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Reservoir Simulation Model Sensitivity and Uncertainty Assessment Through Assisted History Matching (AHM)

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Abstract

Petroleum reservoirs are complicated structures and various uncertainties exist that result low trust in the simulation models. During first years of production, uncertainties play a significant role making the history matching process more complicated and allowing several acceptable solutions. As time increases, the quantity of data allows better history matching (HM), but the complexity of the process increases too because of increasing the optimization process Objective Functions [OF].

These different levels of uncertainty, as functions of reservoir development stages, add extra complexity to the usual procedures. Uncertainty analysis is critical when making value-added decisions such developing new fields and managing older ones. HM a reservoir model is then one of the most important tasks during developing a petroleum reservoir, as matched simulation models are needed to insure trustworthy production forecasts and to increase trust in understanding the geological and reservoir models.

The main motivation of this paper is to present a comprehensive workflow to reduce the time that usually paid to complete the Manual HM. While the Automatic HM is found to be very risky as the reservoir engineers may lose control of the entire process, the Assisted HM then came out to overcome such limitations..

Keywords: *Optimization; Response surface methodology; Long residue hydrotreating; Thermal/catalytic upgrading.*

1. Introduction

The history matching process is a fateful phase in a reservoir simulation study. Its objective is to build a model that integrates all available data and information to reduce the uncertainties on a trustworthy production forecast. The matched model must therefore not only reproduce production data by numerical simulation, but it must also be as consistent as possible with the geological knowledge of the reservoir [2]. The goal of a numerical model study is the prediction of reservoir performance with more accuracy and in more detail than it is possible with simple approaches such as extrapolation. The common traditional history matching process involves modifying the uncertain parameters of a base simulation model following trial and error approach. This method is widely known as Manual History Matching. It often takes too much time, be expensive and depressing process because reservoir performance can be complex with multiple interactions that as a whole, may be difficult to understand.

Making iterations by supposing or by following one's intuition can be expensive and usually will extend the history matching phase of a study. The decision to use such an unstructured approach may result from the impression that experienced reservoir engineers develop a "feel" for the "art" of history matching.

Assisted History Matching has been discussed by many works [2-4]. It's identical to the traditional one except that computer logic is used to adjust the reservoir data rather than direct engineering intervention. Generally; it uses algorithms that are based on minimizing an Objective Function [OF]. Other algorithms are then used to accelerate the process of estimating uncertain parameters. Constraints and prior information are added to limit the space of the uncertain parameter. Finally; search algorithms involving methods that are utilized for the constrained optimization problem. Thus, the assisted history matching technique becomes a mathematical minimization problem.

2. Field review and model set-up

The presented workflow is applied to one reservoir to check its performance over the manual history matching approach. This reservoir is composed mainly of sandstone formation and is producing for 6 years through 9 vertical producers. It's a highly faulted reservoir with a gas cap and involves five main faults that divide the reservoir into six blocks. In some areas, the throw of the faults is so large that there is no sand-to-sand juxtaposition between the fault blocks. Geologists confirmed that the first fault does not extend completely between faults block 3 and fault block 4. Also, where there is sand-to sand contact, there is uncertainty in the transmissibility of the faults. The Geology and Geophysics (G&G) Team agreed that there is a very large aquifer connected to the sides of the reservoir and that the uncertainty in the connection between the aquifer and the reservoir is directly related to the connection angle.

The starting point of a history matching study is to build a base case from which multiple realizations are created to analyze the model's response to variations in the model parameters. The base model grid was defined jointly by geological modelers and reservoir engineers in order to have suitable grids for both geological and flow modeling. It's a black oil model with blocks consist of 28 by 20 dimensions of approximately 244m (800 ft.) in the X direction and 260m (853 ft.) in the Y direction. The model has 5 zones with an average height of 9.48 m (31 ft.) each and about 12826 active cells. The zones are divided into 13 layers and the geometry of the field has been modeled using corner-point geometry. Reservoir Model was built using Schlumberger Petrel; which is a Windows based software for 3D visualization, mapping and reservoir modeling and Simulation. Different reservoir simulators like Eclipse and FrontSim amongst others can be run on Petrel and visualized. The oil water contact (OWC) is at 3390m (11,122 ft.), gas oil contact (GOC) 3070m (10,072 ft.). Figure 1 shows the base case match quality check (QC) plot for the reservoir matching vectors of oil production rate, water cut, and pressure.

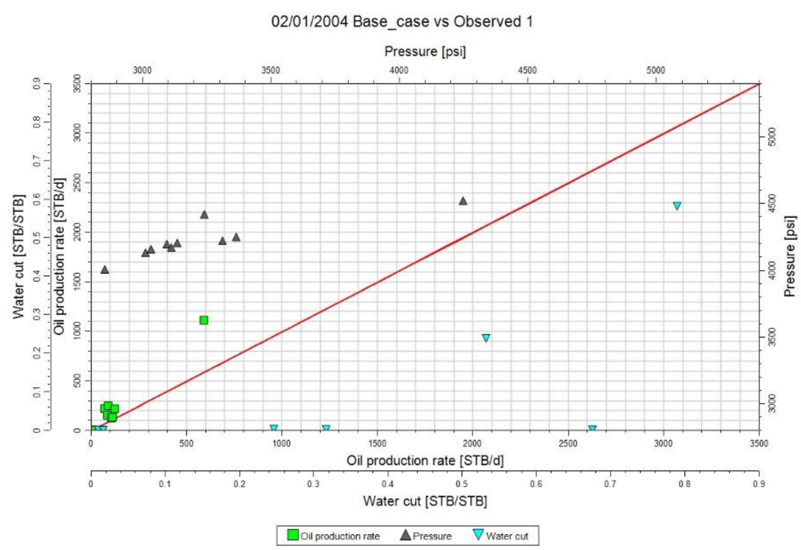

Figure 1. Match quality-check plot of the base case

3. Uncertainties and manual history matching

Collecting and analyzing data and information to characterize the reservoir is the most time-consuming part of the study and was performed in collaboration with the study integrated asset team [5]. Each reservoir property considered uncertain is defined by Low, Mid and High values. The base case values of all the uncertain variables are the Mid. values. Table 1 summarizes the main considered uncertain variables and their expected ranges. Trial and Error approach was manually applied to the uncertain parameters. After several iterations which took around 3 months of extensive works, a reasonable history match model was obtained by changing the entire parameters within their range of initial values [5]. Table 2 lists the final values of the uncertain variables for both the base and manual history matching cases in columns number 3 and 4, respectively. Figure 2 presents the manual history matching case match quality check (QC) plot, which shows good improvement if be compared with Figure 1.

Table 1. Uncertain variables and their associated ranges

(1)	(2)	(3)	(4)	(5)
Group	**Uncertain**	**Low**	**Mid (Base)**	**High**
Fault	Fault 1_ TM	0.05	0.1	0.35
	Fault 2_ TM	0.1	0.2	0.5
	Fault 3_ TM	0.1	0.14	0.5
	Fault 4_ TM	0.1	0.14	1
	Fault 5_ TM	0.05	0.1	0.6
Grid	MULTZ	0.5	2	2.5
	MULTXY	0.5	1.6	2
	MULTPV	0.5	1.5	2
Aquifer	Aquifer_ Perm (md)	10	50	800
	Aquifer_ Angle (°)	5	10	80
	Aquifer_ Radius (ft)	10,000	50,000	70,000
	Aquifer_ Porosity []	0.1	0.15	0.25
	Aquifer_ Ct (1/Psi)	1e-5	8e-5	9e-5

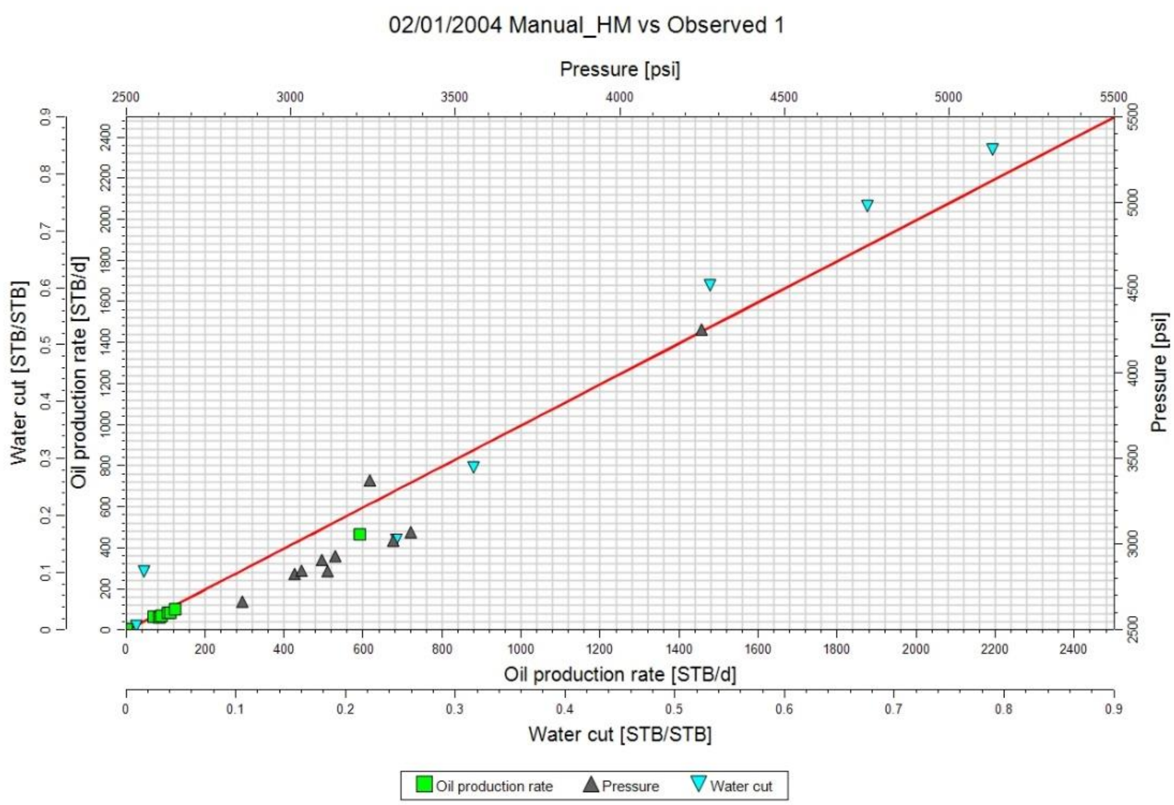

Figure 2. Match quality-check plot of the manual history matching case

Table 2. Uncertain variables in base case, manual and assisted HM cases

(1) Group	(2) Uncertain	(3) Low	(4) Mid (Base)	(5) High
Fault	Fault 1_ TM	0.1	0.2	0.314
	Fault 2_ TM	0.2	0.416	0.424
	Fault 3_ TM	0.14	0.163	0.486
	Fault 4_ TM	0.14	0	1
	Fault 5_ TM	0.1	0.456	0.561
Grid	MULTZ	2	1.5	2.16
	MULTXY	1.6	1	1.03
	MULTPV	1.5	1.1	1.18
Aquifer	Aquifer_ Perm (md)	50	100	706.9
	Aquifer_ Angle (°)	10	10	72.8
	Aquifer_ Radius (ft)	50,000	20,000	50,000
	Aquifer_ Porosity []	0.15	0.25	0.15
	Aquifer_ Ct (1/Psi)	8e-5	1e-5	8e-5

4. Assisted history matching

Assisted history matching study starts by identifying the probability distribution of all the uncertain variables and their associated ranges. If there is no much data available for the selected uncertain variables, it's trustable to consider them as uniform probability distributions [6]. The main steps of the comprehensive workflow that are followed in this study may be summarized as:

1. Run a sensitivity analysis to help selecting the most influential uncertain input parameters based on a defined Objective Function [OF].
2. Run an uncertainty analysis using the sensitivity analysis results to capture the interactions among the uncertain parameters. Those parameters that do not significantly impact the Objective Function should be deactivated before running the uncertainty analysis.
3. Cases generated from the uncertainty analysis can be used as leads to initialize the population of the Evolution Strategy optimizer that will be used in this study. If necessary, re-parameterize the input uncertain parameters based on the uncertainty analysis result and define the distribution and ranges of the uncertain input parameters.
4. Run the model using the base case with the designated uncertain input parameters to generate multiple history match reservoir models.
5. Screen the generated cases by comparing their mismatch with reference (observed data).

If the result of the Objective Function is acceptable, select the matched case(s) and proceed to the prediction phase. The overall objective of this study is to use the Evolution Strategy optimizer to improve the history match by tuning some identified uncertain variables to find parameter sets that closely reproduce the reservoir dynamic behavior and provide meaningful uncertainty estimates for future production.

4.1. Sensitivity and uncertainty analyses

The purpose of the sensitivity study is to identify those uncertain parameters that have strong influence on the simulated results of the given model. During a sensitivity run, one of the input variables normally changes while all other input variables are fixed; i.e. varying one-variable-at-a-time which is commonly known as OVAT [7]. However, the interaction effects between two or more of the uncertain variables are not measured in a sensitivity study.

In the assisted history matching program employed here, there are two options available for performing the sensitivity analysis task; Sensitivity by variable and Sensitivity by process. In the variable-based sensitivity task, one variable from the set of all uncertain variables is varied, while the other variables are kept fixed at their base values. This is done for each uncertain variable, so the total number of runs is equal to the number of uncertain variables multiplied by the number of samples per variable that the engineer enters. In the process-based sensitivity task, all variables that belong to the same process (fault analysis, make aquifer, grid property modification, etc.) are varied simultaneously, while all other variables are kept fixed. The objective of using this task is to try to measure the impact of each modeling process as opposed each modeling variable.

In this study, we applied the variable based sensitivity option. The Equal Spacing Sampler is used to get a set of samples for each uncertain variable. It divides the range into intervals of equal length between the minimum and maximum values and returns a set of sample points that includes the minimum and the maximum values [8]. It is useful for the sensitivity studies to be sure that we have covered the entire sampling space range.

Figure 3 presents a tornado chart that summarizes the results of the sensitivity analysis in terms of oil production cumulative at the end of the historical period (2004). It is a good trick to show the results relative to the base case so that an engineer can easily determine which of the uncertain variables gave a smaller or larger response relative to that reference. Tornado plot is a good common way to get an overview of how sensitive the response is to the uncertain parameters at one time step. If an engineer wants to track the response of all the uncertain variables during the entire history match period at once, it's advised to turn to the cumulative tornado plot.

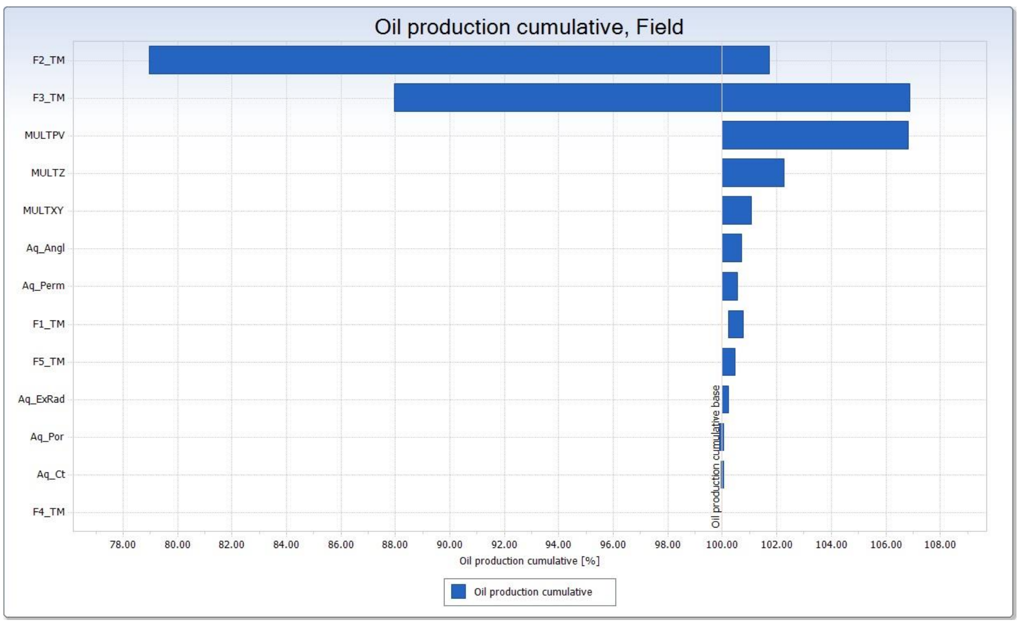

Figure 3. Tornado plot shows uncertain variables effect relative to the base case at one time step (end of the historical period).

According to the said analysis, it's decided to ignore 4 uncertain variables with the least influence from the uncertainty analysis study. These variables are the transmissibility multiplier of the fault number 4, the aquifer properties of total compressibility, porosity and the external radius.

However, the sensitivity analysis doesn't measure the interaction effects between two or more of the input variables and the input distributions were not that important because engineers are interested only in the main effects of each variable [9]. The uncertainty analysis task is run after the sensitivity analysis to help focus more on the most influential uncertain parameters. The goal here is to make runs with different combinations of all of the input variables to assess interaction effects and the influence of each single variable. Based on the outcome of the sensitivity study, engineer can focus on the most influential uncertain parameters in the uncertainty studies. Those parameters that do not have significant impact on the defined response based on sensitivity analysis result should be deactivated in the uncertainty setup. All uncertain variables values are changing simultaneously with each simulation run, unlike the sensitivity analysis. It is important then to get the probability distribution right, as the most probable values will be sampled more often than the less probable values, as we are interested in the interactions of input variables.

We picked up the standard Monte Carlo (MC) Sampler this time. It samples the uncertain variables randomly from their assigned distributions, so a different combination of sampled values is given every time the simulation is run. As some parts of the range of the uncertain might not be sampled at all by this sampler because the values are sampled randomly. Latin Hypercube Sampling (LHS) option is added then for better representation of the input distribution with fewer samples by picking values from equally probable bins and helps to avoid clustering of samples in each variable's range. The uncertainty simulation cases will be used later as the starting leads (initial population) for the Evolution Strategy optimizer.

4.2. Objective function

The mismatch at a given well is quantified by summing up the squared difference between measured and simulated values. The overall mismatch is then computed as a weighted sum of individual well mismatches, where the weights are determined by the engineer. This weight is a non-negative coefficient that controls the influence of the associated well/group on the global history mismatch. The overall mismatch quantified this way is taken as the Objective Function. Prior to optimization, a valid Objective Function must be defined to specify what quantity or numeric expression is to be minimized by the optimization process.

In this study, we selected both oil production rate, reservoir pressure, and water cut vector quantities to be included in the Objective Function. We applied it to the uncertainty analysis folder containing multiple simulation cases before we can use these cases as the starting leads for Evolution Strategy Algorithm.

4.3. Evolution strategy optimizer

The Evolution Strategy optimizer falls under the umbrella of stochastic population-based optimization algorithms inspired by Darwinian evolution. It works starting from supplying initial seeds (may be from Monte-Carlo runs) to initialize the population and then followed by selection of first parents. Variability is applied to the first parents through recombination and mutation to create first children pool, the fittest children are selected among the children pool to serve as second generation population. The process continues until the criteria set met before it terminates.

The Evolution Strategy algorithm mimics biological evolution. Creating a set of new individuals is equivalent to generating a set of multiple reservoir simulation cases.

The newly-created set of individuals, or generation (simulation) cases, inherits input parameters from their parents through combination and mutation. The Objective Function assesses the fitness of individuals so that only the most fit models (that is, the best history matched models) are selected as parents for the next generation.

The algorithm focuses on identifying the globally optimal solutions of the problem under consideration compared to gradient based optimization algorithms that generate only one candidate solution at a time. This algorithm has these characteristics:

- It is implemented using biomimetic operators.
- It operates on a population of candidate solutions referred to as individuals.
- It encodes individuals directly in real numbers instead of string.
- It always mutates, even with small changes.

This optimizer maintains simultaneous knowledge of several promising regions of the search space (this mechanism avoids becoming trapped in a local optima). The optimizer has other benefits such tolerating a small rate of failure to evaluate, such as when a simulation case fails to evaluate candidate solutions in large batches.

The Evolution Strategy optimizer has many parameters/settings that have to be set before the algorithm can be used. The impact of these parameters on the efficiency of the search performed by an evolutionary algorithm can be very high. Therefore, it is important to understand the meaning of its parameters before being applied.

5. Results

Figure 4 presents the global Objective Function versus the case number (i.e. LOOP) to identify the likelihood of obtaining the best matches with the cases that have the minimum global Objective Function. It shows improvement in the reduction of the Objective Function values. Match quality tends to increase rapidly with the first iteration but then slows down. The simulation case with the lowest mismatch values is case number 25; which is named "Base_case_198". This case can further be optimized if the engineer wants to tune it more.

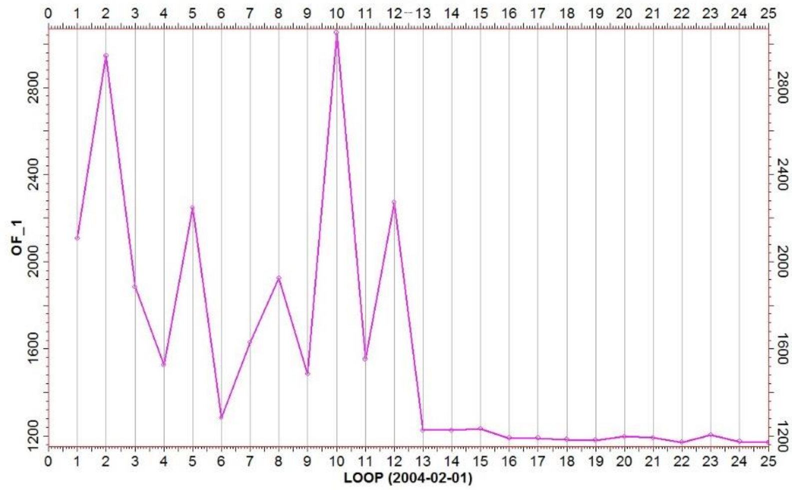

Figure 4. Global objective function versus the case number (LOOP)

It's noted that the matching improvements did not alter the geological concept, yet the production and pressure histories are matched.

As mentioned before, results analysis for multiple simulation cases is better done with the plot of Simulation vs. Observed, which enables the engineer to plot data from one or more cases against an observed data set to analyze the difference. Figure 5 presents the simulated vs. observed plot for the best case. This plot is a convenient way to visualize mismatch between actual and simulated well production and show the improvement in the reduction of mismatch values.

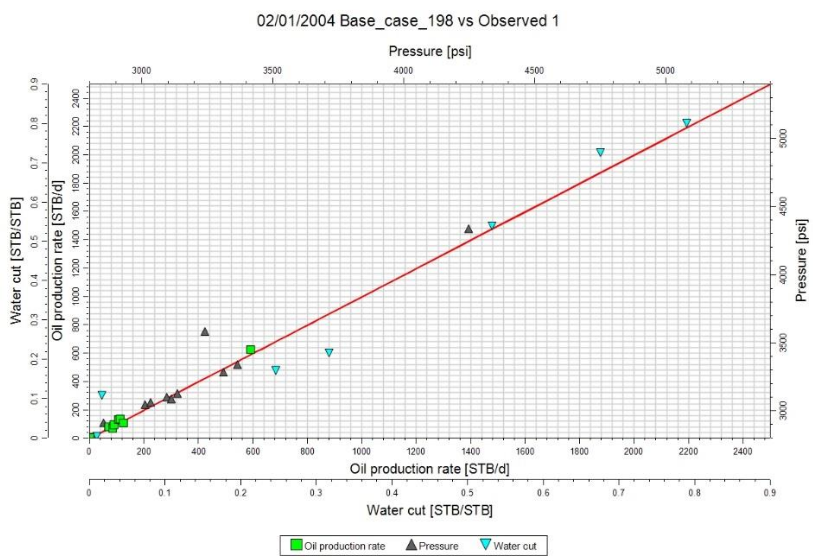

Figure 5. Match quality-check plot of the assisted history matching case

6. Conclusion

This work presents a comprehensive workflow to be followed to perform an assisted history matching. The manual history matching required 3 months to be completed, while the assisted history matching required only 3 days, and achieved much better results. The workflow is discussed as was applied with one reservoir. It was applied for 3 other reservoirs of the same field resulting similar good results. There are some conclusions that can be drawn from this study:

- The sensitivity analysis is essential to quickly select the most influential uncertain variables and understand the overall reservoir performance.
- Double checking the production history is critical to remove inconsistent data. This is especially the case of production rates back-allocated to individual wells with sparse production tests.
- The assisted history-matched models were faster and better matched than the manually matched models.
- The assisted history matching is best applicable to mature fields with sufficient wells and yields most benefit when it is applied from an early stage onwards in the modeling project.

In the particular model presented here, the geological model is good and the reported data are largely error free, and hence the spectacular improvement of most individual well matches.

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References

[1] Chen WH, Gavalas GR, Seinfeld JH, Wasserman ML. A New Algoritm for Automatic History Matching. SPEJ, 1974; 257: 593-608.
[2] Roggero F, Hu LY. Gradual Deformation of Continuous Geostatistical Models for History Matching. paper SPE 49004 – SPE Annual Technical Conference & Exhibition, New Orleans, Sep 98.
[3] Ligero EL, Maschio C, and Schiozer DJ. Quantifying the Impact of Grid Size, Upscaling and Streamline in the Risk Analysis Applied to Petroleum Field. SPE 79677, SPE Reservoir Simulation Symposium, Houston, USA, February 2003.
[4] Reis LC, Hu LY, de Marsily G, Eschard R. Production Data Integration Using a Gradual Deformation Approach: Application to an Oil Field (Offshore Brazil). IFP paper SPE 63064, SPE 2000 Annual Technical Conference & Exhibition, Dallas, Texas, 1–4 Oct. 2000.
[5] Zheng J, Leung JY, Sawatzky RP, and Alvarez JM. A Proxy Model for Predicting SAGD Production From Reservoirs Containing Shale Barriers. J. Energy Resour. Technol., 2018; 140(12): 122903
[6] Huaizhong S, Heqian Zh, Zhaosheng J, Jingbin L, Xinxu H, and Shijie Zh. Numerical Simulation and Experimental Study of Cuttings Transport in Narrow Annulus. J. Energy Resour. Technol.,2019; 141(8): 082902
[7] Papi A, Mohebbi A, and Eshraghi SE. Numerical Simulation of the Impact of Natural Fracture on Fluid Composition Variation Through a Porous Medium. J. Energy Resour. Technol., 2019; 141(4): 042901
[8] Ren X, Li A, Memon A, Fu Sh, Wang G, and He B Experimental Simulation on Imbibition of the Residual Fracturing Fluid in Tight Sandstone Reservoirs. J. Energy Resour. Technol., 2019; 141(8): 082906
[9] Zhang N, Li H, Zhang Y, Deng Q, and Tan Y. A Numerical Simulation for the Determination of the Shunt Ratio at a T-Junction With Different Branch Angles, Viscosities, and Flow Rates. J. Energy Resour. Technol., 2019; 141(10): 102906

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