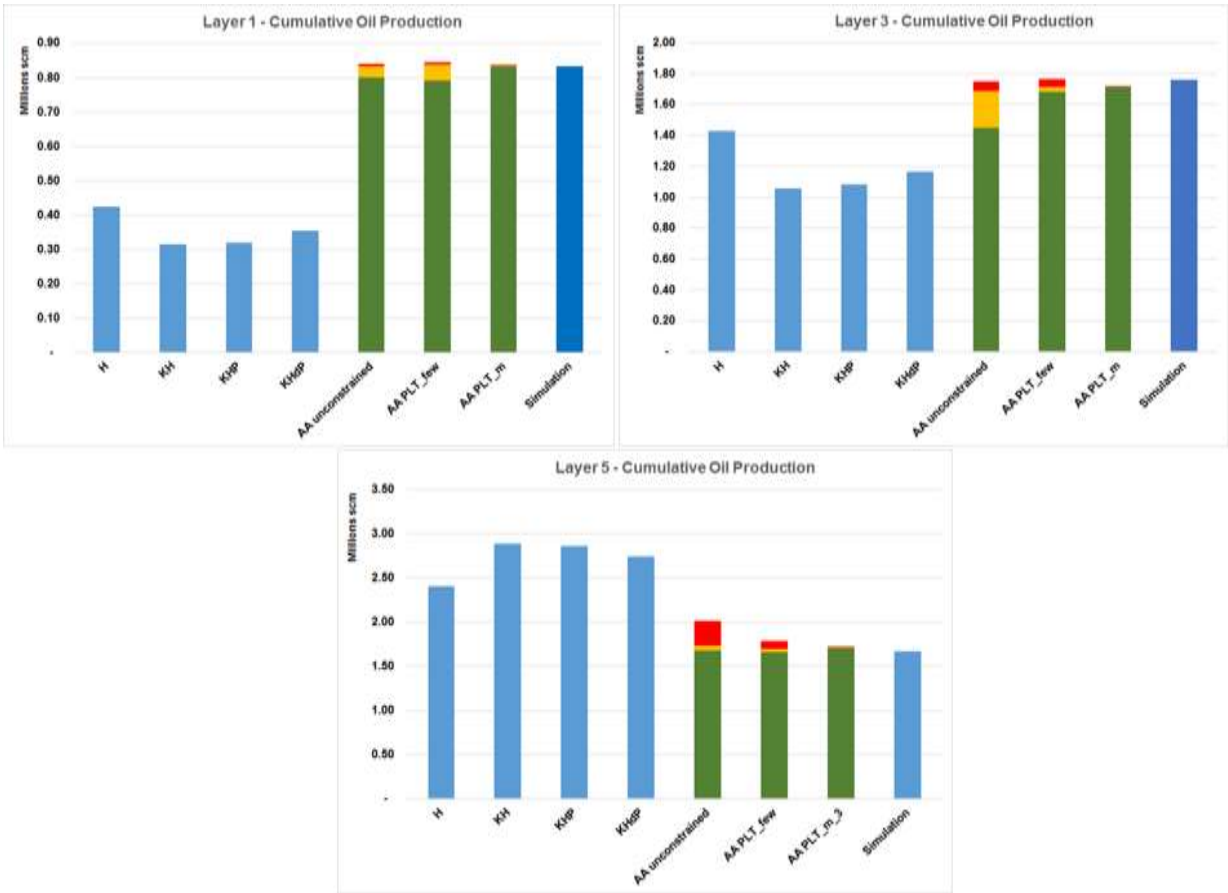

Figure 14: Oil reservoir allocation per layer. Comparison of different allocation methods (SPA and MPA) with simulation. For MPA method, green (min), yellow (mid), red (max)

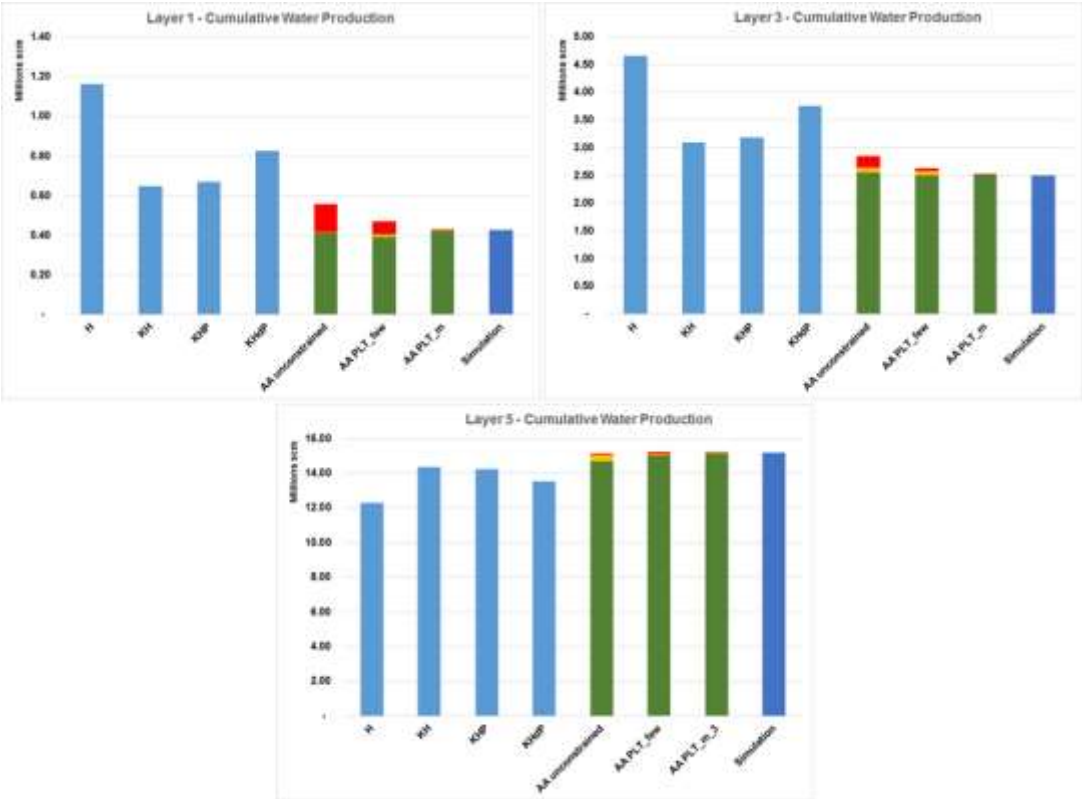

Figure 15: Water reservoir allocation per layer. Comparison of different allocation methods (SPA and MPA) with simulation. For MPA method, green (min), yellow (mid), red (max)

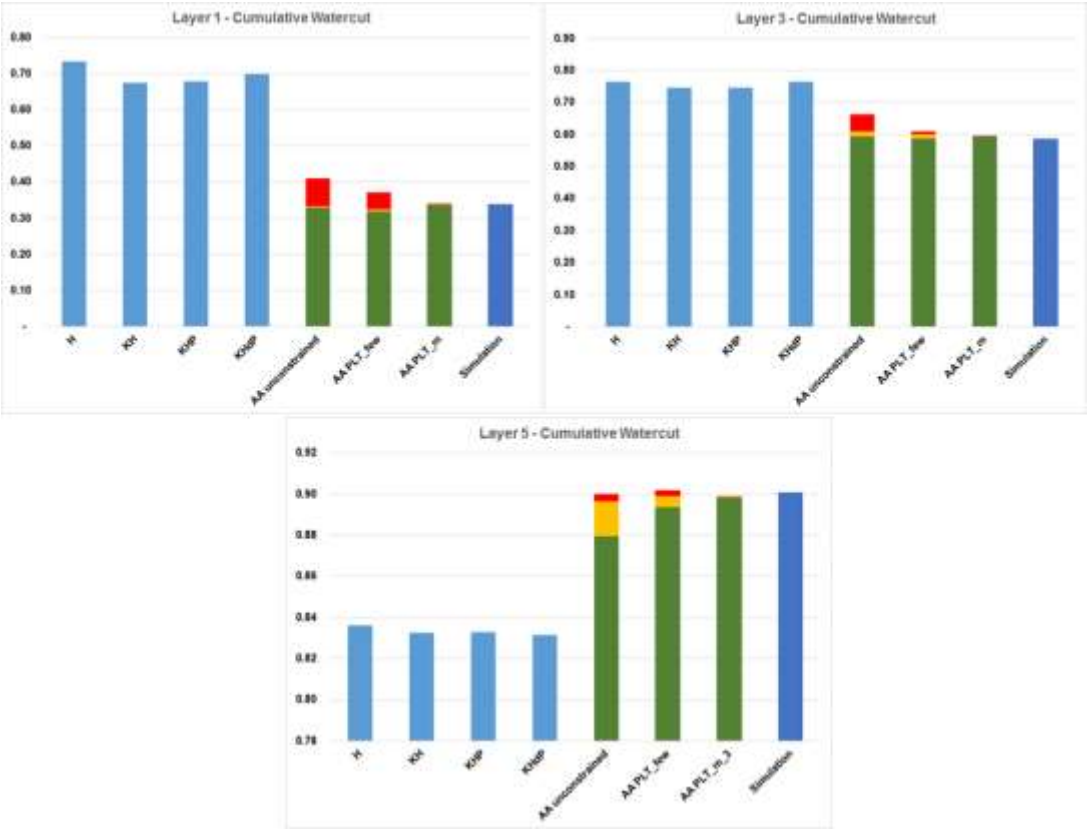

Figure 16: Cumulative watercut per layer. Comparison of different allocation methods (SPA and MPA) with simulation. For MPA method, green (min), yellow (mid), red (max)

It can be noticed that the main advantage of MPA methods is an improvement on production allocation for both phases (oil and water) while keeping oil reasonably well constrained. SPA allocates well oil and water production to all layers proportionally to H, KH or KHP, which could be different from actual oil/water behaviour. MPA takes into account individual watercut evolution for each reservoir which results in different water breakthrough times between layers. It is necessary to mention that if fully unconstrained, MPA provides the range of possible allocation scenarios allowing to perform uncertainty assessment on per well basis. The range of solutions found is visualised for MPA allocation as green (min), yellow (mid) and red (max) bars. Adding one or few PLT points helps to constrain the model and the uncertainty range significantly narrows down.

On the well-layer level, it is better to visualise the allocated results for a commingled producer with complicated events history. For example, well P23 as shown in Figure 17 demonstrates the difference in allocated oil and water production rates between allocation models. Once again, it can be concluded that even few PLT measurements help to decrease allocation uncertainty and find the right solution. All MPA realisations have been utilised in the uncertainty assessment analysis.

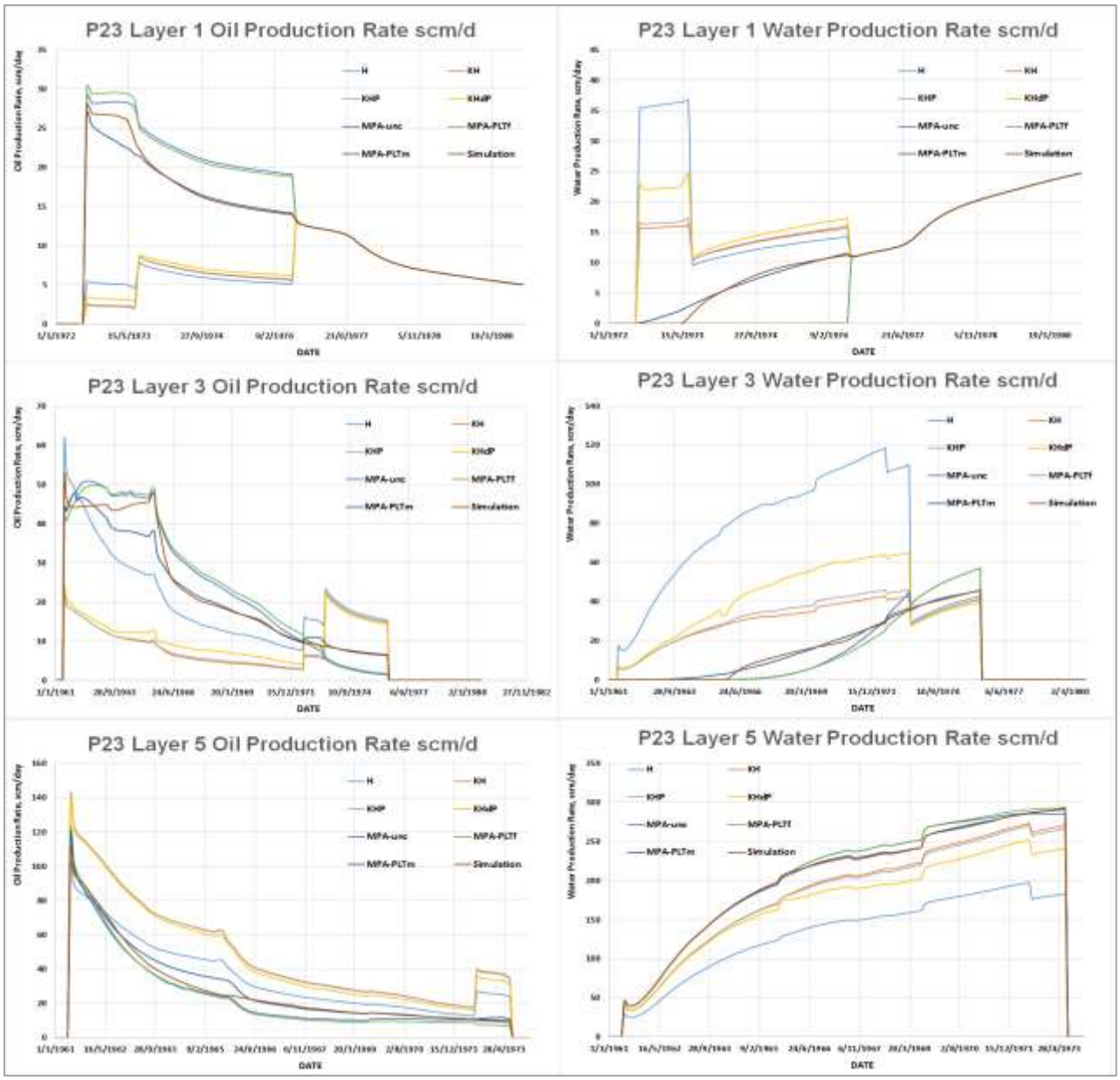

Figure 17: Layers allocation results for well P23 using various SPA & MPA methods.

Defining a measure of allocation uncertainty

In order to estimate the VOI from reservoir surveillance data, we need to define a measure of allocation uncertainty. Assuming a total of Ns acceptable solutions (i.e., found to fit the total well production and honour the expected Np and PLT constraints), a measure of Well Total Allocation Uncertainty, referred herein as "WATU", is calculated. WATU is the sum of production discrepancy (oil, water and gas, if any) of each well, which in turn is defined as the difference between cumulative production of extreme solutions (Min and Max production) for a set of solutions from a well solutions space. For a particular well, high WATU indicates high allocation uncertainty, thus detailed study required for such well including surveillance. Low WATU would mean that regardless the number of solutions found for a well, they all will be similar.

$$\text{WATU} = \sum_{k=1}^{nWell}(MaxWellCumOil_k)^2 - (MinWellCumOil_k)^2 + (MaxWellCumWat_k)^2 - (MinWellCumWat_k)^2 + (MaxWellCumGas_k)^2 - (MinWellCumGas_k)^2 \quad (2)$$

$$\text{MinWellCumPhase} = \sum_{i=1}^{nLayer} MinLayerCumPhase_i \quad (3)$$

$$\text{MaxWellCumPhase} = \sum_{i=1}^{nLayer} MaxLayerCumPhase_i \quad (4)$$

where MinWellCumPhase = well cumulative production for a given (oil, water and gas) for minimum production solution; MaxWellCumPhase = well cumulative production for a given (oil, water and gas) for maximum production solution; nWell = number of wells; nLayer = number of layer

Based on the uncertainty analysis performed utilising WATU-index concept (Figure 18), we can conclude that even a limited number of inflow profile measurements (PLT) are extremely important in constraining the allocation process. For example, the uncertainty of allocated production decreases to about 10 times just with 2-3 PLT tests per well. This is a very important outcome for justifying further field opportunities.

Note that the timing of the PLT measurements was selected to coincide with changes in well events (new perforations, shutting off intervals etc.); if the measurements had taken in a less suitable time, the VOI (reduction of WATU in this example) would have been lesser. It goes without saying that the value of having permanent downhole gauges with real-time data sampling capability, such as pressure and temperature sensors as part of smart well or intelligent well completion, will reduce allocation uncertainty tremendously, which carries equivalent value of having large if not infinite number of PLTs.

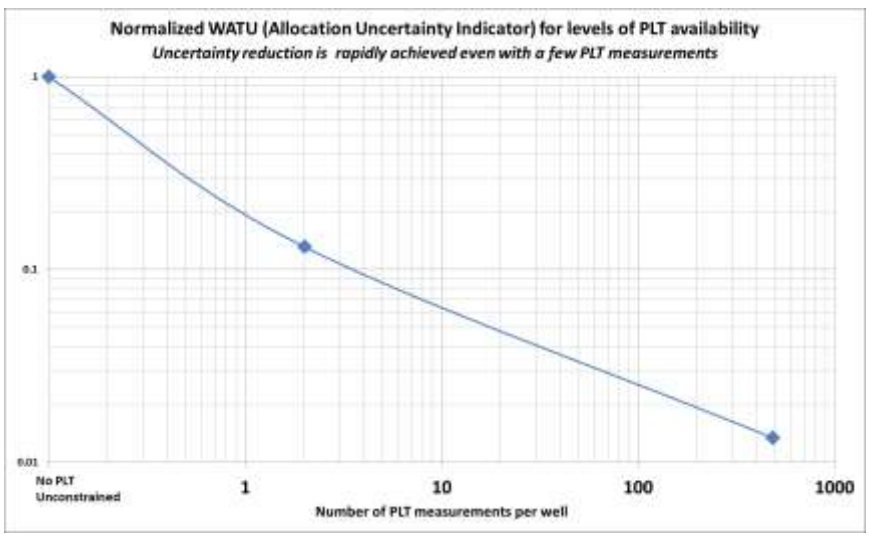

Figure 18: Normalised WATU vs. number of PLT measurements plot.

Field Opportunities

Further analysis for opportunities was carried out using SPA-KH, SPA-KHP, MPA-PLTf, and MPA-PLTm allocation cases. We used recovery factor (RF) vs. CumOil/STOIIP plots for each layer as the analytical approach for reservoirs development efficiency analysis, as shown in Figure 19. In this plot, the RF versus CumLiq/STOIIP for Layer 1, 3 and 5 are shown by the blue, green and orange line, respectively.

It can be seen that for the SPA cases (SPA-KH and SPA-KHP), the obvious layers for new targets with higher opportunities potential are Layer 1 (blue) and Layer 3 (green). The RF is in the range of 19-20% for Layer 1 and 21-22% for Layer 3, respectively. However, for MPA cases with PLT constraints, these 2 layers became less attractive as already higher RF was predicted. As more PLT constraints are being imposed, the closer is the RF trend for each layer compared to a reference case.

Furthermore, PLT measurements could also become a constraint for remaining oil compliant mapping (ROCM) used for the identification of bypassed oil and further in-fill opportunities. ROCM is a mapping algorithm which ensures a realistic saturation or contact movement of water and gas honouring material balance and the fractional flow behaviour of the wells. In this case PLT measurements could be used as control points which would constrain the search during the calculations.

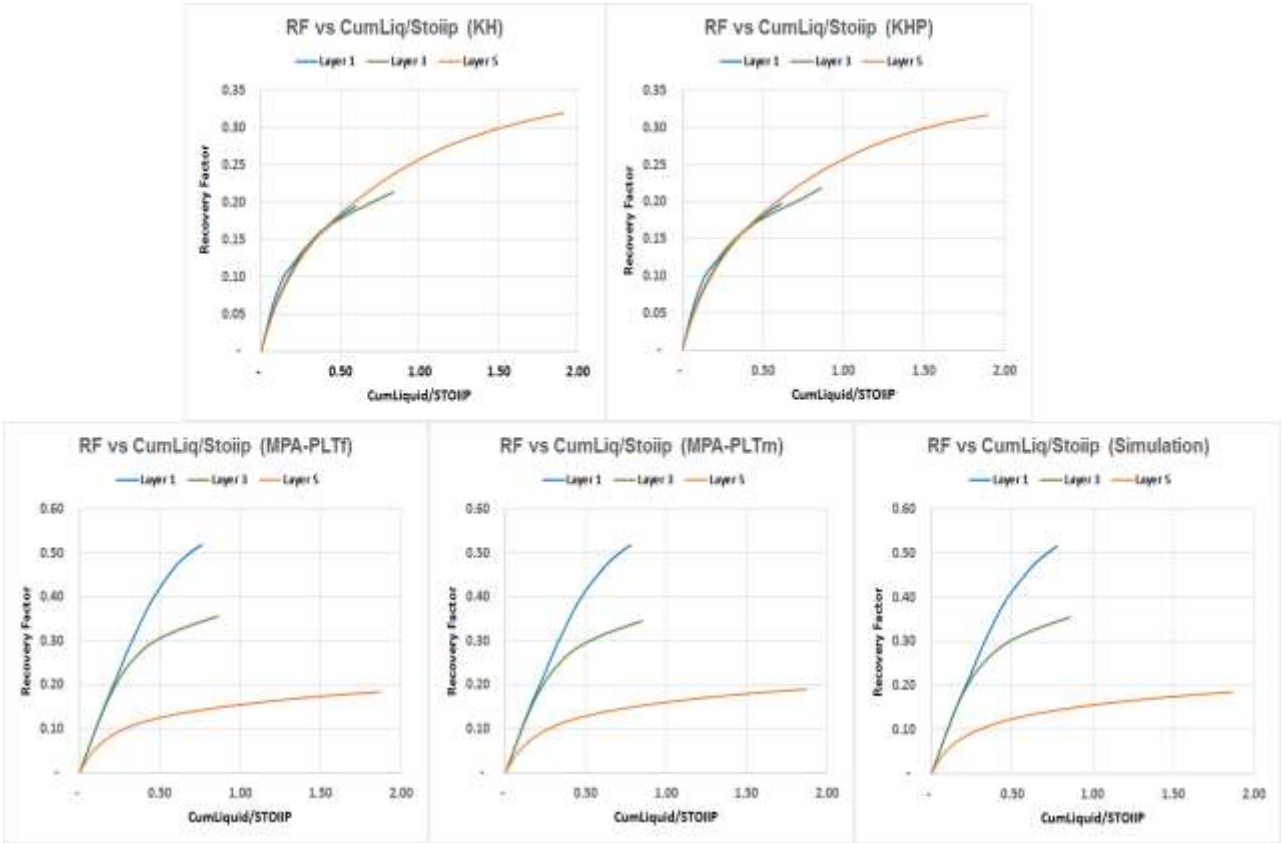

Figure 19: Synthetic model - Recovery factor vs. CumLiq/STOIIP plots for various allocation realisations.

Results and discussion

The Value of Information (VOI) should be treated in terms of reservoir outcomes compared across the possibilities of what could happen in the case of information unavailability. In this paper, authors give a set of examples illustrating the impact of well measurements availability on the overall process of areal and vertical production allocation.

Metering uncertainty and well test frequency will directly impact on areal production allocation. It was demonstrated that high metering uncertainty and insufficient well test data results in bigger error and noise in well production allocation. However, metering uncertainty can be taken into account in allocation process, allowing to distribute production imbalance based on total propagated uncertainty and to construct uncertainty band for wells which further could constraint vertical reservoir production allocation.

The allocation uncertainty had been studied and quantified and correlated with the number of PLT measurements available, which demonstrated that there is a clear benefit of reducing allocation uncertainty by running more PLTs or installing permanent downhole gauges, especially for the new wells.

The authors also recognise that areal allocation could be part of field opportunities uncertainty depending on the production back-calculation workflow with respect to surface measurements accuracies and frequencies. Moreover, there is also the possibility of inadvertent cross-flowing between the different reservoirs with a significant difference in pressure regime during extended well shut-in period which can contribute not only further challenges in production allocation but also to subsurface integrity management which carry Health, Safety and Environment (HSE) value. These were not discussed in the current paper and could be a topic for further study.

Conclusions

Accurate production measurement on platforms coupled with reasonable well test frequency will lead to quite accurate well allocation results, while low accuracy and infrequent measurements will result in the lower back production allocation quality.

Outcomes of commonly used single phase allocation (SPA) methods could be aberrant and misleading. Multi-phase allocation (MPA) methods take into account different watercut behaviour between reservoirs and could act as uncertainty quantifier in case of metering and subsurface data ambiguities.

To narrow down the uncertainty range of vertical allocation process, multi-phase allocation (MPA) methods could be efficiently constrained with surveillance data (PLT) - even a few points per well flow period is enough to significantly decrease the allocation uncertainty.

There are other factors affecting MPA model constraining, such as well events, reservoir properties, fluid contacts and logs, pressure, material balance, predictive analytical methods and even unmatched simulation model runs. Incorporation of such information could restrict allocation uncertainty and limit the risks of development decisions.

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