Well Placement Optimization under Time-Dependent Uncertainty using an Ensemble Kalman Filter and a Genetic Algorithm

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Abstract

Determining the optimal well location in a reservoir is a challenging problem. It involves taking several factors into account, including geological uncertainty, reservoir and fluid properties, economic costs, and technical ability. Most research on well placement optimization under uncertainty has assumed static uncertainty in the reservoir parameters, until the introduction of the pseudohistory concept. The pseudohistory concept incorporates the field’s probable history and results in the determination of optimal locations of future wells with greater certainty. This approach, however, requires an excessive number of simulations and may not be practical for optimization of a reservoir model having a large number of geological realizations.

In this study, we use an ensemble Kalman filter (EnKF) to perform history matching of the PUNQ-S3 reservoir model using data from six production wells over an eight-year period. This is followed by well placement optimization using a genetic algorithm (GA) combined with pseudohistory matching, carried out over two years, following the placement of the first future well. Thus, this approach not only provides increased certainty in optimal well placement but also, using EnKF as a history matching method, requires only a single “best estimate” realization for objective function evaluation during GA optimization. As a result, the total time taken to find the optimal well locations is significantly reduced. We illustrate this through comparison with previous research.

Keywords:
reservoir optimization, reservoir simulation, geological uncertainty,
1. Introduction

Well placement optimization (determination of the optimal number, type, and location of wells) has recently gained significant attention in the petroleum industry because of the increase in the global energy demand and necessity to obtain maximum hydrocarbon recovery with minimum investment in gas and oil fields. Choosing the optimum location and type of well(s) can lead to significant economic gain in hydrocarbon extraction from underground reservoirs.

The well placement problem is a highly nonlinear one that depends on many continuous or discrete decision variables and includes factors such as subsurface geomechanics, well drilling and construction, surface facilities, as well as geological and economic uncertainty. This problem becomes more complex when non-conventional (horizontal, deviated, or multilateral) wells are considered.

The number of possible solution combinations for the well placement variables increases exponentially with an increase in decision variables. Finding the optimum solution to this problem by conducting a few case studies is unlikely, and using intuitive engineering judgment alone may not be sufficient. For almost three decades, attempts have been made to solve this problem through automatic optimization procedures. These approaches have differed mainly in terms of the optimization algorithm, reservoir response modeling technique, and available decision variables and constraints (Nasrabadi et al., 2012).

There is a significant amount of uncertainty in oil and gas reservoir development planning, mainly due to the uncertainty of the geological model used for the estimation of the reservoir response. This can affect the economics of a field development plan, and thus, should be accounted for in the optimization process. Many researchers have developed well placement optimization techniques that include the effect of uncertainty. Some included the effect of uncertainty by using multiple geostatistical realizations in the evaluation of reservoir response (e.g., Güyagüler and Horne, 2001; Yeten et al., 2003). Another approach used to account for uncertainty in well placement is Monte Carlo simulation (e.g., Cullick et al. 2003, 2005). Some other techniques include D-optimality experimental design (Aanonsen et al., 1995;
Vincent et al., 1999), utility theory (Güyagüler and Horne, 2004), quality map method (Loureiro and Fresky, 2005), statistical proxy method (Artus et al., 2006), and ensemble optimization (Leeuwenburgh et al., 2010).

An important contribution to well placement under uncertainty is the inclusion of time dependency on geological uncertainty. Previous studies on well placement optimization under uncertainty assumed static uncertainty, while in reality, if all of the wells are not drilled simultaneously, the amount of geological uncertainty should decrease with time as more production data becomes available. Özdogan and Horne (2006) addressed this problem by introducing the concept of pseudohistory and incorporating time-dependent information in future well placement decisions. They included the effect of time on uncertainty by performing a history match of a future well using the probable reservoir response model (P50 model). However, their approach requires a significant number of reservoir simulations and, given a reservoir model with a large number of geological realizations, this approach may not be practical for field application.

In this study, we use an EnKF for continuously updating a reservoir model, after which well placement optimization using a GA and pseudohistory matching are carried out. The advantage of this approach is not only the integration of time-dependent information in well placement optimization but also the performance of optimization on a single best estimate realization, as opposed to the all of the updated realizations, as done in past approaches (e.g., Özdogan and Horne, 2006). The ensemble mean is considered the best estimate of the permeability and porosity fields that honors the production data from the reference model (and is thus used for future forecasting). The number of objective function evaluations during the optimization process is thus reduced by a factor equal to the number of realizations (which can be several orders of magnitude). This method is applied to the PUNQ-S3 reservoir model in which we carry out history matching using field history and pseudohistory for six production wells over an eight-year period. Well placement optimization of three future wells is then conducted on the best estimate realization following Özdogan and Horne’s well placement approach.

The rest of this paper is organized as follows. Section 2 describes the EnKF history matching algorithm. Section 3 outlines the pseudohistory concept. Section 4 describes GA as the well placement optimization technique. The combined EnKF-GA algorithm for well placement optimization under time-dependent geological uncertainty is described in Section 5. The results of application of the EnKF-GA algorithm to the PUNQ-S3 reservoir model
Section 6. Section 7 concludes this paper with a brief summary.

2. EnKF History Matching

The EnKF method was first introduced by Evensen (1994) for updating non-linear ocean models. Subsequent clarification and support for the use of the ensemble mean as the best estimate was then given by Burgers et al. (1998). EnKF has been successfully used to update oceanography, meteorology, and reservoir engineering models. There is extensive literature on the topic (Evensen, 2009), including an overview of the development and applications of EnKF (Evensen, 2003). Its use in reservoir model history matching was first proposed by Nævdal and Vefring (2002) for updating the near-well permeability field, thereby forecasting reservoir production. Nævdal et al. (2003) further applied EnKF to an entire reservoir model. Gu and Oliver (2006) investigated the suitability of EnKF for updating state variables and the performance of a relatively small ensemble. This was followed by a case study on the North Sea conducted by Seiler et al. (2010), who presented a detailed workflow for updating reservoir simulation models using EnKF. EnKF has also performed well on two further North Sea studies (Evensen et al., 2007; Haugen et al., 2008) along with studies carried out on the PUNQ-S3 model (Gao et al., 2005; Gu and Oliver, 2005).

Updating an ensemble of reservoir models (realizations) involves modifying the model parameters such that the (oil, gas, water cut etc.) production profiles of each of the realizations of the ensemble match, more closely, those of the reservoir’s production history. The main advantage of using EnKF in a well-placement optimization process is that after updating the ensemble, only a single best estimate realization is required to forecast future production. Another advantage is that when new production data is made available, it is necessary to use only that data to update the ensemble, and previous data need not be considered.

EnKF is based on a set of linear equations that allows for updating of large non-linear models. The ensemble update equation is given by Evensen (2003):

\[ A^a = A + K D' \]

where the superscript \( a \) denotes analysis and \( A \) contains both the model parameters to be updated (e.g., permeability [a measure of the conductivity...
of a fluid through a porous medium] and porosity [the ratio of connected space in a porous medium to its total volume]) and the predicted data (e.g., gas-oil ratio [the ratio of the volume of gas to the volume of oil produced from a well at standard conditions] and water cut [the ratio of the volume of water produced to the total volume of liquid produced from a well at standard conditions]), for all ensemble members. $D' = D - H A$ represents the difference between the predicted and observed production data. The Kalman gain matrix, $K$, is given by:

$$K = A' A'^T H^T (H A' A'^T H^T + \Upsilon \Upsilon^T)^{-1},$$

where $H$ is an operator, $H = [0|I]$, that extracts the predicted data from $A$, and $A' = A - \bar{A}$ is the ensemble perturbation matrix. $\Upsilon$ is the ensemble of measurement perturbations, with an ensemble mean of zero. For further details see Gu and Oliver (2006) and Oliver et al. (2008).

EnKF forecasting is based on the approach that, after updating the ensemble, the best estimate of the reservoir model is given by the mean of the ensemble. The spread of realizations about the mean then provides an estimate of the error in the ensemble.

### 3. Pseudohistory Concept

The pseudohistory (Özdogan and Horne, 2006) is defined as the probable (future) response of the reservoir that is generated by a probabilistic forecasting model. Given an ensemble, the simulated response of the P50 realization (or the “probable history”) is used as the pseudohistory. The ensemble can then be updated based on this response, and by doing so, time-dependent information is used to enhance subsequent decisions in an implicit manner. The pseudohistory approach, with, for example, the placement of two future wells, can be described as follows:

1. History matching is carried out on the ensemble until the current time
2. Two possible well locations are chosen
3. The first well is placed at the current time and the ensemble response is measured until the time of the second well placement
4. The P50 realization is determined based on the ensemble response. The future response of the P50 realization (which has just been measured) will then be used as the pseudohistory
5. With the first well in place, the ensemble is then updated until the second well is placed, based on the simulated response of the P50 realization.

Thus time-dependent information is integrated into the model and can be used to implicitly enhance subsequent decisions (because the location of the second future well has already been proposed.) By carrying out the pseudohistory matching, using the probable history, information already available to us is expected to be used more efficiently. For further details on the pseudohistory approach, the reader is referred to Ozdogan and Horne (2006).

4. Well Placement Optimization Technique

Various optimization techniques for well placement exist in the literature. The most common techniques are gradient-based algorithms (e.g., Bangerth et al., 2006; Castineira and Alpak, 2009; Handels et al., 2007; Sarma and Chen, 2008; Vlemmix et al., 2009; Wang et al., 2007; Zandvliet et al., 2008) and GA (e.g., Bangerth et al., 2006; Bittencourt and Horne, 1997; Larionov et al., 2006; Litvak et al., 2007; Yeten et al., 2003). Other techniques such as simulated annealing (Bangerth et al., 2006; Beckner and Song, 1995; Norren and Deutsch, 2002) and particle swarm optimization (Onwunalu and Durlofsky, 2010) have also been applied to the well placement problem with promising results.

We use GA as the well placement optimization technique. The GA concept was first introduced by Holland (1975). GAs are a partially stochastic group of optimization algorithms that are based on natural evolution, including features such as reproduction, selection, crossover and mutation (Goldberg, 1989). The optimization is carried out by a population of strings (or individuals) that is initially randomly selected. Each string is composed of a collection of 1’s and 0’s. Each individual (location) in the search domain is also characterized by a binary string. Once the population size, \( N_p \), is initialized, a predefined objective function (or fitness) is calculated for each individual.

Sets of two individuals are chosen by tournament selection, and crossover occurs at a randomly selected location within each string. The crossover occurs with probability \( p_c \). Following crossover, mutation of one of the bits may occur, i.e., a 0 bit may change to a 1 bit or vice versa. The probability of mutation is \( p_m \). The process of reproduction is completed by selecting
the individual with the highest fitness and saving a copy of its string. This
efforts that the individual with the highest fitness value is neither discarded
nor altered during the optimization. This indicates the end of a generation.
The number of generations, \( N_{\text{max}} \), required to find the optimum locations is
dependent on the complexity of the solution space. Finally, the well locations
corresponding to the individual with the highest fitness are chosen as the
optimal locations.

We calculate individual fitness as the net present value (NPV) of the field.
The NPV for realization \( i \) is given by:

\[
\text{Net Cash Flow}_i(t) = \text{Oil Production}_i(t) \times \text{Oil Price} \\
+ \quad \text{Gas Production}_i(t) \times \text{Gas Price} \\
- \quad \text{Water Production}_i(t) \times \text{Water Handling Cost}
\]

\[
\text{NPV}_i = \sum_t \frac{\text{Net Cash Flow}_i(t)}{(1 + \text{discount rate})^t}.
\]

Note that in our application, operating expenses and capital expenditure
are not affected by well location and hence are not included in the NPV
calculation.

5. EnKF-GA Algorithm

We present EnKF as a history matching technique during well placement
optimization (EnKF-GA) and highlight the benefit of using it over other tech-
niques. The following is a comparison between optimization using EnKF-GA
and Özdogan and Horne’s (2006) algorithm, and illustrates the speed-up time
achieved. We carry out history matching over \( N_t \) time intervals, followed by
pseudohistory matching over \( N_{pt} \) intervals. The EnKF-GA algorithm can
then be outlined as follows:
EnKF-GA Algorithm

1. Define EnKF variables ($N_e, N_t, N_{pt}$)
2. Define GA variables ($N_p, N_{max}, p_m, p_c$)
3. Read field production history
4. Read ensemble of realizations
5. \textbf{for} $t = 1, N_t$
6. \hspace{2em} \textbf{for} $i = 1, N_e$
7. \hspace{4em} Run simulator, recording predicted production history
8. \hspace{2em} \textbf{end}
9. \hspace{2em} Update ensemble using EnKF
10. \hspace{2em} \textbf{end}
11. \textbf{for} $i = 1, N_{max}$
12. \hspace{2em} \textbf{for} $j = 1, N_p$
13. \hspace{4em} Record proposed well locations
14. \hspace{4em} \textbf{for} $k = 1, N_e$
15. \hspace{6em} Run simulator until 2nd future well starts production
16. \hspace{6em} Calculate NPV$_k$
17. \hspace{4em} \textbf{end}
18. \hspace{2em} Sort NPVs and determine the P50 realization
19. \hspace{2em} Record P50 response over pseudohistory period
20. \hspace{2em} \textbf{for} $t = 1, N_{pt}$
21. \hspace{4em} Repeat steps 6 to 9
22. \hspace{2em} \textbf{end}
23. \hspace{2em} Calculate NPV over field lifetime using ensemble mean
24. \hspace{2em} \textbf{end}
25. \hspace{2em} Record the highest NPV and corresponding well locations
26. \hspace{2em} \textbf{end}

The individual with the highest fitness is then chosen as the optimum individual and the well locations that it parameterizes are most likely to give the highest economic return. Özdogan and Horne’s algorithm, which uses gradual deformation as a history matching technique and utility as the objective function, can be outlined as follows:
Özdogan and Horne’s Algorithm

1. Define gradual deformation variables
2. Define GA variables \((N_p, N_{max}, p_m, p_c)\)
3. Read field production history
4. Read ensemble of realizations
5. for \(t = 1, N_t\)
6. for \(i = 1, N_e\)
7. Run simulator, recording predicted production history
8. end
9. Update ensemble using gradual deformation
10. end
11. for \(i = 1, N_{max}\)
12. for \(j = 1, N_p\)
13. Record proposed well locations
14. for \(k = 1, N_e\)
15. Run simulator until 2\(^{nd}\) future well starts production
16. Calculate \(\text{NPV}_k\)
17. end
18. Sort NPVs and determine the P50 realization
19. Record P50 response over pseudohistory period
20. for \(t = 1, N_{pt}\)
21. Repeat steps 6 to 9
22. end
23. for \(k = 1, N_e\)
24. Calculate NPV over field lifetime
25. end
26. Calculate expected utility
27. end
28. Record the highest utility and corresponding well locations
29. end
To illustrate the difference between the total computation time required by steps (23) to (25) in Özdogan and Horne’s algorithm and that required by step (23) in the EnKF-GA algorithm, the following time comparison is made. In well placement optimization, the reservoir simulation time is usually significantly longer than the EnKF updating process, and thus, we do not consider the EnKF update time. It is assumed that this is also the case for the gradual deformation update time. Let $T_h$, $T_{ph}$, and $T_{fl}$ be the times taken for the simulator to run over the history, pseudohistory, and forecasted history periods, respectively. Let $T_{fl}$ be the time taken for the simulator to run over the field lifetime, i.e., $T_{fl} = T_h + T_{ph} + T_{fh}$. Both approaches spend $t_1 = N_e T_h$ during the history update, $t_2 = N_e T_{ph}$ during P50 calculation, and $t_3 = N_e T_{ph}$ during the pseudohistory update. However, Özdogan and Horne’s algorithm requires a further $t_4 = N_e T_{fl}$, while the EnKF-GA algorithm only requires $t'_4 = T_{fl}$. This results in a significant reduction in total CPU time (see Table 1).

### Table 1: Number of Reservoir Simulations and Total CPU Time

<table>
<thead>
<tr>
<th>Simulation Type</th>
<th>EnKF-GA Model</th>
<th>Özdogan and Horne’s Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>History Match</td>
<td>$N_e$</td>
<td>$N_e$</td>
</tr>
<tr>
<td>P50 Calculation</td>
<td>$N_e N_p N_{max}$</td>
<td>$N_e N_p N_{max}$</td>
</tr>
<tr>
<td>Pseudohistory Match</td>
<td>$N_e N_p N_{max}$</td>
<td>$N_e N_p N_{max}$</td>
</tr>
<tr>
<td>Field Lifetime (GA)</td>
<td>$N_e N_p N_{max}$</td>
<td>$N_p N_{max}$</td>
</tr>
</tbody>
</table>

Total CPU Time

$$\begin{align*}
\text{Total CPU Time} & = \left\{ \begin{array}{c}
N_e T_h \\
+2N_e N_p N_{max} T_{ph} \\
+N_p N_{max} T_{fl}
\end{array} \right. \\
\text{EnKF-GA Model} & = \left\{ \begin{array}{c}
N_e T_h \\
+2N_e N_p N_{max} T_{ph} \\
+N_e N_p N_{max} T_{fl}
\end{array} \right.
\end{align*}$$
6. Application of EnKF-GA Algorithm to PUNQ-S3 Reservoir Model

6.1. PUNQ-S3 Model

The PUNQ-S3 reservoir model is based on a real field operated by Elf Exploration Production. It was developed by oil companies and research institutes in the European Union as a test to compare methods for quantifying uncertainty assessment in history matching. The following description is a brief overview of this model and further details can be found in Floris et al. (2001). The model contains $19 \times 28 \times 5$ grid blocks, of which 1761 are active. The gridblocks are uniform, $180 \times 180$ meters. The field is bounded by a fault in the south and east and by a strong aquifer in the north and west (see Fig. 1). A gas cap is present in the center of the dome-shaped field. The field initially contains six production wells located around the gas-oil contact. Due to the strong aquifer influx no injection wells are present. The production scheduling consists of one year of extensive well testing, followed by a three year shut-in period before field production begins. The well testing year consists of three-monthly production periods, each with its own constrained production rate. During field production, each of the wells is shut-in for a two-week period to collect shut-in pressure data. Field production is to be carried out for a total of 16.5 years.

![PUNQ-S3 Simulation Model](image)

Fig. 1: Left: Top surface map with initial 6 well locations. Right: Reservoir model showing the fault (black line), water-oil contact and gas-oil contact. Reprinted by permission of Hajizadeh et al. (2011)
6.2. Generation Of Ensemble

We use the geostatistical data analysis software S-GeMS (Remy et al., 2008) to generate an ensemble of 50 realizations. We then import the porosity data from all five layers of the six well locations into S-GeMS. Sequential Gaussian simulation is then carried out using a simple Kriging interpolation method. We calculate the vertical and horizontal permeabilities using the following correlation (Boss, 1999):

\[
\log(k_h) = 0.77 + 9.03\phi \\
k_v = 3.124 + 0.306k_h
\]  

(4)

6.3. Parallel Processing

To evaluate the objective function in well placement optimization, a reservoir response model is required. We use a commercial reservoir simulator to evaluate the reservoir response. Although this is a reliable technique, a large number of simulations is required by the GA. Including uncertainty can further increase the number of required simulations. The use of parallel computing to distribute the simulations over a network of CPUs has been suggested previously (e.g., Bangerth et al., 2005; Cullick et al., 2005; Parashar et al., 2005) and we implement this here.

During the EnKF update process, data is acquired from the commercial simulator in \(P\) parallel streams, where \(P\) is the number of required slave processes. This is implemented using the Fortran Message Passing Interface (MPI) on the Suqoor supercomputer TAMUQ (2012), which is a 64-node, 512-core computer cluster. The above-mentioned job requires \(P + 1\) cores (\(P\) slave processes and one master process). The master process carries out the ensemble modification and, when required, each of the slave processes invokes the simulator and records the predicted production data from its output. A similar process governs GA with pseudohistory optimization. The master process carries out selection, reproduction, crossover, and mutation and, when required, each of the slave processes represents an individual, invoking the simulator, performing the pseudohistory update, and calculating the corresponding individual’s fitness value.

6.4. Application Results

We carry out EnKF history matching over 40 time intervals (between 1967 and 1975) using production history from the PUNQ-S3 model. This is then
followed by pseudohistory matching with GA optimization. Three additional wells to be drilled are “PRO-16” in year 8, “PRO-17” in year 10, and “PRO-18” in year 12, however, our approach allows for complete flexibility in the number of wells drilled and the dates at which they are drilled. We choose the horizontal permeability, $k_h$, and porosity, $\phi$, as the model parameters to be updated. The oil production rate for all 6 wells remains fixed (e.g., Figs. 2a and 3a) and we use the gas-oil ratio and water cut as the production data to be matched. Table 2 lists the EnKF-GA parameters used.

<table>
<thead>
<tr>
<th>Table 2: Optimization and Economic Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size, $N_p$</td>
</tr>
<tr>
<td>Ensemble size, $N_e$</td>
</tr>
<tr>
<td>History intervals, $N_t$</td>
</tr>
<tr>
<td>Pseudohistory intervals, $N_{pt}$</td>
</tr>
<tr>
<td>Max. number of generations, $N_{max}$</td>
</tr>
<tr>
<td>Crossover probability, $p_c$</td>
</tr>
<tr>
<td>Mutation probability, $p_m$</td>
</tr>
<tr>
<td>Oil price (USD/bbl)</td>
</tr>
<tr>
<td>Gas price (USD/bbl)</td>
</tr>
<tr>
<td>Water handling cost (USD/bbl)</td>
</tr>
</tbody>
</table>

We carry out the optimization of three future well locations following Özdogan and Horne’s approach: the locations of all three wells are proposed when making the location decision of the first future well, i.e., the wells are not sequentially placed. Each set of three locations is represented by an individual in the GA. The optimal locations are chosen based on the maximum NPV achieved. If a proposed well location is in an inactive gridblock, we assign a fitness value of zero to that individual. Each of the proposed wells is perforated in layers 3 and 4.
Fig. 2: Production profiles for “PRO-1” before (blue) and after (red) EnKF application for a) oil production rate, b) bottom-hole pressure (BHP), c) gas-oil ratio (GOR), and d) water cut. The black dots indicate the observed production history. Only 25 realization responses are shown for clarity.

We integrate time-dependent information by continuing from step 11 of the EnKF-GA algorithm. For simplicity, the gridblock saturations and pressures are not updated, and instead, the simulator is run from the beginning of field deployment in order to obtain the predicted production data. The production data profiles of “PRO-1” for each of the realizations before and after the EnKF update are shown in Fig. 2. The production data profiles from “PRO-11” for each of the realizations before and after the EnKF update are shown in Fig. 3. As can be observed from both figures, the profiles after the EnKF update resemble the production history profiles more closely than those before the update. Note that each of the six wells are shut-in from
years 1 to 4.

Fig. 3: Production profiles for “PRO-11” before (blue) and after (red) EnKF application for a) oil production rate, b) bottom-hole pressure, c) gas-oil ratio, and d) water cut. The black dots indicate the observed production history.
Fig. 4: Production profiles for “PRO-1” before (blue) and after (red) EnKF application for a) oil production rate, b) bottom-hole pressure, c) gas-oil ratio, and d) water cut. The black dots indicate the predicted production pseudohistory. Note that the blue profiles in this figure are the same as the red profiles in Fig. 2.

We perform the pseudohistory update from year 8 to 10, the period between “PRO-16” and “PRO-17” beginning production. The ensemble, which already matches the first eight years of production history, is further updated to honor two years of “probable history” with “PRO-16” in place. We perform pseudohistory matching using the production response of the P50 realization over 26 time intervals. The production profiles for “PRO-1” and “PRO-11” before and after pseudohistory matching can be seen in Figs. 4 and 5, and the profiles of the first optimally placed well, “PRO-16,” are shown in Fig. 6. In each case, the profiles after the EnKF pseudohistory update resemble the production pseudohistory profile more closely than those
before the update.

Fig. 5: Production profiles for “PRO-11” before (blue) and after (red) EnKF application for a) oil production rate, b) bottom-hole pressure, c) gas-oil ratio, and d) water cut. The black dots indicate the predicted production pseudohistory. Note that the blue profiles in this figure are the same as the (updated) red profiles in Fig. 3.
Fig. 6: Production profiles for “PRO-16” before (blue) and after (red) EnKF application for a) oil production rate, b) bottom-hole pressure, c) gas-oil ratio, and d) water cut. The black dots indicate the predicted production pseudohistory.
To determine how accurately the EnKF-updated permeability and porosity fields represent the reference model, we calculate the ensemble mean (best estimate) before any update and again after the pseudohistory update. For example, Fig. 7a represents the initial horizontal permeability field for layer 3 of realization 3, while Fig. 7b represents the same field but after the pseudohistory update.

Fig. 7: a) Layer 3 of the initial horizontal permeability field of realization 3. b) Layer 3 of the horizontal permeability field of realization 3 after history and pseudohistory matching.
We find that with each successive update, the rock characteristics of the best estimate model more closely resemble those of the reference model. Fig. 8 shows layer 3 of the reference model along with the best estimate initially and after the pseudohistory update.

Following the well placement optimization, we simulated the reference PUNQ-S3 model using the resulting optimal well locations. The NPV was
calculated over the field lifetime and found to be $1.6257 \times 10^9$. The optimal well locations are illustrated in Fig. 9.

![Fig. 9: The original 6 well locations and optimal well locations of “PRO-16,” “PRO-17,” and “PRO-18”](image)

Given that we use an ensemble size of 50, our approach reduces the time required to calculate the objective function over the field lifetime, $T_{fl}$, by a factor of 50, in comparison with Özdogan and Horne (2006) approach. To determine the overall speed-up of our approach, a ratio of Eq. (3) to Eq. (3) can be made, i.e., $T_{tot}/T_{tot}$. The magnitude of the speed-up is mainly dependent on the ratio of the pseudohistory time to the field lifetime, $T_{ph}/T_{fl}$.

If, for example, pseudohistory were not incorporated (i.e., $T_{ph}/T_{fl} = 0$), then the speed-up would occur by a factor of 46. Conversely, if the pseudohistory period were one half of the field lifetime (i.e., $T_{ph}/T_{fl} = 0.5$), the speed-up would occur by a factor of 2. The length of the pseudohistory period is determined by how soon the second future well is to be drilled.

Simulating the PUNQ-S3 model, the CPU times (for an Intel(R) Xeon(R) processor @ 3.60 GHz, 32.0 GB RAM) for the field lifetime and the history matching period are $T_{fl} = 6.4$ s and $T_h = 2.85$ s, respectively. The time taken during the pseudohistory simulation is $T_{ph} = 1.09$ s. We can then compare the CPU time (Eqs. (3) and (3)) for reservoir simulation for each model, and find that a speed-up factor of approximately 4 is achieved.
7. Conclusions

We carry out well placement optimization under time-dependent uncertainty on the PUNQ-S3 model. Using EnKF as a history matching method, only a single realization is required to determine the GA objective function and therefore the overall optimization time can be significantly reduced. Based on the CPU time required to simulate the history, P50, pseudohistory, and field lifetime production data, and using 50 geological realizations, we could reduce the overall time to obtain the optimal well locations by a factor of 4. Furthermore, the speed-up factor is increased in two ways: i) when using a greater number of realizations and ii) when using a shorter pseudohistory period.
Acknowledgements

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