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Well Placement Optimization Using Simulated Annealing and Genetic Algorithm

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Abstract

The general success ratio of wells drilled lies at 1:4, which highlights the difficulty in properly ascertaining sweetspots. well placement location selection is one of the most important processes to ensure optimal recovery of hydrocarbons. Conventionally, a subjective decision is based on the visualization of the HUPHISO (a product of net-to-gross, porosity and oil saturation) map. While this approach identifies regions of high HUPHISO regarded as sweetspots in the reservoir; it lacks consideration for neighbouring regions of the sweetspot. This sometimes lead to placement of wells in a sweetspot but near an adjoining aquifer; giving rise to early water breakthrough - low hydrocarbon recovery. Recently, heuristic optimization techniques. Genetic algorithm (GA) and simulated annealing (SA) has received attention as methods of selection of well-placement locations. This project developed and implemented GA and SA well-placement algorithms and compared the reservoir performance outputs to that of conventional method. Firstly, a reservoir performance model was built using a reservoir flow simulator. In the base case, the wells were placed based on a subjective selection of gridblocks upon the visualization of the HUPHISO map. Thereafter, JAVA routines of GA and SA well-placement algorithms were developed. The numeric data (ASCII format) underlying the map were then exported to the routines.

Finally, the performance model was updated with new well locations as selected based on the GA and SA-based approach and the results were compared to the base case. The Comparison of the results showed that both GA and SA-based approach resulted to an increased recovery and time before water breakthrough.

INTRODUCTION

The problem of optimizing an oil field is an extraordinarily complex one. In it there are many variables to consider, such as geological variables (reservoir architecture, reservoir and fluid characterization, constraints from trajectory and well azimuth), production variable (well placement, well count, type of platform, platform position, etc.) as well as all importantly, monetary variables reflected on the cash flow models. All these parameters make difficult the determination of an objective function for improved recovery and concurrently its restrictions. This difficulty is however countered by the use of numerical flow performance simulators to determine the objective function. The process of discretization of the reservoir yields great computing cost, such that flow models must exit for each individual gridblock with its clearly defined attributes, hence giving rise to a population of various variables and introducing a probabilistic determination of objective function, especially in the case of static reservoir features.

Well placement entails the gross judgment of reservoir properties, these properties will affect the effective flow of oil from its accumulation to the wellbore. The following are the properties that may affect effective reservoir deliverability;

- Net-To-Gross (NTG)
- Porosity (Ø)
- Oil saturation (S_o)

From classical probability distribution pattern, it is safe to say that the best estimate of these properties comparatively would be a product of these numeric variables, thus for an output argument denotes the best position for well placement, hence the function must be a product of these said properties. i.e.

Mathematically

$$Y = NTG \times Ø \times So \tag{1}$$

where,

Y= well deliverability

NTG= Net-To-Gross

(Ø)= Porosity

(S_o)= Oil saturation

It is with this function that the conventional HUPHISO map used in the industry works with.

Having established the basis of well placement, it is imperative to note that our output judgement is numerically ordered rather than logic, the logic connotes the ability to base judgement on surrounding results. In a discretized reservoir model, results gotten are defined for each grid section but globally this discretization does not exist as it only helps us understand the finite differences and capture events more accurately (Local grid refinement and coarsening). Recall our results are backed up by numeric, defined for a particular grid and hence would not take cognizance of the surrounding events.

Table 1—A typical 2D Reservoir Grid

WATER	HIGH HUPHISO	LOW HUPHISO	
1,1	2,1	3,1	4,1
1,2	2,2	3,2	4,2
1,3	2,3	3,3	4,3
1,4	2,4	3.4	4,4

From our output result we can see the possibility of estimating best position for well placement, but this brings to life the role of logical judgment, as we see, grids (2,2) and (4,1) (4,2) (4,3) (4,4) show high HUPHISO distribution but placing a well at grid (2,2) would certainly yield early water breakthrough, and you might opt to say its obvious grids (4,1) (4,2) (4,3) (4,4) should be the best pick. This might seem true but not exactly applicable in multi-layered reservoir systems with variation in distribution of saturation and other rock properties or even in single layered reservoirs with complex saturation distribution profile, hence the need to develop a better pattern for determining best position for well placement with logical ordering ability.

METHODOLOGY

This project investigates the application of genetic algorithm and simulated annealing for effective well placement for optimal recovery of hydrocarbons. A commercial simulator is adopted (Eclipse 3D black oil simulator, E100) and used in this paper to study how well hydrocarbon recovery can be enhanced.

It is well known that the conventional HUPHISO map used in the industry gives a fairly accurate estimation of sweet spots, this however is dependent on user preferences, hence prone to errors. The use of genetic algorithm and simulated annealing is aimed at achieving better estimation of sweet spots and a comparative analysis done to further understand the favors and possibly the drawback of each of the search technique

This paper is based on generating a model from heuristic search and logical conditions. The Genetic Algorithm (GA) and Simulated Annealing (SA) optimization search technique provide suitable environment for achieving the proposed goal. This study will entail a comparative analysis of the two methods mentioned.

The numeric behind the generated model from Eclipse 100 simulator in ASCII file format, is inputted into the GA and SA algorithm for search to commence, after which output of results (backed by numeric signatures), based on stipulated objective function and in meeting the logical conditions, is then transferred back to the E100 simulator for validation of result and comparison with base case situation for well placement.

The Genetic and Simulated Annealing algorithms receives input based on numerical values of the various properties of the reservoir model, heuristically searches for the best combination of the NTG, Soil, Phi(Ø) within a given fitness range. This however is subject to the predetermined limits of expected results, hence the SA and GA algorithm must produce results from search only within range of expected result and also meeting the logical condition.

This logical condition is simply a command that an optimum placement must be distant from aquifer zones, especially side aquifers. Therefore, the search technique may have a combination of the properties within the desired range but if it does not meet this condition, it is regarded as unfit.

This condition is extremely crucial as it provides an edge over the rigor of cross examination for near aquifer zone (what the normal HUPHISO map would induce).

GENETIC ALGORITHM

Genetic Algorithm is a heuristic search technique that works with the "survival of the fittest" principle proposed by Charles Darwin (Theory of evolution)

Operators of Genetic Algorithm

Population: this refers to the total number of variables present in the model for search function, it is the set of solutions

Selection: This process eliminates the bad solutions, thereby selecting the best possible results based on the selection criteria for continuous evaluation and qualification for crossover

Crossover: this process creates new solution from the existing solutions, this operator exchanges the gene information between the solutions in the mating pool.

Mutation: is the intermittent modification of solution variables to foster diversity in the population.

Elitism: is the preservation of few best solutions of the population pool as crossover and mutation may destroy the solution.

GA has the following advantages;

- Depends on the objective function rather than its derivatives causing constancy in objective function.
- Increased processing speed due to simultaneous sampling of the solution surface.
- Can be executed using parallel computing.
- It is very dynamic and does not get fixed in a local minima.

SIMULATED ANNEALING

Simulated annealing is an analogous method for optimization akin to the process of slowly cooling metals so that there become strong at a low energy state. It is typically described in terms of thermodynamics. Just as from the kinetic theory of gases the temperature of the system is directly proportional to the kinetic energy, conversely simulated annealing process is faster at high temperature and slower at low temperature, it become from a very high temperature and continuously iterate the temperature of the system until it becomes a null (greedy descent). Due to randomness there is possibility of a deviation from the local minima to find regions with low heuristic values; this process (greedy descent) will lead to determination of the local minima.

Simulated annealing is consistent in assignment of numeric to variables. At each step, it selects a random variable. The criteria for acceptance of values is that if values assigned to variable is improving or does not lead to conflicting results, the algorithm accepts the result and there is a new current assignment, otherwise it accepts assignment with some probabilistic measures. *(Poole & Mackworth, 2010)*.

Simulated annealing is also a method for solving unconstrained and bound-constrained optimization problems. it models the physical process of heating a material and then slowly lowering the temperature to decrease defects, hence minimizing the energy of the system.

At each iteration, a new point is randomly generated. The extent of the search, is based on a probability distribution with a scale proportional to the temperature. Simulated annealing (SA) accepts all new points that lower the objective with a certain probability, points that raise the objective. By accepting points that raise the objective, the algorithm avoids being trapped in local minima in early iterations and is able to explore globally for better solutions. (Mathwork, 2018).

Simulated annealing is advantageous because it;

- Objective functions and arbitrary systems are dealt with properly
- Probabilistic conviction of identifying optimal result
- Flexible in code structure and even easier for even larger problems

The simulated Annealing algorithm receives input based on numerical values of the various properties of the reservoir model, heuristically searches for the best combination of the NTG, Soil, Phi(Ø) within a given fitness range. This however is subject to the predetermined limits of expected results; hence the SA algorithm must produce results from search only within range of expected result and also meeting the logical condition.

This logical condition is simply a command that an optimum placement must be distant from aquifer zones, especially side aquifers. Hence the search technique may have a combination of the properties with the desired range but if it does not meet this condition, it is regarded as unfit.

FIELD DESCRIPTION AND RESERVOIR MODELLING

A 3D model was built to depict a typical oil and gas reservoir. A Cartesian grid block of number of cells 112*253*100 in the X, Y, and Z direction was used. The sizes of the grid blocks in the X, Y, and Z directions were 400, 300 and 20 respectively. The field had a total number of 2833600 cells with 24500 being active cells and 2809100 inactive cells. Cells categorized as inactive are based on a criteria set on the minimum pore volume being 60bbl of oil, and a permeability less than 40md. There were 3 reservoirs in the field, due to shale intervals.

The reservoirs A B, C lies between 6364.17 to 6931.43 feet, 6674.21 to 7372.7 feet and 7062 to 7612.5 feet respectively in terms of crest and spill point, with a datum depth of 7612.5feet. The grid is set into 112X253X100 grid cells with 24500 active cells by boundary definition and shaped according to the cross-sections drawn across the reservoir sand map in both X and Y directions. An analytical (carter-Tracy) aquifer system was connected at the eastern flank of the grid. A 3D view of the model

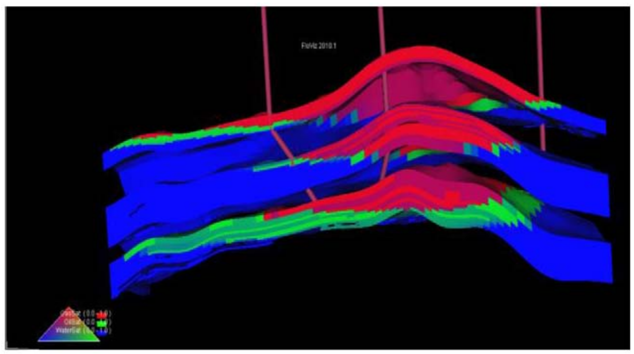

Figure 1—3D view of the reservoir model displaying Ternary Distribution

Objective function

$$f(x) = NTG\ X\ \emptyset\ X\ So = \qquad (2)$$

$$\int_{y_{min}}^{y_{max}} dy \qquad (3)$$

$$\{0.16 \leq y \leq 0.24\}$$

Economic Constraints

$$\begin{Bmatrix} FWCT \leq 95\% \\ WOPR \geq 400bbl \\ Availability \quad Factor = 0.91 \end{Bmatrix}$$

SIMULATION RUN

The simulation run was done using the ECLIPSE Main simulation panel. After each run, the Report Generator was activated to view the result of the simulation run. Errors were noted and corrections made before submission for the next run. Once there was no more error report. We then start cross-examination of reservoir performance.

WELLS MODELS

Three wells were considered in this paper. Two producers and an injector, first is to understand the reservoir energy, which in turn informs on the number of wells considered in developing the field. The initial production performance is examined from the Eclipse Office post-processor, a sensitivity analysis is then done on the production from new spots on the reservoir to confirm if there is a certain level of success and improvement. Also to examine the behavior of the Water cut, Gas Oil Ratio, Oil Gas and Water Saturation maps.

In all approaches, the following constraints were used in the reservoir model.

- Maximum cummulative oil production rate of 6280 bopd.
- Maximum Well production rate of 2500 bopd
- Simulation run time of 4.33 years.

RESULTS AND DISCUSSION

From this study, the genetic heuristic search algorithm alongside simulated annealing seemed to be veritable tools for optimizing well placement and overall recovery factor (NPV).

From the distinct portray of HuPhiSo across the reservoir layers below, we can subjectively define position for well placement, but this brings to mind the non-linearity of the process and introduces the vulnerability to human errors and time conservation. The results shown are with respect to a primary reservoir in a three layered system.

Genetic Algorithm Result

The GA optimization tool was introduced with a target objective function (Eqn 3) already established, and yielded 179 gridblocks satisfying the conditions, but an edge of this study is to mitigate early waster breakthrough and hence the need to objectively terminate neighbouring gridblocks saturated with water ($Sw>0.2$). with this second investigation of grid blocks to the North, South, East and West as well as the Upper and Lower blocks of the block of interest produced a gross screening of blocks down to 3 (Grid 1593504, Grid 1593756, Grid 1733919). A graphical illustration of this effect is analyzed further.

Simulated Annealing Result

SA optimization estimated the global optima of the reservoir system within the specification of the objective function (Eqn 3. Following this, an observation of 181 gridblocks satisfied this conditions and further investigating the neighboring gridblocks of the block of interest in the upper, lower, North, South, East and West boundaries for screening if water saturation is greater than Sw_{ir} (0.2)) produced a large downcut of initialized grids to 3 (Grid 1593504, Grid 1733919, Grid 1593756). A graphical analysis of this selection is shown below.

CASE STUDY 1

Two wells, a producer and an injector in focus of the primary Reservoir (Reservoir 3).

Table 2—Data Comparison (Case Study 1)

	Conventional	GA	SA
No of Wells	2	2	2
Recovery(MMSTB)	1.86	2.8	2.8

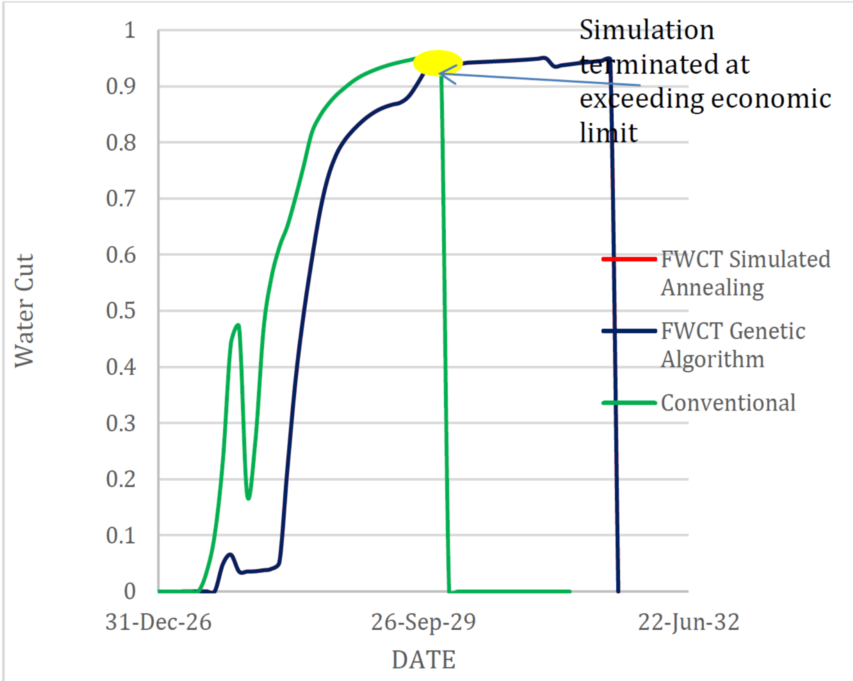

Figure 2—Field Water Cut, Optimized and Conventional

It was observed that there was a great disparity in water cut, with the optimized case as the favourable Scenario, this is invariably the effect of locating wells close to aquifer.

A delay in water production is experienced for about 2 years, the termination of the simulating run is experienced more rapidly and obviously so due to the economic constraints stated i.e. 95% maximum water cut.

It can aslo be observed from Fig-3 that there is an existence of a more maintained pressure system for optimized case compared to the conventional, with the influence of water production more likely to occur for conventional well placement technique.

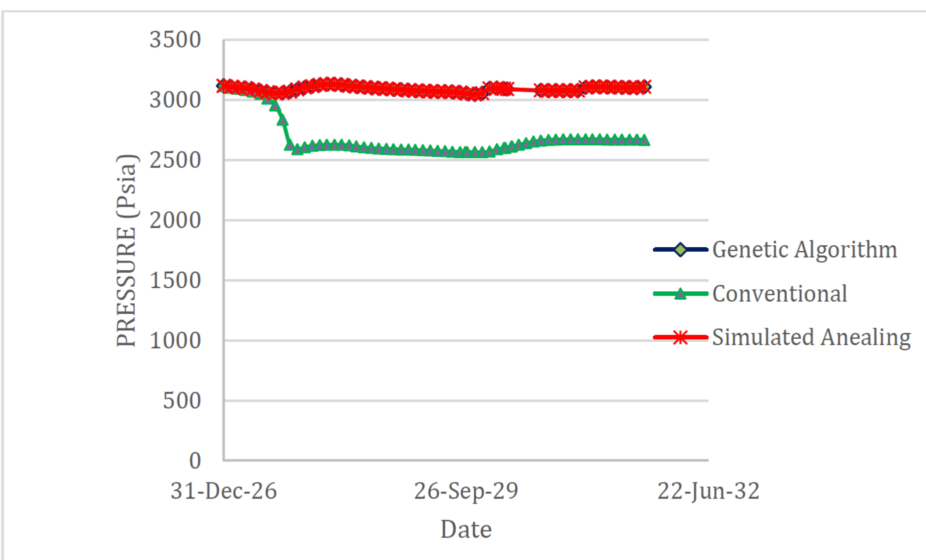

Figure 3—Field Pressure with time.

From Fig-4 we observed that wells placed using Genetic Algorithm and Simulated Annealing, produce better than using the conventional HuPhiSo approach as an extension of the effect of the water cut and field pressure maintenance strategy.

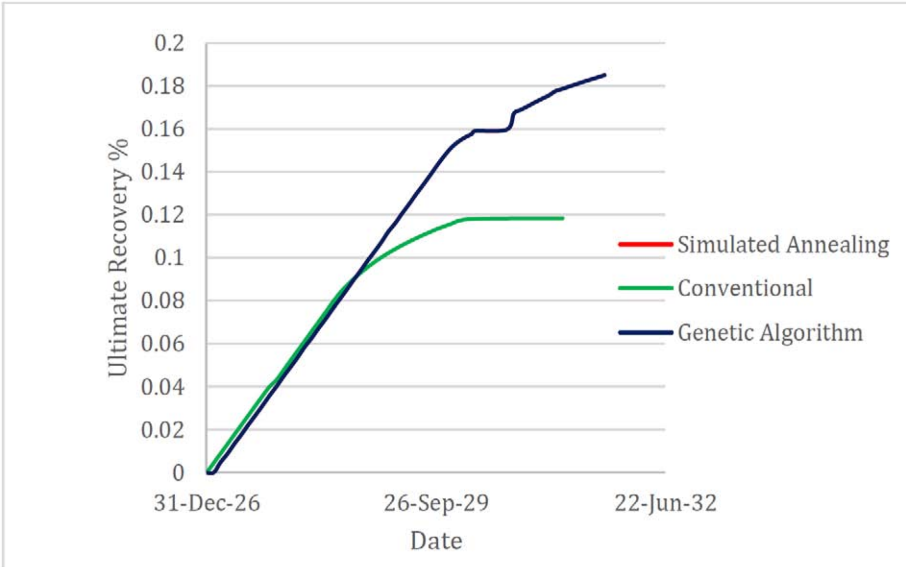

Figure 4—Field Overall recovery for optimized Case.

Genetic Algorithm (GA) Vs Simulated Annealing (SA)

From Table 3 we see no variation from results gotten from genetic algorithm to simulated annealing but for the run time a peculiar difference such that the GA showed a higher rate of convergence.

Table 3—Heuristic search technique comparison

	Genetic Algorithm	Simulated Annealing	% deviation
Grids Allowed	3	3	0
Ultimate Recovery	18.8%	18.8%	0

Sensitivity Analysis

From fig-5 we observe the ultimate recovery with respect to the production rate, with the base rate and Lower rate yielding almost the same recovery, a distinct difference however exists as a result of the accelerated recovery achieved by the base rate, same scenario applies to the higher rate case but it exhibits a sharp decline with increasing time. This is due to the increased drawdown from higher production rate leading to depletion of reservoir (reservoir pressure decline). The critical bottom hole flowing pressure is reached after 3 years of production afterwards a sharp decline is experienced. Illustration of its effects on Field water cut and Pressure is show below.

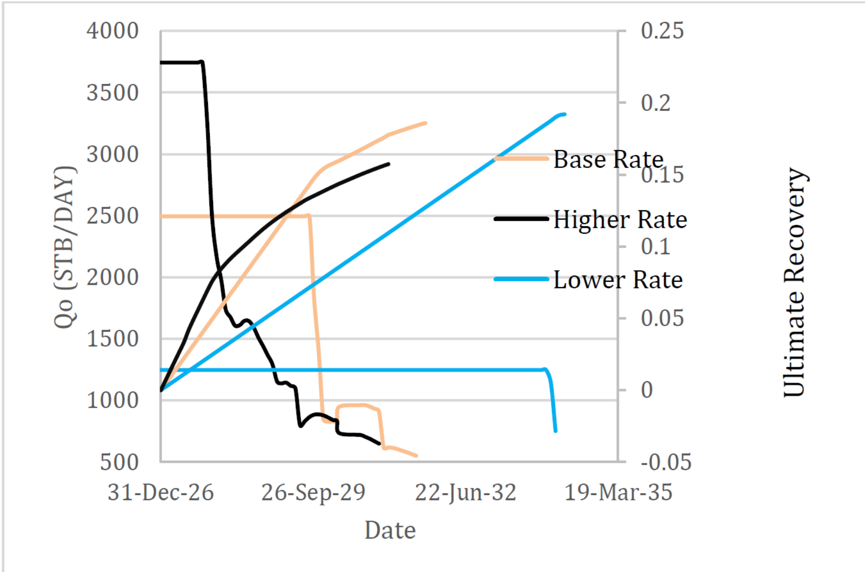

Figure 5—Sensitivity on production rate

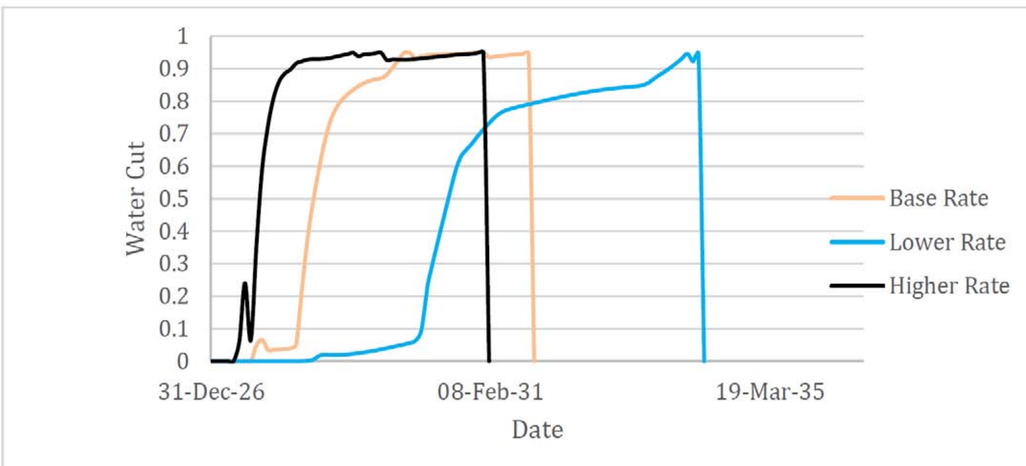

Figure 6—Water Cut Comparison with rate.

Producing at an increasing rate entails an increasing drawdown leading to increasing possibility of viscous fingering, coning and cusping especially in high permeability strata. It is also dependent on the mobility ratio established, thus should it be opted for a high production rate then conversely measures must be taken to circumvent its effect in line with the mobility ratio.

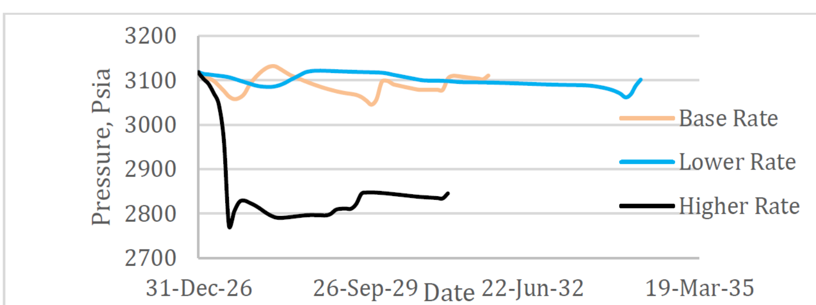

Figure 7—Field Pressure with Changing Rate.

For a constant well rate regime, a continuous threshold drawdown must be met, but this is only possible by concurrent reduction in both reservoir pressure(Pi) and wellbore flowing.

A constant flow rate regime would however come to an end when the critical bottom hole flowing pressure is reached, if continued liquid loading occurs.

Case Study 2: Well Count

Well count in terms of economics certainly affect Ultimate Recovery from field in terms of the accelerated recovery achieved compared to the case of single well development. The key play for decision therefore would be the level of price volatility, cost of development and overall economic implications.

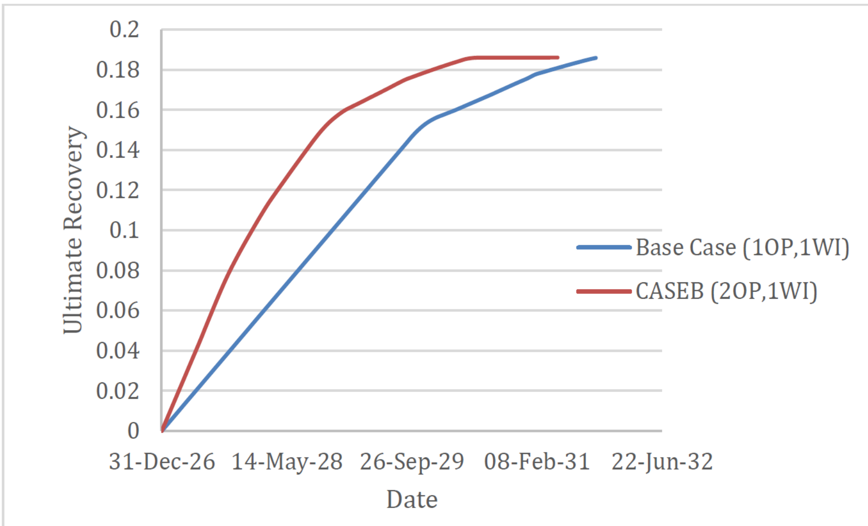

Figure 8—Sensitivity of well count on Ultimate Recovery.

CONCLUSION AND RECOMMENDATION

Conclusion

This paper portrayed an alternative to well placement to optimize recovery from a field yet to be developed. The impact of production rate and well count was duly analysed in this research. Based on the above study the following conclusions can be made.

- Use of genetic Algorithm and Simulated Annealing are veritable tools for optimizing well placement.
- Producing at higher rate prove to yield more production at start but a rapid decline compared to the base rate that was steady, however rate may be chosen in line with development requirements.
- Water cut is affected by production rate, Reservoir contact angle and of course well location.

Recommendation

This project recommends further optimization study for

- Gas reservoirs
- Phase sequential development strategy
- The angle of orientation and the azimuth for the drilling of the deviated and horizontal wells.

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