Extended abstract – Balancing Static and Dynamic Match and Uncertainty Quantification in Stochastic History Matching

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Abstract

The inherent uncertainties in reservoir models pose a major concern for decision making in the development and management of hydrocarbon reservoirs. Uncertainties in reservoir models result from sparse and indirect data measurements that can compromise the production forecasting reliability. History matching is usually used to reduce uncertainties in reservoir modelling related to observed dynamic data but often neglects the geological consistency of the model. Therefore, although being able of reproducing the dynamic response of the reservoir, the models may be characterized by unrealistic geological features. The present work proposes a geologically consistent methodology for reservoir history matching implemented in a standard industry benchmark case. The history matching process encompasses the use of a multi-objective optimisation approach with adaptive stochastic sampling, the Multi-Objective Particle Swarm Optimisation. Geological parameters are optimised and the match to petrophysical properties and production variables is obtained. The uncertainty of predictions is quantified and characterized by Bayesian inference techniques such as Neighbourhood Algorithm-Bayes and Bayesian Model Averaging. The proposed methodology proved that under different model parameterisations, the quality of the dynamic matches is still good and the static data are reproduced better. A good balance between static and dynamic objectives can be identified leading to model distributions more realistic. When inferring predictions, the different model parameterisations not only showed reliable forecasting at individual wells but also regarding cumulative oil and water production with the truth being encapsulated in the credible interval P10-P50-P90.

Keywords: History matching; Multi-Objective Particle Swarm Optimisation; Bayesian inference; good balance; static and dynamic.

1. Introduction

Reservoir simulation is a valuable tool for the decision-making process involved in field development and management. A reservoir simulation model combines rock and fluid properties with a mathematical formulation to describe the fluid flow in porous media (i.e., the reservoir static model). This model is then used to predict the performance of the reservoir by incorporating all relevant information available about the field. In the petroleum literature, history matching is known as the process of incorporating dynamic data in reservoir models and characterized for being an ill-posed inverse problem with non-unique solutions. The amount of independent data available is much less than the number of variables and multiple realisations of the reservoir may give equally good matches to available data (Gilman & Ozgen, 2013).

Over the last years, increased importance has been attributed to the quantification of uncertainty in reservoir performance predictions and reservoir description (Gilman & Ozgen,
It is now more frequent to generate multiple history matched models in order to assess uncertainty about the model parameters. However, generating an ensemble of history matched models that can reproduce the real reservoir observed historical data, does not inevitably lead to a correct assessment of uncertainty (Tavassoli, 2004). Nevertheless, the fact that good quality matches for the production data are obtained does not necessarily mean that the corresponding geology of the reservoir is being realistically reproduced due to the non-unique nature of the history matching.

History matching has been tackled using stochastic population-based algorithms which can be approached by single objective (SO) or multi-objective (MO). When compared to the SO, the MO approach not only increases the speed in the matching but also the diversity in the models found that produce the same low misfits as in the single objective matching (Christie et al., 2013). Furthermore, under different model parameterisations the multi-objective matching still results in a more diverse set of models leading to a more robust and reliable forecast (Hutahaean et al., 2015). According to the literature, the MO approach has only been applied to match production variables which leads to a gap in knowledge regarding the match to petrophysical properties.

In this context, this study aims the development of a methodology for history matching using a multi-objective optimisation (MOO) approach to obtain a simultaneous match to static and production data. The methodology was implemented in the PUNQ-S3 reservoir.

2. Methodology

The methodology proposed under the scope of this thesis poses history match as a multi-objective problem minimizing simultaneously an objective composed by the differences between real and optimised static data at the well locations and other with the difference between observed and simulated production data. The models belonging to the resulting Pareto fronts are used to balance the trade-offs between the objective with the difference in the static data and the objective with the difference in the production data. The workflow for the proposed methodology is illustrated in Figure 1, and can be summarized by the following sequence of steps:

1 – Definition of the parameterisation of the geological model;
2 – Optimisation of the geological parameters of the model using the MOPSO algorithm;
3 – Introduction of the optimised petrophysical properties in the static objective for minimization;
4 – Run a flow simulator to obtain the dynamic response of the optimised model;
5 – Introduction of the simulated dynamic response in the dynamic objective for minimization;
6 – Minimization of both objectives and identification of the models (Pareto Models) that best approximate both petrophysical properties and dynamic response to the truth case;
7 – Characterization and quantification of the uncertainty of predictions of the ensemble of history matched models recurring to the Neighbourhood Algorithm-Bayes algorithm.

The Bayesian Model Averaging was then applied to combine the forecast for the different model parameterisations and obtain a single forecast model.
To evaluate the performance and ability of the proposed MOO technique in both history matching and uncertainty characterization of predictions, the scheme of objective grouping used in this approach was adopted from previous study (Hutahaean et al., 2015) in which the wells are grouped based on geo-engineering judgement in the reservoir model studied.

Figure 1 – Workflow used for history matching the model to static and dynamic data.

The results of the proposed MOO approach were benchmarked against a history matching procedure driven exclusively by the mismatch between dynamic data (Figure 2). After optimising the geological parameters and obtaining the dynamic response of the model from a flow simulator, the algorithm minimizes the misfit function and consequently identifies the reservoir model that best approximates its dynamic response to the historical production behaviour of the field. The uncertainty of predictions of the ensemble of history matched models is then characterized and quantified using the Neighbourhood Algorithm-Bayes algorithm.

Figure 2 - Workflow used for history matching the model to dynamic data.

Five runs of history matching, each with 500 iterations were used to infer about the consistency of the results. The history matching procedure is done using Epistemy's Raven, which is an assisted history matching software using a multi-objective optimisation approach powered by the Particle Swarm Optimisation algorithm. This software is integrated with the fluid flow simulator Eclipse® (Schlumberger) to simulate the fluid flow in each model. The Forecasting and Uncertainty Characterization process is assessed through the study of the uncertainty envelopes obtained for each model parameterisation.
3. Application Example

3.1. PUNQ-S3 Field Description

The PUNQ-S3 model contains 19 x 28 x 5 grid blocks, each one with equal side in the x and y directions of 180 meters, of which 1761 blocks are active. It consists of five layers and the field has six production wells located around the gas-oil contact with no injection wells (Floris et al., 2001). For history matching the model, eight years of production history data which includes gas-oil ratio (WGOR), water cut (WWCT) and borehole pressure (WBHP), are used (Floris et al., 2001). As the available production of the field lasts for 16.5 years, the following 8.5 years were forecasted in terms of production based on the history matched models.

3.2. Different Model Parameterisations

To assess the performance of the proposed history matching approach, different model parameterisations were tested, consisting on a set of 24 parameters. This model set is described as a deltaic coastal plain reservoir with three good quality sand channels of uniform thickness and spacing in layer 1, 3 and 5, encased in a background floodplain. Layers 2 and 4 are classified in a single zone as poor-quality shale and sand, respectively. This gives a total of 12 zones (Figure 3), with 3 channels in each layer 1, 3 and 5, 1 floodplain, 1 homogeneous layer 2 and 1 homogeneous layer 4 (Floris et al., 2001). Each zone has a corresponding parameter for porosity and another for horizontal permeability multiplier, resulting in a total of 24 parameters.

![Figure 3 - Map of model parameterisation in PUNQ-S3 for all 5 layers.](image-url)

3.2.1. Parameterisation A

Model parameterisation A, although based on the geological facies description of PUNQ-S3 to define the porosity range for each zone (Table 1), the prior ranges for the different petrophysical properties were not set considering the prior distributions from the truth case (TC).

<table>
<thead>
<tr>
<th>Zone</th>
<th>Porosity range (fraction)</th>
<th>Kh range (mD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channels (layer 1, 3, 5)</td>
<td>0.15 – 0.30</td>
<td>13 - 30000</td>
</tr>
<tr>
<td>Background floodplain</td>
<td>0.05 – 0.15</td>
<td>1.5 – 1330</td>
</tr>
<tr>
<td>Homogeneous layer (2 and 4)</td>
<td>0.05 – 0.15</td>
<td>1.5 - 1330</td>
</tr>
</tbody>
</table>

\[
\ln(K_h) = \ln(\text{Mult}) + (0.77 + 9.03\delta) \quad (1)
\]

\[
K_v = 3.124 + 0.306K_h \quad (2)
\]

In the model, horizontal and vertical permeabilities are correlated from porosity values obtained based on least square fitting of well data crossplots, using Equations 1 and 2.
This model parameterisation was only used to history match to the production data using the workflow described for history matching the model exclusively to dynamic data.

### 3.2.2. Parameterisation B

In model parameterisation B the prior distributions of the parameters were modified based not only in the distributions of the TC but also in the range in which porosity and permeability vary between wells within the same zones of the model (Table 2). The correlation between porosity and permeabilities is the same used in model parameterisation A (Equations 1 and 2).

<table>
<thead>
<tr>
<th>Zone</th>
<th>Porosity range (fraction)</th>
<th>Kh range (mD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channels (layers 1, 3, 5)</td>
<td>0.05 – 0.30</td>
<td>8 – 1065</td>
</tr>
<tr>
<td>Floodplain (layers 1, 3, 5)</td>
<td>0.08 – 0.30</td>
<td>3 – 903</td>
</tr>
<tr>
<td>Homogeneous layer 2</td>
<td>0.03 – 0.12</td>
<td>1 – 107</td>
</tr>
<tr>
<td>Homogeneous layer 4</td>
<td>0.11 – 0.22</td>
<td>40 – 630</td>
</tr>
</tbody>
</table>

To evaluate the quality of the matches to the petrophysical properties (porosity, horizontal permeability and vertical permeability) at the wells and therefore characterize the uncertainty related to the porous media, acceptance limit values ($\sigma$) for the different properties had to be assigned. Considering the values of these properties at each well and the description of analogue depositional environments and facies, 6 different facies were defined and the wells belonging to the same facies type were grouped. The $\sigma$ were assigned to make a distinction between the facies with good capacity for the fluids to flow, storage hydrocarbons and the ones which have an impermeable behaviour (Table 3). Model parameterisation B was history matched using the proposed methodology to obtain the match for both static and dynamic data (B Sta&Dyn) and also the methodology to obtain the dynamic match only (B Dyn).

<table>
<thead>
<tr>
<th>Petrophysical Property</th>
<th>Facies Type</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fluvial</td>
</tr>
<tr>
<td></td>
<td>Channel</td>
</tr>
<tr>
<td>Phi (fraction)</td>
<td>0.1</td>
</tr>
<tr>
<td>Kh (mD)</td>
<td>200</td>
</tr>
<tr>
<td>Kv (mD)</td>
<td>100</td>
</tr>
</tbody>
</table>

### 3.2.3. Parameterisation C

In model Parameterisation C not only the facies, prior distributions and $\sigma$ were adjusted but also a new zone orientation was tested. The orientation of the channels from layers 1, 3 and 5 was changed as their orientation in the original model is not geologically coherent with the TC. The sigmas used for the different facies types of the wells for history matching the model are shown in Table 4. The ranges in which the parameters vary are similar to the TC (Table 5).
Table 4 - Sigmas assigned to the petrophysical properties (porosity, horizontal permeability and vertical permeability) for the different facies types.

<table>
<thead>
<tr>
<th>Petrophysical Property</th>
<th>Facies type</th>
<th>Fluvial Channel</th>
<th>Floodplain Mudstone</th>
<th>Lagoonal Shales</th>
<th>Distal Mouthbar</th>
<th>Mouthbar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phi (fraction)</td>
<td></td>
<td>0.1</td>
<td>0.03</td>
<td>0.01</td>
<td>0.02</td>
<td>0.05</td>
</tr>
<tr>
<td>Kh (mD)</td>
<td></td>
<td>200</td>
<td>20</td>
<td>10</td>
<td>20</td>
<td>100</td>
</tr>
<tr>
<td>Kv (mD)</td>
<td></td>
<td>100</td>
<td>10</td>
<td>4</td>
<td>10</td>
<td>40</td>
</tr>
</tbody>
</table>

For the floodplain zone and homogeneous layers 2 and 4, the porosity and both permeabilities are correlated using the same equations as in model parameterisations A and B. Regarding the channels from layers 1, 3 and 5, the corresponding correlation from the truth case per individual layer was used. Model parameterisation C was history matched using the proposed methodology (C Sta&Dyn) and also the methodology to obtain the dynamic match (C Dyn).

Table 5 - Porosity and horizontal permeability ranges for the different zones used in model parameterisation C.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Porosity Range (fraction)</th>
<th>Kh range (mD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channels (layers 1, 3, 5)</td>
<td>0.12 – 0.30</td>
<td>14 – 1170</td>
</tr>
<tr>
<td>Floodplain (layers 1, 3, 5)</td>
<td>0.01 – 0.12</td>
<td>0.7 – 178</td>
</tr>
<tr>
<td>Homogeneous layer 2</td>
<td>0.01 – 0.17</td>
<td>0.7 – 201</td>
</tr>
<tr>
<td>Homogeneous layer 4</td>
<td>0.01 – 0.22</td>
<td>0.7 – 514</td>
</tr>
</tbody>
</table>

4. Results

4.1. Misfit Convergence

Figure 4 presents the dynamic and static average minimum misfit per iteration for five runs of the different model parameterisations using both methodologies. The dynamic match of model A is the one characterized by the lowest average dynamic misfit value (4.31 at iteration 512), followed by the dynamic match of model B (4.96 at iteration 426) and model C (5.24 at iteration 280). Models C Sta&Dyn and B Sta&Dyn parameterisations show an average dynamic minimum misfit of 6.44 at iteration 436 and 10.83 at iteration 460, respectively. B Sta&Dyn model description never achieves values close to the global lowest average misfit while model C Sta&Dyn parameterisation reaches the global lowest misfit at iteration 436.

Regarding the static average minimum misfit, model description C is characterized by the lowest value (14.09 at iteration 370) contrasting with the static match of model parameterisation
Model C not only shows the highest convergence speed but also finishes with a lower value of average static misfit when compared to model B.

4.2. Matching the Production Variables

The results presented in Figure 5 correspond to the Pareto Models obtained from the first run of the history match to the production variables (WBHP, WGOR, WWCT) at some individual wells of model parameterisations B and C using the proposed methodology. The dynamic match of the different model parameterisations is not presented in this figure as it is of very good quality. Like it happens with the methodology to match exclusively the production variables, the Pareto Models obtained from the static and dynamic match of both model descriptions B and C (Figure 5) have the ability to reproduce the dynamic response of the reservoir as seen at particular wells (WBHP at Well PRO5; WGOR at Well PRO11; WWCT at Well PRO4). For the static and dynamic match of model B, although some Pareto Models present poor quality matches at Well PRO5, the majority of the Pareto Models are included in the error assumed for the historical data.

![Figure 5 - Dynamic matches of the different production variables at particular wells (WBHP at Well PRO5; WGOR at Well PRO11; WWCT at Well PRO4).](image)

4.3. Geological Consistency

The application of the proposed methodology not only improved the quality of the matches to the petrophysical properties at the wells but also the overall model distributions when compared with the methodology to obtain exclusively the dynamic mismatch.

Figure 6 illustrates the Phi/PermX and PermX/PermZ joint distributions of the Pareto Models for Fluvial Channel Fills (FCF), Floodplain Mudstones (FM), Lagoonal Shales and Distal Mouthbar (layer 2) and Lagoonal Clays and Mouthbar (layer 4) facies types. Although both layers 2 and 4 are featured by different facies types, they are plotted as single layers as there are only one parameter for porosity and another for horizontal permeability multiplier matching each layer. The Figure shows that only the Pareto Models obtained from the static and dynamic match of model parameterisation C reproduce the same Phi/PermX and PermX/PermZ joint distributions types seen in the TC for the different facies. Although the Pareto Models from the dynamic match of model description C also present similar joint distributions (Phi/PermX and PermX/PermZ) of the truth, for layer 4 they tend to concentrate their values in the top parts of both correlations.
Model parameterisations B Dyn and B Sta&Dyn generate Pareto Models that do not entirely follow the trend of the Phi/PermX joint distribution for FCF and FM. For layer 2, they have the ability of reproducing the Phi/PermX and PermX/PermZ joint distributions but regarding layer 4, the same happens as with model description C. In this layer, while the static and dynamic match of model B shows an identical distribution characteristic of the truth, the dynamic match concentrates their values in the top parts of both Phi/PermX and PermX/PermZ joint distributions. Model A is characterized by completely different joint distributions from the truth for the different facies types.

The best dynamic matches at well scale are obtained with the methodology for the dynamic match of the different model parameterisations but the current section proves that these models are not geologically consistent with the truth. On the other hand, when applying the proposed methodology, which encompasses history matching the models to static and dynamic data, it was proved that the models have the ability of reproducing both the dynamic response of the system (section 4.2) and the geological properties of the TC.

4.4. Pareto Front

Comparing both B Sta&Dyn and C Sta&Dyn model parameterisations, C is the one that produces the most consistent Pareto Front models across runs and so less spread of models that can be a solution to the history matching process (Figure 7). Although C Sta&Dyn
parameterisation produces a narrower Pareto Front, and therefore a less diverse set of possible solutions, it minimizes the misfit associated with the static and dynamic matches in a more efficient way than model B Sta&Dyn parameterisation.

![Pareto Front Models for the static and dynamic match of model parameterisations B and C.](image)

**Figure 7** - Pareto Front Models for the static and dynamic match of model parameterisations B and C.

### 4.5. Forecasting Reliability

Figure 8 presents forecasts of production variables used in the history match at some individual wells (WBHP at Well PRO1; WWCT at Well PRO4) for model parameterisations B and C obtained in the first run from both methodologies. Not only the models history matched with the methodology to obtain the dynamic match (i.e. WBHP at Well PRO1 from model C) are able to give reliable predictions but also the models history matched with the proposed methodology (i.e., WWCT at Well PRO4 from model B; WBHP at Well PRO1 from model C). Moreover, at some individual wells, the proposed methodology has the ability to generate reliable and wider P10-P90 credible interval when compared with the methodology to obtain exclusively the dynamic match (i.e., WWCT at Well PRO4).

![Forecasting of production variables (WWCT at Well PRO4; WBHP at Well PRO1).](image)

**Figure 8** - Forecasting of production variables (WWCT at Well PRO4; WBHP at Well PRO1).

Bayesian Model Averaging (BMA) based in dynamic likelihood and static and dynamic likelihood was used to combine the predictions for cumulative oil and water production from model parameterisations A, B Sta&Dyn and C Sta&Dyn. The results presented correspond to the predictions of cumulative oil (FOPT) based in static and dynamic likelihood as similar results were obtained for BMA based in dynamic likelihood. C Sta&Dyn model description is characterized by the maximum static and dynamic likelihood and so is considered the reference model for calculating Normalised Bayes Factor. The BMA uncertainty envelope (Figure 9 (a)) for FOPT (369361.27 sm³) encompasses part of the envelope of model A (260961.19), all envelope of
model B (198620.23 \text{sm}^3) and almost all model C (367892.92 \text{sm}^3). Regarding the average FOPT for the five runs of the different model parameterisations, with the exception of B Dyn model description, the forecasts of FOPT at the end of production from both type of matches and BMAs are reliable with the P10-P90 interval encapsulating the truth value (Figure 9 (b)). The credible interval obtained for the history matched models to static and dynamic data is more reliable and robust than the intervals obtained from the same models only matched to dynamic data.

The P10-P90 interval obtained from model description C Sta&Dyn not only produces a mean P50 close to the truth history value but also has a range of uncertainty comparable with the stochastic uncertainty associated with the True geostatistical model related to the random seed.

5. Conclusions

This work shows that under different model parameterisations the Pareto Models generated in the history matching to static and dynamic data are capable of reproducing the dynamic response of the truth case at well scale. The resulting petrophysical properties in the model are geologically consistent with the reservoir leading to overall model distributions more realistic. The ensemble of history matched models generated is able to give reliable production predictions at well and field scales with more reliability and robustness. Finally, the more geological information from the field is added to the model, the more realistic are the results.

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