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Pattern Effect for Oil Reservoir Waterflooding Using Smart Well

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Abstract: Waterflooding is a primary enhanced oil recovery involving the injection of water into an oil-gas rich reservoir to increase production capacity. Waterflooding is one of the most used enhanced oil recovery technique due to the fact that water is readily available and cheap to maintain. However, with the efficacy of implementing waterflooding recovery technique, only about 35% of the original oil in place (OOIP) is produced. This research is aimed at investigating the effect of placement pattern for non-conventional or smart wells. Comparison is made with respect to previous study where which conventional wells are used. Three cases were investigated on the basis of recovery and complexities in field development. It was observed from this study that conventional wells are not a good candidate for oil well productivity as compared to non-conventional (smart) wells. Conventional wells also pose a limitation to the economic value of the reservoir due to poor well contact. The first, second and third case recorded an NPV of $7.5 trillion, $7.59 trillion and $8.81 trillion respectively. Implementing smart wells also curtailed an early water breakthrough by about 70%. An average gain of 99.7% was also recorded for all cases as against previous study. These results indicated the efficiency of implementing smart wells over conventional wells.

Keywords: Smart Wells, Waterflooding, Net Present Value, Production Rate, Five-Spot Pattern

1. Introduction

Global demand for fossil fuel-based energy has become increasingly prevalent. As a result, oil recovery from ageing reservoirs has become a thing of focus to reservoir engineering researchers [1]. As more sophisticated technology are being created, the need to utilize fossil fuel becomes imminent. In reality, the natural state of recovering oil depletes overtime due to decreasing reservoir pressure or poor sweep efficiency. This necessitates the implementation of enhanced oil recovery strategy [2]. It is known that assessment of unconventional reservoirs is targeted on properties like lithology, oil-gas possibility, stress anisotropy which affects the petroleum accumulation [3]. Enhanced oil recovery involves the practice of implementing mechanical aiders to improve the efficiency of an oil reservoir thereby increasing its recovery [4]. These enhanced based techniques are mostly employed on existing reservoirs that have depleted reservoir pressure. These enhanced oil recovery techniques include waterflooding, steam flooding, polymer flooding etc.

Well placement settings have shown to be a primary determinant in the recovery of oil and gas from reservoirs due to the fact that they are conditions to which oil industries use in obtaining oil to water ratio, and also the economic impact [5]. Oil reservoirs are heterogenous in nature. That is, they exhibit geological uncertainties which predominantly affects optimal well location. For these reason, reservoir engineers are faced with constitutive mechanism of improving reservoir simulation and subsequent optimization for efficient recovery.

2. Literature Review

Some authors have described several approaches to well placement settings. In Grema et al [2], the author evaluated the performance of a smart well in a five-spot pattern via the principle of optimal control theory. The optimal control theory generally constitutes forward and backward integration of adjoint processes. However, this approach has a limitation in observing reservoir uncertainties. Gradient based method has also being applied to well setting optimization [6-9]. Non gradient based approach on the other hand were also implemented for oil well placement optimization [10], where an imperialist competitive algorithm constituting of particle swarm optimization (PSO) and genetic algorithm (GA) was used. In Sun and Xu [11], the authors applied a reduced order optimal control strategy using proper orthogonal decomposition to obtain an optimal well controls to maximize the net present value of a waterflooded reservoir, where the state variables and objective function are directly connected by a partial differential equation. However, all these approaches are in one way or the other computationally time consuming or complicated to realize. Another well placement problem was recorded by Centilmen et al [12] were they used a stationary and case specific inputs to investigate the optimum multi-well locations. Recently, well placement settings were investigated using deep learning algorithm [13-17]. In Marvin et al [18], the authors used a nonlinear autoregressive with exogeneous input (NARx) to predict the recovery of oil from a waterflooded reservoir consisting of eight injection and one production well while in Min et al [19], the authors implemented a productivity potential to investigate the optimal well placement using artificial neural networks. Other enhanced oil recovery such as the use of ultrasound to investigate the permeability effects of rocks on unconventional wells was studied by Bou-Hamdam and Abbas [20]. This is because the permeability of hydrocarbon reservoirs is low with a range of about 1 to 500mD [21]. Apart from the EOR techniques that seeks to influence production efficiency of hydrocarbons, techniques like Extended Reach Drilling (ERD) have been observed as one of the advanced methods used. This is done by keeping the wells in the reservoir a distant away from a specific surface location [22].

In this work, the main goal is to investigate the production performance of three smart well patterns in terms of performance index (oil and water production rate, net present value). These results obtained were compared with the previous work of Grema et al [2], whom in their work implemented a non ICV reservoir wells. Smart wells (or intelligent wells) are basically defined as wells incorporated with inflow control valves or for short ICVs. ICVs have great impact in determining the efficiency of oil well contact during oil and gas recovery.

3. Methodology

Reservoirs are made of complex interconnected pores that contain oil and gas. Due to their heterogeneity, it is suitable to describe their models by a non-linear partial differential equation within the region of time and space [2]. Reservoir simulators are used to describe the discrete reservoir systems by employing conservation of mass and momentum, and these models are designed to constitute three phases of water, oil and gas.

3.1. Reservoir Dynamics

The dynamics of a typical oil reservoir is governed by the principle of Darcy. Reservoirs for multiphase flow systems are described via finite difference representation and is given by the equation [23];

$$g(u, \dot{x}, x, \theta) = 0 \tag{1}$$

Where g is the nonlinear vector function, x is the state vector consisting of oil and gas. u is the input vector otherwise known as the control vector, θ is the model parameter vector. x typically denotes a reservoir model having phase saturation or pressure. u is described by the well flowrates, bottom hole pressure, tubing head pressure, choke setting. θ describes reservoir parameters like the porosity, permeability etc. generally, reservoir state models are represented in a discretized form due to the fact that they are inherently complex to solve analytically. The reservoir model is given in its discretized form as [24]:

$$V(x_k)\cdot x_{k+1} = T(x_k)\cdot x_k \tag{2}$$

Where k represent the time index for a given initial condition [24];

$$x_0 = \check{x}_0 \tag{3}$$

The discrete form of the reservoir is entirely made up of interconnecting layer of blocks known as 'grid blocks', where the properties of the reservoir is constant in the grid space.

A well source vector for a given reservoir model is represented by incorporating a well equation of the form [24]:

$$V(x_k)\cdot x_{k+1} = T(x_k)\cdot x_k + q_k,\ x(0)=x_0 \tag{4}$$

Were x_0 is a vector describing the initial reservoir conditions. The source vector is represented by the pressure difference between the well and grid block. Thus, it is convenient to represent the entire reservoir model with wells as such [24]:

$$q_k^j = \alpha_k^j \cdot w^j \cdot \left(p_{bhp,\,k}^j - p_k^j\right) \tag{5}$$

Were $p_{bhp,\,k}^j$ is the bottom hole pressure of the well having an index j of the grid blocks containing the well. w is a well constant that exhibits the geometric factor. α_k is the control valve and it ranges as a multiplication factor of 0 to 1. Reservoir models are non-linear because of the inherent features of embedded relative permeability and monumental state vectors. For this reason, their simulation time might be prolonged.

Generally, the reservoir output vector y is represented by an input function u and x based on the equation [23]:

$$y_{k+1} = h(u_{k+1}, x_{k+1}) \tag{6}$$

3.2. Reservoir Model Formation

In this work, we adapted the same model configuration with Grema et al [2], except that in our case, inflow control valves were incorporated in the reservoir model. The model used in this work is a rectangular reservoir structure modelled using MATLAB reservoir simulation toolbox (MRST). The reservoir dimension was given to be 2500ft x 2500ft x 150ft for x, y z -axis while a 5 x 5 x 3 cells were used respectively. Each dimension is divided into 5 cells, making a total of 75 cells for all 3 layers in the geometry. Heterogeneous permeability values with a 30% homogeneous porosity were generated and applied to all layers. For this model, the fluid phase was assumed to be multiphase and incompressible containing both oil and water. The viscosity used was 10 centipoise and 1 centipoise for oil and water respectively, while the density used was 700 kg/m^3 and 1000 kg/m^3 for oil and water respectively. The reservoir was simulated with an initial reservoir pressure of 4500 bars and an iteration schedule of 2000 days. The generated permeability is calculated based on the equation:

$$k(x) = \bar{k}(x)\ \vartheta(x) \tag{7}$$

ϑ is the coefficient of modification while $\bar{k}$ is the mean value of permeability distribution.

The performance index used to investigate the optimum well setting is the Net Present Value (NPV), which is given by the equation [25]:

$$J=\sum_{n=1}^{T}\frac{\Delta t^k}{(1+b)^{\frac{t^k}{365}}}\left[\sum_{i=1}^{N_P}\left(P_0 q_{o,1}^n - P_{wP} q_{wp,i}^n\right) - \sum_{j=1}^{N_I}\left(P_{wI} q_{wI,j}^n\right)\right] \tag{8}$$

N_p stands for the Number of production wells, N_I is the Number of injection wells, b is the Discount factor, Δt^k is the Time step size, t^k is the evolution time, T is the time unit. The water injection rates are commonly used as the decision variables. (8) can be written in a matrix form as [11]:

$$\max J=\sum_{n=1}^{T}\frac{\Delta t^n}{(1+b)^{\frac{t^n}{365}}}\left[P_o^T q_o(n) - P_{wP}^T q_w(n) + P_{wI}^T q_w(n)\right] \tag{9}$$

P_o^T, P_{wI}^T, P_{wP}^T are well control vectors.

In this problem, three cases of well placement were used as adapted from Grema et al [2] as well as the rock permeability (Table 1). The first case involves arrangement of one smart injection and production well in a horizontal pattern installed with three inflow control valves (ICVs) named icv1-icv3 and pcv1-pcv3 respectively. The second case has one injection and production well placed in a quarter five spot pattern with each well having three ICVs. The third case is a five-spot arrangement of one smart production well at the center of the reservoir model and four smart injection wells at the corner of the reservoir model. For the third case, each well has three ICVs making a total of 15 ICVs (Figure 1-3). The summary of these configuration is given in table 3. The idea behind this configuration was to determine the effect of well placement on oil recovery as well as the net present value.

The oil reservoir depth used was 8000ft and a rock compressibility factor of 4×10^{-6}psia at a reservoir pressure of 4.5×10^{7}bar was also used.

Table 1. *Rock permeability (adopted from Grema* et al *[2]).*

	Layer 1	Layer 2	Layer 3
x-direction	200mD	1000mD	200mD
y-direction	150mD	800mD	150mD
z-direction	20mD	100mD	20mD

Table 2. *Fluid properties.*

Saturation	K_{rw}	K_{ro}	P_{cow}
0.15	0.0	0.9	4.0
0.45	0.2	0.3	0.8
0.68	0.4	0.1	0.2

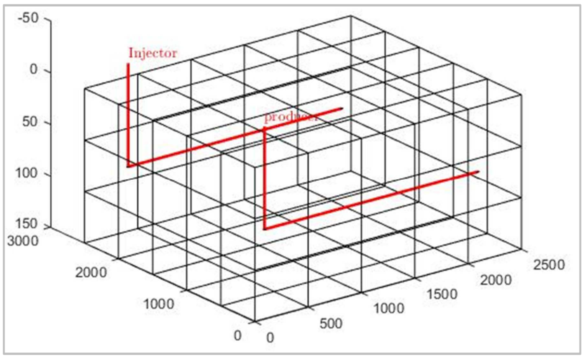

Figure 1. *Case 1 model with a total of 6 ICVs.*

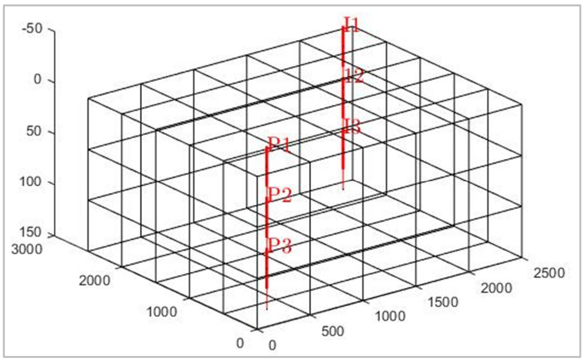

Figure 2. *Case 2 model with a total of 6 ICVs.*

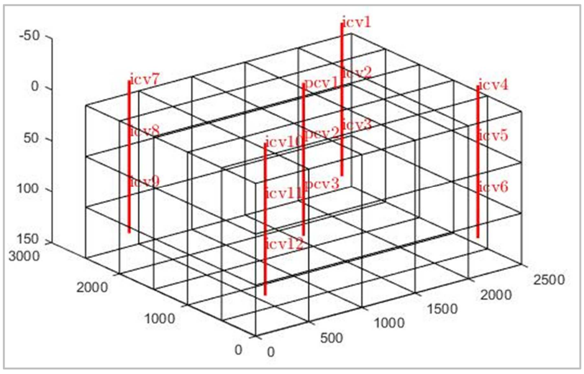

Figure 3. *Case 3 model with a total of 15 ICVs.*

Table 3. *Summary of reservoir configuration for each case.*

Cases	Well properties/pattern
Case 1	Horizontal well arrangement with 1 producer and 1 injector. 6 total ICVs
Case 2	Quarter five spot well arrangement with 1 producer and 1 injector. 6 total ICVs
Case 3	Five spot well arrangement with 1 producer and 4 injectors. 15 total ICVs

4. Discussion of Results

The oil and water production rates were recorded for each well placement case. The smart injectors are rate controlled with an initial water injection rate of 0.127m^3/day, while the smart producers are bottom hole pressure (BHP) controlled with an initial reservoir pressure of 2 x 10^7 bar.

4.1. Case One

For case 1, an NPV value of $7.5 trillion was recorded. The efficacy of the ICVs could be observed with a very large value difference when compared with the work of Grema et al [2]. In this work, an NPV gain of 99.7% was obtained as against that of Grema et al [2] in which an NPV value of 19 billion dollar was recorded. This result indicates the effectiveness of incorporating smart ICVs to oil well for greater economic realization. Likewise, the maximum oil production rate was shown to be 316,353m^3/day (Figure 4). The water production rate on the other hand was achieved at maximum at a rate of 3.4348m^3/day (Figure 5). With the amount of water being produced, it is noteworthy to confirm that the installed ICVs were able to curtal an early water breakthrough thereby increasing the productivity of the oil well. Table 4 gives a summary of the results of case 1 as compared to that of Grema et al [2].

For the BHP, a maximum pressure of 3651bar was observed at initial until a pressure drop was attained at 711.99bar (Figure 6). The effect of the producer ICVs could also be noticed by the pressure difference, while a steady injection rate was maintained all through the period of production.

Table 4. *Case one result summary.*

	Grema et al [2]	This work
Oil produced	176,408.9m^3/day	316,353m^3/day
Water produced	45,345.2m^3/day	3.4348m^3/day

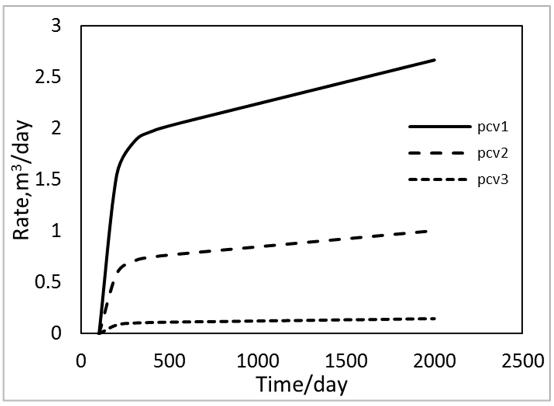

Figure 4. *Cumulative oil production rate (case 1).*

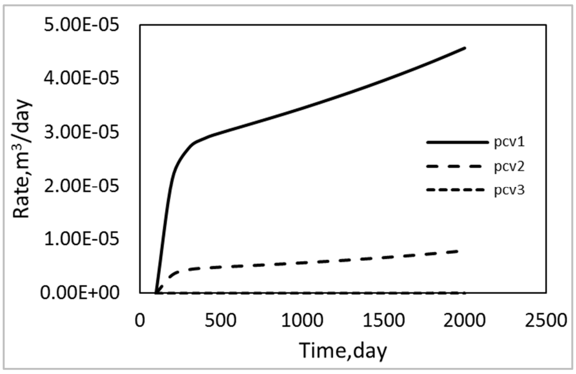

Figure 5. *Cumulative water production rate (case 1).*

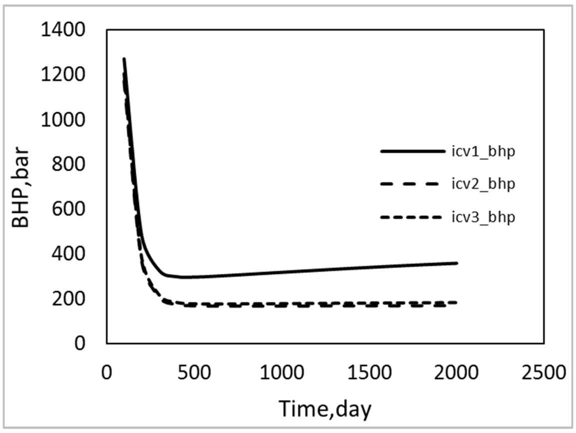

Figure 6. *Bottom hole pressure (BHP) for case 1.*

4.2. Case Two

Case 2 recorded an NPV of $7.597 trillion which indicated a gain of 99.8% as against the work of Grema et al [2] The result for case two also proves that smart wells are a better choice for oil well productivity when compared to conventional wells.

The maximum oil production rate was also recorded to be 318,862.7m^3/day as shown in table 5.

Table 5. *Case two result summary.*

	Grema et al [2]	This work
Oil produced	151,881.05m^3/day	318,862.7m^3/day
Water produced	23,540m^3/day	0.0964m^3/day

Figures 7, 8 and 9 shows the cumulative oil production rate, water production rate and bottom hole pressure respectively, for case two. Also, the BHP value was recorded at the beginning of production to be 3833.8bar dropping down to a pressure of 639.374bar. this also indicates a near perfect ICV implementation.

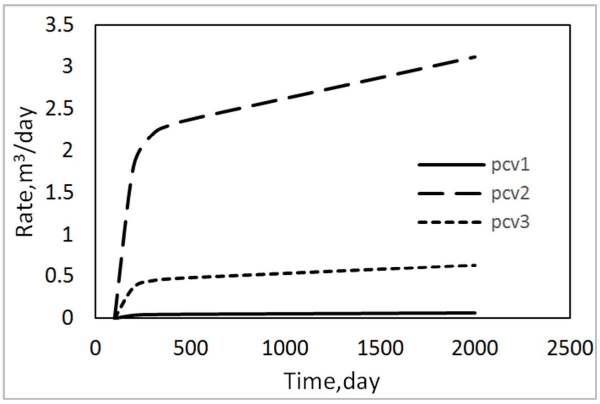

Figure 7. *Cumulative oil production rate (case 2).*

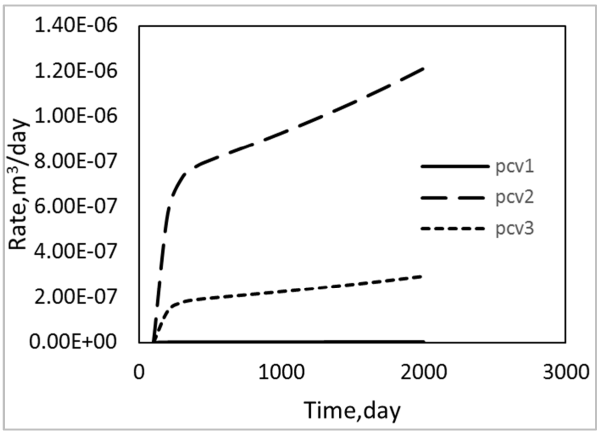

Figure 8. *Cumulative water production rate (case 2).*

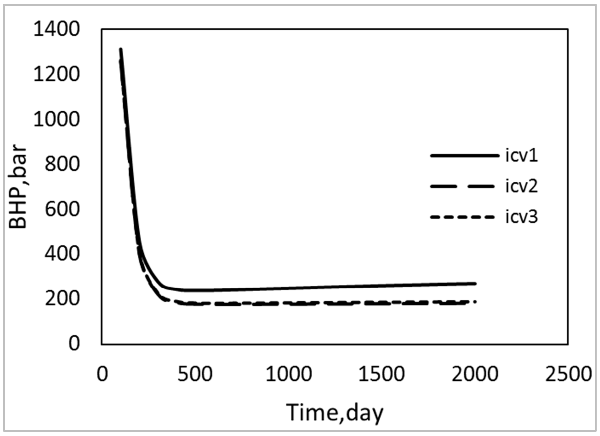

Figure 9. *Bottom hole pressure (BHP) for case 2.*

It's obvious that an early water breakthrough was curtailed judging from the level of water produced and pressure difference during the production period.

4.3. Case Three

For case three, an NPV of $8.81 trillion was obtained incurring a gain of 99.8% over that of Grema et al [2] which obtained an NPV of $17 billion. A total oil production rate of 235,979.2m^3/day was also obtained during period of prdouction (Table 6).

Table 6. *Case three result summary.*

	Grema et al [2]	This work
Oil produced	5,936.8m^3/day	235.979.2m^3/day
Water produced	245.23m^3/day	42,271.2m^3/day

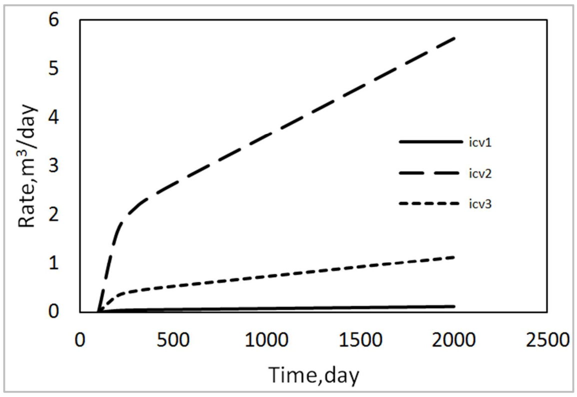

Figure 10. *Cumulative oil production rate (case 3).*

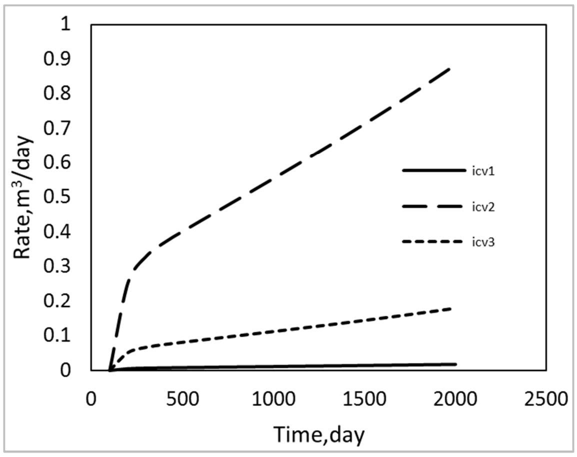

Figure 11. *Cumulative water production rate (case 3).*

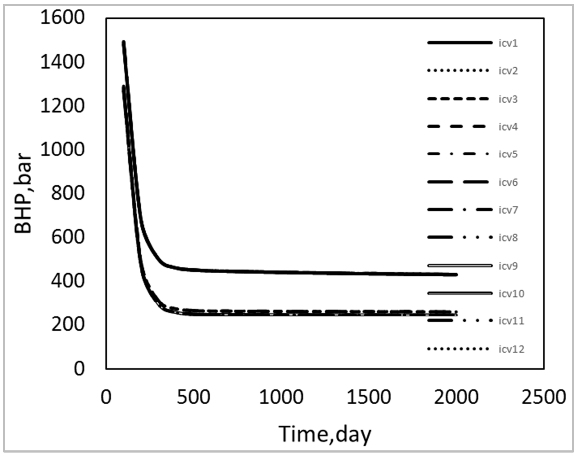

Figure 12. *Bottom hole pressure (BHP) for case 3.*

Table 7. *NPV comparison for all cases.*

NPV	Grema et al [2]	This work	Gain
Case 1	$19.5 billion	$7.59 trillion	99.7%
Case 2	$19.0 billion	$7.59 trillion	99.7%
Case 3	$17.0 billion	$8.81 trillion	99.8%

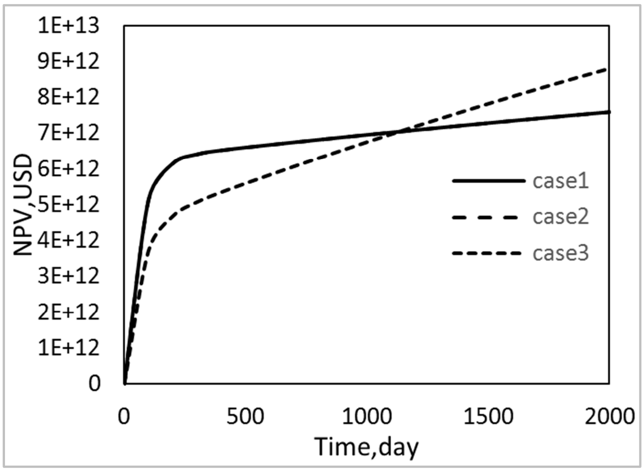

Figure 13. *NPV for all cases.*

Figures 14, 15 and 16 shows the relative permeability curve, reservoir flux intensity and reservoir pressure respectively.

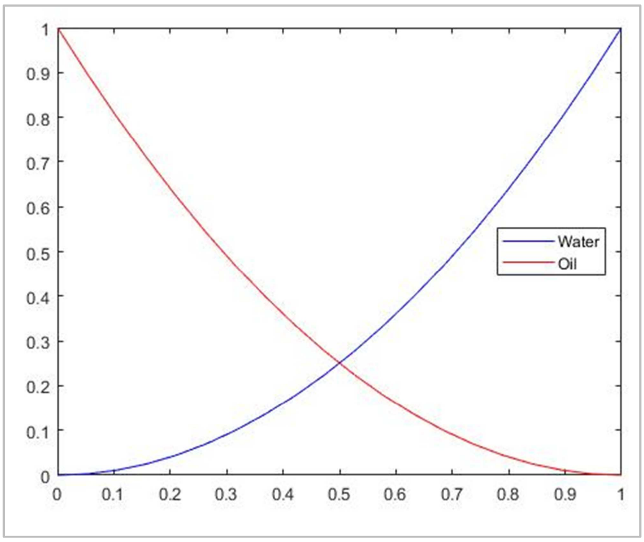

Figure 14. *Relative permeability curve.*

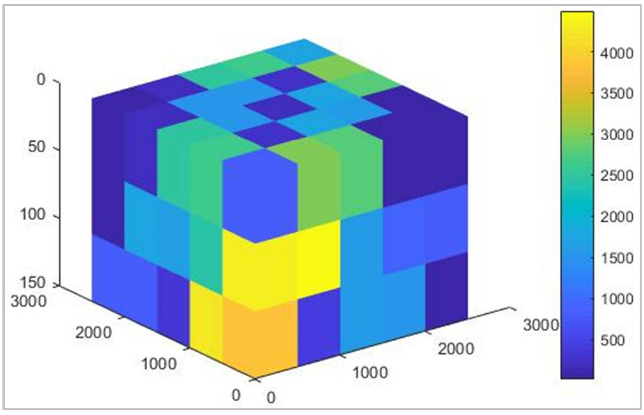

Figure 15. *Reservoir flux intensity.*

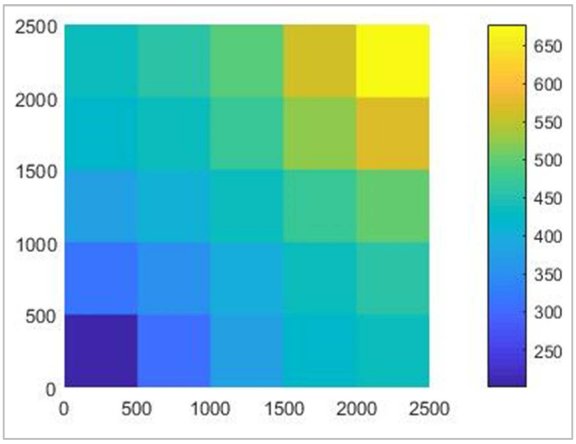

Figure 16. *Reservoir pressure.*

In table 7, we can see the huge difference in the NPV value obtained in this work against the previous work of Grema et al [2]. This implies that for efficient oil well productivity, smart wells could stand a chance of higher preference. Oil well contact with an appropriate mitigation of early water breakthrough is shown to be imminent. Case three from this study was shown to have a higher NPV which establishes the bases for number of injection wells efficacy. More injection wells could incur a greater amount of oil that will be produced. However, surplus water injection could pose a threat to proper sweep efficiency.

5. Conclusion

In this study, three different smart wells configuration were modelled using same reservoir geometry and fluid property. Comparison is made with respect to previous study where which conventional wells are used. At the end of this study, it was observed that conventional wells are not a good candidate for oil well productivity as compared to non-conventional (smart) wells. Conventional wells also pose a limitation to the economic value of the reservoir due to poor well contact. Hence it is suggestive that for a reservoir to attain to its greatest production potential, smart wells could be the preferential choice. It is recommended that this study be extended to a more complex reservoir geometry having structural uncertainty and faults.

Conflict of Interest

The authors declare no conflict of interest.

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