SPE 154511

Optimization of Proactive Control Valves of Producer and Injector Intelligent Wells under Economic Uncertainty

M. A. Sampaio; C. E. A. G. Barreto; and D. J. Schiozer; SPE, State University of Campinas

Abstract

Intelligent wells can improve oil recovery, mitigate risks and avoid unnecessary well intervention in petroleum fields. However, there is no consolidated methodology to evaluate the applicability of intelligent wells and to represent them in commercial simulators, which complicates the comparison with conventional wells. Moreover, there are two main modes of operation of intelligent well valves, reactive and proactive; each one can provide different benefits. In general, proactive control seeks maximum oil recovery, but it requires larger computational effort and greater knowledge of the reservoir than the reactive control. This paper presents a comparison between different configurations of intelligent wells with proactive control and mode operation on/off: (1) five-spot configuration with conventional wells (producer and injectors), (2) one intelligent producer and four conventional injectors, (3) one conventional producer and four intelligent injectors and (4) one intelligent producer and four intelligent injectors, in order to compare the different behaviors. The objective of this study is to evaluate the potential of proactive operation for each type of configuration and the benefits of the intelligent injectors and producer acting separately or together, considering the effects on production and costs of intelligent completion. For this, a genetic algorithm was coupled to a commercial simulator to optimize the proactive control and to search the maximum net present value (NPV), determining the optimum operation control for each valve. The case study consists of one heterogeneous reservoir model, light oil and three economic scenarios (pessimistic, probable and optimistic). Results show that the use of intelligent injector and producer wells together, in this case study, can increase of oil production and decrease of water production, although it may not be the most advantageous alternative because of the higher investment. On the other hand, the configuration using only an intelligent producer well (lower investment) is capable of increasing oil recovery sufficiently, therefore making the best investment with intelligent completion, in this case study.

Introduction

Nowadays, the intelligent wells (IW) have application restricted to a few oil fields and in many of them they are still used in the form of test or to try to solve some specific problems, despite having high intrinsic value because of their greater operational flexibility, provided by sensors that constantly monitor the production data and valves capable of responding appropriately to the changes occurred during the lifetime production. This is due in large part by the fact that the IWs are more expensive than the conventional wells (CW), and because the real benefits of this technology are still not clear, due to the lack of a consolidated methodology to present the advantages of one completion over the other.

One of the main difficulties presented in the use of the IW is to find the configuration of wells that will bring the best technical and economical results, which will be only with intelligent injector wells, or only with intelligent producer wells, or even a combination of both. This difficulty is mainly because of the complexity of the problem, due to the high number of variables involved in the process. The complexity is also due to the dependence among several parameters related to the selection of production strategies. Thus, there are still many challenges to include an IW evaluation in a global strategy selection process. Another major difficulty is to optimize each valve of several wells in a field, which makes the problem very complex, as the traditional optimization methods cannot solve the problem of feasible computational time. As a result, several studies attempted different methods to solve this problem, among them: simulated annealing (Kharghoria, 2002), conjugate gradient (Kharghoria *et al.*, 2002; Yeten *et al.*, 2002), calculation of gradients (Sarma *et al.*, 2005, Van Essen *et al.*, 2009), direct search (Emerick and Portella, 2007), ensemble-based method (Su *et al.*, 2009), the augmented Lagrangian method with the Karush-Kuhn-Tucker conditions (Doublet *et al.*, 2009), and the gradient-based method (Yeten *et al.*, 2004). Although some of these studies have shown the benefits of one method over the other, there is not an optimization method to quickly and efficiently solve such problems when real reservoirs with many wells are considered. Because classical methods encounter great difficulty in optimizing IW with many valves and also because of the action of several of these wells together in developing a field, this study chose to employ and test a genetic algorithm, since this algorithm shows better performance in searching for the global solution of problems with high number of variables.

The operation of inflow control valves (ICV) can be done in two different ways: proactive (defensive) or reactive control. The first operates to prevent an undesired event that only occurs in the future; and in the second, the control reacts to a specific undesirable event to guide the ICV operation (Brouwer, 2004; Ebadi & Davies, 2006; Addiego-Guevara *et al.*, 2008). In theory, proactive control should yield better results, because it is a type of control that operates before an undesired event occurs. The definition of proactive control is not a consensus in the literature; in this work, the undesirable event is a negative cash flow (for the valve) and the term proactive is used in order to close the valve at any time before this event. However, this type of control is only possible when there is a good knowledge of the reservoir and confidence in the prediction tool, but this is very appropriate to evaluate the potential of production of an oil field, mainly in the phase of strategy selection. For this reason, proactive control with operation mode on/off is used in this work to find the better configuration of IW under economic uncertainty and to understand the benefits of this type of operation and representation. The representation of IW in commercial simulator is made by monitoring the pressure drop due to flow in the area of the cross section. Using the Eclipse simulator (keyword WSEGVALV), each of the cross sections represents an ICV. This kind of operation is widely used (Alghareeb, 2009; Yeten, 2002; Valvatne, 2003; Ebadi& Davies, 2006; Emerick, 2007).

Literature Review

Initial studies of Yeten *et al.* (2002) employed the conjugate gradient method in conjunction with the commercial simulator to optimize the intelligent control of multilateral wells. In this work, Yeten used a five-spot configuration for the vertical producer and injector wells, in order to maximize oil production through optimization of the flow control. It is employed for this a type of control which is able to vary over time, using an on/off mode that allows reopening an ICV. The optimizations were performed dividing the simulation period into several periods, and in each time interval obtained, the optimization of the valve parameters was performed to maximize the objective functions. The simulation continues in the next step with the parameters optimized in the previous period. This is done to complete the total period of simulation. The method was applied in different types of wells (conventional and intelligent) and geological models. The results showed an increase in cumulative oil production due to optimization of flow control from 1.8 to 64.9% compared to CW, with an average increase of 27.2%. This wide variation was a result of the variation of the geological model considered; showing that this technology is economically viable when there is a high degree of geological uncertainty in reservoir.

Later, Sarma *et al.* (2005) developed an algorithm for optimizing production using optimal control theory. This paper explores the application of adjoint models for efficient optimization using an efficient calculation of gradients in order to avoid the limitations typical of the optimizations with gradients. The algorithm was used to optimize production with CW and also IW, and for these, sections of wells could be individually controlled. The results showed that the application of the adjoint models was effective to the calculation of gradients and consequently to the optimization of production, causing increases in NPV and oil production and the reduction of injection and water production.

As an example of application in real fields, Emerick *et al.* (2007) implemented an algorithm of direct search to optimize production in IW by varying the parameters of control valves through proactive control. The algorithm was coupled to a commercial simulator to study two real Brazilian offshore fields for search (Campos and Potiguar Basins) to quantify the benefits of IW in relation to the conventional completion. Cases were studied with the valve of the types open-close and multi-position, wells with different numbers of valves, producers and injectors with intelligent completion. The results showed that the intelligent completion was able to increase oil production from 7.2 to 12.8% and decrease water production and injection.

Recently, Almeida *et al.* (2010) used a genetic algorithm (GA) to select the best operation of the valves in the control of IW. A representation of chromosome was employed to allow the formulation of a strategy to control all valves, presenting an alternative, for a certain time. She also used Monte Carlo Simulation (MCS) for the treatment of uncertainties (failures of valves and geological). For the technical uncertainty of valve failures it was used probabilistic failure model introduced by Yeten (2004). Through a proactive control strategy, the algorithm employed a search to find the best values of aperture of the valves from fully closed to fully open, using continuous variation over the lifetime of the reservoir. This study demonstrated the advantages of using the IW by employing synthetic models simplified (box model) to obtain increases in the NPV of around 4% over the base case studied by decreasing water production and increasing oil production. In more complex reservoirs (close to the real models), the benefits of IW were from 2 to 12% of increase in NPV. The contribution of this work was to apply a viable optimization method to be executed, performing the continuous variation of the aperture of values, showing that a intelligent control of valves produces a uniformity in the advance of water, which can, according to the author, allow an increase in oil production and a decrease of water production by increasing the efficiency of the drag of water in secondary oil recovery.

Methodology

The methodology is divided in three parts: (1) modeling IW in a simulator, (2) optimization of ICV operation using a genetic algorithm, and (3) analysis of economic uncertainty.

Representation of Intelligent Wells and Valves

The modeling of IW operation is performed with proactive control, using operation mode of the on/off type (2 positions of aperture of the valves: open and close). In this work, it is used ECLIPSE as reservoir simulator and its tools to deal with intelligent completions.

IW can be represented in a simulator, grouping blocks to form independent completions with a valve that will control the flow through the segment, with independent oil and water productions, but united by production tubing to form the well. In the Eclipse simulator, used in this work, this grouping of the layers can be done by using the keyword COMPLUMP.

For proactive control, one operation mode (on/off) is used to control valves by monitoring the pressure drop due to flow in the area of the cross section, using the keyword WSEGVALV. This type of control involves adjusting areas of valve aperture, such as settings of ICV that act as subsurface chokes. Then, the problem is to find the optimum ICV configuration. This study uses five valves in the vertical wells (one valve for each two layers) for both types of wells (injectors and producer). To perform the optimization, the simulation time (30 years) is divided into intervals of 2 years. So, every two years, it was necessary to determine the aperture of each valve in order to maximize the NPV of the field. This results in 15 intervals. Thus, the problem is to optimize five valve apertures in 15 time intervals for each IW used in each case.

The pressure drop across an ICV is calculated for a single-phase flow considering the sum of effects of constriction and any additional friction pressure loss due to flow through the ICV (Schlumberger, 2006). Mathematically:

$$\delta P = \delta P_{cons} + \delta P_{fric} \tag{1}$$

where δP_{cons} is the pressure drop due to flow through constriction and is given by:

$$\delta P_{cons} = C_u \frac{\rho v_c^2}{2\, C_v^2} \tag{2}$$

where C_u is a unit conversion constant, ρ is the density of the fluid mixture, v_c is the flow velocity of the mixture through the constriction and C_v is a dimensionless flow coefficient for the valve.

And δP_{fric} is additional friction pressure loss in the segment containing the valve, given by:

$$\delta P_{fric} = 2\, C_u\, f\, \frac{L}{D} \rho v_p^2 \tag{3}$$

where f is the Fanning friction factor, L and D represent the length and diameter of the pipe segment and v_p is the flow velocity of the mixture through the pipe. In this work, it was not considered a component of friction. Therefore, the ICV configuration depends on total pressure drop, which is a function of the cross section area of the valves. These areas changed between open and close, in order to maximize sweep efficiency, increase oil production and delay the arrival of water in the well (maximizing the NPV).

Optimization of ICV Operation

Due to the high number of variables and very large solution space, this work employs a genetic algorithm, which is a global optimization method that performs the search for an optimal (or suboptimal) solution using concepts of the theory of evolution and natural selection (Goldberg, 1989, Koza, 1992, Mitchell, 1994). This method is based on the simulation of evolution of species through selection, mutation and reproduction. It uses a population of structures called chromosomes or individuals, which are structures applied to genetic operators, such as recombination and mutation, among others, that simulates reproduction and genetic mutation, respectively. Each individual is submitted to an evaluation that assigns its quality as a solution to the problem. This evaluation determines which chromosomes will apply genetic operators to generate offspring. Therefore, genetic algorithms have a random component but use current information to search more adapted individuals than the individuals of the initial population.

To solve the problem proposed in this paper, an optimization algorithm is coupled to the commercial reservoir simulator. For representation of genes on chromosomes, the real form was used in order to be the most intuitive and best suited to solve the problem. The genes in this study are the aperture in each of the five valves of each IW or states open/close for CW. The valves operate in one system (on/off), determined by the optimal aperture found by the genetic algorithm to maximize the NPV of the field. Thus, the methodology used can be considered an optimal strategy of the aperture position of the valves on the wells at different times over the exploitation of the field in order to maximize the profitability of the production.

A genetic algorithm creates an initial random population of real numbers, transforms into the corresponding aperture for each valve and uses the simulator to predict production, and posteriorly calculates the NPV, which is the objective function of the optimization process. These values are selected and classified, after being evaluated and submitted to the action of the genetic algorithm operators, such as crossover, mutation and elitism. This sequence is performed up to the number of generations provided in the program. The number of generations and population size provided should be enough to lead to the convergence of the best individual or very close to it (genetic convergence). At the end, the program gives the optimal (or suboptimal) set of apertures for each of the well's valves (or whole well for CW) that maximizes NPV. Figure 1 shows the flowchart that summarizes the steps taken to optimize the closing of the valves.

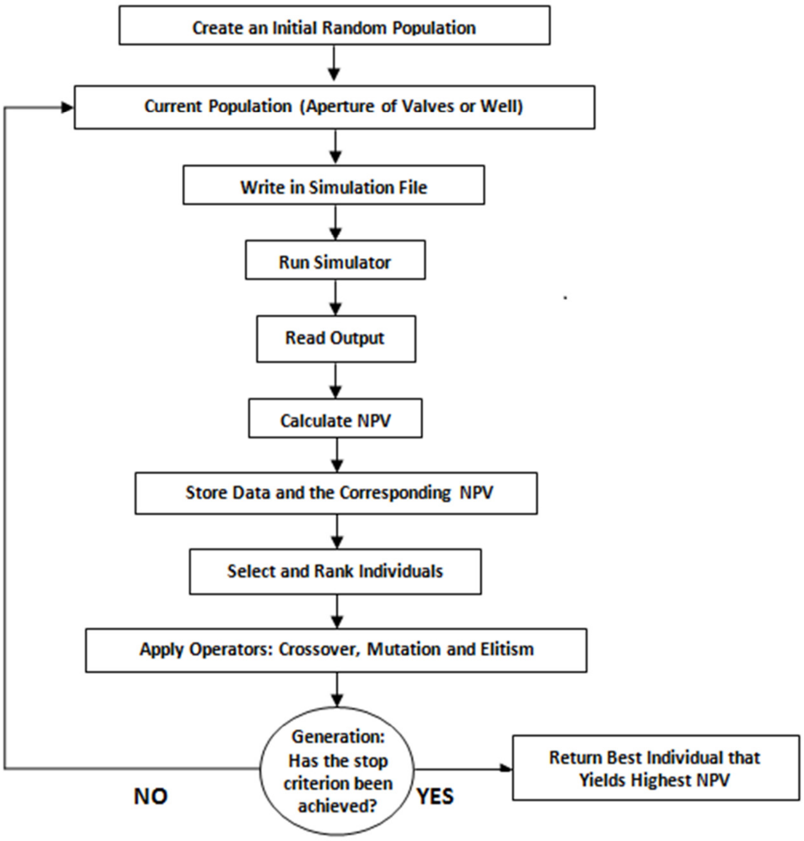


Figure 1: Flowchart of the optimization framework

Analysis of Economic Uncertainty

To evaluate the performance of an IW under economic uncertainty, the difference of expected monetary value (EMV) between an IW and a CW is used (ΔEMV), which takes into account the probability of the occurrence of each economic scenario, given by:

$$\Delta EMV = \sum_{i=1}^{3} p_i . \Delta NPV_i \tag{4}$$

where p_i is the probability of the occurrence and ΔNPV_i is the difference between NPV of an IW and a CW for each economic scenario.

Case studies

In this work, a synthetic reservoir model is selected, representing a part of a heterogeneous reservoir (drainage area of a producer), studied with a maximum simulation time of 30 years, under a water injection recovery method.

In order to make a comparison between different configurations of IW with proactive control and mode operation on/off in five-spot configuration to compare the different behaviors, four cases are considered:

- Case 1: conventional wells (producer and injectors)
- Case 2: one intelligent producer and four conventional injectors
- Case 3: one conventional producer and four intelligent injectors
- Case 4: one intelligent producer and four intelligent injectors

These four cases are studied in three economic scenarios: pessimistic, optimistic and probable. Each case is optimized for each of the economic scenarios, as seen in Figure 2 below.

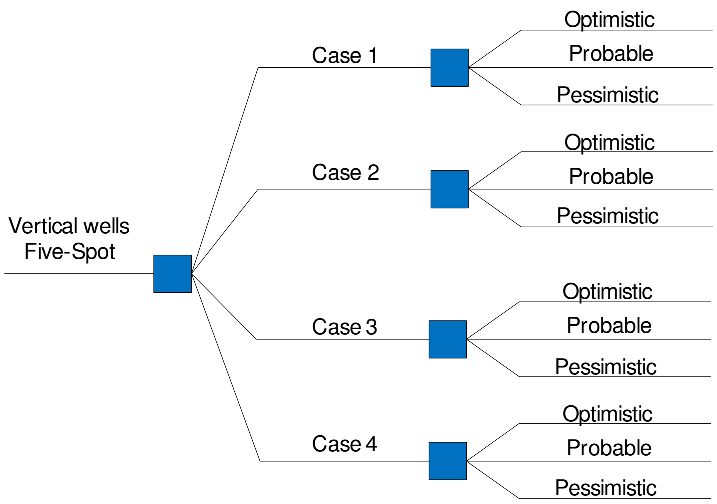


Figure 2: Scheme of each optimization performed

Reservoir Model

The reservoir dimensions are 20x20x10m and the grid dimension is 21x21x10 blocks. Table 1 presents the data of the model's rock and fluid properties.

Table 1: Properties of Rock and Fluids

Reference Pressure of Rock	315.56 (bars)
Compressibility of Rock	5.41 x 10^{-5} ($bars^{-1}$)
Reference Pressure of Water	0.98 (bars)
Compressibility of Water	4.99 x 10^{-5} ($bars^{-1}$)
Density of Water	1.01

All cases have a density of 31.9°API (light oil). Table 2 presents the properties for the heterogeneity of model.

Table 2: Distribution of permeability and porosity

	Heterogeneity of Model
Permeability in x	Lognormal (μ=500mD;σ=200mD)
Permeability in y	130% of permeability in x
Permeability in z	10 % of permeability in x
Porosity	Normal(μ=0.25; σ=0.05)

Well Configurations

A five-spot configuration with a single vertical producer at the center and four vertical injectors on the corners is used (Figure 3).

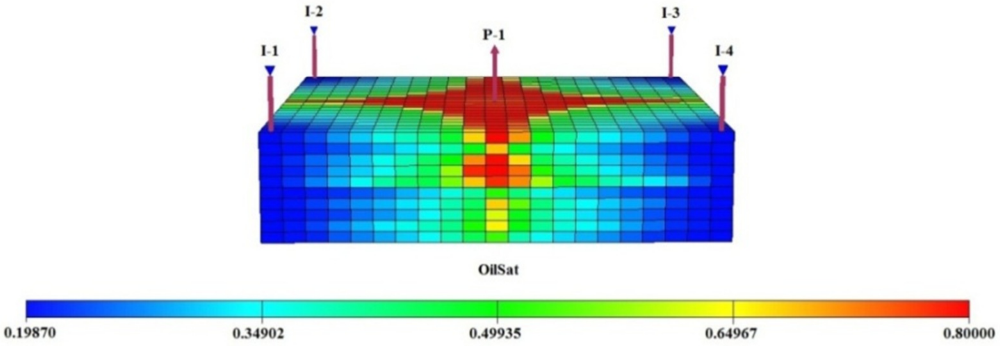


Figure 3: Reservoir model used in this work

Each IW consists of five inflow control valves (ICV), one for each two layers. The operational restrictions of the wells are listed in Table 3.

Table 3: Operational restrictions of the wells

Producer Wells		*Injector Wells*	
Control Mode	Liquid Production	Control Mode	Water Rate
Maximum Rate Minimum BHP	700 m^3/day 200 bars	Maximum Rate Maximum BHP	600 m^3/day 400 bars

For injectors, the maximum rate of water injection is equivalent to the fluid production volume, considering reservoir conditions to avoid high pressurization.

Genetic Algorithm Parameters

Table 4 presents the genetic algorithm parameters used in each case. There are 15 variables for the CW (one variable for each interval time) and 75 variables for each IW with proactive control (five variables for each interval time).

Table 4: Genetic algorithm parameters

Algorithm parameters	*Case 1*	*Case 2*	*Case 3*	*Case 4*
Number of Generations	50	200	150	200
Size of Population	20	50	100	100
Number of Elite Individuals	2	2	2	2
Crossover Rate	0.8	0.8	0.8	0.8

Economic Scenarios

To analyze the operation of the valves by proactive control of the IW and the CW under economic uncertainty, three economic scenarios are considered: pessimistic, probable and optimistic. The values for each scenario are shown in Table 5.

Table 5: Economic data

Economic Scenarios	*Discount Rate (% p.a.)*	*Oil Price (USD/bbl)*	*Oil Production Cost (USD/bbl)*	*Water Production Cost (USD/bbl)*	*Water Injection Cost (USD/bbl)*
Optimistic	8.8	65.00	8.00	0.70	1.00
Probable	8.8	50.00	8.00	1.00	1.00
Pessimistic	8.8	35.00	8.00	1.50	1.00

The economic base model is selected following a simplified Brazilian fiscal regime, assuming the data presented in Table 6.

Table 6: Economic parameters used in a simplified Brazilian fiscal regime

Economic parameter	*Value*
Corporate tax	25%
Royalties	10%
Social contribution	9%
Linear Depreciation (years)	10

In all cases, the NPV is reduced by the investment value of USD 70 million, corresponding to the sum of the investments in the platform, drilling of CW and cost of abandonment representing part of the total investment for a field with several wells, proportional to this sector of the field.

For the IW, the values of Table 7 below are considered, for the additional investment of intelligent completion for on/off type of valves. With these values, one IW with 5 valves of type on/off has a cost of USD 625,000.

Table 7: Additional Cost for Intelligent Completion

	Cost of Intelligent Completion (USD)
Intelligent completion on/off	200,000
Additional for each on/off zone	85,000

In the economic analysis of this work, the differences in NPV between the CW and the IW are considered for each case, determining the profitability of using this technology.

Table 8 shows the probabilities of each considered scenario.

Table 8: Uncertainty of the economic scenario

	Pessimistic	*Probable*	*Optimistic*
Probability	25%	50%	25%

Results and Discussions

The main results are presented for all cases and economic scenarios, but only for the probable economic scenario the results will be presented with more details. It must be noted that, except for the intelligent control, all operational parameters are kept fixed in all cases, not being part of the optimization process. In all cases the optimization was based on the maximization of the NPV; oil and water productions were consequences of the best alternatives for each case.

Case 1: Conventional Wells

Table 9 shows the results obtained for the optimization of CW in three economic scenarios. It should be noted that due to the fact that the CWs were optimized in the same way that the IWs, i.e., the wells could open and close every 2 years over 30 years of production.

Table 9: Results of economic and production evaluation for Case 1

Case 1	*Oil Production (10^6 std m^3)*	*Water Production (10^6 std m^3)*	*Water Injection (10^6 std m^3)*	*NPV (USD millions)*
Pessimistic	1.48	0.56	2.55	1.29
Probable	1.57	1.49	3.60	53.40
Optimistic	1.65	2.95	5.16	107.14

Figure 4 shows the results of a conventional producer well, (a) production and (b) the time when the CW closes. This case is considered the base case because the other three cases will be compared to this, to obtain the benefits to change the conventional by intelligent completion. As can be seen in the graph (b), CW does not have valves, so when it closes, it closes entirely without distinguishing the productions in each part of the well.

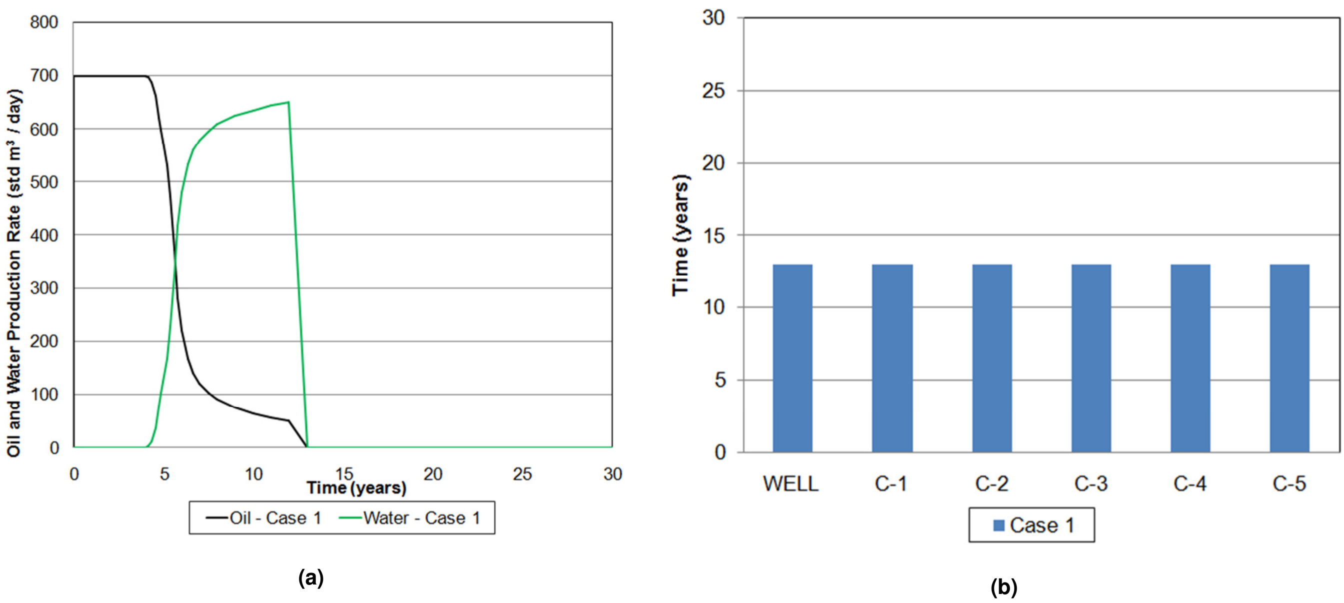


Figure 4: (a) Production of CW and (b) time of well closure for probable economic scenario

Case 2: One Intelligent Producer and Four Conventional Injectors

Table 10 shows the results obtained for the optimization of configuration with one intelligent producer well and four conventional injectors wells in three economic scenarios. It can be seen that only one IW is able to increase oil production and the NPV when compared to the CW, but with increasing water production (probable and optimistic scenarios). In general, for the cases tested in this work, the higher production of oil and water was a consequence of a longer period of production that resulted from the optimization process due to a more efficient ICV operation. The results show that it is advantageous the use of IW with operation mode on/off.

Table 10: Results of economic and production evaluation for Case 2

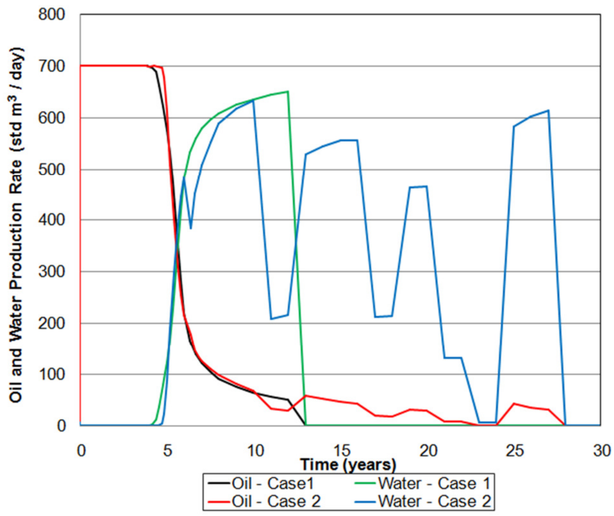
Case 2	*Oil Production (10^6 std m^3)*	*Water Production (10^6 std m^3)*	*Water Injection (10^6 std m^3)*	*NPV (USD millions)*	*ΔNPV (USD millions)*
Pessimistic	1.49	0.48	2.47	1.34	0.05
Probable	1.72	3.17	5.44	54.38	0.98
Optimistic	1.71	3.14	5.37	109.27	2.13

Table 11 presents the percentage differences in the types of completion: IW in relation to CW (Case 2 in relation to Case 1). The results show that IW is able to increase oil production significantly, because with this type of control, there is a better sweep efficiency. However, in this case, the increase in oil recovery is accompanied by a substantial increase in water production (probable and optimistic scenarios), due to increased production time.

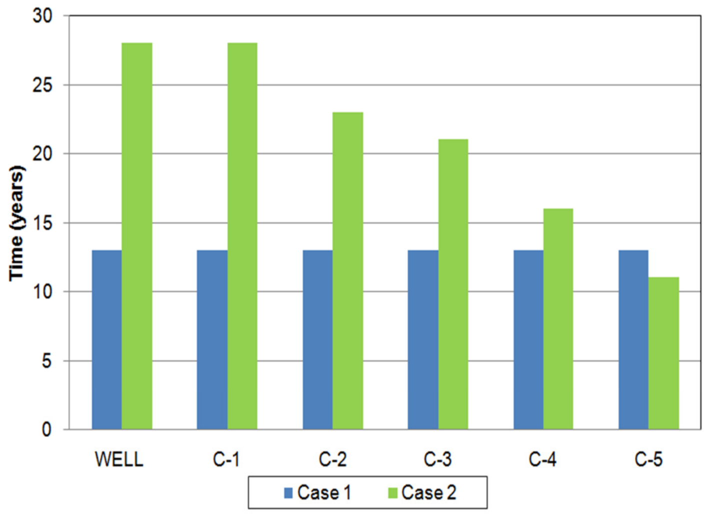
Table 11: Percentage differences in indicators for Case 2 in relation to Case 1

Case 2	*Oil Production*	*Water Production*	*Water Injection*	*NPV*
Pessimistic	+ 0.48 %	- 16.91 %	- 3.28 %	+ 3.39 %
Probable	+ 8.63 %	+ 52.84 %	+ 33.80 %	+ 1.81 %
Optimistic	+ 3.03 %	+ 5.99 %	+ 3.89 %	+ 1.95 %

Figure 5 (a) shows the results of IW production (Case 2) together with the results of the CW (Case 1) for probable economic scenario. The increase in production time of the field, oil and water can be seen in the first graph. The results also show an oscillation, which is a consequence of the type of operation (on/off mode). This is also a solution generated by the genetic algorithm that may be the suboptimal; a smoother solution can be constructed manually (or using an algorithm based on gradients) at the end of the process but with no significant change in the results. The second graph highlights the time at which each valve closes permanently in the IW and the time at which the CW closes. It can be seen that the last layers, with higher permeability, are the layers whose valves close first, since the water comes before these valves. On the other hand, as the CW does not have sensors (and valves), it is not possible to automatically detect water production in different regions of the well (and control them).



(a)



(b)

Figure 5: (a) Productions of Cases 2 and 1; (b) time of closing of completions (or well) for Cases 2 and 1 for probable economic scenario

Case 3: One Conventional Producer and Four Intelligent Injectors

Table 12 shows the results obtained for this configuration. It can be seen that in this configuration there are better results in relation to water production and injection (pessimistic and optimistic scenarios) than in the Case 1 (base case). This happens because the use of intelligent injectors allowed a better control of water flow through of reservoir model. In all economic scenarios, intelligent injectors are able to increase the NPV. The best results for IWs occur in pessimistic scenario, increasing oil production and NPV, together with the decrease of water production and injection. This is due to the fact that, in the pessimistic scenario there is an economic penalty of high cost of water production, which leads IWs to have better performance compared to CW.

Table 12: Results of economic and production evaluation for Case 3

Case 3	*Oil Production (10^6 std m^3)*	*Water Production (10^6 std m^3)*	*Water Injection (10^6 std m^3)*	*NPV (USD millions)*	*ΔNPV (USD millions)*
Pessimistic	1.51	0.48	2.43	1.53	0.24
Probable	1.65	2.40	4.55	53.93	0.53
Optimistic	1.64	2.22	4.36	107.93	0.79

Table 13 presents the percentage differences between Cases 3 and 1. The results show that this configuration showed benefit over the base case and still had a positive impact on the NPV for the additional cost of completion.

Table 13: Percentage differences in indicators for Case 3 in relation to Case 1

Case 3	*Oil Production*	*Water Production*	*Water Injection*	*NPV*
Pessimistic	+ 1.86 %	- 15.86 %	- 4.81 %	+ 15.51 %
Probable	+ 4.54 %	+ 37.66 %	+ 20.83 %	+ 0.97 %
Optimistic	- 0.65 %	- 32.56 %	- 18.59 %	+ 0.73 %

Figure 6 (a) shows the results of production of Case 3 together with the results of the Case 1 for probable economic scenario. As noted earlier, the results for Cases 3 were not only the increase of oil but also the water production. The increase in the water production is due to the increase in production time, as can be seen in the part (b) of graph.

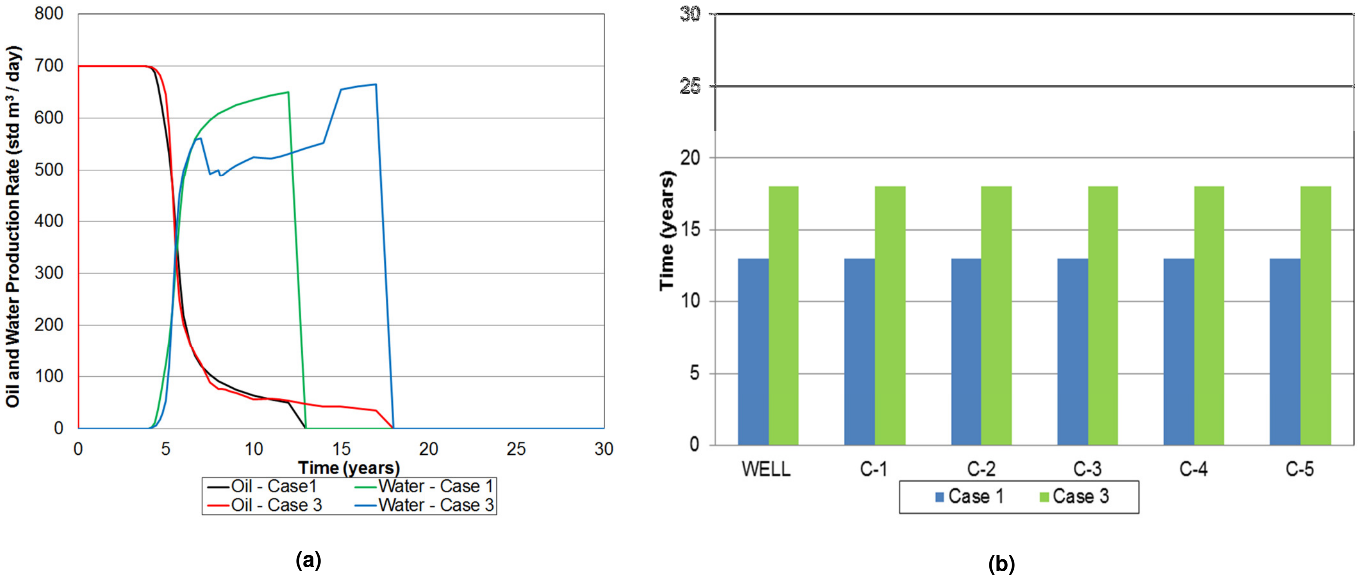


Figure 6: (a) Productions of Cases 3 and 1; (b) time of closing of completions (or well) for Cases 3 and 1 for probable economic scenario

Case 4: One Intelligent Producer and Four Intelligent Injectors

Table 14 shows the results obtained for the optimization of configuration with one intelligent producer and four intelligent injectors in three economic scenarios. In this case, can be seen that all IWs acting together are able to increase oil production and NPV (pessimistic and probable scenarios), when compared to the CW, and decreasing water production (pessimistic and optimistic scenarios). It can be seen that this case has a combined behavior between the Cases 2 and 3, ie, increase of oil production combined with greater control over the water production. However, this case is not economically attractive due to higher investment with intelligent completion in all wells.

Table 14: Results of economic and production evaluation for Case 4

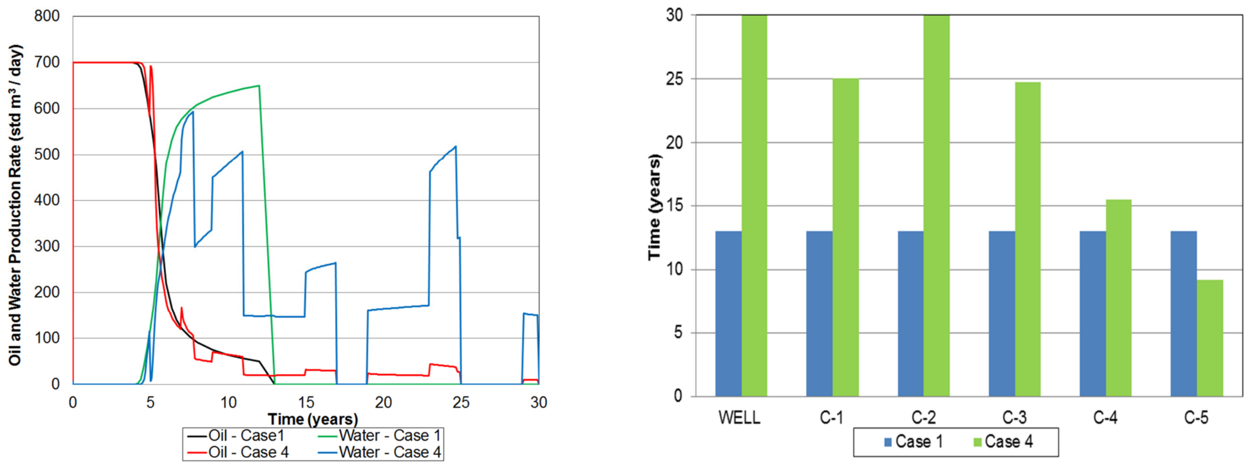
Case 4	*Oil Production (10^6 std m^3)*	*Water Production (10^6 std m^3)*	*Water Injection (10^6 std m^3)*	*NPV (USD millions)*	*ΔNPV (USD millions)*
Pessimistic	1.57	0.43	2.47	0.95	- 0.34
Probable	1.67	2.12	4.32	53.61	0.21
Optimistic	1.64	2.39	4.59	107.11	- 0.02

Table 15 presents the percentage differences between Cases 4 and 1.

Table 15: Percentage differences in indicators for Case 4 in relation to Case 1

Case 4	*Oil Production*	*Water Production*	*Water Injection*	*NPV*
Pessimistic	+ 5.21 %	- 29.57 %	-3.40 %	- 36.25 %
Probable	+ 5.82 %	+ 29.47 %	16.63 %	+ 0.40 %
Optimistic	- 0.68 %	- 23.42 %	- 12.54 %	- 0.02 %

Figure 7 (a) shows the results of IW production (Case 4) together with the results of the CW (Case 1) for probable economic scenario. As also noted in Case 2, the increase in the production time of the field, oil and water can be seen in the first graph. The results also show an oscillation, which is a consequence of the type of operation and was a solution generated by the genetic algorithm (suboptimal). Again, a smoother solution can be constructed manually at the end of the process or using an exact algorithm (gradient method) but with no significant change in the economic indicators, as this solution found is very close to the optimal solution. The second graph highlights the time at which each valve closes permanently in the intelligent producer and the time at which the conventional producer closes. It can be seen again that the last layers, with higher permeability, are the layers whose valves close first, since the water comes before these valves, differently from the CW that close entirely. As noted earlier, for the cases tested in this work, the higher oil and water productions was a consequence of a longer period of production that resulted from the optimization process due to a more efficient ICV operation.



(a) (b)

Figure 7: (a) Productions of cases 4 and 1; (b) time of closing of completions (or well) for cases 4 and 1 for probable economic scenario

Optimization Process

Figure 8 shows the results of the optimization process for probable economic scenario. For the Case 1, with only CWs, it is necessary to maximize NPV, having 15 variables for the CW (states open and close for each interval of time). In this case, the maximum value of NPV was reached with 615 simulations. For the Case 2, 135 variables were necessary, corresponding to the optimal apertures of each valve of producer well and states open/close for injectors. The value maximum of NPV was reached, in this case, with 4360 simulations. In the Case 3, 315 variables were used, because of four wells with 5 valves in each well (and 15 for conventional producer), 1707 simulations were necessary to reach the maximum value of NPV. And for Case 4, 375 variables were used (5 wells with 5 valves in each at 15 time intervals) and 6524 simulations were necessary to reach the maximum. Thus, the optimization process is faster for the Case 1 and slower for the Case 4. From the graph, it can also be seen that the parameters of the genetic algorithm chosen are sufficient to achieve the convergence for a better solution (optimal or suboptimal). As noted earlier, in this economic scenario, the Case 2 obtained higher NPV, showing that it is not advantageous to invest in more expensive valves for all wells as in Case 4. It should be noted that the algorithm used in this work was a simple genetic algorithm (with very simple genetic operators: one point crossover, rank selection and static parameters set for crossover and mutation rate) and more efficient algorithms are being developed to make it faster to search for better solutions.

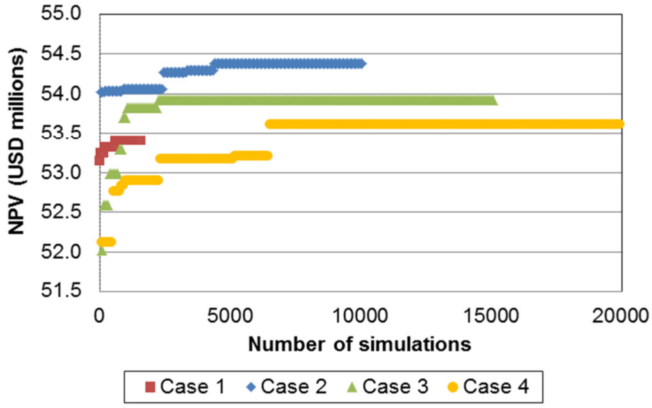


Figure 8: Number of simulations required to achieve the maximum NPV for each case in the probable economic scenario

Figure 9 shows the graph of NPV against oil production and the second, the graph of NPV against water production for Case 2 and probable economic scenario. The solution with the highest NPV and the corresponding oil and water productions can be seen. The solution of maximum NPV does not always correspond to the highest oil production or the lowest water production. Depending on the objectives of the company, the manager can choose a solution with slightly lower NPV, but that produces less water, for example.

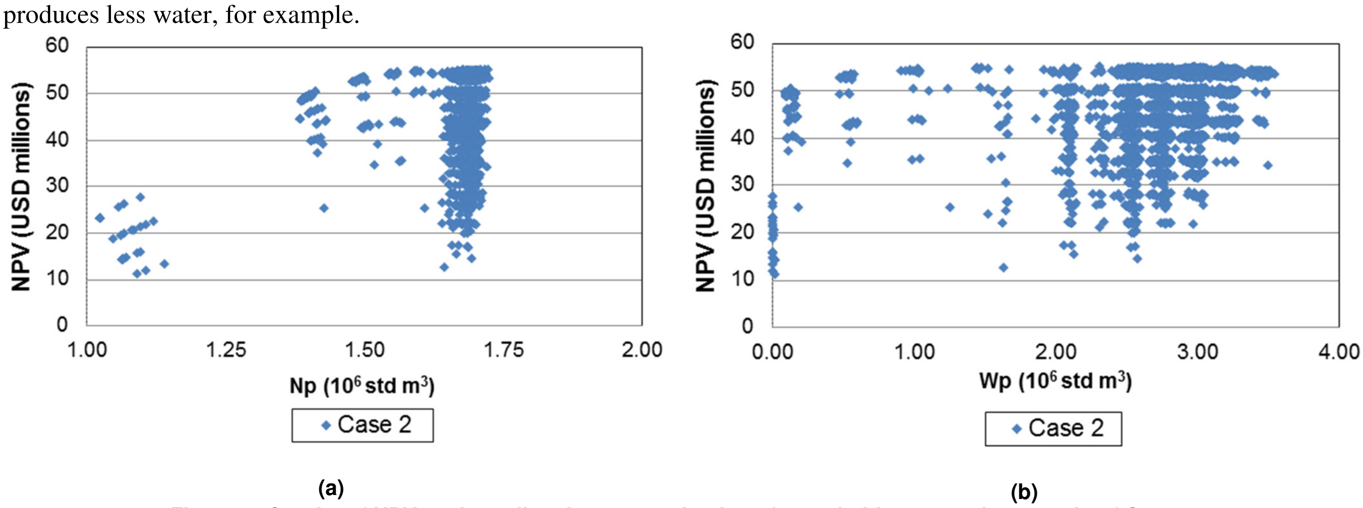


Figure 9: Graphs of NPV against oil and water productions for probable economic scenario of Case 2

Economic Uncertainty and Decision Analysis

For the previous results, the ΔEMV are calculated for three cases (Cases 2, 3 and 4 in relation to Case 1), as shown in Table 16 below. This table could help in making a decision between the cases that will be better used. As presented in this case study, the Case 2 is the best choice, because of the oil production increase and it is not as costly as Case 4, where all wells have valves, resulting in the lowest ΔEMV value. The Case 3, with intelligent injectors, showed better results in relation to water control (production and injection) than the base case and economic benefits between Cases 2 and 4.

Table 16: Results of ΔEMV for three cases studies in relation to base case (Case 1)

	ΔEMV *(USD millions)*
Case 2	1.04
Case 3	0.52
Case 4	0.02

Figure 10 (a) shows the expected monetary value of each case (in relation to base case), also showing the mean and the standard deviation of each component of ΔEMV due to each economic scenario; and (b) the NPV risk curve of each one. The first graph, presents the best results for Case 2 in relation to others cases. The second graph shows the Case 2 with the lowest risk, a medium risk in Case 3 and the highest risk of Case 4.

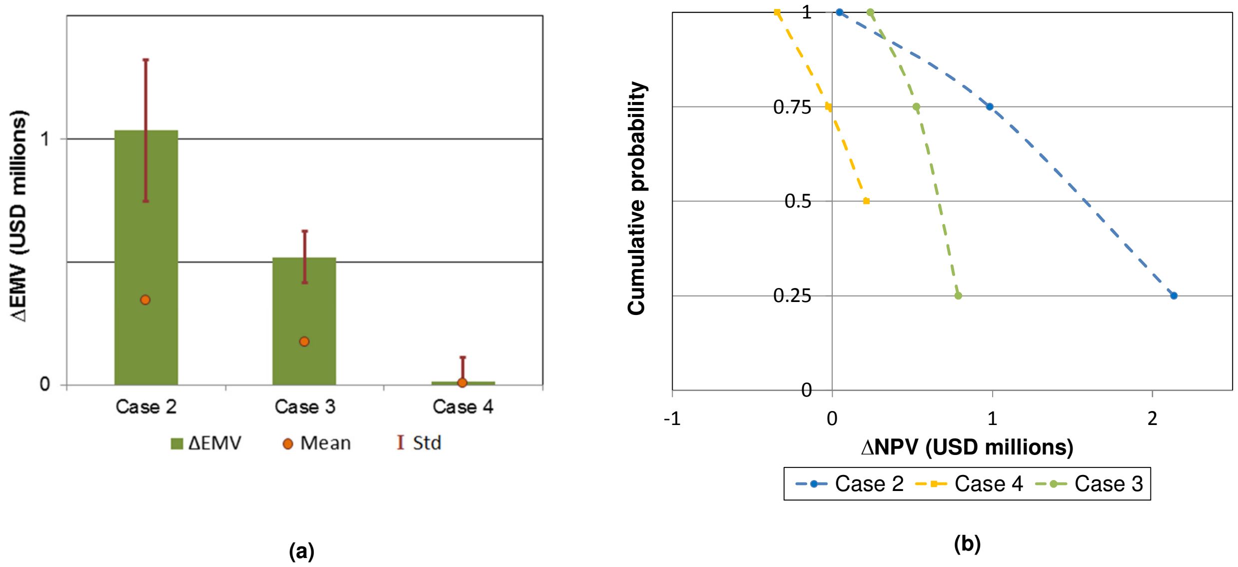


Figure 10: (a) Graph of EMV variation and (b) risk curve for three cases under economic uncertainty

Conclusions

The results presented here show that the proactive control can yield an increase in NPV as a consequence of a more efficient operation, higher production time and oil recovery, although with additional water production due to longer production time. These results were based on the maximization of the NPV but other options can be selected depending on the objectives of the company.

In the cases tested, the results have shown the advantages of employing the configuration of the Case 2, with intelligent producer and conventional injectors. This can be explained by the fact that in Case 2, the oil production and NPV increased sufficiently to overcome the cost of intelligent completion of only one well. Case 4 also increased the oil production and the NPV, but the cost of intelligent completion in all wells was not as advantageous as the configuration of Case 2. The configuration of the Case 3, with intelligent injectors, did better water control than the base case, but the profit is lower than Case 2.

The economic advantages are important if compared with the additional investments. Case 2, for example, points to an additional investment in intelligent completion of USD 625,000; however it had a gross return of 1.66 million and a net return of 1.04 million, showing that it is more advantageous to replace a completion to another.

These results were generated without geological and technical uncertainties. This implies that these differences between IW and CW may be increased if other uncertainties are considered, due to the fact that a IW has a high operational flexibility to attend the uncertainties involved in the process. This will be tested in a future work.

Nomenclature

BHP – Bottom Hole Pressure
CW – Conventional Well
EMV - Expected Monetary Value
ICV – Inflow Control Valves
IW – Intelligent Well
NPV – Net Present Value
MCS - Monte Carlo Simulation

Acknowledgments

The authors would like to thank Baker Hughes, CNPq, Petrobras, UNISIM and Cepetro for supporting this research and development project.

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