

## RESULT

**Enhancing REServoirs in Urban development: smart wells and reservoir development, Geothermica Project Number 200317**



### RESULT-D4.2:

**Optimized well and completion design for demo site (in Zwolle)**

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## Executive summary

This report presents results of the application of the well trajectory optimization workflows investigated in the RESULT project to the envisaged doublet construction in Zwolle. In particular, two main optimization approaches are demonstrated, namely: a robust optimization under prior uncertainty and the Drill & Learn approach (recently presented in RESULT report D3.1 and D3.2) which leverages learning from drilled wells to further enhance the optimization of subsequent wells.

The robust optimization approach is used to support the selection of the well concept for the Zwolle site by enabling the comparison of the three well concepts considered (quasi-vertical, sub-horizontal and multi-lateral, see D4.1) based on optimized configurations for each of them.

As input prior (and updated) uncertainty for both optimization workflows, an ensemble of (dynamic) reservoir flow models was generated to represent the underlying geological uncertainty associated with the characterization of the properties of the target reservoir formation at the Zwolle location (from RESULT report D4.1).

The three well concepts (quasi-vertical (exp1), sub-horizontal (exp2) and multi-lateral (exp3) have been compared for Zwolle in the context of well location and trajectory optimization. For each well concept, optimization was able to significantly improve techno-economic performance of the doublet system in Zwolle site by changing locations and trajectories of both wells resulting in an improvement of economic performance from prior LCOE of 7-9 €/cts/kWh to ca. 5 €/cts/kWh.

The differences in economics between the optimal solutions for various well concepts are relatively small in terms of expected LCOE: 5-5.5 €/cts/kWh. However, the optimal well locations are significantly different than the initial guess and they reveal a trend in location of the optimal development area. This suggests that it is not only the shape of wells, but the combination of shape and location of wells which determine the techno-economic performance of the doublet.

Optimization results show that both sub-horizontal and multi-lateral well concepts are good candidates outperforming the quasi-vertical choice. The sub-horizontal scenario resulted in higher NPV on average across the geological realizations, however the multi-lateral solution delivers lowest economic risk (in terms of reduced spread in NPV and LCOE distribution) whereas the quasi-vertical scenario is marked by highest spread.

In addition, two Drill & Learn experiments for the quasi-vertical well concept have been performed by varying which well is to be drilled first (producer or injector). The analysis of the results revealed also some interesting non-trivial insights into the order in which the wells should be drilled (injector first, then producer) in order to maximize the benefits of the learning from well-logs to further improve the optimized well trajectories.

The results obtained show the added value of optimization in assisting reservoir engineers to achieve improved development strategies with optimized well trajectories, including providing quantitative insights and supporting evidence to guide the selection of the most suitable well concept. It is important to note that the results of optimization workflows remain as reliable as the underlying models considered within the optimization and their completeness in terms of realistically capturing practical aspects related to the implicated decisions. Despite the complexity and realism of the geological scenarios, reservoir model realizations and well trajectory geometries taken into account, this is still a modelling study - there may be other considerations related to the execution and operations of wells in real-life that are not represented (e.g., technical risks related to the feasibility of drilling the proposed well trajectories). In addition to well concept optimization, the results confirm the potential of the Drill & Learn framework developed in RESULT (previously

tested in a synthetic case) to unlock additional optimization value in a realistic case. The Drill & Learn exercise also allows for a rough practical assessment of the value of information (VOI) to evaluate the expected impact of additional measurements from drilling and logging activities of the first well(s) on upcoming field development decisions. Such a VOI assessment serves as the basis to justify information gathering activities, e.g. the deployment of new sensors / instruments and the acquisition of additional exploration campaigns (wells or surveys).

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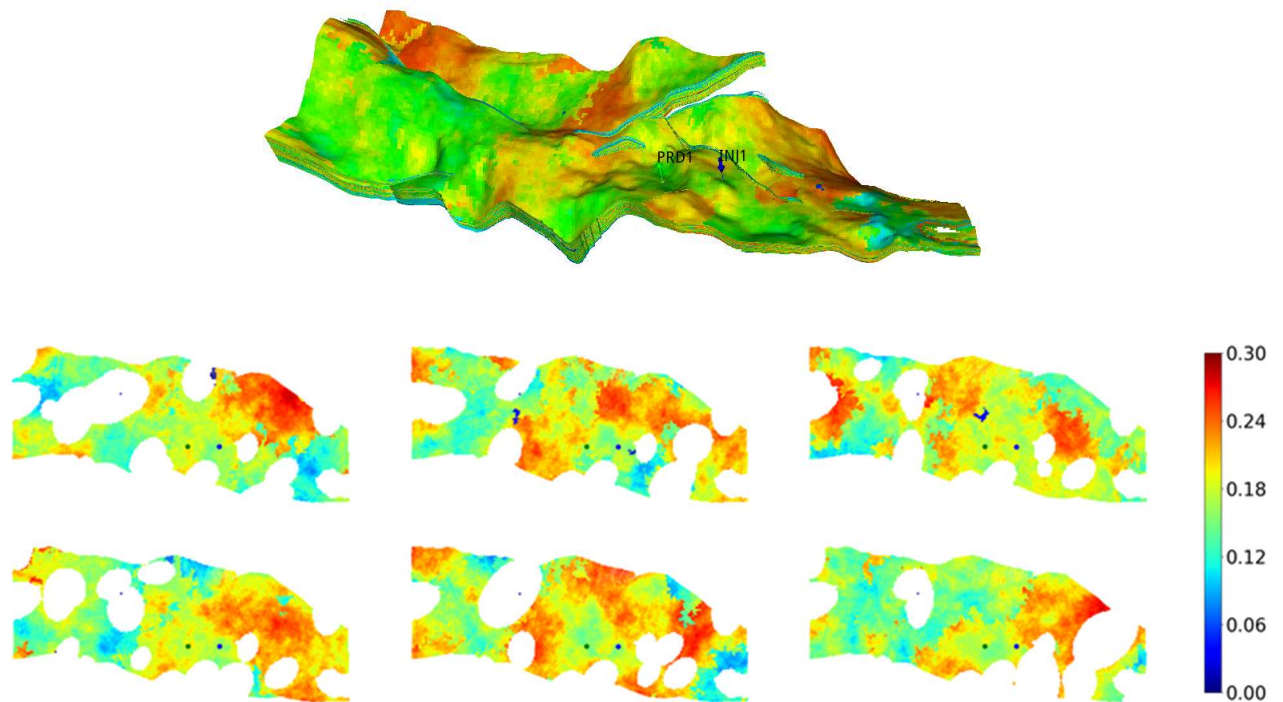
# 1 Introduction

This report presents results of the application of the well trajectory optimization workflows investigated in the RESULT project to the Zwolle case study. In particular, two main optimization approaches are demonstrated, namely: a robust optimization under prior uncertainty and the Drill & Learn approach (recently presented in RESULT report D3.1 and D3.2) which leverages learning from drilled wells to further enhance the optimization of subsequent wells. An ensemble of (dynamic) reservoir flow models was generated to represent the underlying geological uncertainty associated with the characterization of the properties of the target reservoir formation at the Zwolle location (from RESULT report D4.1). Moreover, the robust optimization approach is used to support the selection of the well concept for the Zwolle site by enabling the comparison of the three well concepts considered (quasi-vertical, sub-horizontal and multilateral, see D4.1) based on optimized configurations for each of them.

The results obtained show the added value of optimization in assisting reservoir engineers to achieve improved development strategies with optimized well trajectories, including providing quantitative insights and supporting evidence to guide the selection of the most suitable well concept. It is important to note that the results of optimization workflows remain as reliable as the underlying models considered within the optimization and their completeness in terms of realistically capturing practical aspects related to the implicated decisions. Despite the complexity and realism of the geological scenarios, reservoir model realizations and well trajectory geometries taken into account, this is still a modelling study - there may be other considerations related to the execution and operations of wells in real-life that are not represented (e.g., technical risks related to the feasibility of drilling the proposed well trajectories). In addition to well concept optimization, the results confirm the potential of the Drill & Learn framework developed in RESULT (previously tested in a synthetic case) to unlock additional optimization value in a realistic case. The Drill & Learn exercise also allows for a rough practical assessment of the value of information (VOI) to evaluate the expected impact of additional measurements from drilling and logging activities of the first well(s) on upcoming field development decisions. Such a VOI assessment serves as the basis to justify information gathering activities, e.g. the deployment of new sensors / instruments and the acquisition of additional exploration campaigns (wells or surveys).

## 2 Zwolle case study

In RESULT Task 4.2 “Optimized a-priori design for the (backup) site and business case”, optimization of well design was applied to the Zwolle model documented in report RESULT-D4.1. The numerical model is a representation of the target reservoir at the Rotliegend formation in the area of interest. The geological static model was generated by EBN using the Petrel software (Schlumberger) based on all the available knowledge of the geology of the area of interest. A number of scenarios have been considered concerning the cementation assumptions, and the best-guess scenario has been provided to TNO. The Petrel project provided by EBN contains an internal Petrel workflow to automate the generation of geostatistical model realizations for the best-guess scenario, which has been used to create an ensemble of 100 realizations of the spatially heterogeneous model with different static properties (i.e., porosity and permeability fields) to reflect the inherent geological uncertainties. The model consists of a grid with  $219 \times 101 \times 169$  grid cells covering an area of approximately  $45 \text{ km}^2$  ( $= 11 \text{ km} \times 4 \text{ km}$ ) at an average depth of 2,400 m and thickness ranging from 50-80 m, with a total of about 950,000 active cells (which varies slightly per model realization). Figure 1 depicts several of model realizations randomly selected from the ensemble of 100 realizations.



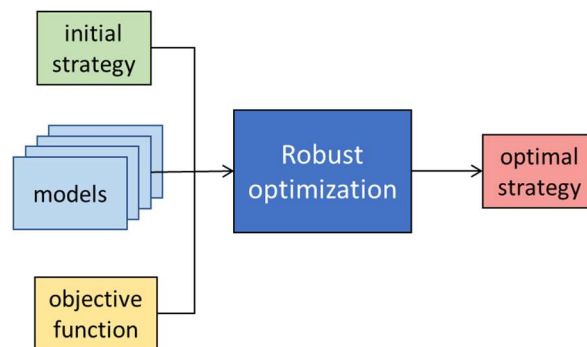
**Figure 1:** Zwolle reservoir model: (top) 3D view of the model with heterogeneous porosity distribution and initial doublet placement, (bottom) top view of six randomly selected realizations of layer 40 with varying porosity distribution. The white patches correspond to bodies where the pores have been clogged (see RESULT report D4.1)

Once the static model was available, TNO prepared a dynamic reservoir simulation model by introducing typical thermodynamic properties for the fluids present in the reservoir, along with rock-fluid interaction and rock compressibility and thermal properties, and initialization of reservoir pressure (240-250 bar) and temperature conditions (85-90°C). In addition, a geothermal doublet was inserted by placing a production well and an injection well (both vertical) in one of the central sectors of the model – these serve as starting point for the optimization exercises described next. The producer is operated at a prescribed target flow rate of 7,000 m<sup>3</sup>/day (~300 m<sup>3</sup>/h) with a minimum bottom-hole pressure limit of 190 bar. The injector is assumed to operate in voidage replacement mode, where all produced volume is re-injected, with a maximum allowed bottom-hole injection pressure of 300 bar. The volumetric flow rate targets / limits were selected based on typical flow rates for existing geothermal doublets in the Netherlands and reflecting achievable limits with pumping technologies given typical well diameters.



### 3 Optimization of the a-priori well design

In this section we present the results of the robust optimization performed to optimize the well design (i.e., well path) in the Zwolle case study under prior geological uncertainties. The theoretical background of robust optimization was described in more details in report RESULT-D2.3 prepared by TNO in earlier studies of the RESULT project. The general idea behind robust optimization is to formulate an optimization procedure aiming at finding a single solution which is optimal over an ensemble of model realizations. This is typically achieved by considering an objective function calculated as the mean (or average) of the objective function values computed individually for each model realization, while all realizations are assumed to be equiprobable. The robust solution is often not the best performing one for each model realization, but it is the best performing one in terms of average model response (note: this is the average response of the ensemble of models, not the response of the average model). The rationale is that a solution obtained through such procedure is robust against the uncertainty (or variability) of models considered. As presented in report RESULT-D2.3, TNO's in-house optimization technology (EVEReST), built upon the recently developed stochastic gradient-based optimization technique StoSAG (Fonseca et al., 2017), allows to perform robust optimization in a computationally efficient manner – i.e. with much fewer numerical simulations required when compared to alternative techniques. Figure 2 depicts schematically the robust optimization process.



**Figure 2:** Schematic representation of the robust optimization process in terms of input and output.

In this study, we refer to optimization under prior geological uncertainties meaning that the model realizations considered within the optimization characterize the initial state of uncertainty – i.e. the model realizations reflect the knowledge of the local geology available at the design phase, before drilling any of the planned wells. Thus, here the prior ensemble of model realizations refers to the collection of models described in Section 1.

The optimization variables in this robust optimization experiment are the coordinates of the guide points defining the well path geometry, following the same approach described in reports RESULT-D3.1 and RESULT-D3.2 (and introduced in Barros et al., 2020) where well path optimization was applied to a simple synthetic benchmark model representative of sedimentary geothermal reservoirs in the Netherlands. The parametrization of well trajectories through a few guide points allows the optimizer to explore a variety of well design configurations, ranging from vertical to deviated and horizontal wells.

## 4 Comparison of well concepts

Activity 4.2 of the RESULT project also aimed at supporting the selection of the well concept for the doublet to be drilled in the Zwolle site. We approached this task by confronting the expected optimal performance of doublets with varying well concepts as a means of achieving fair comparison between them. For this part of the study, the economic model has been revised to accommodate in a consistent manner the costs of the different well concepts considered and allow the derived economics of the different cases to be compared against each other.

### 4.1 Techno-economic model for optimization

The well trajectories are optimized to maximize the economics of heat production of the geothermal development over the production life-cycle of the project. To account for the time-value of heat production, the discounted net present value (NPV) is computed from the simulation forecasts. Basically, it can be represented by:

$$\text{Equation 1} \quad J_{NPV}(\mathbf{u}) = \sum_{k=1}^{N_t} \frac{(r_h \cdot e_{\text{prod},k}(\mathbf{u}) - r_p \cdot (e_{\text{pump},k}^{\text{prod}}(\mathbf{u}) + e_{\text{pump},k}^{\text{inj}}(\mathbf{u})) - c_k(\mathbf{u}))}{(1+b)^{t_k/\tau}},$$

where  $\mathbf{u}$  is the control vector parametrizing the well trajectories,  $e_{\text{prod},k}$  is the heat production during the  $k^{\text{th}}$  simulation time interval,  $e_{\text{pump},k}$  is the energy consumed to operate the required pumps,  $c_k$  are the costs (CAPEX and OPEX, which may vary for different well trajectories),  $r_h$  is the heat price [€/GJ] (including subsidy SDE+ over a 15-year period),  $r_p$  is the electricity cost [€/GJ] for the operations,  $b$  is the discounting factor,  $t_k$  is the time at  $k^{\text{th}}$  simulation time-step,  $\tau$  is the reference time for discounting cashflow and  $N_t$  is the total number of simulation time-steps.

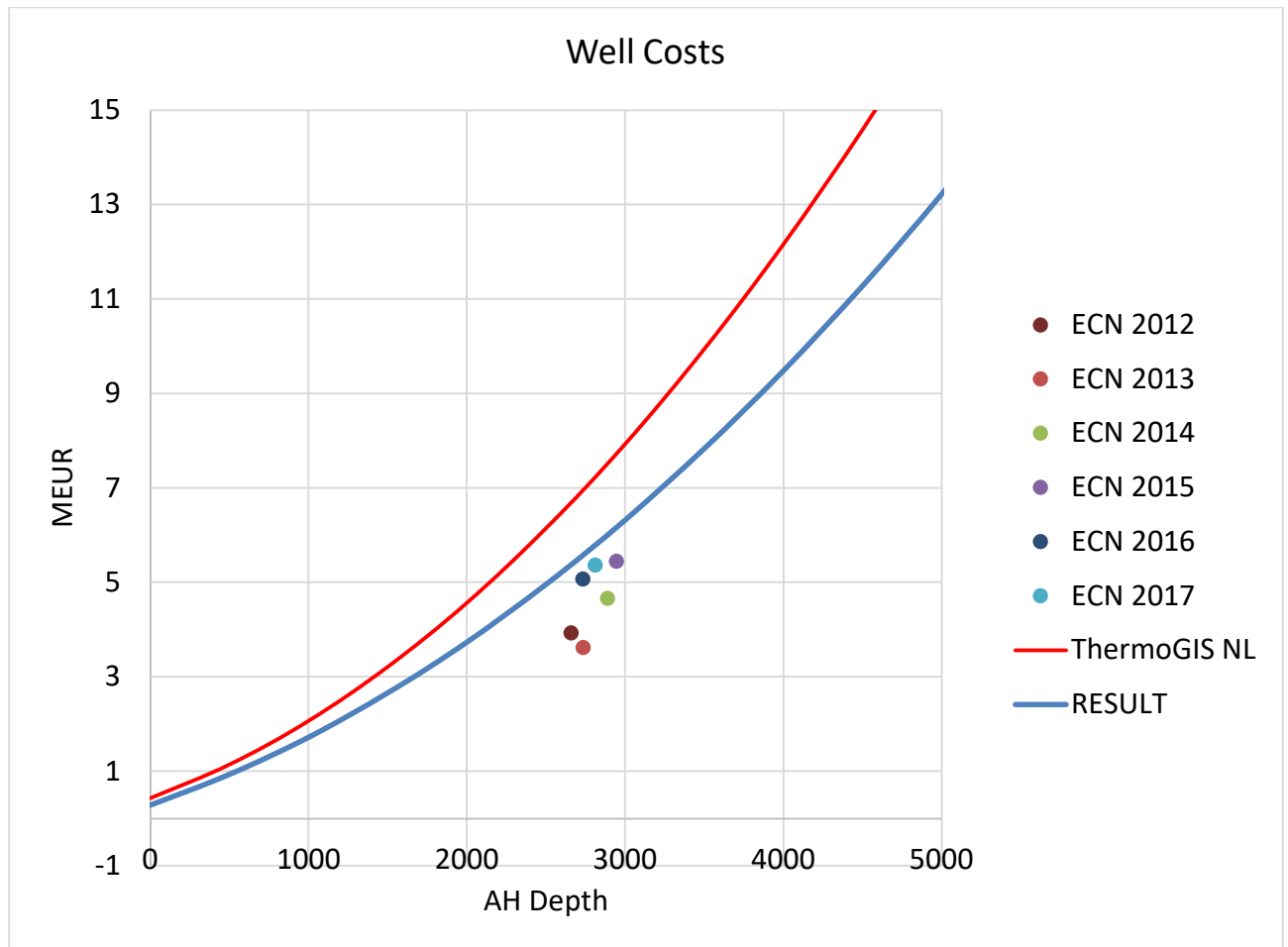
The techno-economic model parameters, as well as the discounting factors, are based on ThermoGIS (thermogis.nl). The parameters of the cost model are shown in Table 1, allowing for full transparency of the model.

The well cost model is following a cubic function with cumulative Along Hole Depth ( $z_{ahd}$ ) of the constructed injector or producer. Note that this is a simplified way of accounting for the variable cost of wells (which would typically be a direct function of duration of drilling operations and equipment / material used) in order to steer the optimization towards sensible well lengths and avoid unrealistically long wells.

$$\text{Equation 2} \quad \text{capex}_{\text{well}} = (1 + C_c) w_s \left( w_b + w_l z_{ahd} + w_c z_{ahd}^2 \right)$$

For multi-lateral wells,  $z_{ahd}$  is the sum of the AHD of the main branch and the additional legs measured from the branching points. The meaning of the parameters and the values used for the RESULT techno-economic model for optimization are given in **Error! Reference source not found.** The RESULT cost parameters are in close agreement with the ECN analysis.





**Figure 3:** ThermoGIS well costs based on (eq.1), assuming  $w_b = 0.25$  mln€,  $w_l = 700$  €/m,  $w_c = 0.25$  €/m<sup>2</sup>,  $w_s = 1.5$  and contingency of 15%, compared to reported well costs in ECN studies to determine SDE+ feed-in. The ECN cost models assumes a linear increase in well costs per m, and have been rising from 2012 until 2017. In addition the well cost model preferred for RESULT is shown, with assuming  $w_b = 0.25$  mln€,  $w_l = 1000$  €/m,  $w_c = 0.25$  €/m<sup>2</sup>,  $w_s = 1.0$  and contingency of 15%, in agreement with the cost parameters in Table 1.

The preferred RESULT simple well cost model (eq. 1, Table 1) has been compared with the detailed well cost model of RESULT D2.2. The D2.2 well cost model appears to predict significantly lower well costs than the simplified ThermoGIS/RESULT well model predictions and

show hardly any variability with respect to reservoir depth in

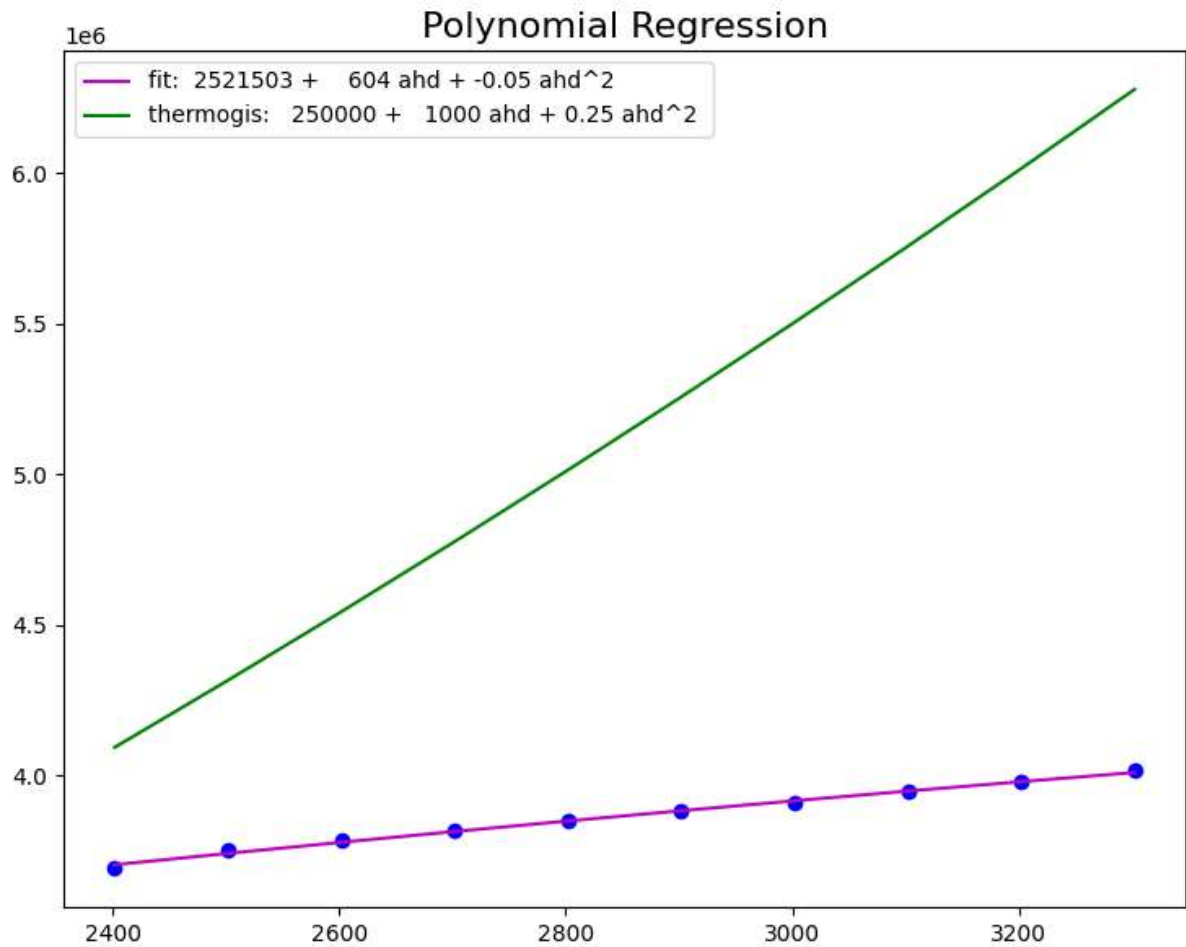
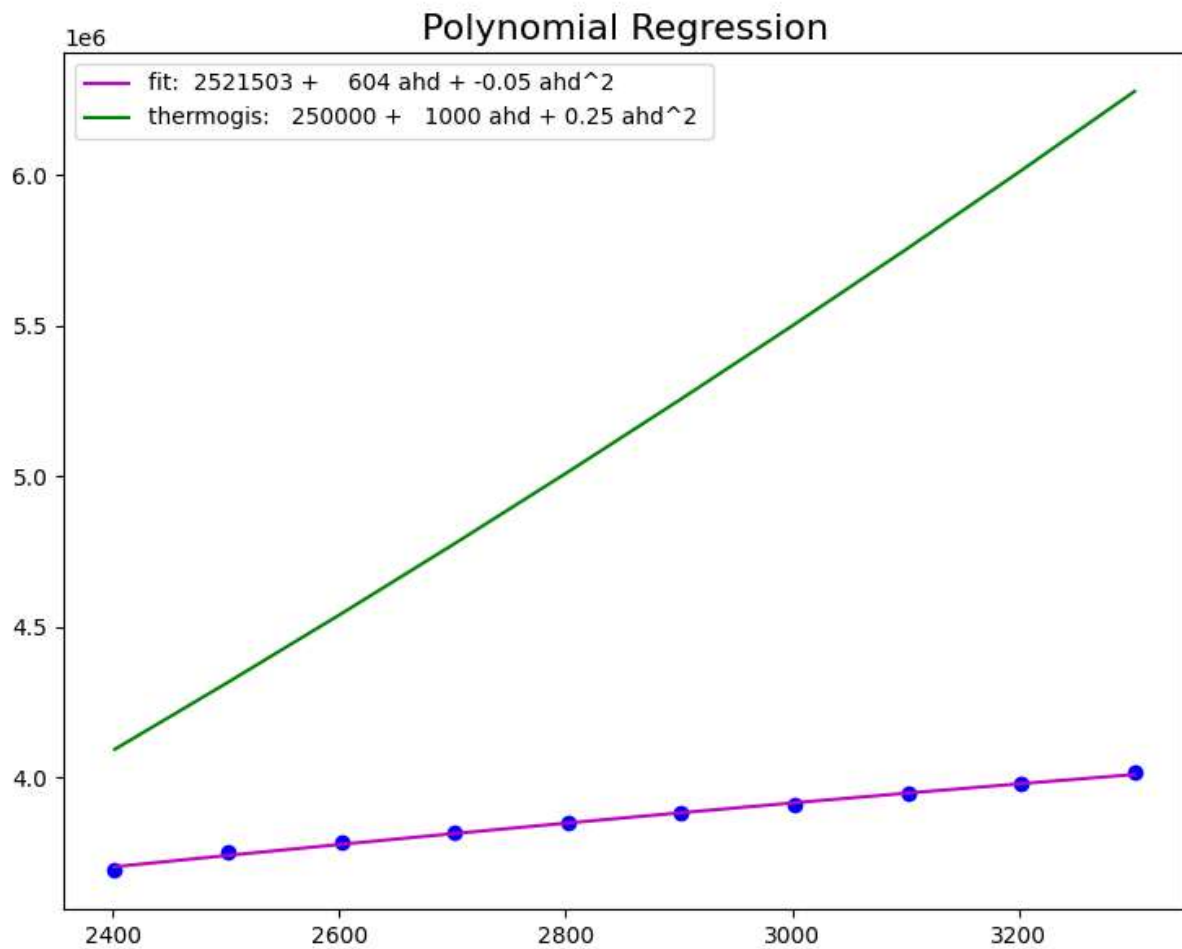
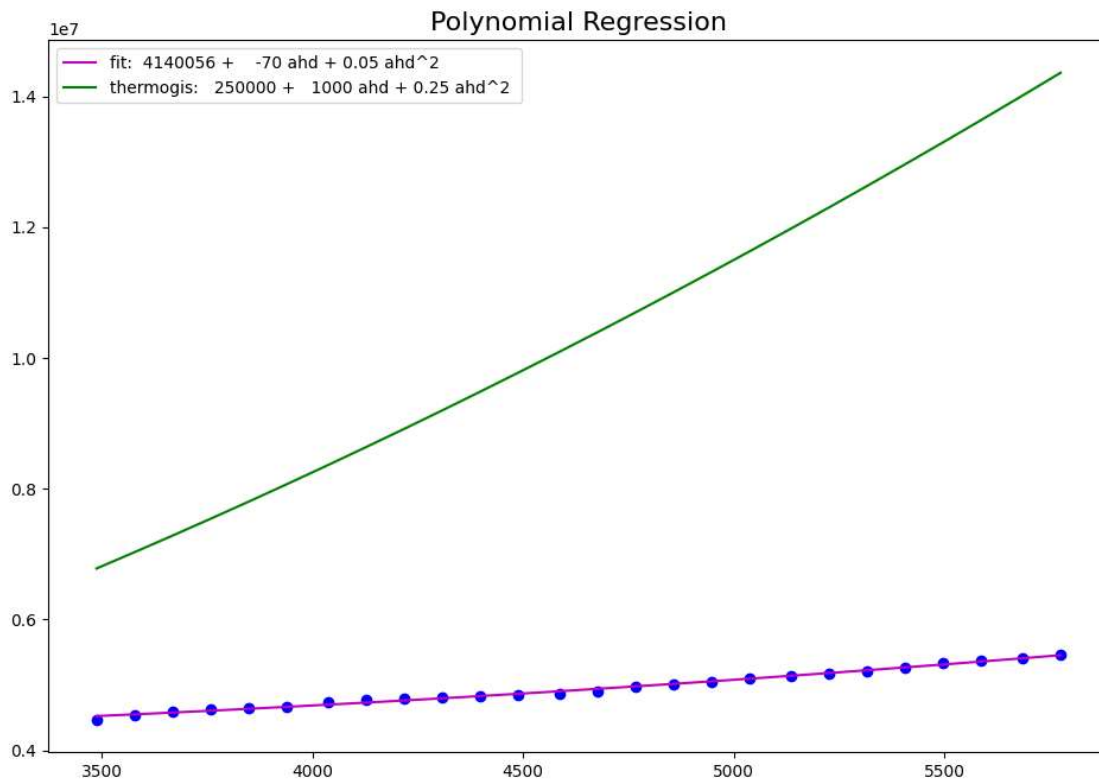


Figure 4 and a sub-horizontal leg length in Figure 5. The lack of variability in costs with varying reservoir depth and leg length is attributed to the fact that the D2.2 model is insufficiently suited for different depths, lengths of legs, etc. For this reason, the well cost model of ThermoGIS has been used in this study with the RESULT parameters as listed in Table 1.



**Figure 4:** Single inclined (conventional) well costs (excluding contingency) according to the RESULT D2.2 detailed cost model (purple) vs. RESULT well cost model (green, parameters as in Figure 3) excluding contingency) as a function of along-hole end depth corresponding to a bottom depth of 2000-3000 m. The well along hole end depth is shown on horizontal axis. The inclination of the well at reservoir depth is 45°. The outstep of the well is 800 m. The D2.2 well cost model assumes Normal steel 8.5" Inner Diameter completion and includes the installation costs of an ESP.



**Figure 5: Cost of a sub-horizontal well with an inclination of 85° at a reservoir depth of 2400 m (bottom) and a variable outstep of 1400 to 4000 m resulting in a longer/shorter subhorizontal leg. The D2.2 well cost model assumes Normal steel 8.5" Inner Diameter completion and includes the installation costs of an ESP. Same colour conventions as in Figure 4.**

**Table 1: Technical and economic parameters for the cost calculations**

Parameter	Value	Unit	Symbol	Notes
<b>Technical aspects reservoir and wells</b>				
Reservoir salinity	254000	ppm		Rectification notes RESULT_WP4.1 EBN, affects viscosity, also brine heat capacity
injection temperature	45	°C		
Well tubing diameters	7	inch		
Well tubing roughness	0.1	Milli-inch		
<b>Economic</b>				
economic lifetime	30	years	$N_t$	
Load hours	6000	hours	$h_{load}$	
Feedin period	15	years	$f_{nfi}$	
inflation	2	%	$f_{inf}$	
equity share	20	%	$f_{eq}$	
Loan interest rate	5	%	$f_{int}$	
Loan period	15	years	$f_{nloan}$	
Effective discount factor	7	%	$b$	Approximate discount factor
Tax rate	25	%		
<b>Well costs</b>				
Wellcost base	0.25	Mln €	$w_b$	Base costs eq.1
Wellcost linear	1000	€/AHD (m)	$w_l$	Linear costs eq. 1
Well cost cubic	0.25	€/AHD <sup>2</sup> (m)	$w_c$	Cubic costs eq. 1
Well cost scale factor	1		$w_s$	
Well curvature factor	1.05		$a_s$	Scaling factor for segmented well path, used

				for well path representations in simulations
Pump cost	0.5	mln €	$p_s$	
pump efficiency	0.65		$p_e$	
pump life	50	years	$p_l$	Workover costs of pumps are included in OPEX
<b>CAPEX &amp; OPEX</b>				
Surface CAPEX base	3	mln €	$C_b$	Surface CAPEX base costs
Surface CAPEX variable	50	€/kW	$C_v$	Surface CAPEX per kWth installed
CAPEX contingency	15	%	$C_c$	applied to all CAPEX items including wells
OPEX base	10	k€/y	$O_b$	
OPEX variable	50	€/kW/y	$O_v$	Yearly costs per kWth installed
<b>Energy prices</b>				
heat price	5 <sup>1</sup>	€/kWh	$r_h$	
electricity price	5	€/kWh	$r_p$	

The investment costs of the wells is complemented by CAPEX for surface facilities and the pumps. The total investment costs are written as:

$$\text{Equation 3} \quad capex_{total} = \sum capex_{well} + p_s + C_b + C_v E_{doublet} (t = 0) ,$$

where  $E_{doublet}$  is the nominal power of the doublet, estimated from the reservoir flow simulator as:

$$\text{Equation 4} \quad E_{doublet}(t) = Q \Delta T(t) B_c ,$$

where  $Q$  is predicted production flow rate [m<sup>3</sup>/s],  $\Delta T(t)$  is the predicted temperature difference between producer temperature and injection at production year  $t$ , and  $B_c$  is the brine heat capacity at the production temperature and salinity (cf. Van Wees et al., 2012).

The OPEX is determined by:

$$\text{Equation 5} \quad opex_{total}(t) = (O_b + O_v E_{doublet}(t) + r_p \frac{\Delta P(t)}{p_e} 10^3 Q h_{load} + p_s(t)) (1 + f_{inf})^t + r_{loan}(t) ,$$

where  $p_s(t)$  is costs for replacement of pumps (every  $p_l$  years),  $r_{loan}(t)$  is the payment term for the loan,  $\Delta P(t)$  is the pressure to drive the flow in the doublet and the wells.

Such that the yearly cash flow is given by:

$$\text{Equation 6} \quad LCOE \left( \frac{\text{€cts}}{\text{kW}} \right) = 100 \frac{\text{sum of discounted energy sales (kWh)}}{capex_{total}(\text{€}) + \text{sum of discounted yearly costs } opex_{total}(t)(\text{€})} ,$$

and NPV as:

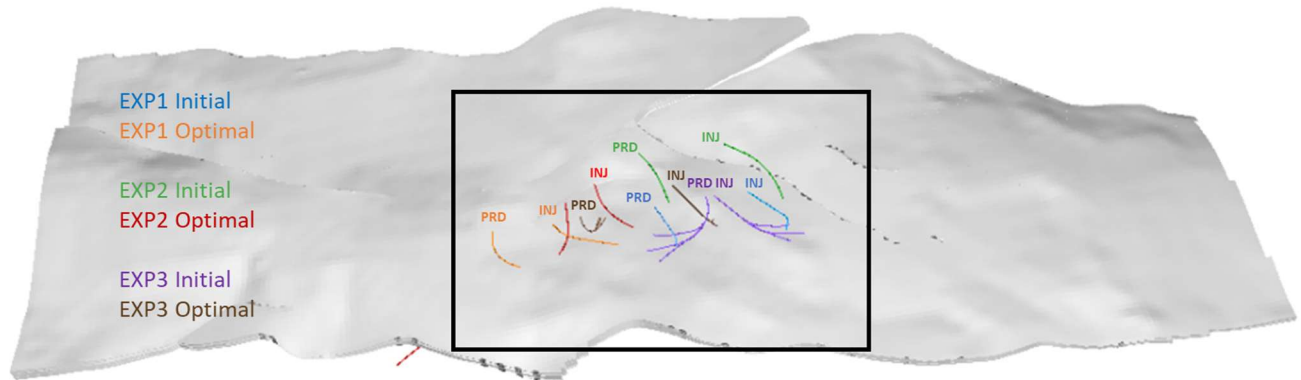
$$\text{Equation 7} \quad NPV (\text{€}) = \text{sum of discounted energy sales (kWh)} \times 0.01 \times (LCOE - r_p) .$$

## 4.2 Optimization experiments

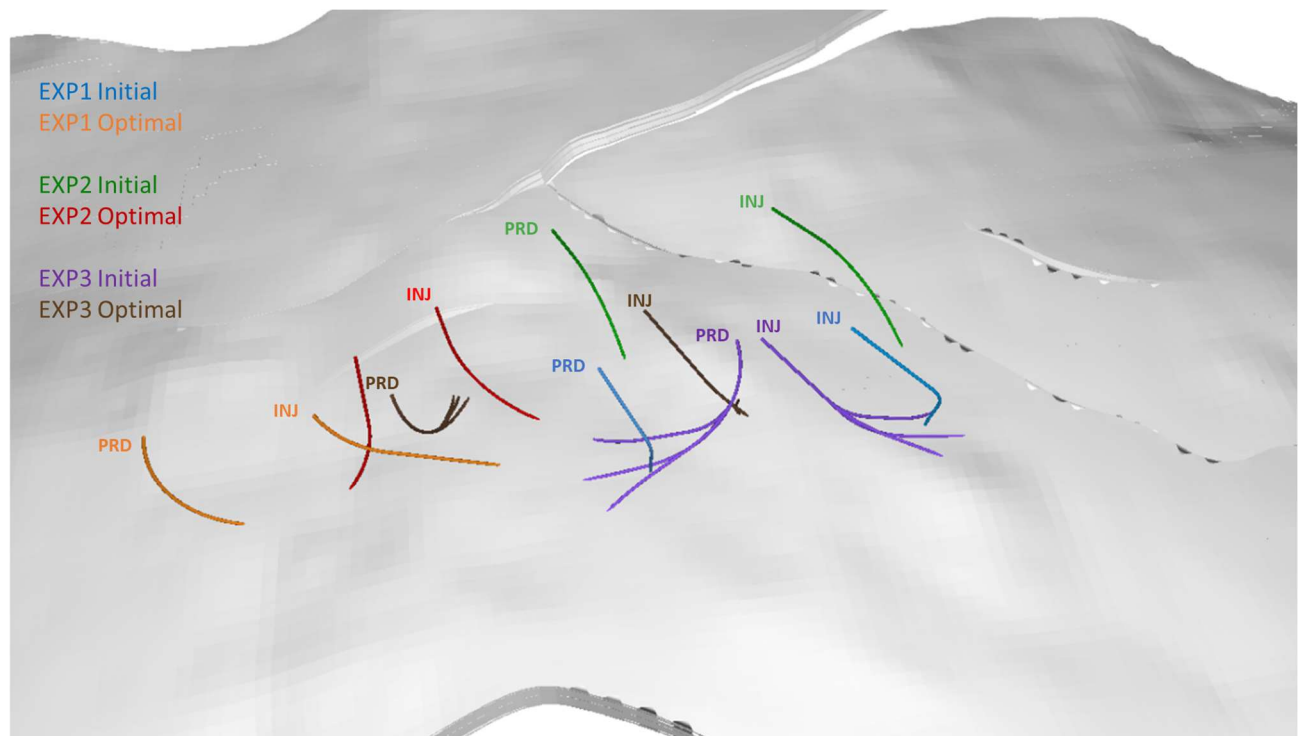
Three well location/trajectory optimization experiments have been performed with different initial well concepts: (1) slightly deviated, (2) strongly deviated and (3) multi-lateral wells. In the first two experiments, the optimizer has the freedom to explore more broadly different well shapes (from almost horizontal to almost vertical). In Experiment 1, we start with slightly deviated wells. In Experiment 2, we start with strongly deviated wells. In Experiment 3, we consider multilateral wells with two additional legs in addition to the main branch (i.e. 3 branches in total) of both, injector and

<sup>1</sup> The heat price with feed-in and without is assumed both the same

producer. The search space for the shape of multilateral wells is constrained by imposing a maximum allowed inclination of  $60^\circ$  for each of the branches. The general location and the distance between the injector and producer in the reservoir for the initial guesses of all experiments have been kept similar i.e.  $\sim 1000$  meters. During the optimization, in addition to other economic costs of the project, we also take into account the variable cost per length of each well. In case of multilateral wells, this means sum of the cost of the main branch and cost of the lateral branches by basing the calculation on the total combined well length. For more details on the initial well locations and trajectories, see Figure 6, Figure 7 and Figure 8.



**Figure 6:** Well locations for initial and optimal solutions of each experiment in the Zwolle case.

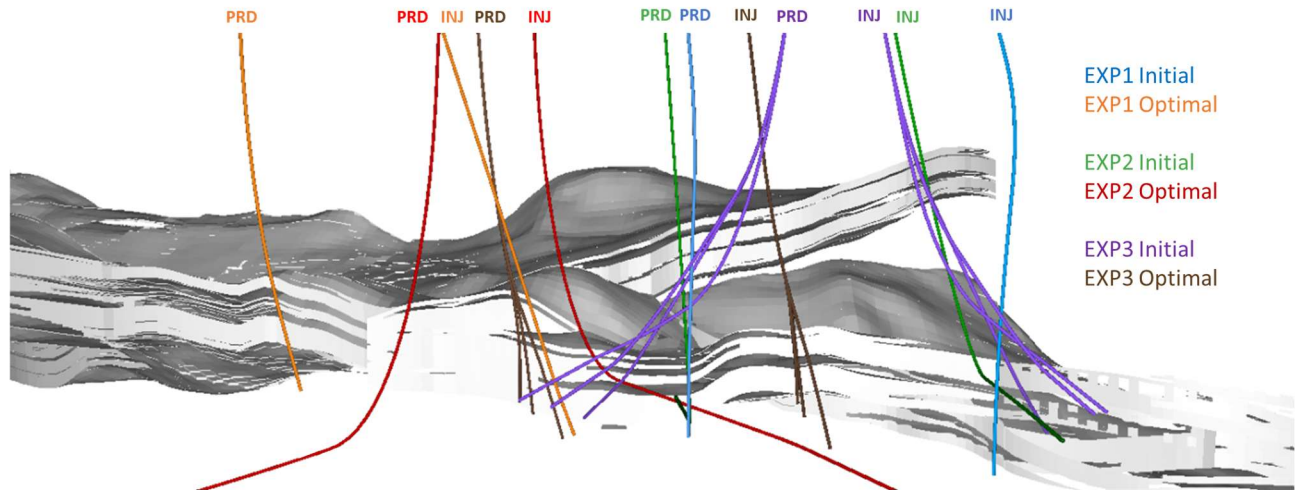


**Figure 7:** Well locations for initial and optimal solutions of each experiment in the Zwolle case (zoom-in target region).

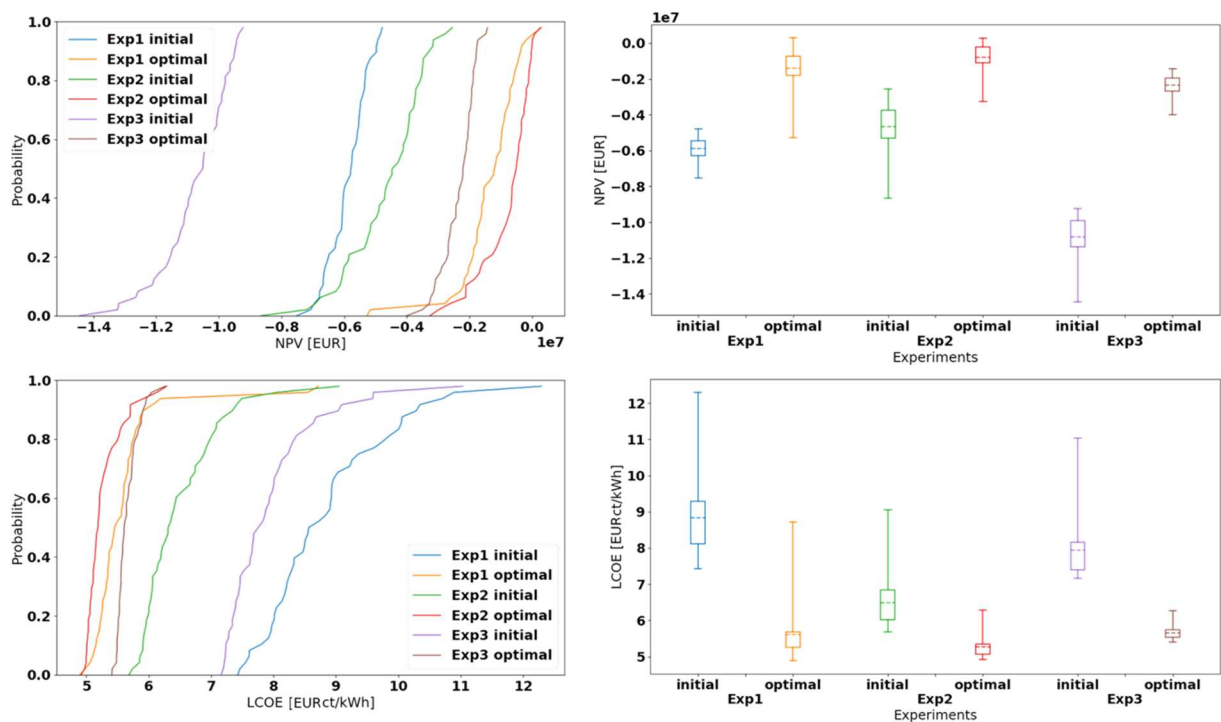
We notice that optimal locations of the wells for all the three experiments follow some pattern by moving in the same (west) direction, see Figure 6 and Figure 8. However, the shapes of the optimized well trajectories differ considerably across the experiments. When starting with slightly deviated wells (Experiment 1), trajectories for both wells stay slightly deviated. On the other hand, when starting with strongly deviated wells (Experiment 2) and providing more freedom for the well shape to change throughout the optimization, we observe differences in optimal well shapes. Only



the trajectory of the producer becomes slightly deviated, while the shape of the injector remains strongly deviated as in the initial guess in order to sustain high enough injection rate (affected by higher viscosity of cold water) to meet the production rate. For experiment with multilateral wells, the optimal branches are closer to vertical and the tie-in is deeper due to constraint on maximum inclination for each leg.



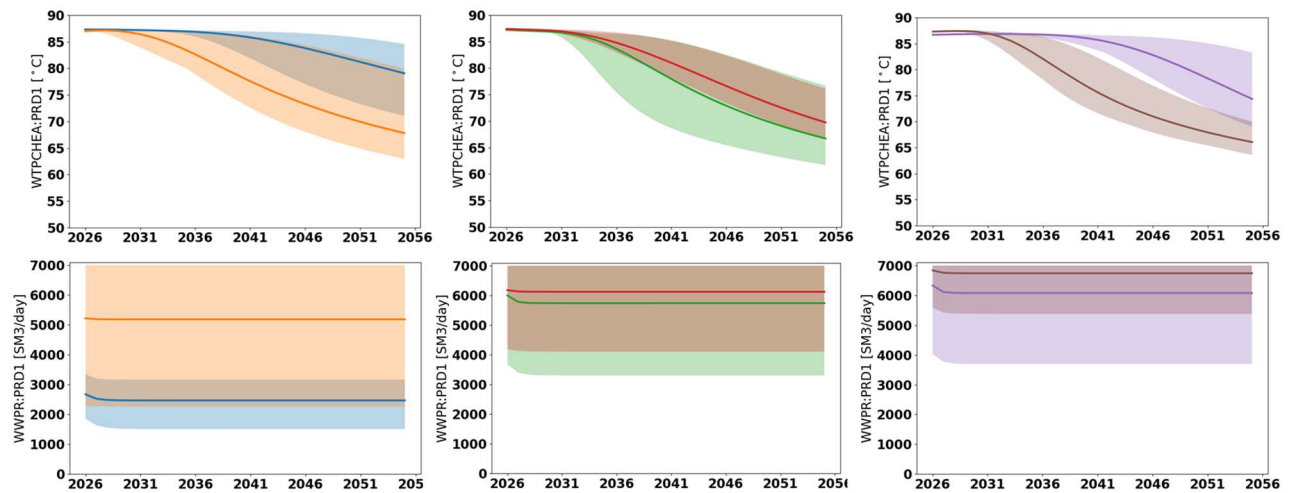
**Figure 8:** Cross section of the Zwolle model overlaid by well trajectories for initial and optimal solutions of each experiment.



**Figure 9:** Cumulative density functions (CDFs) of initial guess and optimal well locations/trajectories of the experiments.

In the case where the optimal shape of the injector is strongly deviated (Experiment 2) the resulting NPV is higher on average compared to the other experiments, and the resulting LCoE is lower on average, see Figure 9. However, the spread or uncertainty on both NPV and LCoE associated with the optimal solution for multilateral wells (Experiment 3) is the lowest, even though the optimization

was not explicitly set up to reduce this spread. If we compare the NPV and LCoE of the initial solution of all experiments, we can also see that an improvement is achieved by simply switching from slightly deviated to strongly deviated wells, however this improvement is significantly lower comparing to the improvement found by any of the two optimization experiments. This provides evidence that it is not only the shape of wells, but the combination of shape and location of wells which determine the techno-economic performance of the doublet. For multilateral wells, initial solution is the worst. In terms of economics which is due to higher drilling cost, i.e. the achieved well rate and production temperature for initial solution are comparable or better than initial solutions of the other two experiments, see Figure 10.



**Figure 10:** Temperature and production rates in producer for initial and optimal well locations/trajectories.

The resulting water injection/production rates and production temperature time profiles (both calculated by the reservoir simulator) have significant impact on the project economics. We note that optimization in Experiment 1 (with slightly deviated wells) was able to increase injectivity mostly by finding better well locations. This, however, resulted in significantly earlier arrival of the cold water in the producer, see Figure 10. In Experiment 2, (initial guess with strongly deviated, longer wells) we start with better injectivity, however also with earlier cold water breakthrough in the producer. In that scenario, optimization was able to improve upon both aspects (i.e. delaying the arrival of the cold water in the producer and increasing injection/production well rates) by simultaneously determining optimal well locations (including well distance) and adjusting well trajectory shapes. For multilateral wells (Experiment 3) we start with relatively high injectivity and late cold water breakthrough. However, in optimal solution the increased injectivity comes at the cost of earlier cold water breakthrough.

## 4.3 Conclusions

Different well concepts (subvertical (exp1), sub-horizontal (exp2) and multi-lateral (exp3) have been compared for Zwolle in the context of well location and trajectory optimization. For each well concept, the optimization was able to significantly improve techno-economic performance of the doublet system in Zwolle site by changing locations and trajectories of both wells resulting in an improvement of economic performance from prior LCOE of 7-9 €/kWh to ca 5€/kWh.

The differences in economics between the optimal solutions for various well concepts are relatively small in terms of expected LCOE: 5-5.5 €/kWh. However the optimal well locations are significantly different than the initial guess and they reveal a trend in location of optimal development area. This suggests that it is not only the shape of wells, but the combination of shape and location of wells which determine the techno-economic performance of the doublet.

Optimization results shown that both sub-horizontal and multilateral well concepts are good candidates outperforming the sub-vertical choice. The sub-horizontal scenario resulted in higher NPV on average across the geological realizations, however multilateral solution delivers lowest economic risk (in terms of reduced spread in NPV and LCOE distribution) whereas the sub-vertical scenario is marked by highest spread. We note that these results are also conditional to the doublet operational conditions assumed within the models, namely the choice of maximum flow rate allowed ( $= 7,000 \text{ m}^3/\text{day}$ ) which may be too restrictive for well concepts with higher productivity potential.

## 5 Value of information

In this section we describe the results obtained by employing the Drill & Learn workflow developed in the RESULT project and presented in reports RESULT-D3.1 and RESULT-D3.2 to:

1. Validate that the Drill & Learn framework also leads to improved well design / placement solutions in the realistic Zwolle case study
2. Demonstrate how the Drill & Learn framework can provide insights into the value of additional information to further improve field development and well design decisions.

The Drill & Learn framework is essentially a closed-loop optimization framework where optimization and information feedback are alternated sequentially in a series of cycles (or loops). Learning from the gathered measurements is leveraged through model updates to match observations of the real system, acting as a feedback loop. During each loop of the Drill & Learn framework, the field development strategy (and well design concepts) are (re-)optimized based on the latest available model updates. By continuously updating the models based on the latest information (here, the well-logs at the fixed well locations in the previous loop), uncertainty is reduced and the predictive power of the models is increased, which, in turn, makes the optimized strategies more suitable for the real system. Once again, the optimization of well trajectories follows TNO's EVEReST workflow for model-based optimization under uncertainty (Barros et al., 2020). And the data assimilation step for the ensemble-based model calibration to hard data obtained from wells with the ERT open-source framework. Both methods and underlying tools are described in more detail in the RESULT-D2.3 and RESULT-D3.1 reports. For a more extended explanation of the Drill & Learn framework (including a step-by-step description of the procedure), we refer to report RESULT-D3.1, and to Hanea et al. (2018) and Jansen et al. (2009) for more information on other Drill & Learn and closed-loop optimization applications.

In the case of the Zwolle case study where we aim at optimizing the well trajectory design of the two wells forming a doublet, the Drill & Learn approach consists of seven steps:

- i. Perform robust optimization to optimize trajectories of both producer and injector simultaneously under prior geological uncertainties (as described in section 3 and applied in 4)
- ii. Fix trajectory of first well to be drilled as the one optimized in step (i) and gather well-log data (here, generated synthetically by assuming a "truth" model)
- iii. Evaluate performance of optimization well configuration obtained in step (i) on "truth" model
- iv. Update ensemble of models by conditioning them to well-log data through data assimilation (i.e., history matching)
- v. Perform robust optimization to optimize trajectory of the second well to be drilled (here, the first well is kept fixed) under posterior geological uncertainties characterized by updated ensemble of models
- vi. Evaluate performance of re-optimized well configuration obtained in step (v) on "truth" model
- vii. Quantify improvement in performance on "truth" model due to Drill & Learn

The procedure above implies two main choices: selecting a model realization as the "truth" model and selecting which one of the wells (producer or injector) is to be drilled first. For the first choice, we have simply generated one additional model realization (which is not part of the prior ensemble) to play the role of "truth". Regarding the choice of drilling producer or injector first, we have considered both situations to investigate which one leads to better results. In other words, two Drill

& Learn experiments have been performed: Experiment 1 (drilling producer first) and Experiment 2 (drilling injector first). These two experiments consider drilling of quasi-vertical wells.

## 5.1 Robust optimization for quasi-vertical wells

### 5.1.1 Simplified economic

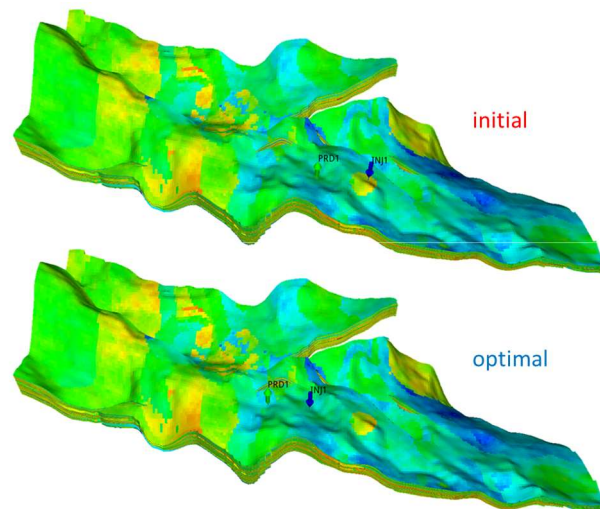
The VOI analysis has been performed with a simplified economic model, compared to Section 4, as listed in Table 2. These simplified assumptions focus on the trade-off between well costs and optimal placement, and are marked by relatively low CAPEX for surface facilities compared to the more detailed cost engineering used in Section 4 (Table 1). In addition, we evaluate for the economic key performance indicator Net Present Value (NPV) instead of LCOE.

**Table 2:** Simplified Technical and economic parameters based on the cost calculations used in Section 4.

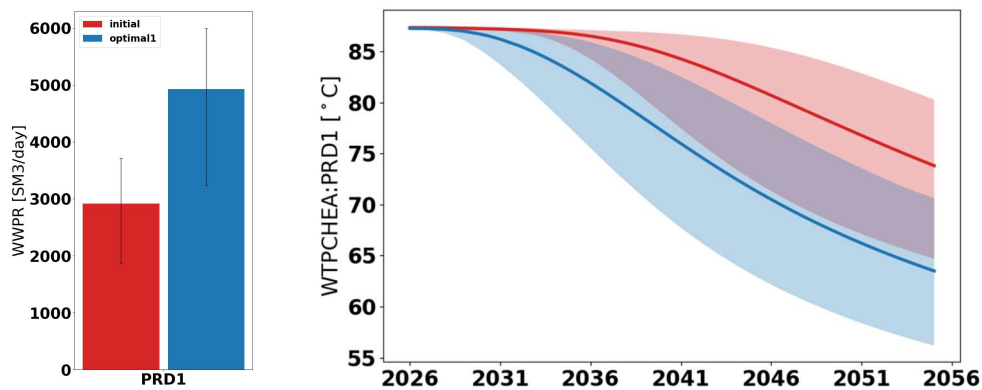
Parameter	value	unit
ESP	1	mIn €
injection pump	0.5	mIn €
pump efficiency	0.65	
pump life	3	years
CAPEX drilling	2	mIn €/km
OPEX well	0.25	mIn €/y
discount factor	8	%
heat price	5 <sup>2</sup>	€/GJ
electricity price	13.3	€/GJ
economic lifetime	30	years
injection temperature	35	°C

Results of the robust optimization of well trajectories under prior uncertainty show that significant improvements can be achieved in terms of NPV as shown in Section 4. Also In this exercise, as a first step, the trajectories of both wells are optimized simultaneously. Figure 11 displays comparison of initial and optimal well placements depicted for one model realization (note that well trajectories were optimized while taking into account all realizations). By shifting the doublet towards the west and adjusting the spacing between the wells (which become slightly deviated instead of vertical), higher production rates can be achieved on average across the 100 model realizations (Figure 12). This contributes to a sensible increase of about 5.95 million EUR on average in the cashflow of the project.

<sup>2</sup> The heat price is doubled the first 15 years to include the effect of feed-in



**Figure 11:** Comparison of initial and optimal well placement based on robust optimization of well trajectories under prior uncertainty for the Zwolle case.



**Figure 12:** Comparison of production rate and temperature with initial and optimal well trajectories in the Zwolle case. The solid lines and shaded areas indicate the average value and the variability spread over the ensemble of 100 model realizations. This relates closely to the left panels in **Figure 10**

## 5.2 VOI Results of Experiment 1: drilling producer first

After performing the Drill & Learn calculations, three development strategies with different well trajectories can be compared in terms of the predictions from the ensembles used within the optimizations and the behavior of the “truth” models for these different strategies, namely:

1. Initial strategy
2. Optimized strategy under prior uncertainty (1<sup>st</sup> loop)
3. Re-optimized strategy under posterior uncertainty (2<sup>nd</sup> loop)

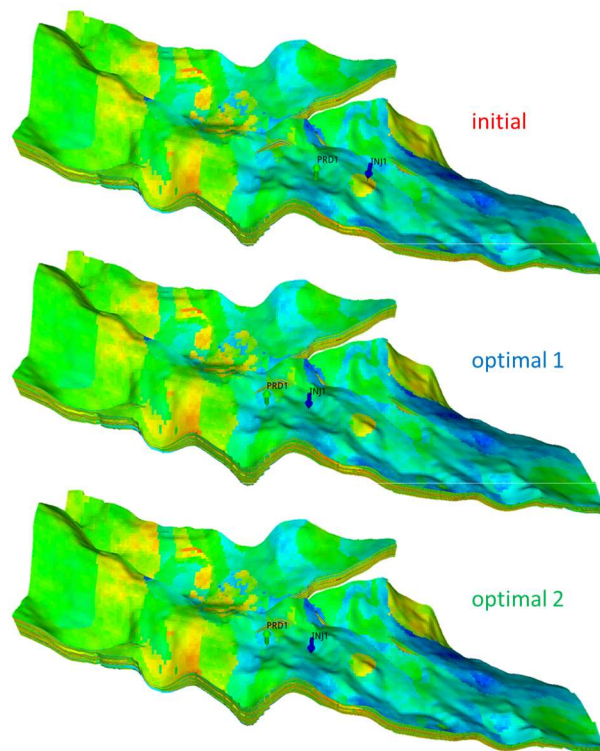
Figure 13 shows the well placement of these three development strategies. Note that the optimized strategy from the first loop of the Drill & Learn (i.e. optimal 1) is the same as reported in Figure 11 from Section 5.1. The re-optimized strategy from second loop (i.e. optimal 2) is similar but a little different from strategy optimal 1: the trajectory of the producer remains the same because that is the first well to be drilled in this experiment, and the trajectory of the injector is slightly adjusted.

The updates in the optimal well trajectories from first and second loops of the Drill & Learn workflow are a result of the model updates that take place when incorporating well-log data from the production well. The model updates are achieved through ensemble-based data assimilation



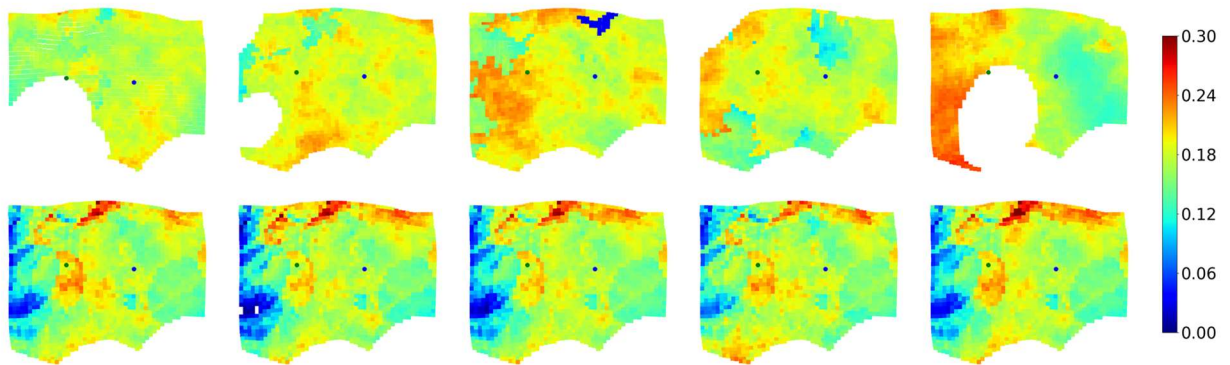
(or “history matching”) which adjusts the uncertain model parameters (i.e. permeabilities and porosities) of the model realizations from the prior ensemble to derive the posterior ensemble conditioned to the well-log observations from the production well. Figure 14 and Figure 15 illustrate the model updates achieved through data assimilation, focusing on the area in the vicinity of the considered doublet. We note that the heterogeneities in the posterior models resemble much more closely the porosity distribution observed in the “truth” model, thereby reducing the uncertainty and consequently the variability of model responses (see smaller spread within green curves in Figure 16).

The optimization performed over the posterior ensemble of models allows the well path of the injector to be better tailored to the new posterior models. We observe that, despite a slightly lower production rate being achieved by re-optimizing the well trajectory of the injector, the cold water breakthrough at the producer is significantly delayed (~4 years), which contributes to improve both the heat recovery and the cashflow of the project. Because of their stronger resemblance with the “truth” model, the improvement in the performance of the posterior ensemble with the re-optimized well trajectory results also in an improvement in objective function (NPV) for the “truth” model, as it can be seen in Figure 17 and Figure 19. This incremental increase in NPV of approximately 250,000 EUR from strategy optimal 1 to strategy optimal 2 is an indicator of the added value of the Drill & Learn approach (and the value of information of acquiring / processing well-log data) in Experiment 1. Figure 18 shows that optimization accounting for a techno-economic objective function results in a well placement strategy leading to a well spacing which is just large enough to avoid cold-water breakthrough in the producer and lower costs.

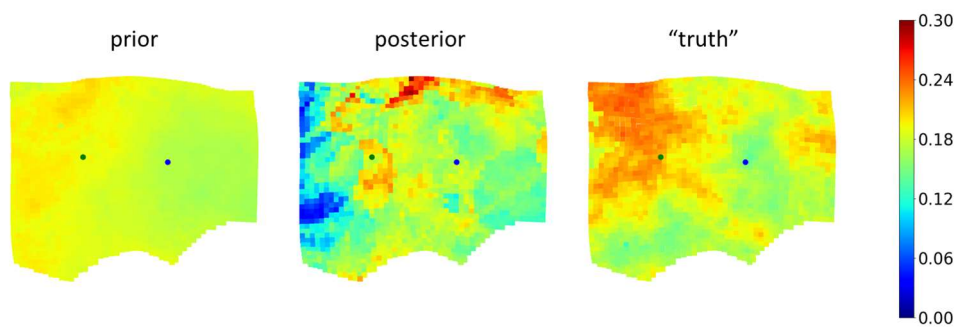


**Figure 13:** Comparison of initial, optimized and re-optimized well trajectories as a result of Experiment 1 of Drill & Learn performed in the Zwolle case.

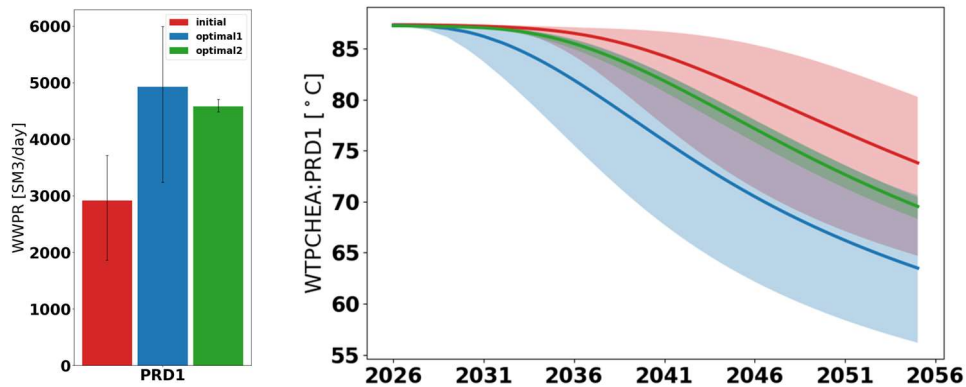




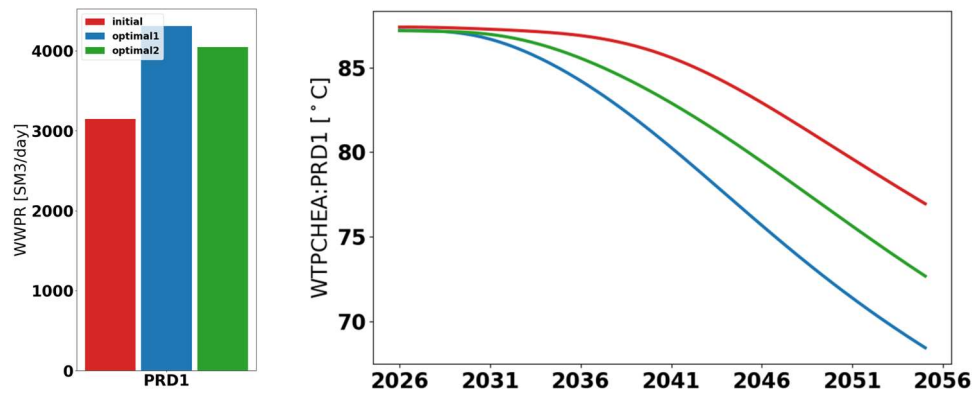
**Figure 14:** Comparison of five (randomly selected) realizations of the porosity field from prior (top row) and posterior (bottom row) ensembles in Experiment 1 of Drill & Learn performed in the Zwolle case.



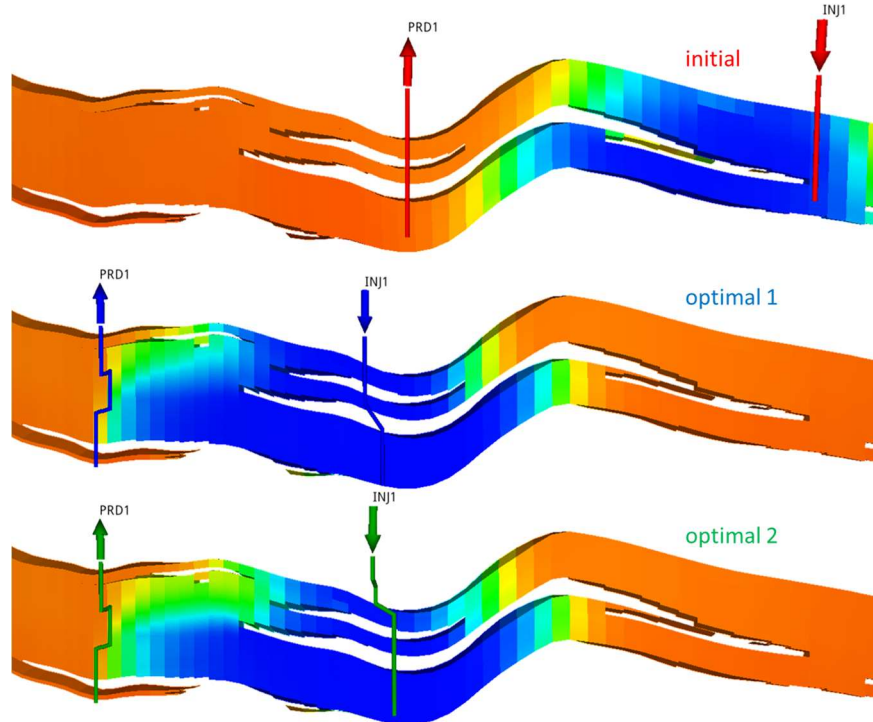
**Figure 15:** Comparison of the average porosity field from prior (left) and posterior (middle) ensembles against the porosity field of the "truth" model in Experiment 1 of Drill & Learn performed in the Zwolle case.



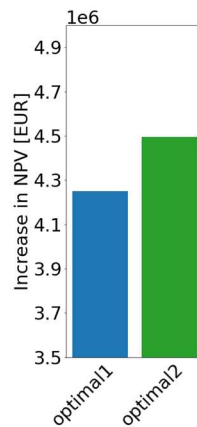
**Figure 16:** Comparison of production rate and temperature with initial (red), optimized (blue) and re-optimized (green) well trajectories over the ensembles of models from the Experiment 1 of Drill & Learn in the Zwolle case. The solid lines and shaded areas indicate the average value and the variability spread over the ensemble of 100 model realizations.



**Figure 17:** Comparison of production rate and temperature with initial, optimized and re-optimized well trajectories for the “truth” model from the Experiment 1 of Drill & Learn in the Zwolle case. The solid lines and shaded areas indicate the average value and the variability spread over the ensemble of 100 model realizations.



**Figure 18:** Vertical cross-section of temperature profile after 30 years of operations with initial, optimized and re-optimized well trajectories for the “truth” model from the Experiment 1 of Drill & Learn in the Zwolle case.

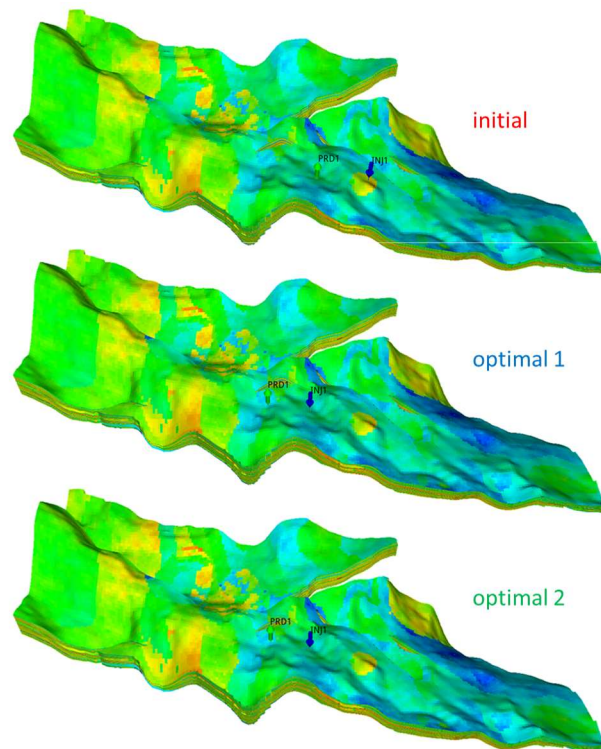


**Figure 19:** Comparison of NPV increase with optimized and re-optimized well trajectories (with respect to initial strategies) for the “truth” model from the Experiment 1 of Drill & Learn in the Zwolle case.

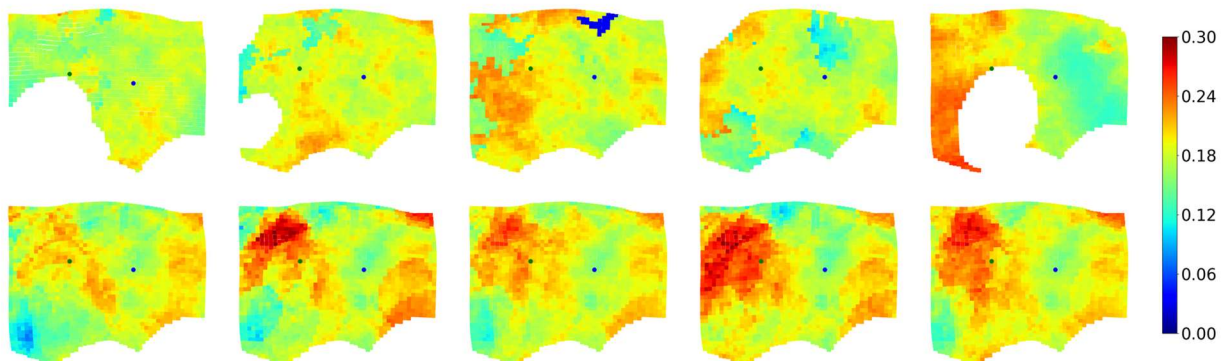
### 5.3 VOI Results of Experiment 2: drilling injector first

The same analysis from Experiment 1 was repeated for Experiment 2, with the only difference that in this case the injection well is assumed to be drilled first, allowing the well trajectory of the production well to be optimized based on posterior knowledge (with additional well-log data from the injector). Figures Figure 20, Figure 21, Figure 22, Figure 23, Figure 24, Figure 25 and Figure 26 can be compared with the figures from Section 5.2.

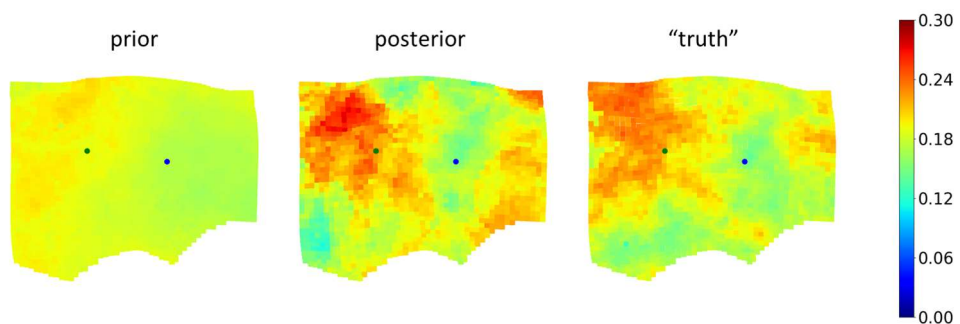
We observe that the assimilation of the well-log data from the injector well seems to produce posterior models that resemble even closer the “truth” model than in Experiment 1, which contributes to re-optimized well trajectories of the producer better suited for the “truth” model. Besides that, due to the way voidage replacement constraints have been imposed within the reservoir simulator (re-injection of all produced volumes), it appears to be more effective to optimize the trajectory and location of the producer once the location of the injector is fixed than the other way around. As a result, even better techno-economic performance for the heat recovery can be achieved for the posterior ensemble and, consequently, for the “truth” model. In this case, the incremental increase in NPV is of approximately 500,000 EUR from strategy optimal 1 to strategy optimal 2 (250,000 EUR more than in Experiment 1), which suggests that here the Drill & Learn approach and additional well-log information are more valuable when the injector is drilled first. Once again, we observe that the most optimal well placement strategy has a just large enough well spacing to avoid cold-water breakthrough in the producer and lower costs within the project life-cycle.



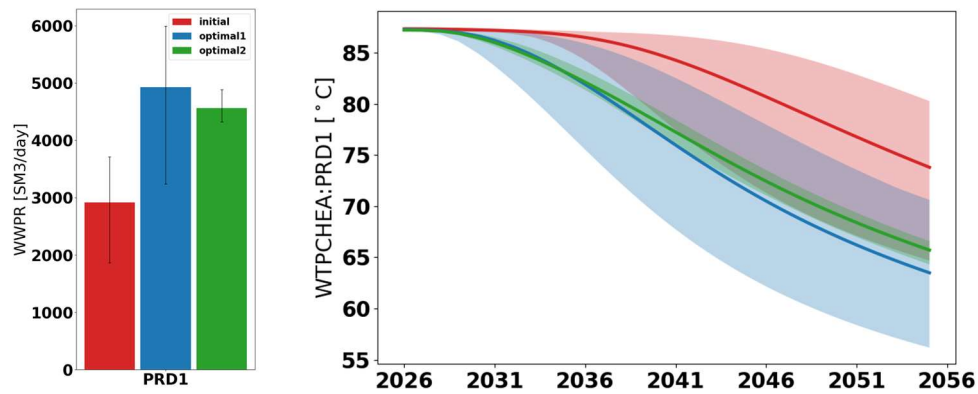
**Figure 20:** Comparison of initial, optimized and re-optimized well trajectories as a result of Experiment 2 of Drill & Learn performed in the Zwolle case.



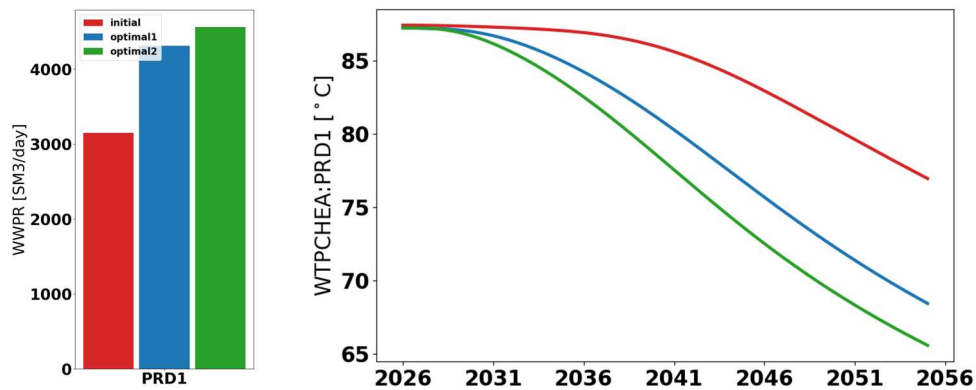
**Figure 21:** Comparison of five (randomly selected) realizations of the porosity field from prior and posterior ensembles in Experiment 2 of Drill & Learn performed in the Zwolle case.



**Figure 22:** Comparison of the average porosity field from prior (left) and posterior (middle) ensembles against the porosity field of the "truth" model in Experiment 2 of Drill & Learn performed in the Zwolle case.

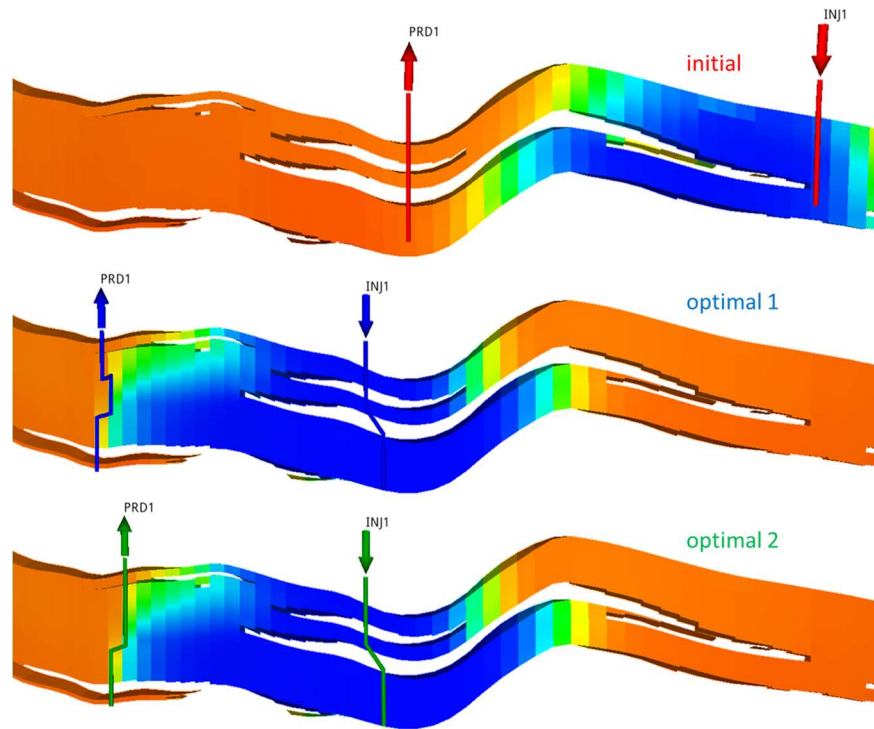


**Figure 23:** Comparison of production rate and temperature with initial (red), optimized (blue) and re-optimized (green) well trajectories over the ensembles of models from the Experiment 2 of Drill & Learn in the Zwolle case. The solid lines and shaded areas indicate the average value and the variability spread over the ensemble of 100 model realizations.

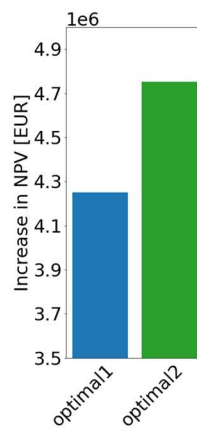


**Figure 24:** Comparison of production rate and temperature with initial, optimized and re-optimized well trajectories for the “truth” model from the Experiment 2 of Drill & Learn in the Zwolle case. The solid lines and shaded areas indicate the average value and the variability spread over the ensemble of 100 model realizations.





**Figure 25:** Vertical cross-section of temperature profile after 30 years of operations with initial, optimized and re-optimized well trajectories for the “truth” model from the Experiment 2 of Drill & Learn in the Zwolle case.

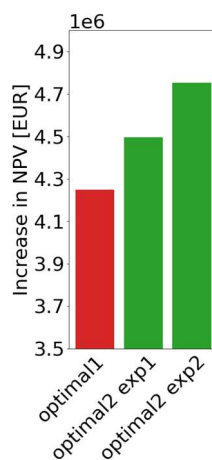


**Figure 26:** Comparison of NPV increase with optimized and re-optimized well trajectories (with respect to initial strategies) for the “truth” model from the Experiment 2 of Drill & Learn in the Zwolle case.



## 5.4 Conclusions

The Drill & Learn framework developed in WP3 of the RESULT project has been successfully applied to the Zwolle site assuming 1 planned doublet (1 producer + 1 injector). An ensemble of 100 realizations of the dynamic simulation model for the Rotliegend reservoir has been generated to characterize the prior (i.e. initial) geological uncertainties. Robust optimization and Drill & Learn experiments have been performed to showcase how the effect of incorporating additional well-log information from the first well to be drilled can help practitioners achieve improved field development strategies. The results obtained validate that the Drill & Learn optimization ideas are also feasible and valuable in realistic case studies.



**Figure 27:** Comparison of NPV increase for the “truth” model in the two Drill & Learn experiments: Experiment 1 (drilling producer first) and Experiment 2 (drilling injector first).

Two Drill & Learn experiments have been performed by varying which well is to be drilled first (producer or injector). The analysis of the results revealed also some interesting non-trivial insights into the order in which the wells should be drilled (injector first, then producer) in order to maximize the benefits of the learning from well-logs to further improve the optimized well trajectories, see Figure 27. This suggests that, in the presence of large uncertainties, smart field development strategies comprise the evaluation of well locations not only to achieve the highest expected performance given the currently available knowledge of the system, but also to maximize the information content of additional data from the first drilled wells. Combining both performance and information gathering considerations within the same optimization framework will lead to the ultimate best solution to this problem where exploration and exploitation objectives must be balanced. Both robust optimization and Drill & Learn frameworks covered in this report constitute the key components to establish such an exploration vs. exploitation optimization approach in the future.

The Drill & Learn exercise also allows for a rough practical assessment of the value of information (VOI) to evaluate the expected impact of additional measurements from drilling and logging activities of the first well(s) on upcoming field development decisions. Such a VOI assessment serves as the basis to justify information gathering activities, e.g. the deployment of new sensors / instruments and the acquisition of additional exploration campaigns (wells or surveys)

## 6 Key messages

The application of the well trajectory optimization workflows to the Zwolle case study successfully demonstrates two main optimization approaches for three well design concepts considered (quasi-vertical, sub-horizontal and multilateral):

- Robust optimization under prior uncertainty
- Drill & Learn approach (which leverages learning from drilled wells to further enhance the optimization of subsequent wells)

As input prior (and updated) uncertainty for both optimization workflows, an ensemble of (dynamic) reservoir flow models was generated to represent the underlying geological uncertainty associated with the characterization of the properties of the target reservoir formation at the Zwolle location (from RESULT report D4.1).

The three well concepts (subvertical (exp1), sub-horizontal (exp2) and multi-lateral (exp3) have been compared for Zwolle in the context of well location and trajectory optimization. For each well concept, optimization was able to significantly improve techno-economic performance of the doublet system in Zwolle site by changing locations and trajectories of both wells resulting in an improvement of economic performance from prior LCOE of 7-9 €/kWh to ca 5€/kWh.

The differences in economics between the optimal solutions for various well concepts are relatively small in terms of expected LCOE: 5-5.5 €/kWh. However the optimal well locations are significantly different than the initial guess and they reveal a trend in location of optimal development area. This suggests that it is not only the shape of wells, but the combination of shape and location of wells which determine the techno-economic performance of the doublet.

Optimization results shown that both sub-horizontal and multilateral well concepts are good candidates outperforming the sub-vertical choice. The sub-horizontal scenario resulted in higher NPV on average across the geological realizations, however multilateral solution delivers lowest economic risk (in terms of reduced spread in NPV and LCOE distribution) whereas the sub-vertical scenario is marked by highest spread.

Two Drill & Learn experiments for the sub-vertical well concept have been performed by varying which well is to be drilled first (producer or injector). The analysis of the results revealed also some interesting non-trivial insights into the order in which the wells should be drilled (injector first, then producer) in order to maximize the benefits of the learning from well-logs to further improve the optimized well trajectories. The results indicate that, in the presence of large uncertainties, combining both performance and information gathering considerations within the same optimization framework will lead to the ultimate best solution to this problem where exploration and exploitation objectives must be balanced. Both robust optimization and Drill & Learn frameworks covered in this report constitute the key components to establish such an exploration vs. exploitation optimization approach in the future.

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