

Evaluation of Intelligent Wells Performance in a Five-Spot Arrangement

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Abstract- The efficiency of water flooding processes can be improved by installing intelligent wells which are good candidates for control and optimization. Optimal control theory based on adjoint formulations was found to be efficient for reservoir optimization. However, this solution approach is local and may not be suitable for comparing design alternatives. In this work, an approach for determining an optimal starting point for optimal control theory procedure was developed to give near global optima. The performance in terms of net present value (NPV) of two forms of five-spot pattern was compared. The method results to similar performances of the two alternatives because it was formulated to give true optimal solution trajectories. It was found that regular five-spot pattern results to an NPV in excess of \$4,900 over inverted design. Respective increase in oil and water productions of 0.23% and 0.22% were recorded for former design against the later.

Keywords- intelligent wells; adjoint; optimal control theory; global optimum; water flooding

1 INTRODUCTION

The current population explosion experienced by the modern world and the increasing level of rural-urban migration had over-stretched energy resources of most nations. Energy derived from oil and gas resources are needed now more than ever due to its demand, thanks to industrialized nature of human life. These underground resources are brought to light using technologies that exploit reservoir pressure to pump them to the surface of the earth. Information from United States' Department of Energy says the amount of oil produced worldwide is only one-third of total oil available (Salem *et al*, 2011).

Looking at recovery status of matured oil reserves and huge investment cost of exploiting new and remote oil and gas reserves, the need to optimize and enhance oil recovery from depleted and semi-depleted oil and gas reservoirs cannot be over emphasized. One of the most economical and easy technology employed in enhancing oil recovery is water flooding method. It entails flushing of water into the reservoir so as to maintain the pressure needed to sustain production. Heterogeneity of some reservoir properties hinders the effectiveness of water flooding improving the recovery of oil. This shortcoming increases the amount of water produced up to a point that production no longer becomes economical.

Several remedies have been proposed with regards to the potential problems associated with water flooding. One among them that stands out and receiving research attention is the use of smart or intelligent production and injection wells (Brouwer *et al*, 2001, Brouwer *et al*, 2004, Meum *et al*, 2008, Volcker *et al*, 2011, Grema and Cao, 2016, Grema *et al*, 2016a, Lu and Xu, 2017, Ogbeiwi *et al*, 2018, and Hourfar *et al*, 2019). Although known for its attendant limiting productivity and lack of susceptibility to optimization techniques, conventional wells are more predominant. In contrast, smart wells are equipped with in-ground instrumentation for control and measurement of flow rates, temperatures and pressures. This added value of intelligent wells makes it open to optimization.

They are also found handy when it comes to dealing with reducing well intervention activities, enhancing oil recovery and ensuring increased production. Smart wells allow shifting from passive/reactive production scenarios to active/proactive production control (Brouwer *et al*, 2001). The well is segmented by inflow control valve which enable the control of the important process parameters (Meum *et al*, 2008).

The flowrates or pressures of injection and production out of the reservoir determine flow of fluid in to the reservoir's various zones (Grema and Cao, 2016). The ability to control flowrates and pressures by smart wells improve water flooding initiatives; this ultimately enhances oil recovery. This recovery process is facilitated by imposing desirable pressure profile along injection wells. Optimization was found to be an important tool in many engineering applications (Akinropo and Olarinoye, 2019, Bajeh *et al*, 2019). Research activities on the optimization of flow of fluid in porous media had received much attention recently. Brouwer and Jansen (2004) deployed optimal control algorithm for recovery maximization. The study targets smart well performance optimization in water flooding process.

Other few works also reported the use of adjoint-based method and Kalman filter technique for optimization purposes. This is reflected by works reported by (Brouwer *et al*, 2004; Lorentzen *et al*, 2006; Sarma *et al*, 2008). The optimization of the operations of a smart well using Explicit Singly Diagonally Implicit Range-Kutta and quasi-Newtonian Sequential Quadratic Programming was subject of the work reported by Volcker *et al* (2011). An extension to this was presented by Capolei *et al* (2012) to include gradient computation based on continuous-time adjoint equation.

Recently, the benefits offered by smart wells over conventional ones in a five-spot pattern of wells arrangement have been demonstrated (Grema *et al*, 2016a). Five-spot pattern involves placement of four injection wells at the vertices of a rectangular geometry with one production wells at the center which are repeated sequentially. An inverted pattern is also possible where four production wells are located at the vertices

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with one injection well at the center (Singh and Kiel, 1982). In this work, the performances of five spot pattern alternatives (regular and inverted) are compared. The performances were evaluated through dynamic optimization using optimal control theory. Being a local optimizer, the problem of starting point is also addressed in the paper.

2 METHODOLOGY

2.1 RESERVOIR DYNAMICS

Reservoir was represented mathematically in a discrete form (Grema *et al*, 2016b) and modified here as

$$g(\mathbf{u}^k, \mathbf{x}^{k+1}, \mathbf{x}^k, \boldsymbol{\varphi}) = \mathbf{0} \tag{1}$$

Where g is a nonlinear function, \mathbf{u}^k is the input vector at time step k which can be injection rates, production rates and or/bottom hole pressure, \mathbf{x}^k and \mathbf{x}^{k+1} are reservoir states at times k and $k+1$, and $\boldsymbol{\varphi}$ is a vector of parameters. The model is complete with an initial condition as

$$\mathbf{x}_0 = \tilde{\mathbf{x}}_0 \tag{2}$$

Output vectors which consist of production rates are function of state and input variables $\tag{3}$

and can be represented by $\mathbf{h}(\mathbf{u}^k, \mathbf{x}^k, \mathbf{y}^k) = \mathbf{0}$

2.2 OPTIMIZATION USING OPTIMAL CONTROL APPROACH

In reservoir water flooding optimization, the task is to find optimal injection and production trajectory that will optimize a performance index such as net present value (NPV) or oil recovery over a period of time or to the economic limit of the reservoir. Optimal control theory was found to be very efficient in carrying out this exercise (Grema *et al*, 2016a). In this work, NPV is used as the objective function which is given as follows:

$$J^k = \left\{ \frac{\sum_{j=1}^{N_{prod}} [r_o(y_{o,j})^k - r_{wp}(y_{w,j})^k] - \sum_{i=1}^{N_{inj}} r_{wi}(u_{w,i})^k}{(1+b)^{\frac{t^k}{\tau}}} \right\} \Delta t^k \tag{4}$$

where r_o , r_{wi} and r_{wp} are oil production, water production and water injection costs respectively, y_o , y_w and u_w are oil production, water production and water injection rates, b is the discounting factor, τ is reference time for discounting, and t^k is time at k^{th} step. In the case studied the value of r_o , r_{wi} and r_{wp} are kept at \$100/bbl, \$10/bbl and \$10/bbl respectively. The discounting factor is zero.

The optimal control calculations involve a forward integration of the reservoir dynamic system, Equation (1) and a backward integration of adjoint systems which are required for gradient computation. Here, the reservoir system is regarded as an equality constraint by summing it to the objective function using a set of Lagrange multipliers which gives rise to a modified objective function written as

$$\bar{J} = \sum_{k=0}^{K-1} J(k) + \lambda(k+1)^T g(k) = \sum_{k=0}^{K-1} \mathcal{H}(k) \tag{5}$$

where $\mathcal{H}(k)$ is called the Hamiltonian. The following constitutes the optimal control of waterflood optimization (Brouwer and Jansen, 2004).

- the reservoir dynamic system Equation (1)
- initial conditions of the dynamic system
- a set of injection and production rates, \mathbf{u}
- time steps, $k = 0, \dots, K - 1$
- adjoint equation (Brouwer and Jansen, 2004)

$$\lambda(k)^T = \left[-\frac{\partial J(k)}{\partial \mathbf{x}(k)} - \lambda(k+1)^T \frac{\partial g(k)}{\partial \mathbf{x}(k)} \right] \left[\frac{\partial g(k-1)}{\partial \mathbf{x}(k)} \right]^{-1} \tag{6}$$

where $\frac{\partial J(k)}{\partial \mathbf{x}(k)}$ is a vector of partial derivatives of the

objective function with respect to the states, \mathbf{x} while $\frac{\partial g(k)}{\partial \mathbf{x}(k)}$

and $\frac{\partial g(k-1)}{\partial \mathbf{x}(k)}$ are the Jacobians of the reservoir dynamic

system with respect to the states.

- Final conditions of the adjoint systems, and for a free terminal state problem is given by (Brouwer and Jansen, 2004).

$$\lambda(K)^T = \mathbf{0}^T \tag{7}$$

With the above ingredients, the solution procedure of the water flooding optimization problem involves repeating the following steps until a set of optimal controls is obtained (Brouwer and Jansen, 2004):

- Forward numerical simulation of the reservoir dynamic system by numerical integration of Equation (1) over entire time interval 0 to K while taking the initial conditions, Equation (2) into consideration as well as initial or updated \mathbf{u}
- Backward numerical simulation of the adjoint system by numerical integration from time K to 0 starting with the final condition expressed by Equation (7)
- The gradients of the Hamiltonian with respect to the controls are computed which are (Brouwer and Jansen, 2004):

$$\frac{\partial \mathcal{H}(k)}{\partial \mathbf{u}(k)} = \lambda(k)^T \frac{\partial g(k)}{\partial \mathbf{u}(k)} + \frac{\partial J(k)}{\partial \mathbf{u}(k)} \tag{8}$$

- Improvement in \mathbf{u} is calculated using a line search technique and obtained derivatives in Equation (8).

However, the above gradient-based optimization method which rely on initial guess will only lead to a local solution, and so the comparative analysis may be biased. To overcome this shortcoming, the reservoir optimization tool is integrated with MATLAB optimization toolbox where *fmincon* function locate an optimum initial guess in an iterative fashion. Although, *fmincon* solves for a local optimum, an iterative technique was developed in this work to find an optimal starting point in such a way that the difference in optimal NPV of two successive runs is below a tolerance limit. The initial guess found by *fmincon* is continuously passed to the reservoir optimizer for optimal control calculations.

2.3 CASE STUDY

The reservoir model used in this study was adopted from MRST package (SINTEF, 2014) and modified to suit our

purpose. The reservoir size is 100 m x 100 m x 10 m which is represented by Cartesian grids of 20 x 20 x 5 cells. It has heterogeneity in vertical permeability which divides the reservoir into five distinct layers. The permeability values from top to bottom are 200 mD, 500 mD, 350 mD, 700 mD and 250 mD. However, the reservoir porosity was assumed uniform at 0.3 with two-phase of oil and water (Grema *et al*, 2016a).

Two forms of five-spot well arrangement were considered: the regular five-spot pattern where four injection wells are located at the corners of the reservoir with a production well at the center, and inverted five-spot pattern that has an injection well at the center and a production well at each corner of the reservoir (Fig.1 and Fig. 2). In both cases, the wells were completed with smart ICVs which are installed in each of the reservoir layers. That is, five ICVs for each well and total of 25 ICVs for each design scenario. In Fig. 1, the injection ICVs are labelled I1 – I20 while the production ICVs are labelled P1 – P5. For the inverted design shown in Fig. 2, the injection ICVs are labelled I1 – I5 and P1 – P20 for the production ICVs. The optimization is run for two years with time step size of two months, that is, six-time steps for each scenario.

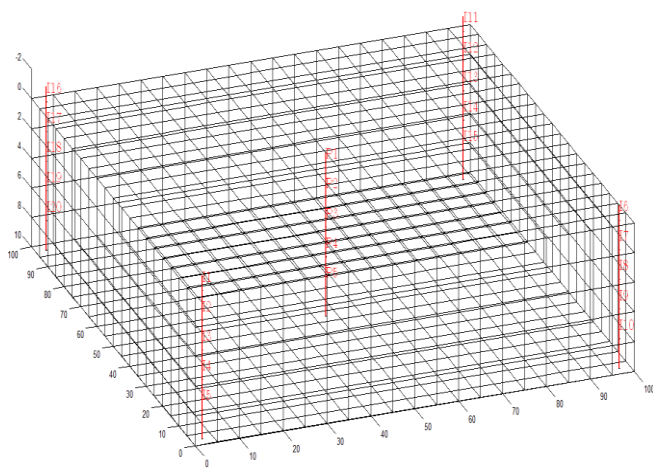


Fig. 1: Reservoir and Wells Arrangement for Regular Five-Spot Pattern

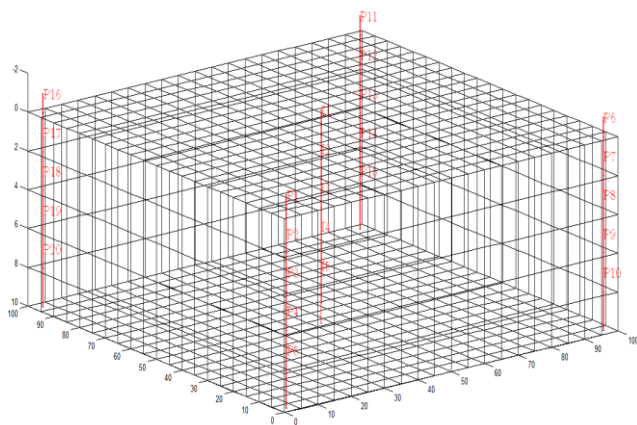


Fig. 2: Reservoir and Wells Arrangement for Inverted Five-Spot Pattern

3 RESULTS AND DISCUSSION

To show the influence of starting point on adjoint method, different initial injection and production rates were used to optimize the water flooding process using both design alternatives and the results are shown in Fig. 3. It can be seen from the figure that optimal NPV for the process is highly affected by the starting point used. For the regular five-spot pattern, the difference between the highest and lowest NPV is \$4,600.00 while for the inverted case, this difference is \$3,000.00. A higher variability was recorded for the regular design with a standard deviation of \$1,429.69 than the inverted case where the standard deviation is \$1,263.15.

The optimization results are summarized in Table 1. The regular arrangement is seen to have a better performance than the inverted configuration. In terms of NPV, the former approach yields an NPV in excess of \$4,900.00 over the later. A slight increase in total productions is also with regular five-spot. This difference in performance can be explained when the optimal injection and production trajectories are analyzed.

Table 1. Performance Indices of Regular and Inverted Five-Spot Patterns

| Design | NPV (\$) | Total Oil Produced (m ³) | Total Water Produced (m ³) |
|----------|--------------|--------------------------------------|--|
| Regular | 7,843,800.00 | 16,319.00 | 11,289.00 |
| Inverted | 7,838,900.00 | 16,281.00 | 11,264.00 |

Observing the pattern of water injection for the regular five-spot in Fig. 4, it can be seen that for a particular injection well, only the topmost and the lowest ICVs are opened at all-time intervals, the rest are almost shut-in. This may give an idea of the number of ICVs that is actually required for optimal production. These sections of the reservoir with high injection requirement correspond to low permeability zones. Due to the strategic positioning of the production well, we can observe an almost uniform production (for both oil and water) from the producing ICVs (Fig. 5 and Fig. 6). For all the ICVs, oil production peaked at 180 days – 240 days (Fig. 5) while water break-through also occurred at that range of periods (Fig. 6).

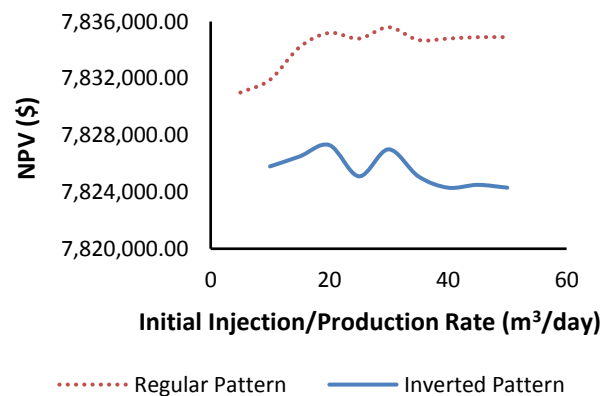


Fig. 3: Effects of Starting Points on Optimal NPV

Water injection rates for the inverted design are shown in Fig. 7. It can be observed that high volume of water was injected to the least permeable layer (with permeability of 200 mD) while the reverse is the case for the most permeable layer (700 mD). This is for effective control of water produced for better NPV. However, oil and water are almost uniformly distributed among the producing ICVs owing to its (ICVs) number (see Fig. 8 and Fig. 9). Attainment to peak production period varies among the ICVs; for example, ICVs 1 – 10 attained peak production from 180 days to 240 days from start of production while for ICVs 11 – 20, peak period varies from 240 days to 300 days (Fig. 8). Furthermore, water break-through was seen to occur at an average of 200 days for all producing ICVs.

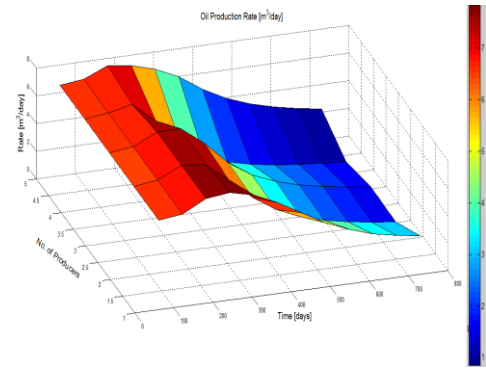


Fig. 5: Oil Production Rates for Regular Five-Spot Pattern

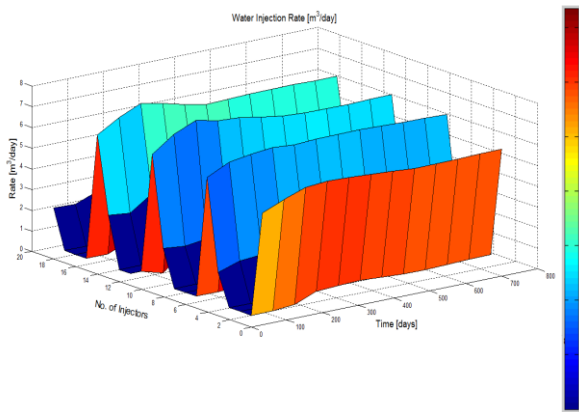


Fig. 4: Water Injection Rates for Regular Five-Spot Pattern

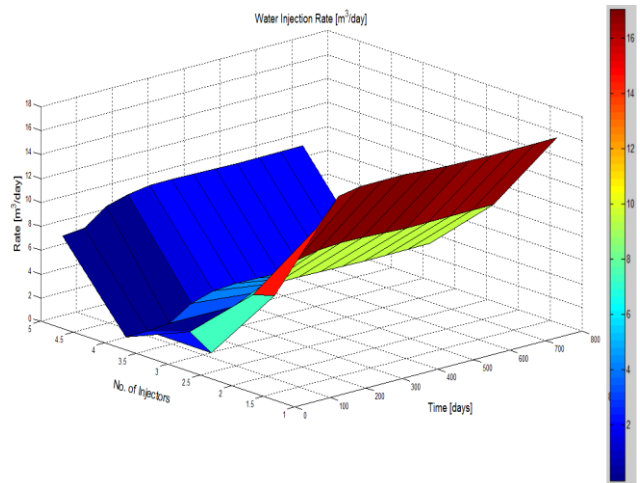


Fig. 7: Water Injection Rates for Inverted Five-Spot Pattern

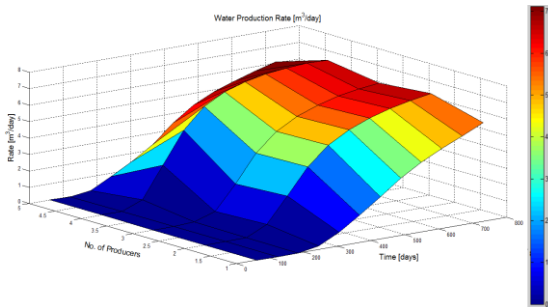


Fig. 6: Water Production Rates for Regular Five-Spot Pattern

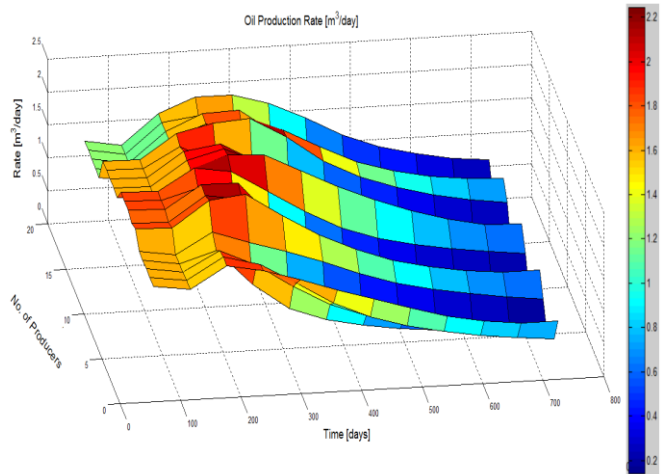


Fig. 8: Oil Production Rates for Inverted Five-Spot Pattern

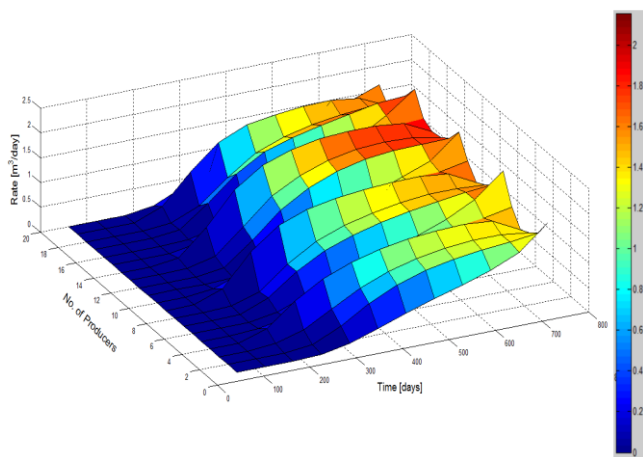


Fig. 9: Water Production Rates for Inverted Five-Spot Pattern

4 CONCLUSION AND RECOMMENDATION

A comparative study of five-spot options of water flooding was carried out. The comparison was formulated as an optimization program which was done using optimal control theory. Known for its efficiency in reservoir optimization, solutions provided by optimal control theory are local optima and hence might be biased for comparative exercise. For this reason, a procedure was developed in this study to obtain an optimal starting point for each case study to avoid entrapment in local optima. The following conclusions were drawn:

- The optimal performance for the two design alternatives - regular and inverted five-spot patterns were found to vary significantly with optimization starting points, which necessitated its (starting point) systematic selection.
- The performances in terms of NPV of the two design approaches (with appropriately selected initial points) are almost similar with similar production potentials. This is largely because the number of controls (ICVs) used for both designs are the same, and hence, have same control capabilities.
- It can therefore be concluded that, in order to assess the full potential of this type of venture through optimization study using gradient-based algorithm, selection of good starting points is paramount important.

It is recommended that a field-wide case should be tested and the objective function should include other items such as equipment fixed costs, maintenance costs.

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