5
Case studies

In this chapter, we present the case studies done to evaluate the proposed approach. As described in the previous chapter, the most time-consuming part of the computational effort associated with this methodology lies in the reservoir simulations required to determine optimal proactive control strategies. For this reason, in the first case study we propose a simple model to allow a proof of concepts for the timing for control. There are varieties of strategies that follow the general approach, differing by the degree of flexibility that is afford to the strategy at each step. The exact solutions from the simple model are known, and yet is sufficiently detailed to portray and delineate the valve optimization problem, so we can use it to validate the flexible optimization process proposed, and incorporates both model uncertainty and future information under very low computational cost. We also consider a synthetic reservoir model with properties similar to a real reservoir in the remaining case studies, incorporating geological uncertainty and future information by wells and field measurements.

We divided the tests into 4 case studies. In Case 1, we seek to proof some concepts of methodology (described in chapter 4), and for that we use a "toy" model to verify that our approach has potential for the valuation of flexibility. Case 2 is a preliminary reservoir study, representing the first attempt to apply the proposed approach on a reservoir model, with 50 geological realizations chosen randomly. Case 3 considers the same reservoir model presented in Case 2, but with an improved reservoir development plan, and the importance of prior information in detection the influence of the flow restriction by the smart wells. Finally, Cases 4 and 5 we consider the full approach, including validation, considering "toy" and reservoir models, respectively.

5.1.
Case 1 - Using a "toy" model to proof the concepts of the proposed approach

In order to evaluate the proposed approach, verifying that our concept has potential for valuation of flexibility, we choose to start the study cases, using reservoir models, because the nonlinearity of the solution space makes it difficult to be certain for comparison with the proposed solution. Before that and the considerable computational cost resulting from the high degree of combinatorics of the problem and the subsequent optimization process, we developed a simple demonstration-class analytical problem for which exact solutions are known, and yet is sufficiently detailed to portray and delineate the valve optimization problem.

The main concept of the optimization strategy proposed in this thesis is that the consideration of uncertainties and acquisition of information during the optimization process can allow us to get more certain answers, reducing the probability of losing money, dynamically responding to reducing uncertainties. As result we can better quantify the benefit of operation flexibility, here represented by valves control. So we want to proof this basic concept before proceed with a large scale application that make use of costly reservoir simulations.

This "toy" model, named "single tank model", was proposed to evaluate the approach to value flexibility previously described in chapter 4, when we incorporate both model uncertainty and future information. It can also incorporate the issue of reliability, considering that when a valve setting change is requested, there is a probability that this request will fail.

5.1.1.
Single tank model

The single tank model is a demonstration-class problem used to validate the approach proposed in this thesis, and evaluate the performance of the methodology in a study case that we know the optimal solution. It considers a large "tank" which contains a mixture of oil and water. For simplicity, we assume no emulsion at the oil/water contact. A schematic of a proposed continuous tank model is shown in Figure 5.1.The tank height and diameter have equal values of 101.44 ft. This tank has three output valves, a valve located exactly half-way up (50.72 ft), another located at the top of the tank (101.44 ft), and a third valve located between these two (76.08 ft). The valves control an outflow aperture that varies continuously between 0 (fully closed) and 100% (fully open). In order to conserve mass, this tank has continuous water injection at its base. In this greatly simplified problem, we do not consider the effects of pressure or fluid compressibility.

Figure 5.1: The canonical tank of oil.

The objective is to find the valve settings over time that provide the greatest net present value (NPV). The simplified NPV is computed using the current oil price of US$ 90.00/bbl, a water processing cost of US$ 25.00/bbl, and a discount rate of 0.08. We consider the simulation time horizon equal to one year.

In real reservoir development there is uncertainty associated with the geological parameters. Despite the canonical tank is not a reservoir model, it can still be used to represent the problem, through the incorporation of uncertainty on the model that describe the tank. The uncertainty considered in our canonical model is the depth of the water/oil contact (OWC), which is unknown and following a uniform distribution ranging from the bottom to the top of the tank. We simply the problem by subdividing the tank height into 11 “bins”, i.e., the oil/water contact may take one of 11 discrete (height) positions (Table 5.1). This particular tank model problem can be trivial once future information is available.

Table 5.1: The binning of the depth of the water/oil contact.

OWC Index	OWC Height (ft)
0	0.00
1	10.14
2	20.29
3	30.43
4	40.57
5	50.72
6	60.86
7	71.01
8	81.15
9	91.29
10	101.44

5.1.2. Test 1 – Valuing considering uncertainty and future information

According our literature review on chapter 2, it is possible to incorporate geological uncertainty in the optimization workflow considering or ignoring the information at some level, so we analyze the impact of incorporating information in the optimization process. In this test, we choose the best flow control strategy for the tank considering: 1) optimization with clairvoyance, 2) optimization with prior information (both optimization strategies described on literature review in the second chapter) and 3) optimization assuming future information (this last one is the approach proposed in this thesis, described on the previous chapter). Since this tank model be extremely fast to evaluate, we use an exhaustive search to find the optimum valve settings.

Considering no uncertainty in the tank model, i.e., the OWC is known, the expected NPV is equal to US$4.6 x 10^6. For each scenario we know exactly the OWC, adjusting the valves to close as the water comes, so for the case where the tank is fully filled with oil, the NPV is equal to US$8.3 x 10^6, while for the case fully filled with water, the NPV is zero, because no valve is open.

Optimization assuming clairvoyance is done considering perfect information, ergo this optimization is based on OWC information that is assumed to be previously identified, for example, the optimist, pessimist and/or realist model. In this study case, since all uncertainty models have the same probability to occur, we choose just one scenario to be the realist case, considering no more uncertainty about the OWC. For this we consider a tank water saturation equal 50%, OWC height is 40.57 ft (bin 4). As the optimization with clairvoyance consider a perfect information we just need to do a determinist optimization, but the best flow control strategy here (specifically for this tank model) can be easily identified using a reactive strategy – when the water/oil contact arrives at the valve, the optimal response is to close it. The Table 5.2 shows the flow control strategy for this deterministic case, and the associated NPV is equal to US$ 5.5 x 10^6. If we observe the flow control strategy for this case, we can note that the valve closest to the contact oil/water considered is maintained fully open only for the first time step and its flow is approximately 70% reduced at time 1, and at time 2 this valve is closed. Valve 2 is maintained fully open until time 7 and from this time it is closed. Only valve 3 is maintained fully open for the entire time horizon. This results in a production 100% of oil because every time when the water contact arrive to the valve, the valve setting are readjusted.

Table 5.2: Optimal flow control strategy for the tank model with no uncertainty in the depth of the contact. In this case, the oil/water contact is at 40.57 ft., located a few feet below the valve 1.

Time Step	0	1	2	3	4	5	6	7	8	9	10	11
Valve 1	100	31	0	0	0	0	0	0	0	0	0	0
Valve 2	100	100	100	100	100	100	100	100	0	0	0	0
Valve 3	100	100	100	100	100	100	100	100	100	100	100	100

To calculate the expected value of the optimization with clairvoyance we need to apply the optimum valve settings (Table 5.2) to the 10 uncertainty scenarios remaining. As we can see in Table 5.3, when we apply the best valve settings found by optimization with clairvoyance to the remain OWC scenarios, the NPV`s are large for all case with the OWC below the true height (since they won't produce water), and degrade for the cases with higher OWC (since more higher is the contact more water it will produce). The expected NPV is calculated as an average over all values, totaling US$ 3.0 x 10^6. These results show that although this valve settings may be optimal for the model with an OWC at bin 4, the results is certainly not optimal when the goal is to maximize expected NPV over the range of model uncertainty.

Table 5.3: Assuming the water/oil contact height bin 4 as the most probable model, we compare the NPV for each possible water/oil contact height with the expected NPV over these 11 height possibilities.

	Deterministic											Expected
OWC Index	0	1	2	3	4	5	6	7	8	9	10	
NPV (US$E+06)	5.6	5.6	5.6	5.6	5.5	4.3	2.9	1.0	-0.1	-0.9	-1.5	3.0

Optimization with prior information considers the maximization of expected NPV over the range of uncertainty scenarios. This is the most used approach for optimization under uncertainty. The optimal strategy found holds valve 1 closed and valves 2 and 3 open for the entire time horizon (Table 5.4). The associated NPV results are shown in Table 5.5. Although this valve setting allows for water production in some scenarios where the oil/water contact is very high, the expected NPV is positive since this flow control strategy allow positives NPVs for the most of the contact models, and consequently results in a higher expected NPV. Comparing the expected NPV obtained by optimization with clairvoyance (1) with the optimization with prior information (2) we demonstrates that the optimization with prior information achieves a 7% improvement in expected NPV. The value of information is the difference between the ENPVs with and without information, so the value of information here is US$ 2 x 10^5. Note that while the expected NPV is increased, the effect of this strategy on the NPV of the individual models has mixed results, with some improving and some worsening.

Table 5.4: Optimal flow control strategy for maximizing expected NPV while accounting for model uncertainty.

Time Step	0	1	2	3	4	5	6	7	8	9	10	11
Valve 1	0	0	0	0	0	0	0	0	0	0	0	0
Valve 2	100	100	100	100	100	100	100	100	100	100	100	100
Valve 3	100	100	100	100	100	100	100	100	100	100	100	100

Table 5.5: Comparison of expected NPV with the individual model NPVs for an optimal strategy that maximizes expected NPV over the range of model uncertainty.

	Deterministic											Expected
OWC Index	0	1	2	3	4	5	6	7	8	9	10	
NPV (US$E+06)	6.2	6.2	6.2	5.9	5.1	4.3	2.8	1.1	-0.1	-0.9	-1.7	3.2

Finally, we applied the methodology proposed in this thesis, optimization incorporating both: uncertainty and future information. For future information, we use the appearance of water on the commingled outlet pipes as the only measurement. The optimization process starts by finding the valve settings that maximize expected NPV over all time, neglecting all future information. This result is same as the one shown in Table 5.5. With these optimal settings for time 0, we then acquire information on the appearance of water in the outflow pipe at time 1 for each of the models. These measurements are used to cluster the uncertainty models into two groups, those with water production and those without. As is shown in Figure 5.2, there are 3 models with water and 8 without water at time 1. Thus, even after only one time step, the incorporation of future information has significantly reduced model uncertainty. The optimization problem is then split into two parts, with a separate optimization being run for each of the two clusters. The valve settings for time 0 are kept fixed to those found in the first optimization, but the settings for all later times are allowed to vary in order to maximize expected NPV for the two reduced problems. Thereafter this process of optimization followed by clustering and re-optimization is recursive until either all time steps are complete or all uncertainty in a branch is eliminated. In the end of this process, the methodology delivers a decision tree that describes a flexible strategy of optimum valve settings that properly accounts for future measurements and their impact on uncertainty reduction. This tree is illustrated in Figure 5.3Figure 5.3. We can note that for the branch of the tree showing water at time 1, all uncertainty is eliminated by time 3, while the “without water” branch requires up to time 7 to resolve all uncertainty. The resulting expected NPV is shown in Table 5.6.

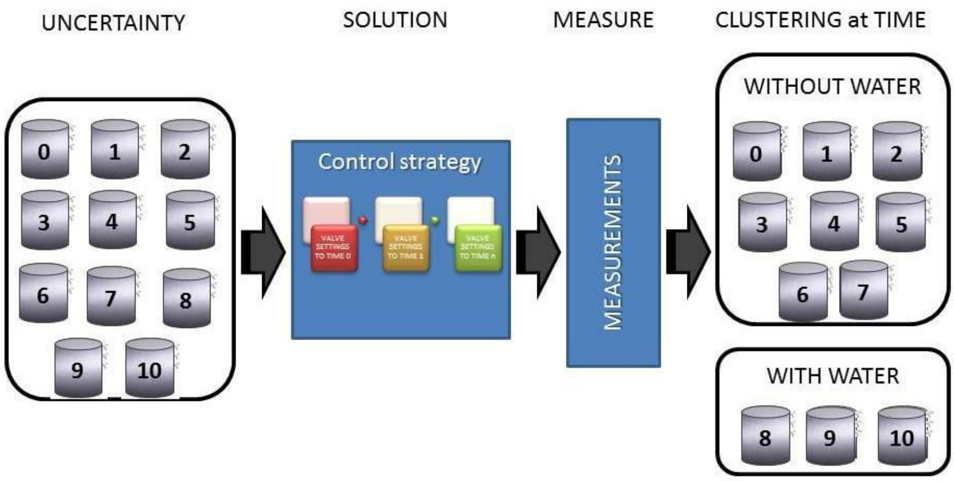


Figure 5.2: Illustration of the first time step of our optimization strategy that considers both model uncertainty and future information.

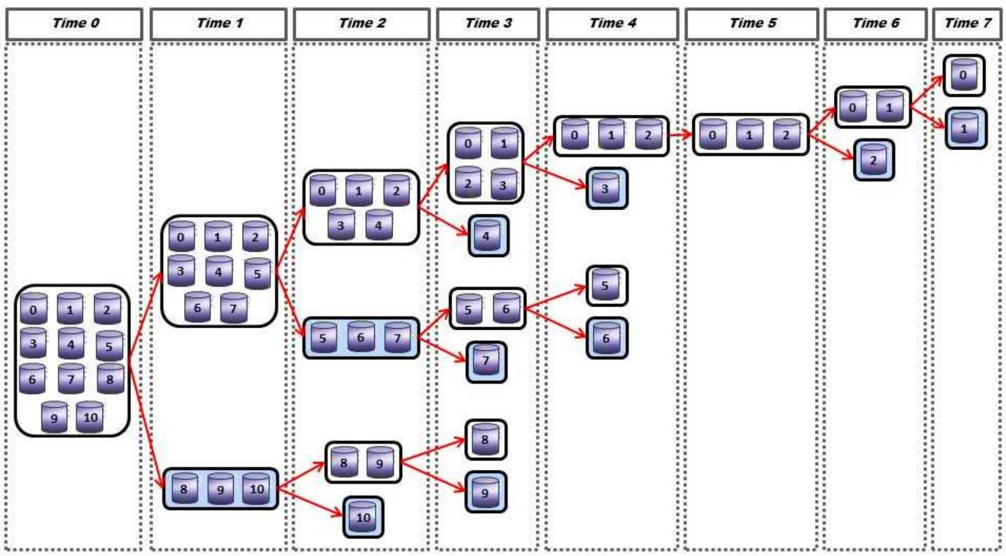


Figure 5.3: Complete decision tree for our optimization strategy that considers both model uncertainty and future information. Models associated with commingled water production are highlighted in blue.

It is important to emphasize that the valve settings found by optimization with future information for the first time step are the same as those found by optimization with prior information. This ensures that the ENPV obtained by the proposed approach (that considers both uncertainty and future information) never will be less than the ENPV obtained by the optimization with prior information. Future information can reduce the uncertainty over time, allowing us to make better decisions. Again comparing the expected NPV obtained by optimization with clairvoyance (1), but now with the optimization with future information (3), we can see the use of future information improves the expected NPV by 38%, and the value of information increase to US$ 1.2 x 10^6.

Table 5.6: Comparison of expected NPV with the individual model NPVs for an optimal strategy that maximizes expected NPV while accounting for both model uncertainty and future information.

	Deterministic											Expected
OWC Index	0	1	2	3	4	5	6	7	8	9	10	
NPV (US$E+06)	8.0	7.6	6.9	6.2	5.2	4.6	4.0	3.1	2.2	1.0	-0.2	4.4

While improving the average NPV is advantageous in improving the results of a portfolio of oilfield assets, it is also important to consider the exposure to downside risks in pursuing a particular strategy. One approach for doing this is to compare the deterministic NPVs for each individual model in the expectation ensemble. This is done in Table 5.3, 5.5 and 5.6 under the column labeled "Deterministic". Examining the downside first, both the deterministic and uncertainty optimization cases yielded losses for three of the eleven models, while the optimization using future information yielded a loss in only one of the models, and this loss was minimal. On the upside, the use of future information significantly improved the NPV of each of the models over the results for optimization under uncertainty. Another way to examine risk is by plotting the cumulative probability of achieving a particular NPV (Figure 5.4). The three curves represent the three optimization approaches we have considered. As the cumulative probability curve moves to the right, downside risk is reduced and upside gains are increased. Note that the downside risk of optimization under uncertainty is the same as that of deterministic optimization in this example, while a comparison of the up sides shows that optimization under uncertainty provides more upside potential. Meanwhile, optimization incorporating future information is superior to both other methods on both the up side and the down side. In particular, the probability of losing money is about 9% when future information is considered, and is 27% for the other two strategies.

We also compare the cumulative probabilities of the NPV obtained by the optimization considering uncertainty and future information, as proposed in this thesis, with the case without uncertainty, as shown in Figure 5.5. We can note that the probability of to lose money, even considering uncertainty, is low when the future information is also considered.

5.1.3. Test 2 – Timing for measurement assimilation

As described in the previous chapter, the measurement assimilation reduces uncertainty over time. In this test we use the single tank model to evaluate the smartness of the methodology proposed, showing that the use of measurements as future information can define when a set of valves should be re-optimized based on uncertainty reduction.

To better investigate the influence of measurement assimilation, we continue the use of the tank model with a time horizon of one year, but we increase the number of steps to change the valves from once a month to every day. This change allow us to re-define the valves setting 364 times, but we want to investigate if so many re-optimizations are really needed in order to accurately determine the value. To compare the results we also look for a reduction in the number of evaluations required.

We remind that this approach allows us just to re-optimize the valve settings if the data measurement acquired may reduce the present uncertainty, otherwise we keep the previous valve settings, reducing the need of extra optimizations, since the search space remain the same. We can observe on the results at the Table 5.7 that was possible to reduce in 99% the number of simulations done and still possible to find a similar expected NPV. We also compare the number of simulations found in dictionary and the total simulations required. The results confirm our expectation about the smartness of the approach that just require for new optimization if the uncertainty scenario change.

Table 5.7: Comparison about optimizing all time steps and the approach that uses the measurements to define the optimization time steps.

	Optimizing all times	Non-optimized all times
ENPV (US$E+06)	2.124	2.122
Simulations done	124856	642
Simulations found in dictionary	1045489	44278
Total simulations required	1170345	44920

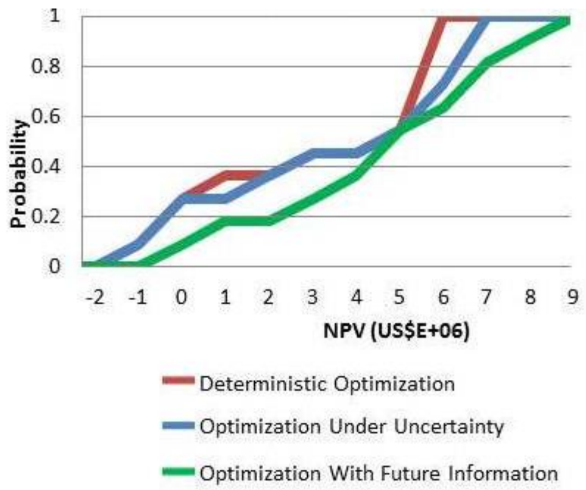


Figure 5.4: Comparison of the cumulative probabilities of NPV for the three flow control optimization strategies.

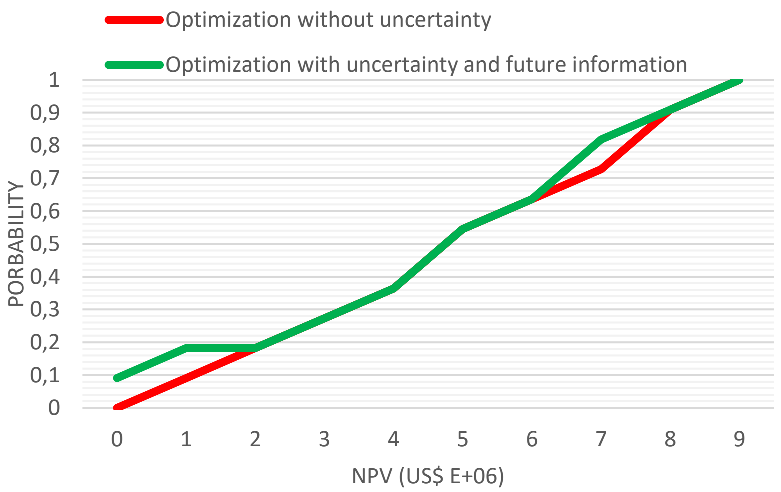


Figure 5.5: Comparison of the cumulative probabilities of NPV for the case without uncertainty and the case considering uncertainty and future information.

5.1.4.
Test 3 – Accounting for technical uncertainty

Against the possibility of valve fail, in this test we investigate the performance of the proposed approach accounting for this technical uncertainty. As described on Chapter 4, in this thesis we consider that there are some ways to accounting for technical uncertainty, where they distinguish of each other by the way that the flow control strategy are defined, i.e., including or not possible failures on the proactive strategy (being pessimist or optimist) and considering or not if the failures effectively happen during the life time (being lucky or unlucky). We can summarize the proposed considerations saying that they can give to us an evaluation of the smart well considering failures whose value is between: 1) the case that account for fail all time, and the fail already happen (Unlucky Pessimist case) and 2) the successful case that the proactive strategy does not account for fail and failures never happen as well (Lucky Optimist case).

Generally when valves fail they will be stuck with the valve aperture that they were previously assigned, but for some valve types there is also a (small) possibility that the valve will be stuck in a different position, including fully open or fully closed. As with the failure of many devices, it is often the case that the failure rate of valves is higher at early or late times. One possible model for the failure rate of valves that can capture this behavior is a specific failure distribution, but to simplify our analysis somewhat, and in the absence of relevant data to justify more complicated models, we shall assume that the failure rate of valves is constant. In all that follows it would be easy to modify our methodologies to include a more sophisticated model of valve failure. We also will only consider failures in which the valve is stuck in its previously assigned position.

First of all, to understand possible impact of failure on value we considered an extremely pessimistic case when all of the valves fail at the same time. We did that because all others failure case will have a result between the cases when all valves never fail and all valves fail. We also consider that the valve can fail just in the previous settings. In Figure 5.5, we analyze the tank model behavior when the failure occurs at the beginning (Time 1) (as an Unlucky Pessimist approach proposed), middle (Time 5) and end (Time 10) of the time horizon (according the

Unlucky Optimist approach). We also compare the results with the results by optimization with prior information (Table 5.5), as it is the most used approach we are calling it as the base case, and the results by optimization with future information (Table 5.6). We can observe that if all valves fail in the Time 10 the expected NPV still the same and if the failures occur in the Time 5 the NPV lost is just around 5%. But if all valves fail at Time 1 the NPV is basically the same if the strategy adopted was the strategy of the base case, that optimize without incorporate future information.

In order to know the failure influence for each uncertainty scenario (water/oil contact) we did the same analyses for each scenario individually. Again, we compare the results with the value given by optimization with prior information (base case) and the optimization with future information, considering that the valves never fail. The others 3 curves, in the graphics of Figure 5.7 represent what happen if all valves (by the strategy of optimization with future information) fail at Time 1, Time 5, and Time 10. We can note that when the valves fail at the beginning the failure influence on NPV is higher than when the valve fails at other times. Consequently, the NPV does not have a bit varied when the valves fail close to the end of the time horizon. Otherwise, we can note that if all valves fail at the middle and at the end of the time horizon the NPV curves continuous close to the best curve when the valves never fail. In addition, if all valves fail at the beginning the NPV curve is the same of the base case. So we can said that if the worst case happen and all valves fail in the beginning we yet don`t lose more money compared with we adopted just an uncertainty optimization. Therefore, in that case, if we choose to use the flexible optimization approach, the minimum NPV obtained is the same NPV got with an uncertainty optimization without future measurement.

We know that in some valves design it is possible that the valve fail in a completely open or closed position, independently of its previous position. Therefore, we can observe in Figure 5.8 that, compared with the case that the valves never fail, even in this setting, there is only a significant loss of value when failure occurs at early times and on a fully close position. However, if these happen the expected NPV for the failure case will be the same of the base case. Therefore, the results show once again that the improvement in the NPV will always be the same or better than the results acquired by the optimization with prior information (base case).

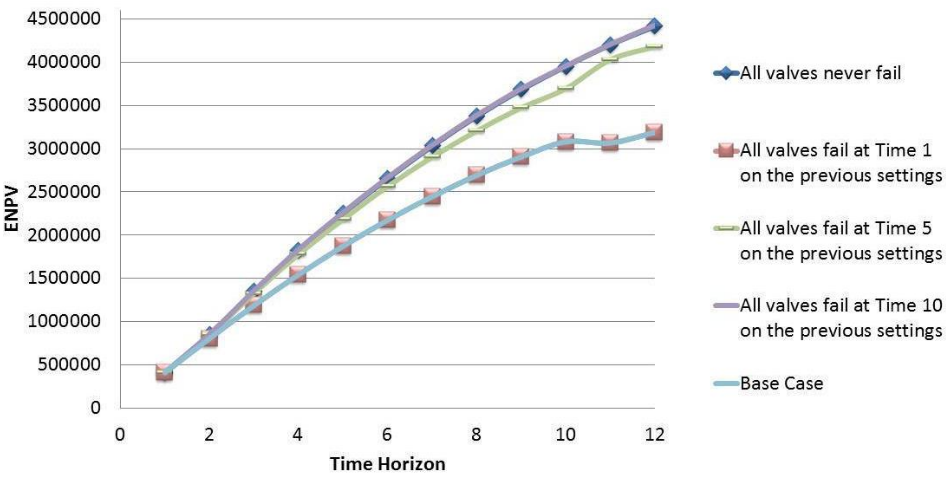


Figure 5.6: ENPV behavior when all valves fail on the previous settings vary the time fail.

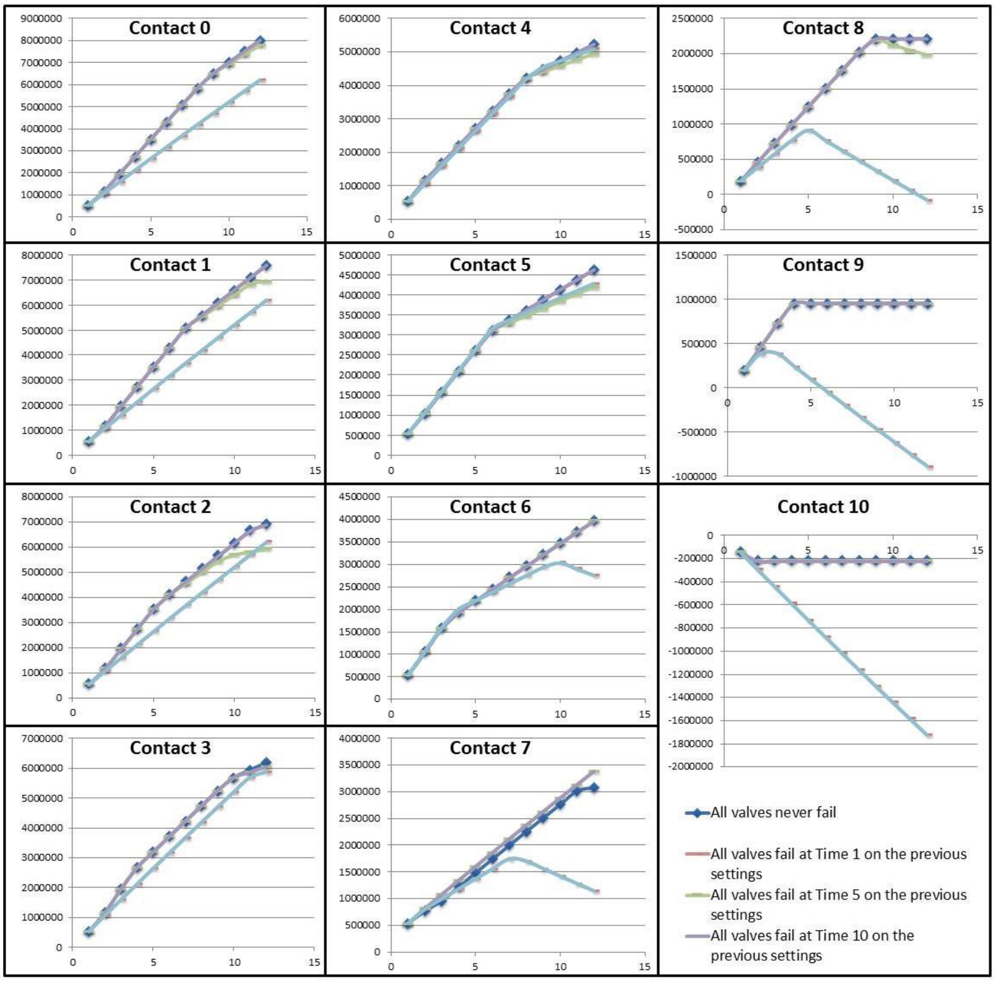


Figure 5.7: ENPV behavior when all valves fail on the previous settings varying the time of failure for each uncertainty scenario.

We also analyze theses ENPV results presenting them in groups of three, as shown in Figure 5.9. For comparison, the horizontal blue line shows the value resulting from the optimistic optimization with no failure. The horizontal red line shows the value of static valves whose settings are optimized, without considering future information, to maximize ENPV (Valve 1 is fully closed and Valves 2 and 3 are fully open , as in Table 5.4, resulting in the NPV values shown in Table 5.4). The leftmost group presents the case where the valves fail in the position of the previous setting. We can observe that if all valves fail at the end of the time horizon (Time 10), the ENPV is not impacted, and exactly equals the no-failure case. This happens because the no-failure policy does not change the valve settings at the end of the time horizon. If failure occurs in the middle of the time horizon (Time 5), the ENPV is reduced by only around 5% compared with the no-failure case. If all valves fail at the beginning of the time horizon (Time 1), the ENPV losses are greatest, reducing the value down to the base case (red line) because this is now equivalent to the optimized static case. This analysis shows that in the event of failure, our no-failure policy never produces ENPV results that are worse than optimized static valves when the valves fail into their previous positions.

The middle group in Figure 5.9 examines what happens to the ENPV when values failure into an open position. Once again, the ENPV increases as failure occurs later in the time horizon. However, the ENPV is consistently lower than it was in the previous failure case. In particular, in the beginning- and middle-time failure cases, the ENPV falls below the red line that indicates the ENPV of the optimized static policy. These additional losses happen because the valves fail in the open position, while the optimal static policy requires that Valve 1 be in the closed position, and thus the higher-than-optimal production rate induces additional losses due to increased water production. The rightmost group in Figure 5.9 examines what happens to the ENPV when values failure into a closed position. These results possess the same features as the case with failure in the open position, namely monotonic improvement with later failure times and the poor results in early and middle times, but present even lower ENPV that the previous two cases. The reason for this should be clear, because failure in the closed position causes valuable production to be lost whenever there is a failure.

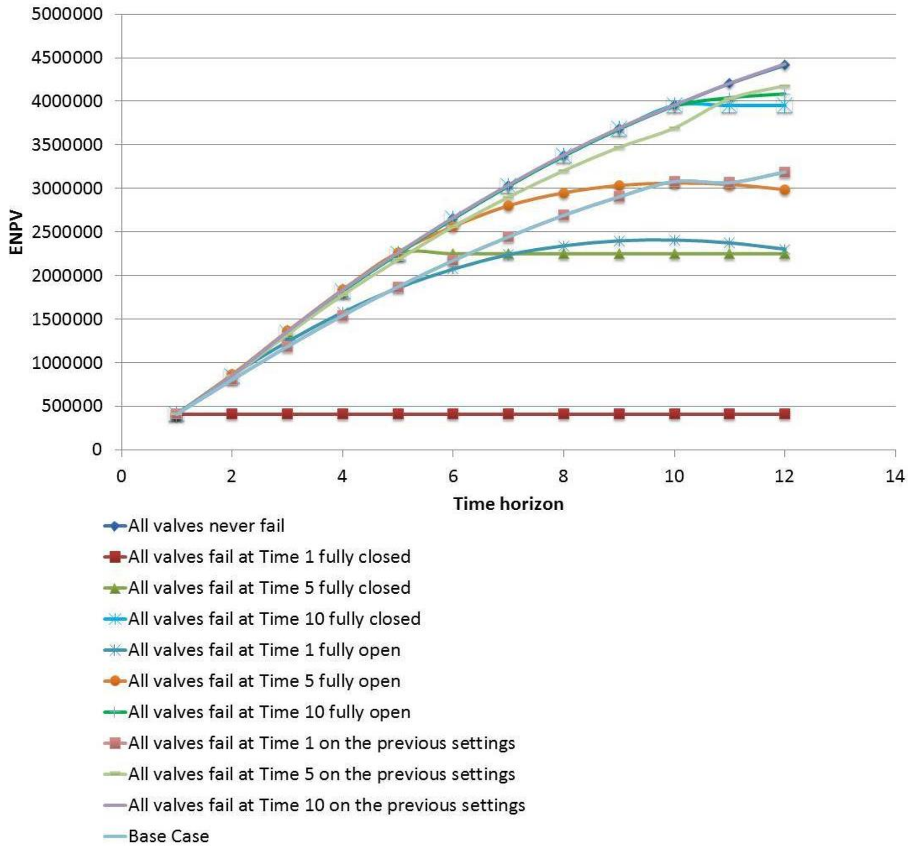


Figure 5.8: ENPV behavior over time when all valves fail fully open or fully closed varying the time of failure.

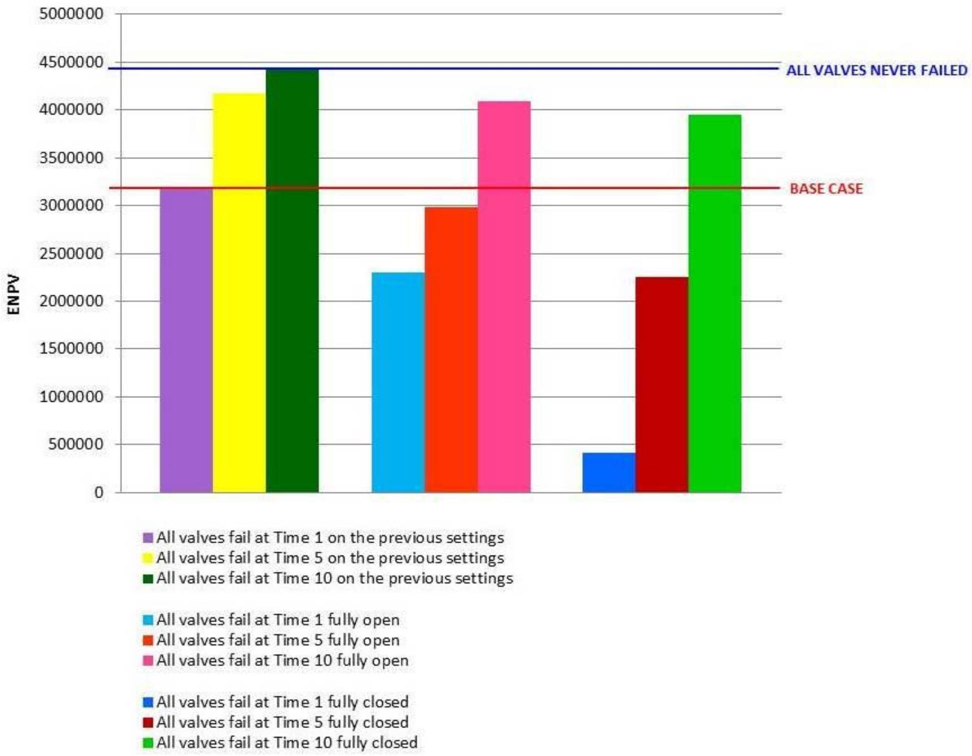


Figure 5.9: The cumulative ENPV behavior when all valves fail fully open or fully closed.

To understand possible impact of failure on value we considered an extremely pessimist case when all of the valves fail at the same time. Even in this setting, there is only a significant loss of value when failure occurs at early times and on a fully close position. So due to analysis results did about failure case, we also analyze when the valves can fail on each time with probabilities that consider if a valve fail or do not fail in the past, as showed at the Table 5.8. So we assume that the probability of the valve failure in the begging is higher than the probability of failure in the end of the time horizon, showing the probability failure proportion at time. So at the graphic showed by the Figure 5.10, we can see the impact of failure probability on the expected NPV, considering that the valve just can fail on the previous settings, but it can fail at the beginning, middle or end of the time horizon. The probability of failure was vary between 0 and 1, where 1 mean 100% of failure.

Table 5.8: Probability of the valve failure on the previous settings on time.

Time	Probability of failure
Time 1	α
Time 5	α*(1-α)
Time 10	α*(1-α)*(1-α)

We can see clearly that when the probability of failure alpha grow the expected NPV decrease and yet for the case with probability of failure is 1 the expected NPV is equal to the base case. This results show that for this case we can have a higher probability of failure and continue been advantage using the flexible optimization proposed in this work, this justify the same results found when we considered probability of failure during the optimization process and when we do not consider failures.

However, if we want consider that the valves also can failure fully open or fully close with a certain probability β? On this case we want to show the influence of β on the expected NPV. For that we fixed α value equal 0.1 and vary β between 0 and 0.2. As happened with α, if β grows the expected NPV decrease, as show the graphic showed by the Figure 5.11. The red line represent the limit where the expected NPV from the base case is located, so bellow this line represent cases where our approach considering failure has lower ENPV then the base case without failure.

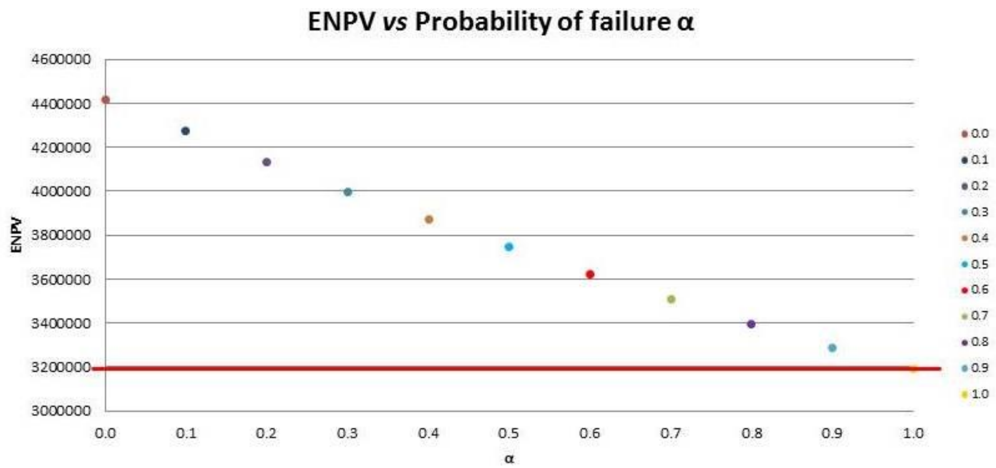


Figure 5.10: ENPV behavior when all valves fail with different probability of failure alpha considering that valve fail on the previous settings. The red line represent the limit of ENPV obtained by the base case without consider failure.

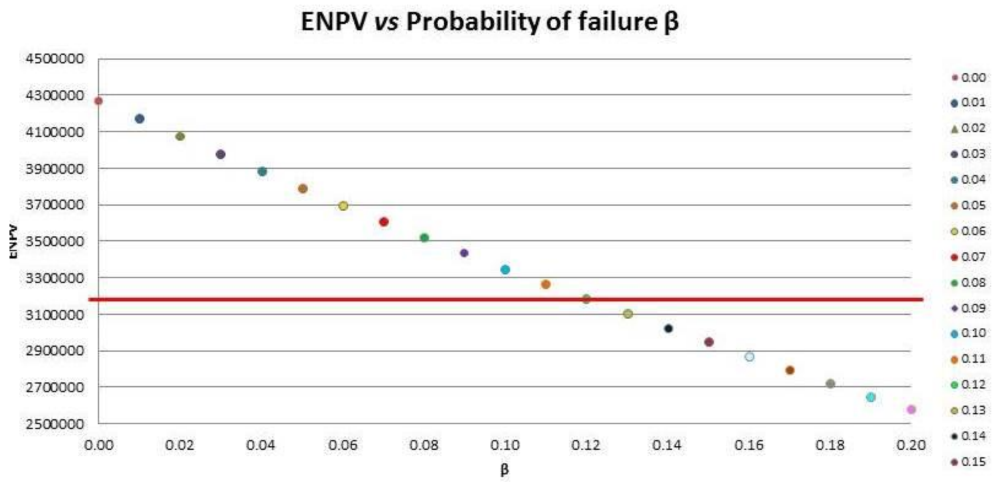


Figure 5.11: ENPV behavior when all valves fail with different probability of failure beta considering alpha constant equal 0.1 and that valve fail fully open or fully closed position. The red line represent the limit of ENPV obtained by the base case without failure

We consider that with the technology advancement the probability of the valves fail fully open or fully close may be lower than the probability of the valve failure on the previous settings. Therefore, how we establish alpha equal 10% the cases more realistic are with beta less or equal alpha. In the curve at the graphic showed by the Figure 5.10, we can note that just when beta is more than 12% the

ENPV is below to the red line. This show that for the tank model the best solution found using the flexible optimization approach proposed here is robust enough to have equal or better ENPV compared with the base case even we consider a probability of failure vary on time, like on the real problems.

In order to mitigate possible losses by valve failures, we performed a test using the Lucky Pessimist approach. Applying the Lucky Pessimist approach to our tank case with 3 valves this multiplies the number of scenarios to be considered by 8 (2^3), representing the possible failure scenarios at time. We assumed that failures occur with probability alpha whenever a setting change is applied (independently and identically distributed). We considered that each valve can fail only when your control is being changed, and the fail means that the control will remain the same as defined in the previous control. Using this model fails, the probability of failure is allocated for all possible combinations that the valves may fail. We consider a probability of failure equal 10%.

As expected according the previous analyses, we obtained as results the same valve settings found for the flexible optimization approach without consider failure (Figure 5.3), i.e. it is not worthwhile altering our strategy in response to future possibility of failure. This is because in the tank model, the water contact always proceeds from the bottom to the top of the tank, and so there is no mitigating strategy for a failed valve. In a real reservoir setting, such a linear progression of water is rarely present, allowing neighboring valves to be adjusted to reduce the impact of a failed valve. Nevertheless, we keep in mind that the use of rolling static optimization allows us to have a Lucky Pessimist approach, generating reasonable results accounting for failure.

5.2.
Case 2 – Preliminary investigation with a reservoir model

After we apply the proposed approach to a “toy model”, this approach was evaluated against a reservoir model based on the Namorado field, Campos Basin, Brazil. We compare the results with scenarios involving a conventional well, i.e., without smart completions, and an entirely proactive control strategy, that does not consider future information. We choose to use the synthetic reservoir model known as UNISIM-I. The UNISIM-I model (Gaspar et al., 2013) was built by the UNISIM group in UNICAMP as a benchmark problem that can be used to facilitate, and give a direct comparison between research efforts among participating Brazilian universities. The reservoir model is intended to be used for projects that have a focus on history matching and optimization of reservoir production design and management.

The geological model used in this test describes the Namorado field, part of the Campos basin offshore from Brazil. The reservoirs of the Namorado field represent marine turbidite deposits lying above the Albian limestones of the Macaé formation. The reservoir models therefore shows coarse sand deposits (with high porosity and permeability) intercalated with shale deposits (showing low porosity, permeability and net-to-gross ratio). Along with the UNISIM-I model, a project has been launched that provides a case study for optimizing well placement. This project assigns a complete set of rules for well placement along with rules for production and injection. It also was provided a simplified economic model for the capital costs associated with the well-placement strategy and the operating revenue and costs (UNISIM-I, Avansi, & Schiozer, 2014).

5.2.1. Modified UNISIM – 9 wells

The UNISIM-I model was built using seismic and production data provided by ANP (Agência Nacional de Petróleo - Brazilian National Petroleum Agency), along with petrophysical logging data provided by Petrobras. The reservoir is split into two blocks by a fault which was assumed to be sealing (see Figure 5.12). The smaller East block is believed to have a lower oil-water contact than the larger west block. The model includes four vertical wells (all penetrating the larger western block), along with history data for the first 1461 days of production from these wells. Indeed one such optimized well-placement solution has already been released for the UNISIM-I-H case study (Maschio et al., 2013), a study designed with the aim of history matching production data for the UNISIM-I model.

The simulation model provided with UNISIM-I was built for CMG's IMEX simulator. To be able to include a more sophisticated handling of the completions equipment and to be able to use our existing workflows, it was necessary to use an equivalent model constructed in Eclipse. The detail about UNISIM model for Eclipse simulator can be found on Appendix B.

Along with the UNISIM-I model, a project (UNISIM-I-AD, *Gaspar et al.*) was launched that provides a case-study for optimizing well-placement. This project assigns a complete set of rules for well placement along with rules for production and injection. It has a simplified economic model for the capital costs associated with the well-placement strategy and the operating revenue and costs. The challenge of optimal well-placement falls outside the scope of this project, although it would be possible to produce a reasonable plan for the development of the reservoir. It is expected that in the coming months optimized well-placement strategies (without the use of intelligent completions) will be produced by the universities of the SIGER group who are participants in the UNISIM-I-AD project. In this work, we will be able to use these strategies as a base case to which intelligent completions can be added.

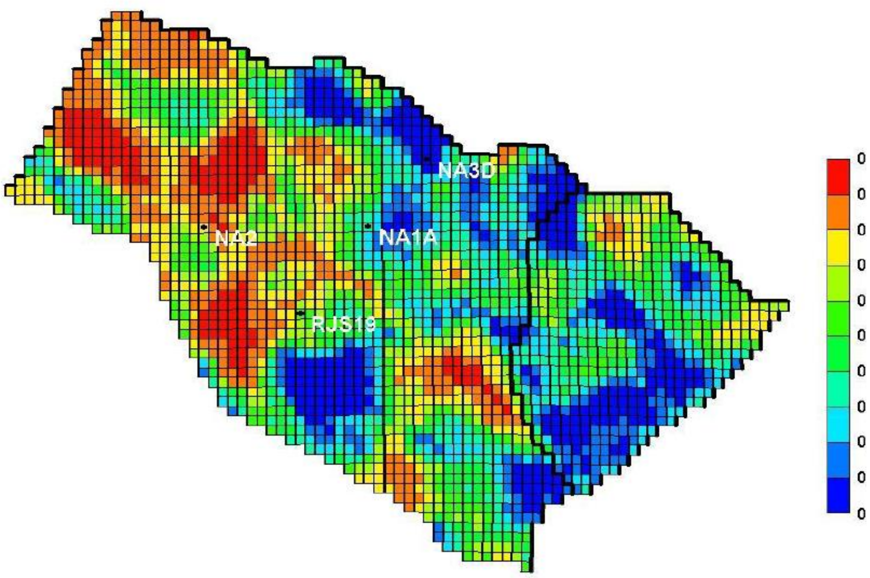


Figure 5.12: Porosity map of UNISIM-I showing position of the perforated wells and the location of the fault.

The model of operating revenues and costs and NPV calculation from UNISIM-I-AD is also useful for this project. The model for the NPV is defined by

$$NPV = \sum_{j=1}^{N_t} \frac{NCF_j}{(1+r)^{t_j}} \tag{5.1}$$

where NCF_j is the net cash flow at period j, N_t is the number of time periods, t_j is the (average) time of period j, and r is the discount rate. In turn the net cash flow during each time-period is defined by

$$NCF = (R*(1-Roy-ST)-CO)*(1-T)-Inv-AC, \tag{5.2}$$

where the variables are defined in Table 5.9.

The total expenditure on facility investments and abandonment costs will not impact the absolute gain that can be achieved by the introduction of intelligent well technology. The cost of this technology can of course be included as an investment cost; however, within the scope of this project it is reasonable to contrast the gain in value against the cost of the technology. The UNISIM-I-AD model does not specify either a price or a production cost. We therefore assume that gas production is revenue neutral with the production costs balanced out by the sale of gas. The values for the economic parameters important to this project are given by Table 5.10.

Table 5.9: Components of net cash flow

R	Gross revenues from sale of oil and gas
Roy	Royalties rate (charged over gross revenue)
ST	Social taxes rate (charged over gross revenue)
CO	Operational costs (oil production, water production/injection)
T	Corporate tax rate
Inv	Facility investments
AC	Abandonment costs

Note that the cost of water production/injection is much lower than the revenue generated from oil production. There is no strong incentive to minimize the rate of production of water itself; however, under liquid-rate control the production of water leads to a loss of oil production, reducing revenue. We therefore expect that for this model strong gains will only be achievable while the well is under liquid-rate control rather than bottom-hole pressure control.

Table 5.10: Values of economic parameters

Variable	Value	Unit
Oil price	50	USD/bbl
Oil production cost	62.9	USD/m^3
Water production cost	6.29	USD/m^3
Water injection cost	6.29	USD/m^3
Corporate tax rate, T	34.0	%
Social taxes rate, ST	9.25	%
Royalties rate, Roy	10.0	%
Annual discount rate, r	9.00	%

For the tests performed here, we used a development plan with 4 vertical producer wells, previously allocated as in Maschio et al. (2013), surrounded by 5 nearby horizontal injector wells, totaling 9 wells, for that reason we call this model as the Modified UNISIM model (Figure 5.13). For this case, the smart well technology will be applied to just the producer wells. In Appendix D, we described how the multi-segment wellbore was modeled in the Eclipse simulator.

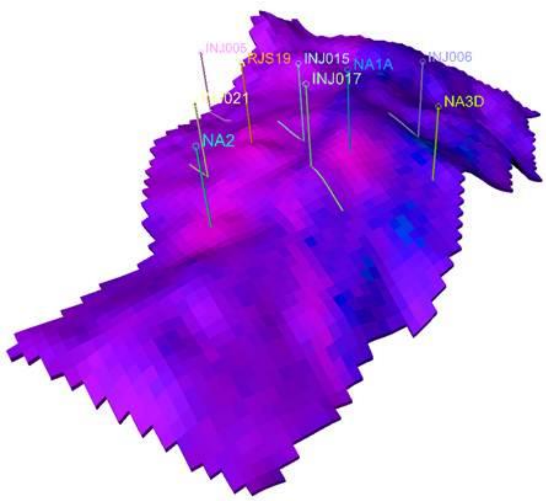


Figure 5.13. Modified UNISIM - Reservoir and well model

In addition to the reference model, UNISIM-I-AD also describes the geological uncertainties associated with the model. The principal uncertainties relating to the entire model were the petrophysical properties (porosity, horizontal and vertical permeabilities, net-to-gross) and water relative permeability.

There is additional uncertainty in the smaller eastern block, where the PVT properties and the oil-water contact are unknown. The uncertainty in the petrophysical properties was captured by 500 images and by a distribution of values of a vertical permeability multiplier. The petrophysical images were generated by sequential Gaussian simulation of both facies and the properties themselves. Data from well-logs for the four wells used in the simulation model were used to constrain the petrophysical properties and to define the geostatistical correlations and variograms (Avansi and Schiozer).

The uncertainty in the water relative permeability corresponds to an uncertainty in the relative permeability when the rock is fully saturated with water. The relative permeability models (0, 1, 2, 3, 4) correspond to maximum water relative permeability values of (0.42, 0.15, 0.24, 0.33, 0.51). Note that the permeability models are therefore best ordered as (1, 2, 3, 0, 4) to indicate increasing permeability to water.

Knowing that the reservoir model used in this study case has 500 geological models, to perform the tests we must select limited number of uncertainty models, so that the methodology is feasible to evaluate, since our approach requires reservoir simulations. In the following initial investigation with the UNISIM model, we randomly selected 50 uncertainty scenarios over the 500 scenarios available, varying the relative permeability and petrophysical characteristics.

In the field, the downhole valve adjustment was done from surface by a computer command. Nowadays, there is no operating limit on the interval adjust of the valves, but we have imposed a 50-days minimum duration between consecutive valve adjustments. This was reflected in simulation reporting times. Consequently, considering 3700 days, there are a maximum of 74 times at which an adjustment of the valves settings can be applied.

5.2.2. Test 4 – Static versus flexible strategies

This test consists of an initial investigation with the UNISIM model, considering 50 uncertainty scenarios randomly selected, where the main objective is to compare the possible improvement by flexibles strategies over static strategies (detailed on “Timing for Optimal Control” section, in the previous chapter). As a first test, we consider change the valve settings at three time intervals, after 400, 1200 and 2000 days of production, with a total simulation period of 10 years. Each producer well contains a valve that permits us to restrict flow from the lower section of the reservoir. The base case used to compare the obtained results consists of two producers fully completed in the reservoir and two producers completed in only the upper section of the reservoir. This base case was chosen for this case study based on the best combination of open/closed completions for the producer wells in this reservoir model and well placement strategy.

For comparison, we first performed an optimization under uncertainty without considering future information (optimization with prior information), using both static and flexible strategy. As described on the previous chapter, the static strategy chooses a single setting for each valve over the entire time horizon, while the flexible strategy allows each valve to be adjusted at each of the three time steps. The results obtained with static and flexible optimization under uncertainty (Table 5.11) show that the use of smart wells in this case can be promising, increasing the expected NPV compared with the base case that represents the use of conventional wells. Therefore, we can say that the use of smart wells for this reservoir model can be attractive.

Continuing our investigation, we next considered the value of incorporating future information using the proposed approach. The acquisition of future information is done passively, using measurements from each well of the oil and water production rates and the bottom hole pressures and the cumulative production of water and oil by the field. We applied both the rolling-static and the rolling-flexible policies. We report these results in Table 5.11. The rolling-static and rolling-flexible optimization policies allow further increases to the expected NPV. This can be attributed to using the combined system (with uncertainty and future measurements) to optimize the flow control valves. We also note that there is not a big difference between the values for the rolling-static and rolling-flexible policies. We suspect this is due to the limited number of time steps (only three) at which the valves can be adjusted, and project further gains as the number of steps is increased.

Table 5.11: The Expected NPV and increase obtained using different optimization strategies

	ENPV (US$ E+09)	Increase (US$ E+06)
Base case	1.72881	---
Static Optimization	1.73743	8.62
Flexible Optimization	1.74008	11.27
Rolling-Static Optimization	1.75631	27.50
Rolling-Flexible Optimization	1.75862	29.81

The use of future information significantly improved the NPV of each of the policies over the results for optimization under uncertainty. One way to examine risk is by plotting the cumulative probability of achieving a particular NPV. This is shown in Figure 5.14. The curves represent the four optimization approaches we have considered. As the cumulative probability curve moves to the right, downside risk is reduced and upside gain is increased. In order of increasing ENPV, the policies show cumulative probability curves that consistently move to the right with few, if any, cases showing a reduction in NPV. While the variation in NPV due to uncertainty is far greater than the gain that can be expected due to the use of smart well technology, such a consistent gain still shows a clear value. There is a slight tendency towards greater increases in NPV amongst those models that represent an initially lower NPV, i.e. the reduction in downside risk appears greater than the increase in upside gain. For this case, our solution is naturally slightly risk averse.

Rolling-flexible optimization is superior to the other methods in both the increase of upside gain and the reduction of downside risk.

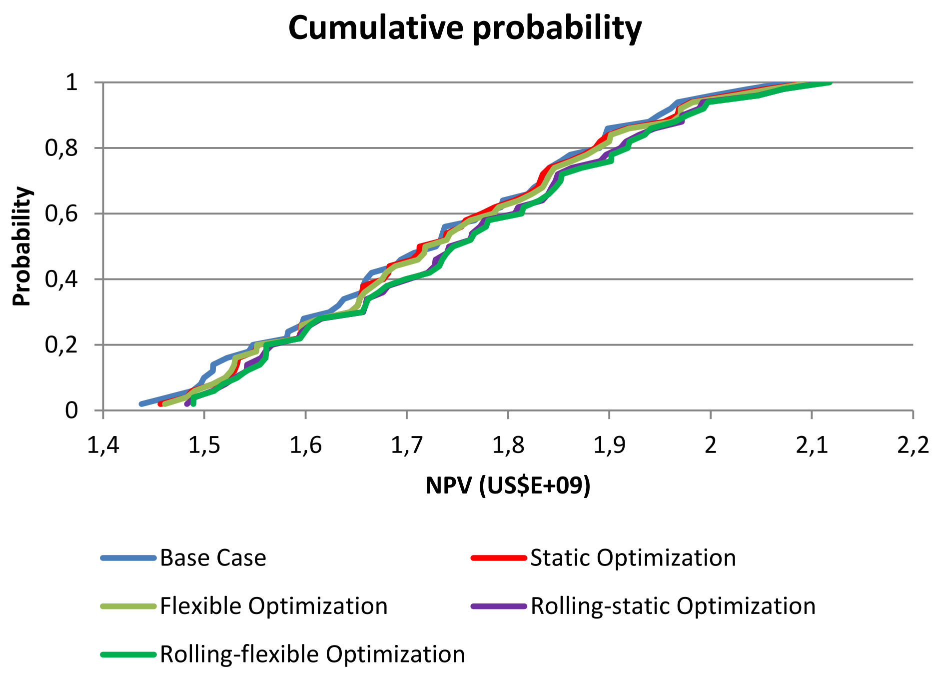


Figure 5.14. Comparison of the cumulative probabilities of NPV for the optimization strategies

Our methodology designed the optimal usage of smart wells and assigns a quantitative value to the benefits that they provide, both in terms of the flow control valves (flexibility) and measurement gauges (information). The methodology proposed here considers both uncertainty and future information, and provides a qualitative valuation that indicates whether a field benefits from intelligent completions. The results here demonstrate some economic benefit of using smart well technology for the field case considered, showing that this methodology can efficiently optimize the flow control strategy while reducing risk and increasing NPV compared with other methods. Now we want to investigate if we can apply our approach to a set of uncertainty scenarios where the smart wells can be even more attractive.

5.3. Case 3 – Performance of the proposed approach with a reservoir model

This study case intend to demonstrate the proposed approach on a reservoir model that highlights its novel aspects: asset optimization under uncertainty, flexible control based on future information, quantifying the value of flexibility and future measurements, and considering potential financial loss due to the failure of a smart completion.

We want to demonstrate that the proposed approach yields the highest ENPV. The sensitivity of the approach to changes in the number of time steps used for both proactive and reactive control was also considered. For proactive control, the sensitivity analysis examined frequency of valve adjustment in the absence of new information and for reactive control, how fast one needs to react to new and revealing measurement data. This examination revealed that while being operationally proactive is important, there is no value in planning for frequent valve adjustments when there is an absence of new information.

5.3.1. Modified UNISIM – 18 wells

After the promising previous results, we increase the number of wells in the reservoir development plan from 9 to 18 wells, strategic located since the complexity of the reservoir model and number of uncertainty scenarios available. As described on Section 5.2.1, the two key uncertainties in UNISIM model are the distributions of porosity (φ) and permeability (k) across the reservoir and the end points of the water relative permeability curves. Within UNISIM-I the uncertainty of porosity and permeability is represented by 500 equiprobable realizations of geological models, along with five distinct relative permeability curves. These realizations exhibit several layers of low porosity and low permeability that cover much of the reservoir and correspond to shale bodies. The lateral extent, and uniformity, of these bodies also represents a major source of uncertainty. Smart wells are deemed suitable here in order to isolate the production from the zones either side of each shale body, but the optimal control of the wells may be affected by whether there is communication these pay zones.

A basic reservoir development plan has 18 vertical wells, as shown in Figure 5.15. Production is planned for 10 years. The development plan used is restricted to vertical wells, and is largely based around injection of water from the margins of the reservoir. Among the producers, three distinct groups exist:

- wells that probably did not intersect any low permeability zones and might be susceptible to water coning;
- wells that intersect many low permeability layers and are likely to have lower flow rates; and
- wells that probably intersect a single low permeability layer that might run across much of the reservoir.

The smart wells considered are equipped with flow control valves in two production zones, as Figure 5.16 shows. Annular flow control valves are used for production in the upper and lower regions. The adjacent log view shows the shale probability map that is useful for creating a preliminary completion design before actual petrophysical log data is available. The simulation results show us that the water saturation around the smart wells can change a lot according the uncertainty geological scenario considered (Figure 5.17), and is known the ability of smart wells to restrict the flow rate in different production zones is better used for the cases with different water breakthrough per zones. In Figure 5.17, the well depicted with a red line corresponds to one of the smart wells considered. Missing grid block cells correspond to zero pore-volume cells, for which the water saturation is not defined.

Smart wells could also be useful in the case of mitigating-water coning. While we acknowledge that water coning is a complex phenomenon that is affected by numerous aspects of the reservoir and geometry, for the purposes of this thesis, we ensured that water coning would not impact our results. This was achieved by making the vertical distance between the OWC and the lowest completion in the string as large as possible. Tests using analytic approximations for critical rate (Papatzacos et al, 1989) (Yang & Wattenbarger, 1991) confirmed that water coning would not be manifest during the period of simulation. The wells with lower productivity indexes were unlikely to produce large volumes of water over the 10-year timeframe, and so smart wells would have limited utility. Finally, the wells that typically intersect a single low permeability layer were capable of producing significant volumes of water from either the lower or upper zones over the timeframe. They are, therefore, better suited for smart well application, with the use of packers at the likely location of the low-permeability layer (thereby isolating production from the upper and lower zones). There are three such wells in this development plan, thus leading us to consider a problem with six valves (for each well there is a valve in the upper and lower zone).

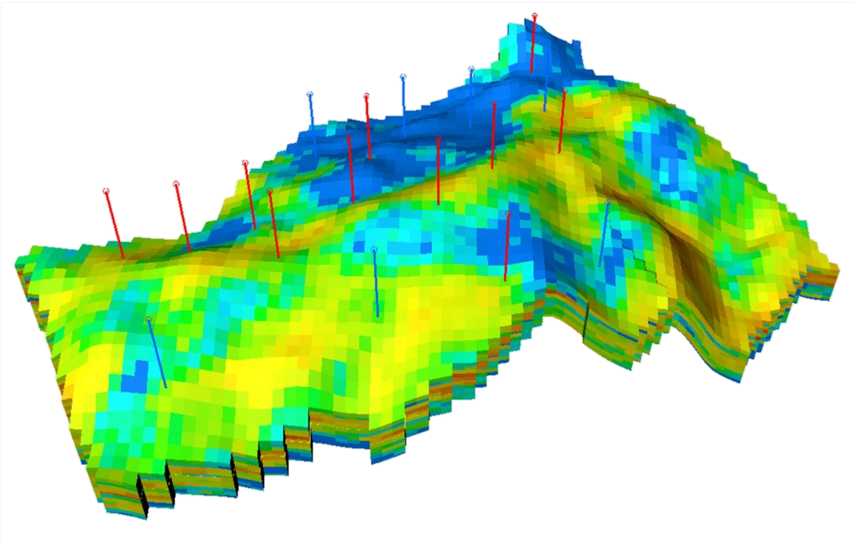


Figure 5.15.: Reservoir and well model, with producer wells in red and in water injector wells in blue.

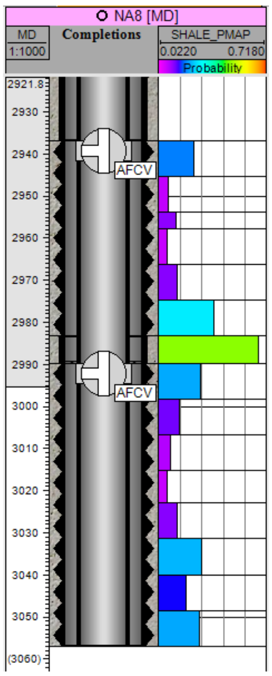


Figure 5.16 Design of a completion string, with packers at the top of the reservoir and at the level of the low permeability layer.

We follow the economic model of Avansi & Schiozer (2014), as detailed described on Section 5.2.1, where the total expenditure on facility investments and abandonment costs will not impact the absolute financial gain that can be achieved by the introduction of smart well technology. The cost of this technology can be considered as a capital cost; however, within the scope of this paper, it is reasonable to contrast the gain in net value against the cost of deploying the technology. For gas production, the UNISIM-I model specifies neither unit production revenues nor costs. We therefore assume that gas production is revenue-neutral (production costs balanced out by gas sale).

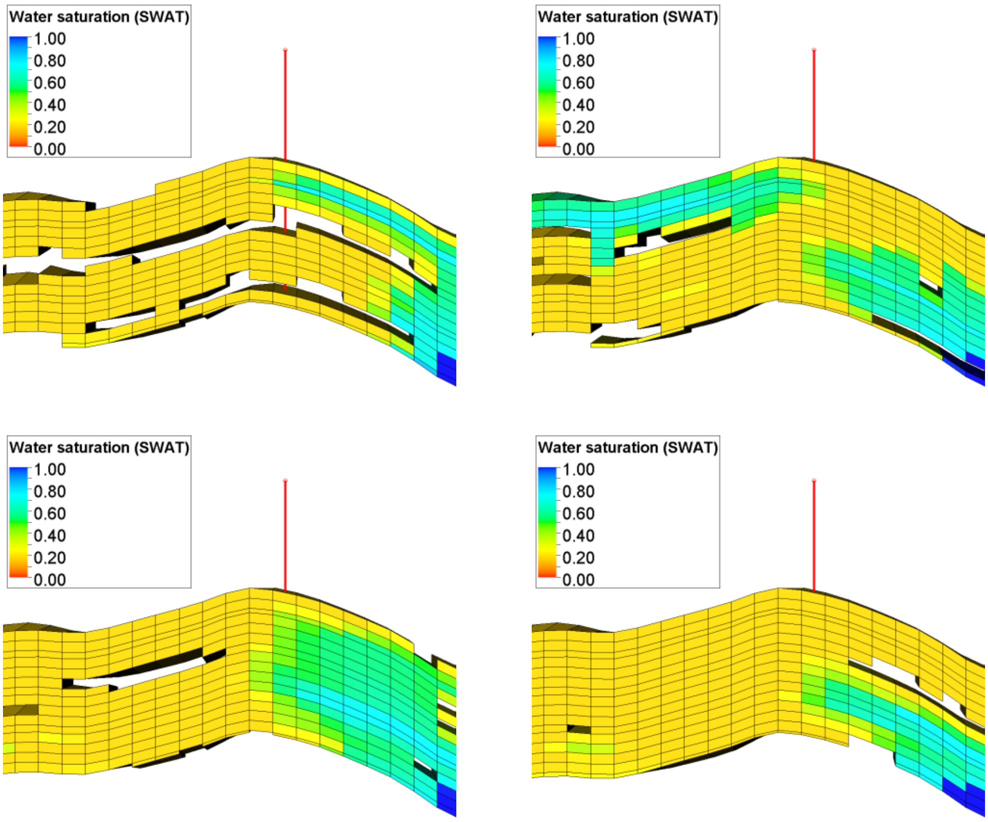


Figure 5.17: Multiple realizations of the water saturation after 6 years of production with conventional completions.

We have imposed a 50-day minimum duration between consecutive valve adjustments. This is reflected in simulation reporting times. Consequently, there are a maximum of 74 times at which an adjustment of the valve settings can be applied.

As described previously, this methodology uses simulated measurement values as future information to reduce the uncertainties over the time. Five different measurements were used in all of the following tests: the bottom-hole pressure from each of the three smart wells and the field oil and water production rates. The decision resolutions used for the bottom-hole pressure and flow production rate are, respectively, 50 bars and 1000 Sm^3/day.

5.3.2. Test 5 – Rolling strategies considering full range of uncertainty scenarios

In this test, we evaluate the smart strategies by simulating the reservoir model over 3700 days (around 10 years), using various time-periods for valve control. The full enumeration of models representing uncertainty amounts to 2500 different, where we randomly consider 50 scenarios by them to describe reservoir uncertainty in this test. We consider 8 time steps approximately evenly spaced over the 10 year simulation and valuation period to adjust the valves and for the future information acquisition, used by the rolling strategies, the same measurement information was used: the total field oil and water production, and extremely low resolution (only to within 50 bars accuracy) BHP values.

In Figure 5.17, we show the distribution of percentage changes in the final NPV, and cumulative oil and water productions for several different valuation approaches, namely robust optimization without future information for both static and flexible controls, and rolling strategies with differing numbers of time steps for proactive control.

Note that although the percentages refer to changes relevant to the field as a whole, they are calculated by comparison relative to the productions of the group of wells that contain intelligent completions. The NPV for this group of wells is calculated using the group oil and water production rates and an 'injection rate' that is equal to the total group liquid production rate to account for pressure maintenance. We believe that the percentage change relative to the group production is the most relevant quantity since with only a fraction of all wells in the field containing intelligent completions it is clear that the impact is smaller. Also note that the NPV does not include any capital expenditure, and percentage gains may be significantly higher once this is taken into account.

From Figure 5.18 we notice that the exact details of the proactive control are not as important as the use of future information, where the horizontal bars represent the P10, P50 and P90 values respectively, with the solid marker representing the mean or expected behavior. Without future information, in this case, there is relatively little difference between static and flexible controls. While this certainly is not universally true, in this case there is almost no net gain from the use of flow control valves when no future information is available. This is because cases where we should choke valves to reduce water production are balanced out by cases where the pressure drop is already too large to maintain production at the desired rate, and introducing an additional pressure drop will only serve to reduce the total production. Without knowing which case our reservoir corresponds to it is not possible to determine how we should adjust the flow control valves.

Once basic data from the reservoir is available flow control valves provide a clear potential for benefit. The benefit that is obtained depends significantly on the particular scenario, with some cases showing significant increases in the NPV and oil production and decreases in water production while other cases see little to no gain (but also no loss) from the use of flow control valves. At least for this case, there is not a large difference between the results obtained for each of the different possible number of time steps used for proactive control (rolling-static, rolling-flexible-*k*, and full rolling-flexible). Nevertheless, while there is essentially no difference between the rolling-flexible-2 and the full rolling-flexible case, we do see some differences for the rolling-static approach. The NPV and total oil production have a somewhat lower expected value and particularly P50 value with the rolling static approach, and a significantly lower reduction in the total produced water volume.

The large difference in the reduction of total volume of produced water between the rolling-static approach and the rolling-flexible approaches suggests that for assets with higher productivity (or lower maximum production rates) the rolling-static approach might show a larger difference in the optimized NPV. We therefore believe that while rolling-static has some attractive features (reduced number of reservoir simulations required as Table 5.12 shows, it is generally preferable to include some proactive flexibility in the optimization. However, it appears that even with only two time steps in the proactive optimization scheme we ultimately obtain a result that is almost identical to that of the fully flexible optimization scheme. Therefore, due to the lower number of reservoir simulations required to obtain a near identical result we believe that rolling-flexible-*k* with *k*=2 (or a similar small number) is generally the best approach, and is the approach that we shall use in the remainder of this results section.

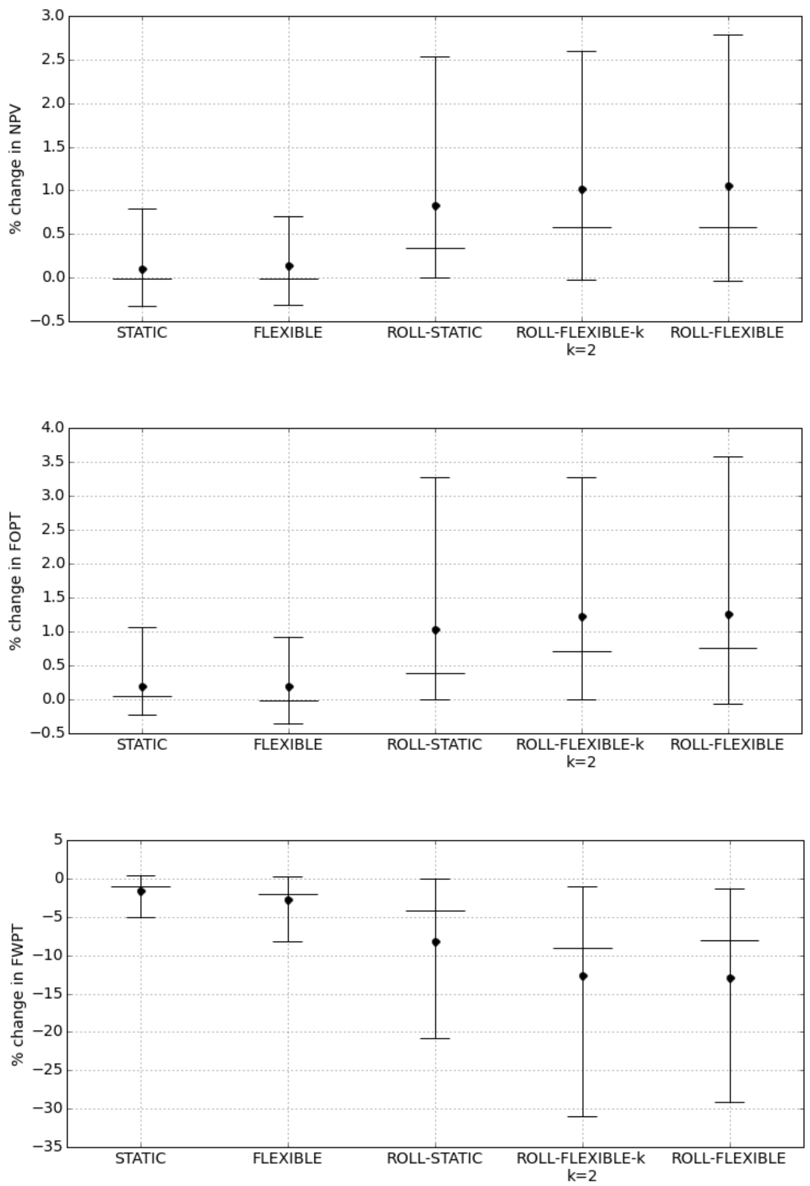


Figure 5.18. Percentage changes in NPV and cumulative oil and water production for each of the different approaches, relative to the base case without flow control valves.

We also note that although we have demonstrated a gain from the use of intelligent completions, the gain in the expected NPV was not particularly high. Given the robust nature of the calculation relative to reservoir uncertainty, the demonstrated gains are likely sufficient to justify the use of intelligent completions based on a simple comparison with the cost of the equipment. For this synthetic study, and with the use of vertical wells, pressure maintenance and a low productivity index relative to the planned production rates are major challenges.

Table 5.12. ENPV gain and total number of reservoir simulations required for each of the approaches shown in Figure 5.14

	Gain in ENPV ($US x 10^6)	Number of reservoir simulations
Static	1.4	980
Flexible	1.9	3430
Rolling static	10.8	3926
Rolling-flexible-*k*, *k*=2	13.3	6653
Rolling flexible	13.7	14060

Since flow control valves restrict flow by generating an additional pressure drop across the valve, when a well is under bottom-hole pressure control it is inevitable that using flow control valves to restrict the flow from a particular section, will also reduce the overall liquid production rate. As this case study also has low costs associated with water production relative to the value of produced oil, it is therefore usually only beneficial to use the intelligent completion when the well is under rate control. In real reservoirs, as the pre-salt, we expect that wells will have much higher productivity indexes both because of high formation permeability and because of greater formation thickness. Production from pre-salt wells is more likely to be limited by vertical flow performance and surface processing facilities, meaning that intelligent completions can be used to restrict flow from water producing zones without a corresponding reduction in the liquid production rate.

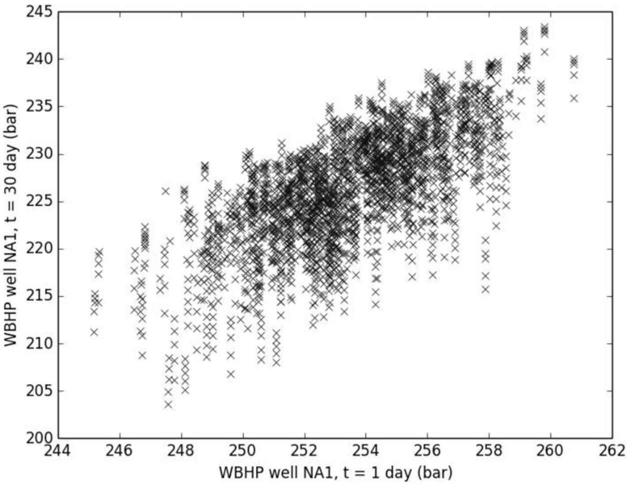
5.3.3. Test 6 – Rolling strategies considering limited range of uncertainty scenarios

Simulating 500 uncertainty model we could observe that the most part of them control the valves aperture by the operational constraints by the BHP limit. For that reason we expected that the use of promising uncertainty scenarios in the test can allow us to find better results. Continuing our analysis with small gains in the expected NPV, due to limited capacity to restrict flow leads to a large number of wasted reservoir simulations (corresponding to reservoirs where intelligent completions are not beneficial). For that reason the follow tests will be done using a selected set of uncertainty scenarios, instead of to choose it randomly.

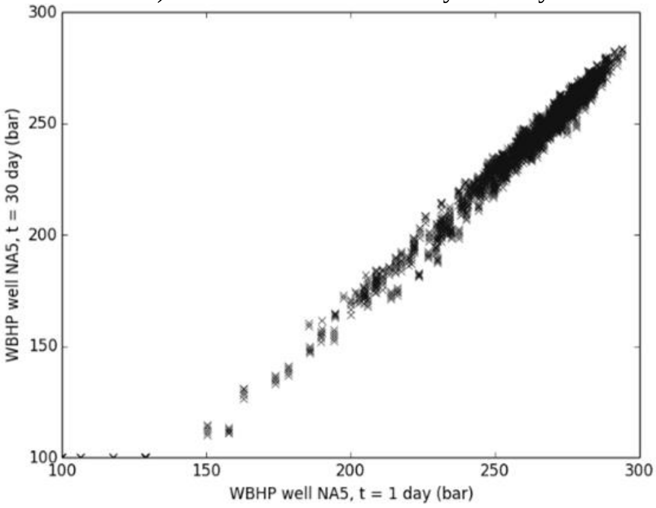
Therefore, before we evaluate the performance of rolling strategies, we try to choose the ensemble of uncertainty scenarios where the smart valves could be more useful. We judge that the uncertainty scenarios considered on the previous test was not so appropriated, since it was choose randomly and in many case the BHP limit lead the flow control. So in order to choose a set of uncertainty models that really can allow the valves be operated without extrapolate the BHP limit we check their pressure confronting the first day and the end of the first month. We did it for the three producer wells. We can observe on the graphics in Figure 5.19 that some models have the wells reaching the pressure limit just on the first month and we are interested on the models that it will take as much as possible.

We plot the BHP of the wells: NA1 vs NA5, NA1 vs NA8 and NA5 vs NA8, as the Figure 5.20, respectively. We can observe in the graphic of BHP of well NA5 vs BHP of well NA8 that some uncertainty scenarios are less influenced by the minimum pressure limit. Considering that we have five water relative permeability, we re-plot the graphic (c) of Figure 5.20, but coloring the models according these values, as shown in Figure 5.21. We can note that basically the uncertainty models that has the water relative permeability altered has the pressure behavior smoothly modified. For this reason, we firstly selected the uncertainty models with the higher water relative permeability and then we try to select at most 50 models with the higher BHP by well NA5 vs NA8. We used a cutoff equal 270 bar for each of the two wells used in the selection and 48 models were selected (Figure 5.22).

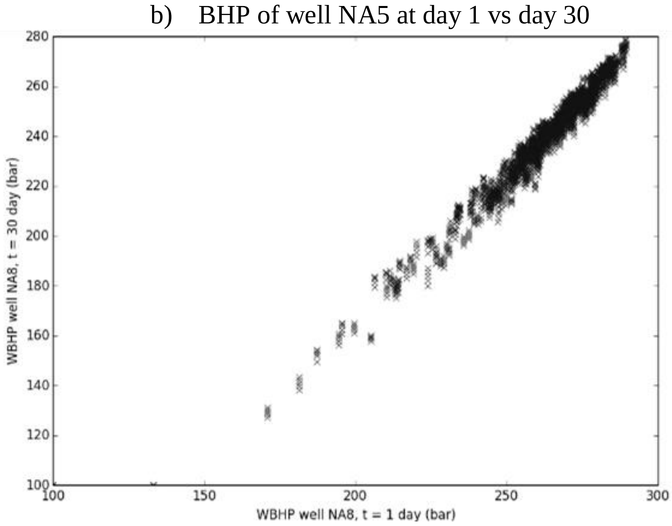
So that we may consider a case related to the synthetic case study for which intelligent completions are more useful, we therefore restrict the set of representative models to models with higher values (upper quintile) of the productivity index of the wells that might be installed with intelligent completions. In practice, this information can be determined relatively easily through a formation test, so it is not entirely unreasonable that this information could be available before the final completion design is chosen. Figure 5.23 shows the bottomhole pressure over time for the same well considering both the original set of uncertainty scenarios, selected randomly, and the new set of uncertainty scenarios that will be used in future sections.



a) BHP of well NA1 at day 1 vs day 30

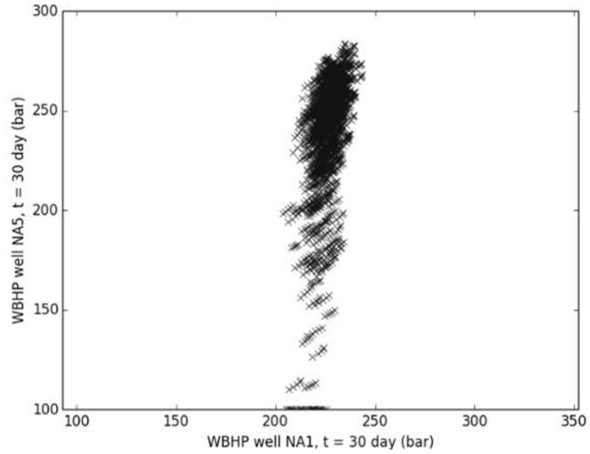


b) BHP of well NA5 at day 1 vs day 30

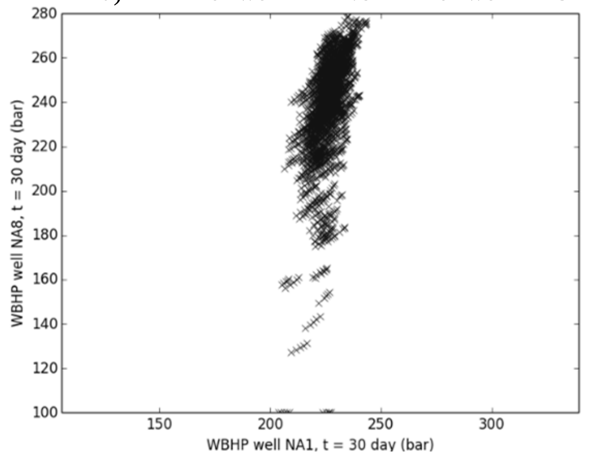


c) BHP of well NA8 at day 1 vs day 30

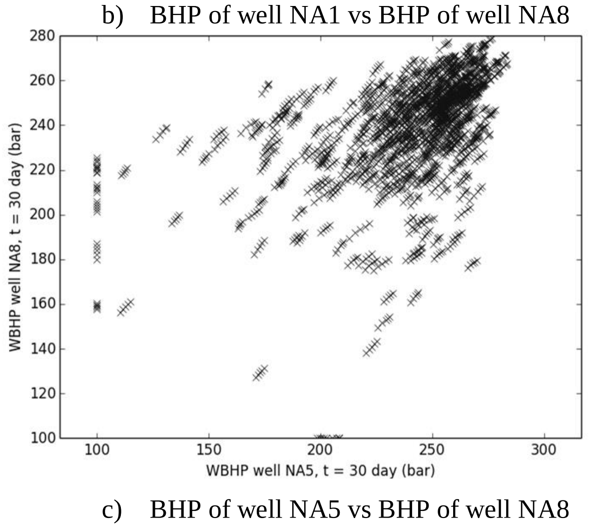
Figure 5.19: BHP of the smart wells varying from day 1 to day 30.



a) BHP of well NA1 vs BHP of well NA5



b) BHP of well NA1 vs BHP of well NA8



c) BHP of well NA5 vs BHP of well NA8

Figure 5.20: BHP of each smart well.

The plot in Figure 5.24 shows the pressure for the conventional completion, with the dashed and solid line representing the P10/P90 and P50 values respectively. We show the pressure for both the original sample of models and for the new sample of models, taken after adjusting the uncertainty model by filtering out cases with lower well productivity indexes. In almost all cases, the well is never under bottomhole pressure control and so there is more scope for creating a pressure drop within flow control valves without affecting the total liquid production.

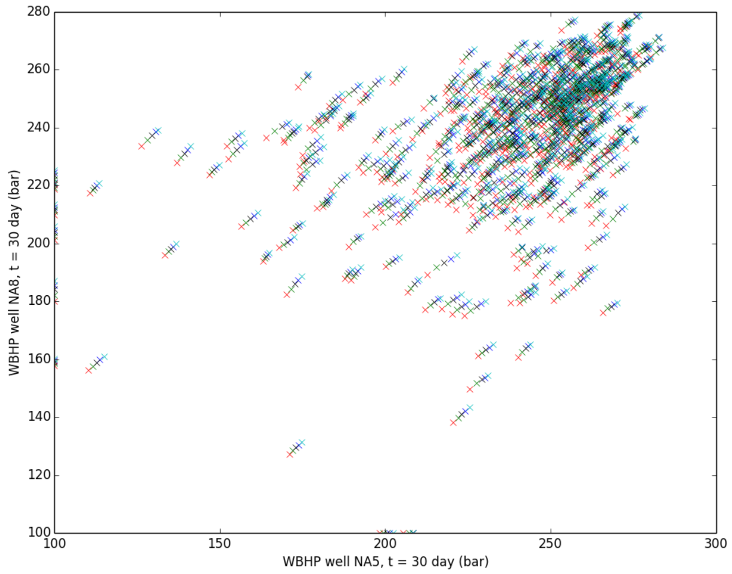


Figure 5.21: BHP of well NA5 vs BHP of well NA8, coloring the water relative permeability.

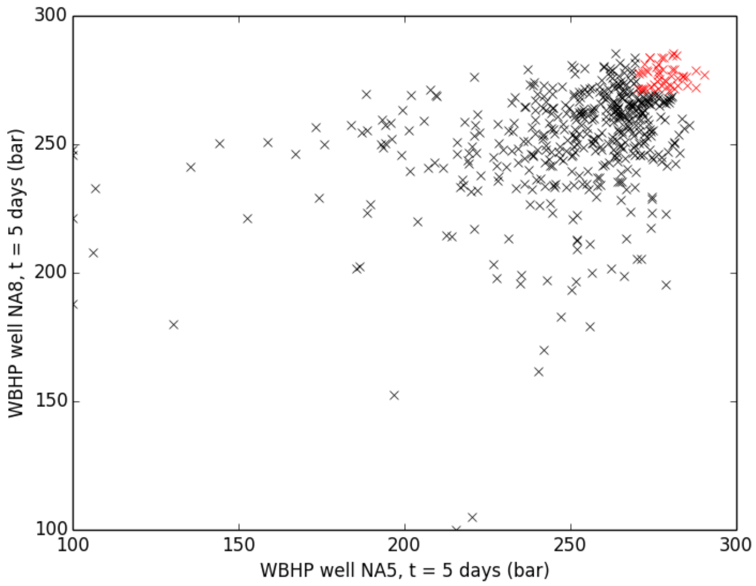
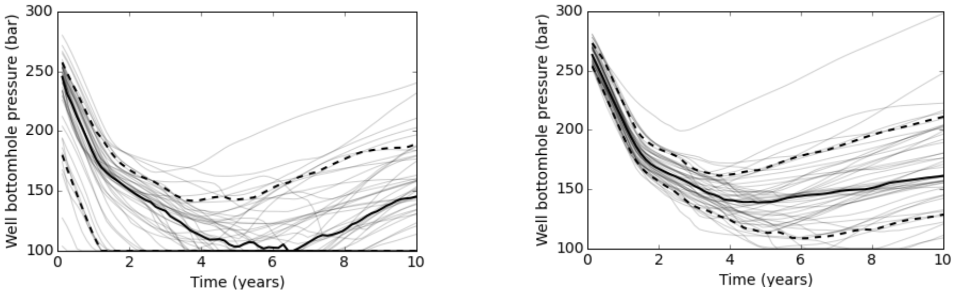


Figure 5.22: BHP of well NA5 vs BHP of well NA8 with the 48 selected uncertainty models.



Before filtering After filtering

Figure 5.23: Bottomhole pressure over time in one of the wells that is considered for installation of intelligent completion.

The main objective of this test is to identify the better parameters to be used on the optimization strategy, i.e., the rolling policy that return an expected NPV with a number of simulations acceptable. We exercise the optimization approach using the Rolling static, flexible and flexible-k strategies and we consider the number of time steps equal to 4. For the rolling-flexible-k we consider k equal to 2 with a geometry time partition, i.e., for each time step the valves can be adjusted 2 times, with the valve settings being held constant between these times, while the time horizon is divided in 2 partitions where the size of successive partitions increases approximately geometrically. As the total simulation time is equal 10 years, 4 times steps means that the valves are adjusted with an interval of 2.5 years.

As described on the chapter 4, the measurements are used by this methodology as future information to reduce the uncertainties over the time. The measurements used in this test are five: the BHP of each smart wells and the oil and water production rate from the field. In this test we are interesting in evaluate the possible economic gains by the optimization strategy proposed by us. So we compare the expected NPV obtained by our optimization strategy that includes future information (highlighted on the follow tables), with:

1. The expected NPV obtained by an optimization strategy without information, called Optimization without future information.
2. The expected NPV obtained by the strategy with no flexibility, called Base Case.

The Table 5.13 shows the expected NPV obtained by the optimizations without future information and the optimization strategy proposed in this thesis that incorporate future information, showing the gain in ENPV compared with the base case (representing an alternative with conventional wells). Analyzing the results obtained on the tests with static, flexible-k and flexible strategies, we can note that incorporating future information on the optimization strategy definition allows us to have better revenue and the gains obtained exceeds US\$ $32x10^6$. We also can observe that using 4 time steps the rolling policy that returned the higher expected NPV was the rolling flexible-k. Comparing the ENPV obtained by the base case with both optimization, with and without future information, we can note that for all cases performed, using 4 time steps, the biggest gains were obtained when future information was incorporated. We could also observed that the rolling flexible-k returned higher or as good as profit compared with the rolling static and the rolling flexible.

Table 5.13: Economic comparison between the base case and the optimization strategies with and without future information, considering 4 time steps.

Rolling policy	Strategy *without* future information ENPV (US\$ x 10^6)	Gain in ENPV (US\$ x 10^6) compared with base case	Strategy *with* future information ENPV (US\$ x 10^6)	Gain in ENPV (US\$ x 10^6) compared with base case
Static	3791.52	19.50	3804.08	32.06
Flexible-k	3791.80	19.78	3805.79	33.77
Flexible	3797.48	25.46	3805.98	33.96

5.3.4.
Test 7 - Increasing the number of time steps

To check if increasing the number of time steps also increase the expected NPV we performed a test applying our optimization strategy to the 48 uncertainty models. As we also described previously the reservoir models are simulated over 3700 days, so if the valves are adjusted every possible time, we have 74 time intervals to optimize the valve settings. According the promising results obtained on the previous test, we use the rolling flexible-k policy on the optimization strategy varying the number of time steps. We limited our analyze in 4, 8 or 74 time steps due to the computational cost involved, so all others expected NPV should be less than the expect NPV found by the maximum number of time steps, 74 in our case.

In this test, we also evaluate the possible economic gains by the optimization strategy proposed by us. Therefore, again we compare the expected NPV obtained by our optimization strategy that includes future information with the base case and optimization without future information.

The Table 5.14 shows the expected NPV obtained by the optimizations without future information and compare it with the optimization strategy proposed in this thesis that incorporate future information using 4, 8 or 74 time steps. We can observe that the incorporation of future information still allows us to have increased revenue and the gain obtained are higher when we use more optimization time steps, as expected. Comparing the ENPV obtained by the base case and by the optimization with and without future information, we can note that incorporate future information allows higher gains. For all cases performed with future information the profits obtained exceeds US$ 33 x10^6 and the use of 74 time steps returns higher expected NPV. Despite the use of 74 time steps the expected value is higher, it also requires a huge number of evaluations compared with the use of 4 and 8 time steps, as shown Table 5.15.

Table 5.14: Economic comparison between the base case and the optimization strategies with and without future information, considering 4, 8 or 74 time steps.

Number of time steps	Strategy *without* future information ENPV (US$ x 10^6)	Gain in ENPV (US$ x 10^6) compared with base case	Strategy *with* future information ENPV (US$ x 10^6)	Gain in ENPV (US$ x 10^6) compared with base case
4	3791.80	19.78	3805.79	33.77
8	3792.67	20.65	3809.41	37.39
74	3791.94	19.92	3812.33	40.31

Table 5.15: Number of evaluations required by each rolling policy, considering 4, 8 or 74 time steps.

Number of time steps	Strategy with future information ENPV (US$ x 10^9)	Number of Simulations Required
4	3805,79	4979
8	3809,41	5792
74	3812,33	14613

5.3.5. Test 8 – Evaluating the measurements influence

In the previous tests the measurements used as future information were: the BHP of each smart wells and the oil and water production rate from the field. Knowing that many others measurements are available during the field development, and that this measurements guide the cluster partitioning, in this test we investigate the influence of measurements on the expected NPV obtained.

The measurements consider in this test are: BHP (bottom hole pressure) from the smart wells, OPR (oil production rate) and WPR (water production rate), both from the smart wells or the field. We preliminarily evaluate some sets of these measurements from the field and from the smart well, according first column of Table 5.16. On the optimization strategy, we used the rolling-flexible-*k* policy and the time horizon was divided in 8 steps. These parameters were chosen based on the results found by the last two tests. The Table 5.18 shows the expected NPV obtained by the optimizations varying the set of measurements. Analyzing the results obtained using the different sets of measurements, we can note that well`s measurements have great influence on the expected NPV. The expected NPVs obtained was compared with the optimization strategy without future information and the profits obtained exceed US$ $16 x 10^9$.

Table 5.17 shows the expected NPV obtained by the base case and by the optimization with future information, where the base case represents the alternative with conventional wells. Using only the well`s measurements we could found better results than using fields measurements as well, obtaining profits that exceed US$

$37x10^9$. Although we are increasing the number of measurements when incorporating the field measurements, the measurements only from the wells are more relevant to reduce the uncertainty than the combination of field and wells measurements.

Table 5.16: Economic comparison between optimization strategies varying the measurements used.

Measurements		Strategy without future information ENPV (US$ x 10^9)	Strategy with future information ENPV (US$ x 10^9)	Profit ENPV (US$ x 10^9)
Field	Smart Well			
WPR + OPR	BHP + WPR + OPR	3792,67	3809,41	16,74
---	BHP + WPR + OPR	3792,67	3813,38	20,71

Table 5.17: Economic comparison between the base case and the optimization strategy varying the measurements used.

Measurements		Base Case ENPV (US$ x 10^9)	Strategy with future information ENPV (US$ x 10^9)	Profit ENPV (US$ x 10^9)
Field	Smart Well			
WPR + OPR	BHP + WPR + OPR	3772,02	3809,41	37,39
---	BHP + WPR + OPR	3772,02	3813,38	41,36

5.3.6. Test 9 - Increasing the number of time steps with influential measurements

On the previous tests, we checked the influence of number of time steps and the measurements influence. We could observe that increasing the number of time steps we can also increase the expected NPV and the last test show us that is better to consider just oil and water production by the smart wells instead to use field and smart measurements. Therefore, in this test we again investigate the influence of number of time steps, but now we just consider the smart wells' measurements as future information.

We investigate the impact of the frequency with which measurement information is obtained and decisions are made. With the uncertainty model now predicting higher well productivities, we find that intelligent completions bring value even without future information. As shown in Figure 5.24, even at early times before measurement information is available, the expected final NPV shows a gain of over 20 million USD compared to the base case with conventional completions. Figure 5.24 also shows that a similar gain is also achieved due to the reactive adjustment of the valve controls over time in response to future measurement information. As shown, this gain in value depends on the number of time steps at which the measurement information is taken and that the potential for adjusting the valve settings exists. With only 4 steps, our ENPV is 5 million USD lower than the ENPV that can be obtained when the maximum 74 steps are considered. With 8 steps we obtain a final value that is close to that which we obtain with 74 steps, and the gain in ENPV as new information becomes available occurs during a similar time period.

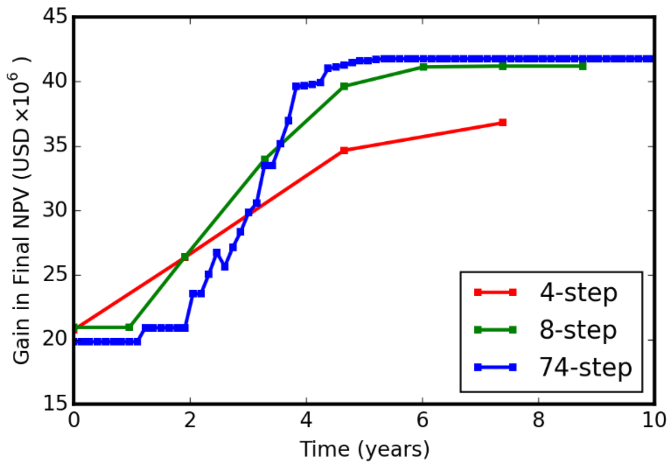


Figure 5.24: Total gain in the final expected NPV as a function of the information available over time. Shows the results obtained with a rolling-flexible-2 approaches with 4, 8 and 74 steps, compared to a base case with conventional completions.

The final expected NPV obtained, and the number of reservoir simulations that were required for applying the methodology with each different number of time steps is shown in Table 5.18. Although the number of reservoir simulations required increases with the number of time steps considered, the increase is sublinear, with large increases in the number of time steps to be considered leading to modest increases in the number of reservoir simulations. This is because we are not required to reoptimize the controls at every time step unless the clustering of the models changes. As the number of time steps becomes large, the number of reservoir simulations required depends on the decision resolution and the number of representative models used to capture the reservoir uncertainty, rather than the number of time steps selected. It is therefore feasible to consider altering the valve settings as often as report steps are generated from the reservoir simulation (every 50 days for our case). With fewer time steps, it may be possible as shown in Table 5.18 to obtain a strategy that yields a similar expected NPV with somewhat fewer reservoir simulations.

Table 5.18 ENPV gain and total number of reservoir simulations required for each of the approaches shown in Figure 5.24

Number of time steps	Gain in ENPV (\$US x 10^6)	Number of reservoir simulations
4	36.8	7128
8	41.2	12935
74	41.8	20041

To aid in understanding the impact that the number of time steps has on the methodology, it is useful to visualize the full decision tree that the methodology yields as a by-product of valuation. In Figures 5.25-27 we show visualizations of the decision tree created for each of the cases shown in Table 5.20. The horizontal axis represents the passage of time as measurements are obtained and decisions are taken. Each line represents a different cluster of models, with the thickness of the line showing the number of models that the cluster represents (and therefore the likelihood that this cluster represents the true reservoir properties). The connections between the lines show the topology of the decision tree. The color of each cluster represents the percentage gain in the final NPV (based on only the present information), compared to the base case with conventional completions. The numbers at the end (leaf) of each branch of the decision tree represents the representative model number used within the methodology. This case is based on a rolling-flexible-2 approach, with a total of 4 time steps for reactive control. These visualizations depict the topology of the tree and show at what times decisions are taken, in addition to showing the percentage gain in NPV that each cluster provides. For both 4 and 8 time steps the initial behavior of the trees are very similar, with similar controls and the same initial clustering after 700 days (the end of the first and second steps in the 4 and 8 step schemes respectively). After this time the results begin to diverge and the topology of the decision tree differs.

In all of the decisions trees it is noticeable that we almost completely resolve the uncertainty by the end of the 10 year period under study. Indeed, there is only one situation where this is not the case - with only 4 steps we are unable to distinguish between models ‘2’ and’38’.

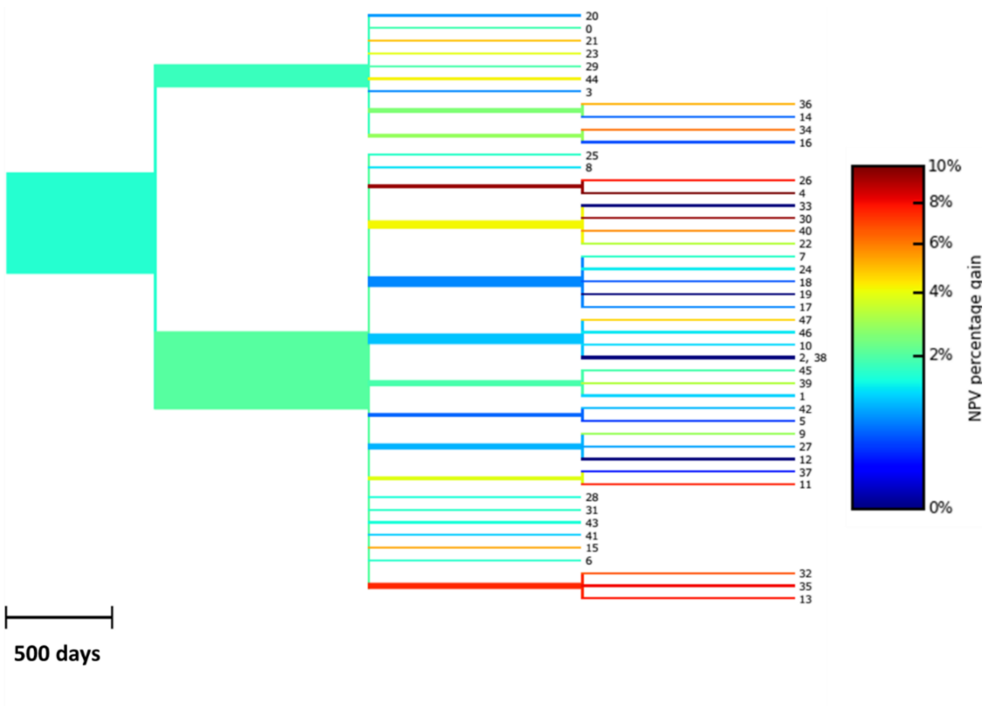


Figure 5.25. An illustration of the decision tree created as part of the rolling optimization procedure.

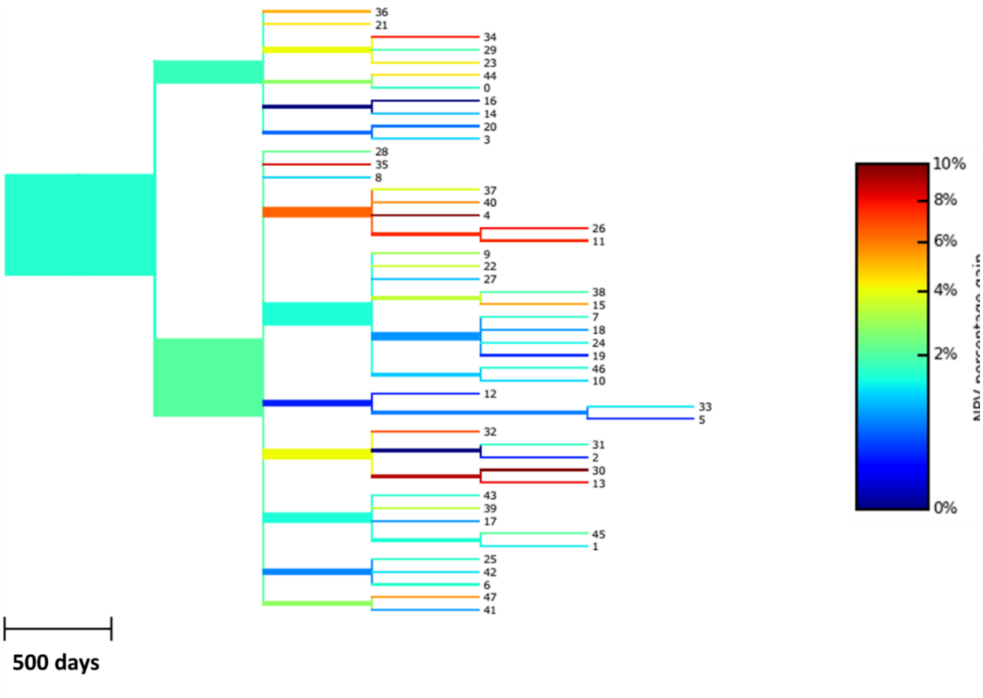


Figure 5.26: Identical plot to Figure 5.25, but with a total of 8 time steps for reactive control.

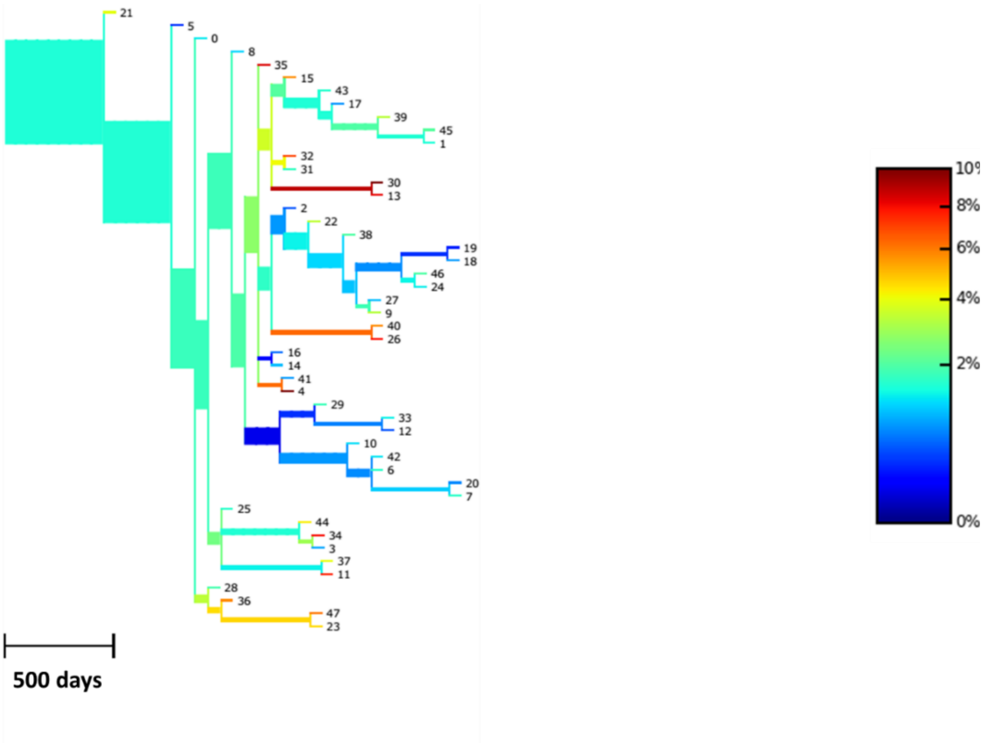


Figure 5.27. Identical plot to Figure 5.25, but with a total of 74 time steps for reactive control.

5.4. Case 4 – Validating the results of the methodology

Since we are proposing an approach that incorporate approximations and clustering, we want to know how reliable are the numbers that represent the value of flexibility and for that reason we need to validate the approach. For that we can split the set of uncertainty scenarios in two groups (drawn from the same distribution), that we call optimization models group and test models group. The optimization models group is a collection of geological models, representing the real reservoir uncertain, used to estimate the value of flexibility and create the playbook (with the flow control settings and reservoir clusters) that maximize the net present value over the time horizon, allowing to value the flexibility. The test models group is another collection of geological models (that was not present on the optimization process), also representing the real reservoir uncertain and that came from the same distribution of the optimization models group, that will be used to apply the playbook (from the optimization process) following the control setting previous optimized according the changes of the reservoir behavior over the time. We call this process, using the test models group, as validation test. Such a procedure forms the basis for validation as we present.

A thorough study of the valuation and validation methodology requires a large number of optimizations and reservoir simulations, with the entire workflow repeated for multiple different numbers of training models and values for the decision resolution. While it is possible to achieve this using simple reservoir simulation studies, the computational cost of numerical simulations will be significant, and in practice it may not be possible to completely remove random noise as the number of uncertainty scenarios required must be limited by constraints imposed by availability of computational facilities. We therefore first consider a thorough study of valuation and validation using a simple toy problem. As we need to generate a big set of uncertainty scenarios without expensive optimization to determine the control, we choose to use a modified version of the canonical tank model that is easily optimized and provides opportunity for consider complex uncertainty scenarios.

5.4.1. Multiple tank model

A schematic of the proposed continuous version of the tank model is shown in Figure 5.28. As in the “toy” model described on Section 5.1.1, in this one the water is introduced into the bottom of the tank, with the tank initially containing a certain volume of oil in the top of the tank. Rather than producing from a limited number of taps that each produce either water or oil, we instead produce from one side of the tank with the production rate of each fluid proportional to the exposed area of the fluid. The area of the fluid that is exposed on this side of the tank may be adjusted by a single, continuously-variable control that prevents flow from the lower region of the tank.

One significant difference between this simple tank model and the real problem in the reservoir is the number of uncertain parameters. The single tank model has only one uncertain parameter - the initial level of the oil-water contact. The number of measurements is equal to the number of uncertainties, and so measurements allow us to directly resolve the uncertainty. This behavior is completely unlike most of the uncertainties that we encounter in the reservoir problem. One method of increasing the number of uncertain parameters is to consider multiple tanks simultaneously. The tanks can be coupled by combining their productions into a single manifold, with it only being possible to measure the comingled production from the manifold, and not the production from individual tanks. This seeks to represent the reservoir behavior in which it may not be easy to continuously monitor the production from individual flow control valves and we may instead only be aware of the total production per well or across the field.

It is also possible to consider some statistical correlation between the water levels in the multiple tanks. This seeks to represent the similar statistical correlations of the uncertain reservoir properties. As the production from each of the tanks is independent, the optimal control can be determined using the method of the previous section once a probability distribution for the initial level of water in the tank has been determined. As measurements lead to clustering, the probability distribution for the current level of water in the tank is modified. We can then recalculate the optimal controls for each tank.

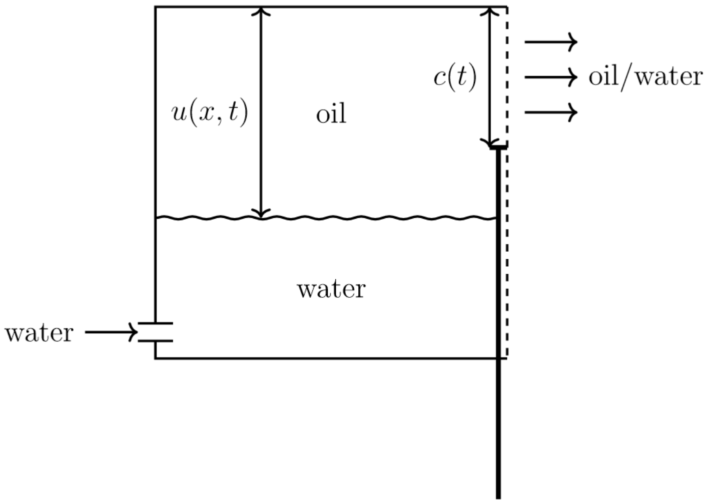


Figure 5.28: Schematic of continuous tank model

We consider one particular case with eight tanks as shown in Figure 5.29. The production from the first four and last four tanks is commingled and we are able to measure the commingled accumulated productions, i.e. Equation 5.3 and 5.4, with similar expressions for the accumulated productions of water. Using accumulated production as our measured quantity has several advantages. Firstly, it may be more representative of the real behavior in production scenarios, where it may take some time to be able to accurately measure the production rates; secondly, it somewhat relieves the situation where this continuous tank model immediately yields information about the water levels within the tanks which would not happen for a real reservoir model.

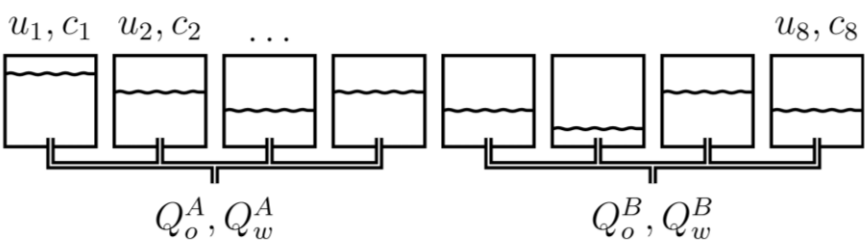


Figure 5.29: Schematic of continuous tank model

We need to develop a model for the uncertain initial water levels within the tanks. We assume that the water level within each tank is uniformly distributed, but we also allow for the possibility that the water levels within the tanks are correlated.

More specifically we use a Gaussian copula (Li et al, 2012) to model the correlation between the water levels in the tanks. The correlation matrix used within the Gaussian copula assumes that the correlation between neighboring tanks is ρ (and e.g. the correlation between tanks 1 and 3 is ρ^{2}, etc.). By varying the correlation parameter ρ between 0 and 1, we can change between non-correlated and fully correlated water levels.

$$Q_o^A = \int_o^t q_{o,1} + q_{o,2} + q_{o,3} + q_{o,4} \, \mathrm{d}t \tag{5.3}$$

$$Q_o^B = \int_o^t q_{o,5} + q_{o,6} + q_{o,7} + q_{o,8} \, \mathrm{d}t \tag{5.4}$$

We intend to apply the developed rolling flexible methodologies to this problem. We therefore need to consider clustering of models based on measurement data. As measurements we use the accumulated commingled oil productions, Q_o^A, Q_o^B. Since given that the controls are known the total volume of produced liquid is known, the water productions do not give any extra information. Using the accumulated production rather than the production rates ensures that it takes time to learn about the uncertainty state, which is a feature that is often present in the real reservoir problem, but which would not otherwise be present in this simple tank model.

5.4.2. Test 10 – Maintaining uncertainty to increase robustness

As mentioned in the description of the methodology, the proposed approach uses the measurements assimilation to reduce uncertainty over the time, where each measurement considered will have an associated “decision resolution”. The decision resolution, in this work, represents both the accuracy of the measurement and also our policy in how much variation or change is needed in a particular measurement in order to motivate the engineer to make a decision. Since the measurement accuracy limits our ability to use measurement information to resolve model uncertainty, in this test we are particularly interested in the impact of the measurement decision resolution on the resulting expected NPV, since this corresponds to the value of having more accurate measurement data.

We therefore apply the rolling flexible methodology for various values of the decision resolution, also varying the correlation parameter ρ and the number of samples used as uncertainty scenarios within the methodology. We have fixed the cost of producing water, $\alpha = 0.5$ and the discount rate, $r = 0.09$. The results are shown in Figure 5.30 as the ‘in-sample’ curves. For all correlation parameters and numbers of samples, decreasing the decision resolution increases the expected NPV as calculated by the rolling flexible methodology, and for a decision resolution greater than around $2m^3$ no information is gained and so there is no further change in the expected NPV as the decision resolution increases. When all of the initial water levels are equal we appear to be approaching a maximum value as the decision resolution approaches zero; however, in the other cases it appears that we would need to reduce the decision resolution still further to show such behavior. The impact of the number of samples used is fairly limited, particularly when there is correlation between the initial water levels.

We can observe that as we increase the decision resolution, the expected value decreases. This behavior can be explained by the proportionality between decision resolution and the decision making under uncertainty, i.e., if we are using a large decision resolution the uncertainty there is a large delay for resolving uncertainty and consequently we continue to optimize over a large set of uncertainty scenarios.

In the previous test we note that as we increase the decision resolution, we decrease the expected value obtained because the uncertainty carried out over the time horizon. In this test we want to investigate how reliable are the optimization values that we have been obtained so far, i.e., we want to validate the flow control strategy and the expected value obtained by our proposed approach.

The resulting expected NPV from the rolling flexible methodology is calculated using the same samples that have been used to optimize the controls. Such an approach could be over-estimating the expected value if the number of samples used is not sufficient for the methodology. We therefore apply the validation methodology with new `out-of-sample' validation models, drawn from the same distribution (with the same Gaussian copula) as that used to provide the training models. We continue to generate new out-of-sample validation models until our estimate of the validated expected NPV has converged.

These out-of-sample estimates are shown in Figure 5.30 as the `out-of-sample' curves. Where there is perfect correlation between the initial water levels, the in-sample and out-of-sample curves are essentially identical. In this case, the measurements allow us to perfectly capture the uncertainty and it is easy for the uncertainty scenario to capture all of the uncertainties. As we decrease the correlation between the initial water levels we find that at small values of the decision resolution the in-sample and out-of-sample estimates no longer agree. This difference becomes more pronounced as the correlation becomes weaker.

Note that we also notice a small difference between some of the in-sample and out-of-sample estimates for large decision resolutions when only 1000 uncertainty scenarios are used for training. This difference represents the error in the Monte-Carlo estimate of the expected NPV when only 1000 uncertainty scenarios are used - the out-of-sample estimate shows the true value as for this calculation keep generating samples until the Monte-Carlo estimate converges.

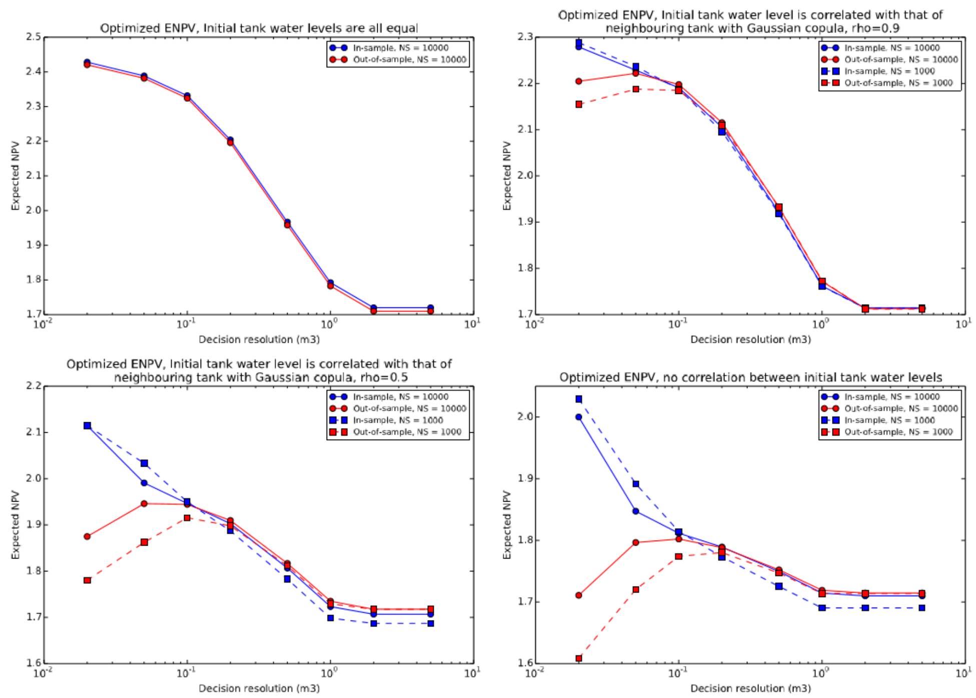


Figure 5.30: Plots of ‘in-sample’ and ‘out-of-sample’ estimates of the expected NPV as determined by the rolling flexible method, with variation in: the decision resolution; the number of uncertainty scenarios used within the rolling flexible method (NS); and ρ, the correlation between the initial water levels in the tanks.

There is also an impact of the number of uncertainty scenarios used to build the decision tree. As more uncertainty scenarios are used, the validity of the `in-sample' result continues for lower values of the decision resolution. For a fixed number of uncertainty scenarios, it appears that there is an optimal choice for the decision resolution that maximizes the out-of-sample estimate of the ENPV. This value serves as a compromise in which we wish to choose a value that is small enough so that we recover information from the measurements, but large enough so that we do not produce excessive clustering as a result of an incomplete model of the uncertainty. In principle, it seems likely that with enough uncertainty scenarios used to train the decision tree, that the value obtained from training would be equal to that obtained by validation; however, the improvement in the accuracy of the valuation is fairly minor given the large increase in the number of uncertainty scenarios. In practice, there is therefore a minimum value for the decision resolution, below which the number of uncertainty scenarios required for an accurate and optimal answer becomes very large.

Determining an appropriate value for the decision resolution for every case, reflecting the extent to which the measurements genuinely inform about resolution of model uncertainty and relevance to optimal controls, may be difficult. The difference between the value obtained for in-sample and out-of-sample valuations can be ascribed to `ensemble collapse' in which we are optimizing a small group of models, or possibly even a single model, that is not representative of uncertainty scenarios that yield similar measurement values. Rather than attempt to avoid this ensemble collapse by increasing the number of uncertainty scenarios for training, or by carefully tuning the decision resolution, we can instead proscribe such small groups of models as a step within the clustering algorithm.

As shown in Figure 5.31, adjusting the minimum number of models used shows a similar impact on the calculated values to that of adjusting the decision resolution. By setting the minimum number of models allowed in a cluster to 10, we obtain a similar value for the expected net present value in both training and validation sets, and this value is close to the optimal value that can be obtained with this number of samples. However, unlike the decision resolution we do not need any specialized knowledge about the impact of the measurement on uncertainty resolution. We therefore expect that the restriction to a minimum number of models will be appropriate for a wide range of studies. We also expect that restricting the minimum cluster size to 10, should ensure that we always have sufficient models to fully characterize the residual uncertainty within each cluster and avoid ensemble collapse.

By enforcing a minimum size for the clusters we avoid ensemble collapse, and thereby yield a strategy that is truly robust to uncertainty with a reliable valuation. However, we should also maintain the original definition of the decision resolution, since it is still important that clusters can be clearly distinguished by available measurement data. The limited number of uncertainty scenarios used to train the decision tree may lead us to underestimate the true value, and produce a development strategy that is robust but sub-optimal, but this is preferable to an overestimation of the value and a non-robust development strategy.

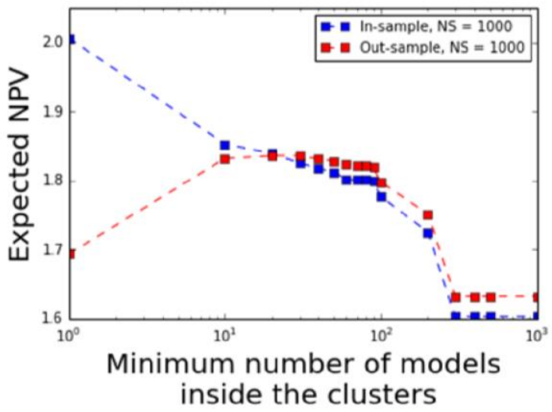


Figure 5.31: Plots of ‘in-sample’ and ‘out-of-sample’ estimates of the expected NPV as determined by the rolling flexible method as a function of the minimum number of models that are required for each cluster. For this example ρ = 0.5.

5.5. Case 5 – Checking approach responses by the use of representative models

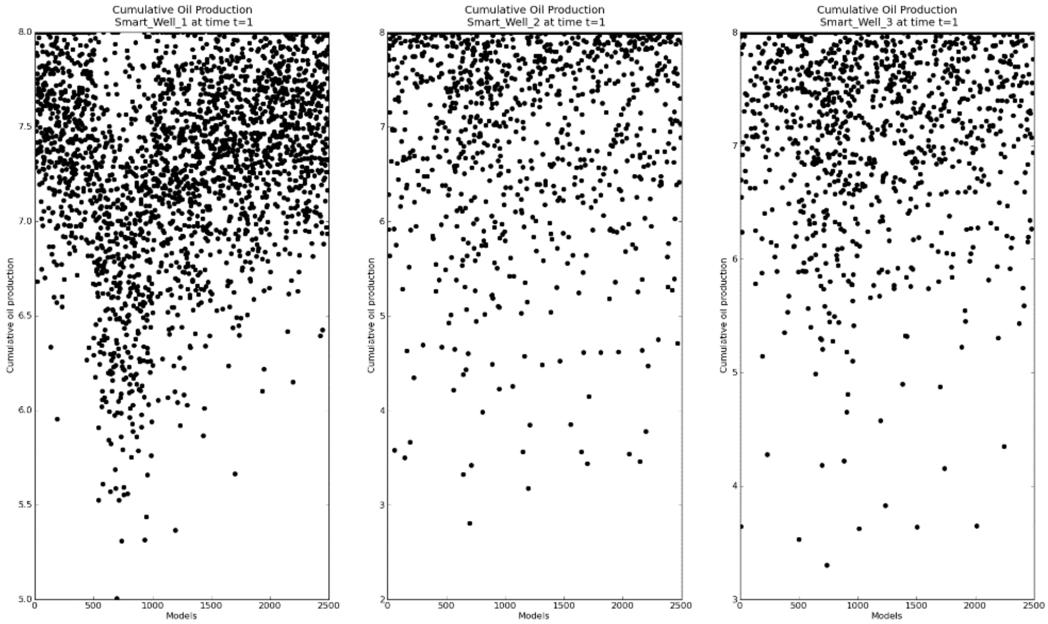
The expected value obtained is sensitive to the number of uncertainty scenarios used. On the previous tests, using the multiple tank model, we could note that there was a small difference between some of the in-sample and out-of-sample estimates for large decision resolutions when we increase the number of uncertainty scenarios used for training (optimization). As the number of uncertainty scenarios increases, the error on the expected optimization-validation value is reduced. This may indicate that considering a large set of uncertainty scenarios to create the flow control strategy can lead us to an impractical approach.

This study case was done in order to check the performance of our approach when we drastically increase the number of uncertainty scenarios from 50 to 400 geological realizations. As described on the previous chapter, we can also apply the proposed approach without to evaluate all uncertainty scenarios during the optimization, and the next test evaluates how much this approximation can influence the optimization and the validation expected values.

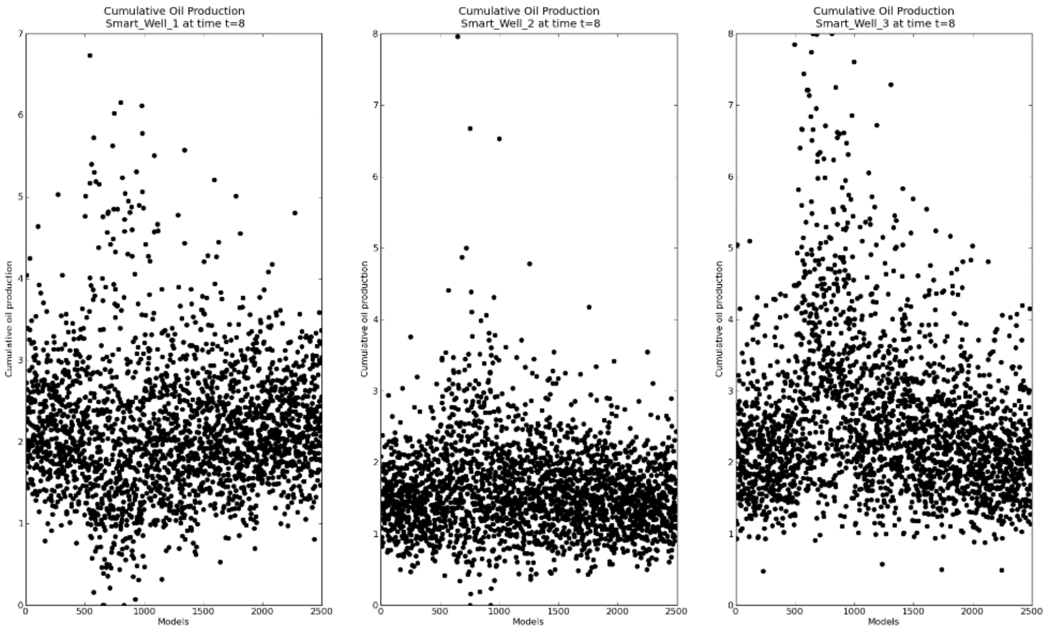
5.5.1. Test 11 – Representative models for optimization

To consider a large ensemble of uncertainty scenarios we again intend to use the UNISIM model, as we have available 500 geological models. All previous tests on the UNISIM case study used around 50 models, but on the previous tests to validate the flow control strategy we could note that increasing the number of uncertainty scenarios considered allow us to reduce the error between the valuation and the validation.

First, we again evaluate the uncertainty behavior to select a set of uncertainty scenarios that can have better response by the use of smart wells. For that we compare the oil and water production by the smart wells, but considering the valves fully open, i.e., without any flexibility. We can compare by Figure 5.32-32 the oil and water cumulative production by all geological models at initial and later time. The production information is presented by smart wells, in order to identify the cases where this king of technology could be more promising. Knowing that smart wells can have a good response when applied for reduce the water production, we choose to use the a set of geological models with higher cumulative water production in later time, and this represent all set of geological models with the higher relative permeability (the models named by 2000 and 2500). Although, there is not a way to optimally define the number of uncertainty scenarios to consider, we choose 500 models, thinking that this amount could be big enough for do not over-estimate the expected value, what can happen if the number of samples used is not sufficient for the methodology.

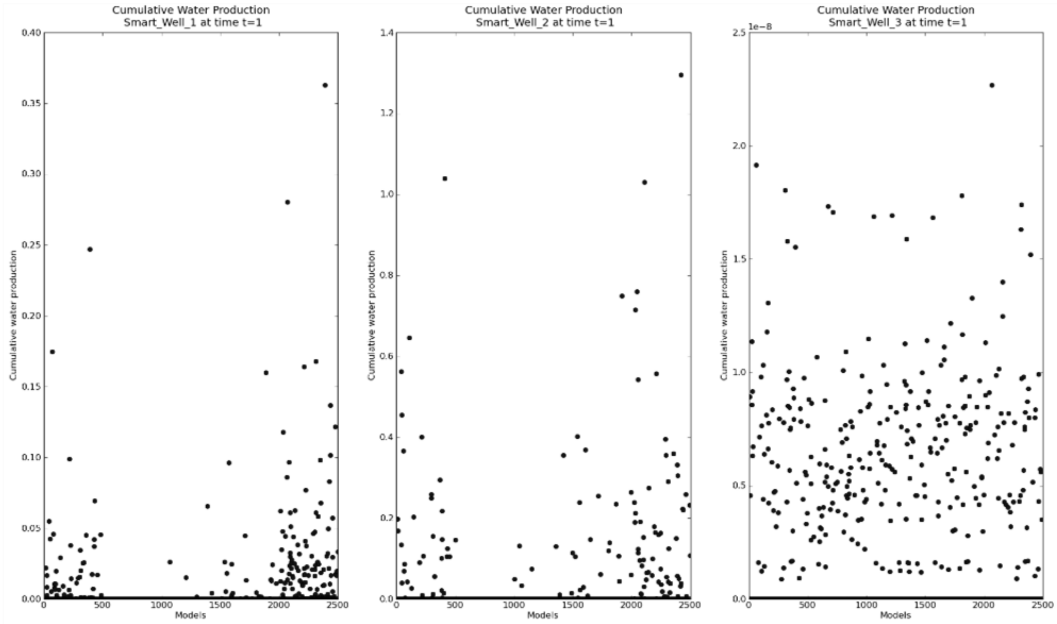


a) Cumulative oil production after the first time step

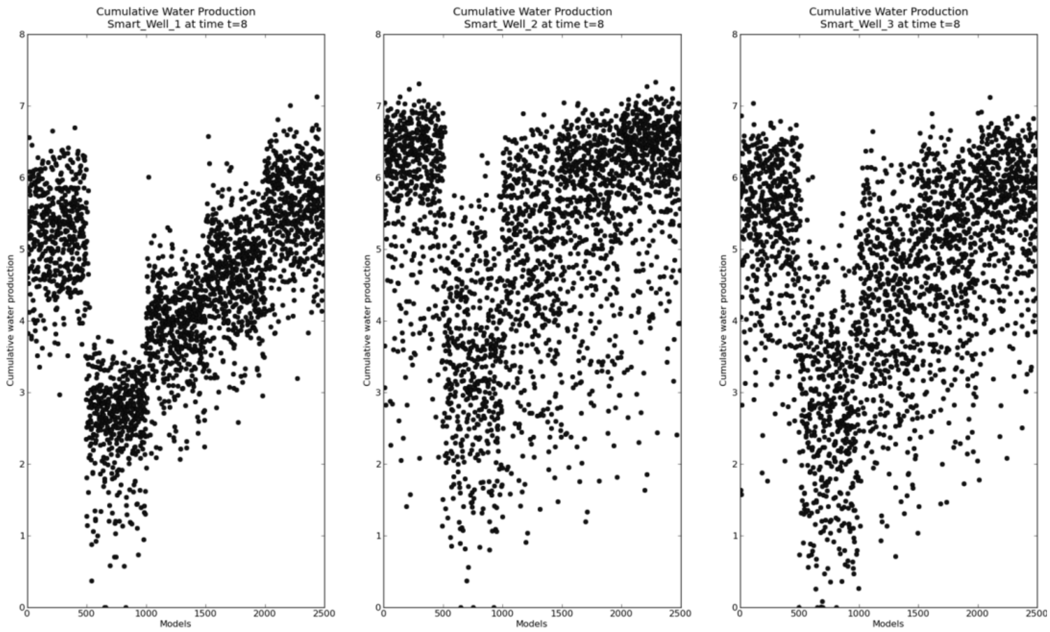


b) Cumulative oil production after the last time step

Figure 5.32 Comparing the cumulative oil production by the smart wells at the beginning and the end of the time horizon.



a) Cumulative water production after the first time step



b) Cumulative water production after the last time step

Figure 5.33 Comparing the cumulative water production by the smart wells at the beginning and the end of the time horizon.

Once we choose the 500 geological scenarios we randomly divided them into two groups: the in-sample models (that will be used on the valuation, to provide the flow controls strategy) and the out-sample models (that will be used to validate the results, applying the flow control strategy, hypothetically, as in a real reservoir situation). The follow tests consider 400 geological scenarios as in-sample models and 100 geological scenarios as out-of-sample models.

In order to reduce the expended computational time required by optimization to then create the flow control strategy, in this test we make use of representative models during the optimization, as proposed and described in the previous chapter. We remain that the representative models are choose at each time step by economics gain to be evaluated during the optimization step and once the flow control strategy is defined we incorporate all uncertainty scenario available, applying the best flow control strategy found and simulated to reduce the uncertainty by future measurements. The follow tests consider 9 representative models to optimize the controls.

As we mentioned, in this test we will use 400 uncertainty scenarios in our in-sample group, that will be used to generate the flow control strategy and we compare the optimization response varying the minimum number of uncertainty scenarios maintained in the clusters. We consider to use 10, 20 and 100 scenarios by the in-sample group as the minimum number of models per cluster, enforcing a minimum size for the clusters. We therefore apply the validation methodology with new 100 'out-of-sample' validation models.

As on the previous tests with the UNISIM models, this one uses the same reservoir development plan described on Section 5.3.1, with 18 vertical wells. Production is planned for 10 years, and the time horizon is divided in 8 time steps. The optimization strategy parameters was choose by the previous promising results. We use the rolling strategy with k=2, considering oil and water production by the smart wells as future measurements. Table 5.19 shows the results obtained by optimization and validation procedures varying the minimum size for the clusters. We can note that increase the minimum size for the clusters leads to decrease the expected value by optimization.

Even we have more robust optimizations, considering big sets of uncertainty scenarios on the optimization, we can get similar answers using a smaller amount of representative models. This is because in our approach since we find the optimum control by a small set of uncertainty models, we always apply the optimum results at time for all uncertainty scenarios available to then reduce the uncertainty by future simulated measurements. This allows us to reduce the number of evaluation required by optimization without loose big improvements on the expected optimization value.

Table 5.19: Expected valued obtained by optimization (considering in-sample models) and validation (considering out-sample models) procedure, with variation of representative models used by optimization.

Number of Representative models used by optimization	Expected Value by Optimization (US$E+06)	Expected Value by Validation (US$E+06)
10	3410	3462
20	3408	3463
100	3405	3462

On the other hand, Table 5.19 also shows the expected value obtained by the validation procedure, when we apply the complete flow control strategy found by optimization to new uncertainty scenarios, which was not included on the optimization process, and simulate them as a real reservoir situation following the control strategy proper to the scenario behavior. We can see that even considering different minimum size for the clusters we could find similar expected results by the validation.