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Abstract

Optimal field development and control aim to maximize the economic profit of oil and gas production. This, however, results in a complex optimization problem with a large number of correlated control variables at different levels (e.g. well locations, completions and controls) and a computationally expensive objective function (i.e. a simulated reservoir model). The typical limitations of the existing optimization frameworks are: (1) single-level optimization at a time (i.e. ignoring correlations among control variables at different levels); and (2) providing a single solution only whereas operational problems often add unexpected constraints likely to reduce the 'optimal', inflexible solution to a sub-optimal scenario.

The developed framework in this paper is based on sequential iterative optimization of control variables at different levels. An ensemble of close-to-optimum solutions is selected from each level (e.g. for well location) and transferred to the next level of optimization (e.g. to control settings), and this loop continues until no significant improvement is observed in the objective value. Fit-for-purpose clustering techniques are developed to systematically select an ensemble of solutions, with maximum differences in control variables but close-to-optimum objective values, at each level of optimization. The framework also considers pre-defined constraints such as the minimum well spacing, irregular reservoir boundaries, and production/injection rate limits.

The proposed framework has been tested on a benchmark case study, known as the Brugge field, to find the optimal well placement and control in two development scenarios: with conventional (surface control only) and intelligent wells (with additional zonal control using Interval Control Valves). Multiple solutions are obtained in both development scenarios, with different well locations and control settings but close-to-optimum objective values. We also show that suboptimal solutions from an early optimization level can approach and even outdo the optimal one at the higher-level optimization, highlighting the value of the here-developed multi-solution framework in exploring the search space as compared to the traditional single-solution approaches. The development scenario with intelligent completion installed at the optimal well location and optimally controlled during the production period achieved the maximum added value. Our results demonstrate the advantage of the developed multi-solution optimization framework in providing the much-needed operational flexibility to field operators.

Introduction

Well location and control settings are critical decisions that need to be made during field development and production optimization studies in order to maximize the economic profit of oil and gas production. Several efforts have been made to develop efficient frameworks to optimize the system with one or multiple types of such decision variables (in this paper we refer to optimization on different variable types as different 'levels'; e.g. the well location optimization is one level and the well production/injection control optimization is another level). Single-level optimization workflows were initially developed to optimize variables at a particular level only, such as well locations (Awotunde and Naranjo 2014, Bangerth et al. 2006, Al-Ismael et al. 2018, Wang et al. 2012) or control settings (Li and Reynolds 2011, Wang et al. 2002, Wang et al. 2015, Haghighat Sefat 2016, Lu et al. 2017b, Wang et al. 2019). These were later extended to multi-level optimization aiming to achieve an optimal solution at multiple levels (e.g. drilling order, well type, location, and control settings) by considering correlation between the variables during the optimization process (Li et al. 2013, Tavallali et al. 2013, Forouzanfar et al. 2016, Shirangi et al. 2018). Current multi-level optimization techniques can be classified as:

1) Joint optimization (Li et al. 2013, Tavallali et al. 2013, Isebor, Durlofsky, et al. 2014, Shirangi et al. 2018): simultaneously optimizing a single augmented vector of all the control variables from all levels (e.g. all well locations and control settings). This, however, could result in optimization algorithm failure due to a large number of control variables.

2) Sequential optimization (Li and Jafarpour 2012, Forouzanfar et al. 2016, Lu et al. 2017a): techniques have been developed to reduce the number of control variables by dividing the main problem into sub-problems, where each sub-problem contains single-type control variables related to an individual optimization level. The field design is iteratively optimized as a sequence of such sub-problems (in order to capture the correlation between the control variables) and the loop is terminated when no major improvement is observed in the objective value (Li and Jafarpour 2012).

Both the gradient-based and the derivative-free algorithms have been used in field development and production control optimization studies. The adjoint gradient –based method has been shown to be computationally fast (Sarma et al. 2005, Kraaijevanger et al. 2007, Bukshtynov et al. 2015) and has been employed in field development studies using in-house reservoir simulators (Brouwer and Jansen 2002, Sarma et al. 2005, Van Essen et al. 2011). However, calculation of the adjoint gradient requires access to the subsurface flow simulation source code, hence this approach cannot be easily used with many commercial, reservoir flow simulators. Alternative algorithms have been developed, that use an estimation of the gradient calculated using black-box simulators, to iteratively move the control state in the approximately optimum direction (Lu et al. 2017b, Sefat et al. 2016). The estimated gradient is approximately calculated using an ensemble of simultaneous perturbation of the control variables. These include Simultaneous Perturbation Stochastic Approximation (SPSA) (Spall 1998), and different variations of Ensemble based Optimization (EnOpt) (Chen et al. 2009) such as the Stochastic Simplex Approximate Gradient (StoSAG) method (Fonseca et al. 2017). SPSA has been used in well placement (Li et al. 2013, Bangerth et al. 2006) and control settings (Sefat et al. 2016) optimization problems, showing its efficiency in handling a large number of variables. StoSAG has been also successfully employed in well control problems (Lu et al. 2017a, 2017b) and has been shown to outperform the classic EnOpt, developed by Chen et al. (2009), in large scale robust optimization problems (Lu et al. 2017b). Gradient-based methods can provide computational advantages in terms of efficiency. They, however, have issues with handling categorical (e.g. well type) variables. Derivative-free optimization (DFO) methods have also been used in the context of field development and control. These include Particle Swarm Optimization (PSO) (Eberhart and Kennedy 1995, Ciaurri et al. 2011, Isebor, Echeverría Ciaurri, et al. 2014) and Genetic Algorithms (GAs) (Holland 1992, Stoisits et al. 2001, Almeida et al. 2010). These methods can handle all types of variables (e.g. categorical, integer, continuous). However, they typically require many more function evaluations than gradient-based algorithms (Zingg et al. 2008). The application of these approaches are described by Tavallali et al. (2018), Lu and Reynolds (2019), Onwunalu and Durlofsky (2010), Panahli (2017), Stoisits et al. (2001), Ciaurri et al. (2011), and Almeida et al. (2010).

This work investigates field development and control optimization in a relatively large-scale problem by employing a sequential optimization approach. One of the limitations of the current sequential frameworks is that only a single optimal solution is provided as the output (Figure 1-Left). However, unexpected issues that commonly arise during operation can impose extra constraints, resulting in operators having to come up with a modified and usually sub-optimal scenario. For instance, the well location solution provided by the optimization algorithm could be impractical (or difficult) to drill, due to the deviation of the well trajectory from the planned trajectory, caused by tools/operational errors. This necessitates the development of a multi-solution framework to provide the much-needed operational flexibility to field operators. Previous works (Sefat et al. 2016, Fonseca et al. 2014) showed that the search space in optimization problems with a large number of control variables contains several local optima with objective values close to each other. Therefore, an efficient optimization framework can explore the search space to identify multiple solutions with distinctly different values of the control variables but still with the close-to-optimum objective values. The developed framework in this study is based on the iterative sequential approach (Li and Jafarpour 2012), however, an ensemble of optimal solutions with close to optimum objective values and different variables are transferred between optimization levels (sub-problems), as shown in Figure 1-Right. Fit-for-purpose clustering techniques are developed to systematically select an ensemble of solutions from each sub-problem. SPSA is employed as the optimization algorithm in this work, however, the developed framework is compatible with other optimization algorithms. The SPSA works by randomly perturbing the given vector of control variables several times at every step, with the subsequent averaging of the resulting ensemble's vector and objective function to find the (approximate) steepest decent direction. The developed workflow is tested on a benchmark case study, known as the Brugge field, for two development scenarios: 1) Conventional wells with surface control only, and 2) Intelligent wells with additional zonal control via Interval Control Valves (ICVs) providing a flexible flow control option managed from the surface (Robinson 2003, Sefat et al. 2016).

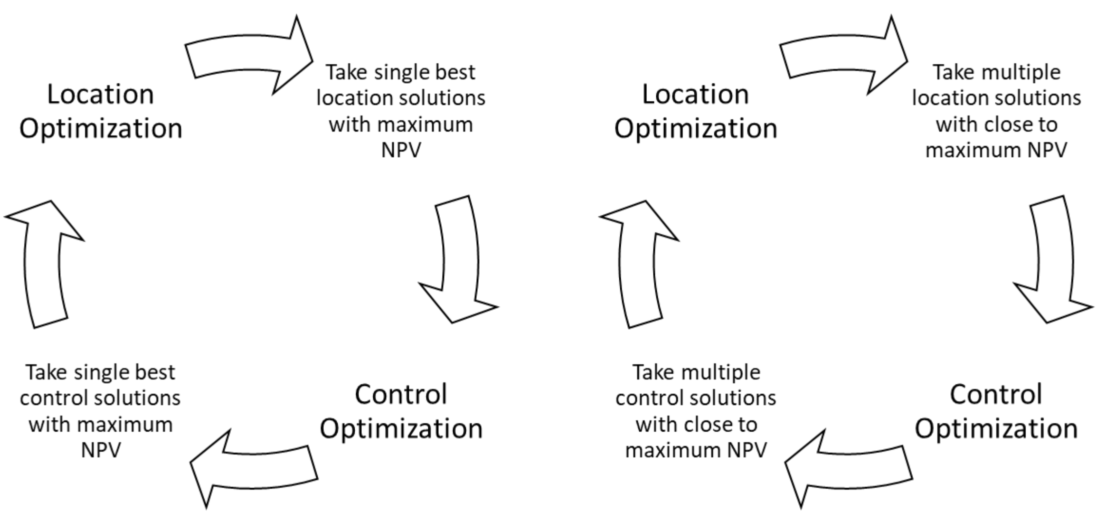

Figure 1-**Left:** Existing single-solution optimization framework for well placement and control, **Right:** Developed multi-solution optimization framework for well placement and control.

The outline of this paper is as follows: first, problem formulation for multi-level optimization of well placement and control is presented. Then, the structure of the developed multi-solution optimization framework is explained, followed by its application to a benchmark case study. Finally, results are presented, and conclusions are drawn.

Problem Formulation

The objective is to maximize the net present value (NPV) of a field for its expected production lifespan. For a given field reservoir model, the NPV is estimated as:

$$J(x,m)=\sum_{n=1}^{S}\left\{\left[\sum_{j=1}^{N_P}\left(r_o q_{o,j}^n - r_{pw} q_{w,j}^n\right)-\sum_{k=1}^{N_I}\left(c_{wi} q_{wi,k}^n\right)\right]\times\frac{\delta t^n}{(1+b)^{t_n}}\right\} \tag{1}$$

where x is the N_x dimensional vector of the optimization variables; m is the N_m dimensional state vector of the reservoir (e.g. saturation, pressure field); n is the n^{th} time step of the reservoir simulation; S is the total number of simulation steps; δt^n is the length of n^{th} simulation step; t_n is the simulation time at the end of the n^{th} time step; the annual discount rate b is in decimal; and N_P and N_I are the number of producers and injectors, respectively. The cost coefficients r_o, r_{pw}, and c_{wi} are the oil price (USD/STB), the water handling cost (USD/STB), and the water injection cost (USD/STB), respectively. $q_{o,j}^n$ and $q_{w,j}^n$ are the oil and water production rates of well j at time step n in STB/day. $q_{wi,k}^n$ is the water injection rate of well k at time step n in STB/day. A simulation run is performed using a commercial reservoir simulator (ECLIPSE-100) (Schlumberger 2017). In this study, Eq. (2) is employed to scale the control variables x from the domain $[x_{min}\ , x_{max}]$ to [0, 1] to eliminate the problem of different type of control variables with different ranges at various optimization levels (sub-problems).

$$u_i=\frac{x_i-x_{min,i}}{x_{max,i}-x_{min,i}} \tag{2}$$

Multi-Solution Optimization Procedure

The developed optimization framework selects an ensemble of representative solutions from each optimization level to be optimized at the subsequent level. The aim is to select an ensemble of close-to-optimum solutions with distinct differences in the values of control parameters from all the optimization iterations performed at each individual level. Hence, these optimal solutions can be treated as suitable realizations of control variable scenarios. Then, a similar approach as the one by Sefat et al. (2016) can be employed to select an ensemble of representative realizations (optimal solutions) from each level, as explained below:

Ensemble Selection: The solutions with 1) low objective function values or with 2) high objective function values but with the decision variable values close to an optimum solution's already selected are not good for the representative ensemble of optimal solutions from each level. Hence, only the representative solutions with distinct difference in decision parameters are selected from the (p%) of the cases with top NPVs. The optimal value of p (p_{opt}) depends on two competing criteria: distinct dissimilarity of the selected solutions, and proximity of the objective value of the selected cases to the maximum NPV. Selecting a large percentage of cases at each level ($p_{opt}\% \rightarrow all\ cases$) captures the maximum diversity between optimization scenarios. However, the selected cases do not all have the potential to achieve the close-to-optimum objective function values after next level of optimization and therefore their use only slows down the optimization speed. In our case a sensitivity study showed that selecting top 20% (by NPV) solutions at each optimization level (i.e. $p_{opt}=20\%$) showed the best performance in both sufficiently capturing the ensemble diversity yet showing a relatively fast optimization speed.

Similarity/Dissimilarity Measure: The similarity/dissimilarity between the selected solutions are measured as a pairwise distance between their corresponding control variable vectors. These control (variable) vectors are normalized into the [0,1] domain using Eq. (2) to alleviate the impact of having control variables of different types and scales. Conventional Euclidean distance is then used to calculate the similarity/dissimilarity between selected ensemble of solutions at the well control optimization level (a similar approach was used by Sefat et al. (2016)). Note that the conventional Euclidean distance of two identical solutions with the well names merely swapped confusingly shows a non-zero distance (or dissimilarity) between them (Figure 2-Left). Hence, a modified measure is employed comparing distances between the reservoir grids with active wells irrespective of the well names (Figure 2-Right).

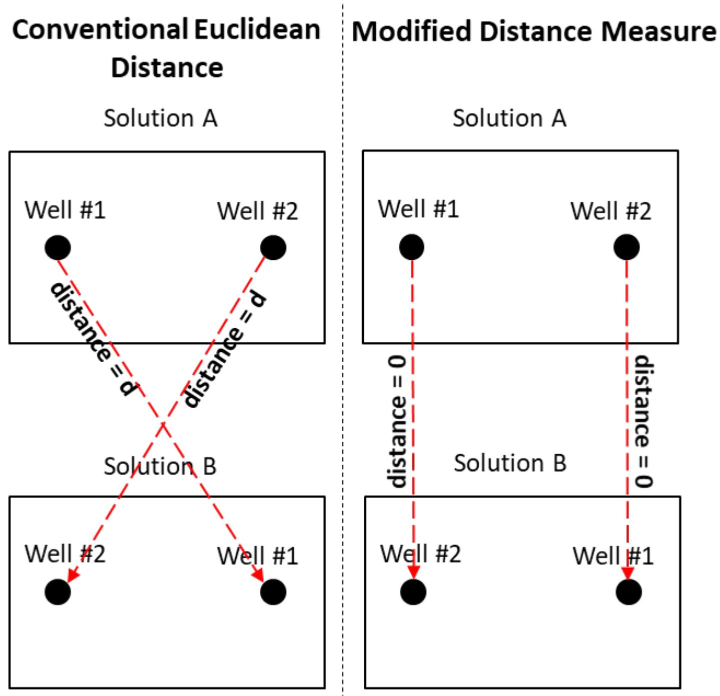

Figure 2-**Left**: Conventional Euclidean distance measure based on well names. **Right**: Modified distance measure based on reservoir grid blocks with active well and irrespective of well names.

Multi-Dimensional Scaling and Clustering: the above similarity/dissimilarity distance measures are used to generate distance matrices of size $ne \times ne$, where ne is the ensemble size of the selected solutions at each optimization level. Multi-dimensional scaling (MDS) is then employed to map the solutions into 2-dimensional space while preserving the characteristics of the data as much as possible (Borg and Groenen 2003, Sefat et al. 2016). Hence, the relative distance between points in 2D space represents dissimilarity of the solution scenarios in the original space. Subsequently, K-means clustering (Seber 2009) is used to group the projected solutions into a smaller number of clusters (N_c). The optimum number of clusters (N_{copt}) is identified by comparing the average silhouette values (Sefat et al. 2016) of all data points for different (N_c), where the maximum silhouette value shows the best clustering performance. A single, representative solution is then selected from each cluster, resulting in N_{copt} solutions as the representative solutions from that particular level of optimization, to be transferred to the next level.

Well Placement and Control Constraints: Maximum and minimum liquid production rate and water injection rate are considered as bound constraints during well control optimization. A minimum inter-well distance constraint is enforced during well placement optimization using the penalty method similar to the one in Lu et al. (2017a). Previous studies (Li and Jafarpour 2012, Bellout et al. 2012, Li et al. 2013, Awotunde and Naranjo 2014, Lu et al. 2017a, Al-Ismael et al. 2018) use inequalities constraints to ensure wells are located within a rectangular domain inside irregular reservoir boundaries. This work accounts for irregular reservoir boundaries by generating a binary matrix with 0 and 1 elements representing null and active reservoir grids, respectively. The well is moved to the nearest active grid if it appears outside the reservoir boundaries during location optimization.

Model Description

Brugge is a benchmark reservoir model developed by TNO based on a North Sea field (Peters et al. 2010). It contains 139 × 48 × 9 grid blocks with a relatively heterogeneous permeability distribution. The original model consists of 20 producers and 10 injectors. Five vertical producers (named $P1$ to $P5$ in the original model) and five vertical injectors (named $I1, I3, I5, I7, I10$ in the original model) are used in this test case due to limited computational resources. Figure 3 shows the top structure of the model with the base case well locations. The wells are completed in all nine reservoir layers. More information on the reservoir rock and fluid properties of the Brugge model can be found in Peters et al. (2010). The objective function NPV (Eq. (1)) is calculated using the economic parameters, as provided in Table 1. 300 iterations are performed at each optimization level to ensure algorithm convergence. While one geological realization is considered in this work, the developed framework can be extended to a robust optimization problem to account for the geological uncertainty in the reservoir model.

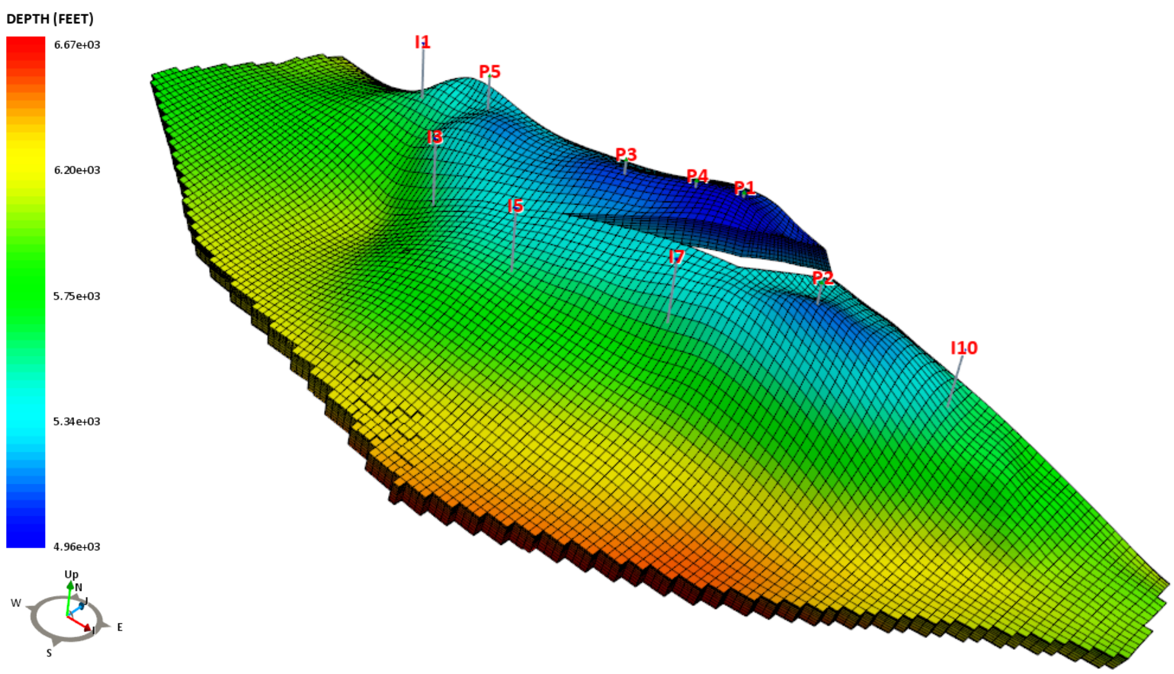

Figure 3-Top structure of the Brugge model.

Table 1-Economic parameters for calculating NPV

Parameter	Value
Oil Price	50 USD/STB
Water handling cost	6 USD/STB
Water injection cost	3 USD/STB
Discount rate	10 %/year

Results and Discussion

Case-1 (conventional well-based field development and control study):

Top (i, j) locations of the vertical wells are optimized during well location optimization over the set of 10×2=20 control variables. The producers are each controlled by its fixed, liquid production rate; while the injectors are each controlled by its fixed, water injection rate, both bounded between 0 and 5000 STB/day. Moreover, the producers are shut when their water cut reaches 90%, because after this WC value the well production is no longer profitable for the oil price and water cost values listed in Table 1. The 30 years of the field production period are divided into six control steps of equal duration (of 5 years) resulting in the total of 10×6=60 well production/injection control variables used in well control optimization.

The NPV of the base case with non-optimal well locations and fully open control settings is 2.111×10^9 USD, which was improved to the maximum value of 2.597×10^9 USD after the first, well location optimization step. The top 20% (by NPV) of the well location optimization solutions ($p_{opt} = 20$) are selected (i.e. 60 out of 300 total iterations) and the dissimilarity matrix is generated using the modified distance measure. Figure 4 shows the projection of the selected solutions into 2D using MDS where each data point represents a well location solution with color showing the NPV. A reasonable degree of variability in the well locations on the sub-set of the solutions is observed while the NPV among them changes within a relatively small range [2.559×10^9- 2.597×10^9USD]. Figure 4 also shows that there are solutions with different well locations but close NPVs confirming that the search space is characterized by different local optima with close-to-optimum objective values.

Figure 5 shows the average Silhouette values of all data points as a function of N_c. Here, the three-cluster set (the red point) is considered to be optimum providing a balance between computation time and clustering performance. The resulting clusters are shown in Figure 6. Selecting one representative solution from each cluster is a critical decision that needs to be made prior to the next level of optimization. Herein, the solution with the maximum NPV in each cluster is selected as the representative of that cluster, considering the objective of selecting solutions with high NPVs. The maximum NPV case (i.e. the solution of the classic sequential approach) is automatically selected as one of the representatives. The representative well placement solutions (L_1, L_2, and L_3) are shown in Figure 7.

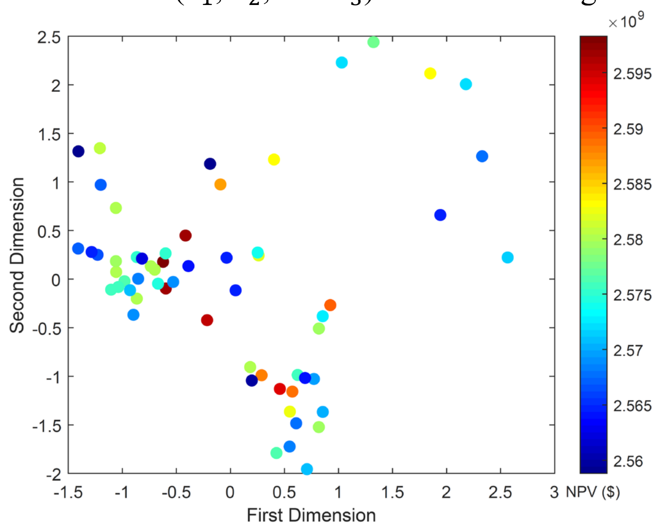

Figure 4-Projection of 60 well location solutions into a two-dimensional space using MDS (associated with their corresponding NPVs)

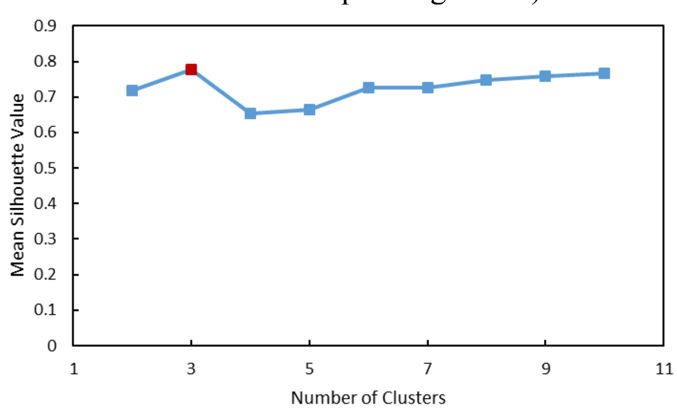

Figure 5– Mean Silhouette value of 60 well placement solutions for different numbers of clusters.

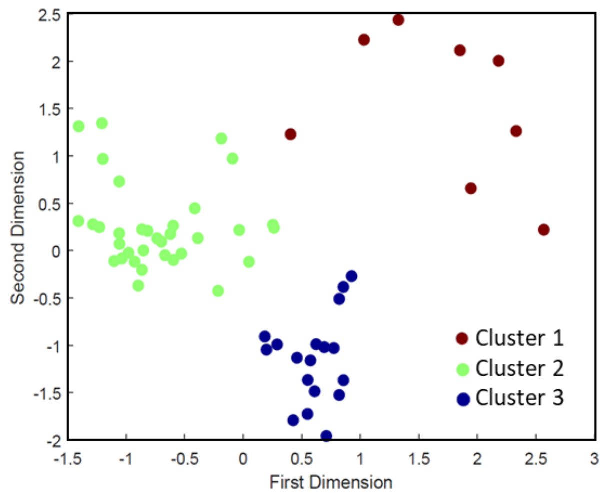

Figure 6-K-means clustering considering three clusters ($N_c = 3$)

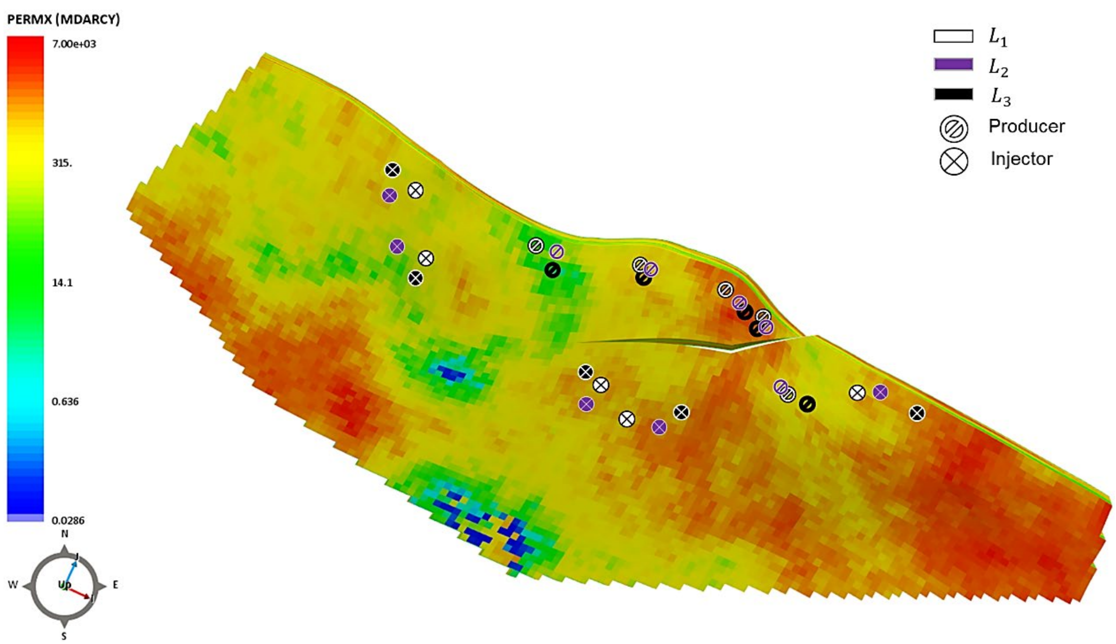

Figure 7- Three sets of optimal well locations: L_1, L_2, and L_3, in the Brugge model

The control settings of the three optimal well locations are then individually optimized at the second optimization level. A similar clustering approach is applied to the control solutions where an ensemble of representative solutions is selected from the top 20% (by NPV) of the cases. Conventional Euclidean distance is used to measure the dissimilarity between control scenarios followed by MDS to map them into 2D (Figure 8). Figure 9 shows the final clusters where the optimum number of clusters (N_{copt}) are identified same as after well location optimization level by comparing the average Silhouette values of all data points for different number of clusters (N_c) while considering the balance between computation time and clustering performance. The control scenario with the maximum NPV is selected from each cluster as the representative of that cluster, resulting in a total of 11 control scenarios, for all three well placement strategies (Figure 10). Figure 10 compares the extra control scenarios obtained by multi-solution framework (grey line) with the classic single solution sequential approach (red line). The sequential optimization loop was terminated since no further improvements in the objective value was obtained.

Table 2 compares the base case NPV (i.e. base case well locations with fully open control), with the improvement after well location optimization, and as a results of best control settings for each well placement strategy. Although L_1 shows the maximum NPV after well placement optimization, L_2 shows higher improvement due to control optimization (15.1%), implying that a sub-optimal solution from the previous optimization level can approach and even outdo the optimal one at the next level. Figure 11 summarizes the tree-structure of the developed multi-solution framework indicating the operational flexibility achieved by different field development and control scenarios with close-to-optimum NPVs.

Table 2-The summary of NPV values, before and after well placement and control settings optimization

Base Case NPV (USD)	Well Placement Solution	NPV after well placement optimization (USD)	% change	Maximum NPV after well control optimization (USD)	% change
2.111×10^9	L_1	2.597×10^9	+ 23.2	2.977×10^9	+ 14.6
	L_2	2.589×10^9	+ 22.7	2.977×10^9	+ 15.1
	L_3	2.583×10^9	+ 22.3	2.922×10^9	+ 13.2

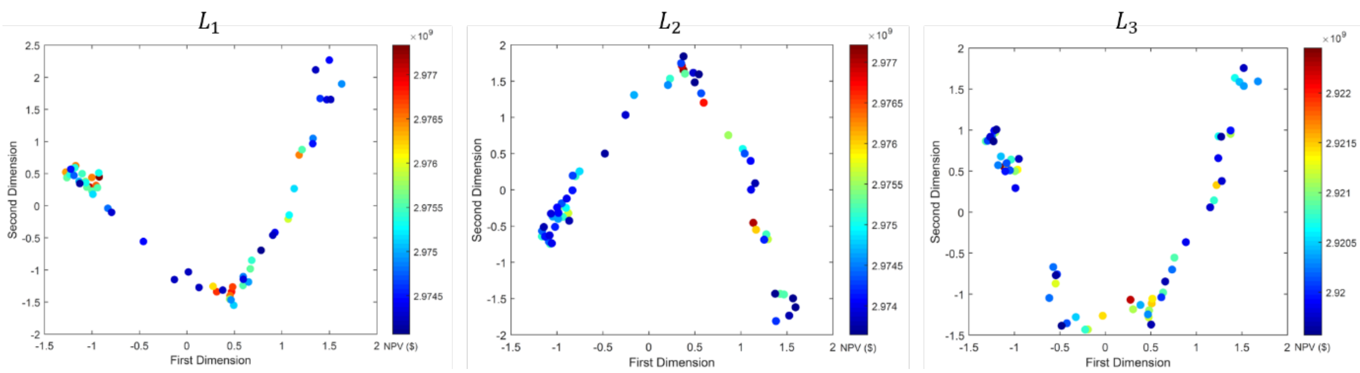

Figure 8- Projection of 60 well control solutions, attributed to L_1, L_2 and L_3 into a two-dimensional space using MDS.

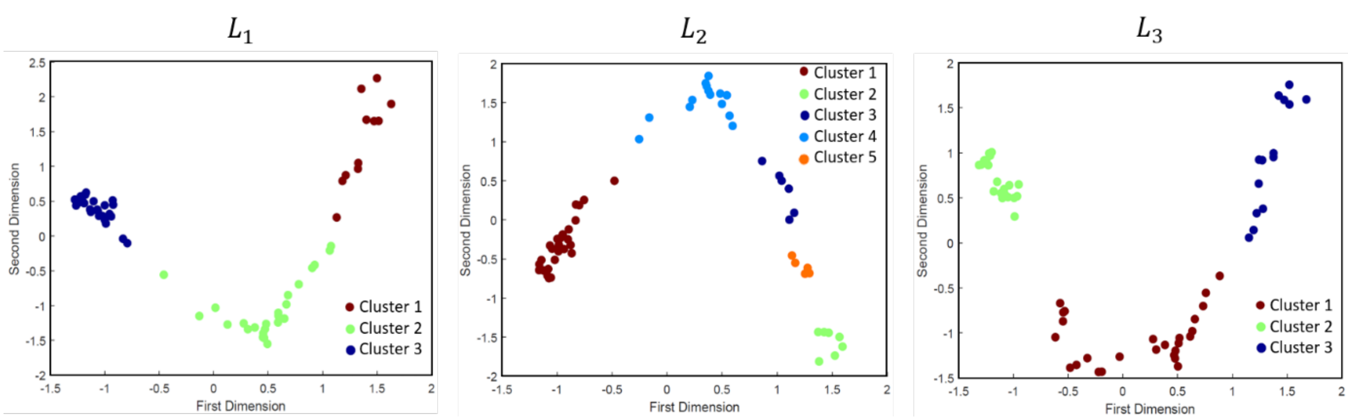

Figure 9-K-means clustering results for well control solutions, attributed to L_1, L_2, and L_3, considering the optimal number of clusters for each ensemble.

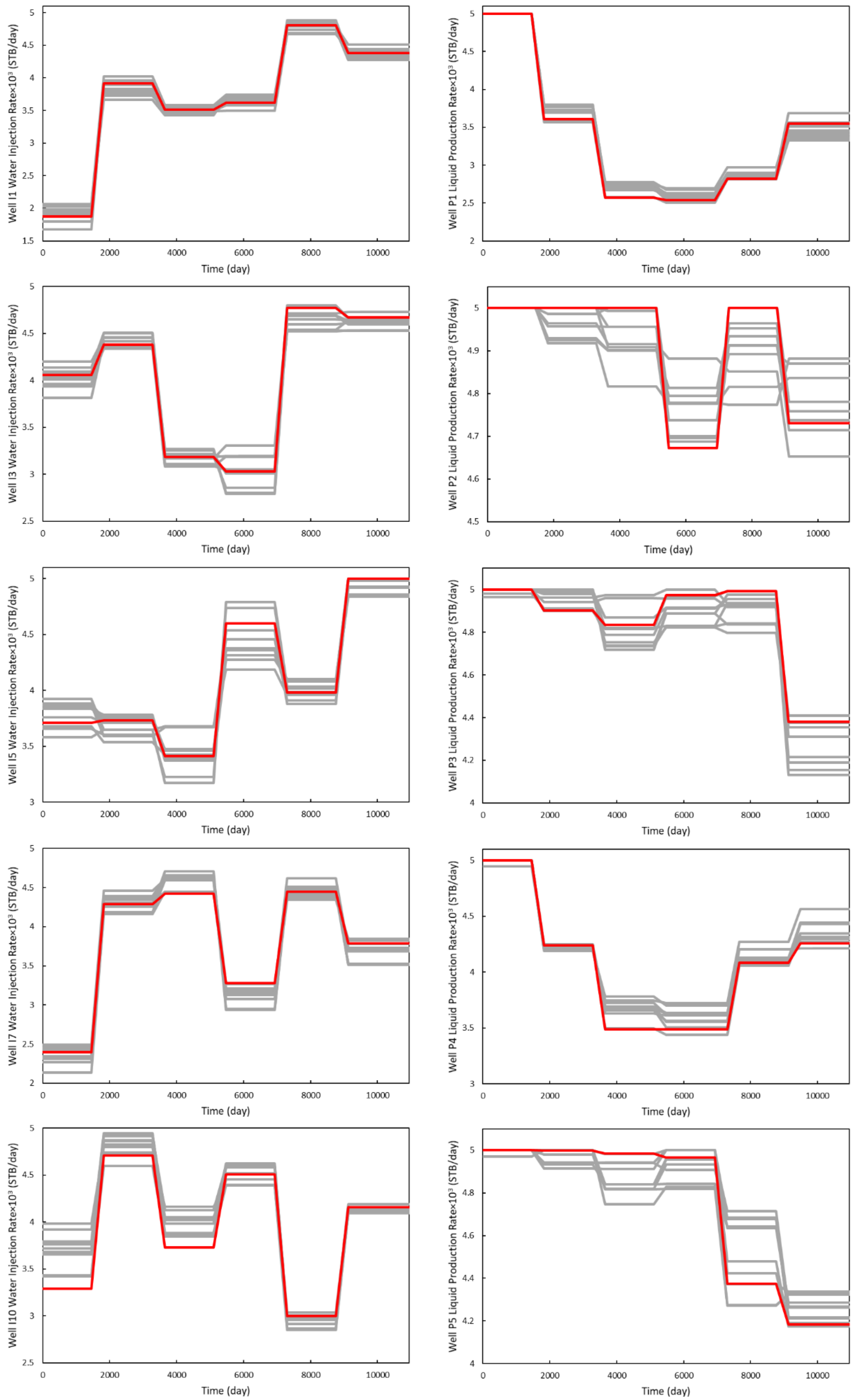

Figure 10- Optimal water injection (left) and liquid production (right) rates for wells in the Brugge model (The red line is the single best solution; grey lines are other optimal scenarios).

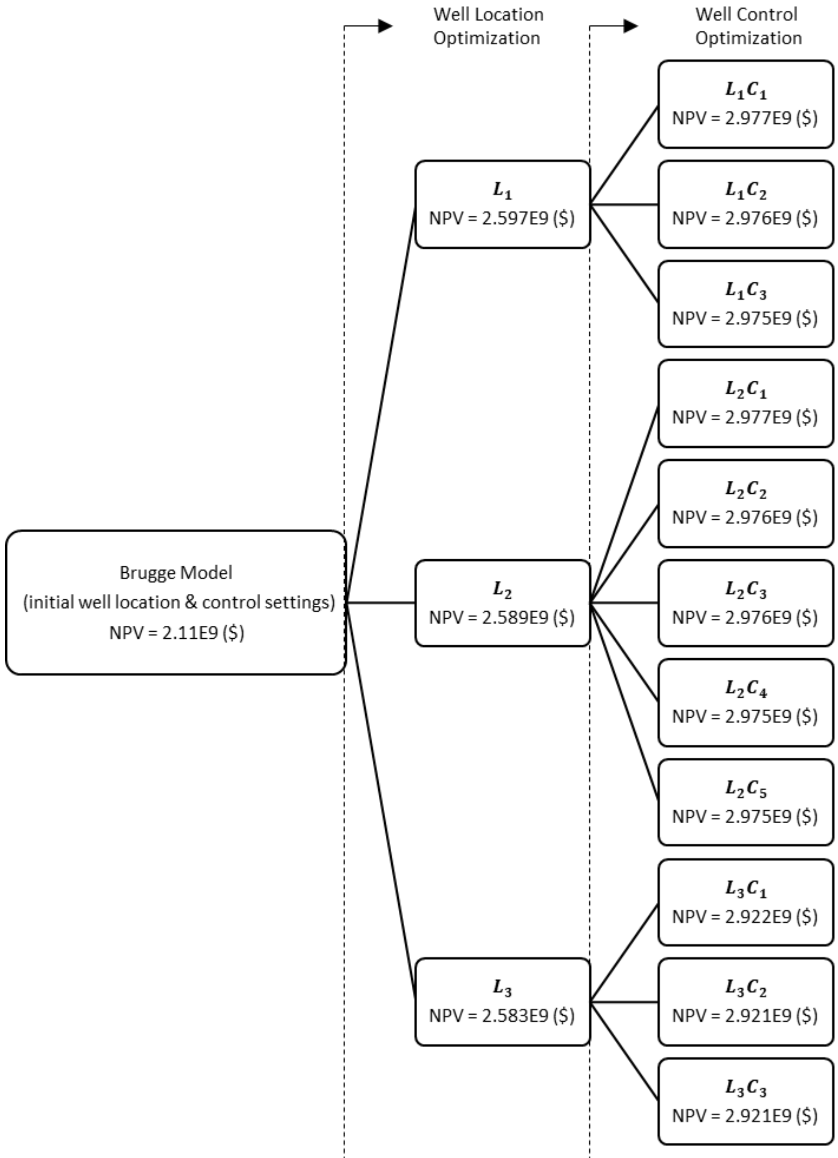

Figure 11-Summary of the multi-solution optimization framework for case 1.

Case-2 (intelligent well-based field development and control study):

Similar to case-1, top (i, j) location of ten wells are optimized, resulting in 20 control variables during well location optimization. Conventional injectors are controlled by water injection rate, bounded between 0 and 5000 STB/day. In this case, zonal flow control in each (intelligent) producer is achieved using three Interval Control Valves (ICVs) with infinitely variable flow area installed downhole. 30 years of the production period are divided into six equal control steps, resulting in 5×6=30 control variables for injectors and 5×3×6=90 control variables for producers during well control optimization.

The multi-solution optimization framework is applied to the intelligent well case in a similar manner as the conventional well case presented before. The initial well placement optimization level gives the same solutions as in case-1 (Figure 7) since here I-wells with initially fully open ICVs provide the same performance as the conventional wells. Zonal control optimization was then performed for each of the three representative optimal well placement solutions. Conventional Euclidean distance was used to measure the pairwise distance between top 20% control scenarios followed by MDS to project them on 2D. The optimum number of clusters for all cases is identified as 3 to provide a balance between clustering performance (i.e. high Mean Silhouette value) and computation time. The optimization loop was terminated since no further improvements in the optimal solutions were observed. Figure 12 summarizes the obtained solutions for case 2 indicating the operational flexibility achieved by different field development and control scenarios with close-to-optimum NPVs. Maximum NPV is achieved when the optimal control is applied to the I-wells located at the optimal location of conventional wells. Higher cumulative oil production, lower cumulative water production, and therefore higher NPVs are achieved in case-2 due to the flexible zonal control provided by ICVs (Figure 13), which is consistent with the previous reports on the added value from zonal control (Almeida et al. 2010, Sefat et al. 2016, Prakasa et al. 2017). Note that this work presents the principal research results and observations from developing a multi-solution optimization framework. Therefore, we use the same number of iterations at each level and do not change the order of the levels.

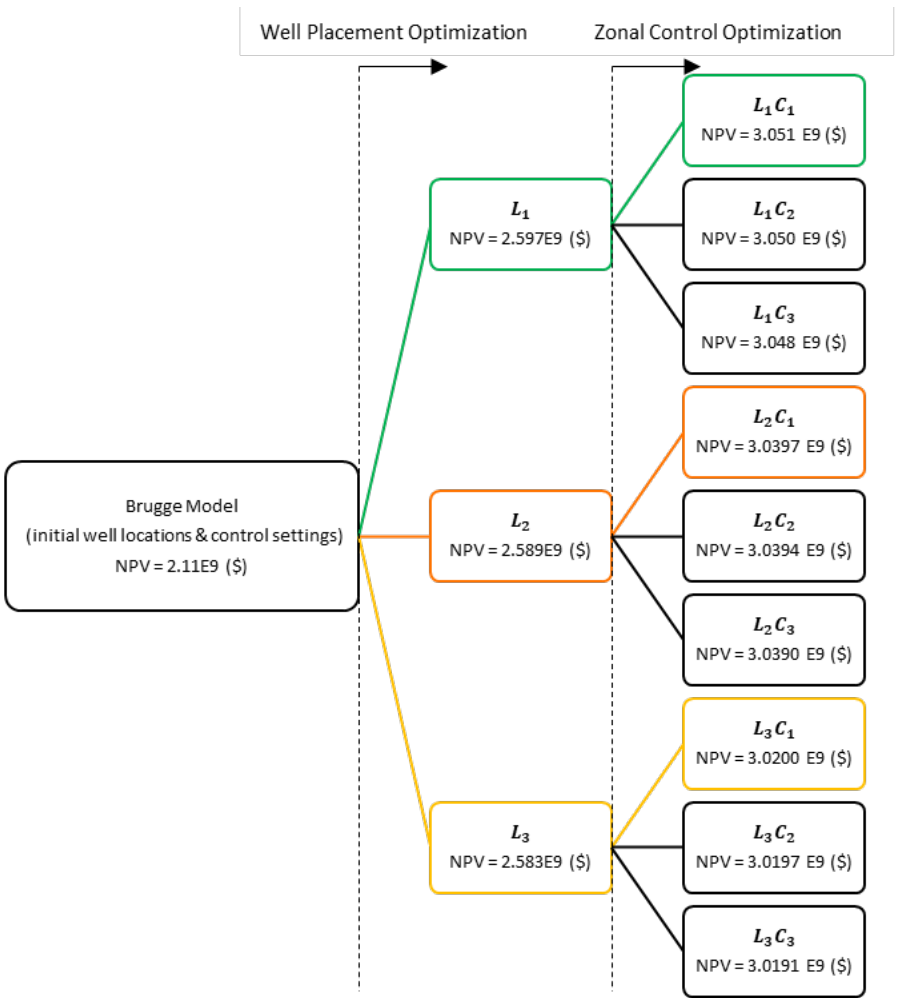

Figure 12-Summary of the multi-solution optimization framework for case 2.

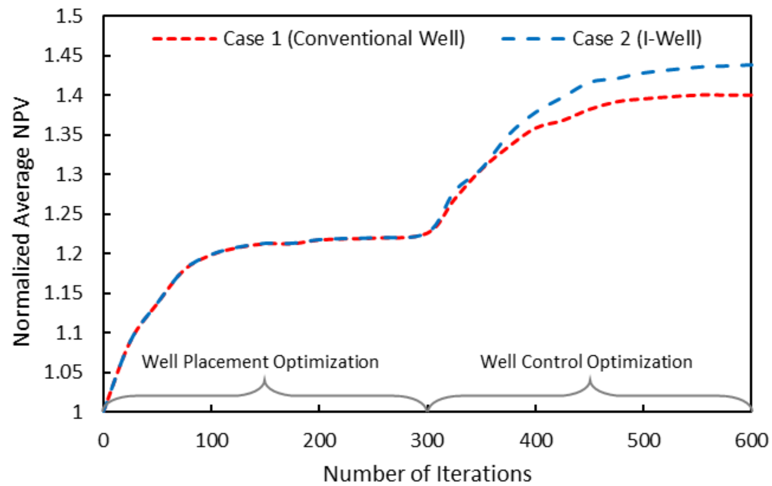

Figure 13-Normalized average NPV over the ensemble of selected solutions in case 1 (conventional well) and case 2 (I-well) versus optimization iterations.

Conclusions

To expand the flexibility of field development and control decisions, and insure against the unexpected operational constraints, this study presented a multi-solution optimization framework that provides multiple optimal solutions by exploring the search space. A systematic clustering procedure was developed to select an ensemble of distinct scenarios with close-to-optimum objective values. SPSA algorithm was employed in a multi-level iterative sequential approach to find optimal well locations and control settings. However, the developed framework is compatible with other optimization algorithms as well. In addition to the constraints on liquid production and water injection rates, a minimum well spacing and a modified procedure of respecting irregular reservoir boundaries were considered within the optimization procedure. The proposed framework has been tested in a benchmark case study, known as Brugge model, considering two development scenarios: conventional and intelligent wells. Multiple optimal field development and control solutions with close-to-optimum objective values but different control variables were obtained. Results demonstrate that suboptimal solutions from an early optimization level can approach and even outdo the optimal one at the higher optimization levels, highlighting the advantage of the here-developed multi-solution framework in order to provide the much-needed operational flexibility in field optimization problems.

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