



Accelerated optimization of CO₂-miscible water-alternating-gas injection in carbonate reservoirs using production data-based parameterization

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Abstract

Enhancing oil recovery in reservoirs with light oil and high gas content relies on optimizing the miscible water alternating gas (WAG) injection profile. However, this can be costly and time-consuming due to computationally demanding compositional simulation models and numerous other well control variables. This study introduces WAG_{eq}, a novel approach that expedites the convergence of the optimization algorithm for miscible water alternating gas (WAG) injection in carbonate reservoirs. The WAG_{eq} leverages production data to create flexible solutions that maximize the net present value (NPV) of the field, while providing practical implementation of individual WAG profiles for each injector. The WAG_{eq} utilizes an injection priority index to rank the wells and determine which should inject water or gas at each time interval. The index is built using a parametric equation that considers factors such as producer and injector relationship, water cut (W_{CUT}), gas–oil ratio (GOR), and wells cumulative gas production, to induce desirable effects on production and WAG profile. To evaluate WAG_{eq}'s effectiveness, two other approaches were compared: a benchmark solution named WAG_{bm}, in which the injected fluid is optimized for each well over time, and a traditional baseline strategy with fixed 6-month WAG cycles. The procedures were applied to a synthetic simulation case (SEC1_2022) with characteristics of a Brazilian pre-salt carbonate field with karstic formations and high CO₂ content. The WAG_{eq} outperformed the baseline procedure, improving the NPV by 6.7% or 511 USD million. Moreover, WAG_{eq} required fewer simulations (less than 350) than WAG_{bm} (up to 2000), while delivering a slightly higher NPV. The terms of the equation were also found to be essential for producing a WAG profile with regular patterns on each injector, resulting in a more practical solution. In conclusion, WAG_{eq} significantly reduces computational requirements while creating consistent patterns across injectors, which are crucial factors to consider when planning a practical WAG strategy.

Keywords Simulation reduction · Practical solution · Flexible solution · Water alternating gas · Production data · Parameterized equation · Field management

List of symbols

C_m^n	Combination of n elements taken m at a time	GOR ^p	Gas–oil ratio of producer p
F	Threshold cut percentage to select the best samples	i	Index representing the injector
$f_p(\text{GOR}_{\text{limit}}^p)$	Control rule function to shut the producer p	I^i	Priority index of injector i
$\text{GOR}_{\text{limit}}^p$	Gas–oil ratio limit value to shut the producer p	N	Sample size generated in each Iterative discrete Latin hypercube iteration
GOR_{max}	Gas–oil ratio maximum value normalizer	NPV(x)	Net present value objective function depending on the decision variable vector x
		$C(x)$	Inequality constraint of the maximization problem
		Eq(x)	Equality constraint of the maximization problem
		m	Number of gas injectors
		m_p^i	Number of producers influenced by the gas injector i
		n	Number of injectors

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n_p^i	Number of producers influenced by the water injector i
nt	Number of minimal time intervals
p	Index representing the producer
t	Time passed from initial management date
t_{end}	Total simulation period
t_{init}^i	Initial time the injector i starts to operate
t_{min}	Minimal time interval
V_g^i	Volume of gas injected by injector i since it has injected water
V_{norm}^i	Gas volume normalizer for injector i
$Well_{gor_limit}$	Baseline strategy
W_{CUT}^p	Water cut of producer p
x	Generic decision variables
x_{lb}	Lower bound of the generic decision variable x
x_{min}	Minimum value for a specific feature
x_{up}	Upper bound of the generic decision variable x

Greek letters

α_p^i	Coefficient of the producer p that are influenced by the water injector i
β_p^i	Coefficient of the producer p that are influenced by the gas injector i
γ^i	Coefficient associate with time term of the parametric equation
δ^i	Coefficient associate with the volume of gas produced term of the parametric equation

Abbreviations

DLHC	Discrete Latin hypercube sampling
GOR	Gas–oil ratio
GOR_{limit}	Gas–oil ratio limit
IDLHC	Iterative discrete Latin hypercube
NPV	Net present value
PMF	Probability mass function
USD	United states dollar
WAG	Water alternating gas
WAG_{bm}	Water alternating gas benchmark procedure
WAG_{eq}	Water alternating gas parametric equation procedure
W_{CUT}	Water cut

Introduction

The Brazilian pre-salt is one of the world's largest polygons of oil and gas discovered in recent decades (Godoi and dos Santos 2021). The oil from many pre-salt fields has high levels of gas–oil ratio (GOR) and CO₂ component (Pasqualetto et al. 2017). This high amount of gas offers

the opportunity to supply the gas market but also poses challenges related to gas handling, storage, and transportation (Ligero and Schiozer 2014). Some of the pre-salt reservoirs also present gas contaminant contents that make their commercialization difficult. To avoid greenhouse gas emissions in the cases where the gas is not profitable, there is a special interest in re-injecting the gas produced. Wang et al. (2023) proposed a solution for CO₂ storage safety by investigating the feasibility of water alternating gas (WAG) injection and brine extraction in a deep saline aquifer. Their study found that WAG injection and brine extraction can enhance CO₂ injectivity and storage safety, with WAG injection reducing structural trapping contribution and brine extraction decreasing the maximum averaged reservoir pressure.

The WAG injection method involves alternating the gas with water, which has a synergistic effect that arises from the properties of both fluids. The water's primary role are pressure maintenance, macroscopic displacement, and improving gas sweep efficiency by controlling gas mobility and stabilizing the gas front, while gas decreases oil viscosity and residual oil saturation, thereby increasing the efficiency of microscopic displacement (Christensen et al. 2001; Kulkarni and Rao 2005; Arogundade et al. 2013; Ramachandran et al. 2010; Afzali et al. 2018; Janssen et al. 2020).

Several studies in the literature have reported the effectiveness of the WAG method in increasing oil recovery and the economic return of oil fields (Chen et al. 2010; Duchenne et al. 2014; Hu et al. 2020; Kong et al. 2021; Mousavi et al. 2011; Sampaio et al. 2020; Schaefer et al. 2017; Teklu et al. 2016). Schaefer et al. (2017) and Hu et al. (2020) conducted a comparison between CO₂-WAG and continuous CO₂ injection using reservoir simulation. In both studies, the WAG method resulted in increased oil production in comparison with continuous CO₂ injection, with approximately 30% and 14% higher oil production reported, respectively. Duchenne et al. (2014) performed a laboratory study to investigate the microscopy efficiency of CO₂-WAG injection on horizontal carbonate cores with light oil under reservoir conditions, and they showed that CO₂-WAG injections provide a faster and better oil recovery than pure CO₂ injection.

To improve production management strategies, it is crucial to optimize the WAG profile, which involves the alternating injection of water and gas into wells. A range of methods have been identified in the literature to optimize the WAG profile, with the most prevalent being the optimization of WAG cycles (Bahagio 2013; Esmail et al. 2005; Nait et al. 2018; Pal et al. 2018; Pereira et al. 2022), i.e., determining the optimal duration of water injection and gas injection before switching back to gas from water, as well as the WAG ratio, which is the ratio between the volume of water and gas injected (Chen et al. 2010; Chen and Reynolds 2016; Kazakov and Bravichev 2015; Panjalizadeh et al. 2015).

Chen and Reynolds (2016) implicitly optimized the WAG ratio for each cycle by optimizing both the target for gas and water injection rates and the target for the producers' bottom-hole pressure (BHP) over time. They considered different numbers of WAG cycles (4, 8, 16, and 32 cycles) and aimed to maximize the net present value (NPV) of the field. The authors obtained better results by increasing the number of cycles, and they suggested that fixing a WAG ratio for the entire field life cycle is inappropriate. Pereira et al. (2022) tested five approaches to optimize the WAG cycle's duration to maximize the NPV of a synthetic reservoir simulation model with pre-salt characteristics. The two approaches that delivered better results were (1) the simultaneous optimization of WAG cycles (same cycle size for all injectors) and the gas–oil ratio (GOR) limit to shut producers; (2) using the best solution from the previous approach, the authors optimized the cycle individually for each injector, followed by a re-optimization of the GOR limit to shut-in producer wells. An important conclusion from their work was that the optimum cycle size could be changed meaningfully according to the operation of other control variables (such as the shut-in of producers).

Supporting the findings of Pereira et al. (2022), Chen et al. (2010) stated that inappropriate selection of the control of injectors and producers may result in unstable pressure distribution, early gas breakthrough and, consequently, a lower oil recovery factor. Bahagio (2013) showed the importance of controlling the WAG parameters (e.g., WAG cycle duration) in a synthetic reservoir of $7 \times 7 \times 3$ grid blocks with a 5-spot pattern containing four injectors and one producer in the middle. The author observed a significant increase in the NPV by optimizing both the duration of WAG cycles and the BHP injection, compared to optimizing only the BHP and maintaining a fixed WAG half-cycle duration of 6 months for both water and gas. The number of water cycles alternated with gas was kept fixed at 30, while allowing the duration of gas and water cycles to vary during each fluid exchange. The author used an equal WAG profile for all injectors, which is appropriate for the homogeneous case studied, but may lead to suboptimal solutions when accounting for reservoir heterogeneities.

Kazakov and Bravichev (2015) argue that describing WAG injection solely by time-dependent periods of gas and water injection is not informative, as injectivity may not remain constant due to varying saturation and reservoir pressure during field production. Similarly, when accounting for geological uncertainties, a time-dependent WAG injection alone may be less practical as the injection and production capacities may vary due to reservoir uncertainties. To address these limitations, a WAG injection control that takes into account production monitoring variables like water cut, GOR, and fluid rates could provide a more flexible and

adaptable solution for the real reservoir's changing behavior over time.

Compositional simulation is generally considered a more reliable approach for miscible enhanced oil recovery (e.g., miscible WAG injection) in reservoirs with light oil and high gas content, such as those found in Brazilian pre-salts. However, the reliability comes at the cost of augmented computational effort as the number of pseudo components required to accurately describe the field's fluids increases (Schlijper 1986). The computational cost is amplified by the optimization of several well control variables, including WAG control, as well as the presence of uncertainties and high heterogeneity of the fields, which demand a large number of blocks for accurate modeling.

Therefore, efforts to reduce computational costs while maintaining high oil production and economic return are crucial for the optimization of miscible enhanced oil recovery. This can be achieved using various techniques, such as representing a larger group of models that honor observed data through a small set of scenarios that still accurately capturing field uncertainties (Meira et al. 2017; Meira et al. 2020; Sarma et al. 2013; Shirangi and Durlofsky 2015), numerically tuning high-complexity reservoir models (Mello et al. 2022), and using coarse models to represent high fidelity ones. For example, Kou et al. (2022) proposed upscaling methods for CO₂ migration in 3D heterogeneous geological systems that reduce computational costs while preserving fine-scale flow mechanisms. The authors tested two percolation-based methods demonstrating the robustness of the upscaling methods with less than 10% computational errors between fine- and coarse-scale models.

A supplementary strategy to alleviate the computational load involves minimizing the number of simulations required for optimization by constraining the search space. By doing so, the optimization algorithm can converge more rapidly toward satisfactory solutions. Expanding on these considerations, the present study introduces a novel WAG parameterization rule that utilizes reservoir production data to expedite the optimization process, while simultaneously maximizing the economic return over the life cycle of the WAG strategy. The proposed rule offers a high degree of flexibility by accommodating individual WAG profiles for each injector, regardless of whether they follow a cyclic pattern or not, while still being easy to implement in practical cases.

As previously mentioned, optimizing the WAG injection profile also requires consideration of the producer wells' operation. Thus, we simultaneously optimize the GOR limit (GOR_{limit}) to shut each producer and the WAG injection under the total gas re-injection constraint to maximize the field's life cycle NPV for two different procedures. The first consists of a WAG parameterization that defines the set of possible solution space for the fluid to be injected by each well at each time step. The solution achieved by this

procedure is only time-dependent, and serves as a benchmark in terms of number of simulations and NPV. Our second and primary procedure involves utilizing a parametric equation to determine the WAG injection profile. This equation considers the gas injection volume during each cycle and the most influential producers for each injector. Each term in the equation has been carefully designed to produce a specific effect on the WAG profile, which will be explained in detail in the methodology section of this paper.

The optimization process involves tuning the coefficients of the parametric equation, which significantly reduces the number of optimization variables compared to the first procedure. The results obtained from both procedures are then compared to the baseline strategy, where WAG cycles are set to 6 months and only the GOR limit for shut-in producers is optimized. This comparison allows the evaluation of the NPV gain achieved by optimizing the WAG profile.

The paper’s organization is as follows: first, a brief explanation of the optimization algorithm used in this study is provided. Next, the methodology section presents comprehensive details on the adopted procedures. The case study, including production constraints and underlying assumptions, is then presented succinctly. We then compare the results obtained from the simulations and the net present value (NPV) achieved for both the procedures and the baseline approach. The following section investigates and discusses whether the terms included in the proposed equation are generating the expected effect on the WAG profile. The paper concludes by summarizing the advantages of the proposed method. It also highlights the limitations of the study and potential directions for future research.

IDLHC optimization algorithm

The optimization algorithm applied in this work is based on the discrete Latin hypercube sampling method (DLHC, see Maschio and Schiozer 2016), a technique that recreates the entire space distribution by randomly sampling the discrete candidate values of each optimization variable. The probability mass function (PMF) of each optimization variable determines the frequency with which each discrete value appears in the sample. For instance, if variable Y has a sample size

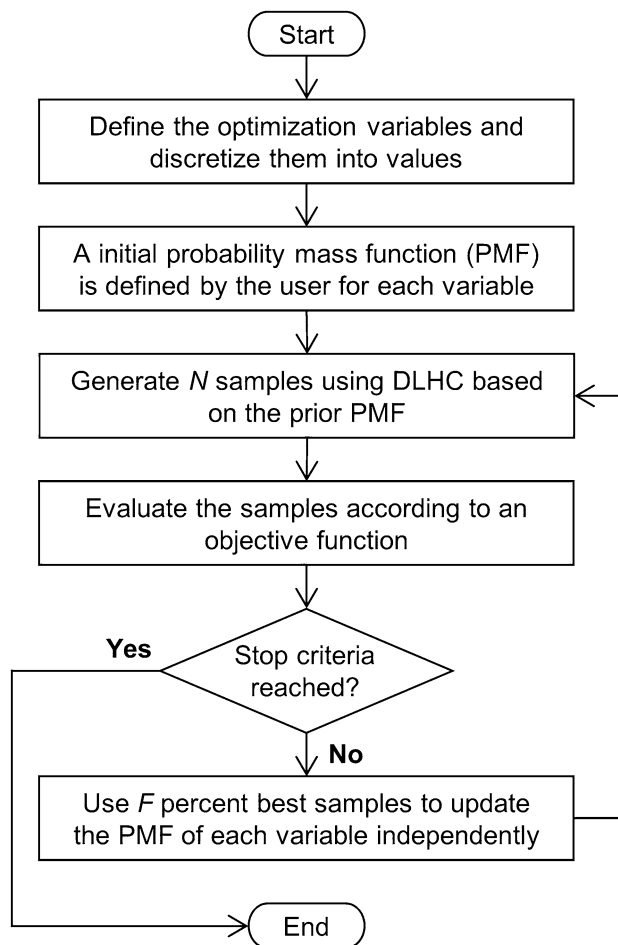
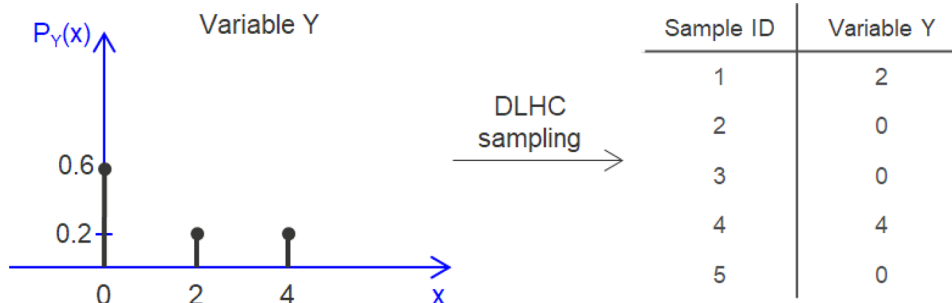


Fig. 2 IDLHC algorithm workflow, which iteratively generates samples using discrete Latin hypercube (DLHC) method, evaluates them using an objective function, and updates the probability mass function (PMF) of each variable based on the F percent best samples. The loop continues until specific criteria are reached

of 10, and its PMF is given by $P_Y(x) = \{0.6, 0.2, 0.2\}$, where the discrete values of Y are represented by $x = \{0, 2, 4\}$, then the number of samples with the values 0, 2, and 4 would be 3, 1, and 1, respectively (as depicted in Fig. 1).

The Iterative discrete Latin hypercube (IDLHC, see von Hohendorff et al. 2016), depicted in Fig. 2, is a

Fig. 1 Discrete Latin hypercube sampling method example for the variable Y . The samples of the variable Y generated with the value x depend on the probability $P_Y(x)$



widely-used optimization technique that performs the following steps: (1) defining the optimization variables and discretizing them into values, (2) generating N samples using the discrete Latin hypercube method based on a initial probability mass function (PMF) defined by the user for each variable, (3) evaluating the samples using an objective function, and (4) selecting the F percent best samples to update the PMF of each variable independently. The updated PMF is then used to generate the samples in the next iteration. The loop continues until a specific condition is reached, such as a maximum number of iterations or a threshold of minimum difference between the maximum and minimum values obtained in the iteration. It is important to note that in the first iteration, the probability mass function of all variables is generally set as equiprobable, and the value of N must be greater than the number of candidate values for each variable.

We selected the IDLHC algorithm for optimization because it has been demonstrated to generate high-quality solutions in numerous published works (Botechia et al. 2021; Loomba et al. 2022; Pereira et al. 2022; Santos et al. 2020; von Hohendorff et al. 2016; von Hohendorff and Schiozer 2018). Some of these works have compared the IDLHC algorithm with other well-established optimization techniques, and the IDLHC has been shown to generate better results. For instance, von Hohendorff et al. (2016) reported that the IDLHC algorithm outperformed a well-established optimization technique in a production optimization problem, demonstrating a faster convergence rate and resulting in a slightly better objective function. Another study by von Hohendorff and Schiozer (2018) showed that the IDLHC algorithm has several advantages, including its simplicity and rapid convergence near the global optimum, compared to a genetic algorithm method, when applied to optimize the well placement production strategy.

Methodology

The method presented herein aims to maximize the net present value (NPV) of a reservoir through an optimization problem, as formulated in Eq. (1). This involves the optimization of parameters related to the baseline procedure (Well_{gor_limit}), the benchmark strategy (WAG_{bm}), and the main procedure which uses a parametric equation to define the WAG injection profile (WAG_{eq}). The WAG_{bm} and WAG_{eq} parameters are jointly optimized with the well limit of gas–oil ratio (GOR_{limit}), which is used to shut-in each producer individually. Furthermore, all wells from WAG_{bm} and WAG_{eq} are capable of injecting alternating water and gas.

$$\begin{aligned} & \text{Maximize NPV}(x) \\ & \text{Subject } x_{lb} \leq x \leq x_{ub}, \\ & C(x) \leq 0, \\ & \text{Eq}(x) = 0. \end{aligned} \quad (1)$$

where x is the decision variable vector subject to lower (x_{lb}) and upper bounds (x_{ub}). The objective function is NPV(x), and the inequality and equality constraints are represented by $C(x)$ and Eq(x), respectively. In the reservoir simulation problem, there are multiple constraints to consider, including well bottom-hole pressures, well and platform rates (inequality constraint), full gas re-injection, and reservoir pressure maintenance (equality constraints).

The methodology's results are first discussed by comparing the best NPV, the optimization algorithm convergence rate, WAG profile, and field production for the Well_{gor_limit}, WAG_{bm} and WAG_{eq}. Subsequently, an analysis of the parametric equation's terms is conducted to determine if each of them are generating the anticipated effect on the WAG profile and whether they should be retained or eliminated. The aim of this examination is to offer significant insights into the effectiveness of the WAG_{eq} and the validity of the modeled behavior.

Baseline procedure (Well_{gor_limit})

This procedure utilizes the measured gas–oil ratio of each producer p (GOR ^{p}) as a monitoring variable. The control rule, f_p (GOR_{limit} ^{p}), operates by shutting down producer p once it reaches the GOR_{limit} ^{p} , as shown by Eq. (2). As a result, the number of optimization variables for this procedure is equal to the number of producers wells, and the value of GOR_{limit} can be different for each producer. Additionally, the WAG cycles are fixed in this procedure, providing a baseline NPV that enables the evaluation of the economic increment capacity of optimizing the WAG profile.

$$f_p(\text{GOR}_{\text{limit}}^p) = \begin{cases} \text{shut producer, } \text{GOR}_{\text{limit}}^p \geq \text{GOR}^p \\ \text{keep producer open, } \text{GOR}_{\text{limit}}^p < \text{GOR}^p \end{cases} \quad (2)$$

This procedure was conducted by Botechia et al. (2021), and the candidate values for the GOR_{limit} and the NPV obtained from the optimized strategy are presented in the application section.

WAG benchmark procedure (WAG_{bm})

Here, we present a parameterization that aims to find the best combination of water injectors and gas injectors over time, while adhering to the constraint that all produced gas must be re-injected. Additionally, each injector well can switch between water and gas injection, with a minimum interval of

t_{\min} between switching. The solution space in this approach consists of the combination C_m^n of all injectors (n) where at least a pre-defined number of gas injectors (m) are operating to ensure complete re-injection (Eq. 3).

$$C_m^n = \left(\frac{n!}{m! \times (n - m)!} \right)^{nt} \tag{3}$$

where nt represents the number of minimal time intervals. This procedure is solely dependent on time and is performed to establish a benchmark value for the number of simulations and NPV that can be expected by optimizing the WAG injection profile. Our primary approach, WAG_{eq} , is expected to deliver an NPV performance that is at least equivalent to this benchmark, while requiring fewer simulations.

WAG parametric equation rule (WAG_{eq})

This procedure aims to optimize the WAG profile over time in a more efficient way while maintaining or even increasing the NPV compared to the previous procedure (WAG_{bm}). It involves the development of a parametric equation rule using the injection priority index (Eq. 4), which determines the order of gas and water injection at each time interval. The index value is used to rank the injectors, with those above a pre-defined threshold rank injecting gas and the others injecting water. The index of each injector (I^i) is determined by several variables, including the field’s lifetime (t), the volume of gas injected (V_g^i) since the well last water injection, the W_{CUT} of the n_p^i producers influenced by the water injector i , and GOR of the m_p^i producers influenced by the gas injector i . The influence is determined by analyzing the streamlines from the injectors to the producers, without utilizing any data beyond that which was available during the WAG_{eq} procedure. The fluid of each injector can be altered within the t_{\min} interval, similar to the WAG_{bm} . Alternative methods, such as trace or Euclidean distance, could be used instead of streamlines to determine the influence of each injector.

$$I^i = \frac{1}{n_p^i} \times \sum_{p=1}^{n_p^i} \left(\alpha_p^i \times W_{CUT}^p \right) - \frac{1}{m_p^i} \times \sum_{p=1}^{m_p^i} \left(\frac{\beta_p^i \times GOR^p}{GOR_{\max}} \right) + \gamma^i \times \left(\frac{t - t_{\text{init}}^i}{t_{\text{end}} - t_{\text{init}}^i} \right) - \delta^i \times \left(\frac{V_g^i}{V_{\text{norm}}^i} \right) \tag{4}$$

The optimization variables are the coefficients of the producer p that are influenced by the injector i (α_p^i, β_p^i), the coefficients γ^i and δ^i , and the gas volume normalizer for the injector i (V_{norm}^i).

To ensure consistent influence on the priority index calculation, all terms in the equation are normalized. The time term is normalized by the difference between the whole

simulation period (t_{end}) and the moment that the injector i starts to operate (t_{init}^i). The maximum gas–oil ratio (GOR_{\max}) is used as the normalizer for GOR^p . The value for GOR_{\max} should be set equal to the maximum candidate value of GOR_{limit} because it represents the highest value a producer can attain before being shut-in. Finally, the W_{CUT} is already a normalized term between 0 and 1.

Each term in the equation used for calculating the injection priority index has a specific role in shaping the WAG profile, as explained below:

- The $\frac{-\delta^i \times V_g^i}{V_{\text{norm}}^i}$ represents the fraction of gas injected by the well in relation to the gas volume normalizer. The gas volume normalizer (V_{norm}^i) is chosen such that the ratio of gas volume injected by the well $\frac{V_g^i}{V_{\text{norm}}^i}$ falls within the range of approximately 0.1 to 1. The negative sign ($-$) incorporated in the term decreases the value of I^i for wells that have injected gas since their last water injection (Fig. 3a). Conversely, water-injecting wells are exempt from this term, resulting in a higher value of I^i and thereby promoting their gas injection during the next fluid exchange period. Therefore, this term is conducive to promoting water alternating with gas injection in the well.
- The expression $\gamma^i \times \left(\frac{t - t_{\text{init}}^i}{t_{\text{end}} - t_{\text{init}}^i} \right)$ exhibits a constant value of $\left(\frac{t - t_{\text{init}}^i}{t_{\text{end}} - t_{\text{init}}^i} \right)$ among all wells with the same t_{init}^i . Therefore, the contribution of this term to I^i increases with positive values of γ^i , which correspond to a greater tendency toward gas injection throughout the well’s lifetime, on the other hand, negative values of γ^i lead to a preference for water injection over the entire life cycle (Fig. 3b). The objective of this term is to establish a consistent injection

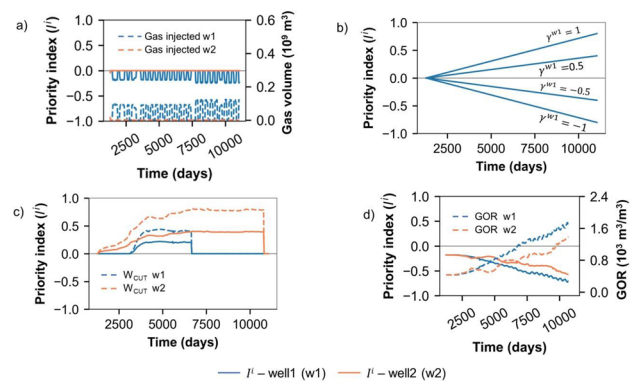


Fig. 3 Impact of each term in the WAG_{eq} procedure. **a** Well 1 (w1) gas injection lowers I^i and promotes water injection in the next cycle. Well 2 (w2) with zero gas injection does not affect I^i . **b** I^i linearly varies over time and its slope depends on gamma. **c** A higher W_{CUT} increases I^i and gas injection tendency. **d** A higher GOR reduces I^i , favoring water injection

pattern for each well, so that if a well initiates a water–gas cycle, this term fosters its continuation until the end of the field’s lifetime or the opening of new wells.

- The $\alpha_p^i \times W_{\text{CUT}}^p$ is always positive and contributes to an increase in the value of I^i . As such, the higher the W_{CUT} of the producers influenced by injector i the higher the value of I^i for that injector (Fig. 3c). As a result the injector tends to transition from water to gas injection during the next t_{min} interval. This term promotes the uniform growth of W_{CUT} among the field’s producers over time, potentially improving reservoir sweep efficiency. In contrast, the $\frac{-\beta_p^i \times \text{GOR}^p}{\text{GOR}_{\text{max}}}$ works in a similar manner, but the negative sign results in a decrease in I^i value (Fig. 3d), and the injectors tend to shift from gas to water injection leading to homogeneous GOR growth among producers.

Application

We begin by describing the benchmark and the premises adopted for the study. Subsequently, we present important dates that are necessary to compute the NPV and also show the production operational constraints. Furthermore, we provide information about the distribution and range of values for the optimization variables, as well as the IDLHC configuration parameters adopted in the procedures.

Study case

Our methodology was applied to the SEC1_2022 benchmark, which is a reservoir simulation model that has been designed to replicate the geological and fluid characteristics of Brazilian pre-salt fields (Chaves 2018; Correia et al. 2020). This model represents a carbonate reservoir with light oil containing high levels of CO₂, and comprises 63 × 120 × 309 grid cells and 77,071 active blocks. Each block corresponds to an average volume of 200 × 200 × 5

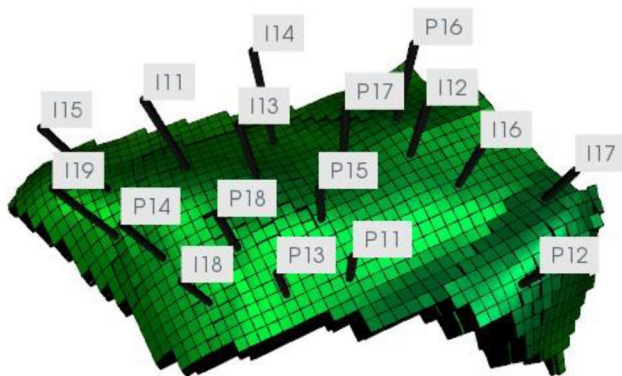


Fig. 4 Reservoir wells placement

cubic meters. Due to the complex characteristics of the fluid, the GEM compositional simulator (version 2020.10) developed by the Computer Modeling Group (CMG) was used to simulate the SEC1_2022 model.

Figure 4 displays the opening of 17 wells in two phases. During the first phase, six producers and seven injectors were opened between May and December/2021. In the second phase, which began in February 2027, the remaining two producers (P17 and P18) and two injectors (I18 and I19) were put into operation.

The case includes historical data from October/2018 to February/2022, and the simulation continues until December/2048. The reference date for updating the NPV is February/2022. The costs associated with the wells and platform installed in first phase are not considered in the NPV calculation because they were installed before the reference date. However, costs associated with the wells drilled and perforated in the second period are considered. The operational constraints for both wells and the platform are provided in Tables 1 and 2.

Assumptions and optimization parameters

The assumptions and optimization parameters for the baseline strategy and the two procedures are outlined below:

- The average reservoir pressure of 61,000 kPa is maintained through water injection rate control
- All produced gas must be re-injected into the reservoir
- Exactly four wells must inject gas at the same time throughout the entire field management
- All injectors can inject both water and gas

Table 1 Wells’ operational constraint

Type of well	Constraint	Value
Producers	Minimum bottom-hole pressure (kPa)	50,000
	Maximum liquid production (m ³ /day)	8000
Injectors	Maximum bottom-hole pressure (kPa)	75,000
	Maximum water injection (m ³ /day)	10,000
	Maximum gas injection (m ³ /day)	4,000,000

Table 2 Platform’s operational constraints

Constraint	Value (m ³ /day)
Maximum oil rate	28,617
Maximum liquid rate	28,617
Maximum water production rate	23,848
Maximum water injection rate	35,771
Maximum gas production rate	12,000,000

- The minimum period (t_{\min}) to switch from one fluid to another is 6 months.

The baseline strategy includes a fixed 6-month period to switch the injected fluid from each injector. One well (I16) is designated to inject only gas during the entire period to ensure full gas re-injection. In WAG_{bm} and WAG_{eq} , all injectors can switch between water and gas, meaning that I16 does not have to inject only gas like in the baseline strategy. The $Well_{\text{gor_limit}}$ strategy was optimized by Botchia et al. (2021), who used candidate values for GOR_{limit} ranging from 600 to 2400 sm^3/sm^3 at 200 sm^3/sm^3 intervals. The optimized strategy delivered an NPV of 7.68 USD billion requiring 150 simulations.

For both the WAG_{bm} and WAG_{eq} procedures, the optimization is conducted simultaneously with WAG parameters and GOR_{limit} , utilizing the same candidate values for GOR_{limit} as Botchia et al. (2021). In the case of WAG_{bm} , the parameters cover all possible combinations of open injectors, with four gas injectors operating throughout the entire management period. When considering GOR_{limit} variables, the search space includes approximately 5.71×10^{113} potential solutions for this procedure.

In the WAG_{eq} procedure, the coefficients and V_{norm}^i are linearly spaced with 11 values between the ranges displayed in Table 3. Furthermore, GOR_{max} is defined as the maximum candidate value for GOR_{limit} (2400 sm^3/sm^3).

The minimum V_{norm}^i value was set slightly below the maximum volume of gas that can be injected by one well in the t_{\min} interval (approximately $7.2 \times 10^8 \text{ m}^3$). The maximum value was defined as ten times greater than the minimum value to ensure that the gas volume term can assume magnitudes similar to the other terms of the equation (between 0 and 1).

We have set the number of samples generated for each iteration based on the IDLHC requirement that N be greater than or equal to the number of candidate values for each variable. For WAG_{bm} , given that the combination of C_4^9 is 126, we set the number of samples to 150. For the WAG_{eq} simulation, we set N to 50. Both simulations had an F value of 30% and were run for 15 iterations.

Table 3 Range of the optimization variables for WAG_{eq} procedure

Variable	Range [min, max]
α_p^i	[0, 1]
β_p^i	[0, 1]
γ^i	[-1, 1]
δ^i	[0, 1]
$V_{\text{norm}}^i \text{ (m}^3\text{)}$	$[5 \times 10^8, 5 \times 10^9]$

Results

First, we identified the producers affected by each injector and the respective fluids (water or gas) in the non-optimized study case, which enabled us to determine the WAG_{eq} terms related to GOR^p and W_{CUT}^p monitoring variables (Table 4). By influence, we mean any fluid streamline from the injector arriving to the producer at any time during the management period. It is important to note that the same producers affected by I16 are identified for both water and gas fluids. This is due to the fact that I16 solely injects gas in the non-optimized scenario, and therefore, it would not have any water streamlines originating from it to impact any of the producers.

The WAG_{bm} and WAG_{eq} approaches significantly enhanced the NPV, resulting in approximately 8.11 and 8.18 USD billion, respectively. In comparison with the $Well_{\text{gor_limit}}$ procedure, the WAG_{eq} yielded a similar NPV of 7.68 USD billion with 50 simulations, while the WAG_{bm} approach required 150 simulations to achieve a slightly higher NPV relative to the baseline strategy. The WAG_{bm} and WAG_{eq} improved the NPV by 436 USD million (5.7%) and 511 USD million (6.7%) compared to $Well_{\text{gor_limit}}$, respectively. This finding highlights the importance of optimizing the WAG profile alongside well producer control variables. Although the maximum NPV achieved by WAG_{eq} (after 720 simulations) was only slightly higher than that of WAG_{bm} (0.9% or 75 USD million), WAG_{eq} required significantly fewer simulations and iterations to converge. At iteration 7 and with fewer than 350 simulations, the NPV was comparable, with the maximum NPV of WAG_{bm} achieved after 14 iterations and with 2051 simulations, as depicted in Fig. 5.

The optimal WAG solutions did not exhibit a cyclical pattern, as shown in Fig. 6. This result underscores the potential limitations of defining the search space based solely on regular cycles, as it may result in suboptimal outcomes. Notably,

Table 4 Producer wells influenced by gas and water streamlines from each injector

Injectors	Producers (gas)	Producers (water)
I11	P14, P18	P18
I12	P11, P17	P13, P15, P17
I13	P13, P15, P17, P18	P15
I14	P16	P16
I15	P14, P18	P14
I16	P11, P13	P11, P13
I17	P12	P12
I18	P13, P18	P13, P14, P18
I19	P14	P14

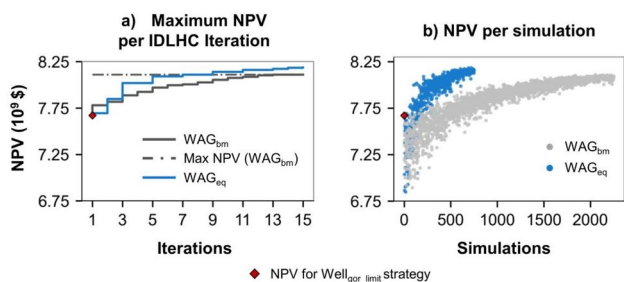
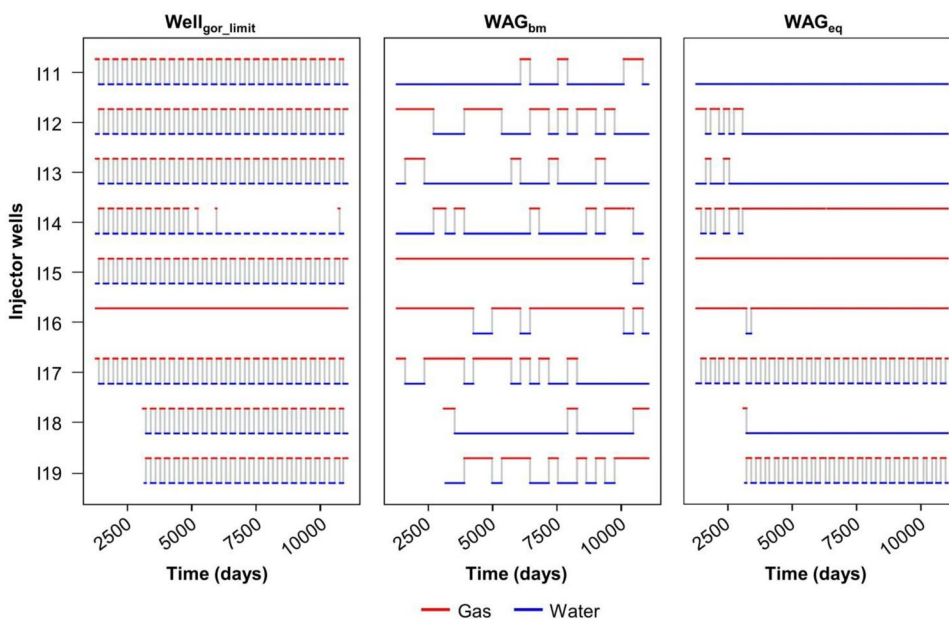


Fig. 5 Comparison of NPV between the proposed WAG procedures (WAG_{bm} and WAG_{eq}) and the baseline strategy (Well_{gor_limit}). The figure shows **a** the maximum NPV achieved by each approach throughout the iterations of IDLHC and **b** the NPV over the simulations

most of the wells in WAG_{eq} predominantly injected one fluid all over the management period. In particular, the I16 and I15 wells had the highest rank of injector priority index (I^i) for the majority of the period, while I11, I12, and I13 exhibited the lower values. The I^i was observed to alternate between I12, I13, I14, and I17 before the second wave and between I17 and I19 after it.

The WAG_{eq} and WAG_{bm} approaches significantly increased oil and water production compared to the baseline strategy. Precisely, WAG_{eq} increased oil production by 11.4% and water production by 272%, while WAG_{bm} resulted in a 9.4% increase in oil production and a 260% increase in water production. Moreover, both approaches injected considerably more water than the Well_{gor_limit} strategy, with WAG_{eq} and WAG_{bm} injecting 43% and 38% additional water, respectively. This maintained average reservoir pressure and rise water and oil production (Fig. 7) indicating the successful enhancement of the reservoir’s sweep efficiency.

Fig. 6 Comparison of WAG profile between the baseline strategy (Well_{gor_limit}) and the best strategy obtained using WAG_{bm} and WAG_{eq} procedures



The production of gas for all three strategies was limited by platform capacity and the gas full re-injection constraint was also observed, as shown in Fig. 8. This demonstrates that the optimal strategies prioritize maximizing gas injection, even if it results in higher gas production costs.

Investigation of the terms of the equation for WAG_{eq} procedure

We conducted further analysis to examine the impact of each term in the parametric equation on the WAG profile and NPV. This was done to determine the necessity of all terms in the equation. To accomplish this, we optimized the parametric equation with all terms except one to observe if the resulting WAG profile lost the specific behavior associated with that term. The optimization parameters and assumptions used were the same as those employed in the WAG_{eq} procedure.

First, we removed $\frac{-\delta^i \times V_g^i}{V_i^{norm}}$ from the equation, which promotes water and gas exchange between injectors as described in the methodology. Figure 9b shows that when this term is removed, the wells indeed tend to inject the same fluid over time. Wells that alternated between water and gas injection in WAG_{eq} (such as I19, I17, and I14) injected almost exclusively one fluid when the gas volume term was removed. The I11, I13, I15, I16, and I18 wells also injected almost solely one fluid over the field management in both WAG solutions.

The WAG profile solution obtained after removing the term $\gamma^i \times \left(\frac{t - t_{init}^i}{t_{end} - t_{init}^i} \right)$ appears less regular for injectors like I12, I14, and I17, which do not primarily inject a single type of fluid for most of the time (Fig. 9c). This indicates that the

Fig. 7 Volumes and rates of production and injection for the baseline strategy ($Well_{gor_limit}$) and for the best strategy of WAG_{bm} and WAG_{eq} procedures

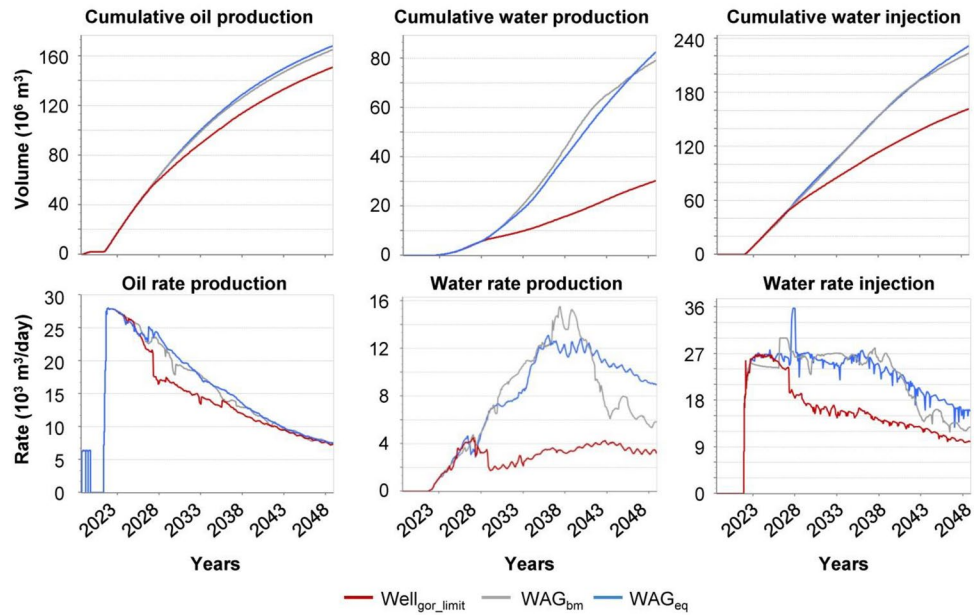
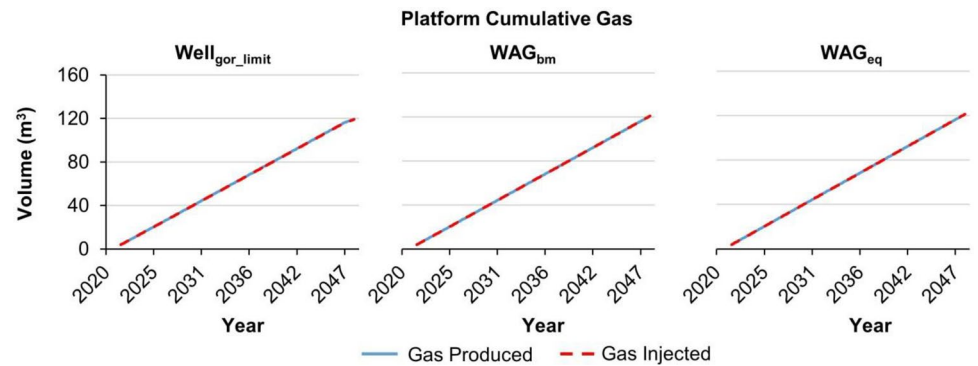


Fig. 8 Cumulative gas production and injection for the baseline strategy ($Well_{gor_limit}$) and for the best strategy of WAG_{bm} and WAG_{eq} procedures



temporal term is necessary to maintain a regular injection pattern from each injector throughout the field life cycle or until a significant event occurs, such as the opening of new wells in the second wave. The temporal term generates more stable strategies that are easier to implement in practical scenarios.

We found that removing the term $\frac{-\beta^i \times GOR^p}{GOR_{max}}$ from the equation leads to more dispersed GOR curves over time compared to the original WAG_{eq} strategy, as shown in Fig. 10. This indicates that the GOR term does indeed induce the desired behavior of making GOR more even among the producers, which could improve sweep efficiency.

After removing the W_{CUT} term from the equation, we did not observe significant changes in the injection profiles of the wells (Fig. 9e). This indicates that the W_{CUT} term had a minor effect on the WAG_{eq} strategy, and the top four injectors' rank, which determines the gas injection wells, remained largely unchanged. The optimal WAG_{eq}

strategy may have prioritized gas production control over water production control, as the former was deemed more pressing. According to Fig. 11a and b, most wells exhibited W_{CUT} values below 0.6 for both the WAG_{eq} original strategy and the strategy without the W_{CUT} term, indicating that water production was not a significant concern in this study case. Nonetheless, the inclusion of the W_{CUT} term may prove beneficial in other cases where water production is a more critical issue.

The results indicate that removing one term of the equation had a minimal impact on both the optimization convergence of the algorithm and the NPV of the best solution, as seen in Fig. 12. The maximum decrease in NPV was 1.2% (95 million dollars) for the WAG_{eq} solution without the gas volume term. Despite the slightly higher NPV of the original WAG_{eq} , it is advisable to retain all the equation terms as it offers a more practical solution from

Fig. 9 Comparison between WAG profile for the best strategy of **a** WAG_{eq} and the WAG_{eq} without one of the following terms **b** gas volume, **c** temporal term, **d** GOR, and **e** W_{CUT}

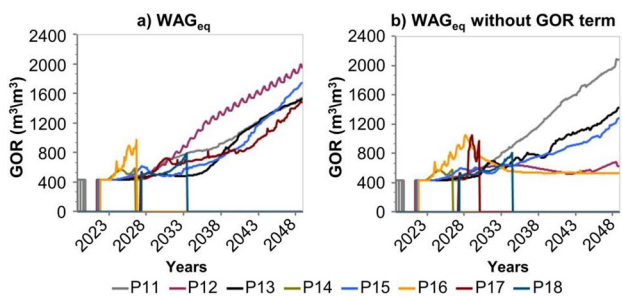
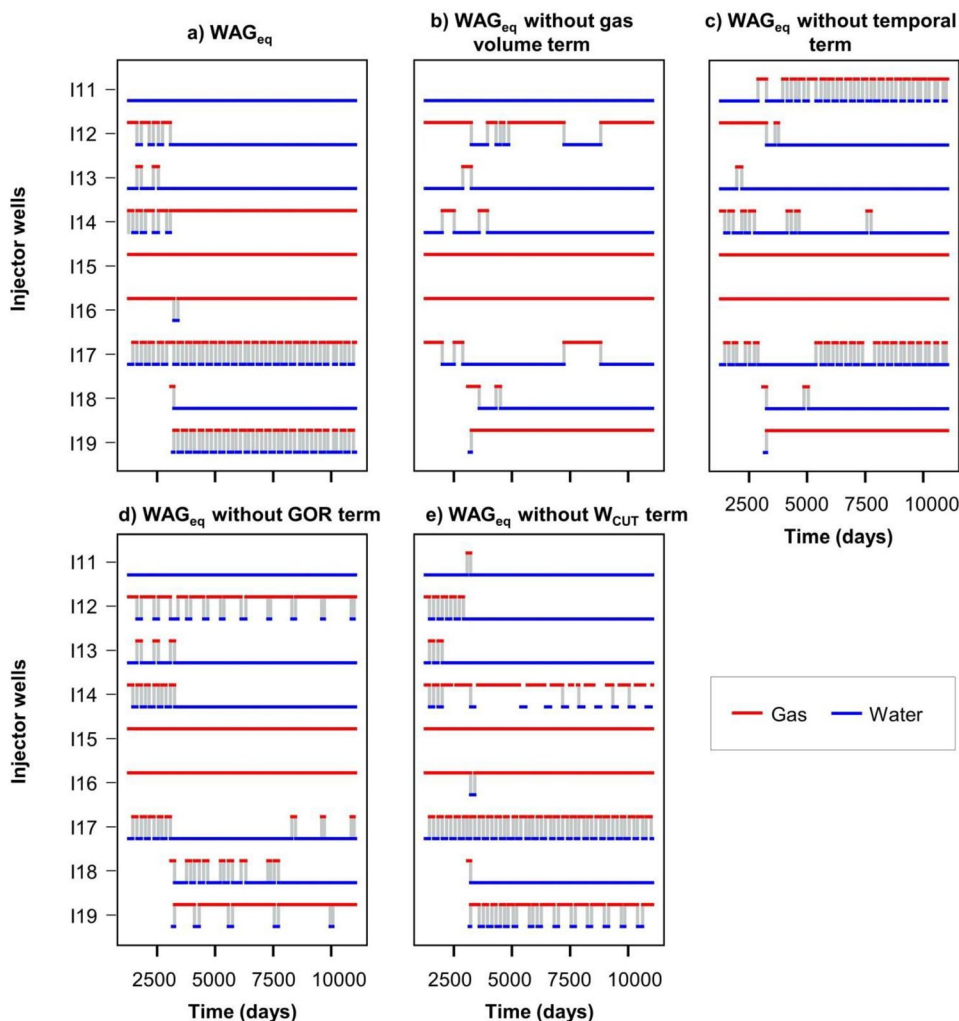


Fig. 10 Gas–oil ratio (GOR) evolution over time for producers P11 to P18 analyzed in two scenarios **a** using the WAG_{eq} method, and **b** using the WAG_{eq} without GOR term

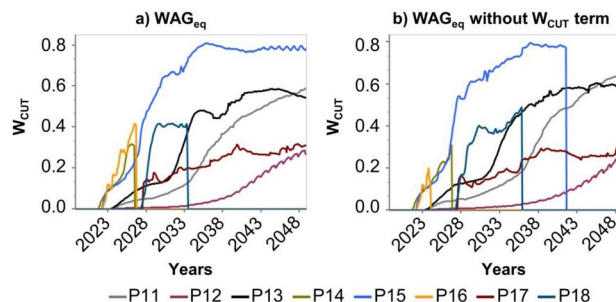


Fig. 11 Water cut evolution over time for producers P11 to P18 analyzed in two scenarios **a** using the WAG_{eq} method, and **b** using the WAG_{eq} without the W_{CUT} term

an engineering perspective. It also widens the search space without affecting the convergence rate of the algorithm, which can be important for other study cases.

Conclusions

Our proposed method, WAG_{eq} , aims to optimize the miscible water alternating gas (WAG) process by using a

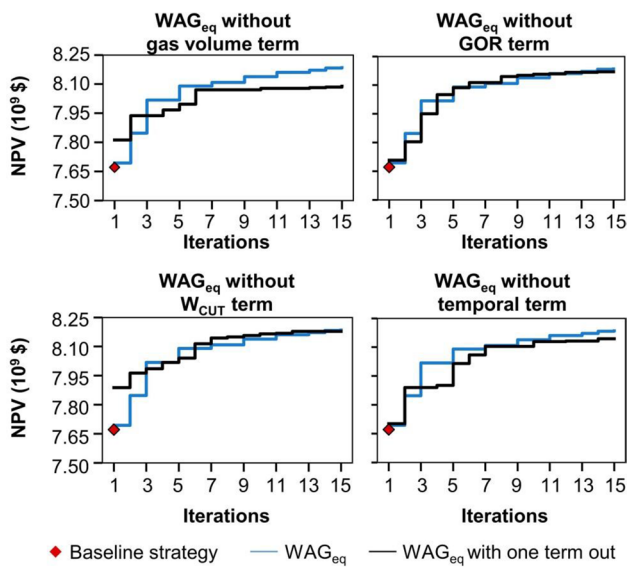


Fig. 12 Comparison of maximum NPV until each iteration from the best strategy of WAG_{eq} and each of the WAG_{eq} best strategies with one term excluded

tailored parametric equation based on reservoir production data. This method offers significant advantages over other methods, and the major conclusions drawn from this study are:

- The WAG_{eq} method successfully achieved its main goal of accelerating the optimization process compared to the benchmark WAG_{bm} procedure, which determines the optimal type of fluid injection (gas or water) for each well over time. The WAG_{eq} reduced the simulations by almost sixfold, while also delivered a slightly higher net present value (NPV) compared to WAG_{bm}
- The WAG_{eq} substantially increased the NPV by 511 USD million (6.7%) compared with the baseline strategy (Well_{gor_limit}), which has fixed WAG cycles of 6 months. This result highlights the significance of optimizing the WAG profile over time for improved economic return
- The WAG_{eq} enables well-behaved WAG profiles for each injector, facilitating practical implementation
- The non-cyclical pattern observed in the optimal WAG solution for most injectors underscores the importance of WAG_{eq} being able to include flexible solutions in the optimization search space
- The WAG_{eq} equation terms, designed to favor alternating water and gas injection, regular injection patterns, and uniform gas–oil ratio production, were successful in generating these desired behaviors in the optimal WAG solution profile. Although the inclusion of a term aiming for homogeneous water cut (W_{CUT}) growth did not demonstrate any significant impact on the optimal WAG

solution in this study, it may be relevant in cases where water production is a concern.

Overall, this paper presents a significant contribution in the development of a practical procedure that addresses crucial factors in real-world scenarios. Specifically, it minimizes computational effort, ensures well-behaved WAG profiles across all injectors and delivers a high NPV, which is helped by the procedure's ability to produce flexible solutions. Future research opportunities include testing its validity for studies cases considering uncertainties and where water production is a more significant issue, as well as combining this approach with machine learning techniques to further reduce computational effort.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Ethical approval The authors confirm that this manuscript has not been previously published and is not currently under consideration by any other journal. Each named author has substantially contributed to conducting the underlying research and drafting this manuscript. Additionally, all of the authors have approved the contents of this paper. They have also agreed to the submission policies of Journal of Petroleum Exploration and Production Technology.

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