Introduction:

Waterflooding has been one of the most preferred secondary recovery methods that is applied all around the world (Temizel et al., 2018, Norouzi et al., 2019). Several data-driven models have been developed to evaluate the performance of waterflooding reservoirs and forecast future production scenarios (Albertoni et al., 2002). However, most of these methods are incapable of providing information on the interaction between wells during flooding processes.

Capacitance Resistance Model is a data-driven method that has been used in several forms for history matching of conventional and smart fields under waterflooding (Yousef et al., 2006, Salehian et al., 2018, Salehian et al., 2019). The Integrated CRM (ICRM), a linearized form of CRM, has been used to match cumulative liquid production history and estimate interwell connectivity (IWC). Although ICRM fits cumulative production data accurately, it usually fails to estimate correct values of total production, where backward subtraction of the cumulative output delivers highly overestimated or underestimated total production rates. After detecting this drawback, to address this issue, a multi-objective optimization approach is presented to minimize the error between both cumulative and total production data through two consecutive constrained objective functions. The developed framework is tested in damaged formations to detect the impact of skin factor on the communication between wells.

Kim (2011) presented ICRM to match the cumulative total production by using cumulative water injections as inputs. The ICRM quantified the interaction between injection and production wells by delivering three model parameters; $\tau_j$ for each producer; $f_{ij}$ for each producer-injector pair, showing the magnitude of IWC, and $J_j$ for each producer. The main equation of ICRM is as follows:

$$N_{P_j}(t_k) = (q_j(t_0) - q_j(t_k))\tau_j + \sum_{i=1}^{n_i} [f_{ij}CWI_i(t_k)] + J_j\left(p_{w_i}^k - p_{w_j}^k\right)$$  \[1\]

In Eq. 1, $N_{P_j}(t_k)$ is the cumulative amount of total liquid (oil and water) produced from the producer $j$ at time step $k$. The $CWI_i(t_k)$ is the cumulative amount of water injected into the injector $i$ at time step $k$. The following constraints should be applied to avoid inconsistent results.

$$\sum_{i=1}^{n_i} f_{ij} \geq 0 \quad (\text{for all } i \text{ and } j) \quad \text{and} \quad \sum_{j=1}^{n_j} f_{ij} \leq 1 \quad (\text{for all } i)$$  \[2\]

The IWCs, time constants, and productivity indices (in case BHPs are not constant) can be estimated via minimizing the following objective function:

$$O_c = \min \left\{ \sum_{k=1}^{n_k} \sum_{j=1}^{n_p} \left[ N_{P_j,\text{obs}}(t_k) - N_{P_j,\text{ICRM}}(t_k) \right]^2 \right\}$$  \[3\]

The objective function (Eq. 3) should be minimized associated with Eq. 1 while considering the logical constrains in Eq. 2. However, due to the compensating effect occurring when matching the cumulative production history, the ICRM match for total liquid production experiences large fluctuations and instabilities. To overcome this issue, we propose a sequentially operating multi-objective history matching scheme (i.e. two consecutive objective functions) such that the objective function for cumulative production match (Eq. 3) is initially applied, and then, the estimated parameters resulted by minimizing $O_c$ are used as initial guess to minimize the second objective function (Eq. 4) for matching the liquid production rate. Total liquid production data to use in $O_c$ can be provided by the backward subtraction of cumulative production data points. Figure 1 depicts the general procedure for multi-objective ICRM.

$$O_t = \min \left\{ \sum_{k=1}^{n_k} \sum_{j=1}^{n_p} \left[ q_{j,\text{obs}}(t_k) - q_{j,\text{ICRM}}(t_k) \right]^2 \right\}$$  \[4\]
1. Validation of modified ICRM

A homogeneous synthetic reservoir (Table 1) was built using commercial simulator CMG IMEX (CMG 2017), consisting of four vertical producers and five vertical injectors (Figure 2).

<table>
<thead>
<tr>
<th>Table 1: Average reservoir and fluid properties in case I.</th>
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<tbody>
<tr>
<td>Number of grid blocks</td>
</tr>
<tr>
<td>Size (ft$^3$)</td>
</tr>
<tr>
<td>Horizontal Permeability $K_h$ (md)</td>
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<tr>
<td>Vertical Permeability $K_v$ (md)</td>
</tr>
<tr>
<td>Porosity (%)</td>
</tr>
<tr>
<td>Producer bottom-hole pressure constraint (psi)</td>
</tr>
<tr>
<td>Reservoir temperature ($^\circ$F)</td>
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<tr>
<td>Oil density (API)</td>
</tr>
<tr>
<td>Formation Volume Factor (bbl/STB)</td>
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<tr>
<td>Fluid Compressibility (1/psi)</td>
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If only the objective function $Q_c$ (Eq. 3) is used, though it would excellently match the cumulative liquid production, it will deliver a poor total liquid production match. Mathematically, only the sum of production rates at any two consecutive time steps are true (Figure 3), while each of those production rates is either overestimated or underestimated (Figure 4).

Figure 3: Cumulative production match by ICRM for case I after minimizing $Q_c$ (Eq. 3).
Figure 4: Total liquid production match by ICRM for case I, after minimizing $Q_c$ (Eq. 3).

To overcome the compensating problem of $Q_c$, the objective function $O_c$ must be minimized right after minimizing $O_L$. The model parameters estimated via $Q_c$ can be used as initial point in the minimization of $O_L$. It can be seen from a high-quality total production match (Figure 5) that the compensating problem of previous method is solved by using the multi-objective ICRM. The calculated ICRM parameters are in good accordance with the imposed geological information.

Figure 5: Total production match by ICRM after using multi-objective scheme (Fig. 1).

2. Waterflood Performance in Damaged Formations

Formation damage is a component of crucial importance in reservoir characterization applications. That is, formation damage skin factor has a notable effect on IWCs. In this section, the relationship between the ICRM parameters and skin factor around a vertical fully perforated producer is studied. Five different values of skin factor (-3, 0, 2, 3.5, 5) around producer P4, basically similar to case I, was considered to investigate the alteration of IWC with skin factor when a waterflooded reservoir is characterized by ICRM. In fact, case I is used as the synthetic reservoir in which the skin factor of P4 is zero. Except skin factor, all features and properties are kept same as case I.

Figure 6: The behavior of P4’s IWC against different skin factor values.

Considering IWCs around P4 (Figure 6), they adversely responded to skin factor of P4 in an exponentially decreasing fashion as it is mathematically expressed below:

$$f_{ij} = Ae^{-B \times S_j}$$ \[5\]
Here, $f_{ij}$ is the interwell connectivity between injector $i$ and producer $j$, and $S_f$ is the skin factor around the producer $j$. The model parameters for the studied homogeneous waterflooded systems are estimated as follows:

$$0.1 < A < 0.3 \quad \text{and} \quad 0.09 < B < 0.2$$

[6]

This decreasing trend accounts for the presence of formation damage around the well which weakens the connection with other injectors. Therefore, as skin factor increases around well, the barrier against the traveling water towards that well becomes more substantial, which in turn, yields to smaller IWCs with other injectors. If we assume that pressure drop around the well directly affects the IWC, then one can conclude that the exponential trend derives from the concept of Darcy’s law where permeability has an exponential relation to do with pressure.

3. Conclusion

The main objectives of this study were to develop the ICRM and use it for characterizing waterflooded reservoirs and damaged formations. A new objective function was developed to tackle the history matching problems in the previously proposed objective function. The multi-objective scheme includes two sequential history matching procedures, first fitting cumulative production and then, total liquid production data. We report that using the second objective function in ICRM is necessary to remove the compensating error introduced by the first objective function.

The modified ICRM’s capability of predicting waterflood performance and detecting the effect of formation damage was shown in this study. We investigated the impact of skin factor on ICRM parameters which revealed that the time constant would decrease in case of more serious formation damage around a vertical producer. As the magnitude of skin factor increases, IWC of damaged well exponentially decreases. After performing exponential regression between IWC and skin factor, a mathematical correlation with two model parameters was presented.

4. References


