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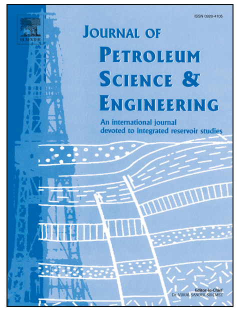

Gaining more understanding about reservoir behavior through assimilation of breakthrough time and productivity deviation in the history matching process

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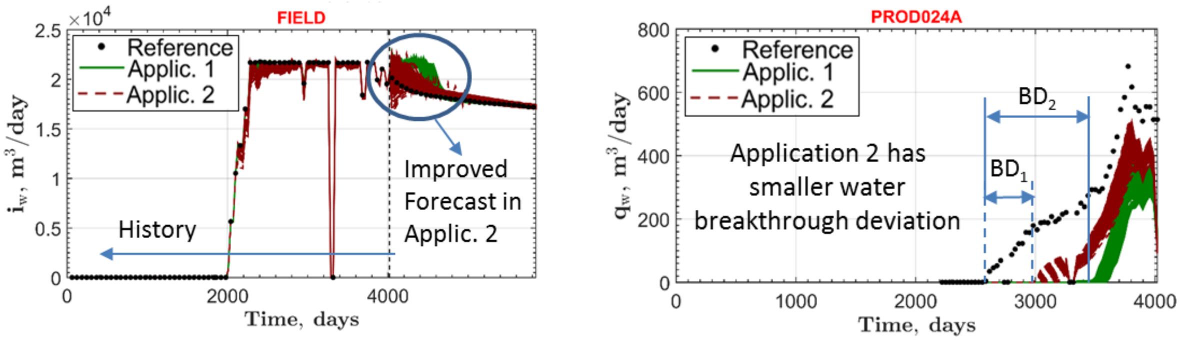

(a)

(b)

Figure 1: Results obtained for field and wells comparing Application 1 (only traditional Objective Functions assimilated) and Application 2 (traditional and additional OFs assimilated): (a) Field water injection rate (i_w) with better predictability for Application 2; and (b) water production rate (q_w) of the well PROD024A showing water breakthrough time closer to the reference for Application 2 when compared to Application 1.

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Abstract

History matching (HM) is an inverse problem where uncertainties in attributes are reduced by comparison with observed dynamic data. Typically, normalized misfit summarizes dissimilarities between observed and simulation data. Especially for long-time series, objective functions (OFs) aggregate multiple events and tendencies relevant to field performance in a single indicator (e.g. water rate and breakthrough time). To capture the attributes influencing the reservoir behavior, we evaluate the assimilation of data series through additional OFs, obtained from splitting time-series data. In this study, two additional OF groups supplement the time-series misfits: Breakthrough Deviation (BD) indicating dissimilarities in water breakthrough time; Productivity Deviation (PD), representing mismatches of the well potential, mainly impacting the transition from history to forecast conditions. The Productivity Deviation (PD) is adapted from previous studies. Instead of simulating the last time of the historical period under forecast conditions, we propose keeping it under historical data. The change is the historical data used as target condition to the simulator: Bottom Hole Pressure (BHP) in place of liquid production and water injection rates; with this, we estimate a mismatch in well productivity, while avoiding the influence of other boundary conditions in the evaluation. Two applications (1 & 2), assimilating different OF quantities, highlight the influence of the additional groups. Application 1 only computes time-series misfit (64 OFs) whereas Application 2 includes the BD and PD (counting 128 OFs). The iterative HM method presents flexibility regarding OFs assimilated and incorporation of uncertain attributes. UNISIM-I-H case allows us to evaluate the HM considering history and forecast data. We examine differences between the 450 scenarios resulting of data assimilation for each application through four perspectives. Application 2 resulted in scenarios with better predictability of the field behavior and smoother transitions between field history and forecast periods. Field cumulative oil production of Application 2 is also forecasted closer to the reference data when compared to Application 1; all forecast periods (1, 5 and 19 years) emphasize this impact. Some wells presented breakthrough time closer to the reference for Application 2. The challenging achievement of exact BD matches leads to the third advantage of the additional indicators. These OFs supply supplementary information to the diagnosis of scenarios, identifying unnoticed problems in the traditional approach. Finally, even with an overall better performance, some of the well OFs presented poorer matches for Application 2. To explain this, we analyzed the relationship between attributes and the OFs used to update the attributes. In conclusion, the improved forecast of the simulation scenarios indicates that superior performance of the HM process is possible by splitting the available dynamic data in relevant additional OFs. This study presents a case application with 11 years of field history, in which additional OFs, derived from dynamic data, add value to the reservoir characterization. They allow the influence of uncertain attributes to be captured for relevant events in reservoir performance. We also show how the increased quantity of OFs assimilated makes the HM harder for some OFs.

Keywords: History Matching; Iterative Discrete Latin Hypercube methodology; Breakthrough Time; Well Productivity; Reservoir Characterization; Transition between Historical and Forecast periods.

1. Introduction

Reservoir simulation models are representations of real petroleum fields used in production forecast and decision-making process. Closed-Loop Reservoir Development and Management (CLRDM) endorses the application of simulation techniques in all stages of the field lifetime. CLRDM methodologies (Jansen et al. 2009; Wang et al. 2009; Schiozer et al. 2015) integrate model-based optimization and data assimilation to support decisions about the physical problem with uncertainties. Silva et al. (2017) propose a closed-loop workflow, constructed with ensemble-based method. They demonstrate the effectiveness of CLRM to improve the predictability of the models, in contrast to ensemble-based separated applications.

Data assimilation is a stage in the CLRDM known as History Matching (HM) in the petroleum industry. It uses the observed dynamic data to afford a better representation and predictability of the physical model through simulation models. The HM is an inverse problem with multiple possible solutions. The complexity to solve the problem increases with dimensionality in terms of number of inputs and outputs.

A wide understading on the inverse theory and history matching, including explanatory examples, is available in the book of Oliver et al. (2008). Oliver and Chen (2011) discuss the progress of diverse HM processes in their paper, detailing advantages and disadvantages of manual, evolutionary, Ensemble Kalman Filter based and Adjoint methods. Rwechungura et al. (2011) sumarizes the evolution of HM techniques through the time and highlights aspects to the integration of 4D seismic. Maschio and Schiozer (2016) offer a more recent overview about HM methods, classifing optimization, probabilitic and mixed methods.

In the HM process, parameters of the reservoir characterization, which are inputs into the reservoir numerical model, are uncertain and represent undetermined reservoir features (fault transmissibility, for instance). These uncertainties in the attributes influence dynamic production estimated by the simulator and the asset team used this data to understand flow and transport in the real petroleum field. The closer the simulator output is to the dynamic data measured in the field (production rate in specific period, for example), the better we expect that the model represents the physical field. In this context, objective functions (OFs) computes the difference between observed and simulation data.

A reservoir analysis based on a deterministic approach considers one or more scenarios that represent a partial set of the possible production scenarios. Nevertheless, this approach can present biased results since it generates production forecasts without adequately exploring the range of production scenarios (Goodwin 2015). In contrast, the probabilistic approach represents the uncertainty toward the reservoir behavior. It supports reliable forecast by addressing questions of risk and uncertainty in reservoir management. This approach incorporates the consideration of several sources of uncertainties involved in the reservoir characterization process and measurement errors in observed data (Maschio and Schiozer 2017).

Some probabilistic methods allow the redefinition of the probability distribution based on the OFs misfit, improving the reservoir knowledge in terms of reservoir characterization. An example of a methodology with this characteristic is the Iterative Discrete Latin Hypercube (IDLHC), method developed by Maschio and Schiozer (2016). The IDLHC is an automated probabilistic method to reduce uncertainty and update probability of the uncertain attributes with nonparametric density estimation. The process consists of applying a correlation matrix to automatically identify relationships between uncertain attributes and OFs. Due to its flexibility in terms of quantity of uncertain attributes and OFs assimilated, it can be adapted to several scenarios of reservoir characterization and information available.

In order to offer a broader understanding and representation of the reservoir model, multi-objective and probabilistic HM processes have been employed. These processes simultaneously evaluate the reservoir behavior through multiple quality indicators associated to observed data in the production and injection wells (Almeida et al. 2014; Kam et al. 2017). Hutahaean et al. (2015) showed that an ensemble of matched scenarios from multi-objective HM provides a more diverse set of matched-scenarios, which leads to a better comprehension on the forecast behavior.

Nevertheless, since multi-objective-HM performance (convergence speed and match quality) can deteriorate under an increasing number of objective functions, Hutahaean et al. (2017) investigates the selection of objective grouping for multi-objective HM. Min et al. (2014) developed an evolutionary algorithm to overcome inefficiencies of multiple-objective constraints by introducing preference-ordering and successive objective reduction to the conventional multi-objective optimization module.

Several studies evaluate the influence of the OF definition in the HM process. For example, Tillier et al. (2013) focused in defining a formulation for incorporating seismic data in the process; Bertolini and Schiozer (2011) compared eight global OFs in the history matching process by assessing the matching quality of synthetic reservoir model.

A normalized misfit called Normalized Quadratic Deviation with Sign computes the difference between simulated and observed data (Avansi et al. 2016). This OF summarizes time-series curves for a scenario (Figure 1-a) in a single indicator (Figure 1-b) and is useful in probabilistic and multi-objective HM approaches (more details in the NQDS section). An acceptance range [-γ, + γ] supports the classification of the scenarios taking into account the sources of errors considered (*e.g.* noise in the history data, measurement errors, level of fidelity of the reservoir simulation model).

Figure 1 - Typical NQDS graphic summarizing data from several scenarios: (a) Curves of oil production rate plotted against time, adapted from Avansi et al. 2016: History data (blue points), selected scenarios that are within an acceptance range ±γ (in gray lines), scenarios with production rates higher and lower than the acceptance range (in brown and red lines respectively); (b) NQDS plot applying the same legend colors, where each dot corresponds to a production rate curve

Due to the high quantity of observed data, especially for long time series, these OFs aggregate into a single indicator, events and temporary trends relevant to reservoir performance. For example, water breakthrough time and changes in the Gas-Oil Rate (GOR) are relevant for the field management; well production trends evolve over time under distinct reservoir conditions (*e.g.* recovery mechanism from natural flow to water/gas injection to pressure maintenance). Different uncertain attributes can influence these events and temporary trends. Once aggregated in a single OF, the relationship between uncertain attributes and OFs may be difficult to capture with mathematical structures as correlation matrix.

Splitting the conventional NQDS into more objective functions is an alternative approach to better understand the reservoir from the dynamic data available. Almeida et al. (2018) presented an introductory study with the application of unconventional OFs to measure the deviation of specific events (Breakthrough Deviation and Productivity Deviation). Each additional OF captures specific well behaviors (not mapped by the conventional OFs) that are influenced by distinct uncertain attributes. Then, the uncertain attributes update process considers the constraints established by both conventional and unconventional OFs. Because of this, the relationships identified between the unconventional OFs and uncertain attributes improved the reservoir calibration and uncertainty reduction process.

1.1. Objectives

This paper aims to evaluate the assimilation of dynamic data series in a way to capture deviations in the breakthrough time and in the well productivity. With that, we aim to assess the possibility of gathering more information from available dynamic data series in the HM process, which improves the reservoir behavior predictability.

When compared to the definitions of Almeida et al. 2018, we propose a distinct way to simulate the scenarios to better capture the physics that surround the well productivity. The proposed computation of Productivity Deviation avoids the influence of other sources of information, such as platform and well capacities, required in the previous work of Almeida et al. 2018. Moreover, this study assesses the additional OFs as a source of information to reveal reservoir behavior, not explored in previous works.

We adapt a history matching methodology (IDLHC from Maschio and Schiozer, 2016) to consider the additional groups of Objective Functions for updating the uncertain attributes and use the same parameterization presented in that paper. Maschio and Schiozer 2016 and 2018 tested the IDLHC methodology and compared it to other methodologies, assuring the quality of the history matching procedure.

2. Theoretical background

After describing the main aspects of the probabilistic HM methodology, this section details the objective functions applied to this proposed work.

2.1. Iterative Discrete Latin Hypercube (IDLHC)

The main advantage of the probabilistic IDLHC methodology proposed by Maschio and Schiozer (2016) is to simultaneously assimilate a large number of OFs to update probability distributions of uncertain attributes. Additionally, the process is flexible in terms of quantity of uncertain attributes and OFs assimilated, being adapted to several scenarios of reservoir characterization and information available. This HM process generates multiple history-matched scenarios per iteration and the last set of scenarios is useful for prediction and optimization studies. In the IDLHC general workflow (Figure 2), the uncertain attributes parameterized in the beginning of the process (Step 2) are the same until the last pre-defined iteration (Iter_{max}). In each iteration, a set of scenarios representing the distribution of uncertain attributes is generated with Discrete Latin Hypercube (DLHC) sampling (Step 3) conceived by Schiozer et al. (2017).

Figure 2 - General workflow for probabilistic history matching (Maschio and Schiozer, 2016).

After running these scenarios in the flow simulator (Step 4), NQDS computation quantifies the misfit between scenarios and observed data for each scenario and objective function (Step 5). In Step 6, selected scenarios are used for the generation of posterior distribution for each uncertain attribute. Maschio and Schiozer (2016) proposed three approaches to update the probability density function (*pdf*) of the uncertain attributes. Figure 3 details method 3, chosen for this study.

Figure 3 - Flow chart from scenario selection, method 3 (Maschio and Schiozer, 2016).

A cut-off (R_c) applied to the coefficients of the correlation matrix (Step 6.1) indicates the existence of relationship between uncertain attributes and objective functions. The *AI* attributes considered correlated to at least one OF are updated. The updating routine starts in Step 6.2 with the first attribute to update, continuing until the last attribute (*AI*). The iterative process around Steps 6.4 to 6.5 guarantees two requirements: (a) a quantity of scenarios between a minimum (*P1*) and a maximum (*P2*) percentage of the scenarios sampled to avoid the collapse of the *pdf*, and (b) the selection of scenarios with smallest computed misfit.

Then, a nonparametric density estimation technique (Step 6.6) leads to updating of uncertain attributes generating histograms representing the posterior distribution of each attribute. These posterior distributions are the prior distributions for the next iteration. The iterative process of Figure 2 continues for the number of iterations predefined ($Iter_{max}$).

2.2. Normalized misfit as indicators of HM quality

In history-matching processes, indicators of quality for a scenario quantify the misfit between the simulation scenario and observed data. Four possible applications are to:

a) conduct the HM process, as objective functions to be minimized;
b) provide data to update the uncertain attributes;
c) diagnose scenarios revealing and guiding the review of reservoir characterization;
d) support the evaluation of performance when comparing different methodologies.

We detail the two out of three normalized misfit groups applied in Step 5 of the HM methodology (Figure 2): NQDS and $NQDS_{BD}$ (NQDS of Breakthrough Deviation). In the methodology section we present the third normalized misfit group $NQDS_{PD}$ (NQDS of Productivity Deviation), because it is subject of modification from previous work.

2.2.1. NQDS

NQDS (Avansi et al. 2016, modified) consolidates the misfit between history and temporal data series of production and injection wells. For example, $NQDS_{qw}$-Well 1 represents the misfit of water rate production for the Well 1 considering a time interval simulated for a given scenario. Similar notation applied to other data series, for example, oil production rate ($NQDS_{qo}$), production BHP ($NQDS_{ppbh}$), water injection rate ($NQDS_{iw}$) and injector BHP ($NQDS_{pibh}$).

Equation 1 computes the NQDS:

$$NQDS = \frac{\left(\sum_{j=1}^{n} Sim_j - Obs_j\right)}{\left|\sum_{j=1}^{n} Sim_j - Obs_j\right|} * \frac{\sum_{j=1}^{n}\left(Sim_j - Obs_j\right)^2}{\sum_{j=1}^{n}\left(Tol * Obs_j + C\right)^2} \tag{1}$$

where Sim_j and Obs_j are the simulated and observed (historical) data measured at the time j. Tol is the tolerance value (%) defined by the user for each data series; C is a constant used to avoid null or excessively small divisor, in case the production rate is close to zero (for example, water production rate in a recently opened well). Physically, the constant C represents the minimal tolerance for a given data series.

2.2.2. Water Breakthrough Deviation ($NQDS_{BD}$)

Water breakthrough is the time when water first reaches the production well. In the field management, this measured time and subsequent Water-Oil Ratio (WOR) trends are usually key performance indicators that also can be indicative of channeling and bypassing problems in the field (Baker 1998).

The historical data of water production in wells is source of two-combined information: (a) water production rate through time, and (b) breakthrough time. In this sense, Almeida et al. (2018) adapted the NQDS as a punctual normalized misfit for breakthrough time (Equation 2), the $NQDS_{BD}$:

$$NQDS_{BD} = \frac{(BT_{sim} - BT_{obs})}{|BT_{sim} - BT_{obs}|} * \frac{(BT_{sim} - BT_{obs})^2}{(AE)^2} \tag{2}$$

where BT is the Breakthrough Time and AE is the Acceptable Tolerance, for example, the maximal time between two consecutive measures of water production. A water rate cut-off to consider water breakthrough time avoids erroneous capture of breakthrough time: smaller water production rates when compared to this cut-off value are treated as residual water production. Even if the water breakthrough has not yet occurred in a given well at the historical period, it may add information to the HM process if some simulation scenarios have earlier breakthrough time.

Figure 4-a exemplifies water production against time for history data and some scenarios. The gray lines represent scenarios with production rate and breakthrough time within the acceptance range [-γ, +γ]. Scenarios 1 and 2 (brown and red lines) have early and late breakthrough time, respectively. Dashed and solid lines correspond to scenarios with matched and non-matched water production rates. The diagnostic of the $NQDS_{qw}$ plot (Figure 4-b) only identifies mismatches in the water production rate,

keeping the two dashed scenarios within the acceptance range. On the other hand, the $NQDS_{BD}$ plot (Figure 4-c) identifies the difference of water breakthrough time for Scenarios 1 and 2. In this graph, two scenarios superpose in the extreme values of $NQDS_{BD}$ because the breakthrough time is identical for dashed and solid lines.

Figure 4 - Breakthrough Deviation illustration - (a) Water production rate series for history data and several scenarios exemplifying differences between the information relative to water production rate and breakthrough time; (b) $NQDSq_w$ plot summarizing the production curves for the scenarios; (c) $NQDS_{BD}$ highlighting the mismatch in water breakthrough time for the scenarios.

3. Methodology: Productivity Deviation, case study, applications and assumptions

3.1. Productivity Deviation ($NQDS_{PD}$)

The transition between history and forecast period can cause fluid rate and bottom-hole-pressure fluctuations (Ranjan et al. 2014). In fact, at this point, the controls of the simulation scenario (boundary conditions) changes: in the history period, liquid or oil production rates are treated as targets; during the forecast period, production restrictions are established (for example, minimal and maximal bottom-hole-pressure for producers and injectors and platform capacity). A possible cause of unconditioned reservoir scenarios is uncertain parameters, which can be wrongly defined or missing during the parameterization.

As large fluctuations in the transition indicate non-realistic forecasted production rates, Almeida et al. (2018) defined an indicator related to the productivity of the well. The normalized misfit of Productivity Deviation ($NQDS_{PD}$) splits the historical dynamic data from wells into two parts simulated differently: (a) history controls, (b) forecast controls. This original implementation of the $NQDS_{PD}$ follows the simulation scenario by changing the control of the last history date from history control to forecast control.

In practical terms, history conditions usually include a target for liquid or oil production rate for the producer wells and forecast conditions apply operational conditions as minimal pressure for producers. Additionally, the simulation of the scenarios in the history period is not conditioned by platform and well restrictions, which is indispensable to perform the forecast simulation.

Two possible limitations may arise from the use of operational conditions to simulate the history period (as presented by Almeida et al., 2018). Firstly, coupling operational conditions in the reservoir simulation requires information that may be uncertain, for example, description of the multiphase flow in wells. Secondly, applying multiple restrictions simultaneously (*e.g.* well and platform capacities) potentially limit the identification of productivity mismatch.

Therefore, we propose an adaptation to the condition given to the last time step of the history from the one presented by Almeida et al. (2018). The measured BHP in the wells are the targets for production and injection wells, meaning that we change the data informed to the simulator. In this way, we limit the informed boundary condition to measured history data. This implementation of the PD indicator is generalizable and independent of other sources of data.

The modifications, in the last time step, of the simulation file are: (a) to reset non-restrictive maximal liquid production and injection for the wells (instead of non-restrictive maximal and minimal pressure applied to previous time steps, *i.e.* all-time steps except the last one); and (b) to inform the registered pressure for each well as new target condition (instead of informing well rates applied to the previous time steps).

Figure 5-a exemplifies, for a given producer well, the deviation for BHP informing the history pressure in the last time t of history. It illustrates most of the scenarios converging the target BHP

condition because (1) liquid rate (Figure 5-b) has no production limit (q_{lmin}=0) and (2) a virtual maximal liquid rate is used to avoid simulation errors (q_{lmax}>>q_l).

Figure 5 - Productivity Deviation illustration - (a) BHP being informed only in the last time step of the history period; (b) Liquid production rate informed for all time steps except the last time steps, where non-restrictive conditions are reset; (c) Indicator of Productivity Deviation for liquid production.

The calculation of the productivity deviation applies to both production wells (*e.g.* for liquid rate - $NQDS_{PDql}$ - and BHP - $NQDS_{PDppbh}$) and injection wells (*e.g.* water rate - $NQDS_{PDiw}$ - and BHP - $NQDS_{PDpibh}$). Equation 3 computes the $NQDS_{PD}$:

$$NQDS_{PD} = \frac{(Sim_t - Obs_t)}{|Sim_t - Obs_t|} * \frac{(Sim_t - Obs_t)^2}{(tol * Obs_t + C)^2} \quad (3)$$

where Obs_t and Sim_t indicate the observed and simulation value in the last time (t) of the history data.

The $NQDS_{PDql}$ plot (Figure 5-c) indicates the deviation of simulated scenarios compared to the reference data. We consider that the scenarios in gray better present well productivity. Therefore, we expect that scenarios with smaller PD will provide better production predictions.

3.2. Case study

We applied the IDLHC methodology (Figure 2) in the UNISIM-I-H reservoir model (Avansi and Schiozer, 2015). This benchmark case is based on real data from the Namorado Field, a marine offshore turbidite reservoir in the Campos Basin – Brazil.

Figure 6 - Bi-dimensional *x-y* view of the UNISIM-I-H with the position of the 13 regions defined by Maschio and Schiozer (2016). The production strategy contains 14 production wells (in red) and 11 injection wells (in green). Wells analyzed in detail in the *Results and Discussion* section are identified: INJ015, NA3D, PROD025A, PROD023A and PROD024A.

The model UNISIM-I- H (Figure 6) has a production strategy with 14 producer wells and 11 injection wells and a production history of 11 years (4 018 days) available. The production forecast data for 19 years allows for the evaluation of methodologies in terms of predictability of the scenarios.

3.2.1. Initial parameterization

The parameterization defined in Step 2 (Figure 2) has 39 uncertain parameters as defined by Maschio and Schiozer (2016). Figure 6 retakes the 13 regions defined according to producer/injector pairs, attempting to capture the main drainage areas. Each region has multipliers of porosity (*mpor*), horizontal permeability (*mkx*) and vertical permeability (*mkz*). Isotropic permeability is taken for *x* and *y* direction; initial *pdf* has uniform distribution for all levels. Table 1 summarizes these uncertainties.

Table 1 - Uncertain attributes presented by Maschio and Schiozer (2016).

3.3. Applications

Two applications performed in this study compute different groups of OFs:

- Application 1: 64 OFs, groups of $NQDS_{qo}$, $NQDS_{qw}$, $NQDS_{ppbh}$, for producer wells and $NQDS_{iw}$, $NQDS_{pibh}$ for injector wells;
- Application 2: 128 OFs resulting from adding the 64 OFs of Application 1, plus the additional OF groups ($NQDS_{BD}$, $NQDS_{PDql}$, $NQDS_{PDppbh}$, $NQDS_{PDiw}$ and $NQDS_{PDpibh}$).

In the *Results and Discussion* section, we compare their results for the field and wells in the history and forecast period.

3.4. Assumptions

Table 2 summarizes the constants and tolerances for each OF applied in the calculation of the normalized misfit. Like Avansi et al. (2016), we defined 5% for controlled-data series ($NQDS_{iw}$); 10% for data series that are dependent on other series ($NQDS_{qo}$ and $NQDS_{qw}$, which are related to liquid rate, a target in the history period). Pressure related NQDS considers a tolerance of 5%. We applied a constant of 10 m^3/day for $NQDS_{qw}$ to moderate its impact on wells with low water rate production through a representative part of the history period. For example, the well NA3D production (Figure 7) reaches a maximum of 150 m^3/day and for this production, the tolerance adds up to 10+0.10*150=25 m^3/day. Higher constant would imply in smaller influence of the variations in q_w of this well in the updating process.

Table 2 - Constants used to calculate normalized misfit.

$NQDS_{BD}$ has an AE of 31 days, the maximum interval between measurements. Productivity deviation are under forecast controls and under uncontrolled conditions. Therefore, we chose a tolerance of 10% for $NQDS_{PDql}$ and $NQDS_{PDiw}$, defining a minimal tolerance of 10 m^3/day for liquid production.

The cut-off applied to consider water breakthrough is 1 m^3/day for all the producers, except for NA3D with 6 m^3/day. Figure 7 shows the observed water production rate for this well, highlighting the portion of water rate considered residual. Applying 1 m^3/day cut-off for this well would mean to consider the breakthrough time of 669 days, which does not correspond to the effective breakthrough time of 3 226 days.

Figure 7 - Water production rate for well NA3D in the history period.

Considering the recommendations proposed by Maschio and Schiozer (2016), the applications consider:

- 450 simulation scenarios per iteration in Steps 3 and 4;
- A cut-off R_c=0.3 to the coefficients of the correlation matrix in Step 6.1;
- An increment of the normalized misfit δ=1 in Step 6.5;
- A minimum *P1*=5% and a maximum *P2*=15% of scenarios sampled to update the attributes;
- A maximal number of iterations $Iter_{max}$=8, set in the beginning of the process.

Moreover, to guarantee the reproducibility of the applications, the first run of the applications uses the same seed, following the random numeric generation twister.

4. Results and Discussions

To evaluate the assimilation of dynamic data series breaking down the conventional NQDS into more objective functions, we firstly exposed their impact with an overview of the indicators for the wells together with the field behavior. Then, examples of additional OFs of some wells were used to complement the discussion. We decided on that approach because details for each of the 128 OFs individually were not feasible, with multiple relationships between OF and uncertain attributes.

The plots presented in this section consider the 450 scenarios of the 8th iteration in the HM process. In order to promote a clean visualization of the impact in the forecast period and avoid fluctuations from changing boundary conditions, these final scenarios were simulated again with liquid production and water injection rate as target during all the history period and the same operation conditions of the reference case in the forecast period.

4.1. History Period

The compilation of the results for the OFs allows for a broader evaluation on the general behavior of the wells resulting from the implementation of the additional OFs. Figure 8 presents graphics for several OFs groups plotting the number of scenarios against the NQD[1] interval, from zero to the *x*-axis value. The higher the proportion of scenarios for a given NQD interval, the better. The *x*-axis is in logarithmic scale.

The assimilation of additional OFs (Application 2) reduces the mismatch of the OFs groups that have higher NQD values in Application 1 ($NQDS_{PDql}$ and $NQDS_{PDiw}$, Figure 8-a and -b). In contrast, the increased complexity of the HM through the assimilation of additional OFs leads to increasing the NQD values of traditional OF groups, exemplified by $NQDS_{qo}$ (Figure 8-c).

Figure 8 – Proportion of scenarios against the NQD interval for OFs groups, semi-logarithmic scale: (a) $NQDS_{PDql}$ for 14 production wells; (b) $NQDS_{PDiw}$ for 11 injection wells; (c) $NQDS_{qo}$ for 14 production wells. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

This analysis indicated that a comparison based only on the history period is insufficient. Therefore, in the next sections, we explore forecast data available for the benchmarking case.

4.2. Transition from history to forecast period

During the history period, the water injection rate is a target for the injection wells in the simulation. We expect scenarios very close to the reference data in this period. Nevertheless, the transition to the forecast period (Figure 9-a) shows fluctuations in the field rate when compared to the reference data. Application 2, including the additional OFs (in brown), provides less fluctuations and smother transition than Application 1.

Figure 9 - Distinct field behavior observed for the final scenarios of the Application 1 (in green) and the Application 2 (in brown) including the history period (4 018 days) added to 5 years of production forecast: (a) Field water injection rate with smaller fluctuation in the transition for the final scenarios of the application that considers additional OFs; (b) Reservoir average pressure with a bias for both application in most of the history period, but Application 2 scenarios with better forecast and larger variability. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

The average reservoir pressure (Figure 9-b) presents a bias for both applications in most of the history period: all the scenarios have reservoir pressure below the reference, and limited variability is observed. This is related to the fact that the initial liquid volume in place (oil and water) of the scenarios are smaller than the reference model (between 87-92% and 88-97% for Applications 1 and 2, respectively). Some scenarios of Application 2 are closer to the reference pressure in the end of the history period and it is closer to the reference in the 5-year forecast period (5 843 days of production). Note that the reservoir (and well) pressure is above the bubble point (around 210.03 kgf/cm^2), justifying the omission of the OFs related to gas production rate.

These results indicate that adding the OF groups related to Productivity Deviation and Breakthrough Deviation has the potential to limit oscillatory behavior and improve the transition between history and forecast periods.

[1] NQD (Normalized Quadratic Deviation) is the absolute value of the NQDS.

4.3. Forecast period

We use risk curves to evaluate the field forecast behavior (Figure 10). In these curves, the cumulative oil production is ploted with the cumulative relative frequency observed in the 450 scenarios. Further than the two applications, we also plot the cumulative oil production for the first iteration (in gray) where all the uncertain attributes are in uniform prior distribution and the value of the reference model (black dotted line).

The three forecast period selected (one, five, and 19 years) show more scenarios closer to the reference value for Application 2. These graphs support that the inclusion of the new OFs has the potential to positively influence the predictability of field behavior.

Figure 10 - Forecast period, risk curves for the scenarios of iteration 1 and iteration 8 for the two Applications for: (a) 1 year; (b) 5 years and (c) 19 years. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

In the next sections, some OFs illustrate the results in terms of well behavior, individually.

4.4. Breakthrough Deviation

The assimilation of $NQDS_{BD}$ in Application 2 leads to the improvement of the breakthrough time of the scenarios for most wells. From the analysis of importance of the OFs groups assimilated in the application (Appendix A), Breakthrough Deviation was the additional OF group that contributed the most in the Application 2. Figure 11 shows the water production rate, $NQDS_{qw}$ and $NQDS_{BD}$ for the well PROD024A. Application 2 presents smaller breakthrough deviation than Application 1. In addition, the water rate of Application 2 is closer to the reference when compared to Application 1.

Figure 11 - Well PROD024A: (a) Water production rate for the 450 scenarios of both applications in the history period; (b) Indicative of better $NQDS_{qw}$ for Application 2; (c) $NQDS_{BD}$ of the well PROD024A revealing improvement in the BD, but still with a significant mismatch. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones

Water production of the well NA3D (Figure 12-a) indicates that neither water rate nor breakthrough time match the history data for both applications. The inclusion of the $NQDS_{BD}$ in the process was not sufficient to adjust the water breakthrough time (Figure 12-b) and, for some scenarios, lead to a worse water rate production (Figure 12-c). In fact, the parameterization is limited to the regional multipliers and this result indicates the need of adding different uncertain parameters, for example, flow barriers with uncertain transmissibility.

Figure 12 - Well NA3D: (a) Water production rate for 450 scenarios of each application; (b) $NQDS_{BD}$ revealing large mismatch for all scenarios of both applications; (c) $NQDS_{qw}$ with some scenarios in the same range for both applications. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones

Therefore, a benefit of the additional OFs is to assist the identification of limitations in the reservoir parameterization defined. The analysis of these extra indicators of reservoir quality can be useful when reviewing the reservoir parameterization by supplying supplementary information to the scenarios' diagnostics, identifying unnoticed problems in the traditional approach.

4.5. Productivity Deviation

With the implementation of $NQDS_{PD}$, we observe an improvement in the transition from history to forecast periods for several wells as expected from the field results (Figure 9). The objective functions related to water injection rate and liquid production rate have higher impact in the history matching process. In the Appendix A, we show that this OFs groups are used to update a higher number of uncertain attributes when compared to $NQDS_{PD\mathit{ppbh}}$ or $NQDS_{PD\mathit{pibh}}$. The justification for this behavior refers to the definition of Productivity Deviation setup, which has BHP define as boundary condition to the last time step (target informed to the simulator).We select as example production well (NA3D) and injection well (INJ015) to exemplify the positive impact of the assimilation of the additional OFs.

Figure 13-a presents BHP for the well NA3D during history and forecast periods with a total of 5 844 days (5 years of forecast). The plots $NQDS_{\mathit{ppbh}}$ and $NQDS_{PD\mathit{ppbh}}$ (Figure 13-b and -c) highlight pressure of the well closer to the reference (Application 2) data and with more variability around the history pressure than Application 1. In this sense, the scenarios of Application 2 are considered better conditioned than those in Application 1 for the OFs analyzed. Jointly, these graphs provide evidence that scenarios with smaller indicators of Productivity Deviation provide better forecast behavior.

Figure 13 - Well NA3D: (a) Bottom hole pressure of well NA3D with history data and 5 years of forecast (total 5 844 days), (b) $NQDS_{\mathit{ppbh}}$ and (c) $NQDS_{PD\mathit{ppbh}}$ highlighting the differences between the applications. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

The transition of water injection between history and forecast period improved for several wells. The injection rate for well INJ015 (Figure 14-a) and its corresponding $NQDS_{PDiw}$ (Figure 14-b) is an example of better conditioning of scenarios in the transition.

Figure 14 - Well INJ015: (a) Water injection rate of well with history data and 5 years of forecast (total 5 844 days), (b) $NQDS_{PD\mathit{iw}}$ highlighting the fluctuations in the last point of the history data simulated with forecast conditions. $NQDS_{\mathit{iw}}$ omitted because all scenarios matched the history data. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

4.6. Detailing some OFs with poorer match

We also observe some objective functions with higher misfit for Application 2 than for Application 1. For these OFs, the addition of the unconventional OFs is not beneficial.

In our example, we explore the OFs of the well PROD023A. We detail this analysis from the bottom hole pressure for the history and 5-years forecast period (Figure 15-a). Highlighted by the NQDS plots (Figure 15-b and -c), the scenarios of Application 2 are limited to scenarios with higher-pressure levels than the reference. At the same time, Application 1 presents scenarios with higher variability, including scenarios with lower pressure values and closer to the reference.

Figure 15 - Well PROD023A – (a) Bottom hole pressure of well with history data and 5 years of forecast (total of 5 844 days); (b) $NQDS_{\mathit{ppbh}}$ showing the scenarios of Application 2 (in brown) limited to models with higher-pressure levels than the reference, meanwhile, Application 1 (in green) has more scenarios in the range [-10, +10]; (c) $NQDS_{PD\mathit{ppbh}}$ showing that the assimilation of additional OFs is not beneficial for some OFs. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

The *mkz* of the region 12 influences only the $NQDS_{ppbh}$ well PROD023A in the Application 1 (Figure 16) but 6 OFS in the Application 2 ($NQDS_{ppbh}$, $NQDS_{PDppbh}$ of the well PRD023A and $NQDS_{PDql}$ of the wells PROD023A, PROD024A and PROD025A, Figure 17). For the second application, in order to provide a better match for $NQDS_{PDql}$ PROD025A, this uncertain attribute is updated in a detrimental manner from the perspective of the other OFs.

We investigate this effect through the correlation matrix, identifying the relationship between uncertain attributes and OFs. In the IDLHC methodology (Figure 3, step 6.1), the correlation matrix with the cut-off R_c captures this relationship for each of the 8 iterations. The number of iterations that a given OF is correlated to an uncertain attribute is added up and presented in two plots: Figure 16 and Figure 17 consider traditional and additional OFs, respectively. Each line corresponds to an uncertain attribute. In Figure 16, the R12 line corresponds to the region 12. White color means that the correlation coefficient is lower than the cut-off *Rc* in any iteration. Black color means that the correlation is higher than the cut-off *Rc* in all the 8 iterations. The transitional colors correspond to intermediate values between 0 and 8 iterations.

The groups of the 64 conventional (Figure 16) and additional OFs ($NQDS_{BD}$ and $NQDS_{PD}$ – Figure 17) are plotted in the matrix with the uncertain attributes. Our focus is on the behavior of the objective functions influenced by *mkz* (R12), marked with vertical lines in the plots. The analysis of the attribute *mkz* (R12) is direct because the only conventional OF correlated to it is the $NQDS_{ppbh}$-PROD023A. Figure 16 is built with data from Application 1. The attributes for vertical permeability multiplier (*mkz*) of region 12 are marked with a horizontal line because it influences the $NQDS_{ppbh}$-PROD023A. Because Application 2 has this same relationship, we do not present correlation matrix computed for the additional OFs.

Figure 16 - Matrix identifying the correlations captured in the 8 iterations for the group of 64 conventional OFs, Application 1. Black color means that the correlation was of higher value than the cut-off R_c in all the 8 iterations. White color means that the correlation coefficient is lower than the cut-off R_c in any iteration. The transitional colors correspond to intermediate values between 0 and 8 iterations, as presented by the legend. The orange lines highlight the intersection between attributes and OFs mentioned in the text.

For Application 2, the $NQDS_{PDppbh}$ of the well PROD023A (Figure 15) is highlighted together with the other OFs influenced by this attribute (vertical lines).

Figure 17 - Matrix identifying the correlations captured in the 8 iterations for the $NQDS_{PD}$ and $NQDS_{BD}$ objective functions, Application 2. Black color means that the correlation was of higher value than the cut-off R_c in all the 8 iterations. White color means that the correlation coefficient is lower than the cut-off R_c in any iteration. The transitional colors correspond to intermediate values between 0 and 8 iterations, as presented by the legend. The orange lines highlight the intersection between attributes and OFs mentioned in the text.

We observe that the $NQDS_{PDql}$ of the well PROD025A (Figure 18-a and -b) is closer to the reference in Application 2.

Figure 18 - The attribute mkz (R12) influences the NQDSPDql of the well PROD025A – (a) Liquid production rate in the history period for both applications highlighting the ranges of productivity deviation in the last history time step; (b) NQDSPDql of the well PROD025A highlighting smaller fluctuation in the transition between history and forecast period for Application 2 than for Application 1. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC

methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

We also present the final distribution of the attribute *mkz* of region 12 (Figure 19). On one hand, Application 1 (in green) presents a higher number of levels (variability) as well as higher multiplier values. On the other hand, Application 2 distribution (in brown) is concentrated to less levels and smaller multipliers (to the left of the *x*-axis).

Figure 19 - mkz of Region 12, an attribute correlated to the well PROD023A. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

This attribute contributed to the behavior described for this OF: smaller *kz* leads to a BHP closer to the reference for PROD025A (the scenarios in Application 1 have lower pressure when compared to Application 2 and the history data). Therefore, $NQDS_{ql}$ for this well is smaller (Figure 18) because the liquid production rate of several scenarios does not diminish as much as in Application 1 to honor the informed pressure.

To summarize this example explaining why some OFs presented poorer match in the Application 2, this uncertain attribute (*mkz* R12) influences traditional and additional OFs ($NQDS_{ppbh}$, $NQDS_{PDppbh}$ and $NQDS_{PDql}$). In order to provide a better match for the $NQDS_{PDql}$-PROD025A, the *pdf* concentrates in some levels but is detrimental to other OFs ($NQDS_{ppbh}$ and $NQDS_{PDppbh}$ of PROD023A).

This result indicates that with a large number of OFs assimilated, and a large quantity of uncertain attributes to update, the relationships between OFs and attributes increases the challenge to match the dynamic behavior and all OFs assimilated.

5. Conclusions

We evaluated the impact of gathering and considering additional information from the dynamic data series in the History Matching (HM) performance. We presented a deep analysis of the assimilation of dynamic data series in an unconventional way, which is based on splitting the available historic time-series into more Objective Functions (OFs), detaching relevant events observed in the historical data. The OFs included measuring the Breakthrough Deviation (BD) and Productivity Deviation (PD).

We proposed an adaptation for the calculation of the additional objective function called Productivity Deviation (PD), which only uses information from the history data. It changes the information provided to the simulator from liquid production or water injection rate to bottom hole pressure.

Two applications show different field and well behavior in the scenarios of the last iteration of the history matching process. The main identified advantages of the unconventional OFs in the HM matching process for this study case were:

- Smoother transition between history and forecast periods for field data;
- Water breakthrough time closer to the reference data for several wells and scenarios;
- Additional indicators of quality of the reservoir model to support the review of parameterization: revealing problems in scenarios unnoticed by applying only the traditional OFs;
- Final scenarios with better predictability behavior of the field in short (1-year), mid (5-years) and long (19-years) term.

Nevertheless, when considering the additional OFs, we observed a situation with traditional OF groups, presenting more distant scenarios from the history data. In fact, the HM problem becomes more complex to solve with the additional OFs because the uncertain attributes considered influence more the OFs. In order to accommodate these additional OFs in the HM process, some traditional OFs result in higher mismatch.

The improved predictability of the simulation scenarios indicates that superior performance of HM process is possible by splitting the available dynamic data. At the same time, the evidences shown in this paper encourage the continuous improvement of HM methodologies and new approaches of data assimilation, which are able to accommodate a higher number of uncertain attributes and OFs.

Nomenclature

BD	Breakthrough Deviation
BHP	Bottom Hole Pressure
DLHC	Discrete Latin Hypercube
HM	History Matching
IDLHC	Iterative Discrete Latin Hypercube
$Iter_{max}$	Maximal number of iterations in IDLHC
i_w	water injection rate
NQD	Normalized Quadratic Deviation
NQDS	Normalized Quadratic Deviation with Sign
OF	Objective Function
PD	Productivity Deviation
pdf	probability density function
p_{ibh}	Bottom hole pressure of injection wells
p_{pbh}	Bottom hole pressure of production wells
q_o	Oil production rate
q_w	Water production rate
R_c	Cut-off to the coefficients of the correlation matrix

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Appendix A: Analysis of importance of OF groups

The graphics below present all the objective functions disposed in groups according to the respective type of production data and application (Application 1 in green, Application 2 in brown). The bar's height represents the number of attributes that a given OF was selected to update uncertain attributes during all iterations. A horizontal line with the mean of all wells supports the differentiation between the two applications. Note that OFs from Figure 20, 21 and 22-*a* are assimilated in both Applications, but from Figure 22-*c*, 23 and 24, only in the Application 2. Also, the plots are in the same scale in y-axis.

NQDS for oil and water rate (Figure 20-a and -b) have similar importance along the wells, with slight difference in the mean values. These plots evidence the complementarity between water and oil production when a simulation model is close to or meets the target values of liquid production informed to the simulator.

Figure 20 – Number of attributes that a given OF was selected to update uncertain attributes by well: (a) NQDSqo; (b) NQDSqw. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

Water injection rate is the boundary condition informed to the simulator in the history period, with exception to the last time which the target is set to be BHP. In Figure 21-a, the mean number of attributes of $NQDS_{iw}$ is higher for Application 2 than for Application 1. Nevertheless, $NQDS_{iw}$ does not update more than two uncertain attributes for any well.

Figure 21 – Number of attributes that a given OF was selected to update uncertain attributes by well: (a) $NQDS_{iw}$; (b) $NQDS_{pibh}$. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

The mean number of attributes of $NQDS_{ppbh}$ is close to 4 for both applications (Figure 22-a), which indicates similar importance. Figure 22-b presents the NQDS of Breakthrough Deviation, which has the higher mean of uncertain attributes updated among the additional objective functions.

Figure 22 – Number of attributes that a given OF was selected to update uncertain attributes by well: (a) NQDSppbh; (b) NQDSBD. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones

Because in the last time step the BHP is a target for the simulator, $NQDS_{PDql}$ group updates more uncertain attributes than $NQDS_{PDppbh}$, on average. Mismatches related to $NQDS_{PDppbh}$, have too small variability for some wells (for example, PROD024A, RJS019) or are uncorrelated with uncertain attributes (for example PROD010).

Figure 23 – Number of attributes that a given OF was selected to update uncertain attributes by well: (a) $NQDS_{PDql}$; (b) $NQDS_{PDppbh}$. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

The same reasoning is applicable for PD of water injection and BHP of injectors. $NQDS_{PDiw}$ groups updates more attributes than $NQDS_{PDpibh}$, on average.

Figure 24 – Number of attributes that a given OF was selected to update uncertain attributes by well: (a) NQDSPDiw; (b) NQDSPDpibh. Note: Application 1 assimilates 64 Objective Functions traditionally applied in the IDLHC methodology, and Application 2 considers 128 Objective Functions consisting in the traditional and proposed ones.

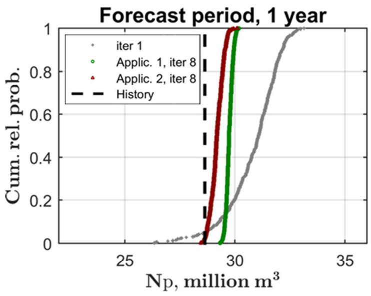
This analysis indicates that among the OFs groups added in the history matching process, the Breakthrough Deviation was more relevant in the process of updating uncertain attributes for the study case applied in this paper.

Table 1 - Uncertain attributes presented by Maschio and Schiozer (2016).

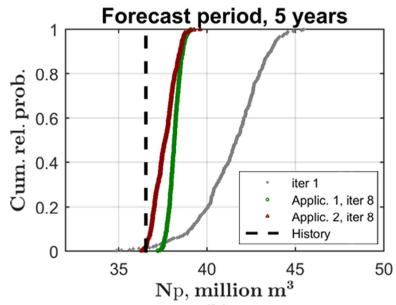
Uncertain attributes (for each region)	Minimum	Maximum	Number of levels	Initial pdf
mpor	0.8	1.2	30	Uniform
mkx	0.1	5.0	30	Uniform
mkz	0.1	5.0	30	Uniform

Table 2 - Constants used to calculate normalized misfit.

OF	C (unit of the variable)	Tol (%)
$NQDS_{qo}$	0	10
$NQDS_{qw}$	10	10
$NQDS_{ppbh}$	0	5
$NQDS_{iw}$	0	5
$NQDS_{pibh}$	0	5
$NQDS_{BD}$	AE=31	0
$NQDS_{PDql}$	10	10
$NQDS_{PDppbh}$	0	5
$NQDS_{PDiw}$	0	10
$NQDS_{PDpibh}$	0	5

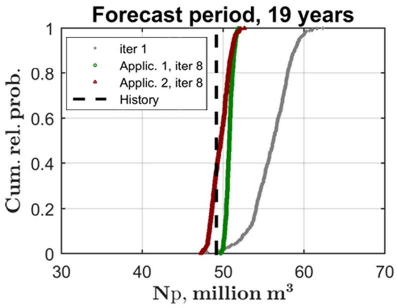

Forecast period, 1 year
iter 1
Applic. 1, iter 8
Applic. 2, iter 8
History
Cum. rel. prob.
1
0.8
0.6
0.4
0.2
0
25
30
35
Np, million m^3

(a)

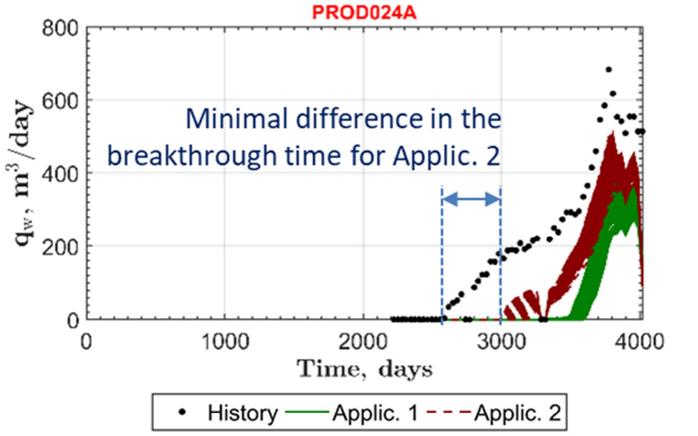


Forecast period, 5 years
Cum. rel. prob.
1
0.8
0.6
0.4
0.2
0
35
40
45
50
Np, million m^3
iter 1
Applic. 1, iter 8
Applic. 2, iter 8
History

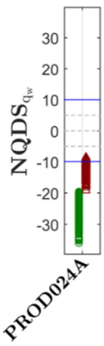
(b)


Forecast period, 19 years
Cum. rel. prob.
Np, million m3
iter 1
Applic. 1, iter 8
Applic. 2, iter 8
History
0
0.2
0.4
0.6
0.8
1
30
40
50
60
70

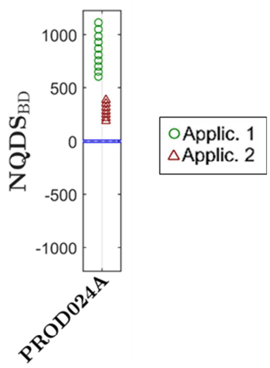
(c)


PROD024A
800
600
400
200
0
0
1000
2000
3000
4000
q_w, m^3/day
Time, days
Minimal difference in the
breakthrough time for Applic. 2
History
Applic. 1
Applic. 2

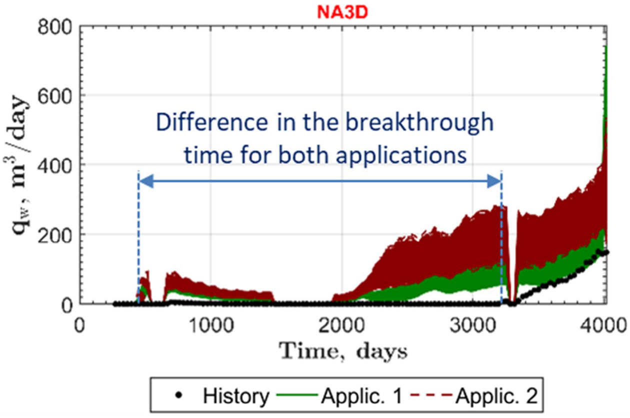
(a)



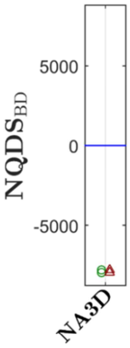
(b)



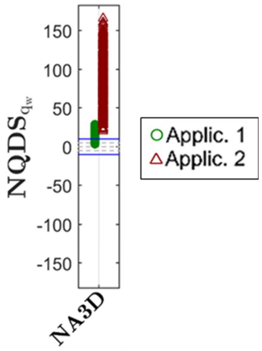
(c)


NA3D
800
600
400
200
0
0
1000
2000
3000
4000
q_w, m^3/day
Time, days
Difference in the breakthrough
time for both applications
History
Applic. 1
Applic. 2

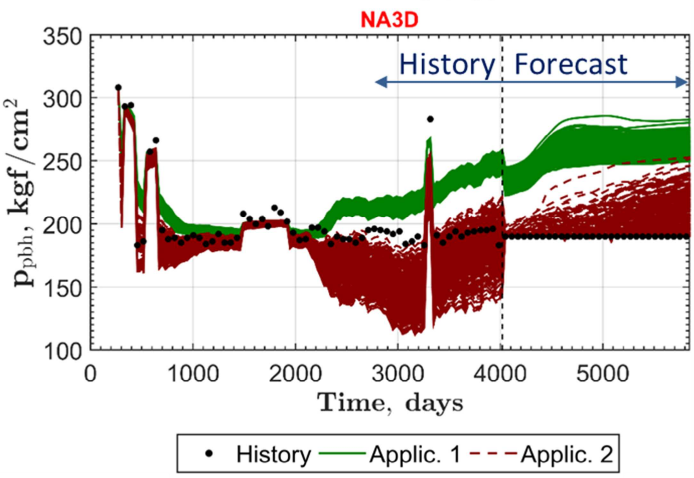
(a)



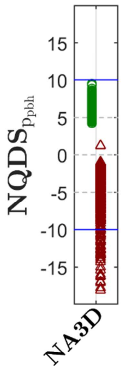
(b)



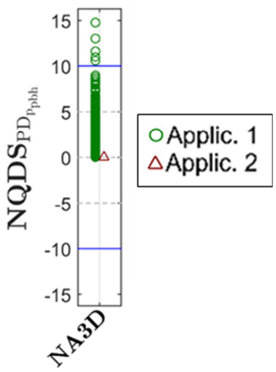
(c)


NA3D
History
Forecast
350
300
250
200
150
100
0
1000
2000
3000
4000
5000
p_{pbh}, kgf/cm^2
Time, days
History
Applic. 1
Applic. 2

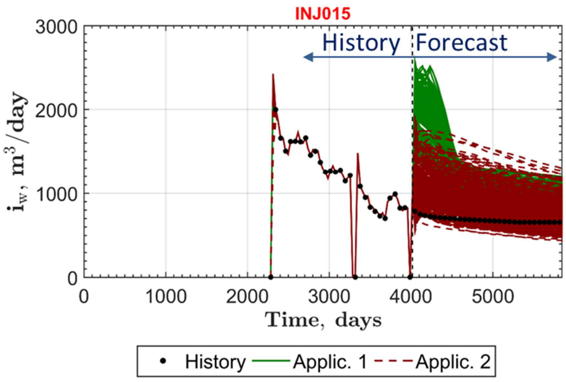
(a)



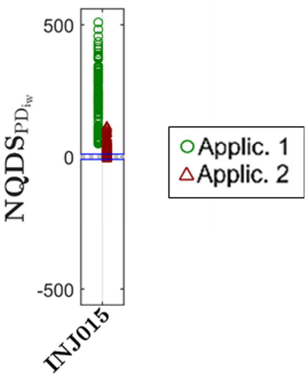
(b)



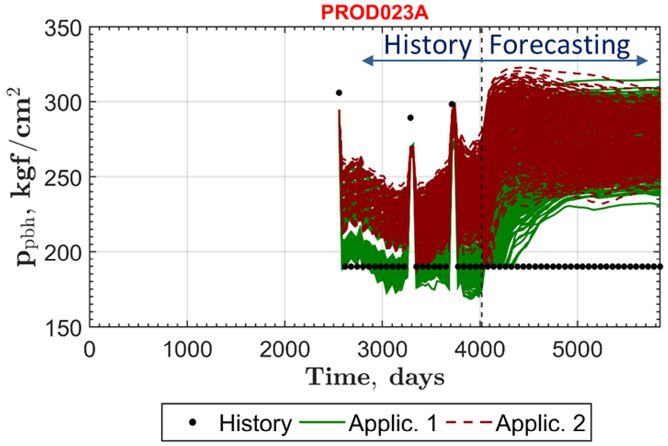
(c)


INJ015
History
Forecast
3000
2000
1000
0
i_w, m^3/day
0
1000
2000
3000
4000
5000
Time, days
History
Applic. 1
Applic. 2

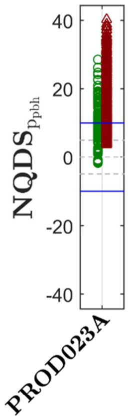
(a)



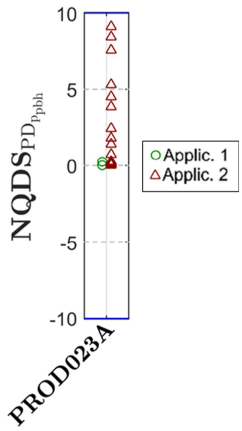
(b)


PROD023A
History
Forecasting
350
300
250
200
150
0
1000
2000
3000
4000
5000
p_{pbh}, kgf/cm^2
Time, days
History
Applic. 1
Applic. 2

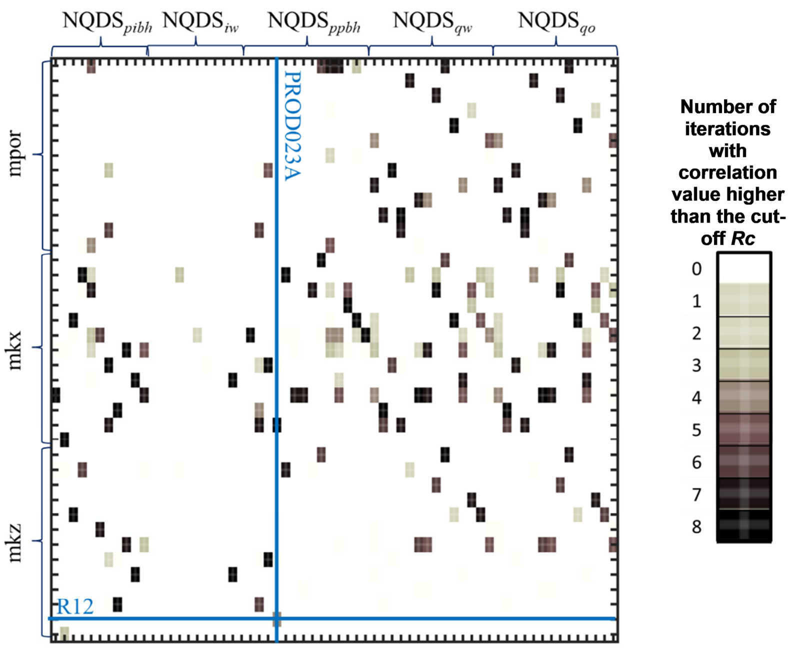
(a)



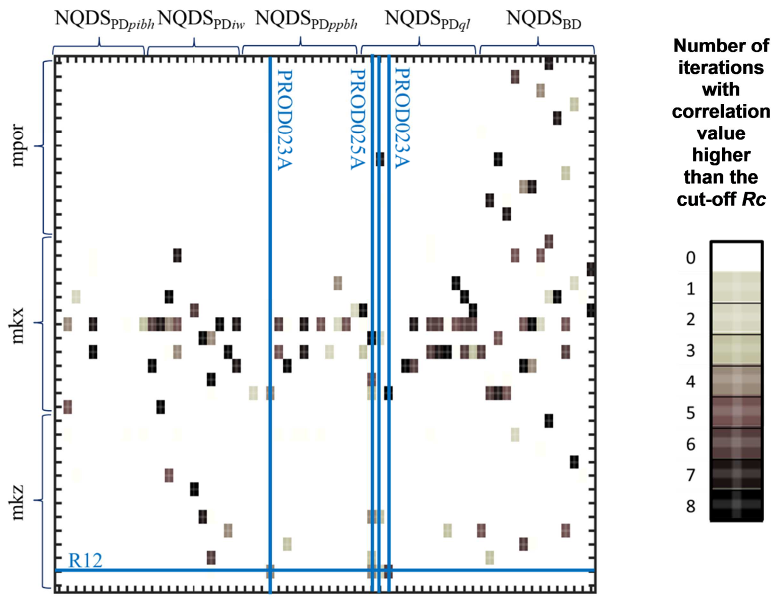
(b)

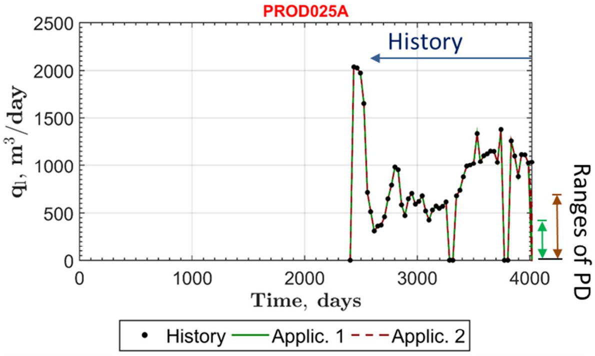


(c)

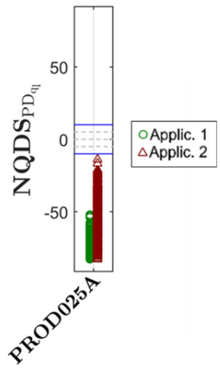


NQDS$_{pibh}$
NQDS$_{iw}$
NQDS$_{ppbh}$
NQDS$_{qw}$
NQDS$_{qo}$
mpor
mkx
mkz
PROD023A
R12
Number of iterations with correlation value higher than the cut-off *Rc*
0
1
2
3
4
5
6
7
8

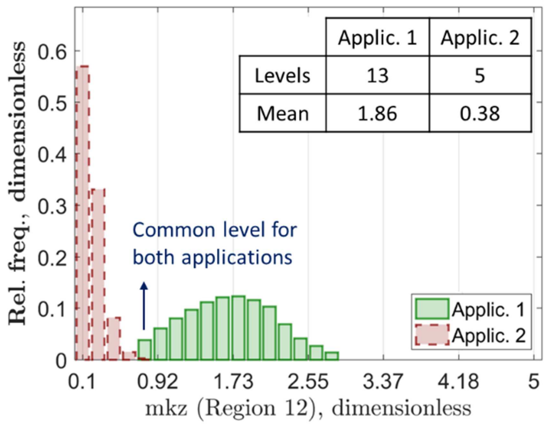

NQDS$_{PDpibh}$
NQDS$_{PDiw}$
NQDS$_{PDppbh}$
NQDS$_{PDql}$
NQDS$_{BD}$
mpor
mkx
mkz
PROD023A
PROD025A
PROD023A
R12
Number of iterations with correlation value higher than the cut-off *Rc*
0
1
2
3
4
5
6
7
8


PROD025A
History
q_l, m^3/day
Time, days
Ranges of PD
History
Applic. 1
Applic. 2

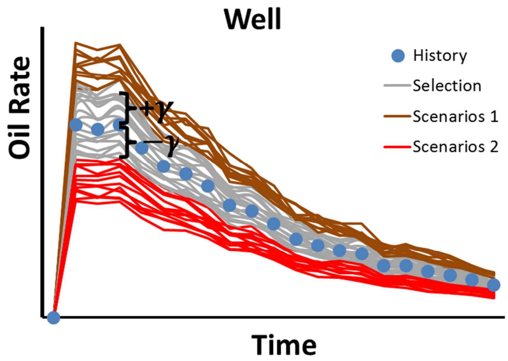
(a)



(b)

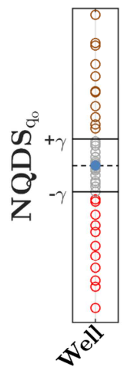


Rel. freq., dimensionless
0.6
0.5
0.4
0.3
0.2
0.1
0
0.1
0.92
1.73
2.55
3.37
4.18
5
mkz (Region 12), dimensionless
Applic. 1
Applic. 2
Levels
13
5
Mean
1.86
0.38
Common level for
both applications
Applic. 1
Applic. 2

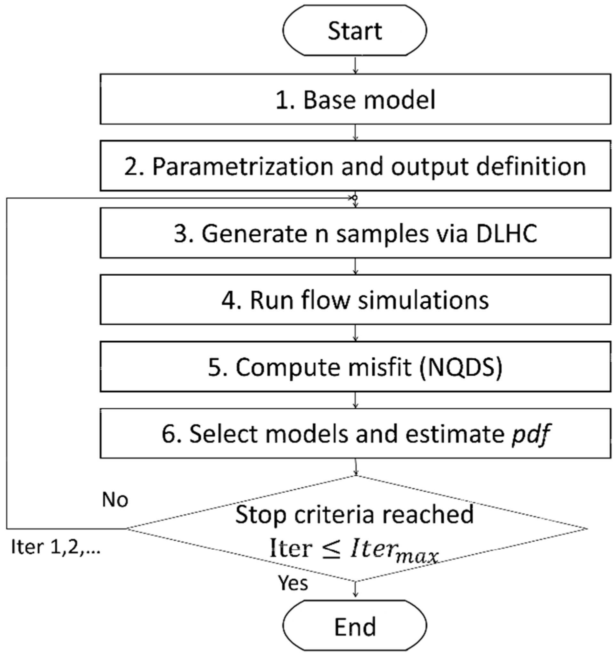


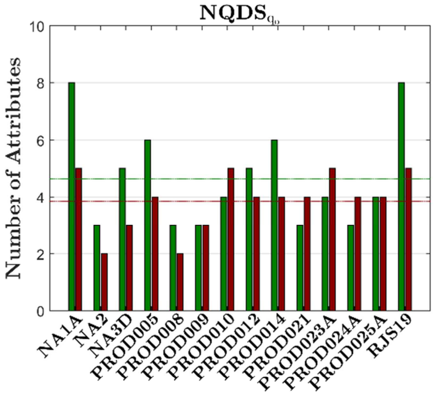
Well
History
Selection
Scenarios 1
Scenarios 2
Oil Rate
Time
+γ
−γ

(a)

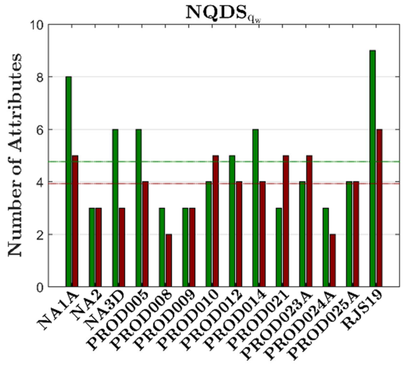


(b)

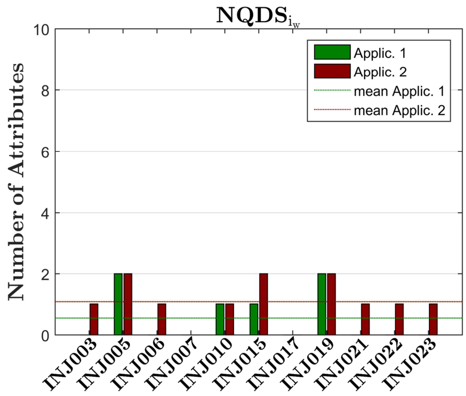

Start
1. Base model
2. Parametrization and output definition
3. Generate n samples via DLHC
4. Run flow simulations
5. Compute misfit (NQDS)
6. Select models and estimate *pdf*
No
Iter 1,2,...
Stop criteria reached
$\mathrm{Iter} \leq Iter_{max}$
Yes
End


NQDS
Number of Attributes
0
2
4
6
8
10
NA1A
NA2
NA3D
PROD005
PROD008
PROD009
PROD010
PROD012
PROD014
PROD021
PROD023A
PROD024A
PROD025A
RJS19

(a)

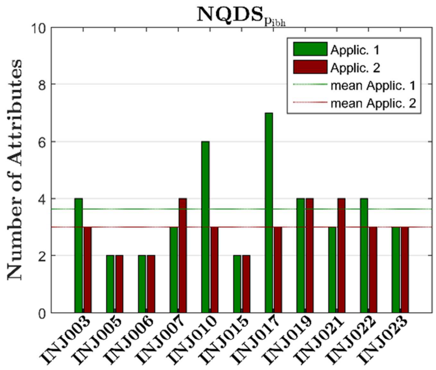

$\mathbf{NQDS}_{q_w}$
Number of Attributes
10
8
6
4
2
0
NA1A
NA2
NA3D
PROD005
PROD008
PROD009
PROD010
PROD012
PROD014
PROD021
PROD023A
PROD024A
PROD025A
RJS19

(b)

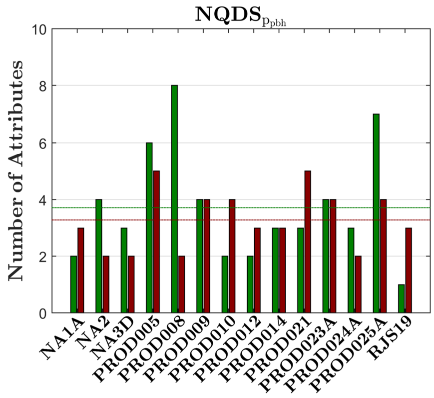


$\mathbf{NQDS_{i_w}}$
Number of Attributes
10
8
6
4
2
0
Applic. 1
Applic. 2
mean Applic. 1
mean Applic. 2
INJ003
INJ005
INJ006
INJ007
INJ010
INJ015
INJ017
INJ019
INJ021
INJ022
INJ023

(a)

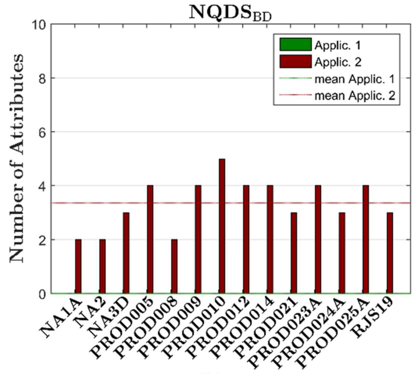

$\mathbf{NQDS_{p_{lbh}}}$
Number of Attributes
Applic. 1
Applic. 2
mean Applic. 1
mean Applic. 2
INJ003
INJ005
INJ006
INJ007
INJ010
INJ015
INJ017
INJ019
INJ021
INJ022
INJ023

(b)

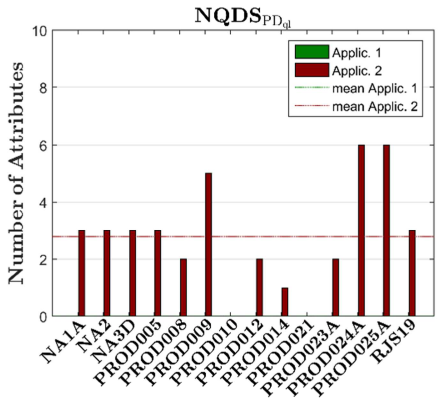


$\mathbf{NQDS}_{\mathrm{p_{pbh}}}$
Number of Attributes
0
2
4
6
8
10
NA1A
NA2
NA3D
PROD005
PROD008
PROD009
PROD010
PROD012
PROD014
PROD021
PROD023A
PROD024A
PROD025A
RJS19

(a)

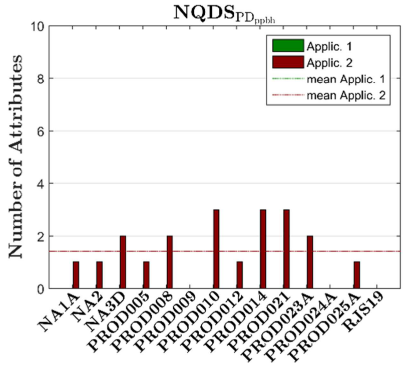

$NQDS_{BD}$
Number of Attributes
Applic. 1
Applic. 2
mean Applic. 1
mean Applic. 2
0
2
4
6
8
10
NA1A
NA2
NA3D
PROD005
PROD008
PROD009
PROD010
PROD012
PROD014
PROD021
PROD023A
PROD024A
PROD025A
RJS19

(b)



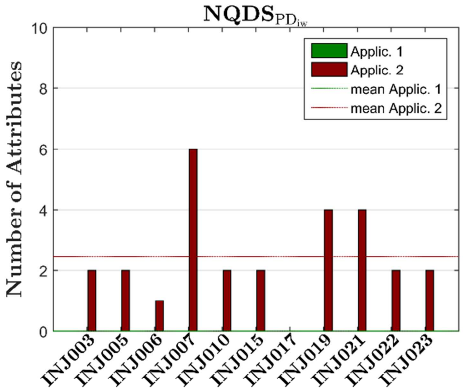
$\mathbf{NQDS}_{\mathrm{PD_{ql}}}$
Number of Attributes
Applic. 1
Applic. 2
mean Applic. 1
mean Applic. 2
NA1A
NA2
NA3D
PROD005
PROD008
PROD009
PROD010
PROD012
PROD014
PROD021
PROD023A
PROD024A
PROD025A
RJS19

(a)



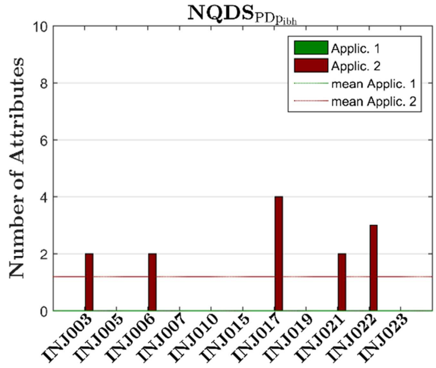
$\mathbf{NQDS}_{\mathrm{PD_{ppbh}}}$
Number of Attributes
Applic. 1
Applic. 2
mean Applic. 1
mean Applic. 2
0
2
4
6
8
10
NA1A
NA2
NA3D
PROD005
PROD008
PROD009
PROD010
PROD012
PROD014
PROD021
PROD023A
PROD024A
PROD025A
RJS19

(b)

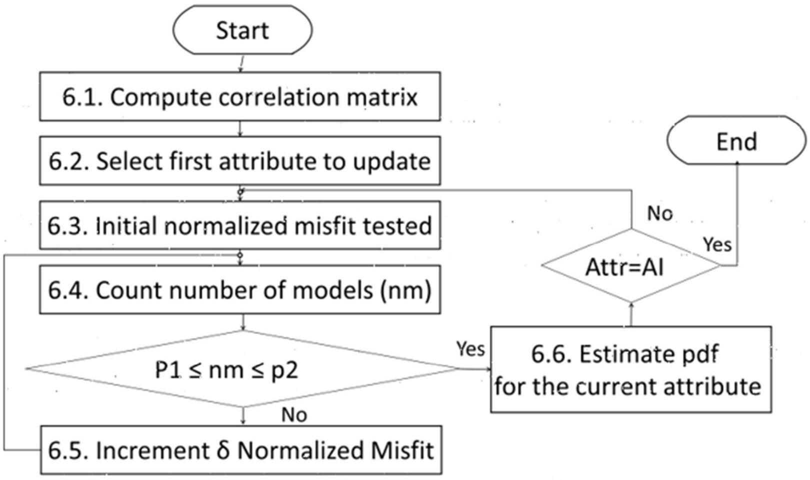


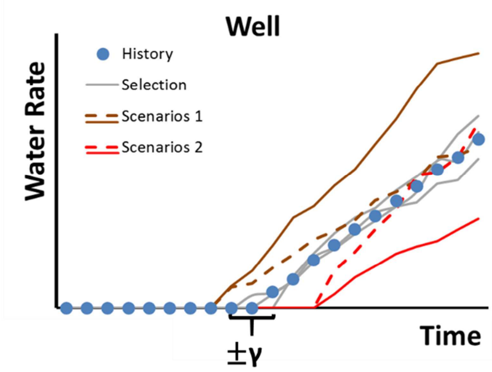
$\mathbf{NQDS}_{\mathrm{PD}_{\mathrm{iw}}}$
Number of Attributes
Applic. 1
Applic. 2
mean Applic. 1
mean Applic. 2
INJ003
INJ005
INJ006
INJ007
INJ010
INJ015
INJ017
INJ019
INJ021
INJ022
INJ023

(a)

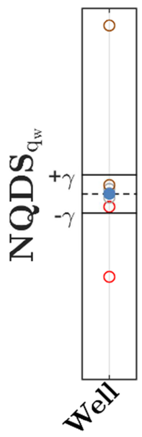

$\mathbf{NQDS}_{PDp_{ibh}}$
Number of Attributes
Applic. 1
Applic. 2
mean Applic. 1
mean Applic. 2
10
8
6
4
2
0
INJ003
INJ005
INJ006
INJ007
INJ010
INJ015
INJ017
INJ019
INJ021
INJ022
INJ023

(b)

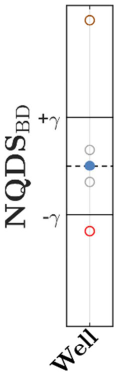

Start
6.1. Compute correlation matrix
6.2. Select first attribute to update
6.3. Initial normalized misfit tested
6.4. Count number of models (nm)
P1 ≤ nm ≤ p2
Yes
No
6.5. Increment δ Normalized Misfit
6.6. Estimate pdf for the current attribute
Attr=AI
Yes
No
End


Well
History
Selection
Scenarios 1
Scenarios 2
Water Rate
Time
±γ

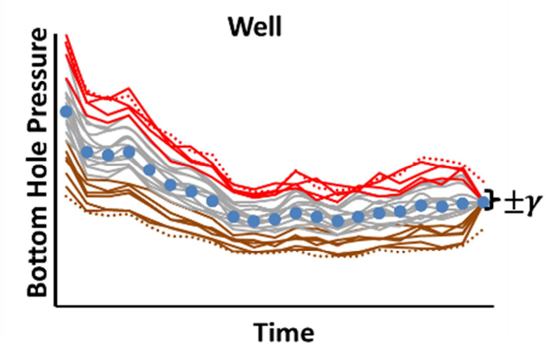
(a)



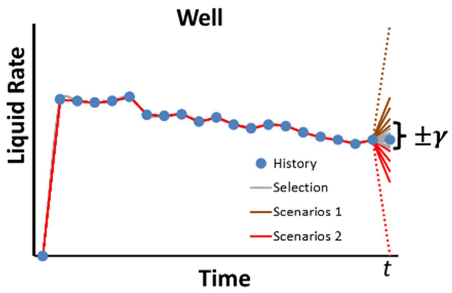
(b)



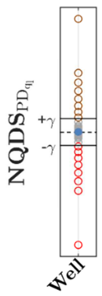
(c)



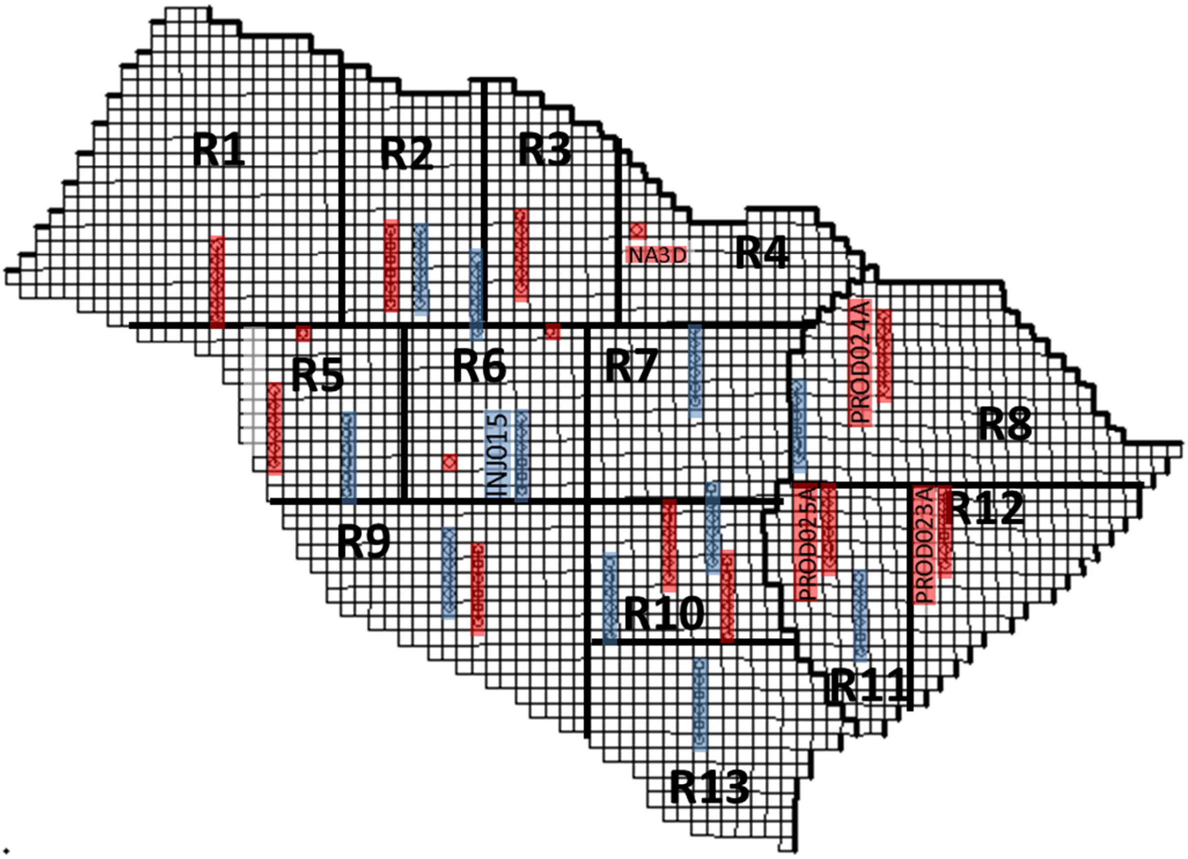
(a)

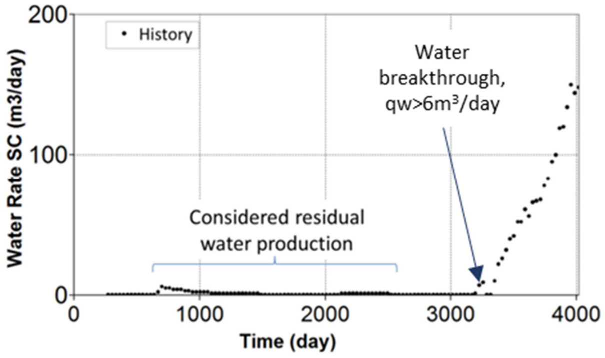

Well
Liquid Rate
Time
t
±γ
History
Selection
Scenarios 1
Scenarios 2

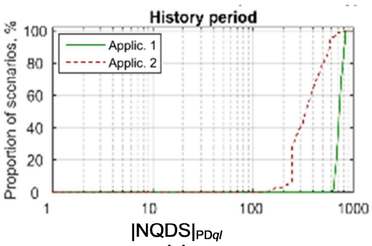
(b)



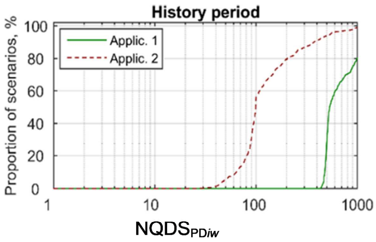
(c)


R1
R2
R3
NA3D
R4
R5
R6
R7
PROD024A
R8
INJ015
R9
R10
PROD025A
PROD023A
R12
R11
R13

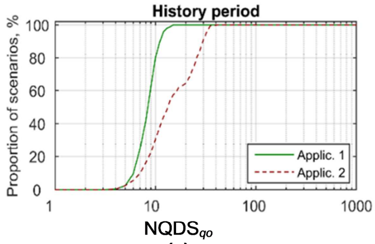

History
Water breakthrough, qw>6m³/day
Considered residual water production
Water Rate SC (m3/day)
Time (day)
200
100
0
0
1000
2000
3000
4000


History period
Applic. 1
Applic. 2
Proportion of scenarios, %
100
80
60
40
20
0
1
10
100
1000
|NQDS|PDql

(a)

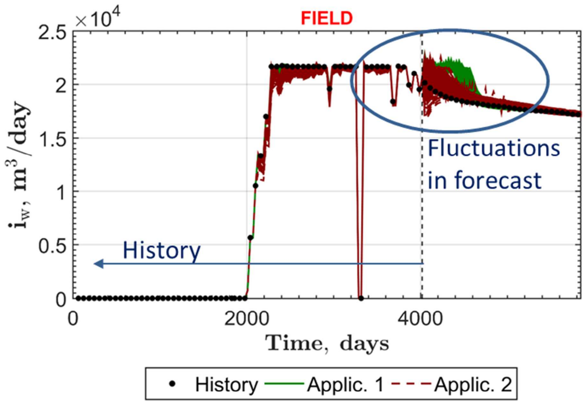

History period
Proportion of scenarios, %
100
80
60
40
20
0
Applic. 1
Applic. 2
1
10
100
1000
NQDSPDiw

(b)

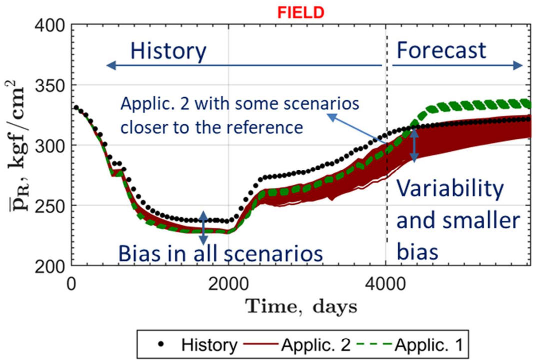


History period
Proportion of scenarios, %
100
80
60
40
20
0
1
10
100
1000
NQDS$_{qo}$
Applic. 1
Applic. 2

(c)


FIELD
×10^4
2.5
2
1.5
1
0.5
0
i_w, m^3/day
0
2000
4000
Time, days
Fluctuations in forecast
History
History
Applic. 1
Applic. 2

(a)



FIELD
History
Forecast
Applic. 2 with some scenarios
closer to the reference
Variability
and smaller
bias
Bias in all scenarios
400
350
300
250
200
0
2000
4000
$\overline{p}_R$, kgf/cm^2
Time, days
History
Applic. 2
Applic. 1

(b)

Highlights

- Better understanding about reservoir behavior by splitting available data in new OF
- Reveal parameterization problems unnoticed by traditional procedures
- Better predictability behavior of the field in short, mid and long term
- Smoother transition between history and forecast periods