History Matching of Interference Tests in the Dogger Formation – Paris Basin: Comparison of a Bayesian Framework and a Multi-Objective Optimization Approach

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ABSTRACT
Getting reliable production forecasts is a key aspect of any geothermal project. A preliminary and mandatory (but not sufficient) step is to history match the associated geothermal numerical model(s) to existing observations and data.

Our application cases are low enthalpy projects, located in the Paris Basin and exploiting the Dogger formation. Typical development plan consists of a doublet (a pair of one injector well and one producer wells) whose long-term sustainable flow rates and thermal breakthrough timing should be thoroughly assessed. The Dogger aquifer has been extensively developed in the 70-80’s, leading to more than 40 geothermal doublets still in operation and most of the time densely implemented close to each other. This proximity of injectors and producers might lead to unexpected pressure and thermal interferences, potentially jeopardizing the long-term sustainability of the existing system or any new nearby development.

The reservoir characterization of the Dogger fractured limestone should include all available static and dynamic observations, from well logs to wells test and production data. An interference test between five doublets in a prospect zone to the South-East of Paris is used to better characterize and assess the hydraulic connectivity in this area. The static and dynamic models are built through an integrated and flexible workflow linking a geomodelling software (PETREL™ software) together with a thermal reservoir simulator (AD-GPRS software).

Two alternative history matching approaches are applied and compared. Both of them capitalize on an extensive use of advanced Design of Experiments techniques for uncertainty space sampling, reliable proxy-models computation, global sensitivity analysis and optimization techniques. The first approach is based on the Bayesian framework for which a proxy-model of the likelihood function is computed through an iterative process. The a posteriori distributions of the uncertain parameters might then be derived from the a priori ones through the Bayes theorem. The former distributions define the history matched samples. The second approach is based on multi-objective functions optimization, typically ending with a Pareto front in a two functions application case.

Both approaches are cutting-edge history matching techniques, with comparable numerical costs and allow a better reservoir characterization of the study area. Also, both of them do have specific advantages – like leaving to the decision maker the compromise to make on alternative competing history matching criteria - which would be described and discussed in detail.

1. INTRODUCTION
Getting reliable production forecasts (in terms of flowrate sustainability and thermal breakthrough, Le Brun et al. 2011) is a key aspect of any geothermal project. A preliminary step is to history match the associated geothermal numerical model(s) to existing observations and data, which might be quite sparse.

Our application cases are low enthalpy projects, located in the Paris Basin and exploiting the carbonate Dogger formation which exhibits large heterogeneities and spatial variability of the key hydraulic facies and properties. Getting history matched models is therefore quite challenging with such heterogeneities (Ungemach et al. 2011, Crooijmans et al. 2016) despite more than 40 years of exploitation knowledge and feedback (Lopez et al. 2010).

Two alternative history matching techniques, already validated and used on oil and gas as well as gas storage assets, are investigated to history match an interference pressure test over five geothermal doublets.

2. RESERVOIR GEOLOGICAL OVERVIEW AND PRESSURE INTERFERENCE DATASET
2.1 Geological overview
The Dogger formations are carbonate deposits from Medium Jurassic which have been one of the main targets for oil exploration (on top of geothermal exploitation) in the Paris Basin, so numerous wells reach or cross these formations.

The reservoir formations in Dogger deposits are mainly oolitic or gravely limestones, from barrier facies (mainly “Dalle Nacrée” and “Oolithe Blanche” facies). It is a multilayer system, and the connectivity between the porous reservoir layers is poorly known. Porosities vary a lot laterally and vertically, in links with compaction, primary and secondary cementations, dissolutions and dolomitization.

The geothermal wells in the central part of the Paris Basin are mainly in the Lower Callovian, Bathonian and Bajocian limestones, all three forming the so-called Dogger reservoir. They cross up to 15 individual productive layers. The most productive zone is the
Bathonian oolithic package (50 to 70 % of the total well production). The Comblanchian deposits (gravel limestone from internal platform, Bathonian) can contribute up to 25 % of the total. The marls/limestones basal alternances (Bajocian) can locally contribute for a limited part.

In the central part of the Paris Basin, the Dogger formation reaches 1900 m deep (Figure 1a), with a thickness of about 200 m and a temperature of around 60-80 °C.

The Dogger geological model is extracted from the wider Storengy geological model of the Paris Basin (including all the aquifer gas storage assets of Storengy) with a database of more than 250 wells.

The area of study concerns the four geothermal wells in Cachan (GCA), the doublet in La-Haï-les-Roses (GHLR), the doublet in Chevilly-Larue (GCHL) and the two geothermal wells in Fresnes (GFR). At top Dogger depth, wells of a doublet are around 1000-1200 m apart from each other’s, and 1200 m apart at minimum between doublets (Figure 1b). All wells are deviated with a kick-off point at around 400 m depth and a final producing open-hole section with a deviation in the range of [30,40] degree.

These wells are located in a faulted zone with two East-West faults, one in the North, isolating the northern-most well of Cachan, and one in the South, isolating the Fresnes wells. Two North-South faults close the area; one, more than 6km far to the West, and the other one, 850m East of the Eastern well (GCHL). The top Dogger reservoir depth reaches between -1440 m and -1540 m below the sea level.

**2.2 Pressure Interference Test**

The pressure interference test considered for this study was one of the deliverables of a joint project (Hamm and Giuglaris 2015) between the French ADEME and BRGM entities (respectively the French Environmental and Mining authorities). This project was set up to improve the knowledge and the long-term production forecasts assessment -through doublet scale hydraulic interference recording- of the Dogger formation in a densely doublet-populated area.

It was carried out between the 16th and 20th of September 2013 and involved the five doublets of Cachan 1 and 2, Chevilly-Larue, L’Haï-les-Roses and Fresnes (Figure 2a). Those doublets being used for district heating purpose, they have different operating conditions for winter and summer seasons. The test was conducted at the end of the summer period, before the start of the winter one.

Key features of this hydraulic test are that:

- All doublets were shut-in for 36 hours to stabilize the pressure in the area of study,
- L’Haï-les-Roses doublet was started again (both producer GHLR2 and injector GHLR1) at nominal flow rate for 54 h and pressure interferences were recorded in all other doublets,
- L’Haï-les-Roses doublet was finally shut-in for 6 h.

Measurements were of two types:

- Producing wells – equipped with downhole ESP pumps, were recording pressure and temperature at the well head level,
- Injectors were equipped with downhole and well head pressure and temperature sensors.

Some operational issues during the test led to the fact that pressure data are finally only available for five wells, namely GCHL1, GCHL2, GFR1, GFR2 and GCA2 (Figure 2b).
3. METHODOLOGY

3.1 Geological modelling

Using the PETREL™ software (Petrel User Guide 2018), the numerical geological model (Figure 3a) is made of 62×74×50 cells with a horizontal cell dimension of 100 by 100 m. It includes 4 faults subset from the larger geological structural model (Figure 1b). Three vertical zones are set-up (Figure 3b):

- Zone 1 above the Dogger reservoir with 10 layers (vertical dimension ΔZ of around 30 m),
- Zone 2 which is the Dogger reservoir itself, made of 40 layers with a ΔZ of around 2 m,
- Zone 3, below the Dogger, with 10 layers (ΔZ of around 20 m).

The Dogger interval is modelled with a binary facies set: either a “Flow” or a “No Flow” facies. The “Flow” facies corresponds at the well level to the identified productive intervals. The SIS (Sequential Indicator Simulation) algorithm is used to simulate such facies realizations, which are conditioned to hard well data (Figure 4a). Key inputs of the SIS algorithm are defaulted to:

- Spherical variogram,
- Isotropic horizontal correlation lengths $L_{CX} = L_{CY} = 800$ m,
- Vertical correlation length $L_{CZ} = 2$ m,
- “Flow” facies proportion of 25 % over the Zone 2 interval.

Based on the logs and well test data, key petrophysical data are available for all the wells. The vertical productive thickness is in the range of 5.8 to 17 m, made of 5 to 17 productive intervals. In those reservoir intervals, porosity varies between 10 to 18 %, and permeability between 0.9 and 2.5 D (Table 1). All those data are used as well hard data conditioning points.

The heterogeneity and spatial variability of those carbonate reservoir layers are modelled through geostatistical techniques.

Figure 2: From Hamm and Giuglaris, 2015 (a) Detailed doublet location and well types (blue triangle: injector, red triangle: producer); (b) Wellhead pressure evolution at the observation wells during the interference test.

Figure 3: (a) Model bottom horizon (pink surface); discretized zig-zag faults and vertical section of the three different intervals; (b) Zoom over a vertical section showing the vertical resolution.
The vertical correlation length is in line with the typical thickness of the individual productive intervals identified on the production logs.

Table 1: Wells petrophysical properties over the area of study

<table>
<thead>
<tr>
<th>Well</th>
<th>GCA1</th>
<th>GCA2</th>
<th>GCA3</th>
<th>GCA4</th>
<th>GHLR1</th>
<th>GHLR2</th>
<th>GCHL1</th>
<th>GCHL2</th>
<th>GFR1</th>
<th>GFR2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Productive Thickness (m)</td>
<td>7.4</td>
<td>16.8</td>
<td>11.9</td>
<td>17</td>
<td>5.8</td>
<td>7.2</td>
<td>13</td>
<td>11</td>
<td>8.8</td>
<td>6.7</td>
</tr>
<tr>
<td>Porosity (%)</td>
<td>14</td>
<td>14.5</td>
<td>18</td>
<td>15</td>
<td>15</td>
<td>10</td>
<td>15</td>
<td>13</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>Permeability (D)</td>
<td>2.5</td>
<td>1.2</td>
<td>1.3</td>
<td>1.1</td>
<td>2.2</td>
<td>2.2</td>
<td>0.9</td>
<td>1.7</td>
<td>1.2</td>
<td>1.6</td>
</tr>
<tr>
<td>Productive intervals</td>
<td>6</td>
<td>6</td>
<td>17</td>
<td>10</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>6</td>
<td>?</td>
<td>5</td>
</tr>
</tbody>
</table>

A subsequent facies-based petrophysical modelling is performed over the Zone 2. First, the porosity is simulated with the SGS (Sequential Gaussian Simulation) algorithm (Figure 4b). Then the permeability is modelled with the same SGS algorithm and a collocated co-kriging option, with the porosity as secondary variable. Both porosity and permeability realizations are conditioned to well data. Zone 1 and 3 have constant petrophysical values. Key inputs of the SGS algorithms are defaulted to:

- Spherical variogram,
- Isotropic horizontal correlation lengths $L_{CX} = L_{CY} = 500$ m,
- Vertical correlation length $L_{CZ} = 2$ m,
- Normal Porosity distribution mean $m_{\phi} = 0.15$ % and standard deviation $\sigma_{\phi} = 0.02$ %,
- Log Normal Permeability distribution: mean $m_k = 1.8$D and standard deviation $\sigma_k = 0.3$ D,
- Permeability to Porosity correlation coefficient: $\rho = 0.8$.

The petrophysical properties of Zone 1 and Zone 3 as well as the “No Flow” facies are set to a constant porosity value of 0.01 % and a permeability value of 10E-06 D.

Figure 4: (a) Horizontal section of the facies realization (blue : “Flow” facies, grey : “No Flow” facies) together with conditioning facies logs (b) Associated porosity realization section together with conditioning porosity logs.

3.2 Fluid flow simulation

The AD-GPRS fluid flow simulator from Stanford University is used as (geo-) thermal reservoir simulator (Wong et al. 2015, AD-GPRS User Guide 2018). The reservoir simulation grid has the same dimensions as the geological one (no upscaling step). The default grid cell resolution is in the upper range of what might be acceptable, but a fully implicit numerical resolution scheme ensures that all equations are converging in terms of material and energy balances.

All five geothermal doublets have been operating since the mid 80’s so the early 2010’s (interference test performed in 2013) pressure and temperature fields are definitely impacted by this long-term geothermal exploitation. The AD-GPRS simulation is initialized with a pressure and temperature fields derived from Hamm et al. 2010 (simulated data derived from a full field model including all the Dogger doublets full exploitation history and forecasts up to 2020) and corroborated by Storengy own internal simulations (Figure 5a). The 2010 simulated pressure and temperature fields are assumed to be representative of the initial state for the interference test simulation. Associated Dirichlet Boundary Conditions are set-up (on all 6 external faces cells of the model) through the PSEUDEWELLS AD-GPRS keyword which allows to specify pressure and temperature values for a given cell (Figure 5b), sampled from the initial pressure and temperature fields.

The simulation is started on the 1st of June 2013 and ends up on the 21st of September 2013 (interference test carried out between the 16th and 20th of September 2013).
Apart from the petrophysical, pressure and temperature fields exported from the PETREL™ geomodelling software, the following thermal properties were set-up (Hamm et al. 2010, representative values for the Dogger formation): a rock volumetric specific heat capacity of 1775 kJ/m³K, a rock thermal conductivity of 216 kJ/m-day-K and a water thermal conductivity of 57 kJ/m-day-K.

All well rates, temperatures and Bottom-Hole Pressures are available as simulation results.

Figure 5: (a) Horizontal section of the initial temperature field at the Dogger reservoir level; (b) Two cross sections of the property defining the active PSEUDOWELLS cells (in red).

3.3 Full forward Modelling workflow

The ATOUT™ software (ATOUT™ User Guide 2018) is used to perform the different sensitivity studies and optimizations of this study. It arises and capitalizes on the key features of the COUGAR™ software (COUGAR™ Reference Manual 2015) in terms of experimental designs and proxy models computation while integrating as well some advances optimization features. The forward model is set-up through an automated forward modelling workflow which includes:

- A template text file defining the numerical values of the parameters considered for the current experiment/iteration,
- A batch call of the geomodelling software, launching itself an internal workflow which:
  - Reads the parameters file,
  - Launch the geomodelling internal workflow,
  - Export the petrophysical properties to include files used by the AD-GPRS reservoir simulator – launched also in batch mode
- A post-processing of the simulation results in XML format (to be uploaded by the ATOUT™ software).

All runs are defined, launched and analyzed through the ATOUT™ software graphical user interface.

3.4 Experimental designs and proxy models computation

Design of Experiments or Experimental Designs were used for decades in engineering and Oil and Gas applications (Damsleth et al. 1992), more recently in the geothermal sector (Ciriaeco et al. 2018). They allow for an optimal sampling of the uncertainty space of a given parameters set. Different types are available: classical designs (e.g. Box-Behnken design), Latin Hyper Cube designs as well as adaptive experimental designs (Scheidt et al. 2007), among others.

Experimental Designs are used together with response surface / proxy model computation. A proxy model is an approximation – through a linear combination - of a response of a numerical modeling step (e.g. a fluid flow simulator). Linear and cross-terms of the inputs/parameters are considered by default. If a quadratic Experimental Design is chosen, then quadratic terms are added to the linear combination. Optimal values of the coefficients of the linear combination are derived from the few computed real numerical modeling runs (experiments chosen though the associated Experimental Design). More recent developments include a kriging step – the proxy model then gives exactly the same answer as the real simulation at the experiment points - as well as more advanced mixed-integer kernels. The latter allows for tackling both continuous (e.g. the mean of a geostatistical realization) and discrete parameters (e.g. a seed number). Proxy model use requires a careful and detailed Quality Control step as complex physics (such as non-linear fluid flow simulations) might be challenging to summarize through a proxy.

Typical Quality Control tools are the predictivity and the predictivity with confirmation runs. From $X$ experiments, the former is computing proxies from the $(X-I)$ experiments and computing the difference between the remaining experiment result and the proxy result. Doing so for the $X$ experiments and summing up gives the predictivity. The closer it is to 1.0, the better the quality of the proxy model. The latter is about the same but with $Y$ confirmation experiments on top of the initial $X$ experiments. Here again, the closer it is to 1.0 the better the proxy model. A proxy model with a good predictivity (e.g. 0.75) but with a predictivity with confirmation runs below 0.5 would not be considered as reliable (Blatman 2009, Schaaf et al. 2009).

3.5 History Matching Tools

Two alternative History Matching tools – already validated and used for oil and gas reservoirs as well as gas storages assets - are considered for this study:

- A probabilistic history matching technique with a Bayesian framework (Manceau et al. 2005, Feraille and Marrel 2012),
A Multi-objective functions history matching approach with the computation of a Pareto front. The former is computing a reliable proxy model of the likelihood function (of a single objective function \( OF \)), to derive \textit{a posteriori} parameter distributions from the \textit{a priori} ones (through the Bayes relationship). As many history matched models as requested might be obtained by sampling those \textit{a posteriori} distributions. The latter is computing reliable proxy models of different (two in this study) subsets \( OF_1 \) and \( OF_2 \) of the single objective function \( OF \) (where \( OF_1 + OF_2 = OF \)). A Pareto front might then be computed, allowing alternative compromise over the quality match of \( OF_1 \) and \( OF_2 \).

4. RESULTS AND ANALYSIS

4.1 Parameters set and Experimental Designs

The Dogger formation is a carbonate heterogeneous reservoir exhibiting large geological uncertainties (Lopez et al. 2010, Rojas 1989). Based on geological and reservoir engineering inputs and discussions, five uncertain parameters were identified and considered for this study (Table 2):

- The Seed number used by the SIS algorithm for the facies modelling (alternative seed number allows to generate alternative equiprobable geostatistical realizations through pseudo random path generation),
- The horizontal correlation length \( L_{CX} \) of the SIS algorithm for the “Flow” facies,
- The “Flow” facies proportion,
- The mean of the porosity realization of the “Flow” facies,
- The mean of the permeability realization of the “Flow” facies.

Table 2: Uncertain parameter definitions, ranges and type

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Seed Facies</th>
<th>( L_{CX} ) SIS Facies (m)</th>
<th>“Flow” facies proportion (%)</th>
<th>Mean Porosity</th>
<th>Mean Permeability (D)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower Bound</td>
<td>1000</td>
<td>400</td>
<td>20</td>
<td>0.14</td>
<td>1.5</td>
</tr>
<tr>
<td>Upper Bound</td>
<td>1002</td>
<td>800</td>
<td>40</td>
<td>0.2</td>
<td>2.5</td>
</tr>
<tr>
<td>Type</td>
<td>Integer</td>
<td>Real</td>
<td>Real</td>
<td>Real</td>
<td>Real</td>
</tr>
</tbody>
</table>

Two runs were initially performed to check that everything was running correctly. A linear Latin Hyper Cube Design is then selected which leads to 17 real experiments to perform (i.e. Geomodelling software and AD-GPRS runs). Some extra experiments were finally added (through an augmented Latin Hyper Cube design). The latter might be used as confirmations runs to assess the quality of the proxy-model. Figure 6 gives the details of the 14 first experiments out of 24 ones.

Feedbacks from other technical studies (Swiler et al. 2014, Munoz and Sinoquet 2019) show that considering discrete parameters might be quite challenging to compute reliable related proxy models. Adaptive Experimental Design techniques (Scheidt et al. 2007) are then quite useful to improve the quality of the proxy model until a defined quality criterion is reached. Basically, the user...
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specifies the maximum number $N$ of extra experiments he is ready to invest in, and the algorithm is selecting on an iterative process some new experiments until the proxy model quality criteria is reached or the total number $N$ of runs.

### 4.2 Objective function definition

Once again, some operational issues (during the interference test) lead to pressure data available for only five wells: GCHL1, GCHL2, GFR1, GFR2 and GCA2.

All five wells exhibit a monotonic pressure evolution over the interference test pressure period. For those five wells, the differential $BHP$ (Bottom Hole Pressure) over the GHLR1-2 producing period is considered for the subsequent history matching period (Table 3) rather than the absolute pressure evolution. A standard objective function formulation considering the whole simulated and observed pressure profiles over the test period was not achievable here because:

- Simulation pressure results are only made of Bottom Hole pressures, there is no direct implementation in the ADGPRS software of Vertical Lift Performance tables to derive the Tubing Head pressures from the Bottom Hole ones,
- Observed pressure data were available for the producers only at the Tubing Head level and for the injectors at the Tubing Head and the Bottom Hole levels (no temperature effect of the fluid column is observed, a constant pressure drop links the two pressures),
- No details were given (Hamm and Giuglaris 2015) about the downhole gauge installation depth or datum depth reference.

As such, the correspondence between the observed Bottom Hole and Tubing Head pressures is therefore hypothetical. As the pressure profiles were monotonic over the test period, the pressure evolution trends (positive or negative) as well as their amplitude were assumed the best accessible history matching criteria.

This differential pressure is defined for each well as $DP_{well} = BHP_{well} \text{ (final time step)} - BHP_{well} \text{ (initial time step)}$, with the initial time step corresponding to the start of the GHLR1-2 wells production period and the final time step, the end of the production period (56 hours later), during the interference test.

**Table 3: Observed $BHP$ differential for the 5 observation wells over the GHLR1-2 producing period**

<table>
<thead>
<tr>
<th>Well</th>
<th>GCA2</th>
<th>GCHL1</th>
<th>GCHL2</th>
<th>GFR1</th>
<th>GFR2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Differential Pressure (bar)</td>
<td>-0.4</td>
<td>-0.9</td>
<td>-0.95</td>
<td>+0.5</td>
<td>+0.8</td>
</tr>
</tbody>
</table>

Table 3 thus defined the observation $DP^{Obs}$ of these pressure differentials, for each of the 5 wells.

AD-GPRS reservoir simulation results give access to the simulation values, from which $DP^{Sim}$ are computed.

For each well, a least-square formulation of the objective function is used:

$$OF_{well} = W \times (DP^{Obs} - DP^{Sim})^2$$

where the weights $W$ is linked to the data measurement error through the relationship $W = 1/\sigma^2$ (with $\sigma = 0.05$ bar).

### 4.3 Sensitivity study to the objective function

Before the History Matching process itself, it is common practice to perform a sensitivity study on the history matching criteria i.e. the objective function $OF$. Such study would list and rank the most impacting parameters with respect to the $OF$ thus enabling to skip (for the subsequent history matching process) parameters having little or no impact.

As the number of experiments (24 runs) of the initial Experimental Designs is not sufficient to compute a reliable proxy model (the predictivity with confirmation runs was below 0), an adaptive experimental design is launched to try to improve its quality. Such low quality initial proxy model should not be a surprise as both discrete and continuous input parameters are considered which is quite challenging. The iterative process of the adaptive design ends up after a total of 114 experiments.

The global objective function (out of the 5 wells) is considered at this stage. Using the first 60 experiments to compute a Mixed Integer proxy model and the remaining ones as confirmation runs, a reliable proxy model is generated (predictivity with confirmation runs of 0.53, Figure 7a). Figure 7b underlines the ability of Mixed Integer proxy model to tackle properly discrete parameters.

Having computed a proxy model, both local sensitivity study (through a Tornado plot, Figure 8a) and a global sensitivity study (through a Global Sensitivity plot based on Sobol coefficients, Saltelli et al. 2004, Figure 8b) might be generated. The global sensitivity study confirms that the “Flow” facies proportion parameter is the main impacting one, together with the correlation length. Both parameters might impact the connectivity between wells. The limited impact of the seed number might be due to the quite extensive well data conditioning given the model extent and the “Flow” facies horizontal correlation length.
As the parameters set is quite limited (only 5 parameters), all of them would nevertheless be kept for the History Matching processes, despite the moderate impact of some of them.

4.4 History matching results

First, a probabilistic history matching process is performed in a Bayesian framework. The global objective function OF (out of the 5 wells) is considered in this case. The likelihood function of the Bayes relationship is proportional to exp(-OF). So, minimizing the objective function is equivalent to maximizing the likelihood function.

Computing a reliable proxy model of this likelihood function through an adaptive Experimental Design iterative process and using it together with the a priori parameters distributions (assumed to be uniform, in red on Figure 9), the a posteriori parameters are computed (in blue on Figure 9). The latter are the results of the probabilistic history matching process. N history matched models are obtained from N samples of those a posteriori distributions. This a quite useful and powerful approach as many (alternative and equiprobable) history matched models are compulsory -but may not be sufficient- to compute ultimately reliable production forecasts.

The a posteriori distribution of the Seed parameter is singular (a spike shape, Figure 9a) as it is a discrete parameter. Results of the sensitivity study are also confirmed by those results: a low impact parameter would tend to have a wider (closer to the initial uniform distribution) a posteriori distribution e.g. the mean of the porosity (Figure 9d).

Alternatively, a multi objective functions optimization is run. In such case, one must define the different subset of the objective functions. For instance, if different observation data types are considered, one might compute an objective function for each type. Another approach would be to compute different objective functions based on well location or reservoir segmentation for instance. The latter approach is considered here as the Fresnes doublet (the southern-most one) is in a different structural block.

The first objective function is thus \( OF_1 = OF_{GFR1.2} \) and the second one is \( OF_2 = OF_{GC42,GCHL1.2} \).
For stability reason of the algorithm, both objective functions are taken to their common log values and then normalized between 0 and 1.

Reliable proxy models are computed for both objective functions (predictivity with confirmation runs of 0.97 for $OF_1$ and of 0.93 for $OF_2$). Using those proxy models, a bi-objective functions optimization is then performed. The Seed parameter is still considered uncertain (through a uniform distribution) while the four remaining ones are considered for the optimization (Figure 10a). Through this bi-robust optimization the mean values of $OF_1$ and $OF_2$ are minimized. The result of such bi-robust optimization (and thus of the history matching process) is a Pareto front (Figure 10b) which represents the location of all the experiments leading to optimal ($OF_1 + OF_2$) values. The user is then able to choose the best compromise with respect to the history matching process targets (favoring $OF_1$ over $OF_2$ or the reverse). When dealing with multi objective functions optimization, the user has to compromise at the end.

Figure 9: a posteriori distributions of the (a) Seed; (b) horizontal correlation length (c) “Flow” facies proportion (d) mean of the porosity (e) mean of the permeability – Red arrow : Sample considered
As an illustration, a deterministic sample was run from each optimization techniques:

- Bayesian approach - Sample corresponding to the P50 values of the a posteriori distributions for all 5 parameters (red arrows – Figure 9),
- Bi-optimizations approach - Sample on the Pareto front corresponding to an equal compromise between $OF_1$ and $OF_2$ optimal values (red arrow – Figure 10).
- For both cases, the resulting simulated BHP pressure differential for all 5 observation wells are listed in Table 4.
- BHP evolution (over the differential computation period) for both cases are highlighted over the full 114 runs set (Figure 11).

Table 4 : Observed BHP differential for the 5 observation wells together with the “optimal” Bayesian and bi-optimization results

<table>
<thead>
<tr>
<th>Well</th>
<th>GCA2</th>
<th>GCHL1</th>
<th>GCHL2</th>
<th>GFR1</th>
<th>GFR2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed $\Delta P$ (bar)</td>
<td>-0.4</td>
<td>-0.9</td>
<td>-0.95</td>
<td>+0.5</td>
<td>+0.8</td>
</tr>
<tr>
<td>Bayesian “Optimal” $\Delta P$ (bar)</td>
<td>-0.13</td>
<td>-0.63</td>
<td>+0.06</td>
<td>+0.12</td>
<td>+1.08</td>
</tr>
<tr>
<td>Bi-optimization “Optimal” $\Delta P$ (bar)</td>
<td>-0.26</td>
<td>-0.58</td>
<td>-0.01</td>
<td>-0.25</td>
<td>+1.4</td>
</tr>
</tbody>
</table>

A good match is obtained for most wells, at least in trend if not in amplitude. Matching of well GCHL2 is definitely challenging.
Figure 11: Bottom Hole Pressure evolution – Bayesian approach (red curve) Pareto approach (blue curve) over the 114 runs (grey curves) for (a) GCA2; (b) GCCHL1; (c) GCCHL2; (d) GFR1; (e) GFR2 wells

5. CONCLUSIONS

Using two alternatives history matching techniques – a probabilistic approach and a bi-objective functions optimization – both give good quality history matching of an interference pressure tests between five geothermal doublets. Most impacting parameters as well as optimal parameter values were identified. This is a mandatory step to the subsequent reliable production forecasts computation.

The probabilistic approach is useful as many history matched models might be obtained through a simple sampling of the a posteriori distributions.
The bi-objective functions approach is also giving interesting results. It might however become quite challenging when dealing with many different objects and properties to match.

Both approaches might be considered for geothermal application cases, as it is already the case for oil and gas as well as gas storages applications. So far, an history matching of the pressure interference test in terms of trend and amplitude was considered. Some details were missing for the observation dataset to be able to consider the full observed Bottom Hole pressure profiles. The next step would be definitely to consider the whole pressure profiles as the history matching criteria definition. For this purpose, more details about the pressure gauge installation depth and the datum depth should be gathered (from the pressure interference dataset) and a Vertical Lift Performance table option should be implemented in the fluid-flow simulator.

REFERENCES


Munoz, Z. M. and Sinoquet D., Global Optimization for mixed categorical-continuous variables based on Gaussian process models with a randomized categorical space exploration step, 2019, to appear in INFOR, Information Systems and Operational Research.


