Simulation Optimization of Water Alternating Gas (WAG) Process under Operational Constraints: A Case Study in the Persian Gulf

Saeid Sadeghnejad*, Mehrdad Manteghian, Hossein Rouzsaz

Department of Petroleum Engineering, Faculty of Chemical Engineering, Tarbiat Modares University

* Corresponding Author: sadeghnejad@modares.ac.ir

Abstract

Optimizing the efficiency of WAG flooding projects can guarantee the success of these projects. Many operational constraints can indirectly affect the flooding efficiency. Their effects is not normally considered during routine optimizations. The main aim of this study is to find the influence of these constraints (e.g., maximum water-cut, maximum GOR, and minimum BHP during WAG process). Implementing a reservoir simulator coupled with a simulating-annealing (SA) enables us to discover the effects of these constraints during simulation optimizations. The developed optimizer is applied into a case study from an Iranian formation located in the Persian Gulf. The recovery factor of WAG flooding is compared with that of the conventional waterflooding and gas injection. Moreover, the optimization of individual and simultaneous WAG parameters are analyzed. Results indicate that a) operational constraints not also can alter the production mechanism but also they directly affect the ultimate recovery factor; b) the recovery factor of simultaneous optimization of all WAG parameters is higher than that of individual parameter optimization; c) irrespective to the manner of parameter optimization, WAG ratio (or the volume fraction of injected water to gas) remains almost constant during all optimizations, showing the influence of this parameter during WAG flooding scenarios.

Keyboards: Water-Alternating-Gas; EOR; Optimization; Simulated Annealing; Operational Constraints

1. Introduction

Waterflooding and gas injection are well-established techniques for production enhancement. However, due to the mobility ratio of both injection phases, the fingering effect is a common problem during flooding that can affect the recovery factor. Different methods have been introduced to reduce the drawbacks of these methods [1-5]. In order to use the benefit of the simultaneous injection of both fluids, water-alternating-gas flooding (WAG) was introduced [6, 7]. In this method, by stabilizing the injection front, the remaining-oil saturation of the formation decreases. In addition, gas injection reduces the oil saturation in bigger pores; whereas, water flooding reduces the oil saturation in smaller pores [8]. Thus, WAG flooding can squeeze more volume of hydrocarbon out of a reservoir by combining factors including better mobility control, sweeping un-swept zones (i.e., macroscopic displacement), and improving microscopic displacement efficiency [9, 10].
WAG can be flooded in both miscible and immiscible approach. 79% of the WAG projects are miscible indicating the popularity of this approach [9]. Among miscible flooding processes, CO₂-water-alternating injection is of much more interest nowadays [11, 12]. The most important criterion for miscibility determination is the minimum miscibility pressure (MMP). If a reservoir pressure reaches MMP, CO₂ flooding is miscible. CO₂-Water-alternating injection can effectively enlarge sweep volume and oil displacement efficiency [13]. Injecting CO₂ in oil reservoirs has two advantages: increasing oil production and sequestering CO₂ as an environmental measure [14]. Yan et al. studied the displacing process and exquisite interaction mechanism in pore scale by analyzing adsorbed oil layer during CO₂-WAG injection [15]. Liu and Zhang simulated the injection of CO₂-CH₄ mixtures [16]. There are very good case studies on the application of optimization algorithms in the petroleum literature [17-20]. However, the related studies on finding the optimal conditions during WAG processes are restricted to parameter sensitivity analysis via non-systematic approaches. In those studies, a limited quantity of simulation runs (i.e., without implementing any optimization algorithm) were conducted to determine an optimum condition. For example, an integrated approach to reservoir modeling was used to evaluate the miscible WAG process performance in Alaska [21]. Bedrikovetsky et al. developed an analytical model for a tertiary miscible CO₂-WAG [22]. A simulation study using full-field compositional reservoir modeling were undertaken to manually optimize (i.e., without implementing any optimizer) the design of a miscible or immiscible CO₂-water-alternating flood in a pilot located in Jilin oil field [23]. Ghomian et al. investigated the effect of hysteresis, WAG ratio, slug size, and heterogeneity on a CO₂-WAG flooding without implementation of any optimization tool [24]. Furthermore, Alizadeh et al. in 2014 did a series of numerical sensitivity studies to determine the magnitude of scaling groups and their interaction with recovery factors during immiscible WAG displacement processes [25]. Liu et al. in 2016 investigated the parameters influencing WAG for CO₂ flooding by only using a numerical simulation package in a low permeability block of Jilin oil field [26]. Chen et al. developed a multi-level programming model from a life cycle perspective for performing shale gas supply chain system. A set of leader-follower-interactive objectives with emphases of environmental, economic and energy concerns were incorporated into the synergistic optimization process [27]. Moreover, an inexact multi criteria decision making model with consideration of shale gas production profiles and recoverable reserves was analyzed in details [28].

It is crucial to optimize operational parameters based on economics (e.g., such as net present value, overall project economics, and oil recovery) in WAG projects [29]. There are some studies in the WAG literature that implemented optimization and artificial intelligence algorithms in their applications during WAG flooding but without emphasizing the role of production mechanisms imposed by production constraints. For example, Yang et al. implemented simulated annealing and genetic algorithm and analyzed the capability of these techniques in WAG process optimization [30]. Moreover, a 3-D reservoir simulator
integrated with an EOR expert system has been used to determine the reservoir strategies to optimize the oil recovery from a carbonate reservoir with WAG techniques [31]. Esmaiel and Heeremans for in order to reduce the amount of required simulation runs introduced a response surface proxy model using optimal design by decision-making purpose during WAG flooding [32]. Ma in 2010 used a commercial simulator and a neural network toolbox to build an artificial neural network model for screening and designing WAG processes [33]. Odi and Gupta simulated a CO₂-WAG core flood results by applying non-adjoint based optimization algorithms to find an optimal WAG configuration [34]. In 2013, a heuristic simplex algorithm was used to find the maximum NPV and the best injection scenario in a mixed-integer nonlinear problem optimization during WAG processes [35]. Moreover, Mohagheghian utilized different evolutionary algorithms to optimize hydrocarbon WAG performance in a real case study [36]. He tested the optimization tools with different numbers of controlling variables (e.g., injection rates, cycle ratio, time, etc) to compare the performance, convergence speed, and the quality of the optimal solutions found by those algorithms. The previous studies paid less attention to the role of operational constraints during optimization of WAG scenarios. These parameters, as operative limitations, would alter the production mechanism of a field. Thus, ignoring them during flooding scenarios might result in misleading of optimization results.

The factors that can affect a WAG project success can be categorized in two groups, reservoir parameters (e.g., heterogeneity, petrophysical properties, fluid properties) and operational parameters (e.g., injection pattern, injection rate, WAG cycle, cycle time, etc) [36]. The focus of this study is on optimization of the later parameters. As a case study, the dataset of an Iranian offshore heavy oil formation located in the Persian Gulf was nominated. By coupling of a reservoir simulator to a Simulated Annealing (SA) optimization algorithm, different production/injection scenarios are investigated. In our simulation-optimization approach, we have considered some injection/production parameters as variables and the ultimate oil recovery as an objective function. The main objective of this research is to reveal the role of operational constraints during optimization and evaluating their effects on the optimization results. Subsequent to the natural production period of the field, the injection rate of water and gas flooding are optimized. Afterward, the optimizations of the WAG flooding parameters (e.g., injection rates, WAG ratio, and cycle time) are considered in detail. The ultimate recovery factor of the individual and simultaneous optimization of these parameters are compared together. During all simulation optimization scenarios the effect of operational constraints on finding the optimal scenario with maximum recovery factor are discussed in details.

2. Material and methods

2.1. Statement of the problem

Simulation can be considered as an effective tool to analyze the details of a production process [37] and predictions of its future behavior. In petroleum engineering, production optimization plays an important role in increasing the amount of produced hydrocarbon and increasing its recovery factor. Optimization is one of the best ways to find the proper solution
without needing to investigate all possible statuses during simulations [38]. The purpose of this study is to investigate the role of operational constraints on the ultimate oil recovery of a WAG flooding project during production optimization process.

Many restrictions because of either facility limitations (both down-hole and surface) or economic issues should be considered during a simulation-optimization scenario. For example, during the simulations, each well can operate at a specific target value, including oil/water/gas flow rate or bottom-hole/tubing-head pressure. Changing the control mode of a well from a primary mode to other modes is a routine to meet the operational constraints. For example, due to reservoir pressure reduction the well may not produce more hydrocarbons at the initial rate with a BHP above the minimum BHP-limit set by the user. Therefore, the well producing at an oil-flow-rate target may be converted to a fixed bottom-hole pressure (BHP) mode. The well control mode is then changed automatically to maintain a constant BHP; wherein, the oil production rate will decline. This process can be reversed when the oil production of this well exceeds the oil-rate target by any reason, e.g., well stimulation, secondary recovery, or EOR scenarios. Furthermore, drilling the best location of injection and production wells is a challenging task that can affect the reservoir connectivity between wells [39-44]. In addition, a well or its connections might automatically be closed due to the violation of some other economic constraints. For example, the surface facility of a well is designed to work under a specific gas (or water)-to-oil ratio limit (i.e., an operational limit) and it cannot process excess gas (or water). Examples for such economic well constraints includes, the lower economical-limit for hydrocarbon production rate, maximum water cut (or water-hydrocarbon ratio), and maximum gas-oil-ratio (GOR). Ignoring the aforementioned constraints during any EOR optimization definitely alters the final results. Therefore, the operational constraints should be utilized in case studies. These targets can be considered via constrained optimization approaches.

In order to investigate the role of operational constraints in this study, different scenarios were considered and the results are compared together (Figure 1). In the first scenario, natural production from the field under study was discussed as a base case. The objective of this scenario was to find an optimum production rate with maximum ultimate recovery with consideration of the operational constraints. In the second and third scenarios, the optimum injection rates during waterflooding and gas injection into the field were investigated. The injection in these scenarios started with a lag of 28 years after the natural production period. Furthermore, optimization of injection cycle time, injection ratios, and water/gas injection rates during WAG flooding were examined. These parameters were individually optimized and during each optimization scenario, the optimized values from the previous results were implemented. At the final stage, the simultaneous optimization of all parameters was performed and its results were compared with individual parameter optimizations.

2.2. Goal and scope

The primary goals of this study can be summarized as follows: (a) Coupling a simulated annealing simulator to a black oil simulator to find the best production scenario; (b) finding the best injection-production scenario during natural production, waterflooding, gas injection, and WAG flooding in the case under study; (c) investing the role of operational constrains on production optimization of the
defined simulation scenarios; (d) investigating the role of individual and simultaneous optimization of WAG parameters during finding the ultimate recovery. These goals can be achieved by (a) finding the effect of the following operational constraints: lower economical-limit for hydrocarbon production rate, maximum water cut (or water-hydrocarbon ratio), and maximum gas-oil-ratio (GOR); (b) finding the optimum production rate, water injection rate, and gas injection rate during natural production, waterflooding, and gas injection scenarios, respectively; (c) finding optimum water and gas cycle time, water injection rate, and gas injection rate during WAG flooding scenarios.

2.3. Simulated Annealing (SA) Optimizer

Optimization algorithms offer a potential for a systematic investigation of a broader set of production scenarios under a given condition. These algorithms together with the experienced-judgment of specialists allow a better assessment of formation uncertainty and significantly reduce the risk in decision-makings. Consequently, there is an increasing interest in implementation of optimization algorithms in the oil industry. However, the selection of an appropriate optimization algorithm, runtime configuration, and the dynamic optimization of a reservoir remain a challenging problem [45].

In this study, the SA optimization algorithm was selected as an efficient optimization method. This optimization algorithm has been implemented in the petroleum literature for many different applications [46-49]. SA was first introduced by Kirkpatrick et al. [50] and Cerny [51]. This method and is motivated by an analogy to solid annealing and is classified as a heuristic method [52]. In order to apply the SA method to a specific problem, different parameters should be specified, including the cost function (i.e., objective function), the random neighboring solution, the acceptance probability function, and the annealing schedule temperature (i.e., cooling schedule). The details of this algorithm and the parameters used in our specific simulation-optimization approach are mentioned in Appendix A.

2.4. Simulation Assumption

The key assumption during simulations includes,

- Three-dimension three-phase simulation was performed at the field scale.
- The black oil fluid model was considered in which the oil and gas properties could change with time and pressure but their composition is constant.
- The fluid model was considered slightly compressible in which the fluid compressibility is constant over a certain range of pressures.
- Corner-point gridding based on the notion of co-ordinate lines and corner depths with non-uniform grids was used during simulations.
- A heterogeneous rock model was considered in which each grid cell has its own porosity and permeability.
- A five-point stencil scheme was used for discretizing of the simulation partial differential equations.
- A reversible rock compressibility considered elsewhere.

An E100 package was used as the simulator of this study. The input data file was written based on the data from one of the Iranian formations.
2.5. Coupled Simulation Optimization Approach

To find out an optimum solution, a simulator should be coupled with an optimizer. Fig. 2 illustrates the communications between the implemented simulator and the optimizer. The optimizer package and the related input/output programs are coded in Matlab. The communications protocol between the optimizer and the simulator was made by reading/writing on ASCII files.

The algorithm starts with definition of input parameters for both optimizer and simulator. The optimizer parameters include initial temperature, cooling schedule, equilibrium condition, and final termination condition. The simulator parameters consist of the number of injection and production wells, decision variables, and well constraints. Appendix A discusses the details of the SA approach.

During the optimization of each scenario, the SA optimizer is responsible for generating random neighbor solutions and requesting the simulator to evaluate the objective function value (i.e., ultimate recovery factor). The simulator tries to compute the ultimate recovery of the field at a fixed time after the start of the production (e.g., 50 years) by applying the operational constraints. The optimizer calls the simulator for so many times to reach to an optimum condition in each scenario.

2.6. Case Study

As a case study, an Iranian offshore oil reservoir has been implemented (Fig. 3a). A sector has been selected through the entire reservoir with 7×7×20 blocks (total number of blocks of 980). The dimensions of the blocks in the x, y, and z-directions are 128, 177, and 3.5 m, respectively. The reservoir under study has the initial pressure of 19.3 MPa and contains 680,599 m$^3$ of oil originally in place. Two wells on either side of the model were considered (Fig. 3b). During the natural production period, both wells were producing and during the other scenarios, one of them was considered as an injector of water and/or gas. Table 1 summarizes the rock and fluid properties.

Fig. 4 depicts the water-oil and gas-oil drainage relative permeability data of the formation. As the intersection of the relative permeability curves of the water and oil phase are at a point lower than (but close to) a water saturation of 50%; thus, the reservoir rock is neutral wet. During WAG flooding, three-phase flow conditions and especially hysteresis effects become relevant in the recovery process [53]. Hysteresis effects become larger in processes with fluid flow reversal such in the case of WAG injection. In order to consider this phenomenon, the hysteresis capability of the simulator based on the methodology of Aziz and Settari [54] was implemented during our simulations.

Table 2 summarizes the well production/injection parameters during all scenarios. In this study, the parameters such as maximum water-cut, maximum GOR, minimum BHP, and minimum oil flow rate were investigated as effective operational constraints. The values of these parameters were set based on the operational values of the field under study (i.e., field readings). The considered control modes and well constraints during our simulation are shown in Table 3.
3.1. Optimizing Natural Production Scenario

The type of energy (i.e., production mechanism) available for moving hydrocarbon fluids to production wells is so important for determining the amount of recovery factor during natural production [55]. Moreover, reservoirs are usually subjected to different production mechanisms that may be changed during their production lifetime. The primary production mechanisms of the reservoir under study are compaction-drive and solution-gas-drive. Pressure depletion causes the gas phase to be appeared in the formation because of the release of dissolved gas once the pressure falls below the bubble point pressure. Gas releasing in the reservoir can have either positive or negative effects. The negative factors include either increasing the gas-oil-ratio in production wells may cause some operational problems or the reservoir pressure decreases more rapidly than the pressure drop of an under-saturated reservoir. Nevertheless, if the produced gas has sufficient time to develop a secondary gas cap in the formation then the rate of pressure drop reduces as the gas cap expansion can compensate the pressure drop rate of the formation (i.e., a positive factor).

Fig. 5 displays the results of our optimization to evaluate the optimum production rate of the reservoir under study during natural production. Each point on this graph represents the result of a single simulation run, which was called by the SA optimization algorithm. The figure outlines the result of 652 simulations (i.e., function calls) with different production rates in the range from 48 to 636 m$^3$/d.

As the production rate increases, more gas is produced and a modest downward trend in recovery factor can be observed in Fig. 5. However, there is an unconventional rise in the recovery factor curve from 360 to 420 m$^3$/d (distinguished by two dashed lines in Fig. 5) in which ultimate recovery reaches a peak of 28.9% at the rate of 390.63 m$^3$/d. The dominant production mechanism for the production rates less than 360 m$^3$/d is solution-gas-drive; whereas, the production is being limited by the field maximum GOR caused by the surface facility limitations at rates over than 420 m$^3$/d (Error! Reference source not found.). At the optimum production rate of our study (i.e., 390.63 m$^3$/d), the operational constraints helped the formation to have a higher recovery factor. During the production, the upper perforations of the well were automatically closed due to high-production GOR (i.e., >356.2 m$^3$/m$^3$ from Table 3Error! Reference source not found.); therefore, the lower perforations only continued to produce more hydrocarbon. The closure of the upper perforations resulted in ceasing gas production and consequently developing of a secondary gas cap in the reservoir. Thus, the expansion of this gas cap can maintain the reservoir pressure as a dominant drive mechanism. In this situation, the recovery factor of the reservoir reaches to its maximum value of 28.9%.

To validate the creation of the secondary gas cap in the reservoir, Fig. 6 shows the reservoir average pressure and cumulative gas production for production rates of 48 and 390 m$^3$/d. For the former production rate, the reservoir pressure steady falls, while for the later production rate, pressure dramatically slumps in primary steps ($t<1200$ days) and afterward moderately declines. This sudden reduction in pressure drop rate is due to releasing of the solution gas. After 1200 days, gas production rise continues but with a more moderate rate than before.
This is because of the closure of the upper perforations and creation of the secondary gas cap that can displaces oil below gas-oil-contact in a piston-like manner toward the open completions.

3.2. Optimizing Waterflooding Scenario

The aim of this scenario is to find the optimum water-injection rate. During waterflooding, the production well produced at the rate of 238.48 m3/d. The results of 659 simulations with different water injection rates are illustrated in Fig. 7. The optimum injection rate was calculated to be 164.55 m3/d with the recovery factor of 35.5% that is almost 6.6% higher than the natural production.

At low injection rates \( q_{inj} < 120 \text{ m}^3/\text{d} \), the injected water could not compensate the reservoir pressure drop due to the production (i.e., weak water-drive mechanism) so the recovery factor remained almost constant irrespective to the water injection rate. In contrary, water broke through at high injection rates \( q_{inj} > 370 \text{ m}^3/\text{d} \). After the breakthrough of water in the production well, no more oil could be produced and the sweep efficiency remained almost constant irrespective to the injection rate. Because in these cases, the completions have reached to their maximum-water cut constraint (i.e., 50% from Table 3) and were closed. This behavior can easily be seen in Fig. 8 where an increase in injection rate (e.g., injection rate from 264.55 to 397 m3/d) resulted in a dramatic rise in well water-cut in preliminary time steps. Thus, the well completions automatically were closed, and water-cut plummeted to zero.

Furthermore, Fig. 7 shows a fallen trend of recovery factor from the injection rate of 120 to 370 m3/d. This is because of the availability of a balance between injection and production rates (i.e., strong water drive mechanism). This balance prolonged the breakthrough time and increased the piston-like movement behavior of the injected fluid. However, a sharp jump in recovery factor is observable in this figure around the injection rate of 164.55 m3/d. As this injection rate was lower than the production rate (i.e., 238.48 m3/d); therefore, the injected water could not maintain the reservoir pressure and finally gas was released from the formation fluid (i.e., \( P < P_b \)). The expansion and migration of this gas to the formation gas-cap could support the reservoir pressure; therefore, the maximum recovery of 35.5% could be achieved.

Fig. 9 depicts the average gas saturation, \( S_g \), of the reservoir at different injection rates. In all injection rates (except 164.55 m3/d), as the injection rate increases \( S_g \) falls because that the injected water could support the pressure reduction. The \( S_g \) of the formation rose at primary steps (\( t<11000 \text{ days} \)) and before gas breakthrough. After gas breakthrough, due to the formation depletion as well as gas production, \( S_g \) decreased. The trend of \( S_g \) for the injection rate of 164.55 m3/d is different from the other scenarios. At this rate, the \( S_g \) of the reservoir
went up over time. During waterflooding with this rate, the upper perforations quickly reached to the maximum GOR constraints (i.e., mentioned in Table 3) and were automatically closed. In this situation, the released gas could not be produced. Increasing $S_g$ resulted in the creation of a secondary gas cap in the reservoir and consequently a rise in recovery factor. Thus, the $S_g$ of the formation rocketed despite of the trend of the other scenarios. Again, this phenomenon emphasizes that the operational constraints can influence the production results.

3.3. Optimizing Gas injection Scenario

Fig. 10 depicts the result of 699 simulations during the SA optimization of gas injection rates. The optimum ultimate recovery (39.1%) was obtained at the gas injection rate of 18,122 m$^3$/d, which is 10.2 and 3.7 % higher than the natural production and water flooding scenarios, respectively.

The trend of this figure can be classified in three subsections. The gas fingering effect and breakthrough continuously declined the formation recovery factor at the injection rates higher than 18,000 m$^3$/d. In higher injection rates, gas fingering reduced the injection sweep efficiency and the recovery factor as well. The recovery factor curve reached to its highest point, 39.1 %, at the gas injection rate of 18,122 m$^3$/d. In addition, the recovery factor curve surged at low gas injection rates ($q_{inj} < 12,000$ m$^3$/d). The reason for this behavior is that before gas breakthrough, higher gas injection rates could compensate more reservoir pressure drop due to the production. Further increase of the gas injection rate from 12,000 to 18,000 m$^3$/d resulted in reaching to the operational gas-oil-ratio limit in the production well (Table 3), wherein the production was ceased. In this case, the recovery factor significantly dropped.

Fig. 11 illustrates the cumulative gas production curve versus reservoir average saturation for three different gas injection scenarios (i.e., 8,495, 14158, and 18,122 m$^3$/d). At the same average gas saturation value, the scenario with the injection rate of 18,122 m$^3$/d produced less gas than the scenario with the injection rate of 8,495 m$^3$/d. Therefore, the former scenario could have higher recovery factor. In the scenario with an injection rate of 14,158 m$^3$/d, the injected gas as well as the released solution gas broke through very soon in the production well and due to the maximum GOR constraint limit, the production well ceased to produce more hydrocarbon.

3.4. Single Parameter Optimization of WAG flooding Scenario

3.4.1. WAG Cycle Time Optimization.

Different WAG ratios introduce different amount of mixture zones and displacement mechanisms in a formation. Varying cycle time obviously changes the number of cycles and this might affect the ultimate recovery of a flooding process. Fig. 12 depicts the result of about 1500 simulations during the SA optimization of WAG cycle time with a fix slug size.
As it is clear, optimizing more parameters (i.e., water and gas cycle time) sharply increases the number of function calls (i.e., 1500 simulations) during the optimization.

The optimum recovery factor, 43.3 %, was obtained at a point with water and gas injection cycle time of 81.5 and 180 days, respectively. A better look into the available results reveals that some realizations have a better ultimate recovery than the other realizations. Fig. 12b shows this meaningful trend. These points are some local minimum of the objective function that lies on a straight line, which passes through the origin of this figure. The global minimum at the highest recovery value (i.e., 43.3 %) also lies on this straight line. Considering the water and gas injection rates (238.48 m³/d and 18,405 m³/d, respectively) along with the computed optimum cycle times resulted in the optimum WAG ratio of almost 1:1 (in field unit MSCF/STB).

\[
\text{WAG Ratio} = \frac{\text{Volume of injected water}}{\text{Volume of injected gas}} \\
\approx 1.70 \frac{\text{m}^3}{\text{m}^3} = 1 \frac{\text{STB}}{\text{MSCF}}
\]  

3.4.2. Water Injection Rate Optimizing in WAG Scenario

The second scenario during our WAG optimization was optimizing water injection rate while keeping constant the cycle times and gas injection rate from the previous scenario. Fig. 13 illustrates the function calls during the SA optimization. The behavior of this figure can be divided in three subsections (distinguished by two vertical dashed lines). Before the injection rate of 160 m³/d and due to the insufficient pressure maintenance, the recovery factor was low (i.e. weak water drive mechanism). The optimum injection rate was achieved at a value of 242.6 m³/d with the recovery factor of 43.4 %. In addition, recovery factor plummeted by more increasing in water rate after 270 m³/d due to the quick breakthrough of the water phase in the production well. It worth noting that the calculated optimum injection rate of 242.6 m³/d is very close to the optimum injection rate from the waterflooding scenario (i.e., 238.48 m³/d). In addition, this value is in confirmation with the result of the optimum WAG ratio of 1:1 from the previous section.

3.4.3. Gas Injection Rate Optimizing in WAG Scenario

In this scenario, an optimum condition for gas injection rate during the WAG flooding was investigated. During the optimizations, the optimized values of the water injection rate and cycle times from the previous analyses were implemented. An optimized gas injection rate of 18,859 m³/d was found with a maximum recovery factor of 43.5 % (Fig. 14). The interesting point of the computed optimum rate is that this value is again very close to the optimum WAG ratio (i.e., 1:1 in field unit) calculated from the section “WAG Cycle Time Optimization”. It indicates that the optimum injection rates of water and gas should be in confirmation with the optimum WAG ratio.

3.4.4. Simultaneous Parameter Optimization of WAG Parameters

In contrary to the previous sections in which WAG parameters were individually optimized, the aim of this section is to optimize the WAG flooding parameters (i.e., water and gas injection rates and water and gas injection cycles) simultaneously. As the result of four
parameters cannot be depicted in a single figure, we used water and gas slug size (i.e. injection rate × cycle time) to show all simulation results in a 3-D graph (see Fig. 15a). The optimum scenario resulted in 46% recovery factor for water injection rate and cycle time of 88.24 m³/d and 181 days, respectively and gas injection rate and cycle time of 26,023 m³/d and 110 days, respectively. The first interesting issue with the computed results is that the simultaneous optimization of the WAG parameters resulted in an ultimate recovery factor that is almost 3% higher than that in the individual optimization results. Secondly, in conformity with our previous results, the optimum WAG ratio in this optimization scenario is again 1:1 (in field unit). This behavior is well illustrated in Fig. 15b in which the top view of Fig. 15a is shown for those simulation points with higher recovery factor (e.g., > 38%). All simulation results lie on a straight line showing a WAG ratio of 1:1. This shows that during WAG optimization, WAG ratio can be an important parameter and irrespective to the manner of optimizations will remain almost constant.

### 3.5. Summary

Table 4 summarizes the optimization results of all scenarios. Recovery factor increases from waterflooding to gas injection and rises even more during WAG flooding. As it is shown, the simultaneous optimization of all parameters has the highest ultimate recovery factor.

Fig. 16 depicts the average reservoir pressure during all optimum-flooding scenarios. As it can be seen, subsequent to the natural production period, all scenarios result in nearly constant reservoir pressure maintenance in the formation. In other words, the flooding process could maintain the reservoir pressure after the natural production period with a constant trend.

### 4. Conclusion

In this study, a simulated annealing optimizer was coupled with a reservoir simulator to investigate the efficiency of different production-injection scenarios. The recovery factor was selected as an objective function. The considered scenarios include optimization of natural production, waterflooding, gas injection, individual WAG parameters, and simultaneous WAG parameters. The developed model then applied into a case study from an Iranian offshore formation. The role of different operational constraints including production mode change (i.e., from constant rate to constant BHP), closing perforations above a maximum water-cut, or GOR limit were analyzed.

Our results indicate that: (a) the operational constraints could considerably alter the production characteristics of a flooding scenario by changing the production mechanism (e.g., from solution-gas-drive to secondary-gas-cap drive). Therefore, these production restrictions could alter the final optimal scenario and should always be analyzed; (b) the recovery factor of the optimized WAG scenario (46 %) was clearly higher than that of the optimized natural production (28.9 %), waterflooding (35.5 %), gas injection (39.1 %); (c) the ultimate recovery factor of the individual WAG parameter optimization (in average 43.4 %) was certainly less than the simultaneous optimization of all parameters (46 %). This reveals that to find the best scenario during simulation optimization, all parameters should be optimized.
together; (d) irrespective to the number of variables during optimizations, the WAG ratio (i.e., the volume fraction of injected water to gas) remains almost constant and equal to 1:1 in the field unit.

Our results can facilitate (a) finding the role of operational constraints during optimization of primary production, secondary recovery, and WAG flooding scenarios; (b) the manner of optimization of influential parameters during flooding scenarios. However, during a production-optimization process, many uncertain parameters are available that a scenario-based model cannot completely address them. These uncertainties causes non-uniqueness of solutions that should be obtained with a probabilistic method without overly exhausting simulation resources [56]. Thus, future studies are needed to reveal the effect of different uncertain inputs on the result of simulation-optimizations. One possible approach could be finding the effect of these uncertainties through implementation of the Monte Carlo simulations during simulation optimizations [57-59]. Moreover, the main problem of all reservoir-simulation optimization strategies and history-matched techniques is their high computational cost [60]. Finding a proper optimization algorithm that can handle the non-linearity of complex hydrocarbon formations and reduce the computation time is worthy of researching. Furthermore, in this study only the role of operational parameters were considered during finding the success of a WAG flooding project, while the effect of reservoir parameters (e.g., heterogeneity, petrophysical properties, fluid properties) [36] is open for further investigations. Finally, in this study a rather simple objective function (i.e. recovery factor) was studied. Implementing more complicated objective functions (e.g., net present value) and multiple-objective functions can be the title of future researches.

Appendix A

A.1. Simulated Annealing Strategy

Simulated Annealing (SA) is a probabilistic technique that was originally inspired from the process of metal annealing in metallurgy. This method tries to model the controlled heating and cooling process of a material in order to change its physical properties (e.g., increasing the size of its crystals) by altering its internal structure (i.e., minimizing its thermodynamic free energy).

Fig. A-1 depicts the optimization procedure of SA. The algorithms start with setting the initial temperature and generating a random solution. Next, the objective function value is evaluated for the random solution. Subsequently, a random neighboring solution should be generated by making a small change to the current solution. The new solution's cost is calculated and it is decided whether to move to this solution (i.e., new state) based on an acceptance probability function. This procedure continues up to reaching to the equilibrium condition (i.e., in practice, repeat the process for a large value). Then the system temperature is decreased based on an annealing schedule temperature and the previous steps are repeated until the stop condition (termination condition) is met.
A.2. Annealing Temperature

SA incorporates a temperature parameter, $T$, into the minimization procedure. $T$ is initially set high ($T_0$) and then it is allowed to slowly 'cool' as the algorithm runs. At high temperatures, the algorithm will be allowed to accept worse solutions, which often guarantees to avoid being trapped in local optimums. Thus, accepting worse solutions lets the algorithm to extensively search for optimal solutions. As the temperature declines, the chance of accepting worse solutions reduces; therefore, the algorithm focuses on search spaces that may contain final optimum solutions. Moreover, at each fixed number of steps, the annealing parameters are set to lower values than that iteration number (i.e. $T$ increases). This process is called restarting or re-annealing that again helps the algorithm to escape from local solutions. In our case, we run re-annealing module every 130th iteration. This parameter was tuned by trying a couple of simulation-optimization runs.

A.3. Acceptance Probability

An acceptance distribution probability ($p$) is defined, which depends on the difference between the new cost function value $E_{new}$ and the current saved cost value $E_{current}$ and also the system temperature, $T$. In our methodology, achieving the maximum ultimate recovery was defined as a cost function ($E =$recovery factor). The acceptance probability, $p$, decides probabilistically whether to stay in the current state or to bounce out of it. In our model, if the new state (i.e., the new recovery factor) is better than the current state, it becomes the next solution. While, if the new state is worse than the current state (i.e., the new recovery factor is lower than the current recovery factor), the algorithm can still consider it as the next point with the acceptance probability of,

$$p = \frac{1}{1 + \exp\left(\frac{\Delta E}{T}\right)}$$  \hspace{1cm} (A-1)

where, $\Delta E = E_{new} - E_{current}$. The acceptance probability is between 0 and 1/2. Smaller temperature results in smaller acceptance probability and vice versa. Moreover, larger $\Delta E$ leads to smaller $p$.

A.4. Annealing Schedule

Carefully controlling the rate of cooling of the temperature can guarantee to reach to more optimum conditions. The cooling rate should be low enough for the probability distribution of the current state to be close to the thermodynamic equilibrium. The algorithm systematically lowers $T$ and stores the best state found so far. In our algorithm, the cooling rate obeys the following equation,

$$T = T_0 \times 0.95^k$$  \hspace{1cm} (A-2)
in which, $T_0$ is initial temperature of the system and $k$ is the same as the iteration number until re-annealing. For better optimization purposes, we selected $T_0$ in such a way that the algorithm was able to better explore the entire search space before any cooling. The value of $T_0$ is clearly depend on the scaling of $\Delta E$ and so is problem-specific. To determine $T_0$ in our optimization, an 80% acceptance chance was considered for a change that increases the objective function at initial temperature. By conducting an initial search on our simulation-optimization approach, $T_0$ of 150 K was selected based on the specified criteria.

A.5. Generating Neighboring Solution

During the optimization, the new solutions, $x_{\text{new}}$, are generated from the current solution, $x_{\text{current}}$, according to the formula,

$$x_{\text{new}} = x_{\text{current}} + D \times R \quad \text{(A-3)}$$

$x$ is the vector of variables. Since during our production-injection scenario, parameters such as production rate, water/gas injection rates, or cycle times were considered as our decision variables. $R \in [-1, 1]$ is a vector of random numbers and $D$ is a diagonal matrix which defines the maximum allowable changes for each variable. $D$ is updated after an acceptable change in the state of the solution by,

$$D_{\text{new}} = (1 - \beta)D_{\text{current}} + \beta D_{\text{success}} \quad \text{(A-4)}$$

$\beta$ is the weighting factor (0.85 was considered in our algorithm) and $D_{\text{success}}$ consists of the magnitude of the changes made to each control variable in the new successful state. This equation controls the maximum step size associated with each control variable.

A.6. Terminating Condition

The final $T$ in our algorithm was determined when the system has sufficiently cooled or the search ceased to make progress. In other words, it is either no improvement being found at each temperature, or the acceptance ratio falling below a small value (i.e., $10^{-6}$ in our algorithm).

References

Saeid Sadeghnejad is an assistant professor of petroleum engineering at Tarbiat Modares University, Iran. His research interests include formation characterization using pore-scale methods and EOR. He holds a bachelor’s degree in chemical engineering, and master’s and Ph.D. degrees in petroleum engineering from Sharif University of Technology, Iran.

Mehrdad Manteghian is a professor of chemical engineering at Tarbiat Modares University, Iran. His research interests include industrial crystallization and mass transfer. He holds a bachelor’s degree in chemical engineering from AmirKabir University and master’s and Ph.D. degrees in chemical engineering from UMIST University, UK.

Hossein Ruzsaz obtained his MSc degree in petroleum engineering from Tarbiat Modares University, Iran. His study area is EOR. Ruzsaz holds a BS degree in petroleum engineering, Iran.
Figure 1. Scenarios considered during simulation optimization.

Fig. 2: Schematic illustration of the coupled simulator-optimizer. Optimization actions are shown with filled green boxes and the simulator actions are shown with empty blue boxes.

Fig. 3: a) Porosity map of the formation under study. b) Selected sector of the field showing the initial saturation of the reservoir for three available phases (i.e., oil, water, and gas).

Fig. 4: Relative permeability and capillary pressure data used during simulations.

Fig. 5: Production rate optimization of 652 simulations during natural production. The optimum rate (390.63 m³/d) is shown with a red cross. The recovery factor of rates from 360 to 420 m³/d (distinguished by two dashed lines) behaves differently from the other regions.

Fig. 6: Comparing average reservoir pressure and cumulative gas production of two different production scenarios with production rates of 47.70 and 390.63 m³/d.

Fig. 7: Optimization of water injection rate in water flooding scenario. The optimum injection rate (164.55 m³/d) is shown with a red cross. The recovery factor behaves differently in the three defined injection rates ranges with the vertical dashed lines.

Fig. 8: Comparing production water cut for different injection rates of 164.55, 238.48, 362.49, and 397.47 m³/d. Injecting with higher rates decreases water breakthrough time.

Fig. 9: Average gas saturation of reservoir, $S_g$, for different water flooding scenarios with injection rate of 143, 164.55, 174.89, and 238.48 m³/d. The optimum injection rate, 164.55 m³/d, behaves differently from the other scenarios.

Fig. 10: Recovery factor versus gas injection rate during optimization. The optimum gas injection rate (18,122 m³/d) is shown with a red cross. Three different recovery factor behaviors can be seen (distinguished by two vertical dashed lines).

Fig. 11: Field gas production for three different gas injection scenarios with the injection rate of 8495, 14158, and 18122 m³/d.

Fig. 12: a) Recovery factor from 1000 simulations based on different water and gas injection cycles. In each scenario a value of 238.48 m³/d and 18,405 m³/d was considered for water and gas injection rates, respectively. b) Top view of (a) showing a trend between gas and water injection cycles with higher recovery factor.

Fig. 13: Recovery factor from 560 simulations with different water injection flow rate during WAG flooding. A value of 18,405 m³/d and 238.48 m³/d was considered for gas injection rate and production, respectively during all simulations.

Fig. 14: Gas injection rate optimization of WAG flooding scenario (751 simulations). The optimum gas injection rate of 18,859 m³/d with the ultimate recovery factor of 43.5 % is shown with a red cross.

Fig. 15: a) Recovery factor of nearly 2800 reservoir simulations for different water and gas slug size. During the optimization all WAG parameters considered simultaneously, b) top-view of (a) and by only filtering the simulation results with more than 38 % recovery factor. The simulation results lie on a straight line showing WAG ratio of 1:1.

Fig. 16: Average reservoir pressure for different optimized scenarios, including, natural production (with the rate of 390.63 m³/d), water flooding (with the flooding rate of 164.55 m³/d), gas flooding (with the injection rate of 18,122 m³/d), and WAG flooding (simultaneous optimization of all parameters) showing pressure maintenance of the reservoir during all flooding scenarios.

Fig. A-1: Flow chart of simulation annealing procedure
Table 1: Rock and Fluid properties of the reservoir under study.

Table 2: Production/injection parameters considered during optimization of water flooding, gas injection, and WAG injection scenarios.

Table 3: Well operational constraints in the field under study.

Table 4: Summary of the optimization results.
Figure 1

- **Optimization Scenarios**
  - Scenario 1: Natural Production
  - Scenario 2: Water flooding
  - Scenario 3: Gas flooding
  - Scenarios 4, 5: WAG flooding

- Individual parameter optimization
- Simultaneous parameter optimization
Figure 2
Figure 3
Figure 4
Figure 5

![Graph showing recovery factor versus production rate with categories for Solution-gas drive, Secondary gas-cap-drive, and Operational limitations]
Figure 6
Figure 7

[Diagram showing the relationship between water injection rate (m$^3$/d) and recovery factor (%). The diagram is divided into three sections: Weak water drive, Strong water drive, and Water breakthrough. The diagram also includes a note about Secondary gas-cap-drive.]
Figure 8

[Graph showing water cut fraction over time with different injection rates indicated by different lines and colors.]
Figure 10

![Graph showing recovery factor vs. gas injection rate]

- Weak pressure maintenance constraint
- Gas breakthrough
- GOR

Y-axis: Recovery Factor (%)
X-axis: Gas Injection Rate (m³/d) x 10²
Figure 11

![Graph showing gas production vs. average gas saturation for different injection rates.]

- Blue line: Injection rate of 8,495 m³/d
- Orange line: Injection rate of 14,158 m³/d
- Green line: Injection rate of 18,122 m³/d
Figure 12
Figure 13
Figure 14
Figure 15

a) 3D graph showing distribution of gas and water slugs.

b) Scatter plot relating gas slug and water slug volumes.
Figure 16
Setting $T_0$ and initial parameter values, $x_0$

Calculating cost of solution, $E_{\text{current}}(x_{\text{current}})$

Generating a random neighboring solution $x_{\text{new}}$, Eq. A.3

Calculating cost of solution, $E_{\text{new}}(x_{\text{new}})$

Accept new solution, Eq. A.1

No

Check Equilibrium Condition

No

Check Terminating Conditions

Yes

Decrease $T$ based on annealing schedule, Eq. A.2

$E_{\text{current}} \neq E_{\text{new}}$

$E_{\text{current}} = E_{\text{new}}$

Update $D$, Eq. A.4

End

Yes

Yes
<table>
<thead>
<tr>
<th>Property</th>
<th>Amount</th>
<th>Property</th>
<th>Amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>Porosity (%)</td>
<td>3-32</td>
<td>Oil Density (kg/m³)</td>
<td>935.96</td>
</tr>
<tr>
<td>Horizontal Permeability (×10⁻¹¹ m²)</td>
<td>0-1.35</td>
<td>Gas Density (kg/m³)</td>
<td>1.3</td>
</tr>
<tr>
<td>Vertical Permeability (×10⁻¹¹ m²)</td>
<td>0-0.13</td>
<td>Water Density (kg/m³)</td>
<td>1140.03</td>
</tr>
<tr>
<td>Rock Compressibility (1/Pa)</td>
<td>8.7×10⁻¹⁰</td>
<td>Oil Viscosity (mPa.s)</td>
<td>3.65</td>
</tr>
<tr>
<td>Bubble point pressure (MPa)</td>
<td>18.62</td>
<td>Water Viscosity (mPa.s)</td>
<td>0.55</td>
</tr>
<tr>
<td>Initial reservoir pressure (MPa)</td>
<td>19.31</td>
<td>Gas Viscosity (mPa.s)</td>
<td>0.02</td>
</tr>
</tbody>
</table>
Table 2

<table>
<thead>
<tr>
<th>Well Production/Injection Parameters</th>
<th>Value</th>
<th>Scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Water Flooding</td>
</tr>
<tr>
<td>Production rate (m$^3$/d)</td>
<td>238.48</td>
<td>✓</td>
</tr>
<tr>
<td>Maximum injection BHP (MPa)</td>
<td>20.68</td>
<td>✓</td>
</tr>
<tr>
<td>Water injection rate (m$^3$/d)</td>
<td>238.48</td>
<td>✓</td>
</tr>
<tr>
<td>Gas injection rate (m$^3$/d)</td>
<td>18,405</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gas Injection</td>
</tr>
<tr>
<td></td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>WAG</td>
</tr>
<tr>
<td></td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>
### Table 3: Well Constraints

<table>
<thead>
<tr>
<th>Well Constraints</th>
<th>limit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil flow rate for each well (m$^3$/d)</td>
<td>&lt;31.80</td>
<td>The well is closed if this limit is broken</td>
</tr>
<tr>
<td>Bottom hole pressure (MPa)</td>
<td>&lt;6.20</td>
<td>Production changes from a constant rate mode to a constant BHP mode</td>
</tr>
<tr>
<td>Water cut (%)</td>
<td>&gt;50</td>
<td>The worst-offending connection in the well is closed</td>
</tr>
<tr>
<td>Gas-Oil-Ratio (m$^3$/m$^3$)</td>
<td>&gt;356.2</td>
<td>The worst-offending connection in the well is closed</td>
</tr>
<tr>
<td>Scenario</td>
<td>Optimization Parameter</td>
<td>Optimum Parameter</td>
</tr>
<tr>
<td>---------------------------</td>
<td>------------------------</td>
<td>-------------------</td>
</tr>
<tr>
<td>Natural Production</td>
<td>Production Rate</td>
<td>390.63 m$^3$/d</td>
</tr>
<tr>
<td>Water Flooding</td>
<td>Injection Rate</td>
<td>164.55 m$^3$/d</td>
</tr>
<tr>
<td>Gas Injection</td>
<td>Injection Rate</td>
<td>18,122 m$^3$/d</td>
</tr>
<tr>
<td>Individual WAG Parameter Optimization</td>
<td>Water and Gas Cycle Time</td>
<td>81.5 days, 180 days</td>
</tr>
<tr>
<td></td>
<td>Water Injection Rate</td>
<td>242.61 m$^3$/d</td>
</tr>
<tr>
<td></td>
<td>Gas Injection rate</td>
<td>18,859 m$^3$/d</td>
</tr>
<tr>
<td>Simultaneous Parameter Optimization</td>
<td>Water Injection Rate, Water Cycle, Gas Injection Rate, Gas Cycle</td>
<td>88.23 m$^3$/d, 181 days, 26,023 m$^3$/d, and 110 days</td>
</tr>
</tbody>
</table>

*Incremental recovery with respect to primary production*