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COBEM2023-1842 Application of a StoSAG Algorithm using a Modified Cost Function and Group Constraints in a Three-Phase Reservoir Model

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Abstract. *Optimization algorithms are extremely important to performance and productivity of an oil and gas reservoir. Usually, the NPV function is the objective function to be maximized, which is evaluated by its calculation considering the production of the entire reservoir life. A modified NPV function was proposed to take into account not only the NPV but also the well degradation in the waterflooding optimization, allowing the development of a constructive optimization at each time step (prediction windows of reservoir simulation) using the Stochastic Simplex Approximated Gradient (StoSAG) algorithm. To extend this methodology to three-phase reservoir models, an alternative objective function is derived from NPV function. The optimization algorithm also considered multi-dimensional output constraints, such as well and group production rates that are handled by the reservoir simulator. The methodology is applied in a modified SPE9 field, whose wells are divided into two groups with constraints of gas group production and also well constraints. Results were obtained and compared from two simulations, one using the proposed method and the other under reactive control (RC), which resulted in the NPV of the StoSAG being 7% larger than the NPV of the RC with an acceptable number of reservoir simulations.*

Keywords: *Optimization, MNPV cost function, Group constraints, SPE9, StoSAG*

1. INTRODUCTION

In the field of reservoir management, one of the most challenging problems to be tackled is how the wells should be controlled in order to maximize the overall profit, modelled as a cost function, e.g. the total oil production or the Net Present Value (NPV). Hou *et al.* (2015) states that one of the most effective ways to exploit limited oil reserves more economically and efficiently is to employ closed-loop reservoir management techniques, thus enabling a dynamic and real-time optimal production schedule under the existing reservoir conditions by adjustment of production and injection strategies. It is important to notice that the production optimization is commonly developed as a life-cycle reservoir control, thus aiming to optimize long-term targets. However, long-term perspective is usually in conflict with short-term targets, such as operational constraints (Fonseca *et al.*, 2016). Therefore, several studies have been conducted on how to conciliate short-term and long-term optimization strategies, as seen in the works of Isebor and Durlofsky (2014), Fonseca *et al.* (2016) and Farahi *et al.* (2021).

One of the main components of an optimization problem is the function to be minimized or maximized, known as the cost or the objective function. One of the most commonly objective functions in reservoir optimization is the NPV function (Udy *et al.*, 2017; Hou *et al.*, 2015), which is also found in multi-objective optimization algorithms, the objectives are modelled by altering the NPV's discount factor in order to emulate short and long-term objectives (Farahi *et al.*, 2021). In the field of reservoir optimization, NPV is often modelled as a mathematic relationship between the fluid injection and production rates and their associated costs, or revenues. Fonseca *et al.* (2017), for example, wrote the NPV function considering oil and water production and water injection, due to the reservoir under study being a two-phase model.

Techniques to further modify the NPV function were studied, so physical parameters are also considered. Fortaleza *et al.* (2020) introduced a variation in the NPV evaluation that considers not only the resultant cash flow from the fluid rates, but also the relationship between the fluids produced by the wells, thus obtaining a Modified NPV (MNPV) function, which is further used as the objective function of a search algorithm considering a two-phase reservoir model. Bizzi *et al.* (2020) showed that the MNPV can be used in conjunction to local optimizations in order to generate an optimal global production strategy. Furthermore, Fortaleza *et al.* (2022) used the MNPV formulation in conjunction with a robust linear search and the StoSAG algorithm in order to perform robust optimization in both two and three-phase reservoir models.

Another important aspect of optimization to be addressed is the constraint modelling. According to Suwartadi *et al.* (2012), there are two classes of output constraints in a reservoir optimization problems: one-dimensional and multi-dimensional. For instance, Barroso Neto *et al.* (2022) handled an one-dimensional constraint, being the field water production rate, by complementing each time step with a loop that acts in the total water injection rate depending on the water production. Multi-dimensional constraints are more complicated to deal with, since they can come in a high amount — from well control types (e.g. pressure or rate) to well rate, pressure or even rate constraints from well groups. A common industry practice, in theses cases, is to let the reservoir simulation software handle the output constraints (Oguntola and Lorentzen, 2021).

In the domain of the gradient-free optimization methods, the Stochastic Simplex Approximate Gradient (StoSAG) stands out. Fonseca *et al.* (2017) proposed the StoSAG as an algorithm that optimizes the expected value of the cost function over an ensemble of geological models, which reaches a larger NPV than the standard Ensemble Optimization (EnOpt) technique. Silva *et al.* (2020) used StoSAG in a more complex reservoir known as the OLYMPUS benchmark, presented as a difficult optimization challenge due to the intrinsec characteristics of the geological ensemble (Fonseca *et al.*, 2018). Moreover, Xu *et al.* (2022) evaluated the influence of key parameters of the algorithm, such as the ensemble, step and perturbation sizes, in the results.

Is it important to notice that in Fortaleza *et al.* (2022) and Barroso Neto *et al.* (2022), the reservoir's physical aspect introduced in the objective function used in StoSAG was the water fraction at each producer well. Therefore, for three-phase models, the presence of gas should be considered. In this study, we aim to introduce a variation of the MNPV function that not only considers water, but gas as well. The new objective function, denominated Gas MNPV, is used in the implementation of a StoSAG algorithm in order to optimize the overall production of a simple three-phase synthetic reservoir model. The idea is to show that this approach can outperform basic control strategies, such as the reactive control (RC). Furthermore, we aim to show that, being a constructive version of the StoSAG, the well and group constraints are respected in all iterations, thus combining the long-term objective of optimizing the reservoir's total production and the short-term constraint strategies, going further than the uni-dimensional constraint check implemented by Barroso Neto *et al.* (2022) in the application of constrained optimization techniques.

This paper is organized as follows. First, the development of the MNPV function and the StoSAG algorithm are shown. Second, it is presented a brief description of the synthetic reservoir and the modifications made to it, such as well replacements and group additions. Finally, the numerical results are shown and discussed, mainly by comparations with the RC and the constraint checks.

2. RESERVOIR OPTIMIZATION USING GAS MNPV STOSAG

2.1 NPV

The NPV is defined as being equal to the present value of future returns, discounted at the marginal cost of capital, minus the present value of the cost of the investment (Gardiner and Stewart, 2000). Therefore, this function makes it easier to determine, from a financial standpoint, whether or not the project is worth the investment.

In the oil and gas field, the function takes into account the oil price, the water production cost, and the fluid injection cost (water and gas).This leads to the following NPV approach used by (Fonseca *et al.*, 2017):

$$NPV = \sum_{n=1}^{N_t} \left\{ \frac{\Delta t_n}{(1+b)^{\frac{t_n}{365}}} \left[\sum_{j=1}^{N_P} \left(r_o \cdot \overline{q_{o,j}^n} - c_w \cdot \overline{q_{w,j}^n} \right) - \sum_{k=1}^{N_I} \left(c_{wi} \cdot \overline{q_{wi,k}^n} - c_{gi} \cdot \overline{q_{gi,k}^n} \right) \right] \right\} \tag{1}$$

Where N_t is the total number of time steps; t_n denotes the end time of the n^{th} time step; n is the n^{th} time step; b is the annual discount rate; N_P and N_I denote the number of producer and injector wells, respectively;r_o, c_w, c_{wi} and c_{gi} are, in order, the oil price, the water production cost, the water injection cost and the gas injection cost; $\overline{q_{o,j}^n}$ and $\overline{q_{w,j}^n}$ are, respectively, the oil and water production rates at the j^{th} producer for the n^{th} time step; $\overline{q_{wi,k}^n}$ and $\overline{q_{gi,k}^n}$, respectively, denote the average water injection rate and the average gas injection rate at the k^{th} injector for the n^{th} time step.

2.2 Modified NPV (MNPV)

The concept behind the modification in the NPV function is to introduce physical parameters in its evaluation. Initially, Fortaleza *et al.* (2020) presented a modified NPV, that was calculated from the following cost function:

$$C_F(t,P) = (r_o q(T)_{o,P} - c_w q(T)_{w,P}) - \frac{1}{N_p}\sum_{k=1}^{N_I}(c_{wi} q(T)_{wi,k}) \tag{2}$$

In which the two first terms are equal to the NPV, but the third term represents an approximation to include the water injection cost, where the field value of injection is split into the number of producer, and it is added to each producer. Additionally, in Bizzi *et al.* (2020), it is analytically shown that for a case of 2d gas-cone reservoir, the MNPV function leads to a sequential optimum solution and also suggested that the MNPV approach can be used in reservoir production optimization problems.

In this study, the MNPV function is based on the same cost function. However, a modification is made from the one proposed in Barroso Neto *et al.* (2022)'s work, with the purpose of considering the variation of gas fraction instead of the variation of the oil fraction, as shown in Eq. (3).

$$MNPV(s,P) = \int_{s0}^{s_f} \frac{C_F(s,P)}{ds/dt + \epsilon}\, ds \tag{3}$$

Where s_o and s_f are, respectively, the oil saturation in the beginning of the simulation and at the end of it. In addition, ds/dt is the gas fraction derivative regarding the time for producer P and ϵ is a small value added to avoid a division error due to ds/dt approximating 0. The total MNPV of the reservoir is calculated by adding the MNPV of each producer, resulting in the Eq. (4), which is the function used in this study with the StoSAG algorithm.

$$MNPV_t(s,P) = \sum_{k=1}^{N_P}\int_{s0}^{s_f} \frac{C_F(s_k,P)}{ds_k/dt + \epsilon}\, ds_k \tag{4}$$

2.3 StoSAG Algorithm

According to Fonseca *et al.* (2017), the StoSAG algorithm is a stochastic optimization method based on approximate gradients that can be applied to robust optimization problems. While both Fortaleza *et al.* (2022) and Barroso Neto *et al.* (2022) proposed constructive variants of the singly-smoothed StoSAG presented in Fonseca *et al.* (2017) by modifying the cost function and building a constructive optimization approach, it has to be stated that in both cases, only the aspects of water and oil production were considered in the MNPV function. While it works well in two-phase models, the same does not hold with three-phase models, due to the presence of gas. Therefore, the MNPV formulation presented in Equation (4) considers the gas fraction in its formulation so as to conform the cost function to the behavior of a three-phase reservoir model.

Regarding the constraints, this study models operational limits as output multi-dimensional constraints, mainly the maximum liquid production and water injection rates for the wells and gas production rates for groups, which are sets of wells. The reservoir simulation software is able to deal with all the output constraints.

In short, the proposed variation of the StoSAG algorithm can be divided into the following steps, for each time step (Sanchez *et al.*, 2022):

1. **Search Direction:** A number N_j of control perturbations, $\hat{u}_{l,j}$, are generated by using a uniform distribution, at iteration l, as follows:

$$\hat{u}_{l,j} = u_{l-1} + \frac{1}{\sqrt{l}}\Delta_j, \tag{5}$$

where u_{l-1} is the last iteration's optimum control vector and Δ_j is the j-th uniform distribution parameter. The perturbations $\hat{u}_{l,j}$ are used as a input controls that are applied to reservoir simulations with N_w prediction windows. It is important to notice that the output constraints are handled by the reservoir simulator, and after the simulation span runs, the controls that respect the constraints are recovered to calculate the gradient. Each simulation yields a Gas MNPV value that is used as the cost function $J(\cdot)$, and these values are inputs for the evaluation of the search direction d_l:

$$d_l = \frac{1}{N_j\,||\Delta J||_\infty}\sum_{j=1}^{N_j}\left(\hat{u}_{l,j} - u_{l-1}\right)\left(J\left(\hat{u}_{l,j}\right) - J\left(u_{l-1}\right)\right). \tag{6}$$

2. **Amplitude Search:** In this phase, N_i control candidates are generated and simulated within N_w prediction windows. Each candidate is generated by the mathematical relationship:

$$\hat{u}_{l,i} = u_{l-1} + \alpha_i d_l, \tag{7}$$

in which α_i is the amplitude factor of the search direction and d_l is defined in Eq. (6). Each candidate is simulated and the value of $\hat{u}_{l,i}$ that yields the highest MNPV is chosen as the optimum control u_l of the l-th iteration.

3. **Stop Condition Checks:** At the end of each StoSAG iteration, a check is performed on the total field NPV. The algorithm stops when NPV drops to negative value, thus indicating that the reservoir is no longer profitable.

Regarding the necessary number of reservoir simulation runs the proposed StoSAG executes, each iteration runs at least $(N_i + N_j)$ simulations. Given that there are N_w prediction windows per iteration and the fact a final simulation is conducted in order to evaluate the final optimum controls, the following number of simulation runs N_s are performed by the modified StoSAG, considering that N_l iterations are conducted by the algorithm:

$$N_s = N_l N_w \left(N_i + N_j\right) + 1. \tag{8}$$

2.4 Modified SPE9 Benchmark — Group Separation for Optimization

Originally, SPE9 was created in order to validate black oil simulation in commercial software. It is a synthetic model with dimensions of 7200 ft × 7500 ft × 359 ft divided into a 24 × 25 × 15 grid and a dipping-angle in the x-direction of 10 degrees. It has a constant grid area of side size of 300 ft and the layers have variable thickness that varies from 8 ft to 100 ft (Killough, 1995).

The original SPE9 have been also modified to address problems such as waterflooding optimization (Mfoubat and Zaky, 2020) and history matching (Negash *et al.*, 2017). Fortaleza *et al.* (2022) presents a modified version of the SPE9 model in which some wells were changed from producer to injector, thus resulting in a setting of 18 producer wells and 8 injector wells, which are depicted in Figure 1. Moreover, in this study, the wells were further separated in two groups, as shown in Table 1. We will refer to this modified model as simply SPE9.

Table 1: Group Definitions for the Modified SPE9 model.

Groups	Wells
1	INJE1, PRODU2, INJE3, PRODU4, PRODU5, INJE6, PRODU7, PRODU8, INJE9, PRODU10, PRODU11, PRODU12, PRODU13, PRODU14, PRODU15, INJE17
2	PRODU16, PRODU18, PRODU19, PRODU20, PRODU21, PRODU22, INJE23, PRODU24, INJE25, INJE26

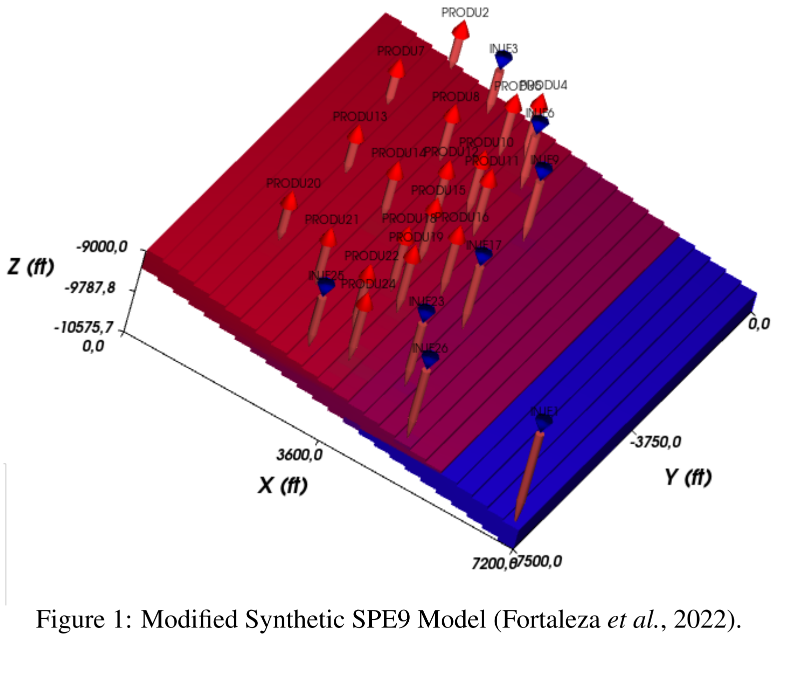


Figure 1: Modified Synthetic SPE9 Model (Fortaleza *et al.*, 2022).

3. NUMERIC RESULTS AND DISCUSSION

Two simulations were conducted on the modified SPE9. The wells were controlled by rate for injectors and by BHP for producers. The injector constraints are: maximum and minimum water injection rates of 4500 stb/day and 0 stb/day, and maximum BHP of 18 kpsi. Whereas the sole producer constraint is the minimum BHP of 1.5 kpsi. Another important constraint is the group maximum gas rate of 15000 Mscf/day.

The costs used for NPV calculation were set as follows: Oil Rentablity (r_o) of 45 USD/stb, Water Production Cost (c_w) of 6 USD/stb, Gas Production Cost (c_g) of -2.68 $USD/Mscf$ (This value indicates that the produced gas has positive economic return), Water Injection Cost (c_wi) of 2 USD/stb and Discount Factor (b) of 0.08.

The results are obtained for RC and for Gas MNPV StoSAG method. For better understanding of the impact of different optimization techniques, the production rates of the PRODU13 well were evaluated. Figure 2 shows a comparison of the oil production rate, gas production rate, and water production rate of PRODU13 of the RC optimization technique and of the StoSAG method with Gas MNPV StoSAG. It can be observed that, for PRODU13, the RC optimization closes the well around year 17, while the MNPV with Gas optimization technique only closes it around year 31. At the beginning, the minimum bhp is not reached, it is caused because the group constraint is not respected in Figure 6, and the reservoir simulator decreases the production of all producers to respect this constraint.

This suggests that Gas MNPV StoSAG algorithm was able to control the production rate of water and gas for a much longer period compared to RC. It is noticeable in Figure 2, initially, that the oil production rate had a similar behavior, despite the differences, until around year 16. However, from the moment PRODU13 was closed by RC, the Gas MNPV case continues to maintain an oil production rate in the same magnitude as in previous years.

While observing the gas production curve in Figure 2, a very similar behavior to the oil production curve can be noticed, but with a higher value. This is due to the fact that the gas in the reservoir is mixed with oil. With the pressure drop experienced by the produced fluids, the gas becomes gaseous at the surface, resulting in both RC and Gas MNPV cases presenting gas production rates (GPR) very close to oil production rates (OPR).

Finally, the water production rate in Figure 2 shows that both cases had extremely low water production until around year 12 for RC and year 16 for Gas MNPV StoSAG. In the RC case, after year 12, the water production remained stable and relatively low until year 16. After that, the water production increases drastically, resulting in the well closing due to the RC algorithm. On the other hand, the optimized case with Gas MNPV StoSAG managed to maintain the water production at not-so-high values, making the well profitable until around year 31, at which point the oil production rate decreases to the point where the well becomes unprofitable.

The difference in productions rates in PRODU13 for each fluid under RC and Gas MNPV StoSAG can be explained by the PRODU13's BHP behavior over time. During the beginning of its production, the BHP on both cases decreases in a similar form, although the BHP under RC is slightly higher. After this decrease, the BHP in the RC case stays in 1500 psi until the reservoir was no longer profitable. In the Gas MNPV StoSAG case, the BHP changed between years 5 and 10, which is not possible under RC. This change allowed the well to control its fluid production more precisely, resulting in less gas production during that period.

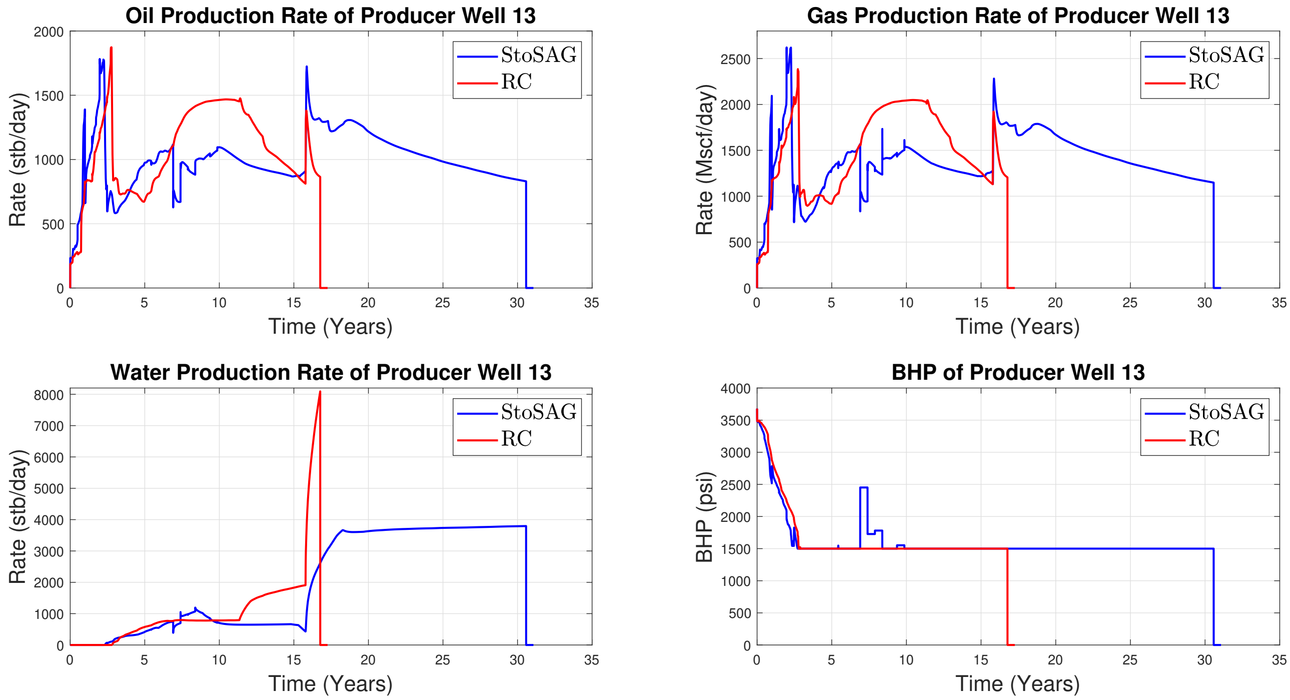
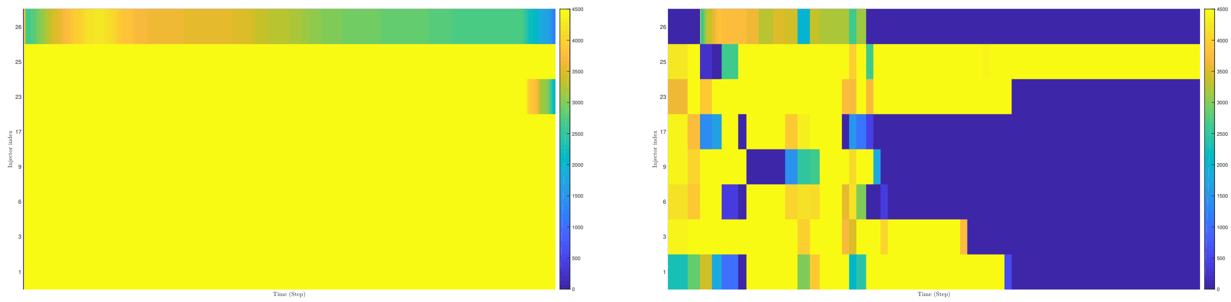
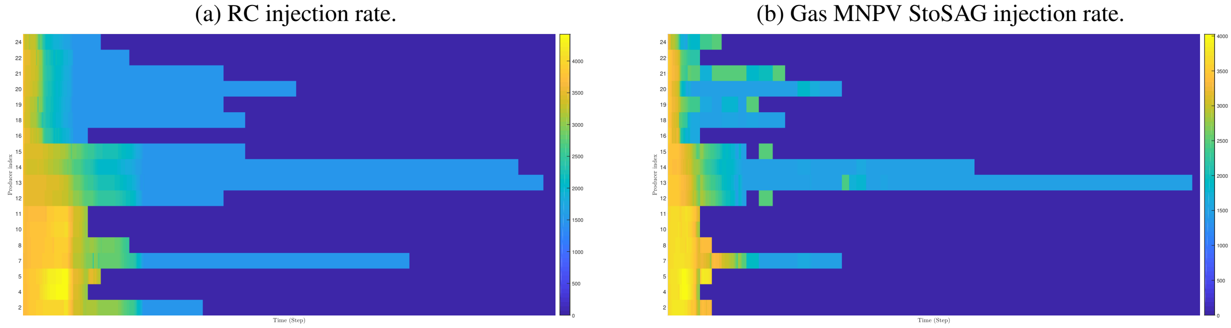


Figure 2: Producer 13's Water, Gas, and Oil Production Rates and its BHP under RC and Gas MNPV StoSAG.

Figure 3 shows, for both RC and Gas MNPV StoSAG cases, the evolution of the water injection rate and the producer BHP in each well. In this figure, each well is represented by an horizontal color gradient, in which dark blue represents 0 psi and, therefore, closed well, and bright yellow represents 4500 psi, with the other colors representing values between these two. It is shown that the Gas MNPV StoSAG employs producer BHPs similar to those found in the RC case. The difference between the algorithms is evident when the water injection rates are considered: by operating around the constraints, the Gas MNPV StoSAG is capable of restriction the water injection when needed, e.g., the injection of RC is not the maximum value injector 26.



(a) RC injection rate. (b) Gas MNPV StoSAG injection rate.



(c) RC BHP of producers. (d) Gas MNPV StoSAG BHP of producers.

Figure 3: Well Controls for RC and Gas MNPV StoSAG.

In Figure 4, the NPV of both cases exhibits a similar behavior until around year 9. From that point on, the NPV growth rate of the RC case starts to decrease, and its peak is reached around year 14. Whereas, although the NPV growth rate of Gas MNPV StoSAG also decreases, it does so less sharply, being able to sustain the increase until around year 31, which resulted in a NPV 7% higher than the RC case. It is important to notice that, even at the time in which RC reaches its maximum NPV, the resultant NPV of Gas MNPV StoSAG is still higher. The same behavior is more or less observed in the Field Oil total production — the Gas MNPV StoSAG maintains an increasing oil total over the years it is active when the RC is already ended, thus resulting in a higher oil return.

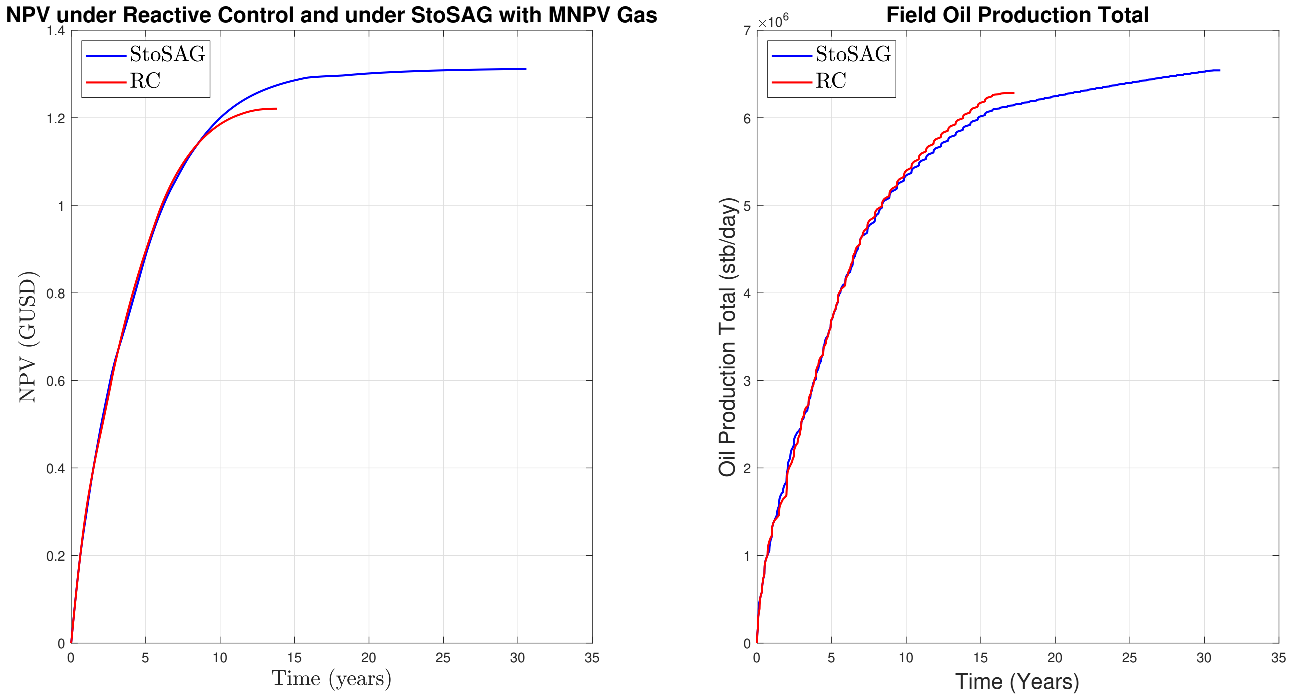


Figure 4: NPV and Field Oil Production Total of RC and Gas MNPV StoSAG.

Figure 5 shows the oil production rate for both reservoir groups. It is observed that for group 1, the difference between the RC and Gas MNPV StoSAG cases is greater than in group 2. In both groups, the RC case exhibits a higher oil production rate at almost all time steps, except for group 1 around the 5th year.

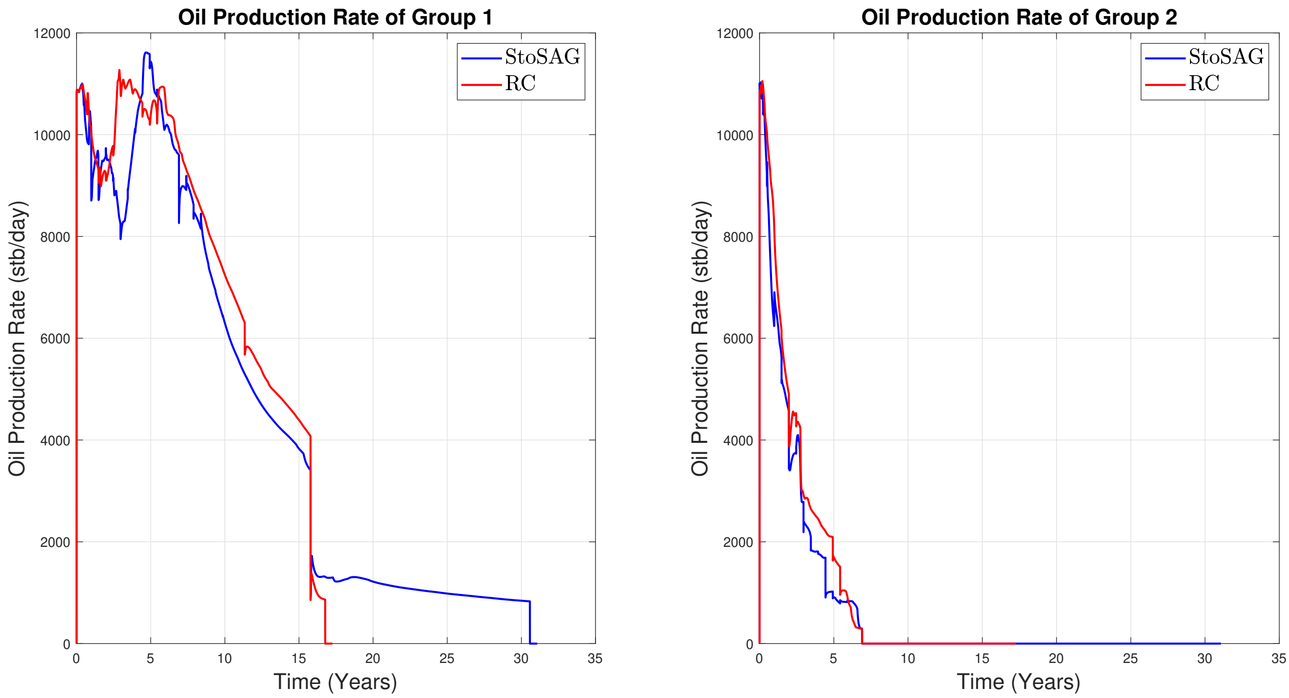


Figure 5: Oil Production Rate of Groups Under RC and Gas MNPV StoSAG.

Figure 6 shows the gas production rate for both groups and both optimization strategies. It is highlighted that in both groups, the constraint was not violated at any time, even it the production is saturated during the first years.

In group 1, it can be observed that until around year 15, the Gas MNPV StoSAG was able to maintain the oil production rate at values lower than RC at almost all time steps, with considerably lower values between years 3 and 5. Such behavior helps to justify the improvement in NPV for the Gas MNPV StoSAG case compared to RC. Furthermore, for group 2, Gas MNPV StoSAG was also able to maintain lower gas production values compared to RC, although this difference appears to be less significant.

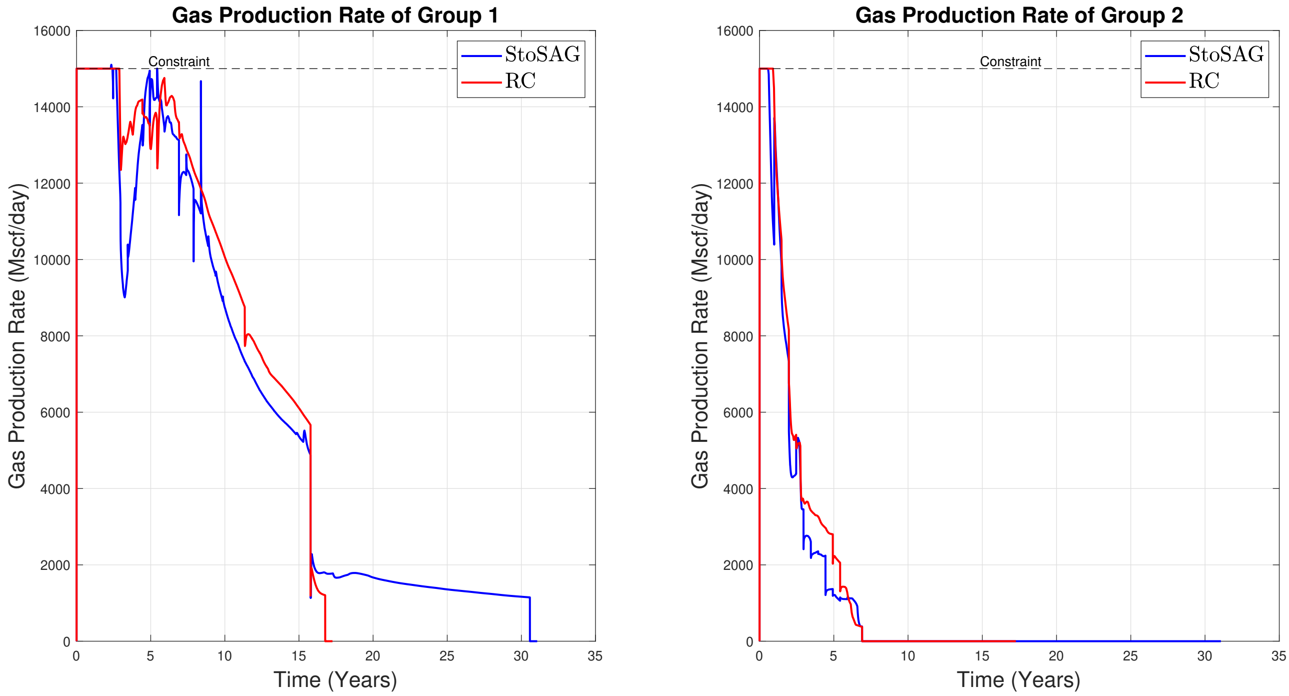


Figure 6: Gas Production Rate of Groups Under RC and Gas MNPV StoSAG.

Finally, Figure 7 shows the water production rate for both groups. In this figure, it is clearly noticeable that the WPR for RC is considerably higher throughout the entire reservoir's life. The ability of Gas MNPV StoSAG to control water production is even more evident in group 1, where between years 9 and 15, the WPR for RC was practically double compared to the Gas MNPV StoSAG.

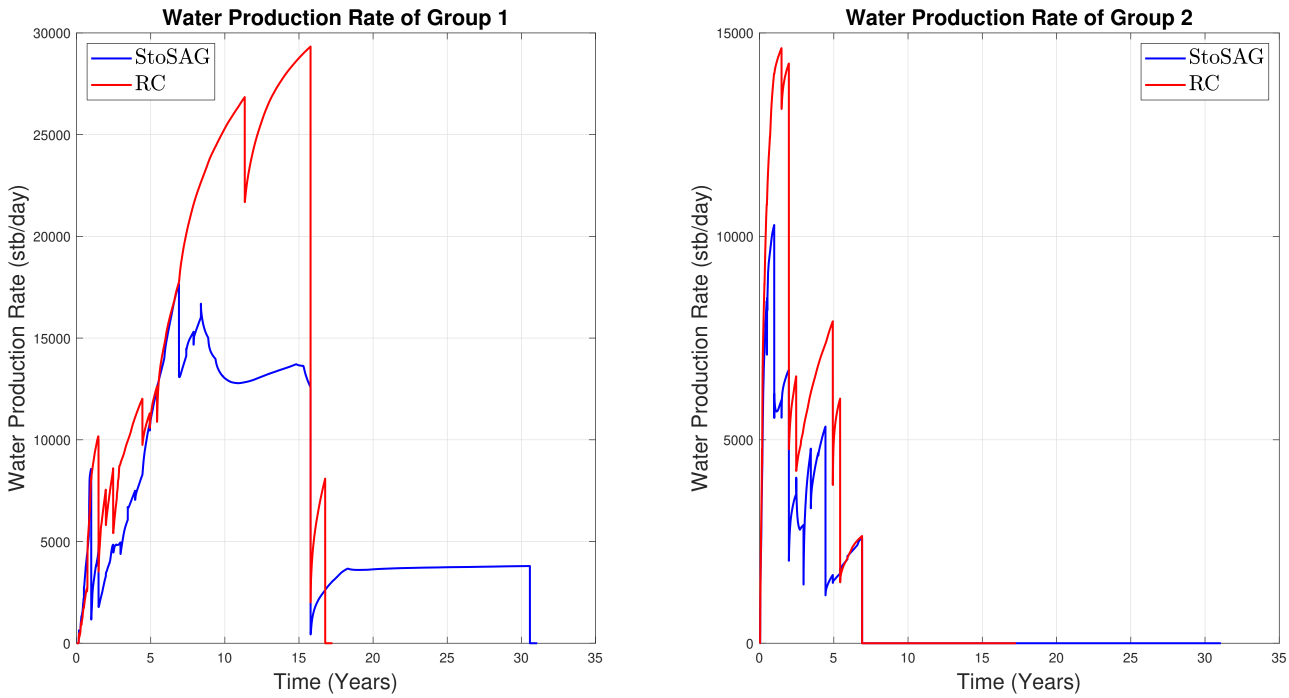


Figure 7: Water Production Rate of Groups Under RC and Gas MNPV StoSAG.

The overall algorithm results for both simulations are shown in Table 2. It is shown that the Gas MNPV StoSAG outperforms the RC in the most relevant variables, such as oil production and the overall NPV, while producing less water.

Table 2: Overall result comparison between RC and Gas MNPV StoSAG.

Method	**OPT** ($\times 10^6$ **stb**)	**WPT** ($\times 10^6$ **stb**)	**GPT** ($\times 10^6$ **Mscf**)	**NPV** ($\times 10^9$ **USD**)
RC	6.283	11.42	8.756	1.221
Gas MNPV StoSAG	6.541	8.738	9.147	1.308

4. CONCLUSION

In this study, a Gas MNPV function was introduced, based on the previous Water MNPV function. It allows extending the constructive optimization with the StoSAG algorithm to three-phase reservoir cases, where the gas saturation is highly relevant. Furthermore, multi-dimensional output constraints, as group and well constraints were addressed in the proposed methodology.

It was shown that the Gas MNPV StoSAG improved the overall NPV in 7% when compared to the RC for the SPE9 benchmark, and both the group and well constraints were respected. The proposed algorithm also contributed to improve the oil production while reducing the other fluids' production rates and the water injection, by controlling the injector wells. The Gas MNPV StoSAG algorithm can be viewed, based on the results with the SPE9 case, as a potential solution to be employed in waterflooding optimization of three-phase reservoirs, since it considers more directly the effect of gas production in the optimization process.

The suggestion for future works is to continue the improvement on optimization methods for three-phase reservoirs with other relevant group constraints and to include the gas voidage replacement measurement, which turns the problem of handling the gas reservoir constrained optimization into a bigger challenge capable of handling the conditions of Brazilian pre-salt reservoirs.

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