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COBEM2023-2337 Waterflooding optimization by producer water cut using PSO Algorithm

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Abstract.
Global optimization using bio-inspired algorithms has been shown to improve Net Present Value (NPV). For example, Particle Swarm Optimization (PSO) can reach larger NPVs than classical techniques. However, PSO requires a high computational cost due to the elevated number of control variables, making its application unfeasible for bigger and more complex reservoir models like Brazilian pre-salt reservoirs. Thus, one-dimensional PSO is proposed to decrease the computational cost, using the water-cut value as a decision variable and closing the producers similar to Reactive Control (RC), but with a different value for each well. The approach was used in two synthetic black oil benchmarks: Egg Model and Olympus reservoirs. As a result, the computational cost decreases considerably in comparison with the typical global optimization and the NPV increases by approximately 2% in relation to RC.
Keywords: *PSO, Reactive Control, waterflooding, optimization.*

1. INTRODUCTION

Various strategies have been investigated in the pursuit of optimizing the Net Present Value (NPV) of oil reservoirs. Inspired by biological behavior, some of them have emerged as effective approaches for maximizing NPV. For instance, in a recent study by Kumar (2021), the particle swarm optimization (PSO) algorithm was used alongside the genetic algorithm and evolutionary adaptation strategy to identify the optimal well controls in waterflooding operation of the Olympus reservoir, ultimately enhancing NPV.

Furthermore, in Harb *et al.* (2020), a hybrid algorithm combining the black hole parameter and the PSO algorithm (BHPSO) was implemented in Olympus to optimize the NPV by determining the optimal configuration of wells, including the number of wells, locations, types and trajectories. The research also involved the implementation of a conventional PSO algorithm for the purpose of comparison with the BHPSO algorithm. The results of the comparison revealed that on average, the BHPSO algorithm demonstrated an improvement of 53.3% compared to its initial testing phase whereas the PSO algorithm achieved an improvement of 36.5%.

Subsequently, Kim *et al.* (2021) employed convolutional neural networks in conjunction with the PSO algorithm to optimize the NPV in the EGG reservoir. This approach involves modifying the producer controls, adjusting the spacing between them, and determining the optimal well number. In another study by Ng *et al.* (2021), the PSO and Grey Wolf Optimization (GWO) algorithms were combined with artificial neural networks to regulate the injector wells over specific time periods of 150 days.

Other optimization options are evolutionary algorithms, as the evolutionary algorithm of global optimization proposed by Pinto *et al.* (2011). It consisted of shutting Inflow Control Valves (ICVs) at water-cut values similar to RC, but each ICV at different water-cut values during. The studied case was a five-spot with four vertical injectors on the corners and a single vertical producer at the center. After 1200 simulations, the NPV showed an improvement in relation to the RC case. An important point about the findings of Pinto *et al.* (2011) is how the ICVs were shut - they were closed in different values of the initial predefined water-cut of the reactive control (RC) and its distribution was almost linear over time with a final water-cut value similar to the RC.

Based on this result and aiming to decrease the computational cost of the optimization, a PSO algorithm is proposed to only discover the minimum value of water-cut that optimized the NPV, reducing the problem to a one-dimensional optimization process. The other producers are closed with a linear interpolation between this minimum water-cut and the maximum, which is defined by the RC. The proposed methodology is applied to producers instead of ICVs.

2. ALGORITHMS

2.1 Net Present Value (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 costs for 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 Standard Reactive Control

Standard Reactive control (RC) is a production oil optimization technique widely used in the industry, given its robustness, easy implementation, and low computational costs - only a straightforward simulation is required. Malakooti *et al.* (2020) classified it as an instantaneously short-term optimization. This technique initially consists of setting all the reservoir wells, producers, and injectors to their maximum capacity. Next, the producer wells are closed whenever they become non-profitable, which is specified in the reservoir simulator through a constant water-cut threshold.

The water-cut value is calculated depending on the fluid costs involved in production. The reactive control acts directly on producer wells, e.g., if a producer starts losing money with a negative NPV without considering the injection value, it is closed. Furthermore, the standard reactive control is the technique to be initially beaten in the Olympus optimization challenge (Fonseca *et al.*, 2018).

2.3 Economic Reactive Control

Economic Water-Cut (EWC) is defined as the water-cut value at which the incremental revenue from producing an additional barrel of oil is equal to the incremental cost of producing that barrel, so the injection cost of producing a barrel is also considered. EWC is calculated using economic parameters such as oil price, water production cost, and water injection cost (Asadollahi *et al.*, 2012).

The economic water cut thresholds (WCTs) are determined through a straightforward analysis that relies on economic parameters. These economic WCTs are regarded as an initial estimation for the shut-in WCTs in the optimization problem. During each time step, the impact of each completion on the overall Net Present Value (NPV), considering the voidage replacement ratio, can be expressed in 2.

$$NI_c = r_o q_{oc} - c_w q_w - c_{wi}(q_{oc} + q_w) \tag{2}$$

2.4 Optimized Reactive Control

2.4.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based optimization technique that was developed in 1995 by Eberhart and James Kennedy (2010). It draws inspiration from the collective behavior observed in swarms of birds and fishes (Eberhart and James Kennedy, 1999).

The PSO algorithm utilizes Equations (3) and (4) to update the movement of each particle within the search space. The velocity of particle i in dimension j is determined by Equation (3). Here, the inertial factor, denoted as w, is typically decreased over time, while the cognitive coefficient c_1, social coefficient c_2, and uniformly distributed random numbers U_1 and U_2 (ranging between 0 and 1) contribute to the update. As a result, the particle's speed is influenced by its current velocity, the particle's best position (y_i), and the swarm's best position (y_s) within the search space.

To update their positions, each particle employs equation (4). As the algorithm progresses through iterations, the velocity decreases, enabling the particles to refine their solutions around an optimal point and facilitating the convergence of the algorithm.

$$v_{ij}^{(t+1)} = wv_{ij}^{(t)} + c_1 \overbrace{U_{1j}(y_{ij}^{(t)} - x_{ij}^{(t)})}^{\text{cognitive component}} + c_2 \overbrace{U_{2j}(y_{sj}^{(t)} - x_{ij}^{(t)})}^{\text{social component}} \tag{3}$$

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)} \tag{4}$$

The pseudo-code for the PSO algorithm is presented in Algorithm 1. The number of dimensions of the optimization problem is denoted by *N*, the number of particles is represented by *S*, and the stopping criteria, such as the maximum number of iterations, is defined as max_{iter}.

Algorithm 1 Pseudo-code for the PSO algorithm

function BASIC-PSO(S,N,c_1,c_2,Max_{iter},$thres$)
  Start swarm;
  $iter = 1$
  for k **do** 1 Max_{iter}
    for i **do** 1 S
      if $f(x_k) \leq f(y_{ik})$ **then**
        $y_{ik} \leftarrow x_k$;
      end if
    end for
    Evaluation and detection of the best fit individual
    calculate y_s using the S fitness values $f(y_{ik})$
    Global best
    for i **do** 1 S
      for j **do** 1 N
        $v_{ij}^{(t+1)} \leftarrow wv_{ij}^{(t)} + c_1U_{1j}(y_{ij}^{(t)} - x_{ij}^{(t)}) + c_2U_{2j}(y_{sj}^{(t)} - x_{ij}^{(t)})$
        $x_{ij}^{(t+1)} \leftarrow x_{ij}^{(t)} + v_{ij}^{(t+1)}$
      end for
    end for
    Actualization
    $iter = iter + 1$
  end for
  return position of the best fit particle x and its fitness $f(x)$
end function

2.4.2 PSO Reactive Control

In this work, the problem under consideration is a one-dimensional optimization problem, it only has an optimization variable control, the minimum water-cut, reducing the complexity of the problem. The other values of water-cut are linearly distributed between this minimum and a maximum constant value, which is defined by the water-cut of the standard reactive control.

As an example, in a reservoir of three producers with a standard water-cut value of 0.9 and a minimum water-cut value of 0.7 determined by the PSO. The first producer to reach this value is closed. Next, the second producer is closed at the water-cut value of 0.8. Finally, the simulation finishes when the last well reaches the standard water-cut value of 0.9.

The **objective function** to be optimized by the PSO is the NPV. Thus. it is a long-term scheme that optimizes the entire lifetime of the reservoir in each round of the PSO swarms.

2.4.3 PSO Reactive Control Implementation

Several tools and algorithms were used in the optimization process, mainly the OPM Flow simulator and the Stormslib Python library. The **Stormslib library** is a Python module that aims to provide a general solution for programmatic execution and post-processing of reservoir simulations, enabling its use in various research problems involving numerical simulation: history matching, production optimization, well allocation optimization, and reservoir uncertainty analysis, among others (Ghisi *et al.*, 2020).

Even using only one variable decision, this approach coupled with the computational cost of PSO itself, it still leads to a high total time, because of the large number of required reservoir simulations. To address this issue, parallelizing the reservoir simulation is a viable solution. The structure of PSO allows independent searching of each swarm and subsequent communication between them, enabling parallel execution.

Additionally, the fact that OPM Flow is an open-source software mitigates the limitation posed by the number of available reservoir simulator licenses, as in commercial simulators. PSO swarms can be launched separately and with a limited number of instances based on the available computing resources.

The general scheme of the optimization process is illustrated in Figure 1. It depicts how the PSO algorithm interacts with Stormslib and the simulator to discover the pseudo-optimal fitness value, specifically the best NPV. The evaluation involves assessing the pseudo-optimal values of minimum water-cut and updating the global best individual until the convergence criteria are met or the maximum number of iterations is reached. Upon convergence, the minimum water-cut, determined by PSO, is considered crucial for achieving the highest NPV.

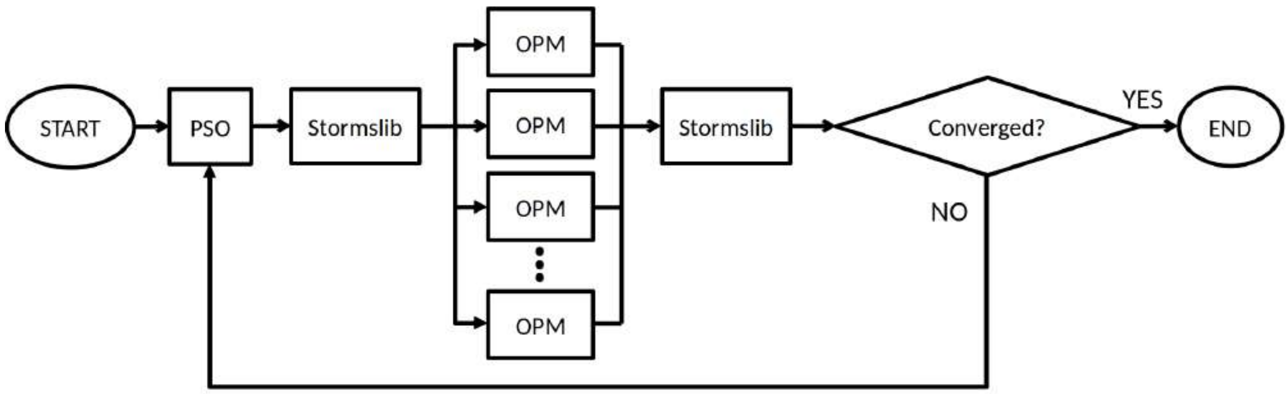


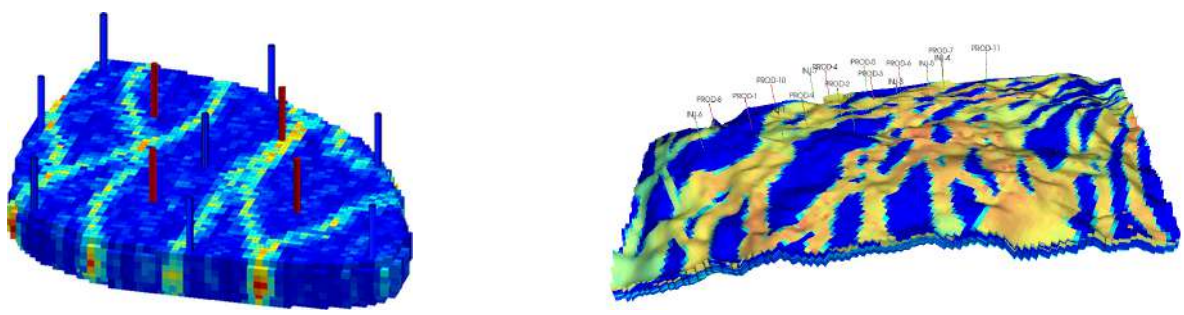
Figure 1: General Optimization scheme.

3. RESERVOIR MODELS

3.1 Egg Model

The Egg Model is a set of one deterministic and 100 permeability realizations of a channelized reservoir modelled with dimensions 8 m × 8 m × 4 m and 18,553 active cells organized in an egg-shape model, hence the name (Jansen *et al.*, 2014). It first appeared as a deterministic model in a study investigating why and under what conditions reservoir flooding problems can be expected to have bang-bang optimal solutions (Zandvliet *et al.*, 2007), and its stochastic set was proposed as a benchmark in a robust waterflooding optimization problem (Van Essen *et al.*, 2009). Figure 2a shows the reservoir model and how its wells are positioned.

In this study, one chosen realization was used. The criteria for the choosing process is to determine which of the 100 realizations yield the median NPV when a reactive control is applied. For the Egg Model, the realization that satisfied the established criteria is the 10th one. Egg model producer BHP and injector rate were set up to 385 bar and 60 m^3/d, respectively.



(a) Egg Model (Jansen *et al.*, 2014). (b) Olympus Benchmark.

Figure 2: A permeability model of the Egg Model and Olympus.

3.2 Olympus

The Olympus is an ensemble of reservoir models suitable for challenging field development optimizations under uncertainty. The model consists of grid cells of approximately 50 m × 50 m × 3 m each and has 192,750 active cells (Fonseca *et al.*, 2018). Figure 2b shows the reservoir model and how its wells are positioned. For this study, the same criteria applied to the Egg Model were used in order to choose an Olympus realization of the 50 available. For Olympus, the realization that yields the median NPV in the reactive case is the 49th one. As in the challenges, the Olympus controls were 150 bar for producers and 235 bar for injectors.

4. Numerical Results and Discussion

In this paper, the EGG and Olympus reservoirs were employed for the purpose of optimizing the NPV (Net Present Value) value by implementing water cut control (WCT). WCT control involves the application of both lower and upper limits. The upper limit is established at 83.48% of water for the EGG reservoir and at 84.31% for the Olympus reservoir using the Economic WCT equations (Asadollahi *et al.*, 2012). However, to achieve the most favorable NPV, the determination of the lower limit necessitates the utilization of an optimization algorithm.

The PSO algorithm was employed to optimize the minimum water-cut of the EGG and Olympus reservoirs. The optimization process utilized 10 swarms, with c_1 and c_2 values set to 2.05, and the maximum search space defined as 0.88 while the minimum search space was set to 0.20. The stopping criterion for the PSO algorithm was specified to terminate after a maximum of 3 iterations, resulting in a total of 30 simulations. The NPV settings for both reservoirs are shown in Table 1.

Table 1: NPV settings.

	Oil Revenue [USD$/bbl]	Water Injection Cost [USD$/bbl]	Water Production Cost [USD$/bbl]	Discount Rate	Water-cut Standard	Water-cut Economic
Egg	20	0.8	3	0.08	0.88	0.8348
Olympus	45	2	6	0.08	0.88	0.8431

4.1 Egg results

Figure 3 shows the NPV curve for the Egg Model using three different optimization techniques: standard reactive control (referred to as Standard), economic reactive control (referred to as Economic), and reactive control optimized with the PSO algorithm (referred to as PSO). It is observed that the Standard and Economic curves overlap throughout the simulation time. However, the results of the PSO start to differ around day 650 and remain superior until the end of the reservoir's life. The optimized case achieves a better NPV of 2.77% compared to the second/third-place Economic and Standard case.

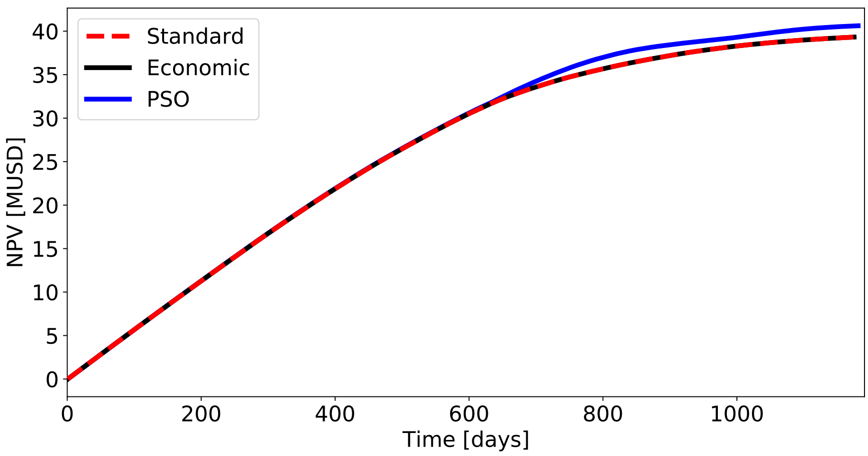
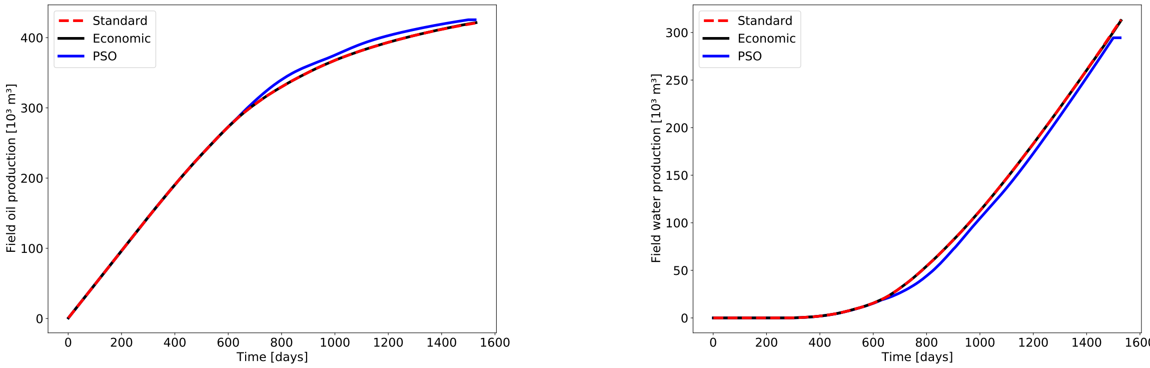


Figure 3: EGG NPV.

The oil and water productions of the Egg Model are depicted in Figure 2. Once again, it is noticeable that the results of the Standard and Economic techniques overlap in both the FOPT and FWPT curves. Figure 4a displays the FOPT results, revealing that the PSO-optimized solution shows improvement starting around day 650 and maintains its superiority until the end of the reservoir's lifespan, with a 0.95% advantage over the other techniques. A similar trend is observed in Figure 4b, which illustrates the water production for the field. Around the same timeframe, the PSO optimization demonstrates its capability to reduce water production by 6.07%, which is desirable as water is an unwanted fluid in the production well.



(a) FOPT

(b) FWPT

Figure 4: EGG FOPT and FWPT.

To better understand the control of the production wells among the different algorithms, Figure 5 illustrates the water-cut in the production wells of the Egg Model. It is noticeable that despite the seemingly similar results of the Standard and Economic techniques in Figures 3 and 2, there are some differences. When observing the water-cut curve for both the Standard and Economic controls, these differences become apparent starting around day 1250, towards the end of the reservoir's life.

However, upon examining the water-cut curve for the different production wells using the proposed PSO technique, it becomes evident that the shutdown of wells occurs at varying, linearly increasing water-cut values. This observation emphasizes that the closure of one well directly impacts the water-cut of other well(s), making it crucial to make the best choice regarding the timing of closure. A summary of the field results of the Egg Model is presented in Table 2.

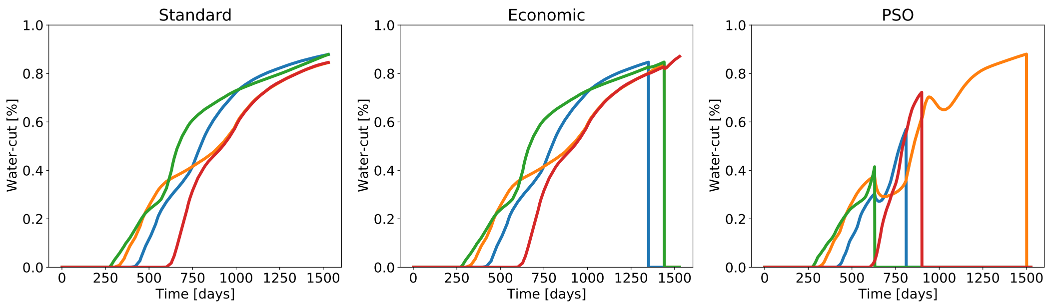


Figure 5: EGG WCT.

Table 2: EGG Model results of reactive controls.

	NPV [USD$]	FOPT [m³]	FWPT [m³]	FWIT [m³]
Standard	3.97E+07	4.21E+05	3.13E+05	7.34E+05
Economic	3.97E+07	4.21E+05	3.13E+05	7.34E+05
PSO	4.08E+07	4.25E+05	2.94E+05	7.32E+05

4.2 Olympus results

Figure 6 shows the NPV curve for Olympus using the three different optimization techniques. It is observed that all three curves exhibit similar growth behavior until around day 1000. After that, the Standard curve shows a slight decline in NPV compared to the other two techniques, despite having the same trend. The Economic curve, although capable of maintaining the NPV increase for a longer period than the others, has a lower maximum value than the leading PSO technique, which, in turn, exhibits a higher and faster peak than the Economic curve. The optimized case achieves a better NPV of 1.04% compared to the second-place Economic case and 3.19% compared to the standard reactive control.

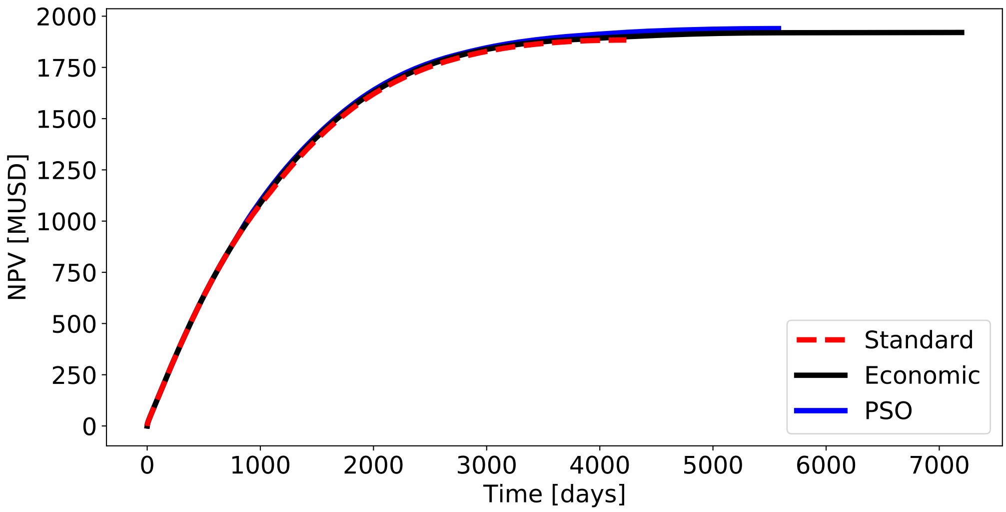
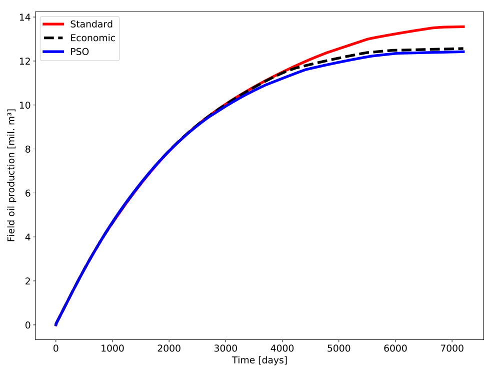


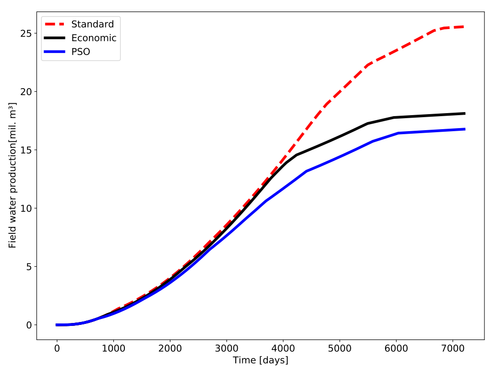
Figure 6: Olympus NPV.

The fluids produced in the reservoir are shown in Figure 7. As seen in Figure 7a, which displays the total oil production over time, the PSO case had the lowest oil production, 1.59% lower than the Economic case, and 8.82% lower than the Standard case. However, in Figure 7b, which illustrates the total water production over time, the PSO case also had the lowest water production, 7.18% lower than the Economic case, and 34.38% lower than the Standard case.

Although the PSO case exhibits lower oil production, this loss is proportionally much smaller than the decrease in water production. On the other hand, oil production has a greater impact on NPV calculation than savings in water production. Thus, the PSO technique has demonstrated the ability to achieve a trade-off in fluid production, resulting in a better NPV among the studied cases and significantly lower computational cost compared to more complex optimization techniques such as constructive optimization or multi-variable decision optimization, which would require more iterations to converge.



(a) FOPT



(b) FWPT

Figure 7: Olympus FOPT and FWPT.

To better understand how the algorithm achieved success, Figure 8 presents a heat map of well saturation over time for the three optimization techniques. It is noted that for practically all wells, the PSO technique closed the production wells in less time than the other techniques. Furthermore, the water saturation achieved by PSO was, on average, lower than that of the other optimization techniques.

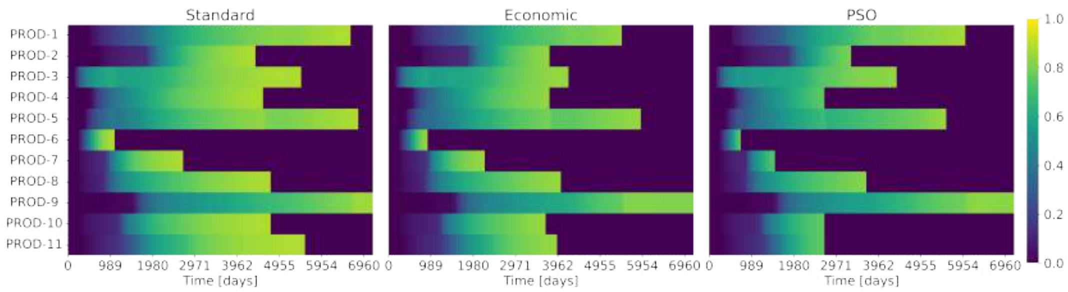


Figure 8: Olympus water saturation values for each producer during each of the tests.

The PROD-6 well is the first well to be closed in all three algorithms, although at different times. Figure 9 illustrates the closure time of this well for the Standard, Economic, and PSO techniques. It can be observed that the PSO technique closes this well earlier than the others, followed by the Economic technique and, finally, the Standard technique. The lower water-cut limit allows the field to achieve higher NPV by allowing other wells to produce oil while avoiding extra water production.

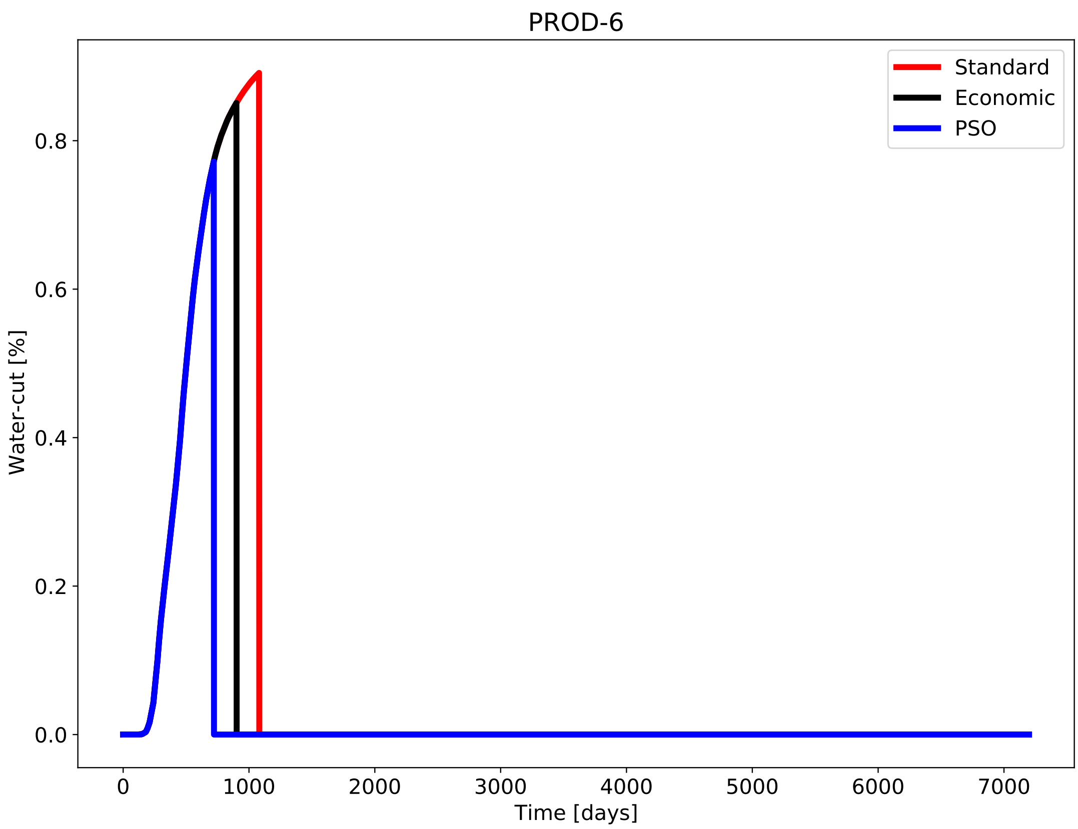


Figure 9: Olympus PROD-6 WCT.

In general, the Standard and Economic techniques close the production wells only when they become unprofitable, as mentioned in Sections 2.2and 2.3. However, oil production is detrimental to the reservoir, and it should primarily occur independently to maximize NPV, i.e., without the simultaneous production of water. Although the Standard and Economic techniques consider this to some extent, they do so imprecisely or too simply, resulting in suboptimal NPV. The optimization technique of minimizing water cut using PSO was able to achieve higher NPVs because it identified that, although the NPV is positive between the closure dates found by PSO and the standard technique, it comes at a high cost. However, if the well is closed earlier, less oil is produced, allowing it to remain in the reservoir for production by another well at a later time. This is what makes the PSO technique the champion in terms of NPV among the studied cases, with low computational cost. A summary of NPV and fluid production/injection values for Olympus using the three optimization techniques is presented in Table 3.

Table 3: Olympus Field Results

	NPV [USD$]	FOPT [m³]	FWPT [m³]	FWIT [m³]
Standard	1.88E+09	1.36E+07	2.56E+07	4.05E+07
Economic	1.92E+09	1.26E+07	1.81E+07	3.20E+07
PSO	1.94E+09	1.24E+07	1.68E+07	3.05E+07

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6. CONCLUSIONS

The proposed technique in this study involves the implementation of a PSO algorithm only using a one-dimensional variable, the minimum water-cut in a reactive control method, in which the producer wells are progressively shut in when they reach water-cuts between this minimum value and a maximum threshold, generated by a linear interpolation. The idea behind the combination of the RC and PSO methods is to employ a well-known algorithm in tandem with a commonly used control in the industry in order to perform optimization with a low computational cost since the number of needed simulations to achieve significant improvements in NPV is considerably lower than in other techniques.

In terms of NPV results, it is shown that the proposed PSO technique improves NPV in both Egg Model and Olympus Benchmarks, up to 2.77% in the Egg Model and 1.04% in the Olympus Case, considering the economical WCT RC. Against the normal RC, these improvements are up to 2.77% for Egg Model and 3.19 % for Olympus. Therefore, for both cases, PSO performs generally better than RC, by maximizing oil production in the Egg Model and minimizing the water production in the Olympus.

There is still room for improvement in the presented PSO algorithm. For instance, the optimization should be able to consider the maximum water-cut as a second dependent variable. Another prospect is to use the combination of PSO and RC in ensemble optimization problems, by using, for instance, all the realizations of both Egg Model and Olympus. Lastly, it should be considered the application of the proposed method in three-phase reservoir models.

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