NTNU
Norwegian University of
Science and Technology

Study of Closed-loop Reservoir Management and Case Development for Production Optimization using Brugge model

Behrouz Maghsoudi

Petroleum Engineering
Submission date: June 2016
Supervisor: Jon Kleppe, IPT

Norwegian University of Science and Technology
Department of Petroleum Engineering and Applied Geophysics

Summary

Improving reservoir performance is at the heart of all reservoir management process. Reservoir optimization enhances decision making which leads to decreased total costs and increased recovery. In practice, manual optimization approaches are widely used for reservoir management, however, they are time-consuming and include many trial and errors. Additional research has been initiated in order to find more systematic optimization approaches.

This work consists of three major parts: (1) a general description of main concepts and tools in reservoir management (2) detailed case description of the developed cases and presentation of the model performance of each and, finally (3) presentation and discussion of the results of each case optimization.

Due to growing interest in applying mathematical optimization techniques to reservoir management, in this thesis we develop interesting and relevant petroleum cases for production optimization, and applying mathematical optimization techniques. Our development process consists of the model conversion of Eclipse 100 model to E300 model. The project is converted into Petrel RE in order to enable design of desired cases such as new wellbore trajectories, create segment models and development strategy for each case. In this process, parameters such as the initial oil saturation, geological features, rapid petrophysical variations in the formation, different well placements, and rate allocations were taken into consideration.

Several cases with different characters were created of which three were selected, based on their attractiveness for production optimization. During this process, factors such as wells setting (horizontal and vertical wells), and field performance (e.g. oil production rate, final oil recovery, water injection and production) were taken into consideration. The cases were developed for research at Petroleum Cybernetics Group at NTNU and are to be used for research and educational purposes.

The cases considered were used to test the built-in optimizer in Eclipse for production optimization. For each case an optimization problem was designed in order to improve the model performance in terms of increased maximization of oil production and the net present value. The implementation of the optimizer was successful and the model performance improved significantly. In case 1, the NPV of the segment was improved by 93% by increasing the total oil production, and decreasing the amount of produced and injected water. In case 2, the total oil production was improved by employing the available water injection. The final oil recovery increased by 10%. In case 3, the NPV of the segment increased by 12.7 % due to the handling of the high water production in the field.

Briefly, we can itemize the main contributions of this study as presented bellow.

- Development of scenarios/cases for research at the Petroleum Cybernetics Group in NTNU. For research purpose, it is important that these cases are realistic in terms of grid geometry, geology, production settings, well-setting, etc.
- Create a set of detailed workflows for case development with various properties. In

this way, other researchers can use these workflows to develop cases specific to their research needs.

- The following detailed workflows are created:

  1. Model conversion from E100 to E300
  2. Eclipse deck conversion into a Petrel RE project
  3. Case development procedure including grid carving, designing new well trajectories, development strategy
  4. Test and create an optimization workflow in Eclipse 300

Preface

This Masters Thesis is submitted to the Norwegian University of Science and Technology (NTNU), Trondheim, Norway, for partial fulfillment of the requirements for the degree of Master of Science in Petroleum Engineering.

I would like to express my deepest gratitude to my supervisor, Professor Jon Kleppe and co-supervisor Mathias Bellout for giving me the opportunity to work with this very interesting subject. Without their support, guidance, and advice I would not have been able to complete this project.

I would also extend my sincere thanks to Dutch Applied Research Organization (TNO) for providing the Brugge field for this study. Last but not least, I want to thank my family for all the dedications and support.

Table of Contents

List of Tables

List of Figures

Abbreviations

CLRM	=	Closed-Loop Reservoir Management
WCT	=	Water-cut
OOIP	=	Original Oil In Place
NPV	=	Net Present value
TNO	=	Dutch Applied Research Organisation
BHP	=	Bottom Hole Pressure
EOR	=	Enhanced Oil Recovery
HD	=	Half-dome structure
HD1	=	Half-dome structure production strategy 1
HD2	=	Half-dome structure production strategy 2
FOPT	=	Field Oil Production Total
FWPR	=	Field Water Production Rate
WBHP	=	Well Bottom hole pressure
WOPR	=	Well Oil Production Rate
WWIR	=	Well Water Injection Rate
WLPR	=	Well Liquid Production Rate
SQP	=	Sequential Quadratic Programming
NTG	=	Net-to-Gross
CNTL Mode	=	Control Mode
BBL	=	Barrel
LRAT	=	Liquid Rate
Psi	=	Pounds per square inch

Chapter 1

Introduction

The rapid population growth and the sustainability of modern societies depend on a steady and predictable source of energy. World's consumption of oil and gas is increasing and according to BP's report for energy consumption 2014, oil and gas stand for more than 50% of primary energy consumption worldwide. Oil remains the world's dominant fuel. Oil and gas will play a crucial role to supply the world's energy demand for several decades to come even within a 2 °C scenario according to the Paris agreement in 2015.

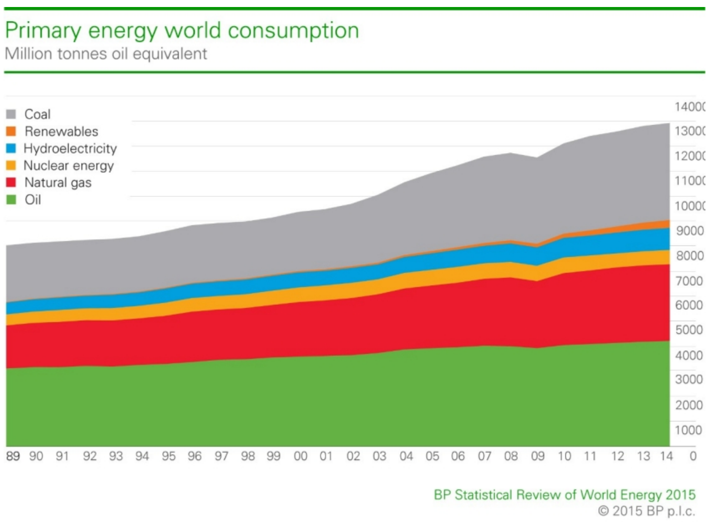


Figure 1.1: British Petroleum statical review of world energy 2015

Due to the fact that fossil energy is non-renewable, it will be difficult to meet this ever-increasing demand for oil and gas. Most of producing fields are already at a mature stage and the "easy" oil has been produced. The discovery of marginal fields is dwindling and it will become very important to maximize oil recovery from existing fields in order to meet the world's energy demand. The most popular methods to increase the oil recovery is water-flooding. In this method, the water is injected into the reservoir to displace the oil and maintain the reservoir pressure. The popularity of water-flooding is due to its relative easiness of injection and the abundance of water (Craig, 1993). Worldwide average oil recovery lies between 20% - 40% of initial oil in place (Muggeridge et al., 2013). The successful reservoir management in Norway has resulted in relatively high oil recovery. This is a result of the application of new technology and enhanced decision making in the Norwegian continental shelf. Still, the amount of remaining oil in the subsurface is huge and can be improved. Improving the oil recovery even with a few percent from large oil fields such as recently discovered Johan Sverdrup in North-Sea will result in a production of billions additional oil barrels. Along with maximizing oil recovery, it will be extremely important to minimize the capital expenditure to ensure that the asset has achieved its maximum potential. Production optimization is a possible approach to cope with these problems. It is a general term that refers to the performance maximization of the oil and gas reservoirs by making optimal reservoir management and development decisions. The motivation behind this work is the growing interest in applying mathematical optimization techniques to reservoir management. Manual optimization approaches are widely used in the reservoir management practice but include a great number of trials and errors. Research has been initiated to find a more systematic optimization approach particularly for oil reservoirs under water-flooding.

This study will review important concepts within reservoir management, such as reservoir modeling and simulation, Closed-loop reservoir management and water-flooding. We will review various approaches to water-flooding optimization and workflow of optimizer facility in Eclipse. We will get insight into the mathematical background of the optimization. The main purpose of this study is to get an understanding of what scenarios/cases are relevant for optimization and develop interesting and relevant petroleum cases in Petrel. These cases will then be subjected to production optimization by using the Eclipse optimizer. This work is a continuation of the specialization project in reservoir engineering from fall 2015. Some part of the theory will be included from the previous work and is marked with ”Maghsoudi (2015)”

1.1 Thesis Outline

Chapter 2 presents the theory of reservoir management. This chapter gives an overview of the concepts and tools in the management process such as reservoir simulation, closed-loop approach and various aspects of water-flooding. There will also be a brief review of the mathematical background of optimization where different approaches are presented and compared. The general structure of optimization problems is also presented. Further, the optimizer facility in Eclipse that was implemented in this study is introduced and the optimization workflow is described in details. The production optimization theory is presented in the next section. This section gives insight into the general terms and previous studies of production, especially in water-flooding operations. The concept of production optimization is quite vast but the most relevant subjects in this study are reactive and proactive controls in water-flooding optimization and adjoint technique. The latter is an efficient method to obtain gradient information when the number of control parameters is large. There will also be a discussion around the formulation of the optimization problems at the end of this chapter. **Chapter 3** presents the developed petroleum cases for production optimization. Three segment models were developed and described in details in terms of grid geometry, geology, petrophysical properties and different development strategies. The base cases were run and the results such as production performance and saturation profiles in the reference production strategy are presented. The detailed workflow for the case development process and optimization is given in **Appendix**. **Chapter 4** formulates the optimization problems for the developed cases. The objective function of the optimization study, relevant control parameters, and constraints are described. The economic parameters in the objective function are presented and we discuss the choice of control parameters and constraints. **Chapter 5** demonstrates the results from the application of production optimization to developed cases and compare the results to the reference cases. In this chapter, the sensitivity to different control parameters, improvements of the objective function, and production profiles are analyzed and discussed. **Chapter 6** presents the discussion of the literature study and experimental work. **Chapter 7** offer concluding remarks in this study with the most significant points and the recommendations for the future work.

Chapter 2

Basic theory and literature study

2.1 Reservoir management

For a very long time, reservoir management was considered mostly dependent and almost synonymous to the concept of reservoir engineering. Understanding the rock mechanics and reservoir characteristics was the key for obtaining a successful reservoir management (Essley, 1965).

The key for a successful reservoir management was mainly understanding the technical and engineering aspects of the field to determine the best strategy for field development. After 1970, experts described reservoir management more precisely and emphasized the importance and value of collaboration between engineering, geology, and detailed reservoir characterization (Maghsoudi, 2015).

A. Satter (1994) defined reservoir management as utilization of all available resources such as human, technological and financial to maximize the profit of a hydrocarbon reservoir by optimizing the recovery factor while minimizing capital investment and expenses. In other words, reservoir management is about participation of integrated, multidisciplinary technologies and other resources in order to mitigate the effect of uncertainties which result in a more detailed reservoir description (Craig, 1977; Harris and Hewitt, 1977). Efficient reservoir management will eventually improve the management process and maximize the asset value by operating the field.

One critical step in reservoir management that continues throughout the lifetime of the reservoir is data management. For obtaining a successful reservoir management, it is essential to gather and evaluate information, a process known as data acquisition and quality assurance. Besides data management, efficient and realistic tools are vital for success in reservoir management to monitor and forecast the future performance of the reservoir.

Different tools are being used to forecast the reservoir performance such as classical volumetric calculation, material balance, and decline curve analysis, in addition to more advanced tools such as reservoir simulators used for estimating reserves and analyzing the future performance. Models are built based on the data acquired in the field description phase. (Maghsoudi, 2015).

These models should be validated to be useful. For this purpose, one need to monitor the production performance of the reservoir in the past. The practice of adjusting the model in order to reproduce the past behavior of a field is called history matching. A major part of the planning in field development and reservoir management is based on different scenarios generated by numerical models. Therefore developing reliable and steady models is crucial for reservoir management. In the next section, numerical reservoir simulation and the governing equations to describe fluid flow through porous media will be presented.

2.1.1 Reservoir simulation

As mentioned, reservoir simulation studies are one of the most significant methods in modern reservoir management process. Simulation studies are the means by which one uses numerical models built based on geological and petrophysical characterizations of a petroleum reservoir to monitor, analyze and predict fluid behavior over a period of time. The simulations are quick and cheap assessments of various production scenarios (Aziz and Settari, 1979a).

The ability of reservoir simulations to forecast production scenarios makes simulations an important tool for reservoir management. The purpose of simulation studies is to optimize development plans for new fields and assist with operational and investment decisions (Fanchi, 2005).

In a very basic form, a reservoir model consists of three major parts that will describe the reservoir by a computer model:

- The grid
- Fluid Flow equations
- Well model

The grid represents the porous rock formation in the form of a volumetric geological model with different petrophysical characterizations. A simple grid in Cartesian coordinate system is illustrated in Figure 2.1. Porosity and permeability are fundamental properties that strongly affect the fluid flow and characterize the reservoir model. Porosity ϕ is a dimensionless quantity that denotes the void space in the porous medium. Permeability, K is defined as the ability of a rock to transmit a one-phase fluid. Permeability is related to shape and level of connectedness of the pores. Although the SI-unit of permeability is m^2, $Darcy$[1] is commonly used in order to give a more intuitive sense of fluid transmission. Permeability and porosity variation within a porous medium may vary rapidly due to different rock types. In a geological model, this variation is described by discretizing the model into cells and assigning each cell with its petrophysical properties. Geological features such as fractures and faults are represented as breakages or cracks in the rock. If the breakage has not been displaced it represents a fracture. It is used to model fractured reservoirs with properties as dual porosity and permeability. Faults are displaced fractures

[1] The definition of 1 Darcy is $\approx 0.988 \times 10^-12m^2$ involving transmitting a fluid through a homogeneous rock with a speed of 1 cm/s and viscosity of 1 cp by a pressure gradient of 1 atm/cm

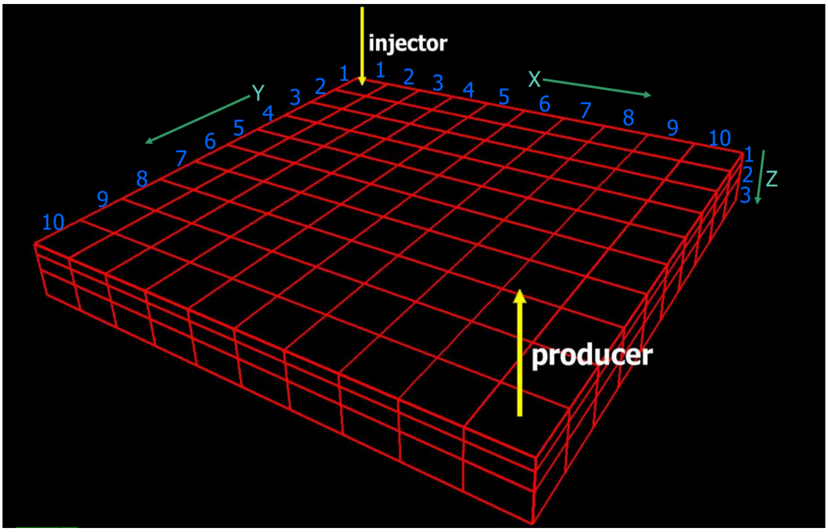


Figure 2.1: Simple grid in a Cartesian coordinate system.

assigned with a transmissibility to either create a barrier or enable fluid to flow through the fault (Ahmed, 2010).

The fluid flow in the porous medium is described by a set of partial differential equations. These equations describe the conservation of mass or volumes of the fluid in the reservoir. Mathematically, it is possible to model fluid flow through a porous medium by combining the principle of mass conservation and Darcys equation (Aziz and Settari, 1979b).

The principle of mass conservation for fluid moving in a representative elementary volume (REV) is:

Fluid accumulation = Fluid Influx + Sink/Source (production/injection)

Like modeling any other process, some assumptions lie on ground e.g. three phase flow of oil, water, gas, isotherm system, immiscibility of oil/gas with water, application of Darcy's equation and small fluid compressibility. These are decent assumptions that simplify the fluid modeling and enables to model the movement of each phase by substituting the relevant terms in the mass conservation equation known as continuity equation. More information can be found in Aziz and Settari (1979b); Chavent and Jaffre (1986).

In the following, the equations that describes movement of fluids in the system will be presented.

$$-\nabla\left[\frac{1}{B_o}u_o\right] = \frac{\partial}{\partial t}\left[\frac{1}{B_o}\phi S_o\right] + q_o \tag{2.1}$$

Equation 2.1 describes the flow of oil in a porous medium where B_o is oil formation volume factor, and u_o is the Darcy velocity of this phase. Rock porosity, ϕ and S_o is the oil saturation. q_o is the oil production rate.

Respectively, Equation 2.2 describes the flow of water phase:

$$-\nabla\Big[\frac{1}{B_w}u_w\Big] = \frac{\partial}{\partial t}\Big[\frac{1}{B_w}\phi S_w\Big] + q_w \tag{2.2}$$

B_w water formation volume factor, u_w is the Darcy velocity of water. Porosity, ϕ and S_w is the water saturation. q_w is the "additional" water in the system. Water production or injection is specified depending on the sign in front of q_w,

Equation 2.3 describes the flow of gas phase.

$$-\nabla\Big[\frac{R_s}{B_o}u_o + \frac{1}{B_g}u_g\Big] = \frac{\partial}{\partial t}\Big[\phi\Big(\frac{R_s}{B_o}S_o + \frac{1}{B_g}S_g\Big)\Big] + q_g + R_s q_o \tag{2.3}$$

Solution gas oil ratio, R_s, u_o and u_g is the Darcy velocity of the oil and gas respectively. Porosity, ϕ and S_o and S_g is the saturation of oil and gas. The fraction, $\frac{R_s}{B_o}$ influenced in relevant places of both sides of the equation represents the amount of dissolved gas in oil in reservoir condition. q_g is the rate of gas production or injection and $R_s \times q_o$ represents the produced solution gas. Additional details can be found: (Peaceman, 1977; Aziz and Settari, 1979a).

The velocity of fluids flowing through porous medium may be expressed by Darcy equation, Equation 2.4:

$$u_l = -\frac{kk_{rl}}{\mu}\Big(\nabla P_l + P_l\frac{g}{g_c}\Big) \tag{2.4}$$

Where l specifies the corresponding physical property (relative permeability, pressure gradient, and phase pressure) of oil, water, gas respectively. K is the absolute permeability, K_{rl} relative permeability, μ is the viscosity of the phase l, ∇P_l is the pressure gradient in phase l, g is the gravitational acceleration vector and g_c is the conversion constant.

The equations are solved to obtain pressure and saturation of each phase. Three additional equations are required:

$$S_o + S_w + S_g = 1 \tag{2.5}$$

$$P_{cow} = P_o - P_w \tag{2.6}$$

$$P_{cog} = P_g - P_o \tag{2.7}$$

Combining equations 2.1 to 2.7 provides a set of nonlinear partial differential equations that are too complex to be solved analytically and must be *discretized* to be solved numerically. Discretization is the procedure where continuous equations are transferred into discrete counterparts (Stetter, 1973).

Solving the discretized equations by a computer is called numerical reservoir simulation where the reservoir is divided into many small grid-blocks, every block with different physical rock and fluid properties to take into account the heterogeneity of the reservoir. Initial and boundary conditions are provided to the simulator to solve the flow equations numerically. The process computes the pressure and saturation for each phase in every grid block. More details (Peaceman, 1977; Aziz and Settari, 1979a).

The third major component in numerical reservoir models is wells. Wells are the most remarkable method to add or to extract fluid from the reservoir. The well models describe the inflow or outflow to the reservoir, typically production and injection scenario. The well models give also an approximate description of fluid behavior within the well-bore by using different mathematical approaches.

As mentioned, the pressure and saturation in each grid block are calculated after discretization of the fluid equations above. The pressure in the well-bore will be remarkably different from the average pressure in the grid blocks. Due to the small diameter of the well-bore compared to the grid blocks, there will be a large pressure gradient in a small region inside the perforated blocks. Therefore, modelling well-bores is seldom done by using point sources and instead is done by using analytical or semi-analytical solution of the form:

$$-q = WI(P_b - P_w f) \tag{2.8}$$

Equation 2.8 relates the well-flowing pressure $P_w f$ to the numerically calculate the pressure P_b inside the perforated blocks. The well index, WI accounts for geometric characteristics of the well-bore and the properties of the surrounding rock (Peaceman, 1978).

The model developed by Peaceman (1978) is based on the assumption of steady state radial flow and a 7-point finite difference discretization. The well index for an isotropic medium with permeability K, in a Cartesian grid block ∇x x ∇y x ∇z is defined as:

$$WI = \frac{2\pi K \nabla z}{ln(\frac{r_o}{r_w})}, \;\; r_o = 0.14(\nabla x^2 + \nabla y^2)^{\frac{1}{2}} \tag{2.9}$$

Where r_w is the radius of the well-bore and r_o is the effective cell radius where the steady state pressure is equal to the calculated grid cells pressure. This model is the first and still most used model to describe the wells. It has been extended to give a more realistic approach for multiphase flow, anisotropic media, horizontal wells, gravity effects and skin (near well-bore effect). The are also models to describe the fluid flow inside the well-bore and coupling to the surface control and processing facilities. More details in (Peaceman., 1991).

Observing dynamic fluid behavior and measuring relevant parameters of a subsurface reservoir is challenging and therefore prediction of reservoir performance is attached to a large degree of uncertainty. After constructing the model, it must be able to reproduce the reservoir behavior in the past, in order to be ”reliable” for forecasting future performance. The process of modifying the reservoir model in expectation of reproducing the past behavior is called history matching. This is a complicated inverse problem that decreases the uncertainty to a certain extent. History matching is performed by modifying the geological parameters to obtain previously production data.

In the optimization studies, the aim is to obtain the optimum operating conditions for the reservoir that maximize the economic value. The history matched models are used to evaluate the ”optimal” operating conditions and measure the financial benefits.

Eclipse reservoir simulation is an industry standard software for simulation studies and is also used in this work. There are other software available in the market for reservoir simulations such as CMG (Computer modeling Group LTD), Nexus Halliburton reservoir simulator and the research-based ”General Purpose Research Simulator (AD-GPRS)” from Stanford university.

In the next section, Closed-Loop Reservoir Management will be introduced. This is a relatively new concept in reservoir management that aims to improve the management process and maximize the asset value. This is done by reducing the geological uncertainty of the models in a near-continuous data acquisition and history matching process and implementing optimization algorithms to the improved model to find the best operating condition.

2.1.2 Closed-loop reservoir management

Closed loop reservoir management is a recently growing concept in the oil industry with different names such as smart fields, i-fields, e-fields, digital fields, field of the future, next generation fields or integrated operations.

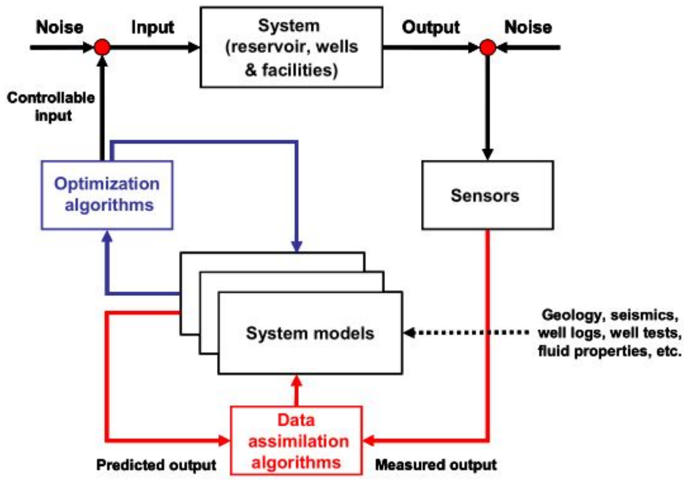
The idea behind this concept is the possibility to increase the life-cycle value of a reservoir by changing the management from a batch-type to a near-continuous process. Jansen et al. (2009) defined the CLRM as ”A combination of model-based optimization and data assimilation aiming to maximize reservoir performance in terms of recovery or financial measures, over the life of the reservoir by changing reservoir management from a periodic to a near-continuous process”.

Traditional history matching, either manual or computer-assisted is a repetitive process. Implementation of closed-loop concept should result in a reduction in time spent on history matching and more time being spent on analyzing and judging the results and decision taking (Jansen et al., 2009).

Figure 2.2 illustrates the key elements of CLRM. The physical elements of the system consist of the reservoir, wells, and downstream facilities. System models (static and dynamic) are presented in the middle of the figure. The sensors are illustrated on the right side of the figure. These might be downhole measurement units to monitor the production or more generally, ”source of information” since the data might as well come from other sources such as well-tests, time-lapse seismic, and etc. The near-continuous process of data acquisition will provide updated data to improve the system models. Thus, the uncertainty is reduced and a better history matching is obtained.

On the left side of the picture, the optimization algorithms can be observed. These algorithms can for example influence the choke setting of wellheads, injection, and production rates, or algorithms aiding in the field development planning phase such as finding the optimal well placement.

Optimization strategies obtained and evaluated by simulation studies are only useful if the models can approximately predict the future performance of the reservoir. The models are usually history matched by performing large analysis on geological parameters which are a computationally expensive process. A new approach in petroleum industry that lately has shown promising results for data assimilation and uncertainty quantification is Ensemble Kalman filter. Enkaf is a Monte-Carlo approach which is originally developed for estimating dynamic variables in oceanography and hydrology. Enkaf can be used to update both static and dynamic parameters. In a petrophysical perspective, porosity and permeability are static parameters, but pressure and saturation are dynamic variables of the reservoir model. The calculations are based on an ensemble of realization of the reservoir model. The numerical reservoir model is getting updated when new measurements are available and are combined with previous model predictions. Model uncertainty is built from the ensemble and when new measurements become available, the filter is used to



Jansen et al. (2005)

Figure 2.2: The main components of closed-loop reservoir management.

update all the realizations of the reservoir model. This means that an ensemble of updates realization of the reservoir model is always available (Naevdal, 2005).

As discussed, the task of the history matching is to update the model parameters on a basis of continuous measurements and deliver reliable models. The second main task of the CLRM is optimization of the production process. This comprises of finding the optimal operating strategy. In this part, the updated reservoir models will then be used to find the optimal reservoir and field development strategy. Finding the optimal strategy has traditionally been done by a large number of trials and errors which are a time-consuming process. Mathematical methods are employed to perform this task more efficiently. Optimization algorithms aim to find the best state with respect to control parameters such as well placement, liquid injection, and production rates, or simply a valve setting. The production performance of the field depends greatly on these variables. The objective function may, for example, be the net present value of an asset or recovery factor of a reservoir. Control variables are subjected to constraints that are basically limitations related to the operating condition or the capacity of the surface facilities such as fluid handling capacity of the separator. Constraints make the optimization problem significantly more complicated and will be discussed in more details later in this work.

In the next section, several aspects of water-flooding are reviewed and discussed. Water-flooding is the most applied method to improve the oil recovery due to its abundance and the relative easiness of injection. (Craig, 1993).

2.1.3 Water-flooding

The overall hydrocarbon recovery after the primary stage of production is often low compared to the potential of oil recovery. During the primary stage, oil and gas are produced by the natural energy present in the reservoir. This results in large volumes of remaining resources in the subsurface. After the primary stage of production, the reservoir often needs additional energy to produce the remaining resources with an economic rate. Water-flooding is under the category of secondary oil recovery methods and is considered as the most dominant method. The injected water into the formation results in higher average reservoir pressure. It also increases the oil production by physically displacing the oil to achieve better sweep efficiency. The oil recovery after the secondary stage may reach as high as 70 % of OOIP under favorable conditions such as homogeneous formation, sufficient porosity and permeability, and optimal wettability conditions (Willhite, 1998; Craig, 1977).

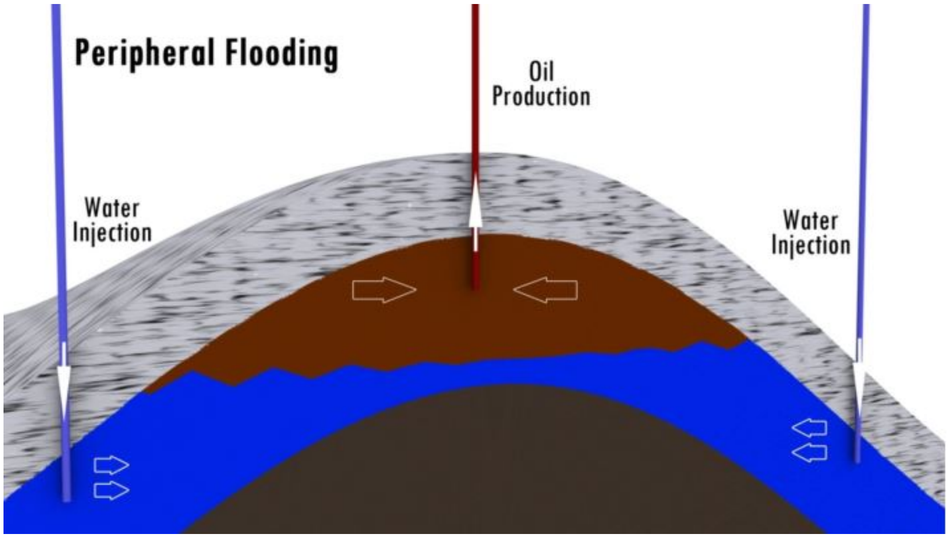
The improvement of oil recovery in water-flooding operations is the result of two mechanisms. The first one, water injection into the reservoir and mobilizing the oil toward the production wells from unswept areas. The second one, production from areas that already have been flooded, but the residual oil saturation is yet large. The overall displacement efficiency is a product of these two phenomena and may be expressed as:

$$E = E_d \times E_v \tag{2.10}$$

E, the overall displacing efficiency by water injection is a product of microscopic displacement efficiency, E_d and macroscopic displacement efficiency E_v (Willhite, 1998). Microscopic displacement efficiency, E_d is a fractional indication of mobilizing the oil droplets at the pore scale. E_d reflects the effectiveness of the extent that displacing fluid (water) is able to mobilize the oil trapped in the pores where the water is in contact with oil and the aiming to minimize the residual oil saturation S_{or}. On the other side, E_v represents the macroscopic displacement efficiency which means to flood a larger portion of the unswept reservoir and mobilize the oil in large scales. The effectiveness of E_v is indicated through the average oil saturation $\overline{S}_{or}$ in the reservoir (Craft et al., 1991). The macroscopic displacing efficiency can be improved through optimization of the liquid injection and production rates to increase the sweep. Microscopic efficiency can be improved through advanced Enhanced Oil Recovery (EOR) techniques such as injecting low salinity water or adding surfactants to the injected water. EOR techniques aim to decrease the surface tension to increase the oil recovery (Willhite, 1998).

The relative location of the water injection wells and production wells depends on several factors. The most important factors are formation geology, type of the reservoir, the volume of the drained area, surface facilities and the economic viability of the asset. There are two general types of well locations that are common in water-flooding operations, pattern and peripheral well-settings. In **pattern-flooding**, the wells are designed to follow a repeated pattern throughout the field. In **peripheral-flooding** the injectors are grouped together in between the producers (Stephens, 1960).

As illustrated in Figure 2.3, In **peripheral-flooding**, injection wells are located in the periphery of the production wells. For this well-setting, there is a possibility to transform producers with high water-cut ratio into new injectors. This transformation reduces the capital investment for drilling new water injectors.

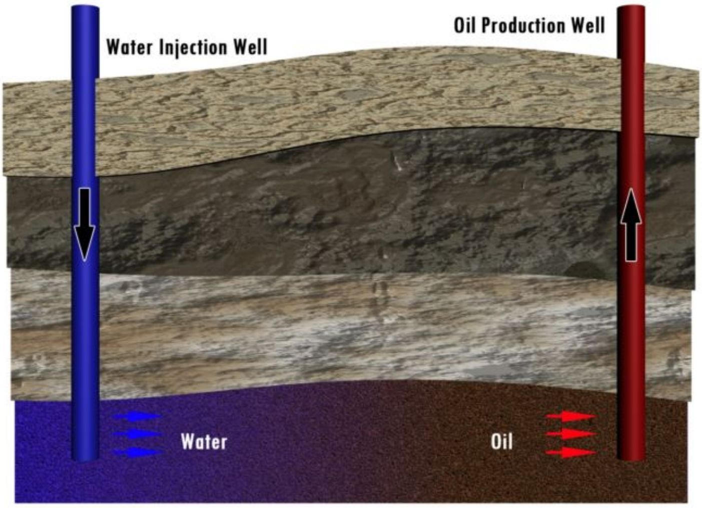


Asadollahi (2012)

Figure 2.3: Peripheral water-flooding.

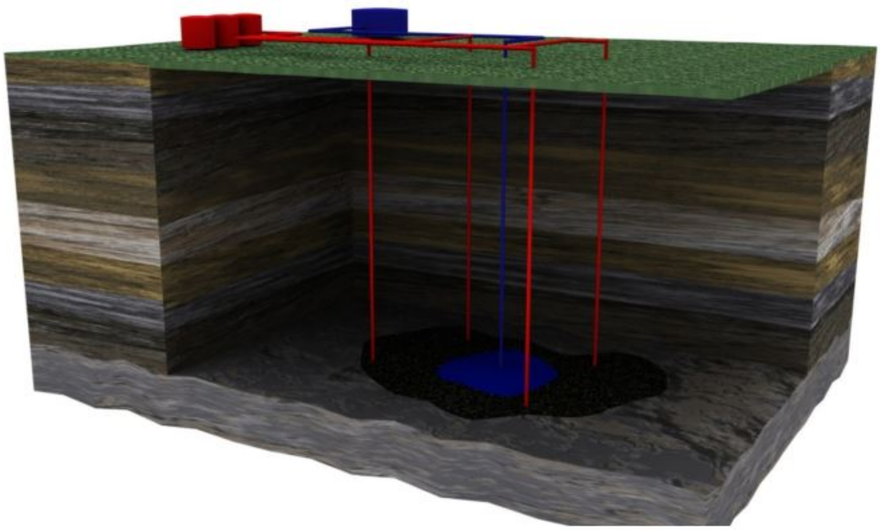
In **pattern-flooding**, the injection wells are located in a repeated fashion between the production wells. In patter-flooding the most common well-settings are **Line-drive** and **Five spot**. In the Line-drive, the injection well is placed in a one-to-one ratio relative to the producer. This is shown in Figure 2.4.

Five-spot well-setting is another common pattern flooding well configuration that contains five wells. In the original five-spot, four injection wells are located at the corners of a square and the producer is located in the middle . *Inverted* five spot well configuration is shown in Figure 2.5. In this well configuration, one injector is located in the middle of four producers and supply the production wells.



(Asadollahi, 2012)

Figure 2.4: Line-drive water-flooding.



Asadollahi (2012)

Figure 2.5: Inverted five spot model.

To conclude, two main mechanism that measures the efficiency of a water-flooding project are microscopic and macroscopic displacement. The microscopic efficiency measures the efficiency of displacing fluid to mobilize the oil once it is in contact with the residual oil in the pores. The macroscopic efficiency measures the efficiency of displacing fluid to sweep the oil bearing zone. The product of these two mechanisms is the total effectiveness of water injection. The most common well locations in water-flooding operations are pattern-flooding(injectors flow a repeated pattern) and peripheral-flooding(injectors are grouped together between the producers).

In the next section, Brugge field, a synthetic field with typical properties of North-sea Brent reservoirs are introduced. This field has been used in several water-flooding optimization and history matching studies and is proved by Dutch Applied Research Organisation (TNO). The production optimization cases developed in this study was carved-out from the Brugge field.

Water-flooding benchmark study: Brugge field review

Brugge field is a 3D field model based on synthetic data which is representative for typical North-sea Brent type reservoirs. The model has been used in many benchmark studies for testing the concept of history matching and optimization. Brugge field was introduced by Dutch Applied Research Organisation (TNO) during the SPE applied technology workshop in Brugge, Belgium in June 2008. The model was provided as a benchmark study for participants in this workshop for the case of data assimilation (computer assisted history matching) and optimization in a closed-loop workflow. Since then, it has been used in a number of recent studies related to history matching and optimization such as Lorentzen et al. (2009), Yan Chen (2010), Asadollahi (2012) F.Dilib (2013), and Yuqing Chang (2016).

The total life of the field is set to be 30 years with 10 years available production data, inverted 4D-seismic data in terms of pressure and saturation changes, and other necessary data for the purpose of history matching. The participants in Brugge workshop had to perform production optimization for the remaining 20 years of the field's life. The model originally consists of 20 million blocks with average cell dimensions of 50x50x0.25 m but is upscaled to 450,000 blocks. A set of 104 realizations has been used to reflect the range of possible geological structures and minimize the uncertainty related to the geological heterogeneities with 44,550 active cells. The realizations contained various geological properties such as permeability in x-,y-,z-direction Net-to-Gross(NTG) thickness ratio, porosity, initial water saturation, and different sedimentary facies. (Peters et al., 2010)

Brugge field contains two phase, water, and undersaturated oil with 756 million STB OOIP. The model consists of four formations, Schelde, Maas, Waal, Schie, respectively from top to bottom. The reservoir is divided into nine layers.

Formation zone	Avg Th [m]	Avg Poro [%]	Avg perm [mD]	Avg N/G [%]
Schelde Fm	10	20.7	1105	60
Maas Fm	20	19.0	90	88
Waal Fm	26	24.1	814	97
Schie Fm	5	19.4	36	77

Table 2.1: Stratigraphy with characteristic geological properties in Brugge Field. Peters et al. (2010)

The structure consists of a half-dome extended from east to west elongated with approximate dimensions of 10 x 3 km and an average thickness of 60 m. Brugge field is illustrated in Figure 2.6. The main geological highlights of the field is a large boundary fault. It is located at the Northern edge of the field and there is an internal fault deviating at the modest throw 20 degrees to the north boundary fault.

As discussed, Brugge field is used as benchmark in many studies to evaluate existing technologies to handle closed-loop reservoir management problems in water-flooding. Therefore, vertical wells in the field are equipped with smart completions with inflow control valve and devices. ”Smart wells” or ”Smart completions” are conventional wells equipped with different tools to monitor, analyze and control the zonal inflow and outflow to the reservoir. It is a relatively new concept but is growing very rapidly in the petroleum industry. This concept will be reviewed in more details in the next section. There are originally 20 producers and 10 injectors in the field. The producers are perforated in the top 8 layers. The injectors are located in the peripheral relative location to the producers and are perforated in all nine layers. Producers from year 0-10 have a production rate of 2000 bbl/d, 725 psi and from year 10-30 have 3000 bbl/d, 725 psi. The injectors have a maximum injection rate of 4000 bbl/d, 2611 psi.

Peters et al. (2010) describes the Brugge field in more details in the original paper by TNO.

Brugge field is used in this study to develop relevant cases for production optimization. Segment models are ”carved-out” of the field and production scenarios are designed for the cases.

In the next section, smart wells will be introduced. As mentioned, these wells are important in production optimization since the well operator is capable of reacting to sudden changes and control the zonal injection and production rates.

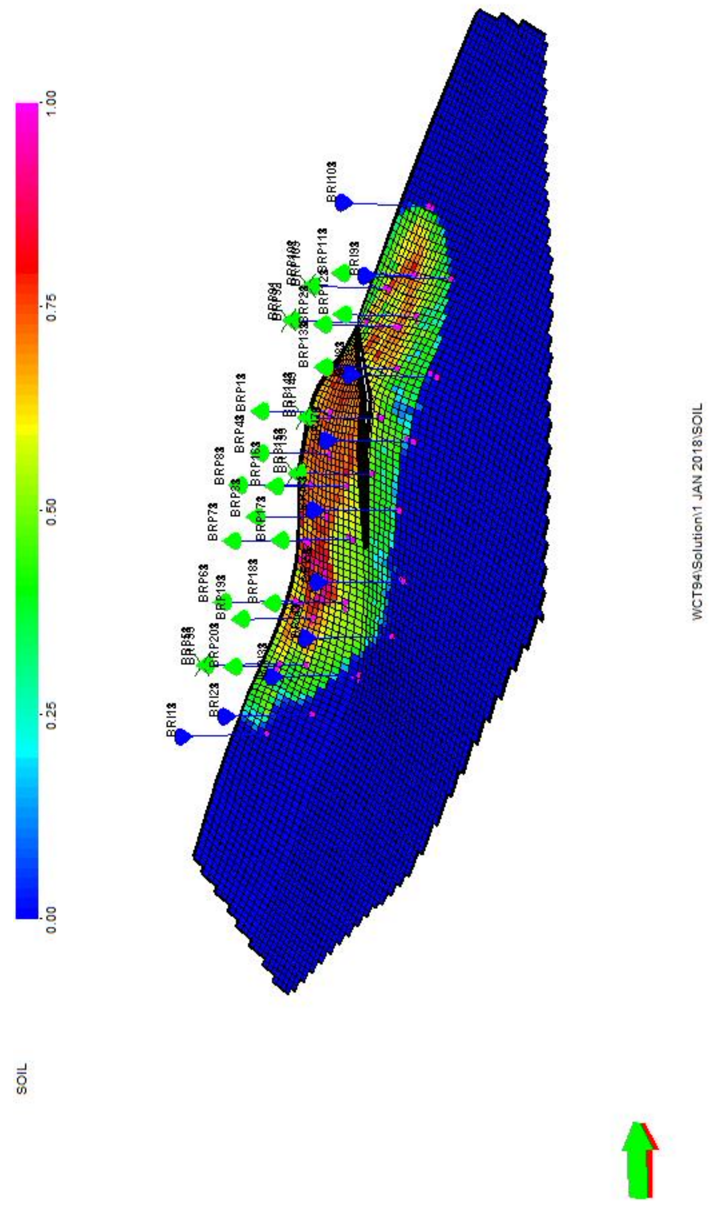
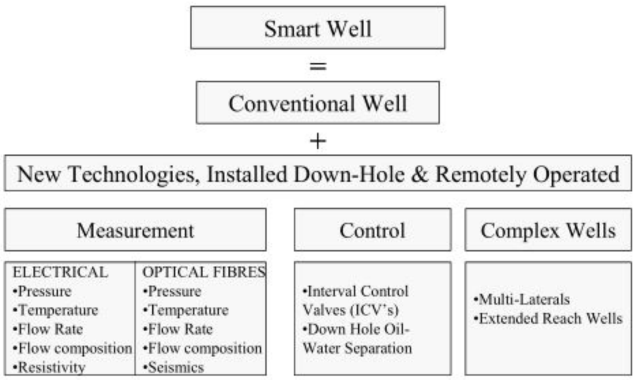


Figure 2.6: Initial oil saturation in the Brugge Field, 1. Jan 2018

Smart well technology

Over the last decade, the need to reduce the costs and increase the oil production more efficiently has resulted in the development of improved methods to measure and control the production. Smart wells are conventional wells equipped with monitoring devices and downhole completion units such as valves or chokes to control and operate the wells remotely (Stratton, 2002).



(Brouwer, 2004)

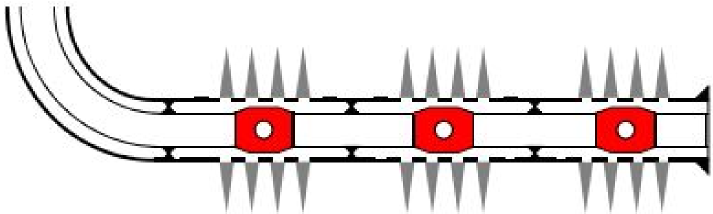
Figure 2.7: Schematic description of a smart well

Downhole sensors have been developed and utilized in smart wells to measure temperature, pressure, distributed acoustic velocities, and fluid composition. The collected data is transmitted to surface for data management without additional cost of well intervention. Moreover, the real-time monitoring data can be used to improve the reservoir management process.

Smart wells are also capable of controlling the production process by having installed downhole hydro-clones and valves. Hydro-clones enables the smart wells to separate oil and water and employ the produced water for re-injection into the reservoir. This reduces the costs related to the surface facilities and reduces the problems with high water-cut. The downhole valves enable to split up the well into several segments as shown in Figure 2.8. The valves enable to control the flux in each segment. The valves were originally developed to shut-in the zones with high water production without well intervention. Especially in offshore wells the cost of well intervention is considerable. Implementation of downhole valves in multi-lateral wells (wells with several branches) allows to commingling production from different zones of a reservoir simultaneously as the production can be regulated from different zones (Brouwer, 2004).

The value of smart wells compared to conventional wells lies in their ability to allow the operators control the wells remotely and optimize the production. This can result in production acceleration, increased ultimate oil recovery and a significant decrease in the production of injected fluid (Well-dynamics, 2011).

Ebadi and Davies (2006) tested the implementation of smart wells technology in different geological scenarios. They built a series of generic reservoir models based on real field operation data. The geological scenarios were tested to determine whether installing intelligent completions resulted in added value compared to conventional completions. Results showed that installing intelligent completions improves controlling the uneven distribution of invading fluid front that has developed along the trajectory. This is due to permeability variations, layered reservoir sections, or different strength of the gas cap or the aquifer. Controlling the uneven distribution of invading fluid can prevent early water breakthrough and result in a better sweep in heterogeneous reservoirs.



Asadollahi (2012)

Figure 2.8: Well with three perforation zones completed with interval control vales (ICVs)

To name a few examples of successful implementation of intelligent well technology, the IOR project in Gullfaks, North-Sea, Rabi field in Gabon, in Aramco's Haradh field, and Nigeria's Usari field. Asadollahi (2012)

To conclude, smart wells are effective tools that allow the operator to react quickly to unexpected changes, reduce the cost by minimizing the well downtime and intervention, enables access to multiple zones using only one well, and allows near-continuous data acquisition. The combination of these abilities enhances the well operation process, thus improving the reservoir management (Maghsoudi, 2015).

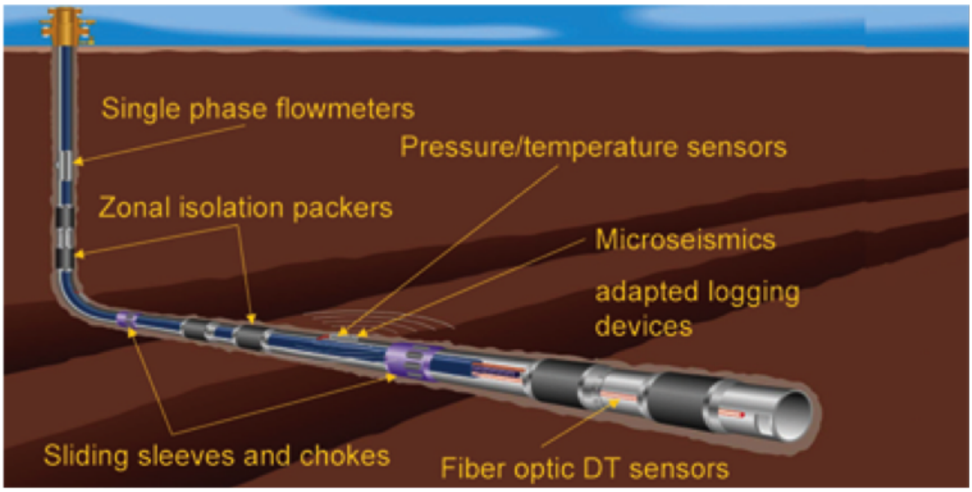


Figure 2.9: Overview of a horizontal smart well equipped with different tools.

2.2 Optimization theory

This section aims to give the reader a brief review of the mathematical background of optimization problems and different approaches for solving them. The concept of optimization is a mature area in mathematics and it is applied in many disciplines such as engineering, economics, research, and modeling (Nocedal and Wright, 2006).

Optimization Problem: Objective function, control parameters, constraints

The problem to be optimized is defined by an objective function, control parameters and constraints. Mathematically the optimization problem can be defined as:

$$\begin{array}{lll} \underset{x}{\text{minimize,}} & f(x), & x \in R^n \\ \text{subject to} & c_i(x) = 0,\ i \in E,\ and & c_i(x) \leq 0,\ i \in I \end{array}$$

x is the vector of unknown variables or control parameters. f is the objective function, a scalar function of x that is either to be minimized or maximized. c_i denotes the optimization constraints that can be scalar functions of x that define certain equality or inequality to be satisfied by the unknown vector x. Here E and I are a set of indices for equality and inequality constraints respectively (Nocedal and Wright, 2006). This formulation of the optimization problem aims to minimize the objective function but can be transformed into a maximization problem by multiplying the objective function with a negative sign (Kalyanmoy Deb, 1993). **Objective function** formulates a quantitative measure of the performance of the system under study. From a reservoir optimization point of view, the reservoir represents the system under study and the objective function can be the net present value (NPV) or the ultimate cumulative oil production. The ”least square error” can be used as the objective function for the purpose of data assisted history matching wherein the objective is to minimize the difference between the calculated and measured data. **Control Parameters or system variables** are the variables of the objective function. In production optimization studies, these can be pressure, liquid injection and production rate, well placement or simply a choke setting. **Constraints** define the restrictions on the control parameters. This can be **pressure limitations** as BHP limitation for fracture and collapse pressure, **production rate** as a result of fluid handling capacity in the separator.

Optimization algorithms

Optimization algorithms are iterative processes that aim to find the maximum or minimum value of an objective function. The procedure usually starts from an initial point(also known as the initial guess, or starting guess) and generates a sequence of improved estimates. This process terminates until no further improvement of an estimate is obtained. Hopefully, at this stage, the optimum is reached. The strategy applied to move from one point to the next, distinguishes one algorithm from another. A proper optimization algorithm should fulfill certain requirements, such as:

- **Robustness:** The algorithm must perform well for any reasonable initial starting points on a wide variety of problems in its class.

- **Efficiency:** It should be able to run without excessive computational capacity.
- **Accuracy:** It should be able to detect a solution with precision, i.e accept a solution within an acceptable range of error tolerance.

There are several methods proposed to solve optimization problems and most of them can be classified under two search methods: **Stochastic** and **Deterministic**

Stochastic and Deterministic search methods

Stochastic algorithms search on a wider solution span to find the optimal solution. In this method, each combination of the optimization parameters has a non-zero chance of occurrence. The initial guess in each step is randomly generated and if the procedure runs long enough, it will eventually find the optimum solution. It typically requires a large number of function evaluations and does not guaranty a steady and continuous improvement of the objective function. **Deterministic** algorithms depend on the initial point and always converge to the same optimum if initiated from the same point of departure with the same setting (e.g. perturbation size). This gives the ability to improve the reached optimum by initialization the optimization algorithm from another improved initial point. Some optimization search methods may perform better depending on the type and setting of the problem. There exist a trade-off between the robustness, efficiency and the obtained results in an optimization search method. Many optimization problems have more than one optimum, also referred to as local optima. Some algorithms aim to find the local optima while others search for the global solution, the best optimal solution between all possible solutions. Figure 2.10 illustrates the optimization domain with several local and the global optimum. As mentioned, deterministic optimization algorithms are initial guess dependent and can be improved by initializing the optimization from an improved initial guess. This approach is usually more efficient compared to stochastic approaches but the chance to get trapped in local optimums is also great (Sethi, 2006). In the comparison between the two general optimization algorithms, stochastic algorithms have a larger chance to find the global optimum since it searches on a wider solution span and the initial guess is randomly generated, but the process of finding the optimal solution is not efficient (Nocedal and Wright, 2006).

Deterministic approach: Evaluation-only methods and Gradient-based methods

Deterministic optimization methods can be divided into **non-gradient or Evaluation-only methods** and **gradient-based methods**. The Evaluation-only or non-gradient methods are more straightforward to implement and do not require the gradient of the objective function. Powell's conjugate algorithms, Hooke-Jeeves pattern search, reflection simplex Nelder-Mead are some of the Evaluation-only methods. The optimization method used in this study is steepest descent method which is a deterministic gradient-based line-search method. It is implemented by the optimizer in Eclipse 300. The optimization workflow will be presented later in this study. In the following, the two methods in the gradient-based approach, trusted-region and line-search will be reviewed.

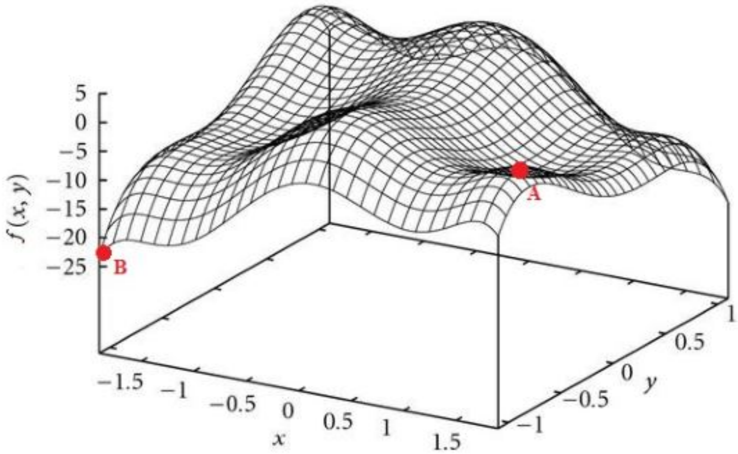


Figure 2.10: A function with several local optimum (point A) and a global optimum (point B) (Passaro and Starita, 2008)

Gradient-based methods: Trust-region and Line-search

Gradient-based methods use the gradients of the objective function to find the search direction. In deterministic **gradient-based** optimization two approaches exists: **Trust-region** and **Line-search**. Trust-region method defines a "trusted" region around the current point and assumes this region to be an adequate representation of the objective function. It chooses the direction and step-length simultaneously. If the step is not acceptable the algorithm will reduce the size of the trusted region and find a new minimizer. The size of trust region is critical for finding the next improved step. If the size of the trusted region is too small, the algorithm misses an opportunity to take a substantial step that moves closer to the optimum of the objective function. If the size of the trusted region is too large it will reduce the size of the region and repeat the process (Nocedal and Wright, 2006).

The other strategy is Line-search. We can start discussing this topic with a physical example by Vanderplaats (2007) that illustrate this method more intuitively. Consider a blindfolded boy standing on a hillside. He wishes to reach the highest point (the objective function) on the hill while standing between two fences (constraints). Since his eyes are covered, he cannot just look up and walk straight toward the hilltop (optimum point). He may take a step in the north-south direction and one step in the east-west direction. The control parameters are the x and y coordinates of the boy. He can sense the slope of the hill and move in the upward direction. In the mathematical sense, he has calculated the direction of steepest ascent by finite difference methods. He can continue his search until he crosses a hill or encounters a fence. Note that he can start outside of the fences as well, and find a feasible design.

Line-search is a strategy where the algorithm solves the optimization problems generally in two steps. The algorithm chooses a search direction p^k, as the boy sense the steepest ascent, and searches along this direction from the current x_k for a new position.

In the second step, the algorithm determines the distance which it is going to move along. This is how far he has to move in each direction until no more progress is obtained. This is done by computing an appropriate step length α through a line-search strategy by generating a limited number of trial step lengths until it finds an improved function value. It is usually a trade-off. The goal is to find the step length that minimizes the function substantially, but at the same time, it doesn't want to spend too much time making the choice. The updated parameters after each iteration of line-search method is given as:

$$x^{k+1} = x^k + \alpha p^k \tag{2.11}$$

x^{k+1} is the vector that contains the values of the improved variables, calculated by the x^k, the vector of control parameter values in the current iteration, α the step-length, and p^k search direction. The success of the line-search methods depends on effective choices of both the search direction p^k and step-length α. The optimization process is shown in Figure 2.11

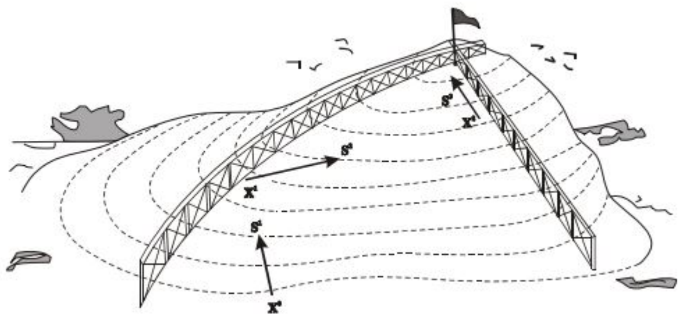


Figure 2.11: Optimization process (Vanderplaats, 2007)

There are several well-known search direction methods. The most famous and used search direction methods are steepest descent method, conjugate gradient method, Newton method and Quasi-Newton method. The main difference between these methods is the way gradient information is used. An example could be the steepest descent method where the information from the first derivative in the current iteration is used to determine the search direction while conjugate gradient method employs the gradient information from previous and current step to determine the search direction Steihaug (1983). The Newton and Quasi-Newton methods employ the first and the second derivative of the objective function. The calculation of the second derivative is not trivial and in the Quasi-Newton method, the second derivative is replaced with an approximation from the first derivatives. As seen, gradient-based methods use the gradient information that can be obtained by means of finite differences method, streamline-based or adjoint technique. (Nocedal and Wright, 2006).

Later in this study, the adjoint technique that is widely used for obtaining gradients in gradient-based approaches is presented. Asheim (1988); Sarma et al. (2005); Jansen et al.

(2009) applied adjoint technique successfully to their production optimization studies and obtained improved objective function. This approach is suited for problems where the number of control parameters is large and the gradient of the objective function is required such as in reservoir optimization problems. This technique calculates the gradients more efficiently and makes gradient-based optimization more promising for dealing with large-scale systems such as in production optimization problems. However, implementation of the adjoint method is not trivial and requires a major programming effort and detailed knowledge of the reservoir simulator.

In the next section, the optimizer module in Eclipse 300 is presented and the optimization workflow is reviewed.

2.2.1 Optimizer module in Eclipse 300

In general, any reservoir simulator can be combined with optimization tools to perform optimization and evaluates the change in the objective function. Eclipse 300 has a built-in optimizer. This optimizer uses gradient-based line-search method to maximize the objective function. As discussed, the optimization aims to maximize some objective function,J which is obtained by variation of a set of control parameters λ. The objective function in reservoir optimization problems may be the ultimate cumulative oil production or net present value of a field. The control parameters in the optimization problem can be the wells bottom hole pressures, liquid production, and injection rates of the field, a group or well scale. The segment cross-sectional area can also be the control parameter (Schlumberger, 2012a).

Reservoir optimization problems are usually non-linear gradient-based optimization. This means that the gradients of a non-linear objective function are required. Using the simulator as a black box to calculate gradients can be a prohibitively expensive process since the finite differences method requires N+1 simulation, N for the number of variables. Instead, the adjoint technique is used to obtain the gradient information. The adjoint technique is a method that efficiently calculates the gradients and is a widely used in reservoir optimization. This method calculates the gradients and improves the performance of the optimization process. The advantage of this technique is the efficient calculation of the gradient information when the number of control parameters is large. The adjoint technique requires only two simulations regardless of the number of control parameters which make the method more efficient compared to finite differences method. The adjoint method is discussed in more details in the Subsection 2.3.3.

The iterative structure in the Eclipse optimizer is based on obtaining a search direction, s, which is obtained from a set of gradients of the objective function with respect to control parameters, $\frac{\partial J}{\partial \lambda}$. A process called for "Line-search" continuously searches for the optimum step length for a certain search direction. After reaching the optimum point for a search direction, a new line-search is performed to find the next optimal step length. This loop is repeated until the termination criteria(s) are met which include lower limits on relative changes of J or λ. The schematic representation of the gradient-based optimization is illustrated in Figure 2.12

The optimizer implemented in Eclipse 300 uses the steepest decent method as the default search direction method but also conjugate gradient method is available. Steepest descent method uses the first derivatives in the current iteration to determine the search direction. The advantage of this search method is a lower computational memory. The conjugate gradient method also uses the first derivative, but the information is used from the current and previous iteration to determine the search direction. The advantage of this method is that it might perform faster than the steepest descent method. However conjugate gradient method performs slightly faster than the steepest descent method, the performance of both methods depends strongly on choosing a proper initial guess.

Every production process has a set of constraints that must be respected during the optimization process. These constraints increase the complexity of the problem and may vary from simple bounds on the parameter values to non-linear inequality functions such as well and group production constraints. Bounds constraints are easily handled by restrictions of the step during line-search while non-linear inequality demands modifications during the search direction step. Production constraints are handled by using a Lagrangian formulation of the problem. Compared to external treatments, Lagrangian formulation improves the speed of handling of the constraints. More information can be found at Schlumberger (2012b).

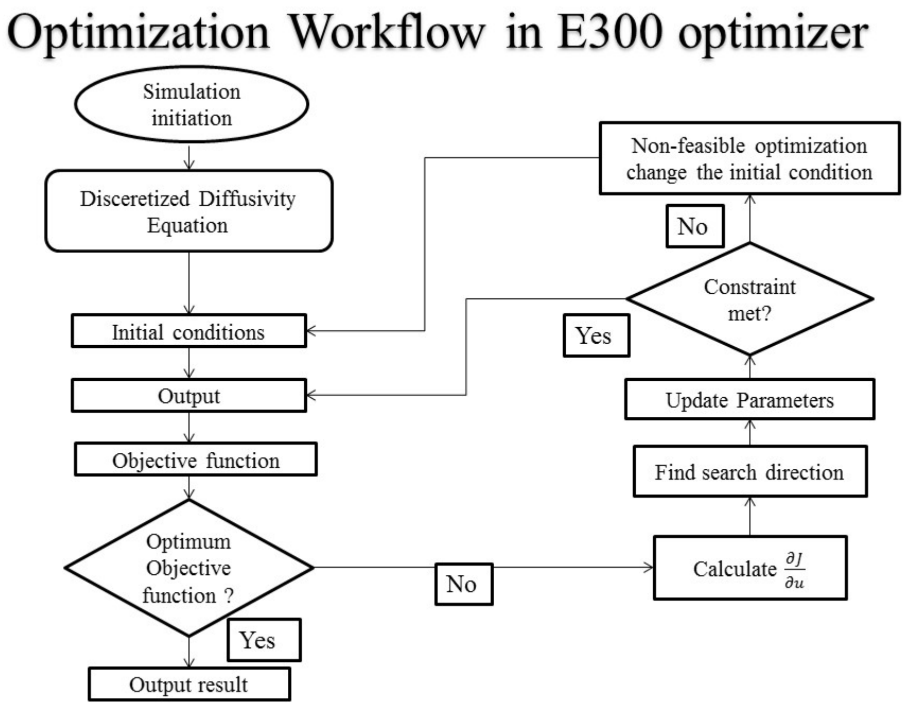


Figure 2.12: The optimization workflow in Eclipse (Schlumberger, 2012b).

2.3 Production optimization: Basic theory and literature

In this section, general terms, definitions and literature study of production optimization are presented. Production optimization is a general term that refers to increasing the asset value by integrating multiple models from subsurface to sales point in the field development plan. Accordingly, the entire process depends upon several models such as the reservoir, well, production, pipeline network and processing facility and economic models for maximizing the asset value. Projects addressing the optimization of subsurface models to increase the recovery or net present value is referred to as reservoir optimization. However, the term ”production optimization” is substituted and used interchangeably with the term ”reservoir optimization” since it is more comprehensive. In the Reservoir optimization, several control parameters vary in order to maximize the reservoir recovery factor or net present value. These parameters may be well placement, production and/or injection rate, and well bottom hole pressures. (Wang et al., 2007; Sarma and Chen, 2008; Zandvliet et al., 2008; Vlemmix et al., 2009; Zhang et al., 2010; Yeten et al., 2003).

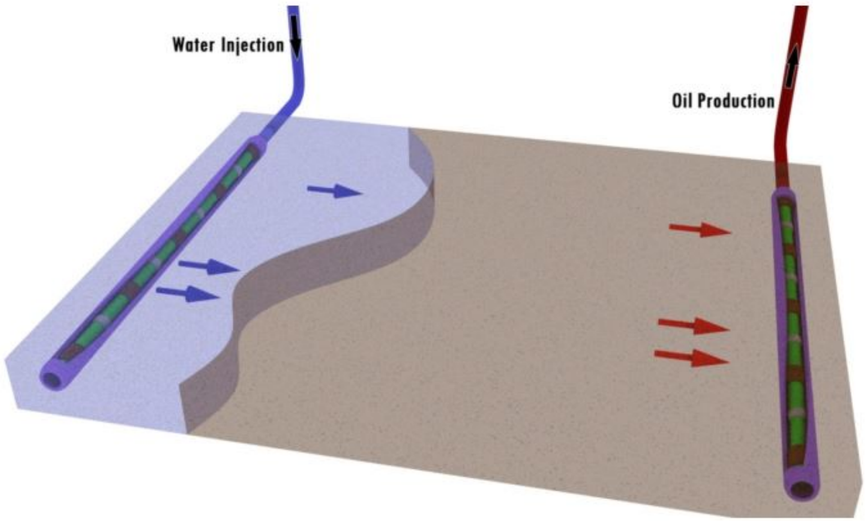
2.3.1 Water-flooding optimization

As discussed in the previous part, water-flooding is the most dominant secondary oil recovery method. Water-flooding can be a very effective method to increase the oil production. But in many cases, the injected fluid may reach the producers without touching a large region of the oil bearing zone. This results in high average residual oil saturation $\overline{S}_{or}$ in the reservoir. The reason for poor hydrocarbon recovery by water-flooding is the geological heterogeneity of the reservoirs. For example, high permeability channels in a reservoir with large permeability variations might yield unfavorable results. These highly conductive channels will affect the movement of the injected water. In many cases, injected water bypasses the oil and flow through the high perm channels resulting in an early breakthrough at the producers (Brouwer and Jansen, 2004).

The idea behind optimizing a water-flooding process is to control the injection and/or production rate in a way that injected water have a ”stable” front and to obtain a better sweep. Over the last decade, a new concept has been introduced to the oil industry called for ”Smart wells” or ”Smart completions”. These wells have the capability of controlling zonal inflow and outflow of liquids and enable to monitor the production. Smart wells were presented in more details in Subsection 2.1.3.

Manual approaches still dominate in the industry but many fields are becoming mature and there is a gradual decrease in discovering large oil field. The aim of recent optimization studies is to find a more systematic approach for water-flooding optimization. In the following, a brief review of some water-flooding optimization studies is presented.

Asheim (1987) used a two-dimensional, two-phase oil/water reservoir model to perform water-flooding optimization. The reservoir was assumed to be a two-layered rectangular slab containing a section with high permeability and a less permeable section. The model contains two injectors and one producer. A method was developed for numerical optimization of water-flooding. This method was used to study optimal control of water drive in a heterogeneous reservoir and resulted in NPV improvements by optimization of injection and production scenarios.



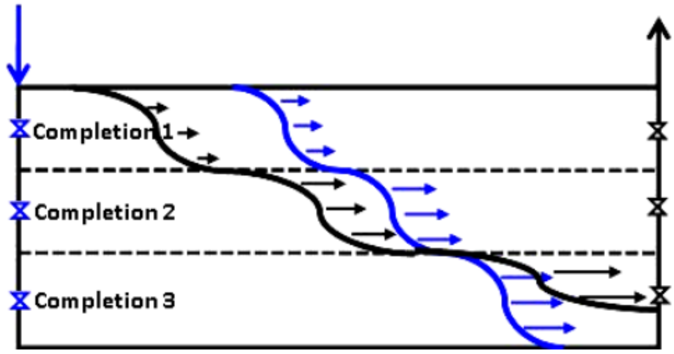
Brouwer and Jansen (2004)

Figure 2.13: Water-flooding optimization in horizontal wells.

Brouwer and Jansen (2004) used an optimization algorithm for optimization of valve settings in smart wells. The reservoir model was a 2D, two-phase heterogeneous model with 2 horizontal wells, one injector, and one producer as shown in Figure 2.13. The study was mainly about the evaluation of the optimal control theory in water-flooding and develop a systematic dynamic optimization approach in a purely pressure and purely rate-constrained operating condition. The conclusion was that implementing smart wells that operate under bottom hole pressure constraints will mainly reduce the water produced. Smart wells, under rate constraint, will mainly result in accelerated production and increased recovery in combination with reduced water production.

Van Essen et al. (2009) used a larger 3D oil/water reservoir model to perform water-flooding optimization study. The model contained eight injection wells and four production wells over a time horizon of 10 years. The model contained 18,553 grid-blocks with seven vertical layers in a fluvial depositional environment. This study aimed to reduce the geological uncertainty in optimal control strategies. Van Essen et al. (2009) implemented "Robust optimization" that uses a set of realization that reflects the range of possible geological structures. In this study, 100 realizations of the 3D model were used. The control parameters were injection and production rates for eight injection and four production wells. The objective was to maximize the net present value. In this study, it was concluded that robust optimization significantly improves the expected NPV value compared to other methods such as reactive and nominal optimization. The 3D model used in the study by Van Essen et al. (2009) has been used in other studies such as Jansen et al. (2009) and a later study by van Essen et al. (2011) to investigate further optimization approaches in closed-loop reservoir management.

In the following, reactive and proactive approaches in production optimization will



Asadollahi (2012)

Figure 2.14: Water-flooding optimization in vertical line-drive. The blue line represent the improvement by rate optimization.

be reviewed. These are among the most important well control strategies for production optimization.

2.3.2 Reactive and proactive approach in optimization studies

Many water injection operations are not successful due to the large geological heterogeneity of the reservoir rocks. The injected fluid may reach the producers without touching a large portion of the oil bearing zone thus resulting in early breakthrough and low recovery factor. As mentioned earlier, smart completions have the ability to control the zonal fluid injection and production, measure downhole pressure and saturation changes. These capabilities may assist the operators to improve the oil recovery by controlling the fluid influx to touch a larger portion of the reservoir G.A. Carvajal (2014), (Maghsoudi, 2015). Smart completions gives the capability to choose different well operating strategies such as reactive, proactive or defensive strategy.

Reactive strategy controls the wells based on downhole observations i. e. any action such as (completions shut-in, injection, and production rate adjustment) are based on downhole events such as high water-cut, or water and gas coning. As mentioned, it is usually no actions undertaken before observing changes in the well which might be a certain water or gas production rate in the well.

Proactive well control is a set of well-controlling actions and strategies that start long *before* water or gas breakthrough and aims to delay or prevent it. Proactive well strategies can be divided into two types of well-controlling strategies, short term and long term. In the short term strategy, minor adjustments to the production system such as valves settings are subjected to optimization based on current and forecasted well performance. In the long term strategy, the whole life of the reservoir is subjected for optimization and the aim is to find a long-term operating strategy to maximize recovery factor or asset value (Brouwer and Jansen, 2004).

The challenge in both reactive and proactive strategies is to determine the optimal rate for the wells or each completion or to find the optimal valve setting. Various techniques can be used to find parameters to optimize the reservoir, but the main challenge is the uncertainty linked to these models, whether it is a reservoir or a well model. The uncertainty can be reduced by continuously updating the models by measured data (Closed-loop approach), or using several geological realizations to count for different parameters of the formation or use a combination of these methods. However, all the actions to decrease the uncertainty do not guarantee reliable prediction of future reservoir performance.

Addiego-Guevara et al. (2008) studied the implementation of a horizontal smart well in a thin oil bearing formation and a used reactive approach to optimize the production. With a cost-benefit analysis, it could be concluded that using reactive well control always yield a neutral or positive return

However, reactive approaches enhance the production and mitigate the uncertainty, still the chance of obtaining a *suboptimal* the condition is huge. In the proactive approach, reservoir-imaging data collected from subsurface is used to enhance decision making in the long term and ideally, reach somewhere close to the optimum point. The proactive approach will be implemented to the developed cases.

To conclude, Reactive well control has shown promising results but the disadvantage of this approach is the large odds of obtaining a sub-optimal condition. On the other side, implementing long-term proactive strategies including early data analysis, well placement decisions, and using updated models may increase the chance to reach near-optimum results (Maghsoudi, 2015).

In the next section, the adjoint method will be introduced with a brief literature review. This method has been used in many water-flooding optimization studies.

2.3.3 Adjoint Method

Adjoint methods have received increased attention for the purpose of production optimization since these methods calculate the gradients in a more efficient way compared to the finite differences method. The latter approach requires evaluating the objective function for perturbation for all control parameters at each time step, but the adjoint methods have the ability to obtain the gradient information using one single additional dynamic simulation. This is independent of the number of control parameters which makes this approach considerably more practical when the objective function is dependent on many parameters such as in production optimization problems (Rijswijk, 1996).

As mentioned, The adjoint method obtains the gradients of the objective function with an additional dynamic simulation, the main procedure is brifly introduced in the following. The objective function to optimize is following:

$$J = \sum_{k=0}^{K-1} J_k[x(k), u(k)] \tag{2.12}$$

In Equation 2.12, J_k is the contribution of J in each time step. This is a function of the state variable $x(k)$, and $u(k)$ which is the control varibales. The problem is subject to the dynamic constraints:

$$g[x(k+1), x(k), u(k)] = 0 \quad x(0) = x_0 \tag{2.13}$$

In Equation 2.13, g represents the simulator and is a non-linear function. g is included in the objective function through the Lagrangian multipliers λ:

$$L = \sum_{k=0}^{K-1} L(k) = \sum_{k=0}^{K-1} (J_k[x(k), u(k)] + \lambda(k+1)^T g[x(k+1), x(k), u(k)]) \quad (2.14)$$

The adjoint equation becomes:

$$\lambda(k)^T = -\left[\frac{\delta J_k(k)}{\delta x(k)} + \lambda(k+1)^T \frac{\delta g(k)}{\delta x(k)}\right]\left[\frac{\delta g(k-1)}{\delta x(k)}\right]^{-1} \quad (2.15)$$

And the optimality equation becomes:

$$\frac{\delta L(k)}{\delta u(k)} = \frac{\delta J_k(k)}{\delta u(k)} + \lambda(k+1)^T \frac{\delta g(k)}{\delta u(k)} \quad (2.16)$$

The optimization problem to be solved by the adjoint method must in the first step run the simulation of the dynamic system, Equation 2.13. In the second step, the objective function must be evaluated in Equation 2.12, and then calculate the Lagrangian multiplier in Equation 2.15. Eventually, it must compute the gradients in Equation 2.16 and calculate the improved control vector. These steps should be repeated until the convergence criteria is met. (Asadollahi et al., 2010) (Maghsoudi, 2015). For more information, see Sarma et al. (2005); Brouwer and Jansen (2004).

Even though the calculation of the gradient by the adjoint method is not trivial and requires a major programming effort, but it is far more efficient than "traditional" methods for obtaining the gradients . The adjoint technique requires a good knowledge of the simulator since it is dependent on the simulator Asadollahi (2012).

One of the first applications of the adjoint technique in reservoir optimization were implemented by Fathi et al. (1984). The method was used to optimize a surfactant flooding problem to maximize the ultimate oil recovery at minimum chemical cost.

Asheim et al. (1985) used the adjoint optimization to maximize NPV of a given production schedule for a single phase oil reservoir. Later in 1987, Asheim (1987) applied the adjoint optimization method into a two-phase reservoir containing oil and water under natural water drive and optimized the water-flooding mechanisms.

Brouwer and Jansen (2004) implemented the adjoint technique for optimization of the injection and production rates in smart completions. The experiments were conducted in a 2D synthetic reservoir model. The optimization problem was separated into two constraint branches, a pressure constrained problem and a rate-constrained case. In the first case the optimization problem focused on respecting a pressure constraint and maximizing the objective function, NPV by decreasing water production rather that increased oil production. In the rate constrained problem, NPV was increased by accelerating the oil production which resulted in increasing ultimate recovery in the combination with reduced water production.

Asadollahi and Naevdal (2009) examined the effectiveness of different formulations of a production optimization problem by using the adjoint technique. It was concluded that

Optimization variable	Choice 1	Choice 2	Choice 3
Producer	WBHP	WOPR	WLPR
Injector	WBHP	WWIR	WWIR

Table 2.2: Combination of control parameters for Brugge field

the proper formulation of the adjoint optimization problem is important for the efficiency of the optimization method.

In the following, different formulations of the optimization problem wherein the adjoint technique is implemented such as the optimizer in Eclipse 300 will be discussed.

2.3.4 Formulation of production optimization problems

In reservoir optimization, the large dimensionality of the problem will slow down the process of finding the optimal conditions to operate the reservoir. This is due to the non-linearity nature of the reservoir optimization problems and a large number of control parameters. In such optimization problems, the chance of reaching a sub-optimal solution is significant. Yet there are manual approaches to ”assist” the optimizer to obtain the optimal operating conditions which enhance the performance and results of the process.

Many water-flooding optimization problems employ gradient-based methods which are prone to get trapped in local optimums For example, in water-flooding optimization problems methods, it is possible to provide a ”logical” initial point to avoid getting trapped in local optimums and to reformulate the problem to decrease the number of control variables.

As earlier reviewed, Brugge field, A benchmark for water-flooding is used in several recent studies, such as Asadollahi and Naevdal (2009); Lorentzen et al. (2009); Asadollahi et al. (2010); Asadollahi (2012) and etc.

The field has 10 injectors and 20 producers equipped with smart wells. With 10 years available production history, the aim is to find the optimal monthly rate for each completion over the next 20 years. There are 84 open completions which make the number of control variables to be optimized as large as 20,160 (84x12x20).

The large dimensionality of the problem makes it a computationally prohibitive process. Asadollahi and Naevdal (2009) studied the sensitivity of three available choices for control parameters in Brugge field. These choices are listed in the Table 2.3.4. The goal is to modify the injection and production rates to prevent or to delay the water break-through as much as possible and achieve a better sweep. The constraints in the field were maximum bottom hole pressure in the injection wells and minimum bottom hole pressure in the production wells along with an upper value on production and injection rate in each well. For more information about Brugge field see in Subsection 2.1.3

They chose six months updating interval (40 time-steps over 20 years), and by having 84 open completions in the field, the total number of control parameter will become 3,360 (84x40).

Choice 1 was chosen as recommended control parameter by Schlumberger (2012b), the well bottom hole pressures in both producers and injector are variables. Choice 2 was the oil production rate and the water injection rate and choice 3 was well liquid production rate and well water injection rate.

(Asadollahi and Naevdal, 2009) tested the performance of conjugate gradient method and steepest descent method by Eclipse 300 optimizer and concluded that using choice 3, injection rate and liquid production rate improved the NPV. The reason for NPV improvement was that most of the wells in the model were under the liquid control mode which makes this a reasonable control variable in optimization even though Schlumberger (2012b) recommends to use the bottom hole pressures.

In the comparison of the two line-search methods, conjugate gradient method acts slightly faster than the steepest descent method, however, the performance of each line-search method strongly depends on the initial guess and choosing a proper initial guess is more important for the performance.

Lorentzen et al. (2009) applied a sequential quadratic programming (SQP) production optimization in Brugge field. They introduced a new methodology for production optimization that made large-scale optimization feasible by reducing the number of control variables. This was obtained through analysis of the field properties and state of art optimization method. The reformulated Brugge optimization problem had 54 control parameters. This is the number of the initially open completions in the producers. They steered the injectors by the voidage replacement strategy, and the producers were producing from all zones initially. The completions that produced too high water-cut were shut. Quadratic programming method was used to optimize these shut-in water-cut values utilizing finite differences method. 10 randomly selected realizations that were history matched out of 104 to minimize the geological uncertainty and verify the robustness. The approach performed well on Brugge optimization problem and achieved substantial optimal NPV. The point in their study was that it is possible to reformulate the problem to decrease the number of control parameters considerably and approach the optimization problem differently.

Asadollahi et al. (2010) used the adjoint method in combination with the multi-scale method to solve the rate formulation problem introduced in Brugge field. An efficient procedure was employed to deal with the high dimensionality of the optimization problem. The procedure starts with two-course groups of production/injection rates over the time. First, the production and injection rates over the time in the beginning of production and the second at the moment that the cumulative NPV is halved. When the convergence criteria are met, each coarse group was doubled in order to the cumulative NPV to become equal over the refined time interval. The most refined control variables were obtained close to the optimal point. The advantage of this method is improved computational process resulting in reaching an improved optimal point in the large-scale reservoir optimization problems. By applying this method, the optimization was accelerated and increased the chance of finding a better optimal solution. This is another approach to handling the large dimensionality of Brugge field optimization problem.

Asadollahi (2012) applied the same approach as Loretzen et al. (2009) and used the shut-in water-cut as the optimization variables. The injection strategy was selected to be unity voidage replacement to maintain the reservoir pressure. The number of variables is reduced to 54 which is the number of initially open completions in production wells. When a certain completion reaches the maximum economic water-cut value, it shuts down earlier and assigns the extra generated production capacity to the neighboring completions with lower water-cut. They applied Guide rate in Eclipse to avoid the direct optimization on high dimensional rate formulation of Brugge water-flooding optimization problem. The guide rate formula distributes the production rate between the producers with higher well potential and penalize the production from wells with high water cut or high gas-oil ratio. Applying this formula and using experimental design, they decided to optimize on one of the constants in the guide rate formula. The highest optimal estimated NPV value was obtained when combining the shut-in formulation and the guide rate formula.

What we can bring forward from this section is that:

- Not always using the wells bottom hole pressures are the best control parameters (Asadollahi and Naevdal, 2009). A sensitivity analysis must be performed in order to see which parameters respond best as control parameters.
- Formulation of the water-flooding optimization problems and defining the appropriate control parameters to be optimized are essential for the performance of the optimization algorithm (Lorentzen et al., 2009).
- It is possible to employ and combine approaches as in (Asadollahi, 2012) where they combined the reformulated Brugge problem and optimized one constant in the guide rate formula to approach the optimization problem in Brugge more efficiently.

Chapter 3

Development of relevant cases for production optimization

In this section, the developed cases for production optimization will be presented. These cases are segment models ”carved-out” from Brugge field. The focus has been on developing relevant cases with high potential for production optimization. These cases are designed for research at the Petroleum Cybernetics Group in NTNU. The developed cases can also be used for educational purposes. Petrel Reservoir Engineering is used for developing the relevant cases. These cases are then optimized using the optimizer implemented in Eclipse 300. Detailed steps of case development in Petrel RE can be found in the appendices.

The first step of case development process was to create an E300 model of Brugge field since the optimizer module of Eclipse is only capable of running the optimization on E300 models. The black oil model provided by TNO (Dutch Research organization) was converted into an E300 black oil model. The model conversion included making changes in the ”PROPS” section, defining new ”Equilibration region” and minor changes as the model could run in Eclipse 300. These changes resulted in alteration of the initial oil saturation in the field compared to the E100 black oil model. There is also a sharper transition zone between the oil-water contact in the modified Brugge field. For the purpose of optimization, this is not of great importance as the results are compared with a base case from the same modified model. The Eclipse deck was then converted into a Petrel project to create segment models, construct new wells, and create development strategies. More information about model conversion can be found in Appendix A.1.

In the case development process, the aim was to create interesting and realistic scenarios in terms of grid geometry, geology, production setting, and well placement. Eight segment models were developed and these cases were run. The performance of the base cases was analyzed in order to identify the potential for production optimization and select the relevant cases. Parameters such as initial and final liquid saturation, factors as rapid variation in permeability, porosity, and geological features such as faults in the segment were taken into consideration. Three cases were selected. In the next section, these cases are introduced in detail and the results from the run of the reference cases are introduced.

3.1 The Half-Dome structure

The Half-Dome structure is cropped from the eastern side of the field near the dome. The grid dimensions are 24 x 11 x 9 but the shape is not squared therefore the total number of active cells are 2358. The grid dimensions are summarized in 3.1

Grid No.	Initial	End	# Grid cells	Length [Feet]
X-direction	90	113	24	9398
Y-direction	25	15	11	5069
Z-direction	1	9	9	200

Table 3.1: Grid dimensions of the Half-dome structure

The segment has approximate measures of 2864 x 1545 x 61 m but varies due to the curvature of the segment and structural heterogeneity. As earlier mentioned, Brugge field comprises of four main formations: Schelde, Maas, Waal, and Schie respectively from top to bottom. The average permeability of Schelde formation is 1105 mD, and is 10 m thick, Maas is 90 mD with 20 m thickness, Waal is 814 mD with 26 m thickness, Schie is 36 mD with 5 meters thickness. The total thickness of the segment is 61 m. The geological characteristics of the field are summarized in Table 3.2

Formation zone	Avg Th [m]	Avg Poro [%]	Avg perm [mD]	Avg N/G [%]
Schelde Fm	10	20.7	1105	60
Maas Fm	20	19.0	90	88
Waal Fm	26	24.1	814	97
Schie Fm	5	19.4	36	77

Table 3.2: Stratigraphy with characteristic geological properties in Brugge Field (Peters et al., 2010)

The permeability distribution for each layer is illustrated in Figure 3.2. The first two layers have high permeability and represent Schelde formation. The next three layers are considerably less permeable and represent Waal formation. Layers 6,7,8 have higher permeability and represent Maas formation. Schie formation has poor permeability. The permeability variations are different layers must be taken into considerations for well placements and development strategy. The fluid system in the segment is two phase, oil-water system with undersaturated oil. As illustrated from an upside view in Figure 3.3, the initial oil saturation is highest in the northwest side of the block and the oil saturation decreases gradually downwards. A sharp transition between the oil and water can be observed.

The Half-dome structure was used to define two cases with different production strategies (Wells type and placement, production and injection's rates, lifetime). In the following, the production scenarios are introduced.

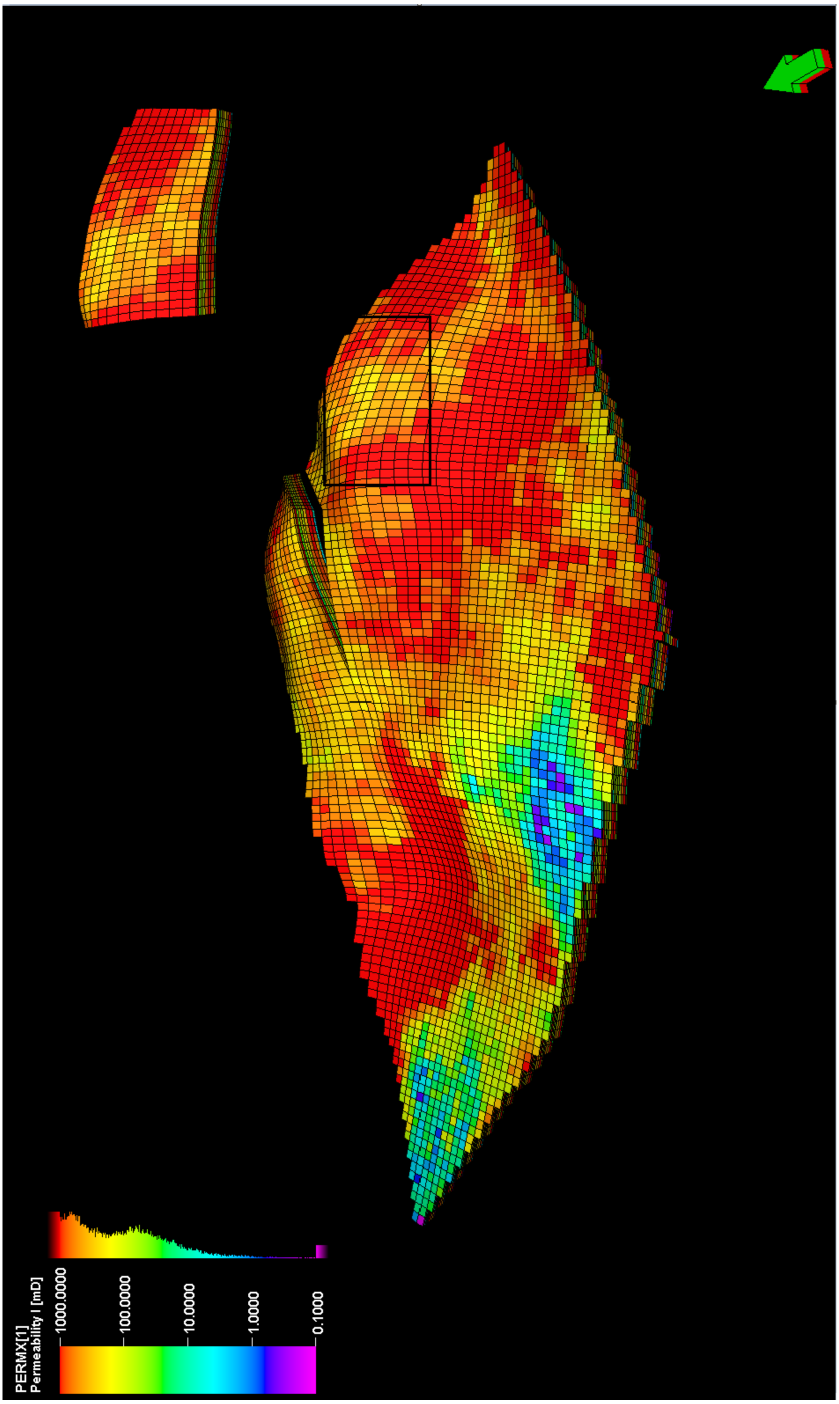


Figure 3.1: Half-dome overview.

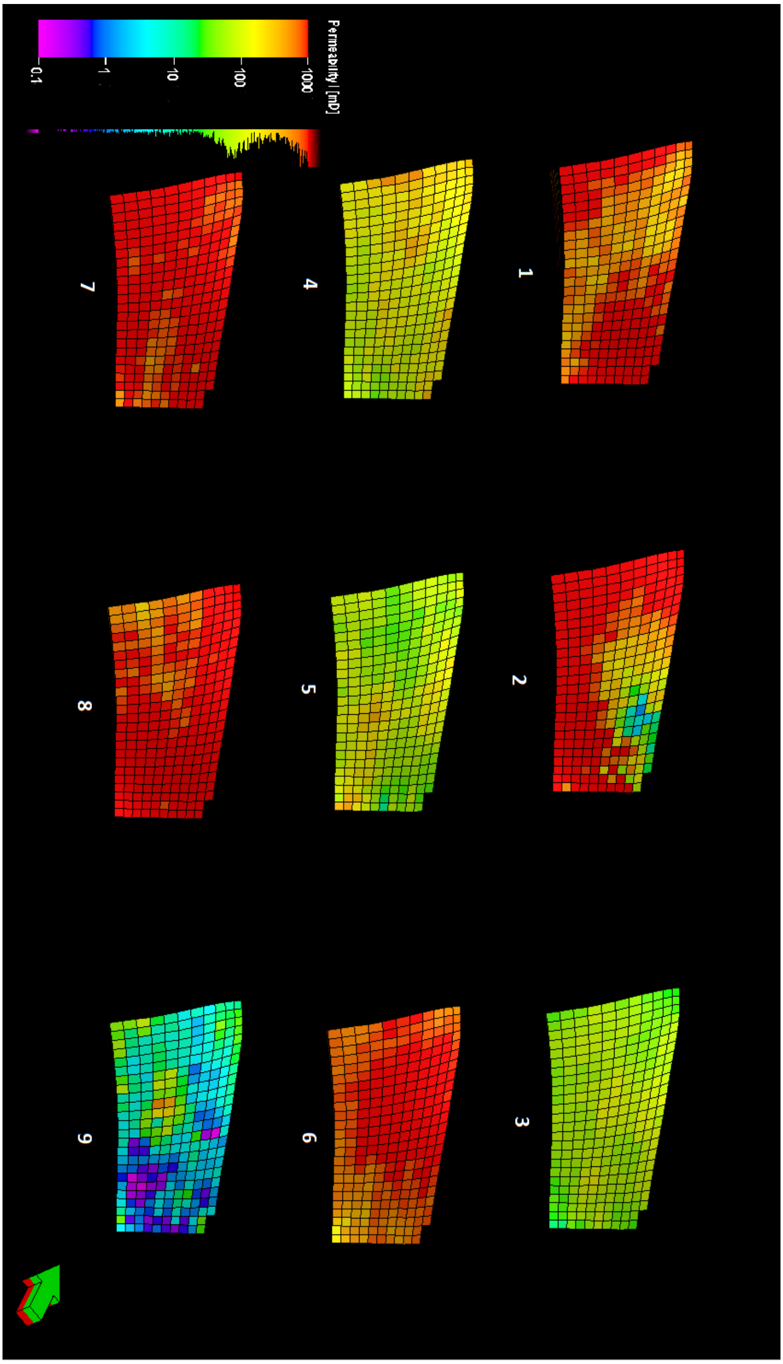


Figure 3.2: Permeability distribution in each layer - Half-dome structure. The first two layers have high permeability(Schelde FM), the next three layers are less permeable (Maas FM), and layers 6,7,8 are of a more permeable characterisation (Waal FM). The last layer has poor permeability (Schie FM).

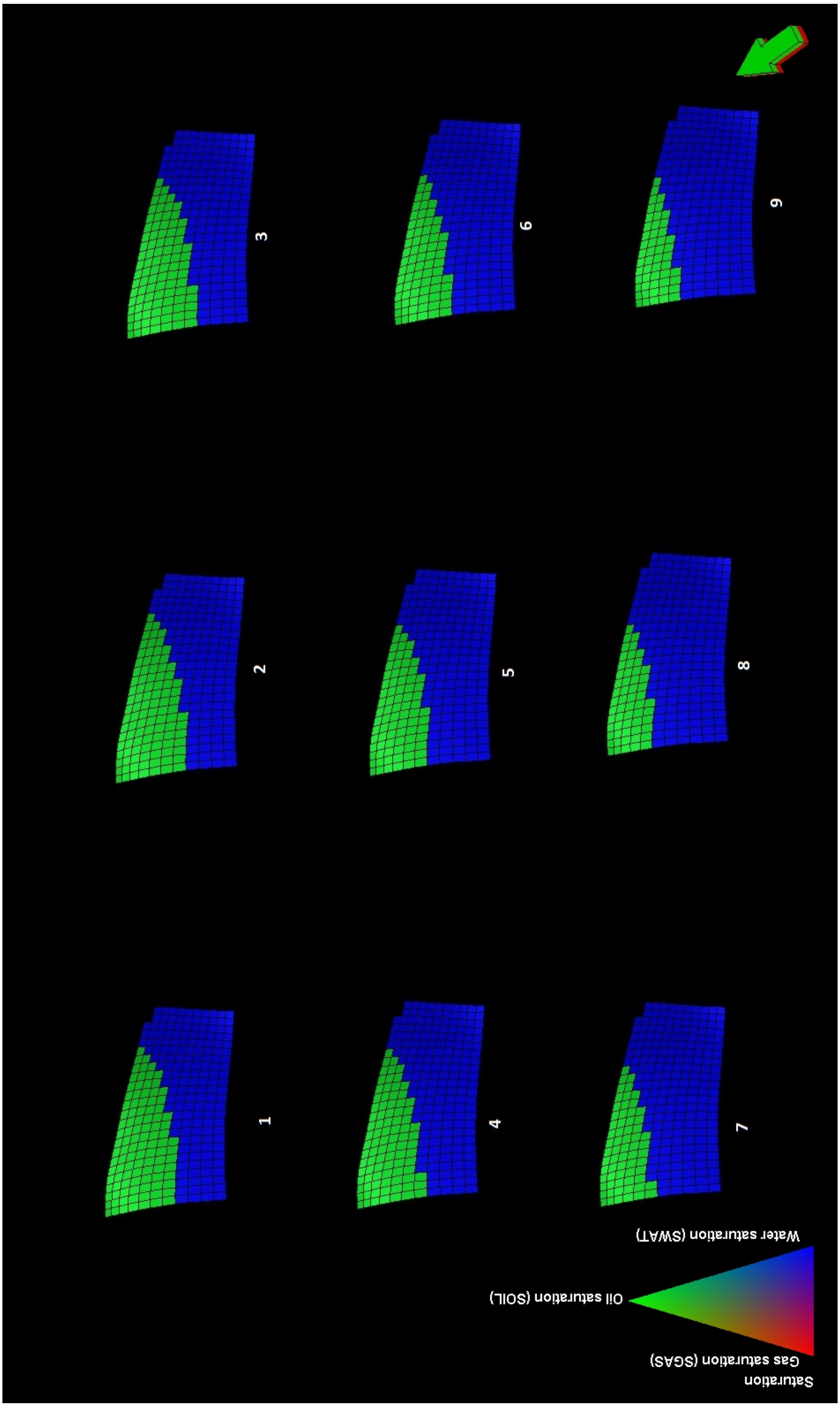


Figure 3.3: Initial oil saturation in the Half-dome structure for each layer.

3.1.1 Case 1: Half-dome Structure Production scenario 1 - Horizontal wells

There are two horizontal wells completed in this segment, one horizontal producer, and one horizontal injector. The wells placement is shown in Figure 3.4. Therefore, the drive mechanisms are depletion drive and water injection in this case. The producer is approximately 966 m long and it is completed in the top formation, Schelde. This is due to the relatively high permeability and porosity of the formation and also the high initial oil saturation in the top layers. The injector is placed further down in the Waal formation. Waal formation has also considerably high porosity and permeability. The injector is 1025 m long and is completed in the whole reservoir section.

For the purpose of this study, the case is on constant rate production strategy. This production scenario runs for 5480 days (15 years) starting from 1 Jan. 2018 until 1 Jan. 2033 and the report output frequency is every 4 months. The producer is on constant liquid control mode and is producing 10,000 stb/d with a bound of the minimum bottom hole pressure of 750 psi. The injector is on water rate control mode with constant rate of 10,000 stb/d and the maximum allowed bottom hole pressure is 2610 psi. The summary of the production strategy is given in Table 3.3.

Wells	Length [m]	Rate [Stb/d]	CNTL Mode	Limits [Psi]	lifetime [Days]
Producer	966	10,000	Rate	Max BHP= 2611	5480
Injector	1025	10,000	Rate	Min BHP= 750	5480

Table 3.3: Production strategy for Half-dome production strategy 1.

After running the case, the final oil recovery factor of the segment is approximately 20% and the saturation map is illustrated in Figure 3.5. As seen, the residual oil saturation is quite high. The graph in Figure 3.7 shows that water production rate starts quite early and increases quickly. The production well is under liquid control mode and is set to produce with 10,000 std/d. The water production of the well becomes higher to maintain the well target rate and compensate for declining oil production rate during the producing time. The average field pressure is illustrated in Figure 3.8. It starts from 1600 psi and quickly declines during the production. The average field pressure declines rapidly. The pressure maintenance is not sufficient although there is completed an injector in the segment. Improved oil production may be achieved by controlling the liquid injection and production rate to prevent an early breakthrough and obtain better sweep.

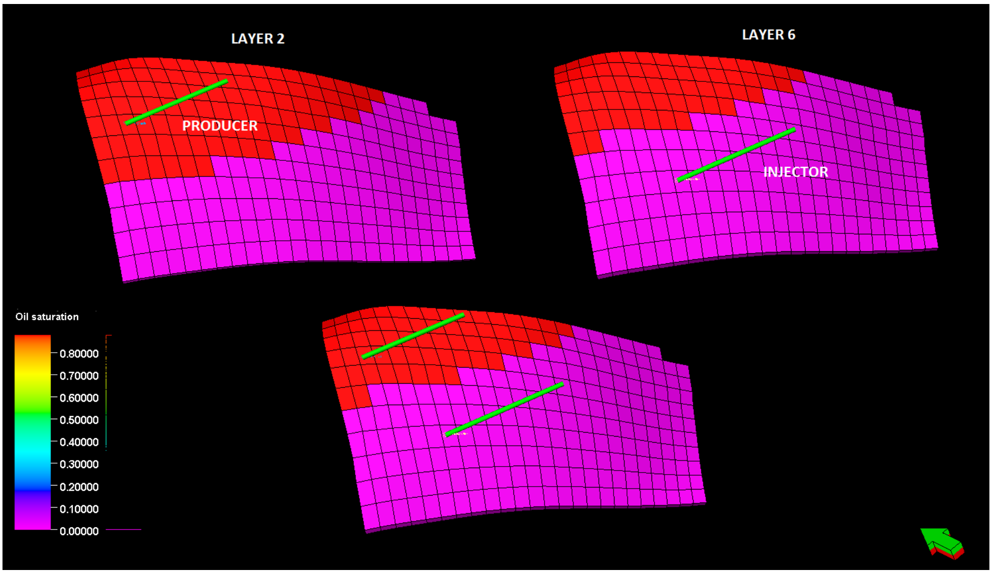


Figure 3.4: Wells placement in HD - production Scenario 1.

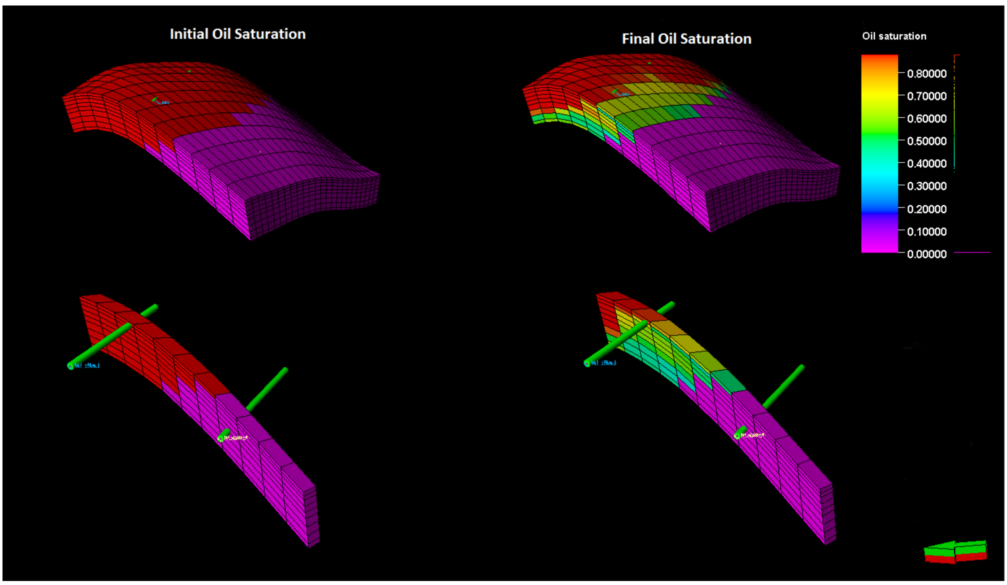


Figure 3.5: Comparison of initial and final oil saturation in the reference HD - production scenario 1.

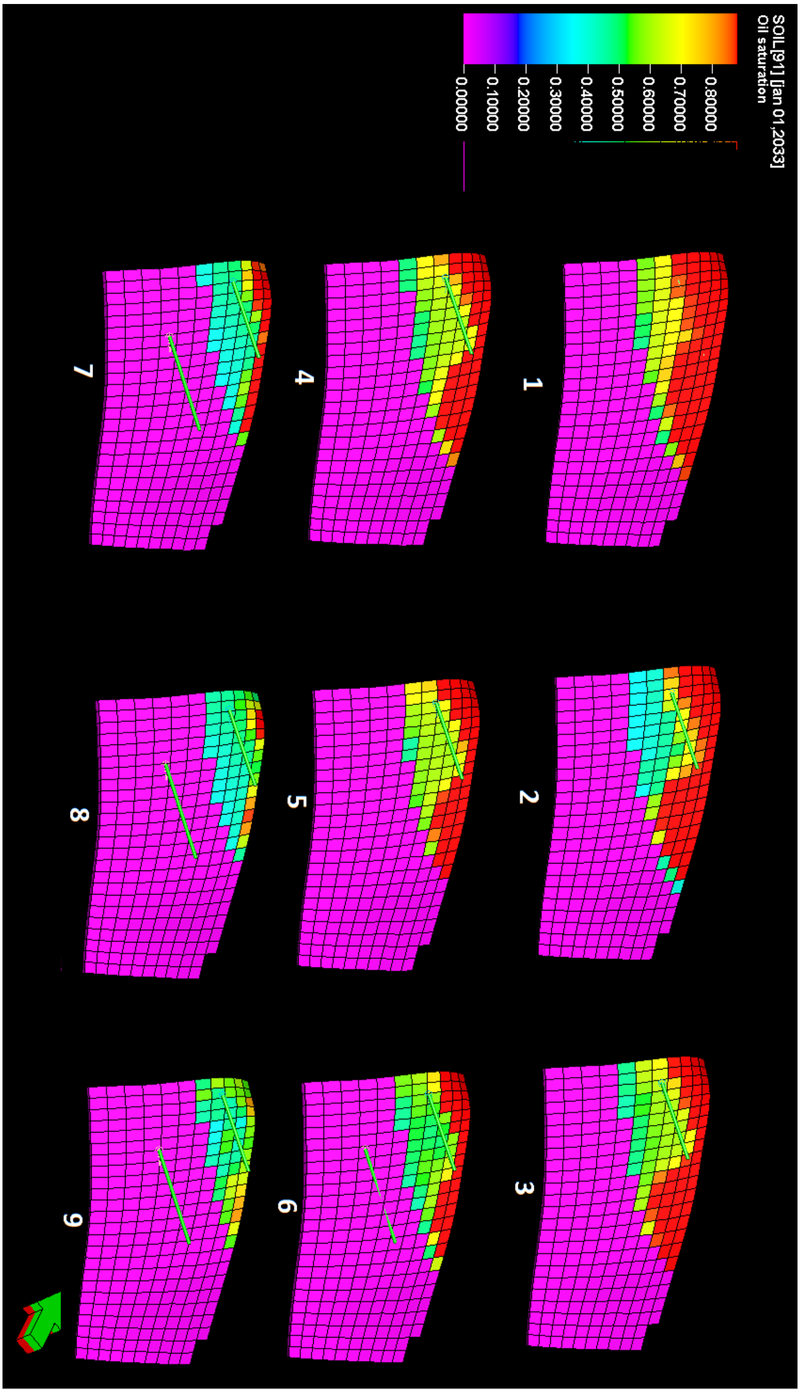


Figure 3.6: Final oil Saturation in Each Layer of HD - production scenario 1.

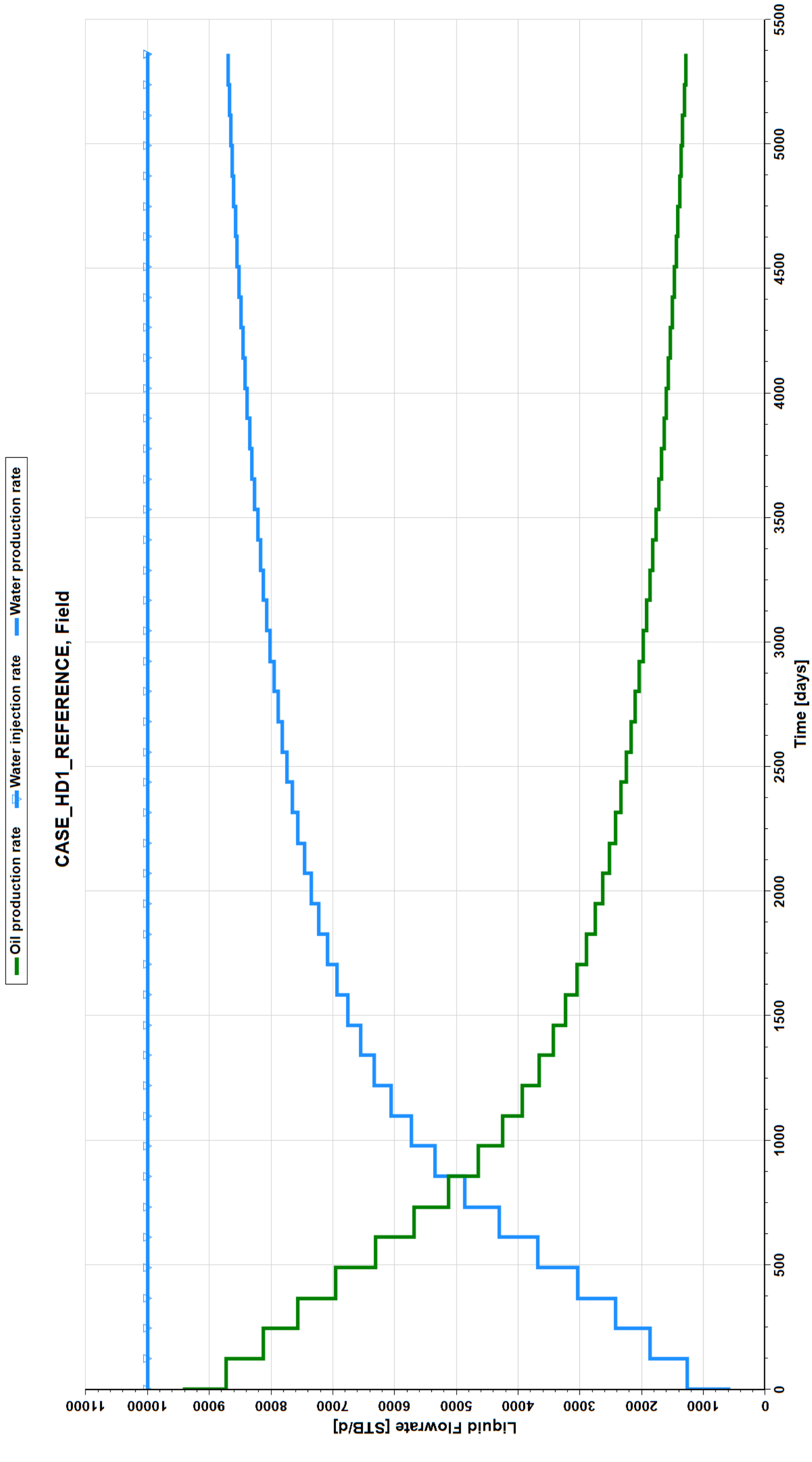


Figure 3.7: Oil and water production rate and injection rate in the reference HD - production scenario 1.

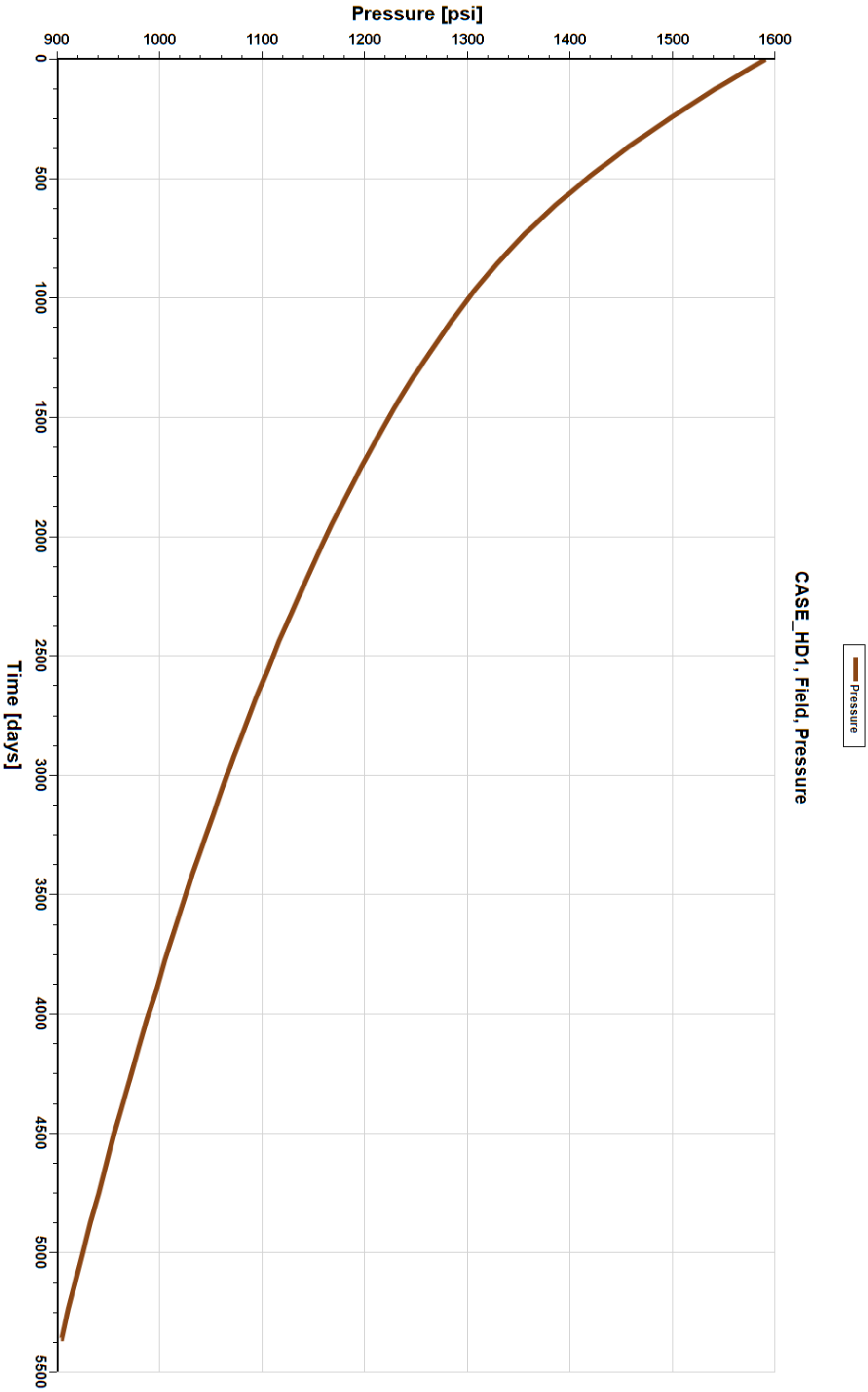


Figure 3.8: Average field pressure in the reference HD - production scenario 1.

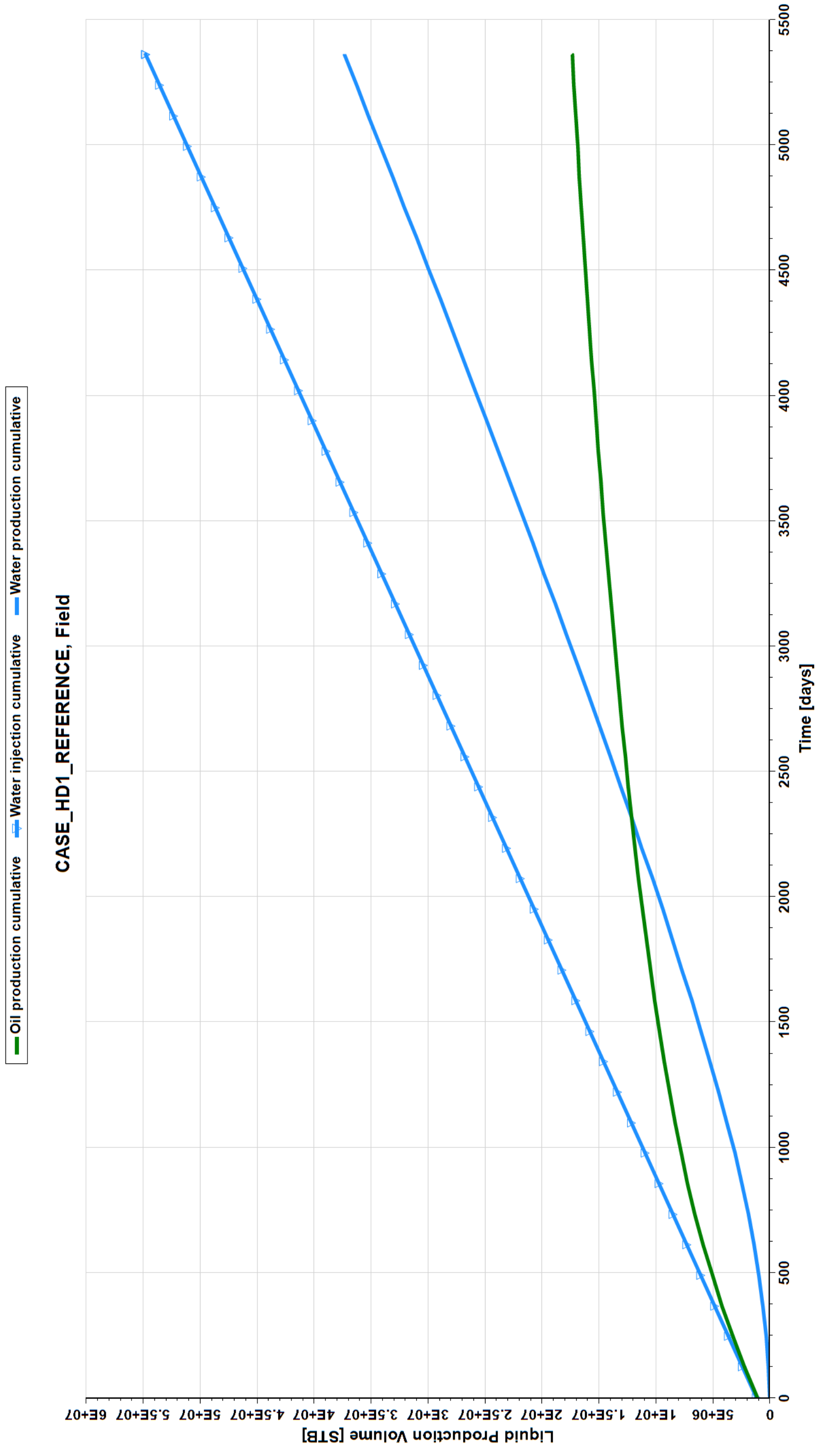


Figure 3.9: Oil and water ultimate cumulative production in the reference HD - production scenario 1.

3.1.2 Case 2: Half-dome Structure Production scenario 2 - Vertical wells

The Half-dome structure - case 2 has the identical same grid and geological properties as case 1. The production scenario is different in this case. There are 8 nearly vertical wells in this case with 4 producers and 4 injectors. Therefore, the drive mechanisms are depletion drive and water injection. The wells configuration is illustrated in Figure 3.10. The wells placement in this water-flooding scenario is close to an inverted 5 spot drive pattern-flooding. A certain well pattern is repeated throughout the segment. In this scenario, all the producing wells are under constant rate control mode with a production rate of 5000 stb/d. The lower bound of the bottom hole pressure is 750 psi. The injectors are under water control mode with an injection rate of 5000 stb/d and the maximum allowed bottom hole pressure is 2611 psi. The model is produced for 2192 days (6 years), starting from 1. Jan 2018 and continues until 1 Jan. 2024 and the report output frequency is every 6 months. A summary of this production strategy is given in Table 3.4

The final oil recovery factor of the segment is approximately 10% by running the case with this production strategy. The initial and final oil saturation map are illustrated in Figure 3.11. Figure 3.12 illustrates the final oil saturation in each layer of the Half-dome structure after production with the current strategy. As seen, the residual oil saturation is high in all layers and can be improved. Figure 3.15 illustrates the production and injection rates. There is a large and quick decline in the oil production rate. As seen, water production rate starts quite early and increases quickly. The production wells are on liquid rate control mode and produce water to maintain the target rate when the oil rate decreases. The average field pressure is illustrated in Figure 3.14. It starts from 1580 psi and quickly declines during the production. The average field pressure declines quickly even though there are completed four injectors in the segment.

Wells	Length [m]	Rate [Stb/d]	CNTL Mode	Limits [Psi]	lifetime [Days]
Injector1	87	5,000	Rate	Max BHP= 2611	2192
Injector2	71	5,000	Rate	Max BHP= 2611	2192
Injector3	78	5,000	Rate	Max BHP= 2611	2192
Injector4	75	5,000	Rate	Max BHP= 2611	2192
Producer 1	68	5,000	Liq.Rate	Min BHP= 750	2192
Producer 2	76	5,000	Liq.Rate	Min BHP= 750	2192
Producer 3	128	5,000	Liq.Rate	Min BHP= 750	2192
Producer 4	165	5,000	Liq.Rate	Min BHP= 750	2192

Table 3.4: Production strategy for Half-dome production Strategy 2

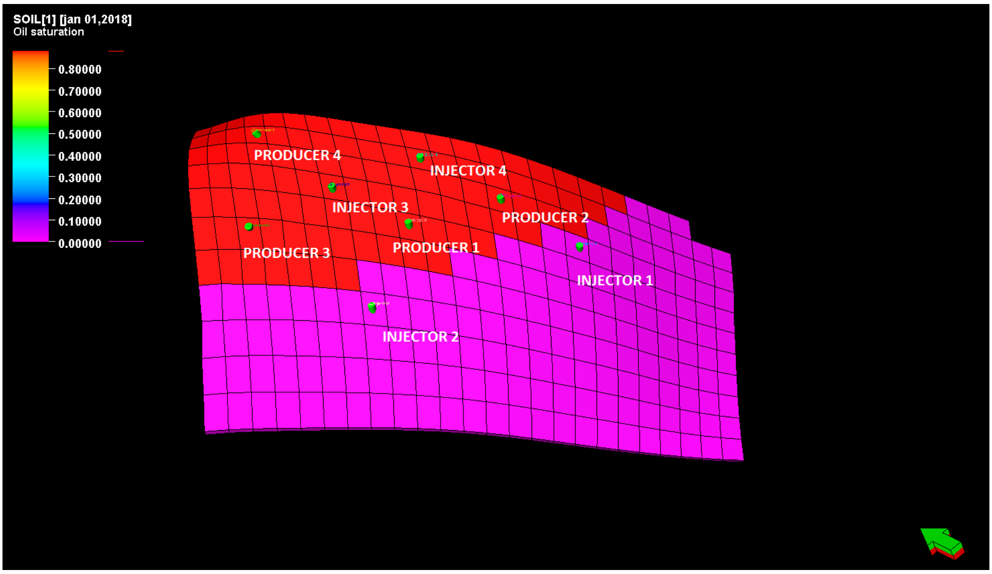


Figure 3.10: Wells placement in Half-dome production strategy 2.

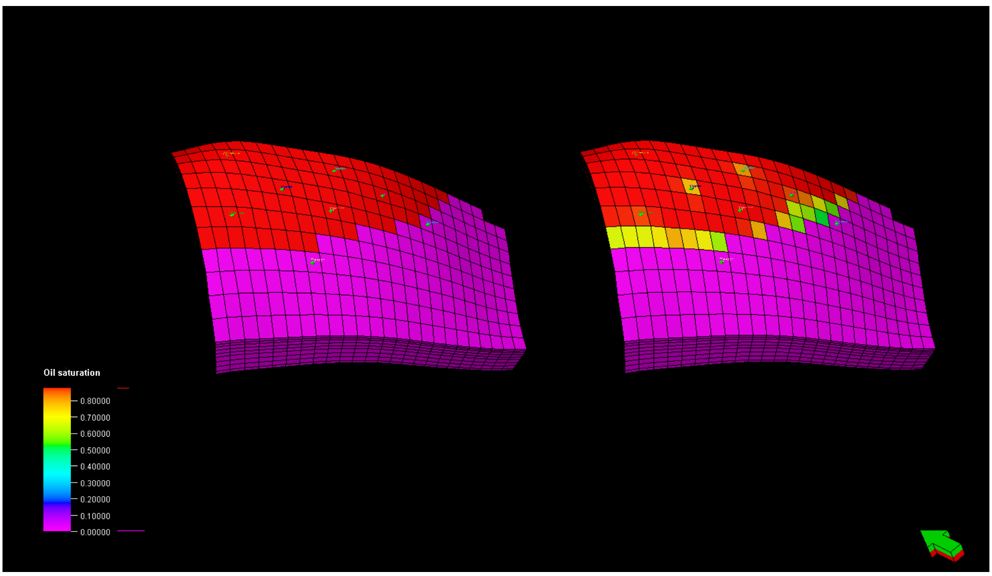


Figure 3.11: Initial and final oil saturation in Half-dome production strategy 2.

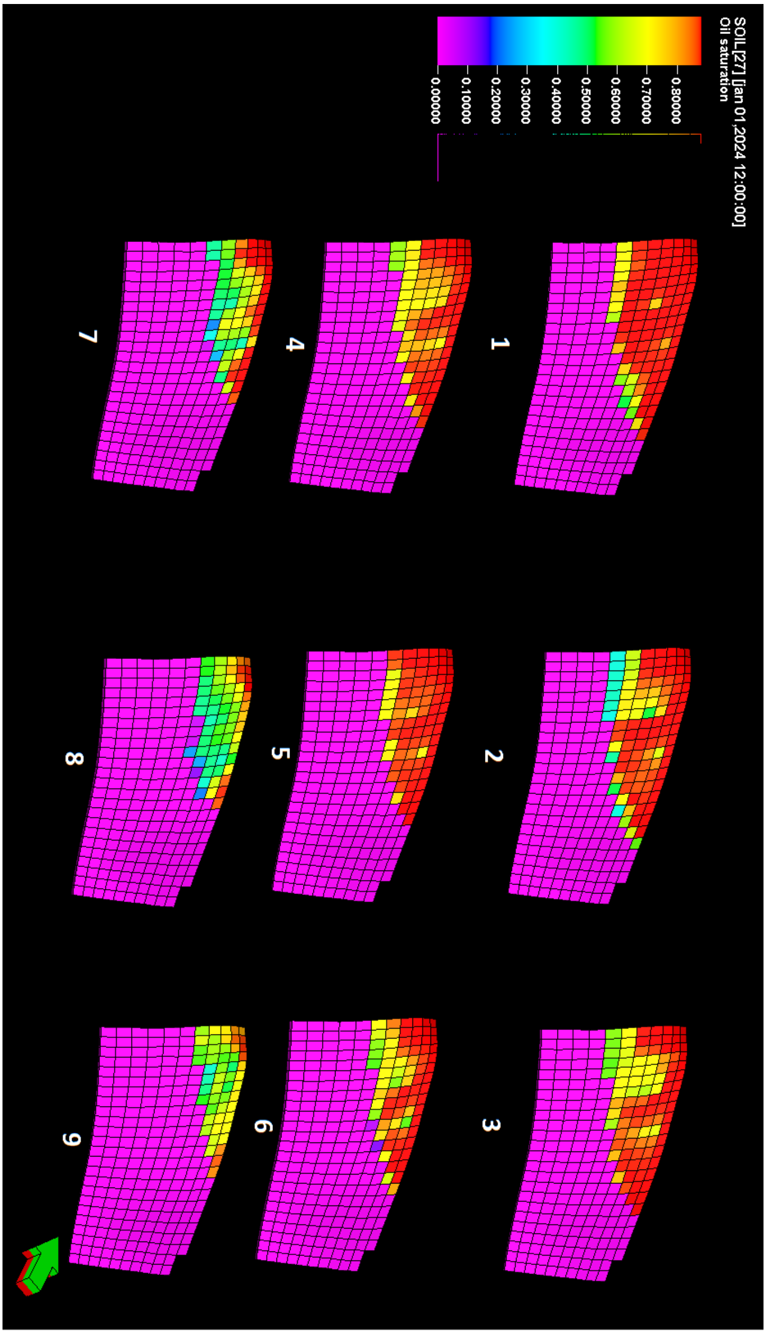


Figure 3.12: Final oil saturation in all layers Half-dome production strategy 2.

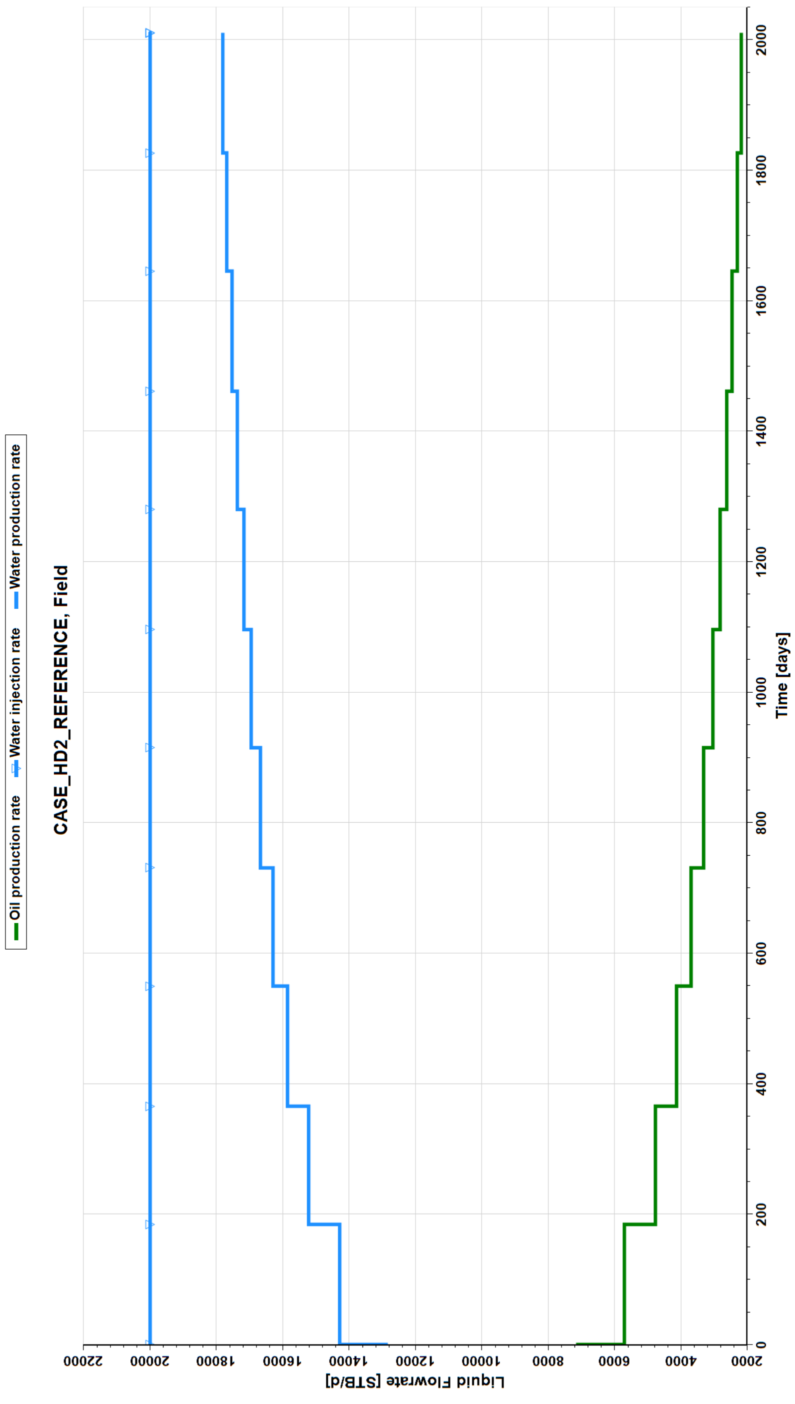


Figure 3.13: The comparison of oil and water production and water injection rate in HD - production scenario 2.

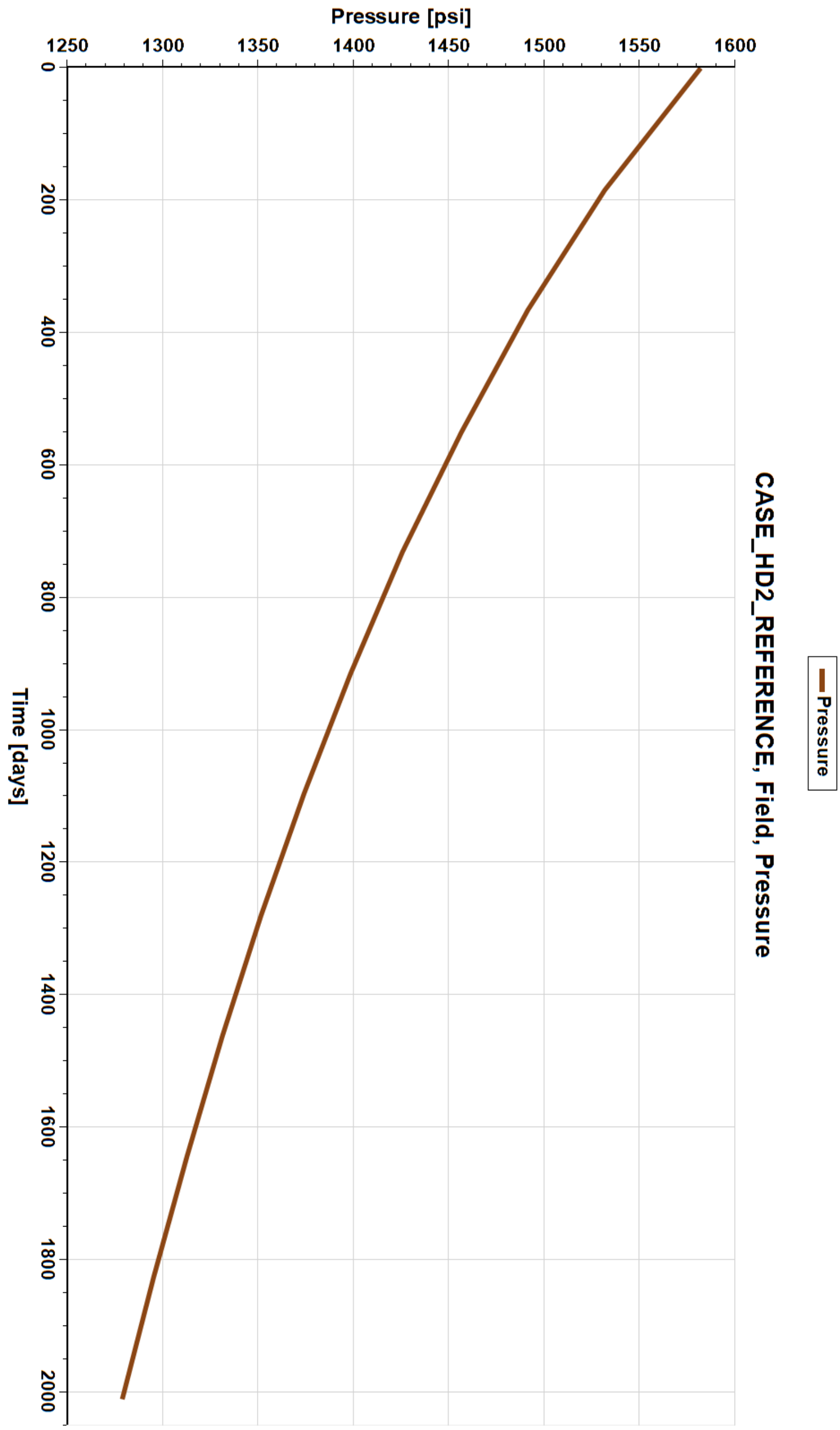


Figure 3.14: Average field pressure in the reference HD - production scenario 2.

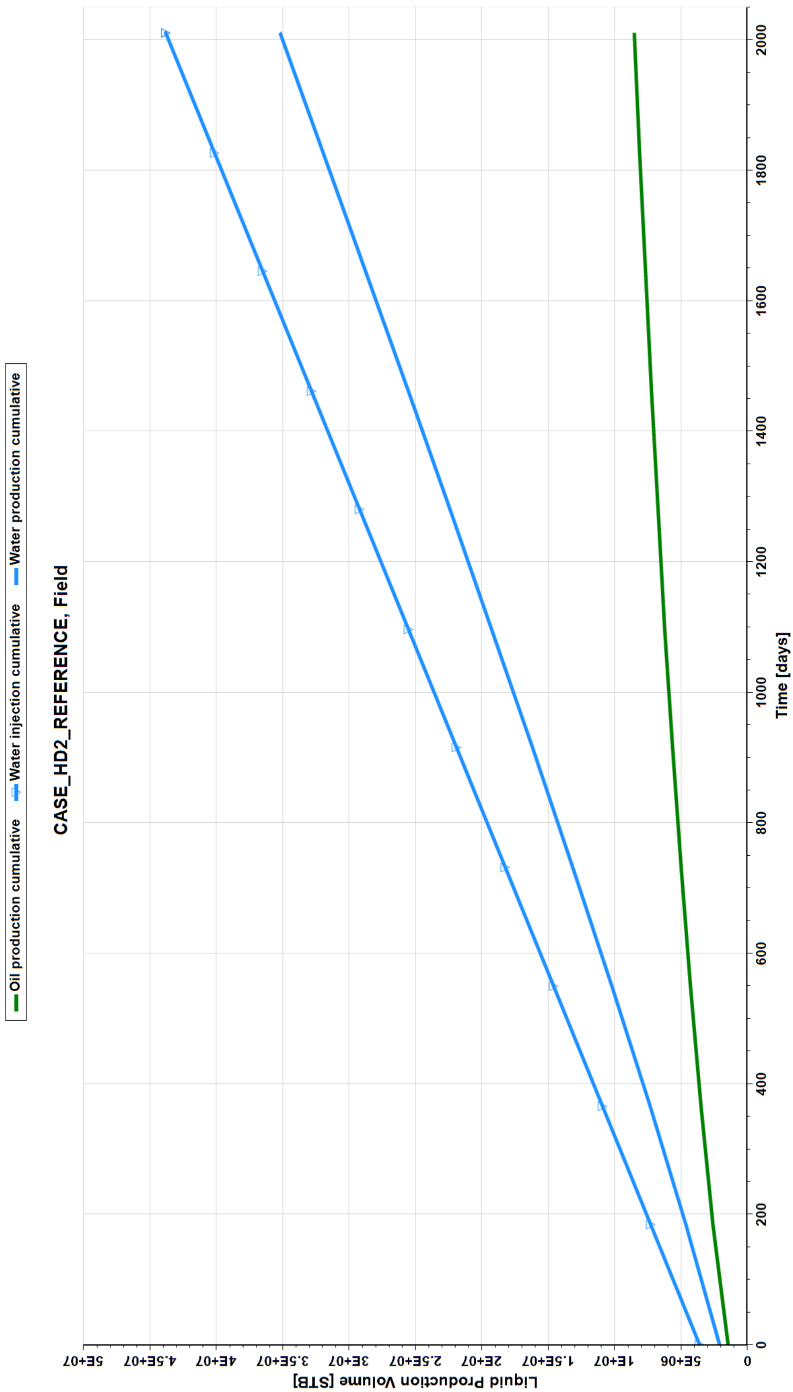


Figure 3.15: The comparison of oil and water cumulative production in HD - production scenario 2.

3.2 Case 3: Rio structure

The grid dimensions in the third case are 24 x 21 x 9 and the total number of active cells in this segment are 3366. This segment is cropped approximately from the same area as the Half-dome structure as seen in Figure 3.16. The permeability distribution is illustrated in Figure 3.18. The segment comprises of four formations as the rest of the field and the stratigraphical properties may be found in Table 3.2. The fluid system in the segment is two phase, oil-water system with undersaturated oil. There are two horizontal production wells completed in the top layers of the segment where the oil saturation and permeability are largest. Production well 1 is approximately 971 meters long, and the entire well is perforated open to flow. Production well 2 is approximately 969 meters long and also fully perforated along the entire reservoir. The wells placement can be observed in Figure 3.17. Production well 2 is placed further down close to the aquifer. Large water production is a challenge for the performance of this well as seen in Figure 3.22.

In this case, the producing wells are on constant liquid control rate of 20,000 stb/d each and the lower bound of the bottom hole pressure in both wells are 750 psi. The model is produced for 3653 days (10 years) and the report output frequency is every 2 months. An aquifer is defined in this case that offers additional pressure support in the segment. This aquifer is a ”Bottom water drive” and is located under the pay zone that feeds it from beneath. The two drive mechanisms are depletion and aquifer drive. The grid dimensions are summarized in table 3.5

Grid No.	Initial	End	grid cells	Length [Feet]
X-direction	91	113	24	9,638
Y-direction	7	27	21	5,000
Z-direction	1	9	9	200

Table 3.5: The grid dimensions of the Rio structure.

Wells	Length [m]	Rate [Stb/d]	CNTL Mode	Limits [Psi]	lifetime [Days]
Prod_1	971	20,000	LRAT	Min BHP= 750	3653
Prod_2	969	20,000	LRAT	Min BHP= 750	3653

Table 3.6: Production strategy for case Rio

After running this case, the final cumulative oil recovery is approximately 23 %. There are no injection wells in the segment, but the final recovery factor is relatively high. One of the reasons is due to the additional pressure support from the aquifer. The average field pressure is illustrated in Figure 3.14. It starts from 1510 psi and declines to 1385 psi during the production. The drop in the field pressure is not large due to the pressure support from the aquifer. One may obtain even higher recovery by optimizing the liquid production rate. As seen in the Figure 3.19, there is a quick decline in the total oil production rate and a large increase in produced water.

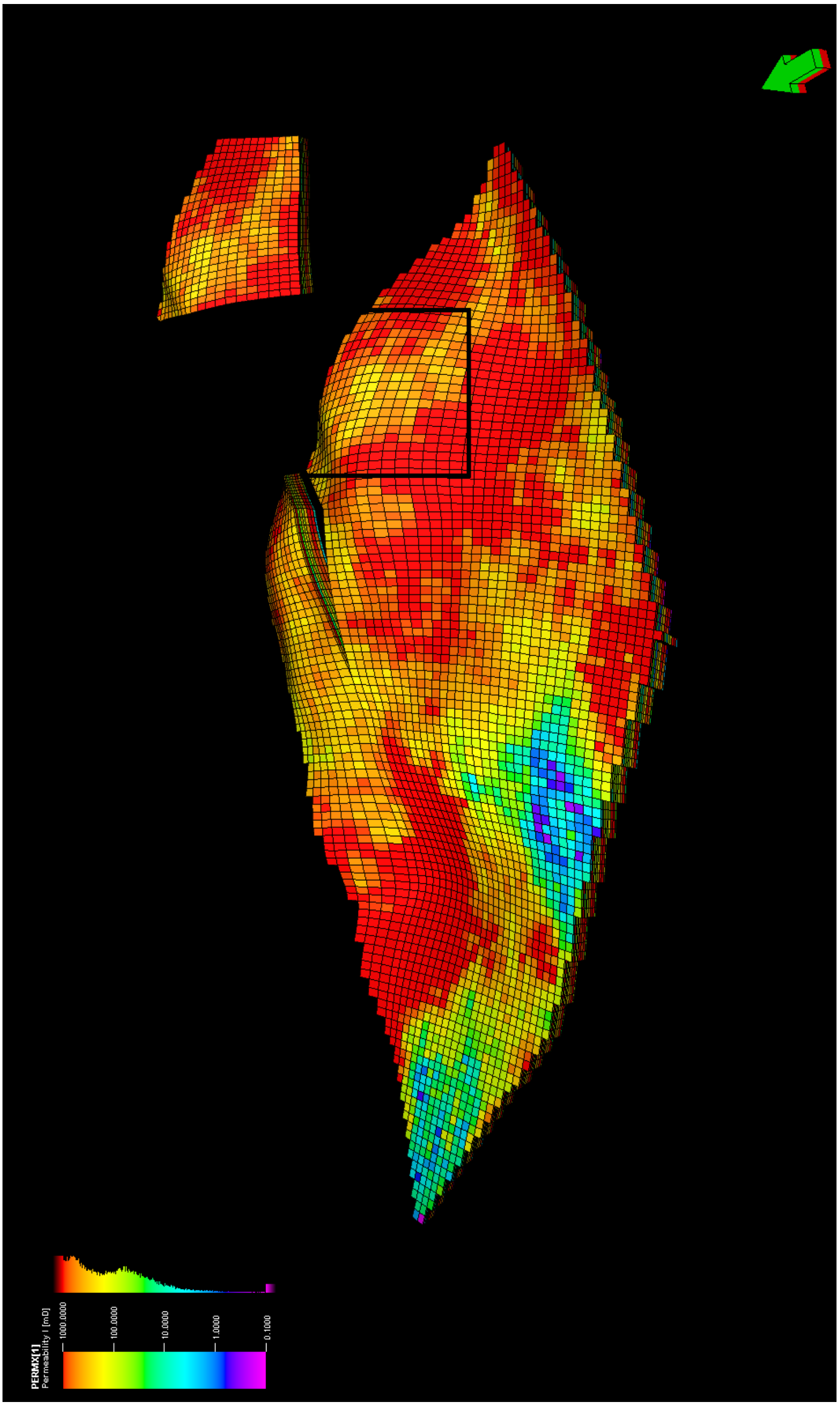


Figure 3.16: Rio overview.

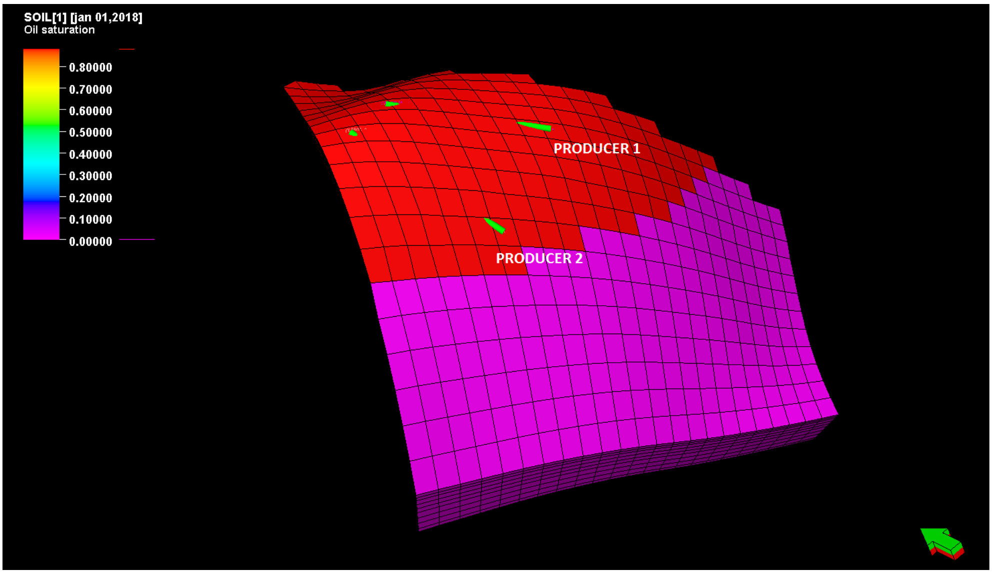


Figure 3.17: Wells placement in case 3, Rio structure. Producer 2 is completed lower in the segment and is closer to the aquifer. This may result in higher water production compared to producer 1.

The Figure 3.22 and Figure 3.21 illustrate the wells performance in terms of oil and water production rate. The comparison of the well performance in this segment shows that production well 1 is performing better than production well 2 in terms of oil production. The water production of well 1 is also less than the water production in well 2. Achieving improved results may be possible by optimizing this case. For example, a proactive control strategy can be applied to control the amount of produced water. This may result in improved performance from production well 2 with high water-cut in the reference case.

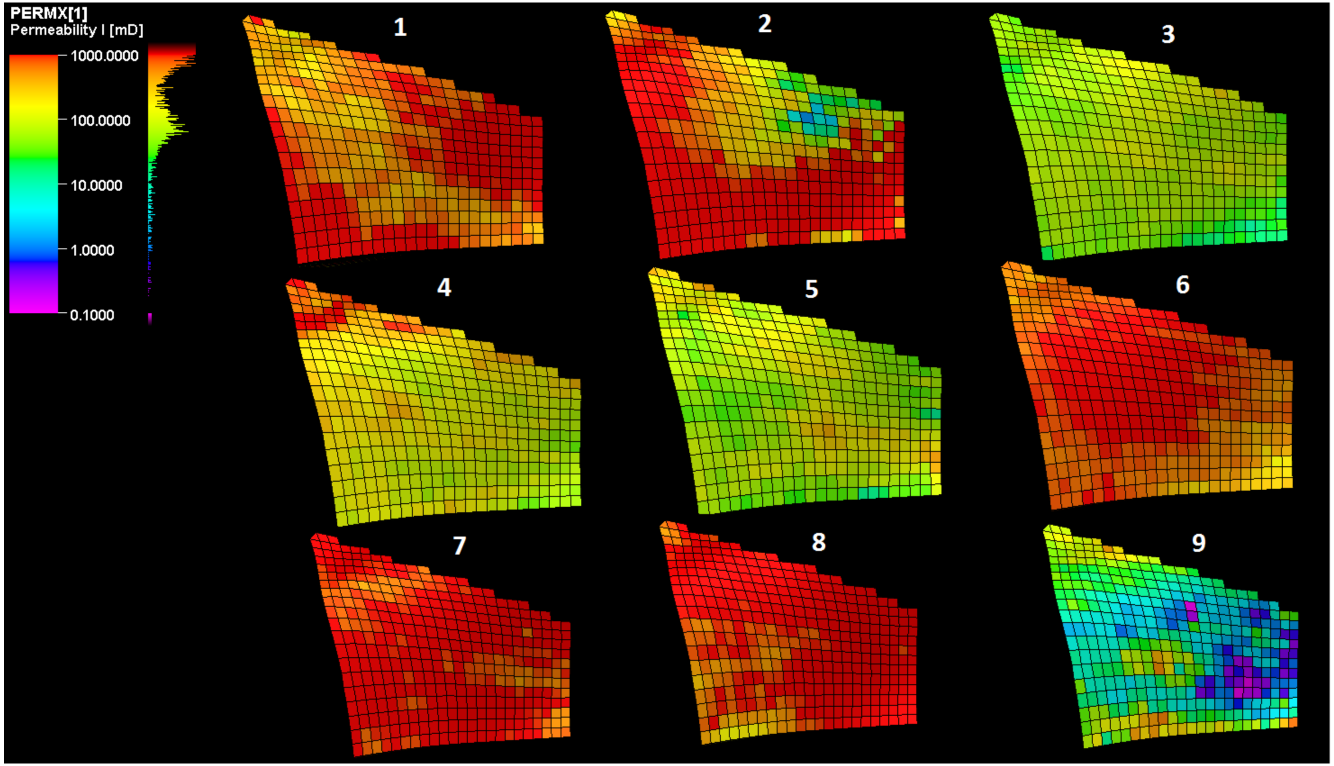


Figure 3.18: Permeability distribution in the layers of the Rio structure is illustrated. As seen the permeability is considerably higher in layers 1,2,6,7,8 compared to in layers 3,4,5, and 9.

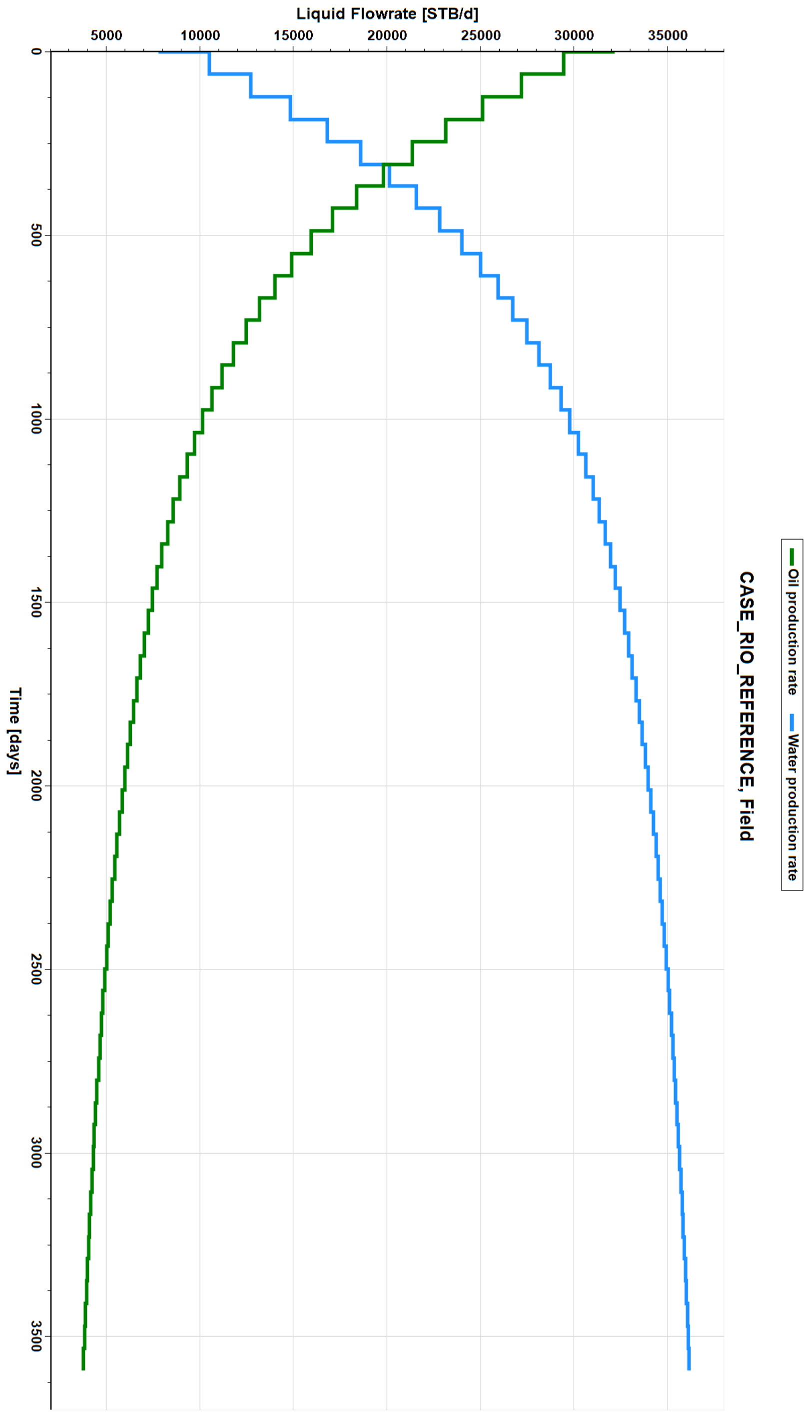


Figure 3.19: Oil and water production rate in case Rio with the reference production strategy.

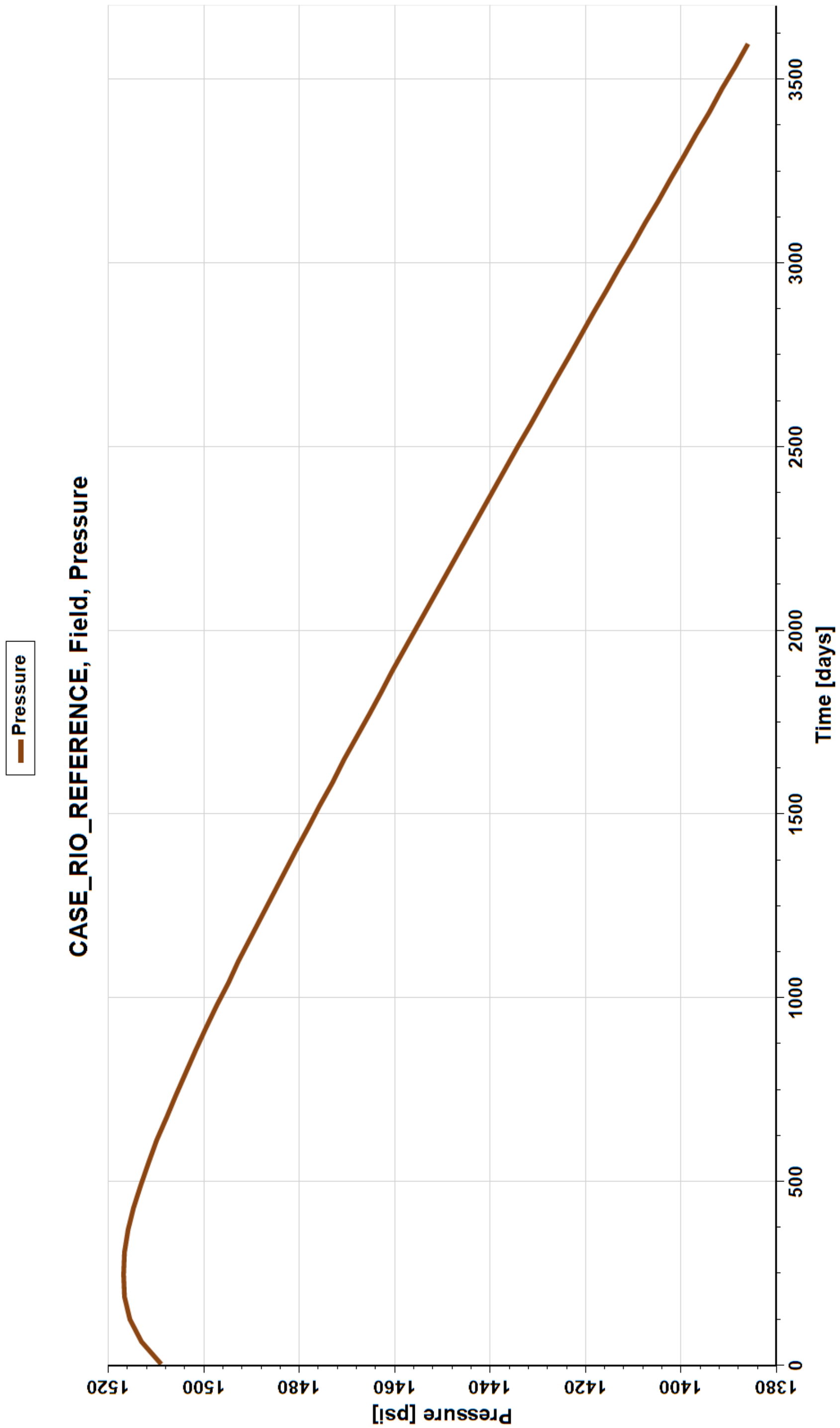


Figure 3.20: Average field pressure in reference case Rio.

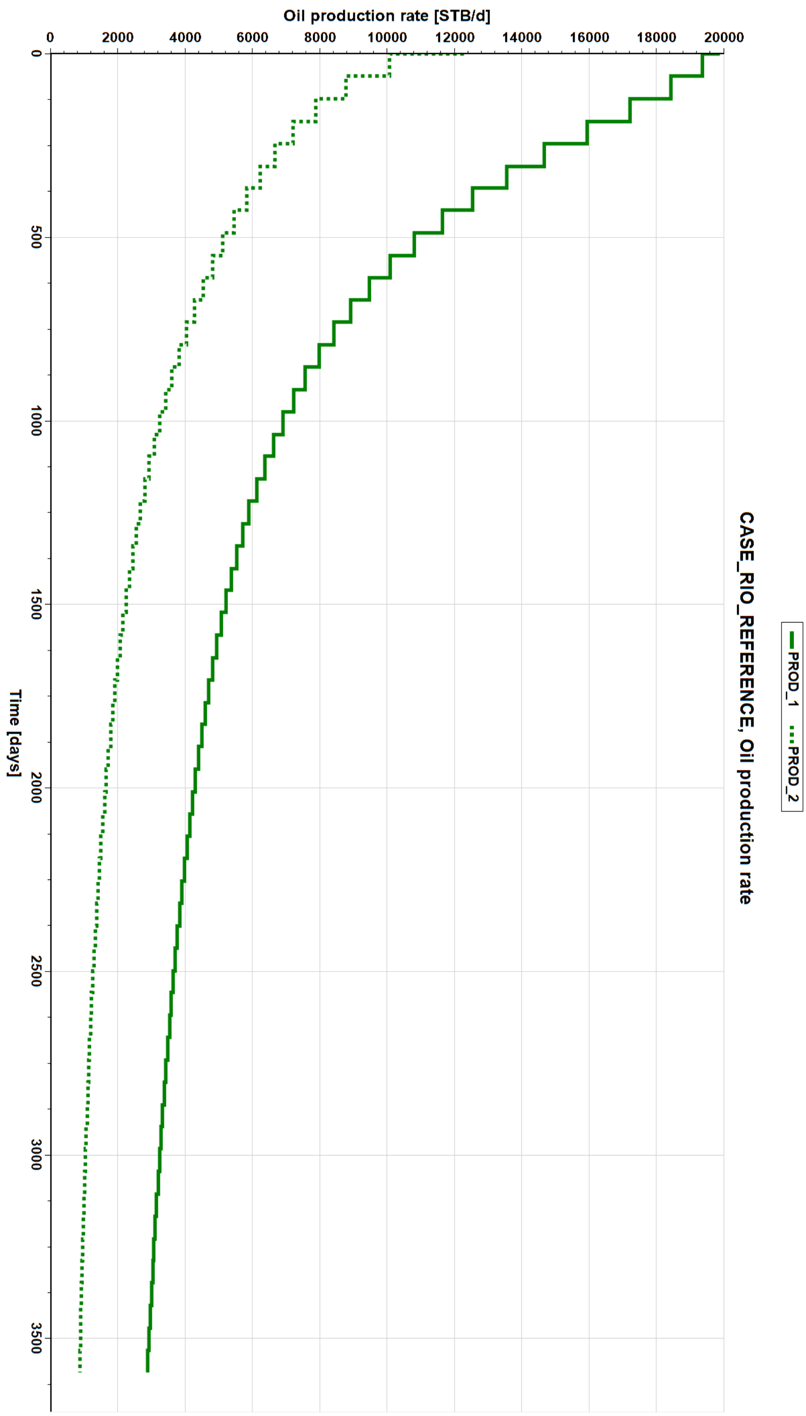


Figure 3.21: Comparison of oil production rate in the production wells in the Rio segment with the reference production strategy.

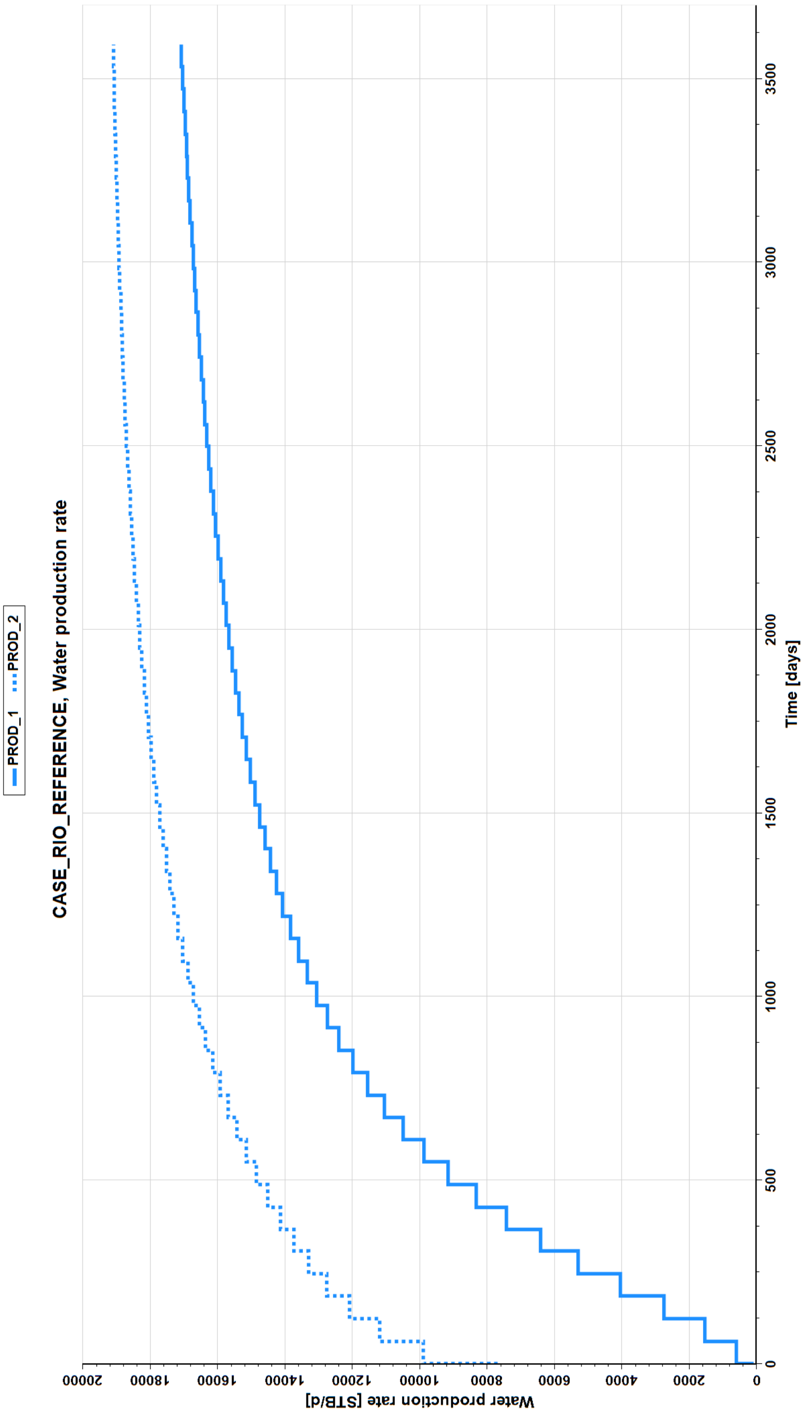


Figure 3.22: Comparison of water production rate in production wells in case Rio with the reference production strategy.

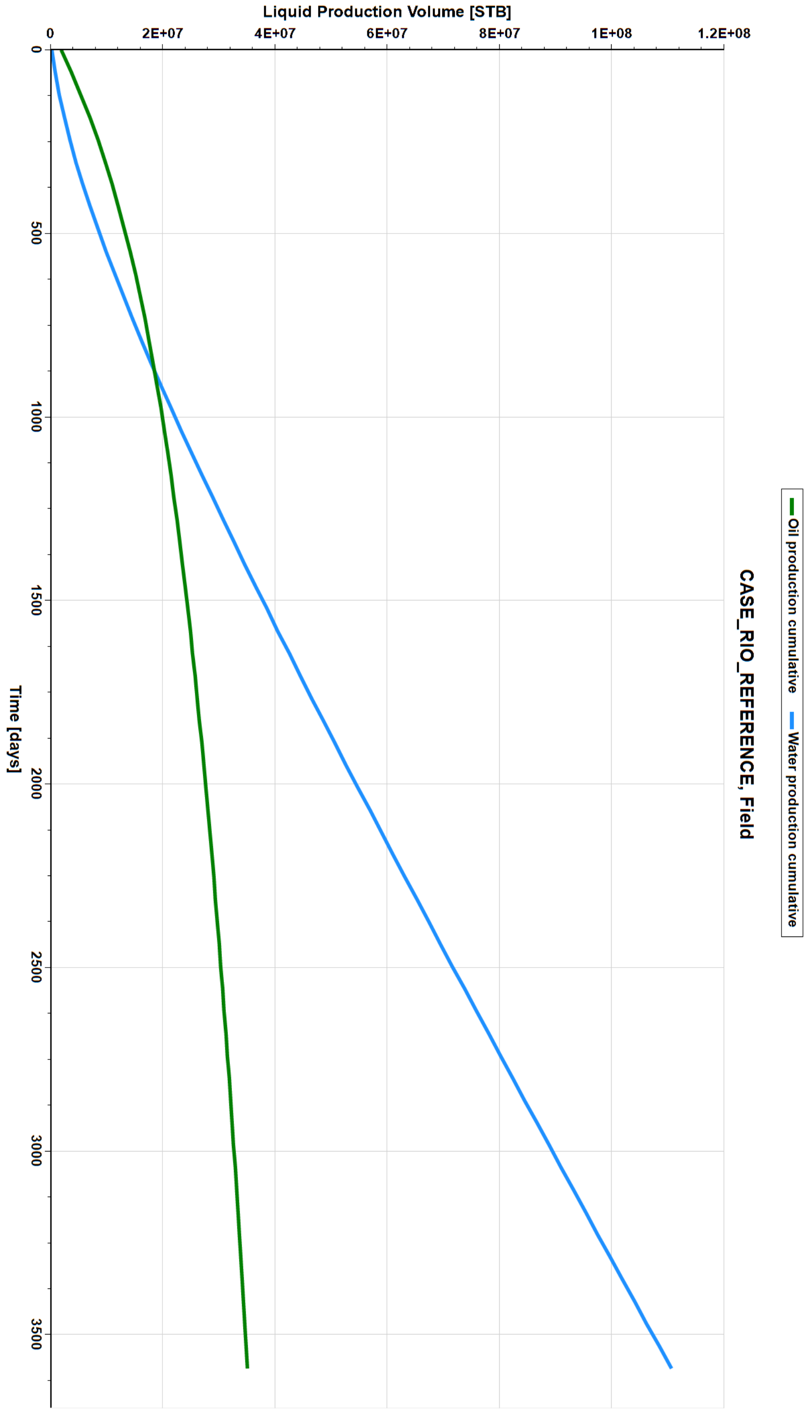


Figure 3.23: Cumulative oil and water production in case Rio with the reference production strategy.

Chapter 4

Experiments: Application of production optimization to developed cases

In this chapter, the objective function, control parameters and constraints implemented in this study are introduced. As mentioned, production optimization problems aim to maximize an objective function with respect to the control parameters. The control parameters have limitations known as the constraints. In this chapter, a description of the production optimization problem is given where different the elements related to the optimization study are introduced for each case.

4.1 Objective function, Control Parameters, Constraints

The **objective function** can be Net Present Value (NPV) or the ultimate cumulative oil production of the segment. Net Present Value of an asset represents the current value of the future investments taking the time value of the capital into consideration. NPV is defined as:

$$NPV = \sum_{k=1}^{M} \Delta t \frac{Q_o r_o - Q_w r_w - Q_i r_i}{(1+\frac{b}{100})^t} \tag{4.1}$$

M represents the total time-steps and starts from 1. Δt is the magnitude of the time-steps. Q_o is the amount produced oil rate in bbl/d and r_o is the oil price. Q_w is the produced water rate in bbl/d, and r_w is the cost of water production per barrel. Q_i is water injection rate in bbl/d, and r_i is the cost of water injection. b is the so-called discount factor or discount rate. It refers to the interest rate used in discounted cash flow to determine the present value of future cash flow. t is the total number of the years starting from 0 for the first year and so on. In this study, the discount factor is ignored in order to simplify the optimization problem.

The economic parameters to calculate the NPV is listed in Table 4.1

Parameter	Value
Oil price [bbl]	50 $
Water Operational cost [bbl]	5 $
Water Injection cost [bbl]	5 $

Table 4.1: The economic parameters to calculate the NPV

Control Parameters: Formulation of the optimization problem and choosing appropriate control parameters is important for the results and the performance of the optimization. From the literature study, there are several useful points that might lead to define the appropriate control parameters:

- The control mode of the wells should determine its optimization parameters
- Bottom hole pressures should also be examined as the control parameters for the wells, due to the complex well-operating conditions and changes between the control modes
- The optimization problem can be reformulated to decrease the number of control variables

Having these in mind, the following control parameters is available for each case:

Optimization variable	Choice 1	Choice 2
Producer	WBHP	WLPR
Injector	WBHP	WWIR

Table 4.2: Combination of control parameters for optimization in developed cases

Constraints: The restrictions on control parameters. These can be minimum or maximum bottom hole pressure, injection, and production rates. The rate bounds can for example correspond to the capacity of the surface facilities. The pressure bound on the wells can for example correspond to bubble point, fracture or collapse pressure.These are specified for each case. In two of the cases (Half-Dome structure 1 and Rio structure), NPV is selected as the objective function and the production constraint is on the maximum economic water-cut value in the segment. The liquid production from the field must respect the break-even water-cut. The water cut is defined as the fraction of water in total liquid produced:

$$WCT = \frac{Q_o}{Q_o + Q_w} \tag{4.2}$$

$$0 \leq WCT_j \leq 1 \tag{4.3}$$

Water-cut ranges between 0 and 1. J denotes the number of the well. The idea behind finding the economic water-cut is to find the limit where the production is economically viable. The relation $Q_o * P_o = Q_w p * C_w p$ yields the point where the profit from production is equal to the water production costs. Inserting this relation into the equation 4.2, the break even water-cut is obtained as:

$$WCT_{Break-even} = \frac{1}{1 + \frac{Q_o}{Q_w p}} = \frac{1}{1 + \frac{C_{wp}}{P_o}} \tag{4.4}$$

By inserting the economic values given in table 4.1, the break-even water-cut value will become $0.909 \approx 0.91$. This value is used as the production constraint in case 1: Half-structure - production strategy 1 and case 3: Rio structure.

Optimization dimensions: The maximum number of iterations and simulations must be specified in Eclipse for optimization of the developed cases. The maximum number of optimization iterations (gradient evaluations) is 20 and the maximum number of the simulations is 100. This indicates that the optimization process terminates when one of these limits are reached.

4.1.1 Case 1:Half-dome structure - production strategy 1

The objective function, in this case, is to maximize the net present value. This case contains one horizontal injector and one horizontal producer and the wells operate on rate control mode. In the base case, the production well produce with a constant rate of 10,000 stb/d. The injection well injects with a rate of 10,000 stb/d. The base case is described in more details in the previous chapter. The well rates are chosen as the control parameters since the wells operate on rate control. The control parameters are well water injection rate for the injector and well liquid production rate for the producer. The wells bottom hole pressures will also be tried as control parameters. The constraints on the production well are the pressure and rate limitations. The minimum bottom hole pressure in the production wells is 750 psi and the maximum bottom hole pressure is 3000 psi. The production rate is between 0 - 20,000 stb/d.

$$750\, psi \leq Bhp_j \leq 3000\, psi \tag{4.5}$$

$$0\, stb/d \leq Liquid\ Rate_j \leq 20,000\, stb/d \tag{4.6}$$

The constraint on the injection well is the maximum limit on bottom hole pressure set to be 2611 psi and the injection rate can vary from 0 - 20,000 stb/d.

$$0\, psi \leq Bhp_i \leq 2611\, psi \tag{4.7}$$

$$0\, stb/d \leq Injection\ Rate_i \leq 20,000\, stb/d \tag{4.8}$$

The choice of these constraints is inspired by the original paper by Peters et al. (2010). The values of the constraints in this study are close to these values used in the original Brugge workshop. The production constraint in this study is to maintain the field water-cut value below the economic break-even value which is 0.91 by the given economic parameter in Table 4.1. The optimization problem is summarized in Table 4.3

Objective Function	Optimization Parameter	Production Constraint
NPV	WLPR, WWIR	FWCT
	0 - 20,000 stb/d	< 0.91

Table 4.3: Optimization parameters for case 1

4.1.2 Case 2: Half-dome structure - production strategy 2

The objective function in case 2 is to maximize the ultimate cumulative oil recovery from the field. There are eight wells completed in this field, four injection wells, and four production wells. In the base case, these wells operate under the rate control mode. The production wells are under liquid control mode with a constant production rate of 5,000 stb/d. The injection wells are under water injection rate control mode with a constant rate of 5,000 stb/d. The base case is described in more details in Chapter 3.

The production wells have a lower limit of 750 psi on the bottom pressure and the injectors have an upper limit of 2611 psi. Choice 2 in Table 4.2, the wells liquid production rate and the wells water injection rate are chosen as the control parameters since the wells operate on rate control. The production wells can produce liquid up to 10,000 stb/d and injection wells can inject water up to 10,000 stb/d.

$$750\ psi \leq Bhp_j \leq 3000\ psi \tag{4.9}$$

$$0\ stb/d \leq Liquid\ Rate_j \leq 10,000\ stb/d \tag{4.10}$$

The constraint on the injection wells is the maximum limit on bottom hole pressure set to be 2611 psi and the injection rate can vary from 0 - 10,000 stb/d.

$$0\ psi \leq Bhp_i \leq 2611\ psi \tag{4.11}$$

$$0\ stb/d \leq Injection\ Rate_i \leq 10,000\ stb/d \tag{4.12}$$

The wells bottom hole pressures will also be tested as the control parameters to evaluate if there may be any improvement in the objective function value. The production constraint, in this case, is to maintain the field water production below 40,000 stb/d. The optimization problem is summarized in Table 4.4

Objective Function	Optimization Parameter	Production Constraint
NPV	WLPR, WWIR	FWPR
	0 - 10,000 stb/d	$<$ 40,000 stb/d

Table 4.4: Optimization parameters for case 2

4.1.3 Case 3: Rio structure

The objective function, in this case, is to maximize the net present value from the field. There are two production wells completed in this segment. In the base case, these wells operate under constant rate control mode and are set to produce liquid with the rate of 20,000 stb/d. There are no injection wells in this segment and the sufficient pressure support is offered by a bottom drive aquifer. As a point of departure, choice 2 in Table 4.2, the wells liquid production rate and the wells water injection rate are chosen as the control parameters. Since the wells operate on rate control, the rate optimization is tried first as the control parameters. The wells can produce in a range of 0-30,000 stb/d but a lower limit of 750 psi in bottom hole pressure must be respected.

$$750\ psi \leq Bhp_j \leq 3000\ psi \tag{4.13}$$

$$0\ stb/d \leq Liquid\ Rate_j \leq 30,000\ stb/d \tag{4.14}$$

A pressure optimization will also be carried out to evaluate any potential improvements. The constraint in this study is to maintain the field water-cut below the economic break-even value which is 0.91 by given economic parameter in Table 4.1. The wells bottom hole pressures will also be tested as the control parameters. The optimization problem is summarized in Table 4.5

Objective Function	Optimization Parameter	Production Constraint
NPV	WLPR	FWCT
	0 - 30,000 stb/d	$<$ 0.91

Table 4.5: Optimization parameters for case 3

Chapter 5

Results

In this chapter, the results of the optimization study of the developed cases will be presented and discussed. The optimizer module of Eclipse 300 was used for the optimization purpose. Sarma et al. (2005) states that in order to recognize the benefits of an optimization process, it is usual to compare the optimization results against a base case/reference case. In chapter 3, three cases with potential for production optimization were developed and the base cases were run. The development strategy implemented in the reference cases resulted in poor oil recovery. Common issues in the base cases were early water breakthrough, large water production and quick pressure drop in the segment. Optimal control is a possible approach to handle these issues. This theory can be implemented through the optimizer of Eclipse to improve the production performance. It is an efficient method that is suitable for application to real reservoirs where the simulation grid can be quite large. For more information, see (Sarma et al., 2005). In the next section, the results from the optimization study are presented and discussed.

5.1 Case 1: Half-Dome Structure - Production strategy 1

The first production scenario of Half-Dome structure contained two horizontal wells completed in different formations. The producer is completed in the upper part of the reservoir, where the oil saturation and permeability are highest. The horizontal injector is completed lower in the segment, in a layer with also high permeability. The injection well was on water injection rate control and the production well was on liquid rate control. This case is running for 5480 days (15 years) on a constant rate control mode. The strategy implemented in the base case resulted in poor sweep and poor pressure support in the reservoir. The base case is described in more details in Subsection 3.1.1.

As specified in the previous chapter, in this case, the objective function was to maximize the NPV with following economic parameters: oil price 50 $, water production cost 5 $, water injection cost 5 $ per barrel. These values are also specified in the previous chapter in the table 4.1. The production constraint in this study is to maintain the water-cut under the break-even value 0.91. The control parameters are selected similar to the control mode of the wells. In the base case, these are well liquid production rate for the producer and water injection rate for the injector. The available operating range for both wells is 0 - 20,000 stb/d. Schlumberger (2012b) strongly recommends testing the wells bottom hole pressures as the control parameters due to the dynamic behavior of the wells control mode during the run. The optimization was run with the BHP as the control parameters. As observed in Figure 5.1, no improvements were obtained in the objective function. The simulator fell into tricky convergence regions and terminated after reaching the maximum number of allowed iterations, 20. Well rates, as control parameters responded successfully with an overall NPV improvement of 93%. As observed in Figure 5.1, the first iteration results in a substantial increase in NPV. There are minor improvements observed in the NPV until iteration number 4 but the graph stabilizes near the obtained value after this iteration.

By analyzing the results from the rate optimized case, it was realized that the injector fell into BHP control mode. It was decided to perform an optimization with the bottom hole pressure as the control parameter for the injector and the liquid production rate for the producer. The NPV of the segment improved by 22.1 % compared to the base case. The optimizer converged after 2 iterations and 5 simulations when the run was terminated. The combined optimization responded better and faster than the BHP optimization. However, this improvement is significantly lower than the improved results from the rate optimization with 93% improvement.

The tables below summarize the optimization result:

Table 5.1: Results of comparison of different control parameters for optimizing the case HD1

Strategy	Iterations	Simulations	NPV(billion$)	Improvement (%)
Base case	0	1	0.389	-
Rate Opt.	20	75	0.75	93
BHP Opt.	20	48	0.389	0
Combined Opt.	2	5	0.475	22.1

The total number of control parameters are 92. There are two wells in the segment and with wells settings to be changed three times a year (4 months reporting frequency) over a period of 15 years (15x3x2=90) + 2 for the base case gives 92 control parameters.

The total time for optimization with well rates as the control parameter was approximately 10 minutes. The optimization was run on a computer with two 2.9 GHz processors each with 8 cores, and 64 GB memory.

In the following, the results from rate optimization will be presented.

The pressure in the base case and in the optimized case are illustrated in Figure 5.2. The pressure in the reference case declines continuously from 1600 psi in the start of production to 900 psi at the end of the run. On the other hand, the average reservoir pressure in the optimized case is increasing from 2020 psi to approximately 2400 psi in a period of 120 days. The pressure is then maintained constant until the end of the production period.

Figure 5.3 illustrates the field water injection rate in the base case and in the optimized case. In the optimized case, the water injection has a minor increase but a decreasing trend can be observed. This decreasing trend continuous until 2250 days after production

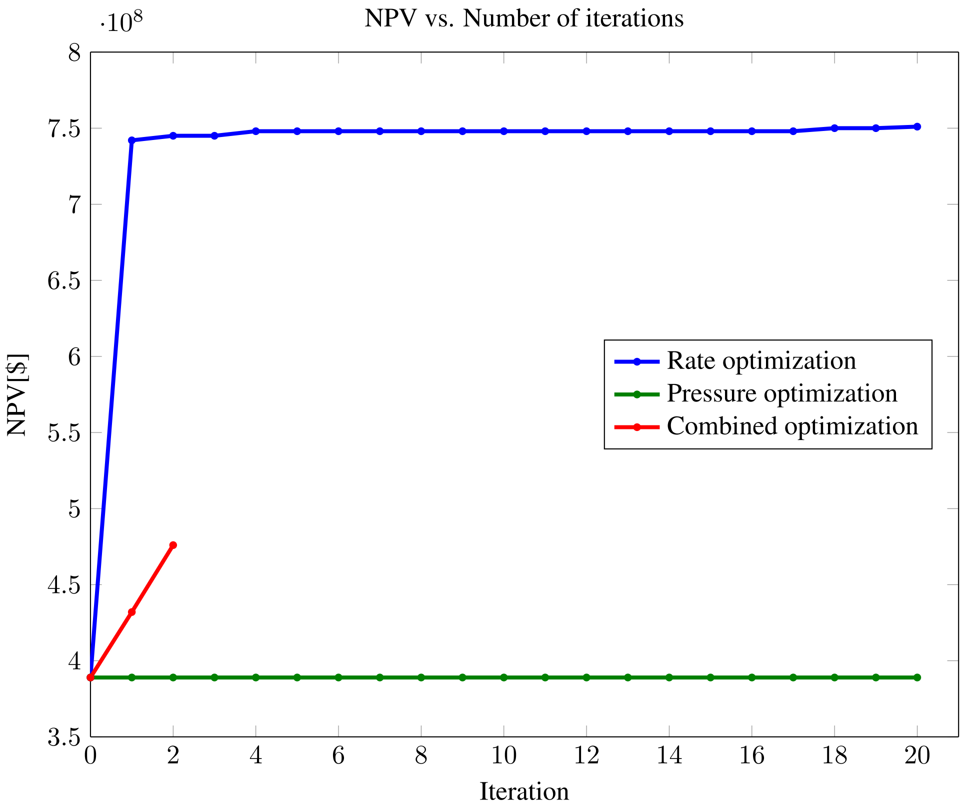


Figure 5.1: Comparison of the optimization performance with different control parameters in case 1.

start. The water injection rate is close to 6,000 stb/d at this time. After this date, the water injection rate increases and reaches 9,000 stb/d in the last days of the run but still is lower than the water-injection rate in the base case. In the base case, the water injection rate is constant on 10,000 stb/d during the entire run.

Figure 5.4 illustrates the liquid production rate in the optimized case and in the base case. As it can be observed, the liquid production rate in the optimized case is generally lower compared to the base case. It starts from 8,750 stb/d, with a sudden increase up to 11,200 stb/d but continuously decreases to 5,700 stb/d in day 2250, when it again starts to increase until the end of the production period.

But as the water injection rate and liquid production rate in the base case are constant on 10,000 stb/d in the base case, the average field pressure in the segment drops continuously as seen in Figure 5.2.

The injection well behavior is reflected through the analysis of the bottom hole pressure progress. Figure 5.6 illustrates the injector bottom hole pressure in the reference case and in the optimized case. As can be observed in the optimized case, the injector's BHP increases quickly to the maximum allowed level, 2611 psi and remains constant during the whole period. The injector falls into the pressure control mode and injects with the highest pressure available into the formation. In the base case, the injector is on water control mode. The pressure is initially at 1720 psi and declines continuously to 1020 psi at the end of run-time.

The BHP of the producer is illustrated in figure 5.7. As can be seen, it increases up to 2300 psi and remains almost constant during the run in the optimized case. The producer is in the liquid production rate control mode and has a relatively high BHP which means that the production is quite prudent. While in the base case, the pressure starts at 1500 psi and declines continuously to 900 psi.

As discussed, in the optimized case the bottom hole pressure in the injector operates at 2611 psi. The bottom hole pressure in the producer operates close to 2300 psi and the average field pressure holds a constant value of 2400 psi. Figure 5.8 demonstrates the difference between the cumulative reservoir volumes injected and produced in the base case and in the optimized case. The black dashed line is the reservoir volume produced in the base case which is higher than the injected volume into the reservoir, dashed blue line. The solid black line is the cumulative reservoir volume produced in the optimized case which is *lower* than the injected volume into the reservoir, solid blue line. Note, that the reservoir volumes produced and injected are considerably lower in the optimized case compared to the base case. This leads to the pressure maintenance in the reservoir in the optimized case.

The oil production rate in the reference case and optimized case is illustrated in Figure 5.9. The optimized oil production rate is higher compared to the base case. The controlled water injection and liquid production strategy lead to improved sweep and pressure maintenance in the reservoir. The cumulative oil production is illustrated in Figure 5.11. The ultimate cumulative oil production is 22% higher in the optimized case compared to the base case.

The field water-cut in the optimized case and in the base case is illustrated in Figure 5.10. The constraint in this optimization study is to keep the water-cut value below 0.91 which is the economic break-even value. As seen in the Figure 5.10, this value is respected with a good margin. It is worth mentioning that this optimization study is a proactive approach in water-flooding optimization. Unlike the reactive approach, this means that the optimization aims to respect the constraint on field water-cut from the very beginning of the liquid production.

The objective function, in this case, was to maximize the NPV that is dependent on oil and water production, and water injection. In the optimized case, the total oil production has increased as seen in Figure 5.11, water production, and injection have decreased as it is seen in Figure 5.12 and Figure 5.13. Therefore, the total NPV have increased by 93 %.

Table 5.2: Summary of the optimization results

Strategy	Total Water Injection [%]	Total Water Production [%]	Total Oil Production [%]	NPV Improvement [%]
Rate optimization	- 23%	-50%	+22%	+93 %

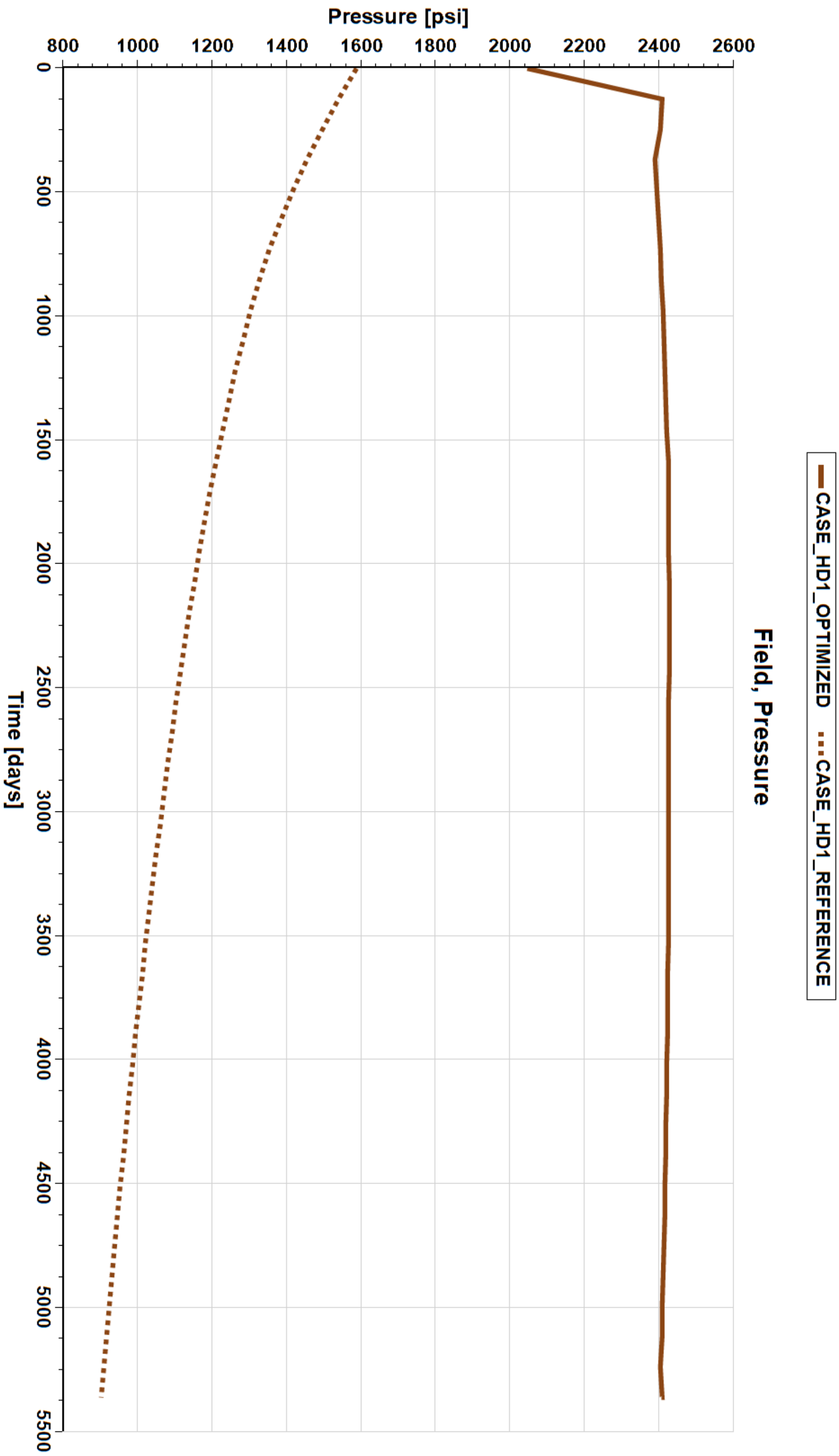


Figure 5.2: The comparison of average reservoir pressure in the reference and optimized case of HD1.

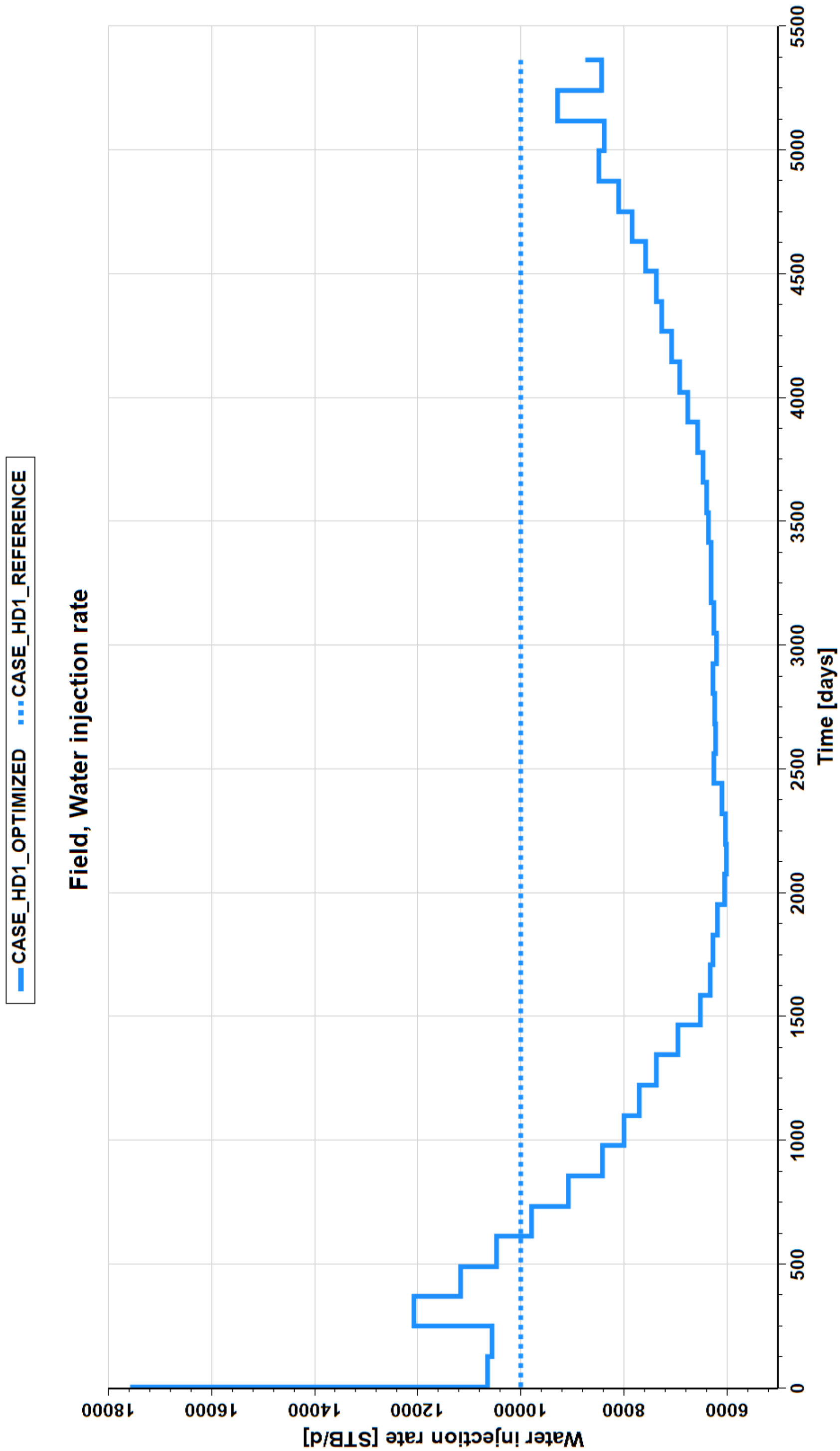


Figure 5.3: Comparison of water injection rate in the reference and optimized case of HD1.

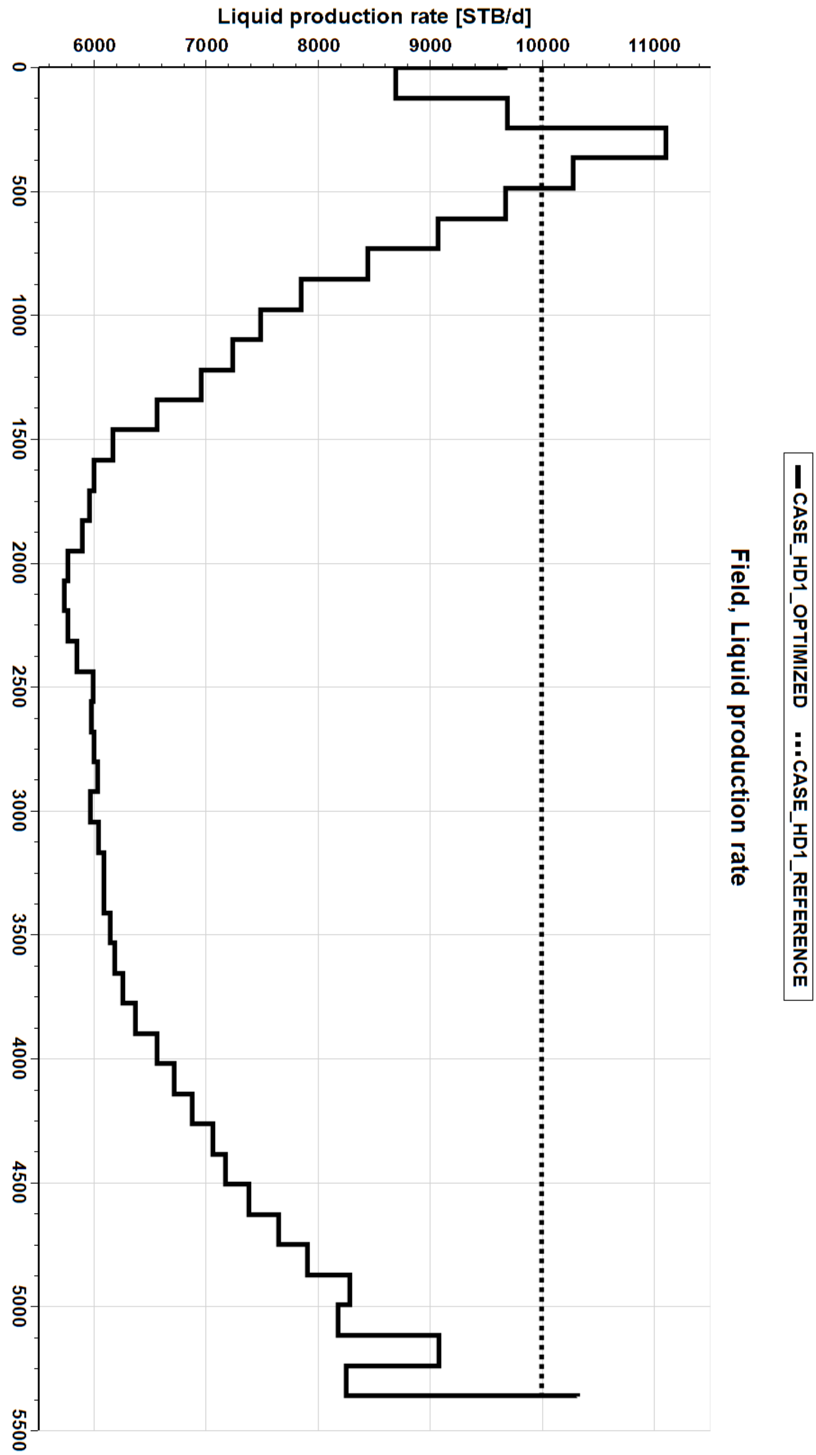


Figure 5.4: Comparison of liquid production rate in the reference and optimized case of HD1.

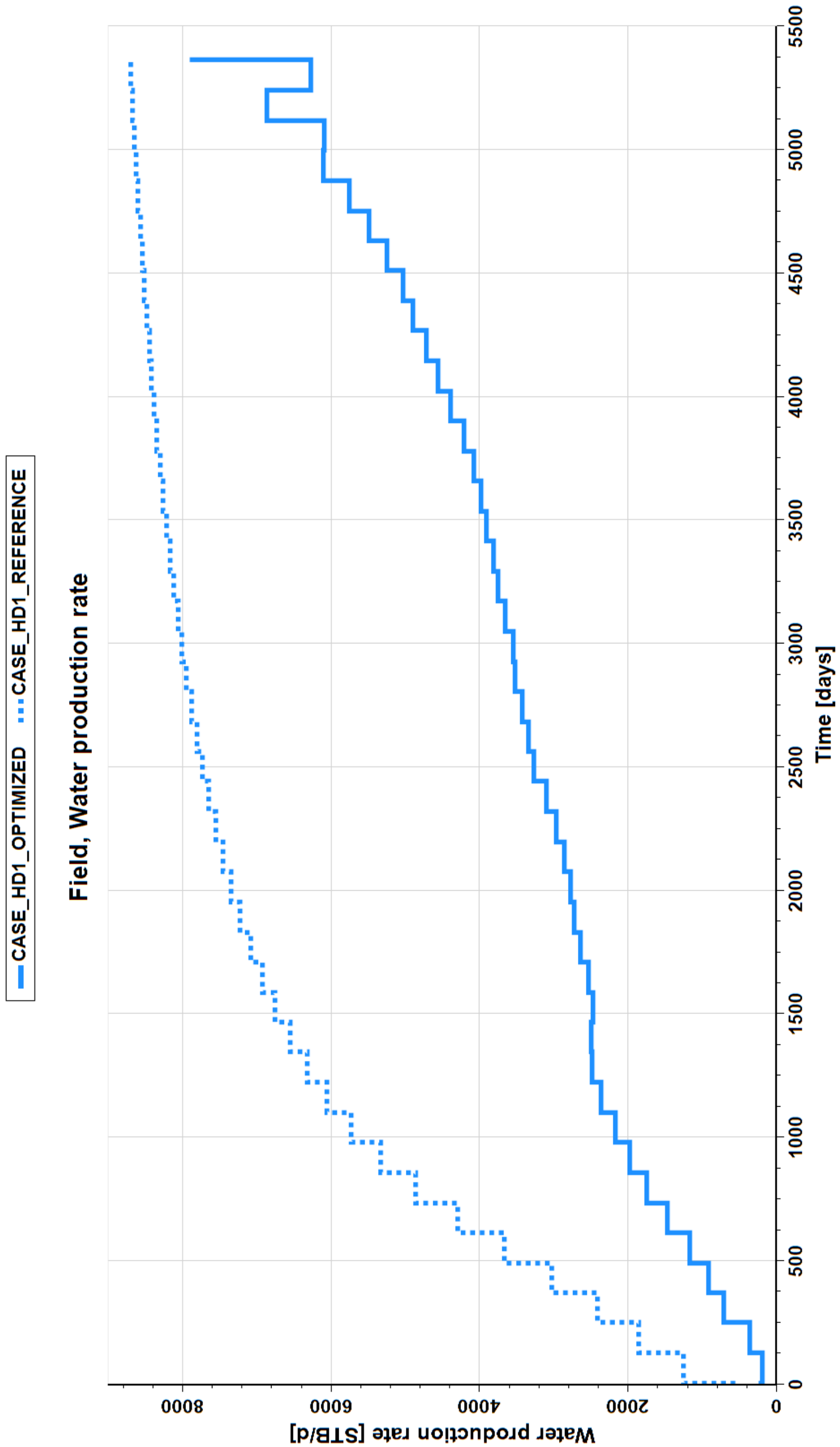


Figure 5.5: Comparison of water production rate in the Reference and Optimized case of HD1.

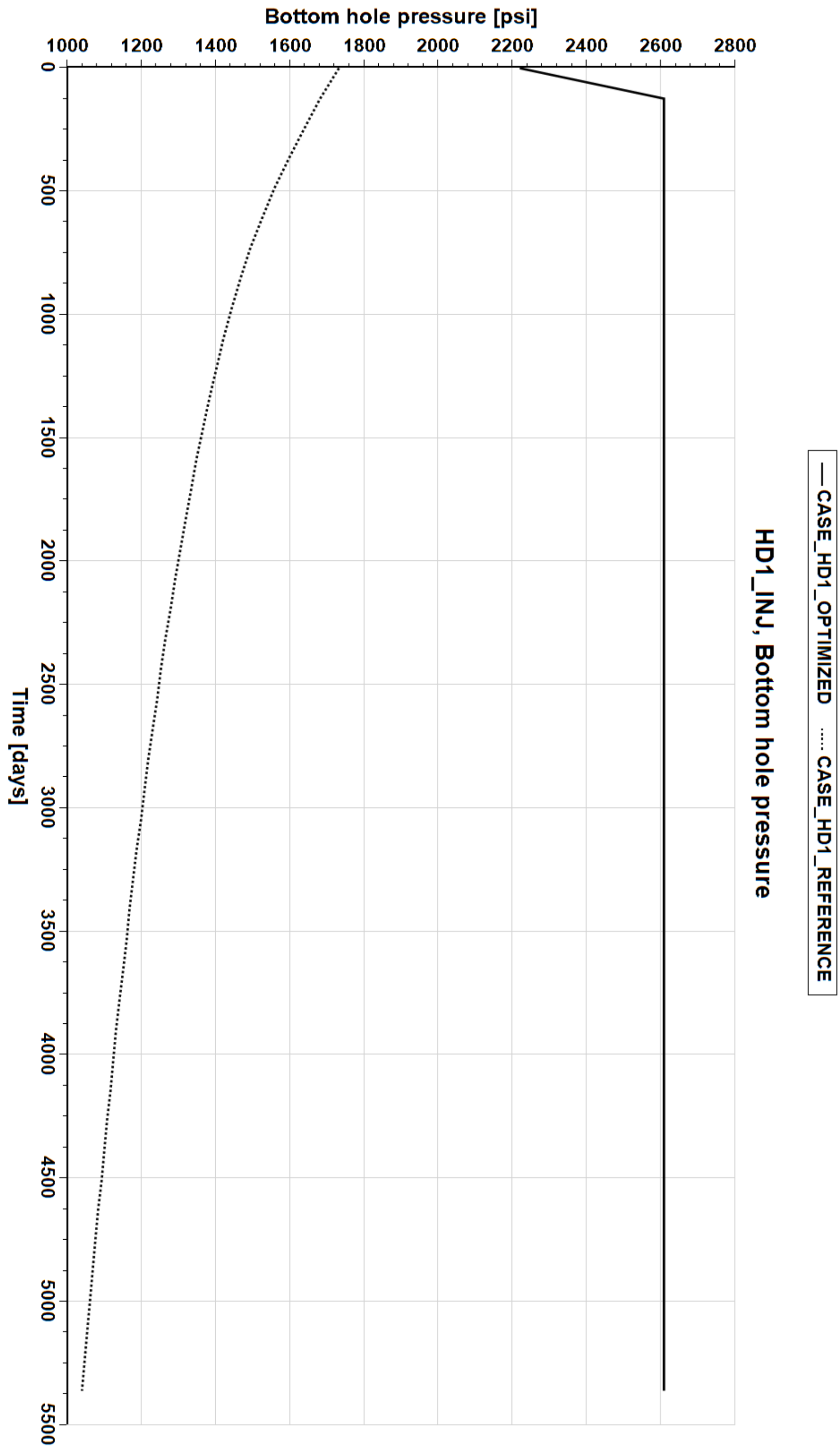


Figure 5.6: The comparison of the bottom hole pressure of the injector in the reference and optimized case of HD1.

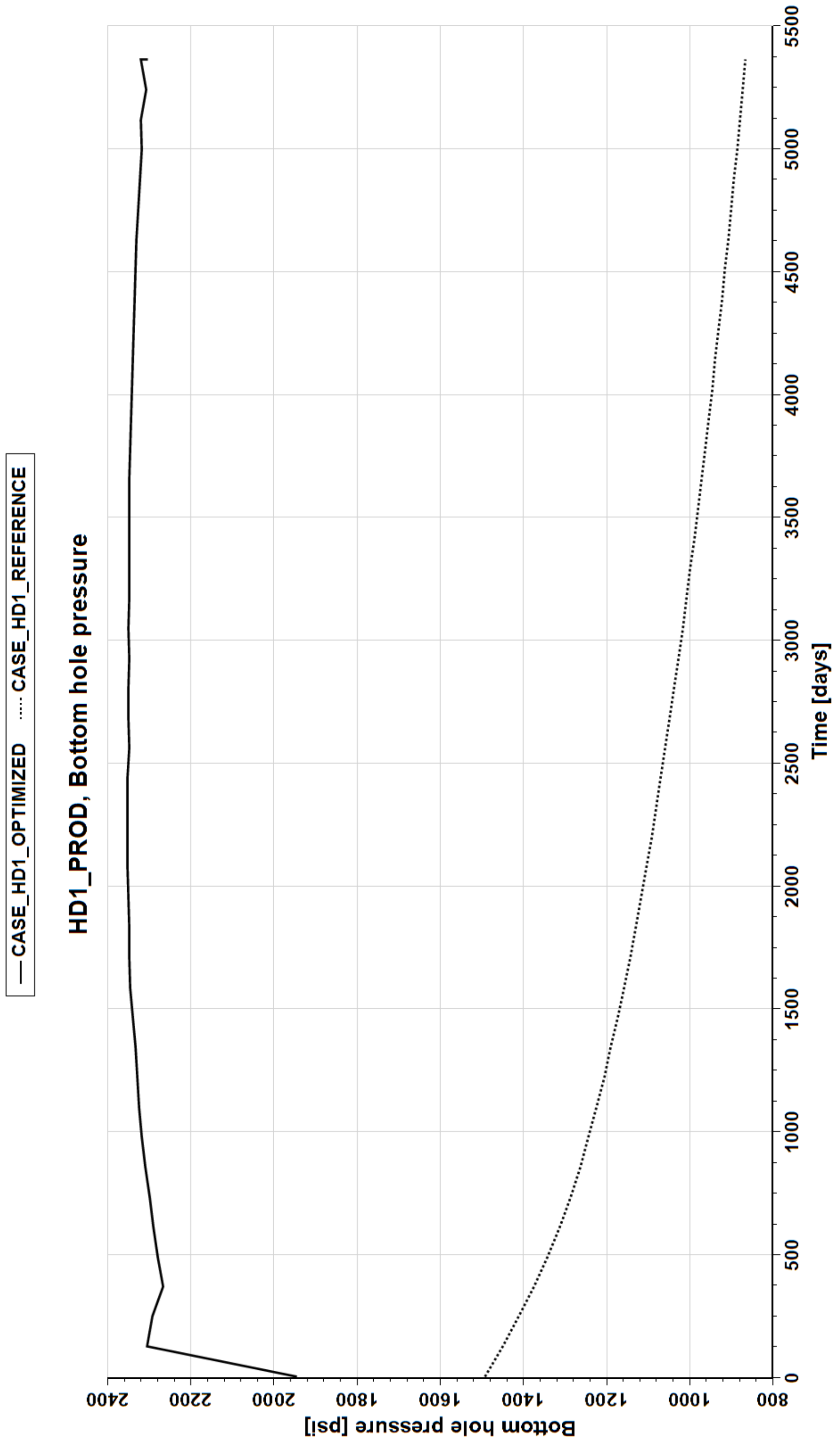


Figure 5.7: The comparison of the bottom hole pressure of the producer in the reference and optimized case of HD1.

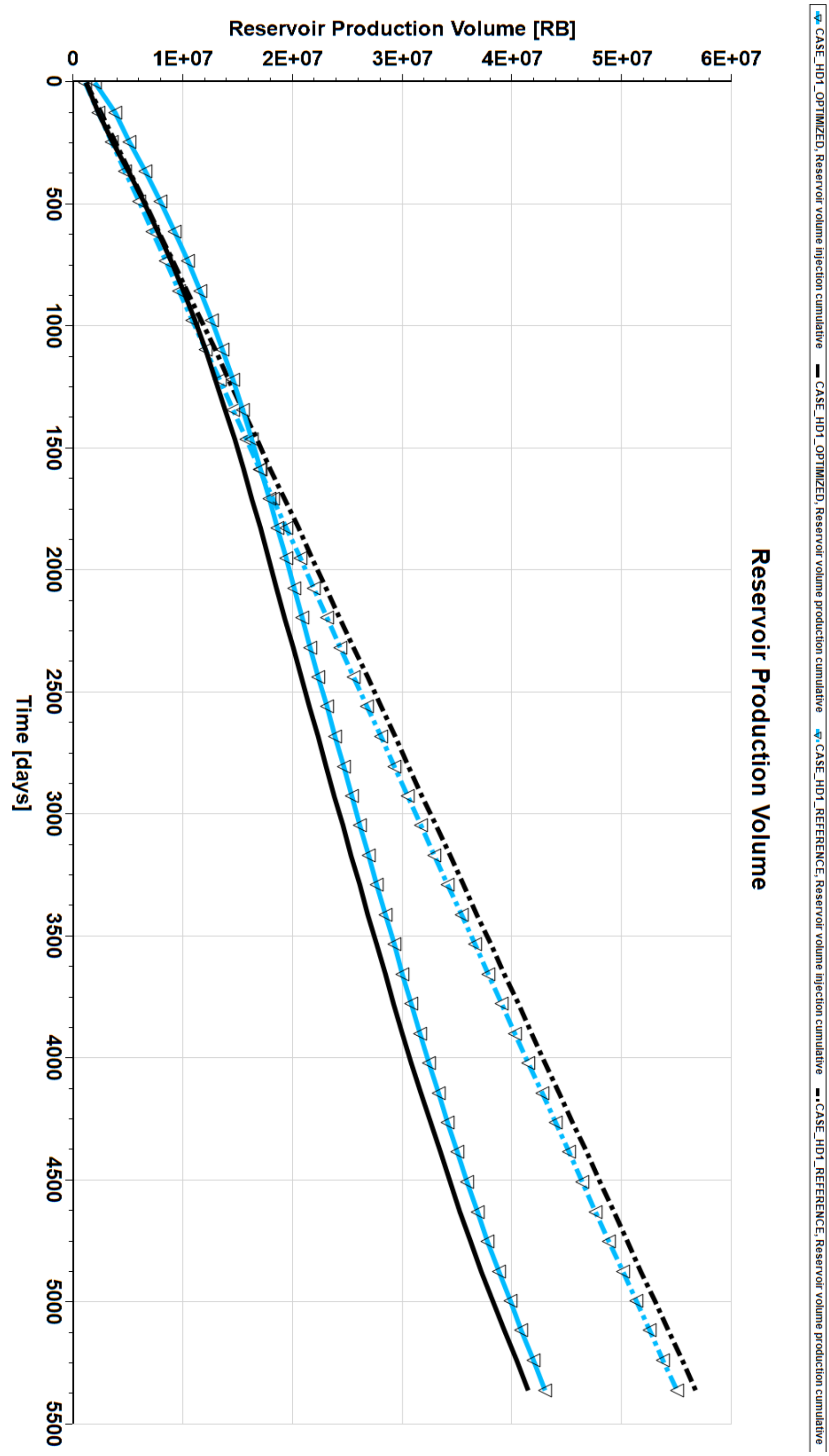


Figure 5.8: Comparison of the reservoir volume injected and produced in the reference and optimized case of HD1.

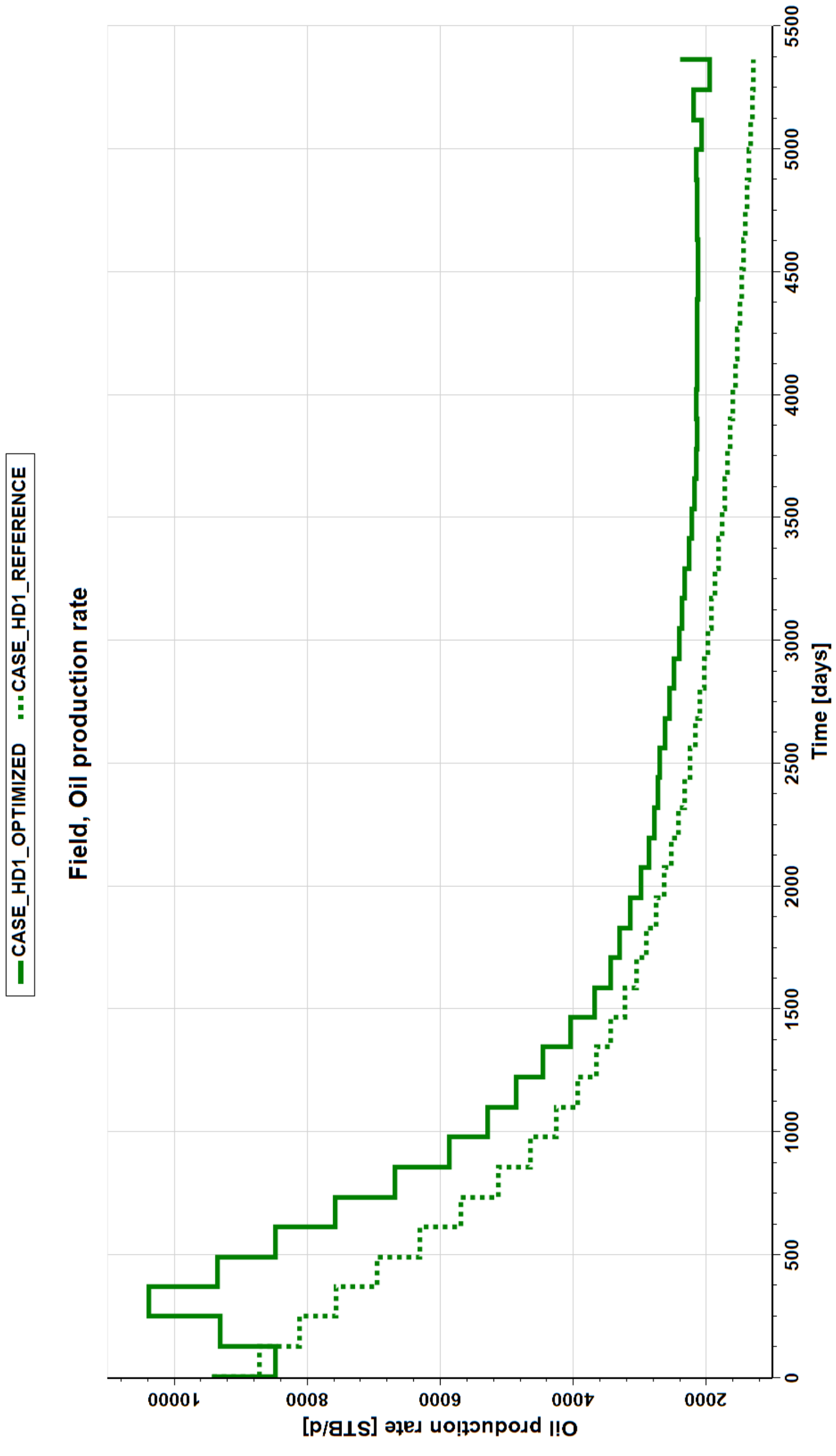


Figure 5.9: The comparison of oil production rate in the reference and optimized case of HD1.

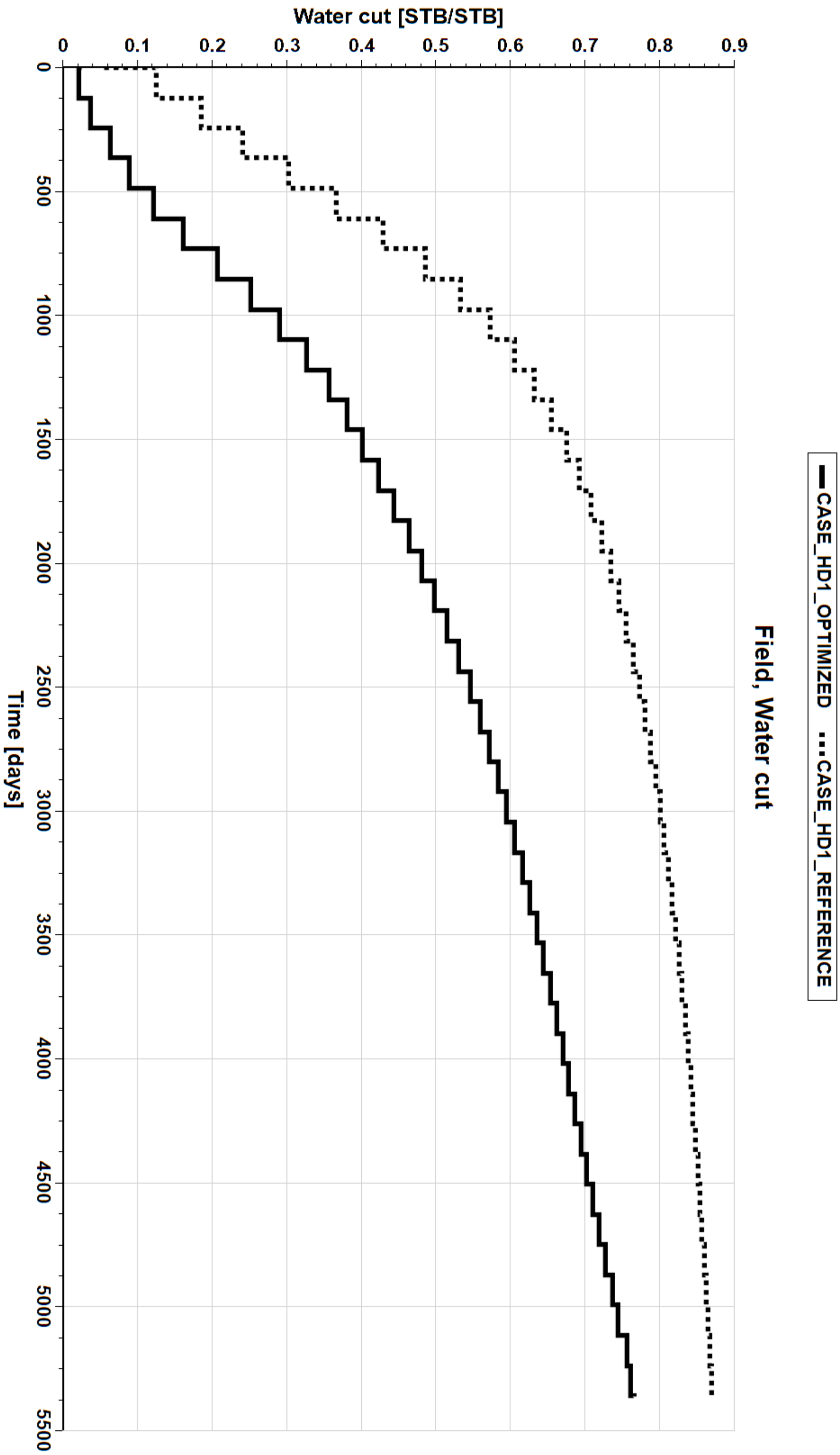


Figure 5.10: The water-cut of the HD1 Segment in the reference and optimized case.

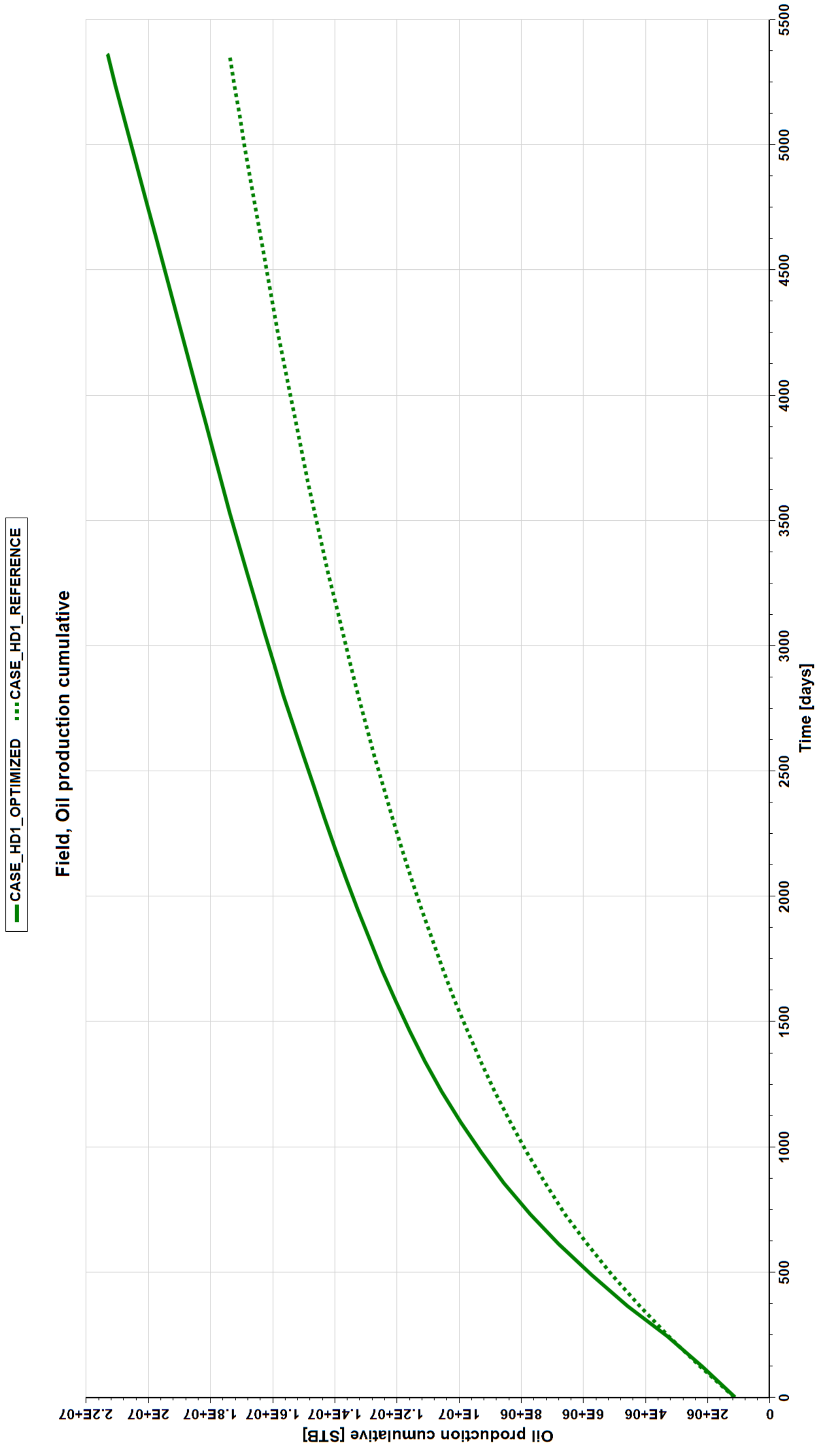


Figure 5.11: The comparison of oil production cumulative in the reference and optimized case of HD1.

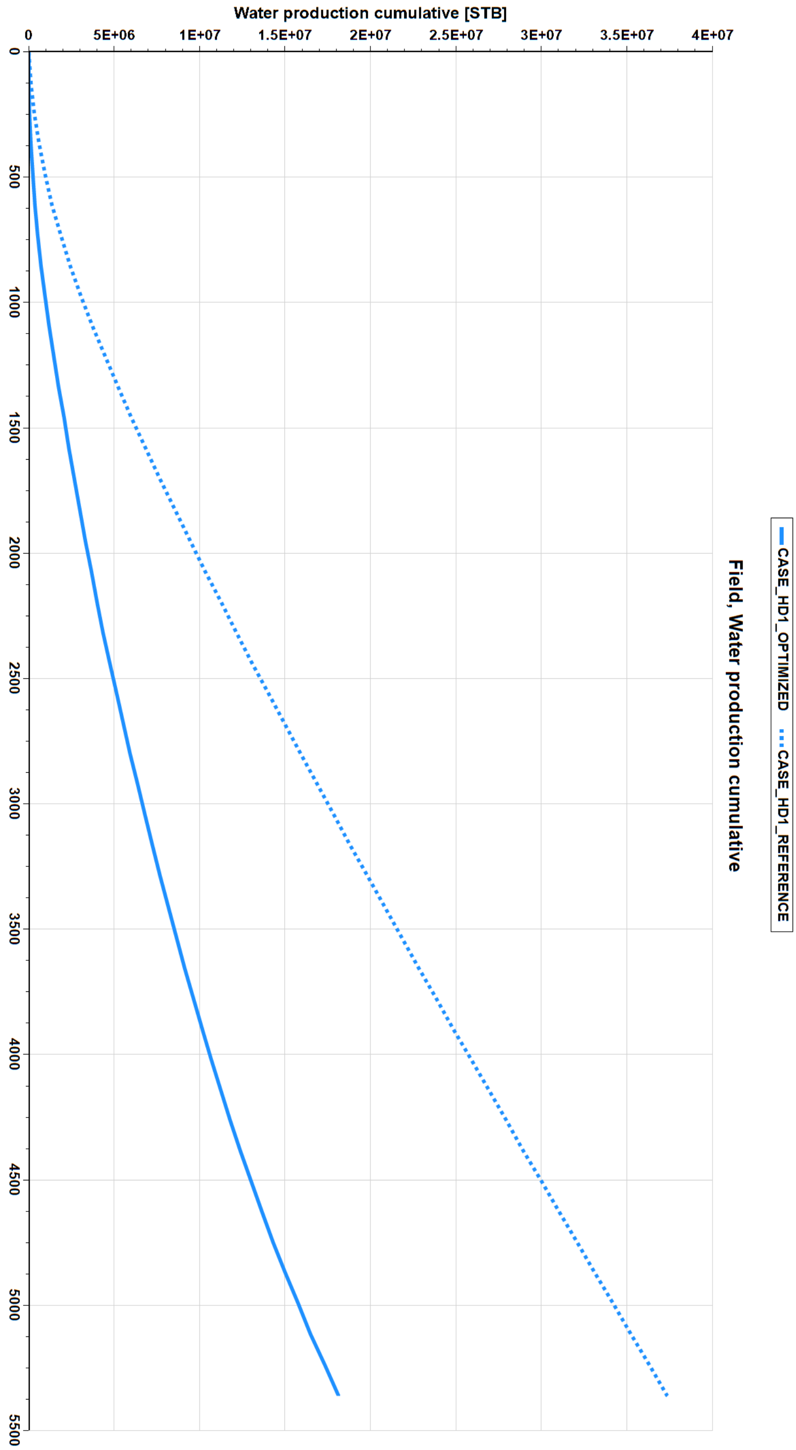


Figure 5.12: The comparison of water production cumulative in the reference and optimized case of HD1.

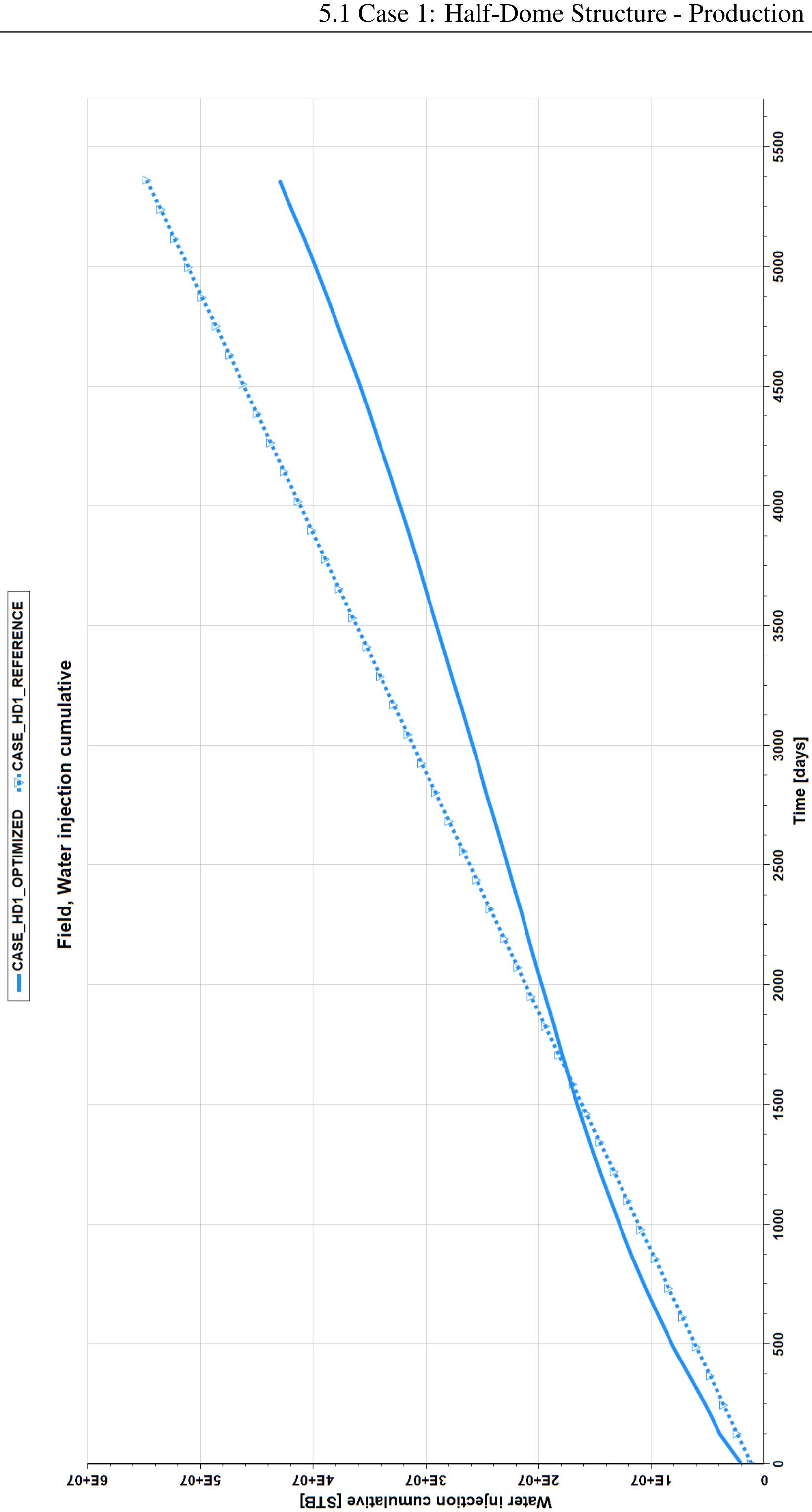


Figure 5.13: The comparison of water injection cumulative in the reference and optimized case of HD1.

5.2 Case 2: Half-Dome Structure - Production strategy 2

The second production scenario of Half-Dome case contains 8 wells, 4 productions, and 4 injections wells. The production and water injection starts from the first day and continuous until the last day, 2192. The base case was run with a production rate of 5,000 stb/d on each production well and an injection rate of 5,000 stb/d on the injector wells. The final average oil recovery factor after running the base case was approximately 10 %. Despite having 4 injectors in the segment, the average field pressure drops rapidly over the life of the field as seen in Figure 5.15. The base case is described is more details in Subsection 3.1.2

The objective of this optimization study was to maximize the ultimate cumulative oil production from this segment. Since the injection wells are under water rate control mode, and the production wells are under liquid production rate mode, these were selected as the control parameters. The available range for well rates was between 0 - 10,000 stb/d. Wells bottom hole pressures were also tested as control parameters. In the pressure optimization approach, the available range for production wells was between 750 - 3000 psi and 0 - 2611 psi for the injection wells. The production constraint was to keep the field water production rate under 40,000 stb/d. Figure 5.14 illustrates the comparison of the control parameters in case 2 in terms of cumulative oil production and number of iterations. This figure illustrates clearly that the rate optimization approach improved the objective function substantially compared to the pressure optimization. The rate optimization increased the cumulative oil production by 100 %, almost twice as the base case. This was obtained after 19 iterations and 100 simulations. The pressure optimization approach increased the cumulative oil production by 46 % compared to the base case. The pressure optimization terminated after 5 iterations and 9 simulations due to the convergence of the objective function.

Table 5.3: Summary of the optimization setup and results

Strategy	Iterations	Simulations	Constraint	Objective function	Improvement
Rate Opt.	19	100	FWPR $<$ 40,000	Max. FOPT	100 %
pressure Opt.	5	9	FWPR $<$ 40,000	Max. FOPT	46 %

The total number of control parameters are 104. There are eight wells in this case and with settings to be changed twice a year (6 months reporting frequency) over a period of 6 years (2x6x8=96) + 8 base case value for each well gives 104 variables. It took approximately 8 minutes for optimization to run on a machine with two 2.9 GHz processors each with 8 cores, and 64 GB memory.

The following improved results were obtained in the rate optimization approach.

Figure 5.15 shows the comparison of pressure development in the base and optimized case. The average field pressure in the base case starts initially at 1580 psi and continuously declines during the run time. The pressure in the optimized case starts approximately from 2,300 psi and increases to 2,380 psi. The pressure is maintained almost constant over the whole life of the field.

To understand the improvement in the average field pressure, one may analyze the wa-

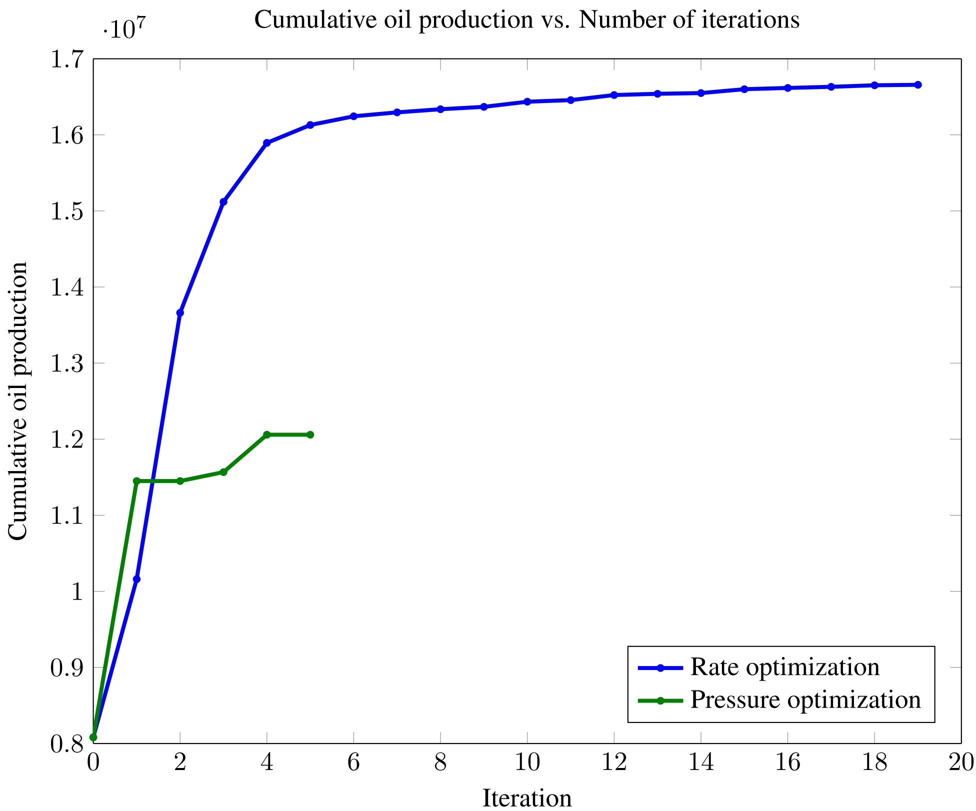


Figure 5.14: Comparison of the optimization performance with different control parameters in case 2.

ter injection and liquid production in the segment. Figure 5.16 illustrates the field water injection rate in the base case and in the optimized case. The water injection in the optimized case is much higher than in the base case. The total water injection rate in the base case is constant on 20,000 stb/d. But in the optimized case, the water injection rate starts approximately from 32,000 stb/d and gradually decreases to 27,000 stb/d at en end of the run. Compared to the base case, a larger volume of water is injected into the reservoir.

Figure 5.17 illustrates the liquid production rate in the base case and in the optimized case. In the optimized case, the total liquid production in the field starts from 30,500 stb/d and gradually decreases to 26,500 stb/d at the end of the run. The liquid rate in the base case is constant during the entire production time. The rate is 20,000 stb/d. In the optimized case, due to the higher volume injected water results in higher liquid production.

The constraint in this optimization study was to avoid a water production rate over 40,000 stb/d. As observed in Figure 5.18, the constraint is respected and field water production is kept below 40,000 stb/d and reaches 24,000 stb/d in its highest level. The water production in the base case is also illustrated in the same figure. It is considerably lower compared to the optimized case.

Figure 5.19 illustrates the oil production rate in the optimized case and in the base case. The oil recovery is improved by employing the available water injection capacity and controlling the liquid production rate. The final oil recovery of the segment is approximately 20 % which is 10% improvement from the base case.

The cumulative oil production is illustrated in Figure 5.20 and the total water produced is shown in Figure 5.21. The cumulative water injected is illustrated in Figure 5.22. The field ultimate cumulative oil production is improved by almost 100 %. The amount of cumulative oil produced is twice as large as the base case.

In the following, the performance of the wells will be analyzed. There are 4 vertical injector wells and 4 vertical production wells in the segment. As mentioned, in the base case the injectors are under water injection control mode with 5000 stb/d. The producers are on liquid production rate and produce 5000 stb/d liquid production rate. Figure 5.23 illustrates the injection wells performance in the base case. The injection rate of all of the four wells in the base case is constant on 5000 stb/d. In the injection wells, the rate varies in order to control the water injection sweep efficiency. The available range of water injection is between 0 - 10,000 stb/d. The variations of optimized water injection rates is illustrated in Figure 5.24.

Injector 1 and 2 (red and brown line respectively) have a major decline in water injection rate compared to the injector 3 and 4 (green and light blue line). Injector 4 operates initially at 9,600 stb/d but continuously decrease the injection rate to 8600 stb/d at the end of the run. The water injection rate in the injector 3 starts to increase from 8,000 stb/d to 10,000 stb/d. At the end of the run, there is a quick and huge fall in the injection rate of injector 3 and 4. The sudden fall in the water injection of injector 3 is 10,000 stb/d to 5,000 stb/d. The injection rate in injector 4 falls from 8,600 stb/d to 5,000 stb/d. The green line overlaps the light blue line. This seems to be a numerical error since such a large decline in injection rate at the last day of the run is not logical.

There are 4 production wells in this segment. In the base case, the wells are on liquid rate control mode and produce a constant rate of 5,000 stb/d. This is illustrated in Figure 5.25. Since the wells are on liquid rate control mode, these are chosen to be the control parameters in the optimization. The available range for liquid production is between 0 - 10,000 stb/d.

The optimized liquid production rates are illustrated in Figure 5.26. Producer 4 has the best performance compared to other producers. This well maintains a liquid production rate of 10,000 until the end of the run while liquid production decline may be observed in producer 3,2,1. The good performance of producer 4 may be a result of sufficient pressure support from injector 3 and 4. Both injectors have higher injection rates compared to injector 1 and 2 as seen in Figure 5.24. The identical numerical error as earlier can be identified for liquid production rates of these four wells at the end of the run.

The oil production for each well in the base case is illustrated in Figure 5.29. There is a quick decline in the oil production rate in the production wells due to the insufficient displacement by water and poor pressure support in the segment. In the base case, production wells 1 and 2, with a production rate of 350 stb/d have a lower production rate compared to the production well 3 and 4. Production well 4 have a higher production rate compared to other wells. It starts producing at 3500 stb/d but declines to 1500 stb/d at the end of the run. Figure 5.30 shows optimized oil production rate.

In the optimized case, the oil production rate in all wells is improved. Production well 4 responded best to optimization. As illustrated in Figure 5.26, It holds a constant liquid production rate of 10,000 stb/d which is the maximum allowed production rate. This well has respectively the highest oil production rate. The initial oil production rate is close to 7,000 stb/d which is the twice as large the initial rate of the base case.

As seen, production well 4 performed best in term of oil production among the production wells. This well is located at the top of the segment close to injector 3 and injector 4 that ensure sufficient pressure support. The cross-section of the upper layer in the segment is shown in Figure 5.31. This figure illustrates the sweep efficiency between the injector 4 and the producer 4. As seen, the sweep in the base case is relatively poor and the residual oil saturation is very high. In the optimized case, the sweep is considerably improved and the residual oil has decreased. The water has swept a larger zone and displaced more oil toward the production well. This is due to the controlled water injection and liquid production in the segment.

The oil saturation map is illustrated in Figure 5.32. This is the upside view of the final oil saturation in the segment in the base and optimized case. There is a clear improvement of the oil recovery and the residual oil saturation is much less in the optimized case.

Table 5.4 summarize the optimization results. The cumulative oil production is increased by 100 %, compared to the total oil production in the base case while the total water production and injection have also increased respectively by 30 % and 52 %.

Table 5.4: Summary of the optimization results

Strategy	Total Water Injection [%]	Total Water Production [%]	Total Oil Production [%]
Rate optimization	+ 52%	+ 30 %	+100 %

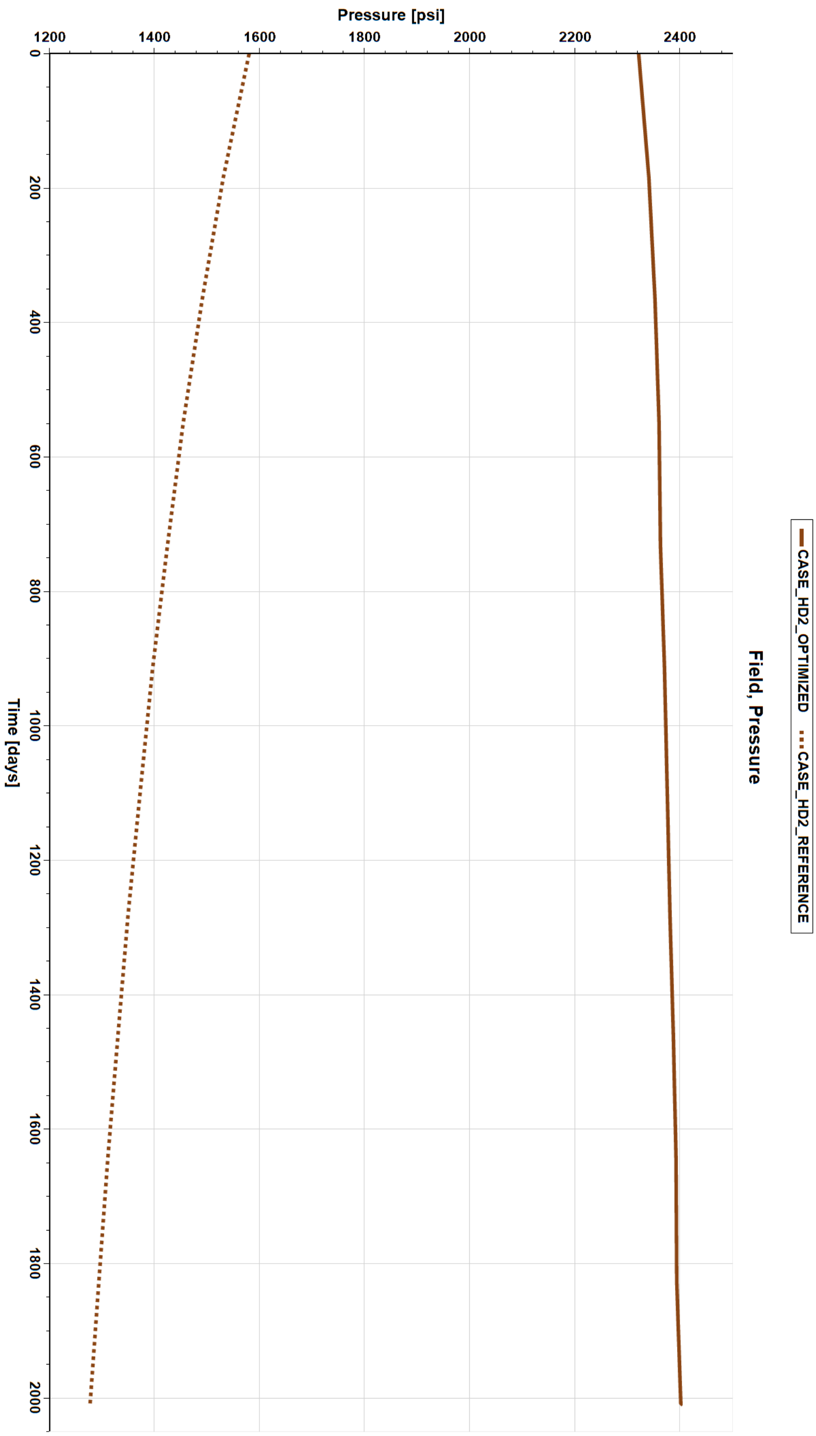


Figure 5.15: The comparison of pressure development in the reference case and optimized case of HD2.

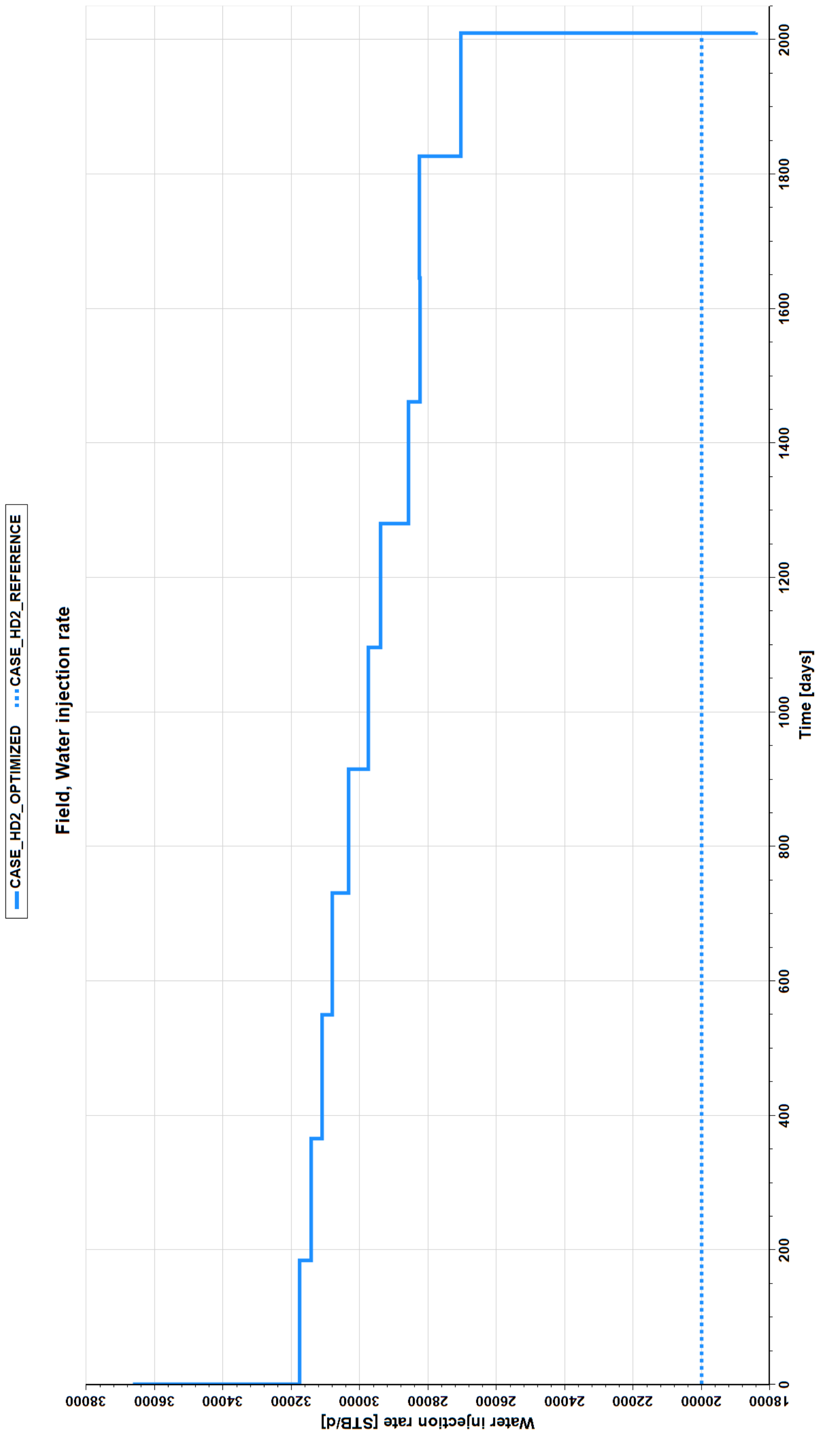


Figure 5.16: The comparison of field water injection rate in the reference and optimized case of HD2.

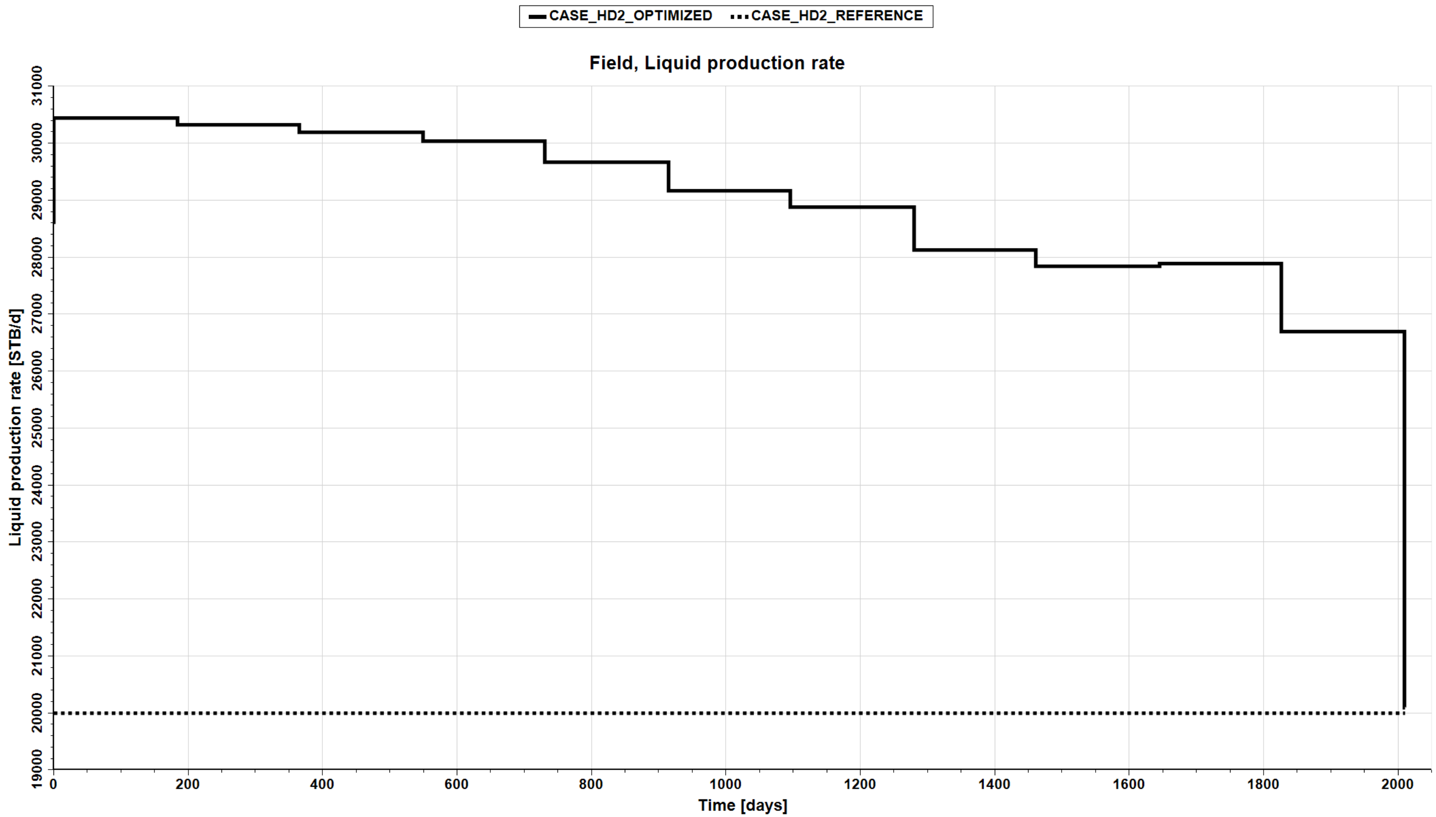


Figure 5.17: The comparison of field liquid production in the reference and optimized case of HD2.

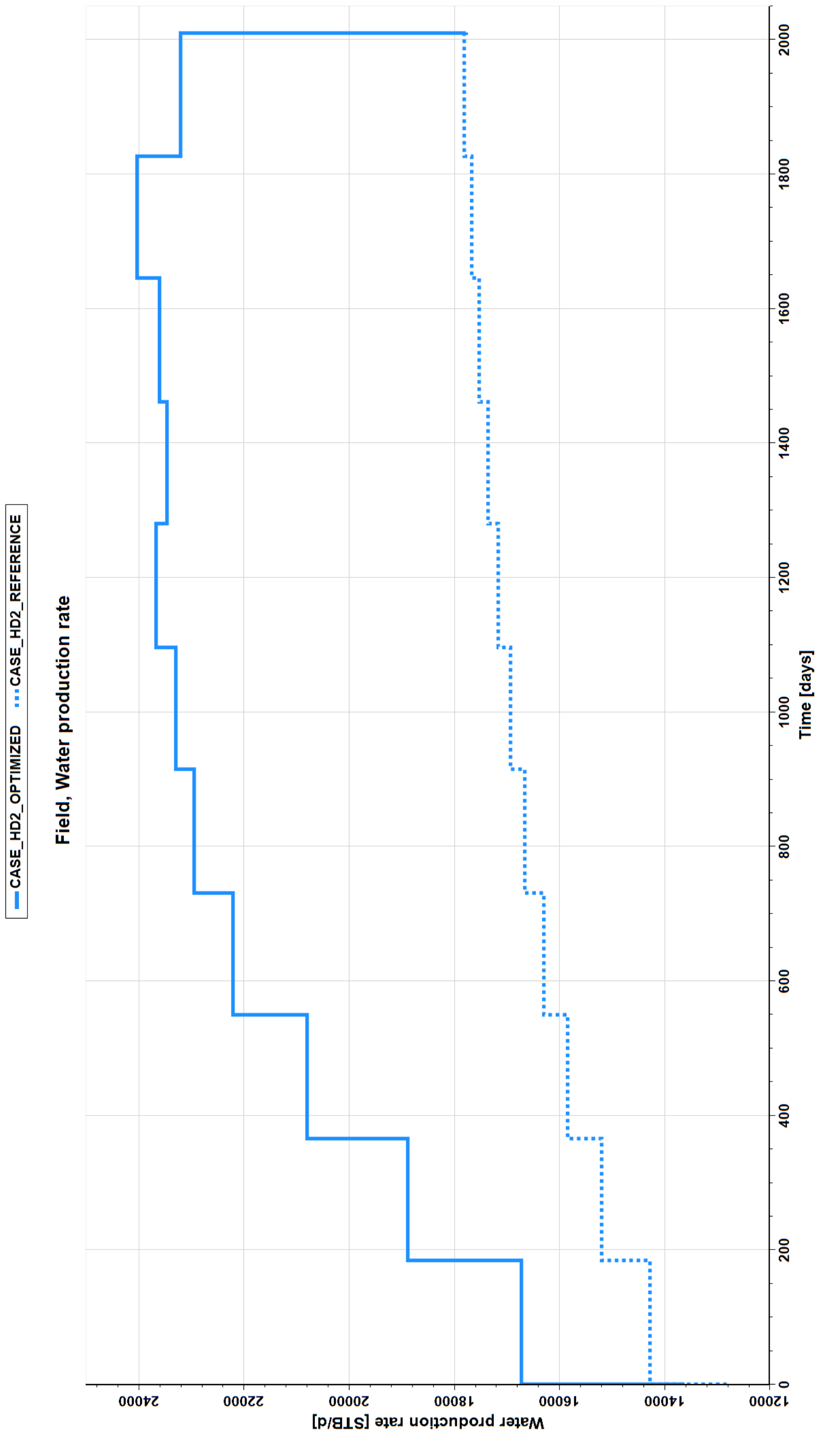


Figure 5.18: The comparison of field water production in the reference and optimized case of HD2.

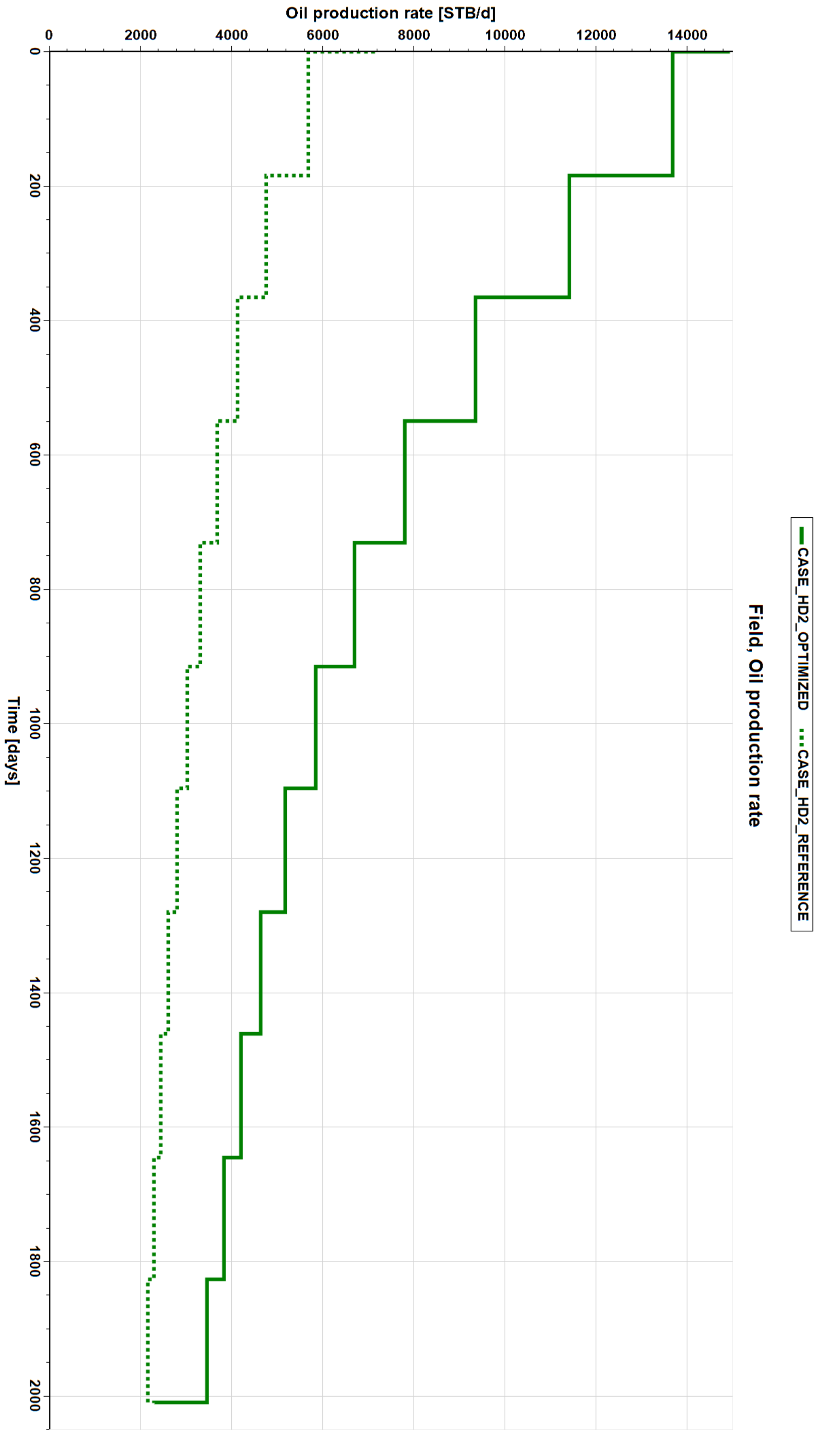


Figure 5.19: The comparison of oil production rate in the reference case and optimized case of HD2.

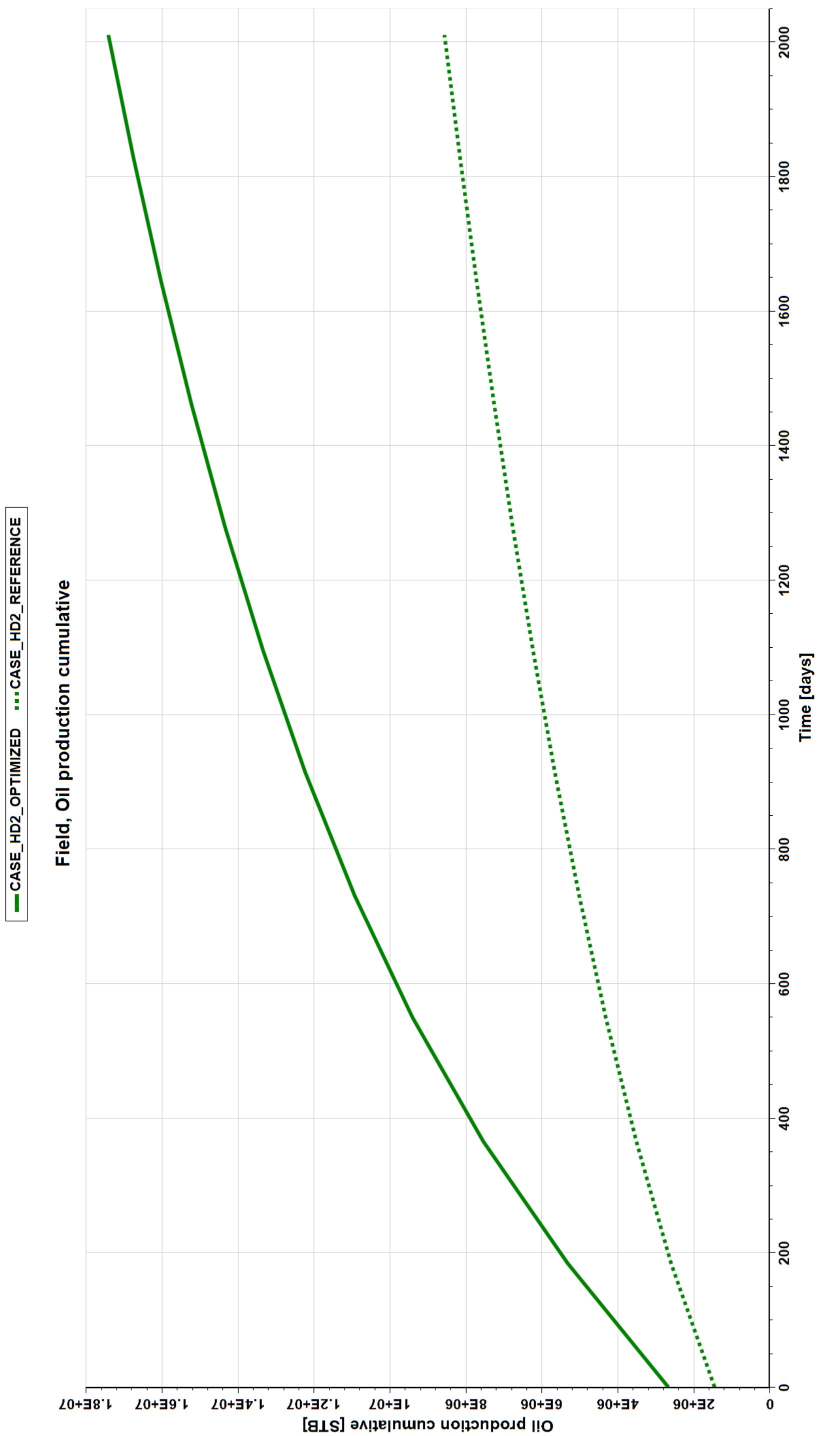


Figure 5.20: The comparison of cumulative oil production in the reference case and in the optimized case of HD2.

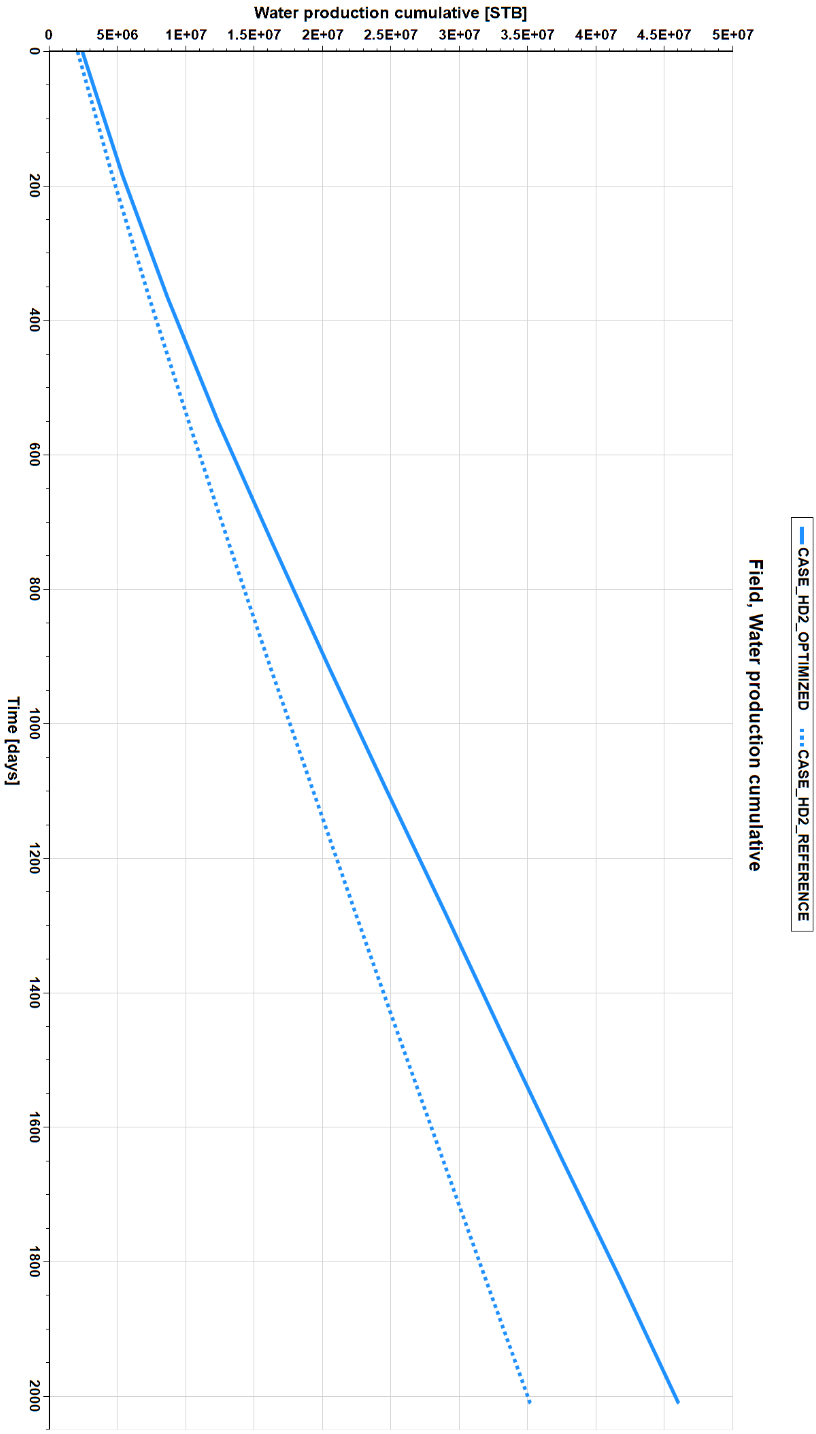


Figure 5.21: The comparison of cumulative water production in the reference case and in the optimized case of HD2.

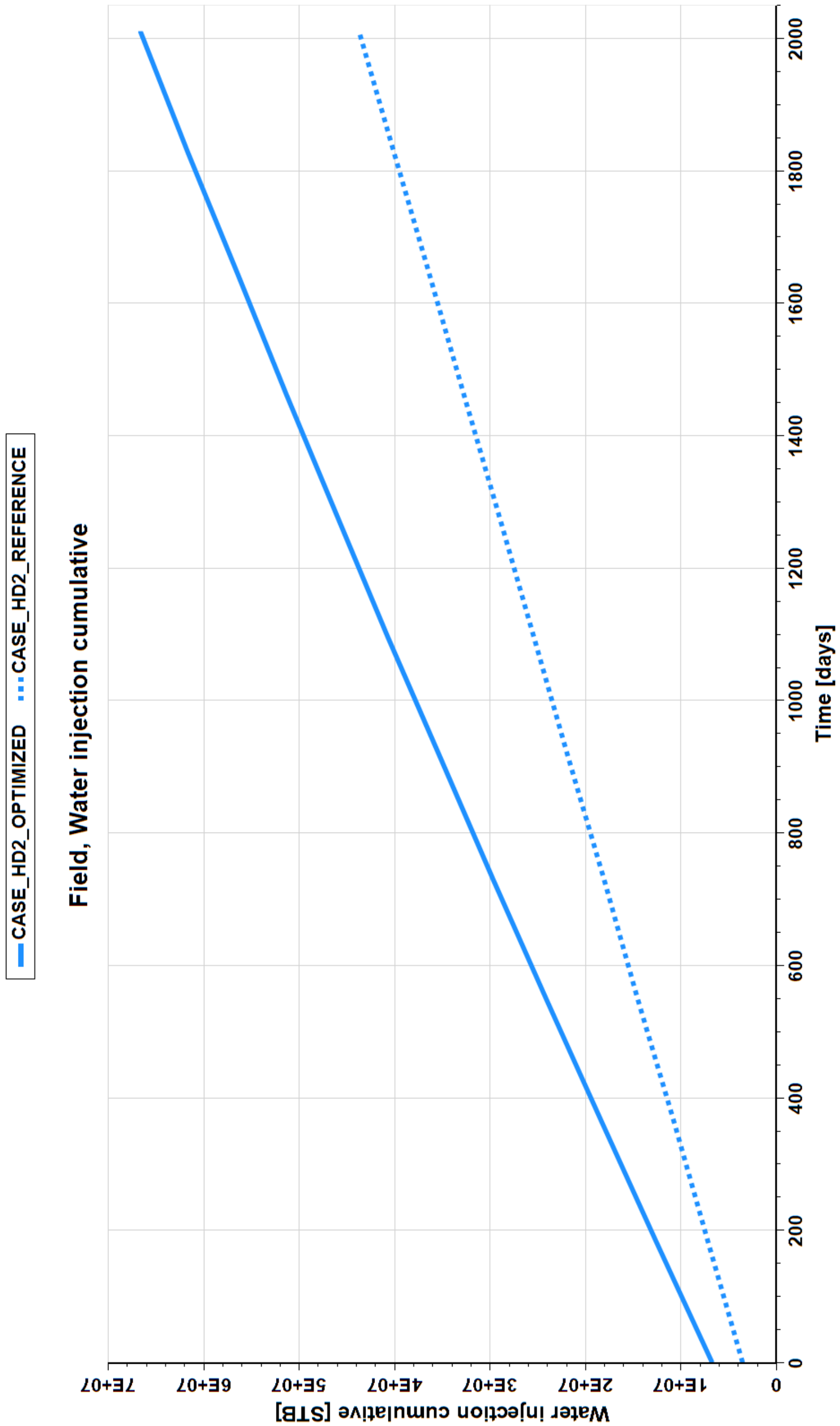


Figure 5.22: The comparison of cumulative water injection in the reference case and in the optimized case of HD2.

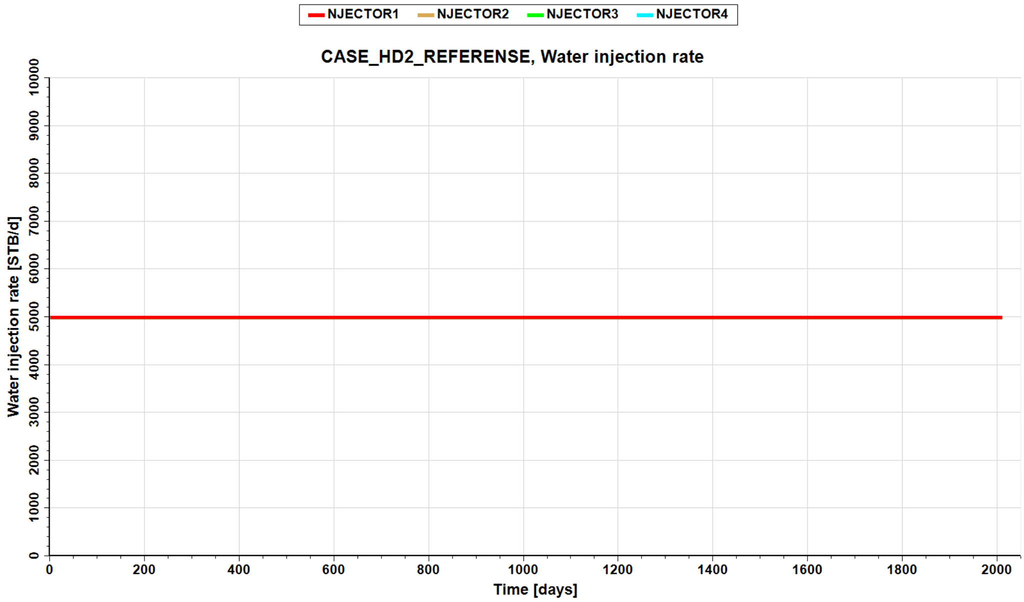


Figure 5.23: Wells water injection rate in the reference case of HD2.

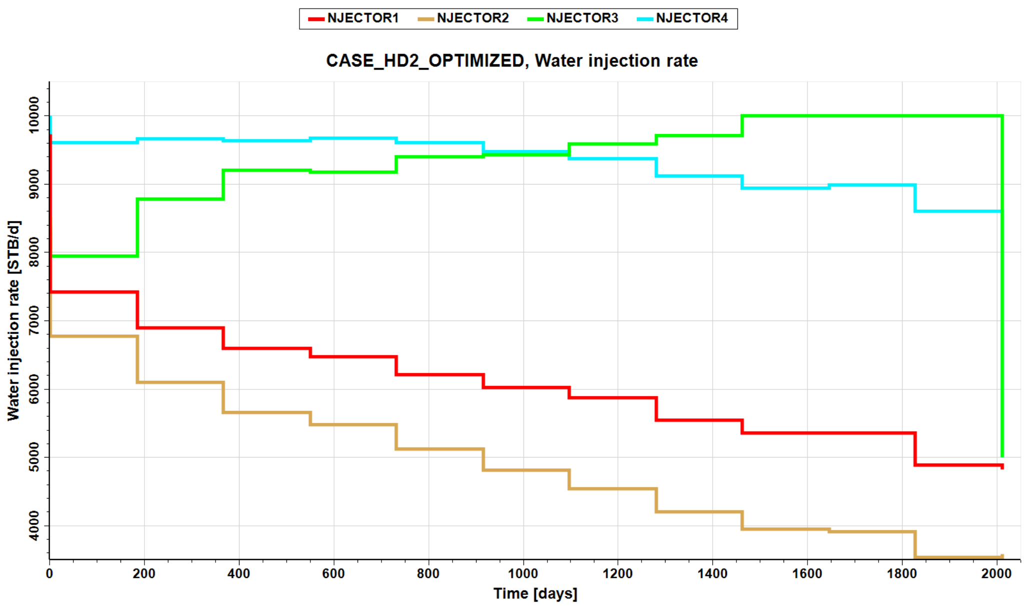


Figure 5.24: Wells water injection rate in the optimized case of HD2.

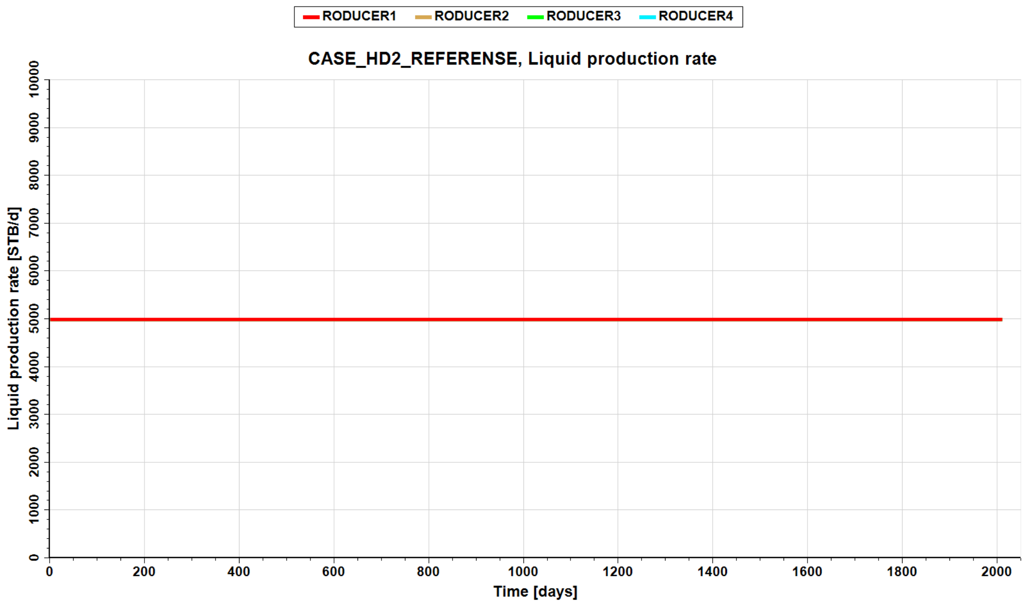


Figure 5.25: Wells liquid production rate in the base case of HD2.

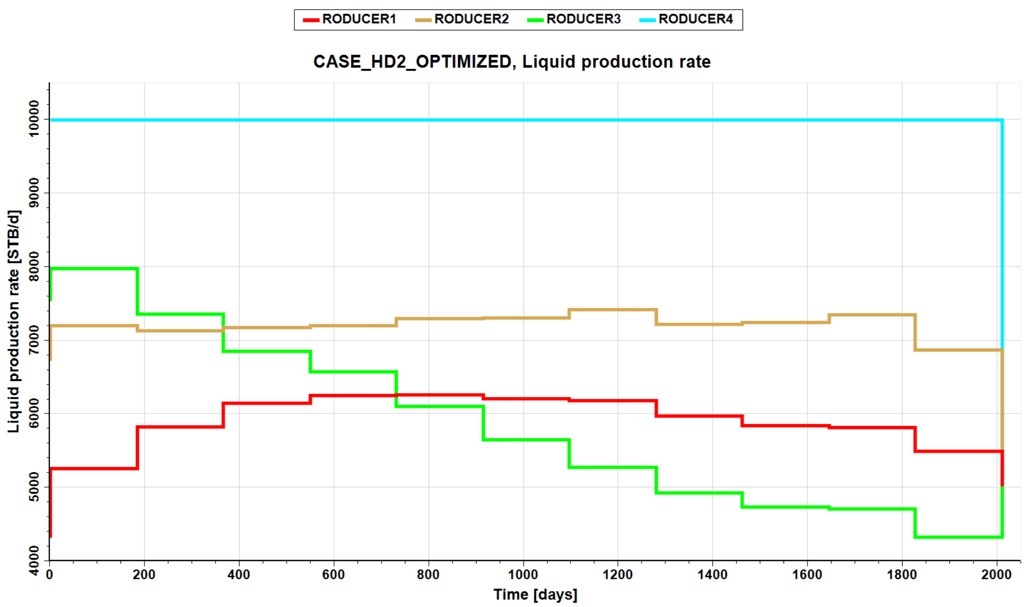


Figure 5.26: Wells liquid production rate in the optimized case of HD2.

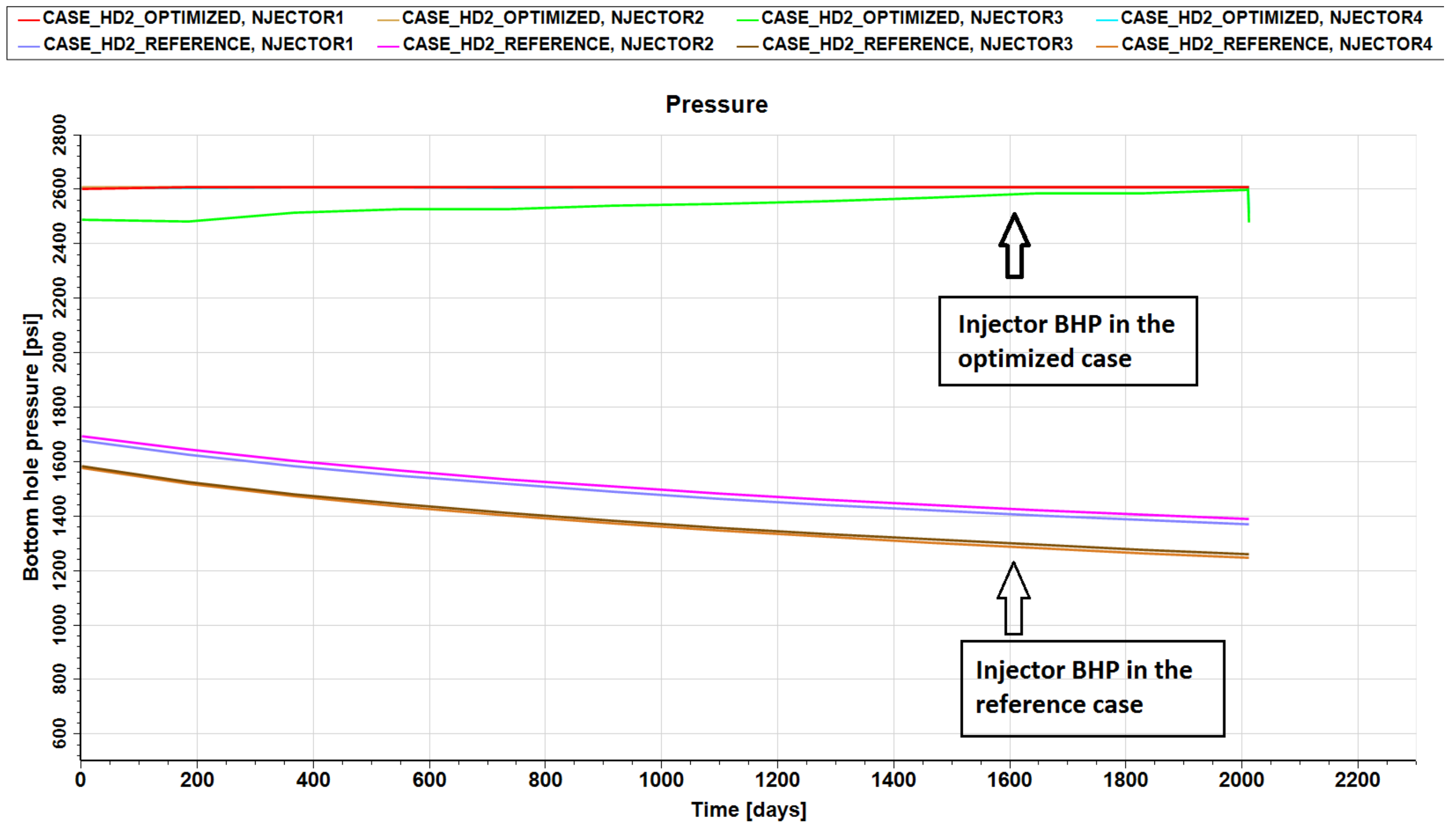


Figure 5.27: The comparison of the BHP in the injection wells pressure in the the optimized case and the base case of HD2. As seen, almost all the injection well are set on the maximum allowed pressure in the optimized case.

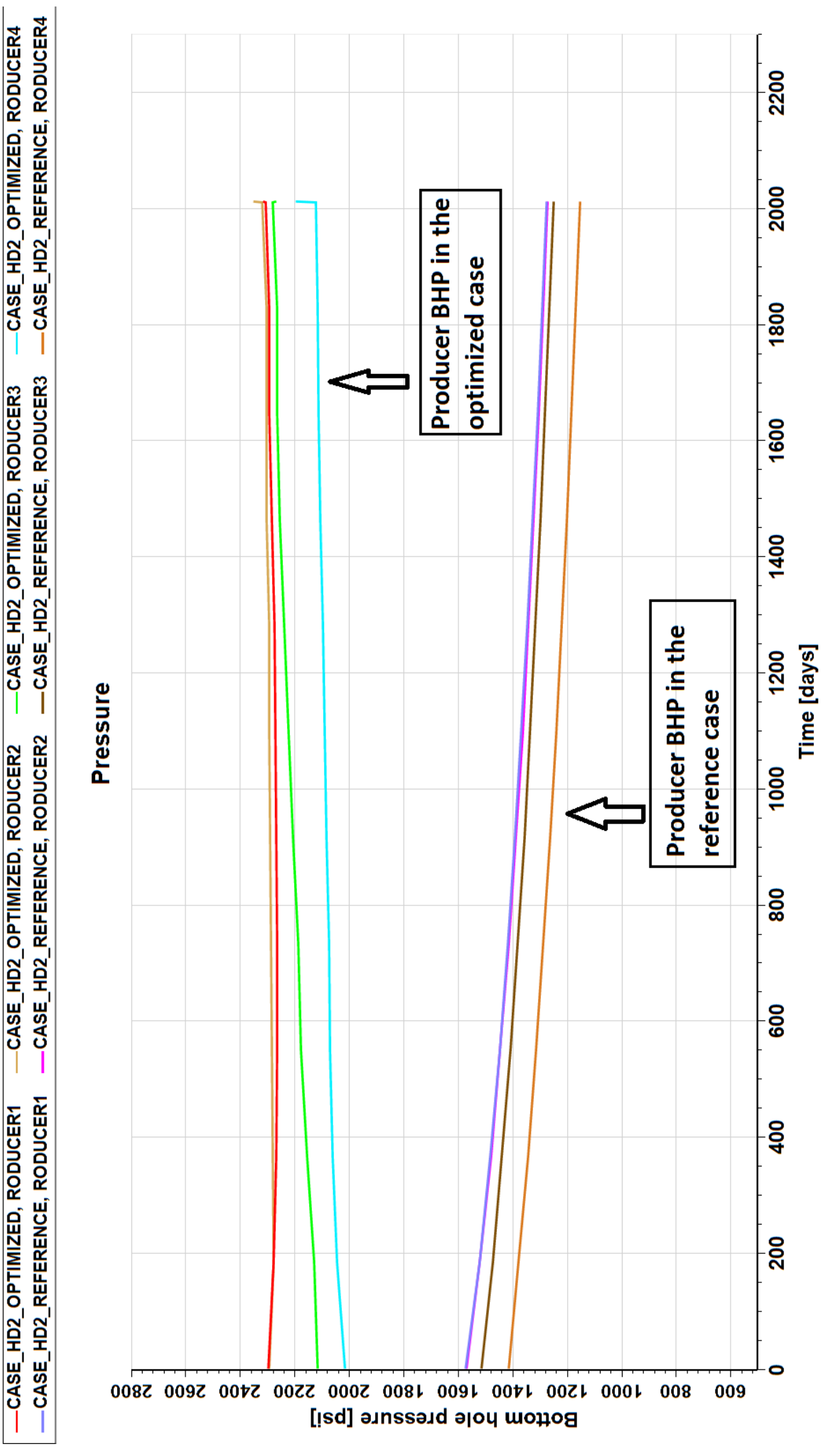


Figure 5.28: The comparison of the production wells bottom hole pressure in the the optimized case and the base case of HD2. As seen, the production wells are set on a higher BHP in the optimized case to produce more prudent.

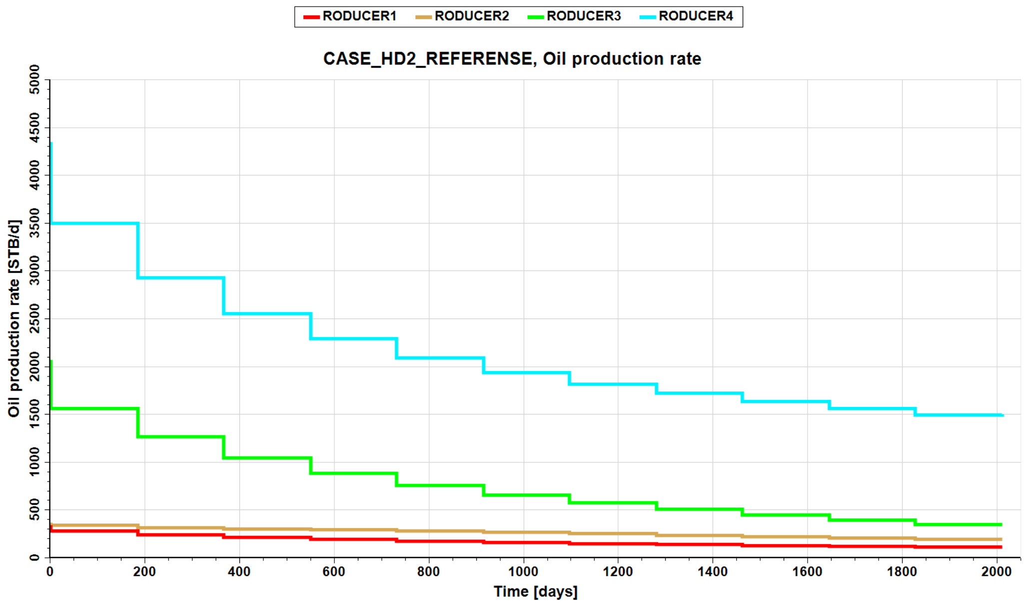


Figure 5.29: Wells oil production rate in the reference case of HD2.

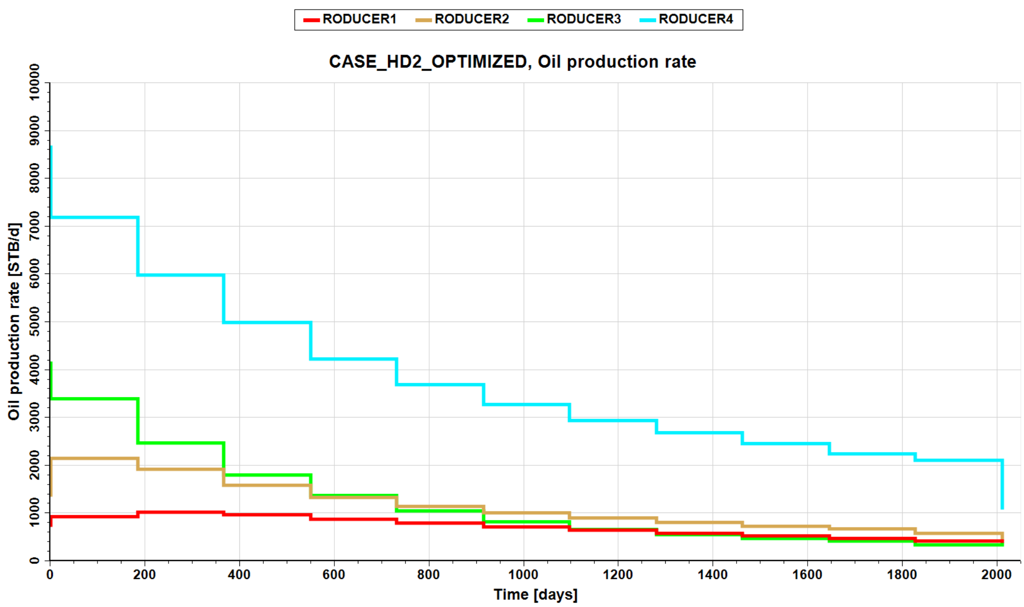


Figure 5.30: Wells oil production rate in the optimized case of HD2.

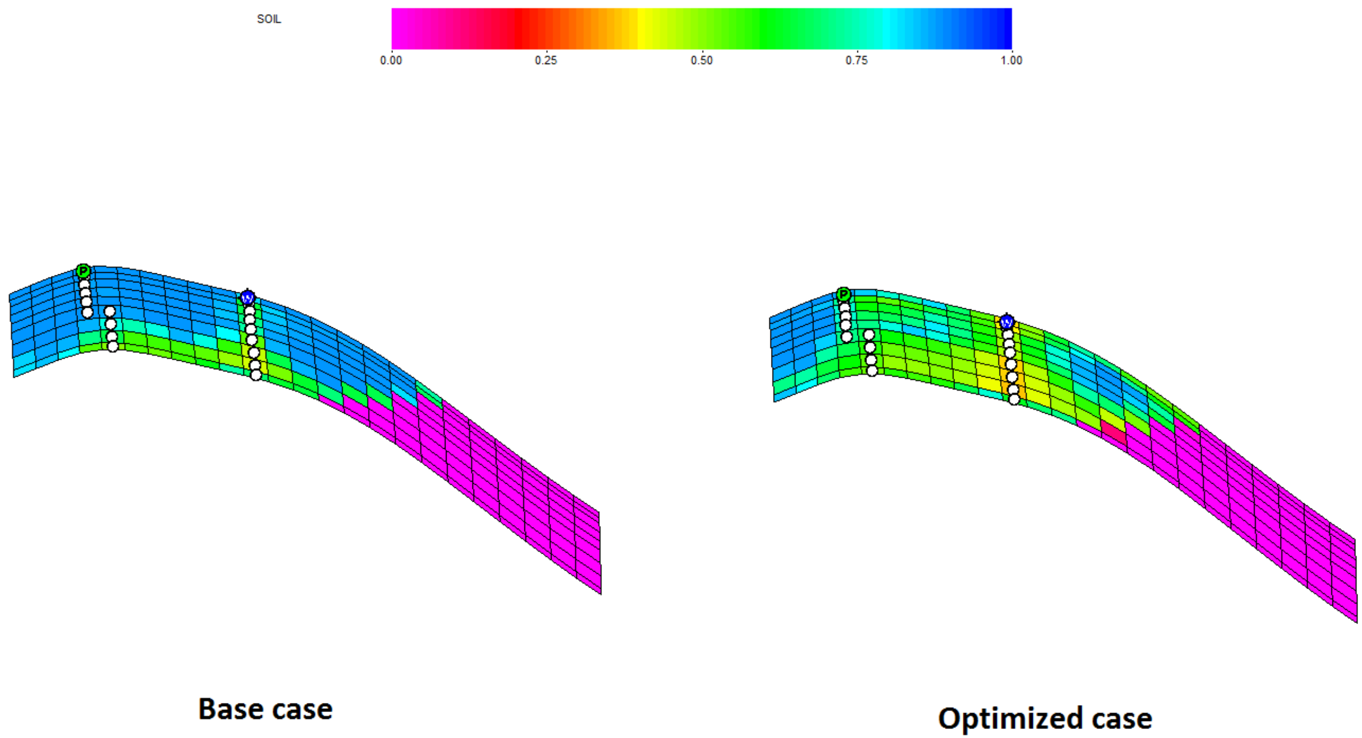


Figure 5.31: Wells one-to-one ratio in the optimized case of HD2. The residual oil saturation in the base case is considerably higher compared to the optimized case.

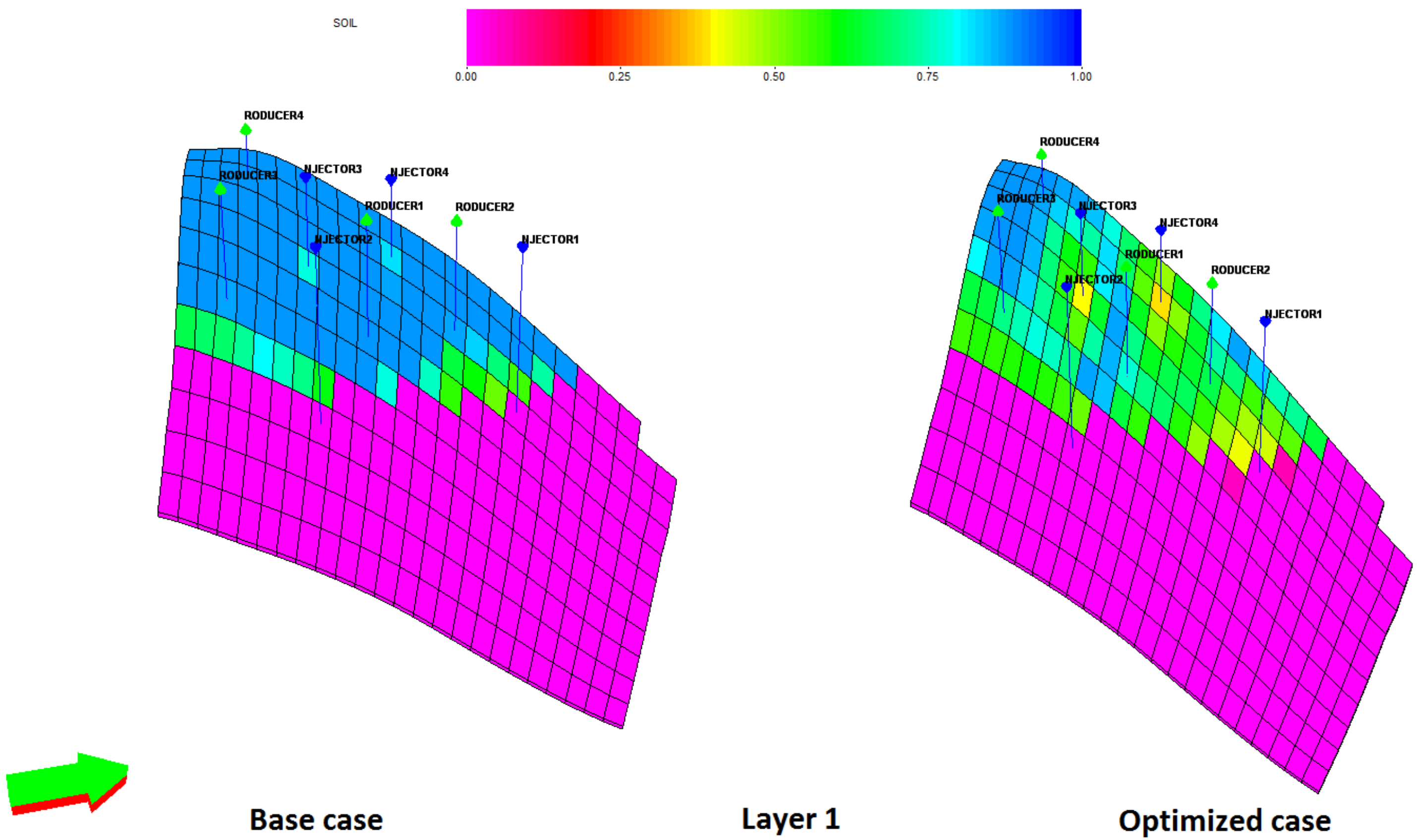


Figure 5.32: The comparison of final oil saturation in the reference case and optimized case in the top layer. There is a clear improvement of oil recovery in the optimized case of HD2.

5.3 Case 3: Rio structure

As earlier described, case Rio is carved out approximately from the same region as the Half-Dome structure. There are two horizontal production wells completed in this segment. There is also defined an aquifer that offers pressure support to the pay zone. The total life of this segment is 3653 days (10 years). The wells are on liquid control mode with a target rate of 20,000 stb/d rate each and there is a lower limit on bottom hole pressure of 750 psi . The ultimate oil recovery after running the base case is approximately 23 %. The base case is described in more details in Subsection 3.2.

In this optimization study, the NPV of the segment is subjected to optimization. There are not any injection wells completed in this segment thus the NPV improvement is only dependent upon the amount of water and oil produced. The production wells can operate on a range between 0 - 30,000 stb/d. The production constraint is to keep the water cut below the break-even water-cut 0.91.

Three control approaches were carried out to maximize the NPV of this segment. The wells control mode and the control parameters were categorized into three groups and optimized. The groups are listed in the table 5.5

	Well control mode	Optimization parameter	Iterations	Simulations	NPV Improvement (%)
Option 1	WBHP	BHP	2	3	1.6%
Option 2	LRAT	RATE	6	37	0.8%
Option 3	LRAT	BHP	8	17	12.7 %

Table 5.5: Comparison of three control performance in terms of NPV improvement

In the first approach, the production wells were set on bottom hole pressure control mode. The target pressure was set on 750 psi with 20,000 stb/d as the upper limit of liquid production rate. The upper limit on production rates was set in order to avoid exceeding the field water-cut in the base case. The optimization terminated after 2 iterations and 3 simulations. The final NPV, improved by 1.6 % compared to the base case in this approach.

In option 2, the wells were on liquid control mode and the optimization parameters were selected to be the liquid rate. These were chosen as control parameters since the wells are on the liquid control mode but the optimization was not successful due to the dynamic behavior of the wells. The total improvement of NPV in this approach was only 0.8% and the optimization terminated after 6 iterations and 37 simulations.

Option 3, having the wells on liquid control mode and optimizing the bottom hole pressures responded best to optimization with an 12.7 % improvement in NPV. The control parameters are on the wells bottom hole pressure with a minimum of 750 psi and maximum 3000 psi. Both wells fell into the BHP control mode during the run and choosing wells bottom hole pressure as control parameter improved the performance of the segment. The optimization converged after 8 iterations and 17 simulations. The total number of control parameters with two wells is 120. The wells settings are to be changed six times a year (2 months reporting frequency) over a period of 10 years is 120, (6x2x10=120), the wells are on "Liquid rate" control mode therefore no "base case" control parameter was calculated for each well. It took approximately 6 minutes to optimize with bottom hole pressure as

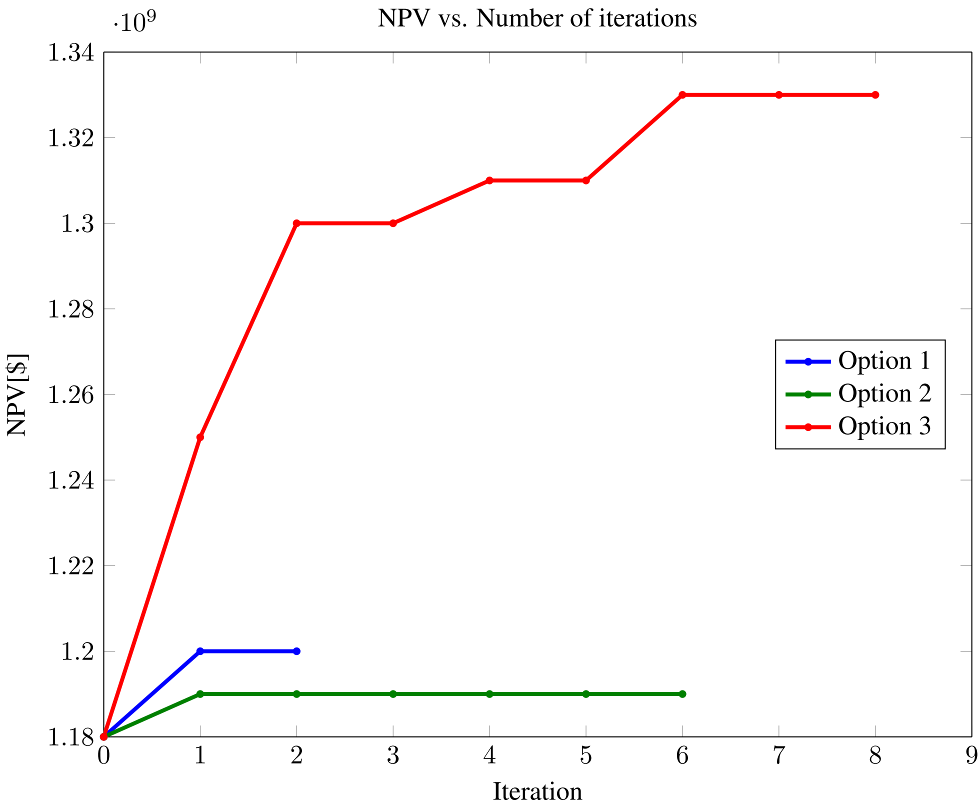


Figure 5.33: Comparison of the optimization performance with different control parameters in case 3.

the control parameter by a machine with two 2.9 GHz processors each with 8 cores, and 64 GB memory.

In the following, results from the third control approach with the highest NPV will be reviewed and discussed.

We will start to present the results by comparing the ultimate cumulative oil and water production. As seen in figure 5.34, the ultimate cumulative oil production in the optimized case is slightly lower than in the base case. On the other hand, the cumulative water production is 23.4 % lower in this case. The cumulative water production is illustrated in Figure 5.35. Since the objective of this optimization study is to maximize the NPV of the segment, one may obtain this by increasing the oil production and/or decreasing the water production. In this case, the oil production is somewhat lower than in the optimized case but at the same time, the amount of total water production has decreased considerably.

In order to analyze field performance in the optimized case, one may start looking at the evolution of average field pressure and liquid production rate. These are illustrated in Figure 5.36 and Figure 5.37, respectively. In the base case, the target liquid production rate is constant on 40,000 from two producing wells. There is a minor increase in the field pressure but after that, a continuous decline may be observed. In the optimized case, the liquid production rate falls from 52,000 stb/d to 14,000 stb/d in a period of 1438 days. During this time period, the average pressure in the field increases from 1450 to 1540 psi before it declines. As the liquid production rate decreases, the average field pressure increases. The average field pressure falls then continuously when the liquid production rate starts increasing more or less over a period of 1300 days until the end of the run.

The drop in liquid production rate in the optimized case can be described by analyzing the field performance in terms of water production. As seen in Figure 5.38, the total water production rate in the base case increases quickest in the first 1000 days of production. Especially production well 2 that produce a considerably larger amount of water as seen in Figure 5.39. In the optimized case, producer 2 is shut-in until 1950 days after production start, but producer 1 that have a lower water production rate is open to flow as seen in Figure 5.40. The wells liquid production rate in the optimized case is illustrated in Figure 5.42. Producer 1 continues to produce until 1950 where the producer cannot flow at the limiting bottom hole pressure. The producer 2 is then opened to flow until day 2922 when it is shut-in again. Producer 1 is re-opened to flow at this day and produce until the end, day 3653.

The optimized well oil production rates are illustrated in Figure 5.43. Producer 1 performs better in terms of oil production rate where the oil production rate starts from 42000 stb/d and follows a declining trend until day 1950 where this wells is shut-in. Production well 2 is then open to flow from day 1950 where the production is 7800 stb/d oil and declines to 4000 stb/d in day 2922 when the well is shut-in.

As mentioned, the bottom hole pressures are the control parameters to optimize the production. The bottom hole pressure of the production wells in the base case is illustrated in Figure 5.45. Production well 1 operates at a lower pressure compared to the production well 2. Since the wells are at target rate of 20,000 stb/d liquid production rate, see figure 5.41, and production well 1 operates on a lower bottom hole pressure, one may assume that the surrounding pressure of the production well 1 is lower compared to the production well 2 which is completed closer to the aquifer as seen in well overview Figure 3.17.

As mentioned, the production well 2 is shut-in until day 1950 when it opens to flow and produce until day 2922 then shut again in the optimized case. This is also illustrated in the Figure 5.46. Production well 1 is open to flow from the start and produce initially with a bottom hole pressure close to 800 psi. Production well 1 produce until day 1950 when it is shut-in since the well cannot flow at the limiting bottom hole pressure but reopens at day 2863 and produce with a bottom hole pressure of 1357 psi.

The production constraint in this study is to keep the water-cut below the break-even limit of 0.91. As seen in Figure 5.47, this constraint is respected throughout the optimized run.

In this optimization study, three approaches were tested to maximize the NPV of this case. Two production wells were on the liquid rate control mode and by optimizing the BHP, an 12.7% improvement of the NPV was obtained. The optimization responded best by choosing the wells bottom hole pressure as the control parameter because these wells fell into pressure control mode during the optimization. During the first 1950 days of production, the optimizer penalized the production from well 2 and shut this well due to high water production. Instead, well 1 produced during this period, with pressure support offered by the aquifer. Since the production well 2 is shut in until day 1950(5 years and 4 months) and only produce during a 972 day period, one may question the well placement, the drilling schedule, or whether this well should be drilled. Production well 1 is shut-in from day 1950 to day 2863, and during this period, one may consider well workover or interventions in order to perform maintenance in this well. The performance of this segment is improved by implementing a proactive production optimization where the strategy included to limit the field water cut under the economic value of 0.91. Unlike, the reactive approach, this means that the liquid production is set to control the water production from the beginning of the run and not shutting the production wells as a ”reaction” to exceeded water-cut value. The total NPV was improved by 12.7 %. The cumulative oil production has slightly decreased by 1.4 % but the NPV improvement is due to the reduced water produced in the field by 23.4 %.

Table 5.6: Summary of the optimization results

Strategy	Water Injection [%]	Water Production [%]	Oil Production [%]	NPV Improvement [%]
Rate optimization	-	- 23.4 %	-1.4%	+12.7 %

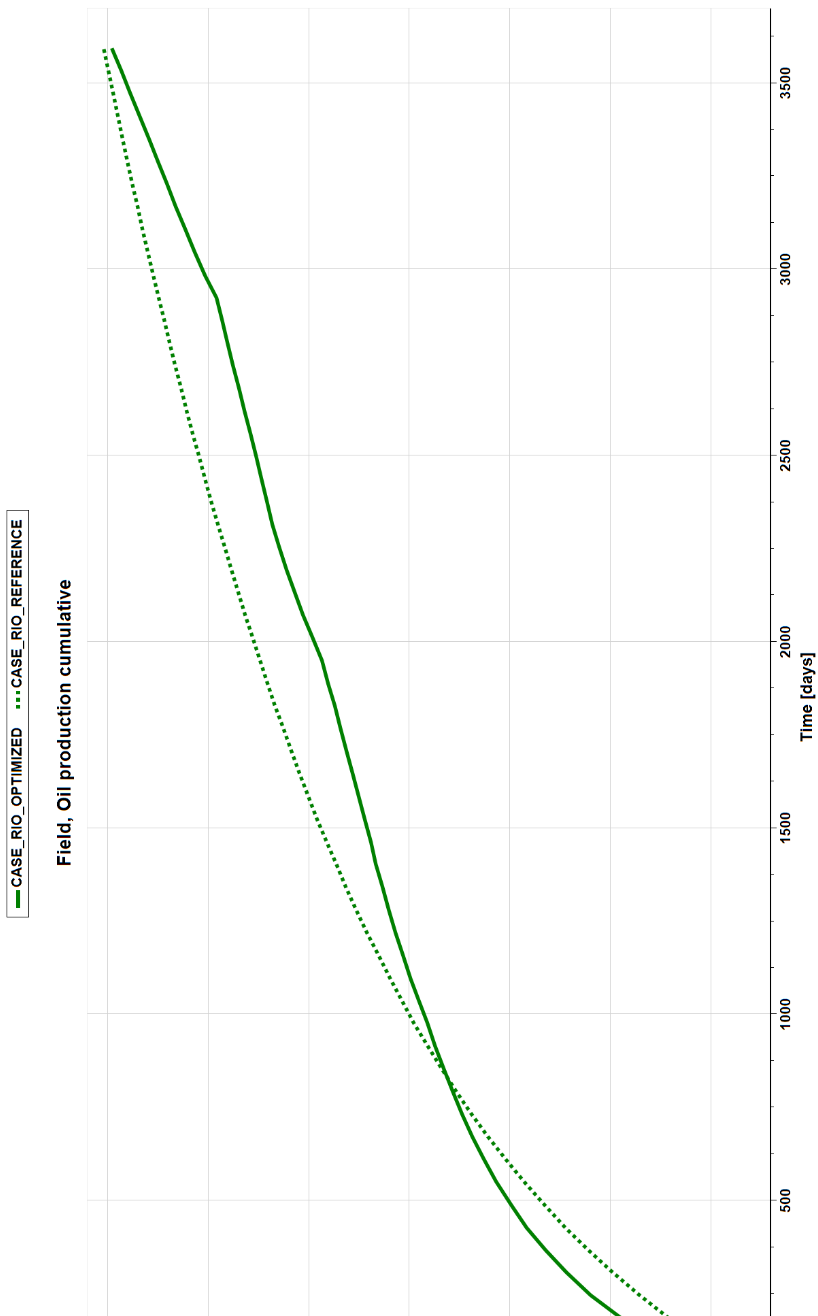


Figure 5.34: The comparison of field cumulative oil production in the reference case and optimized case of Rio.

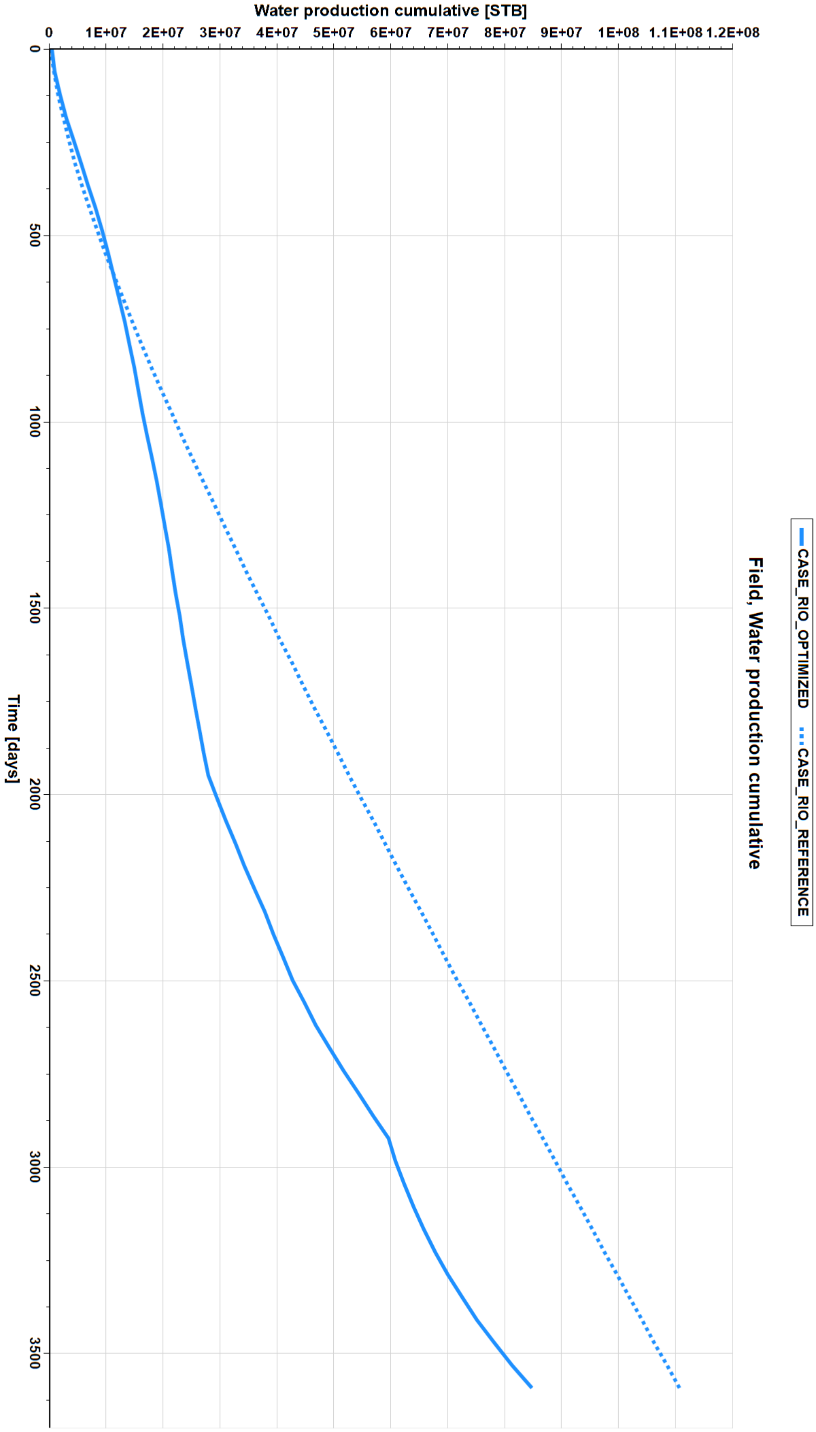


Figure 5.35: The comparison of field cumulative water production in the reference case and optimized case of Rio.

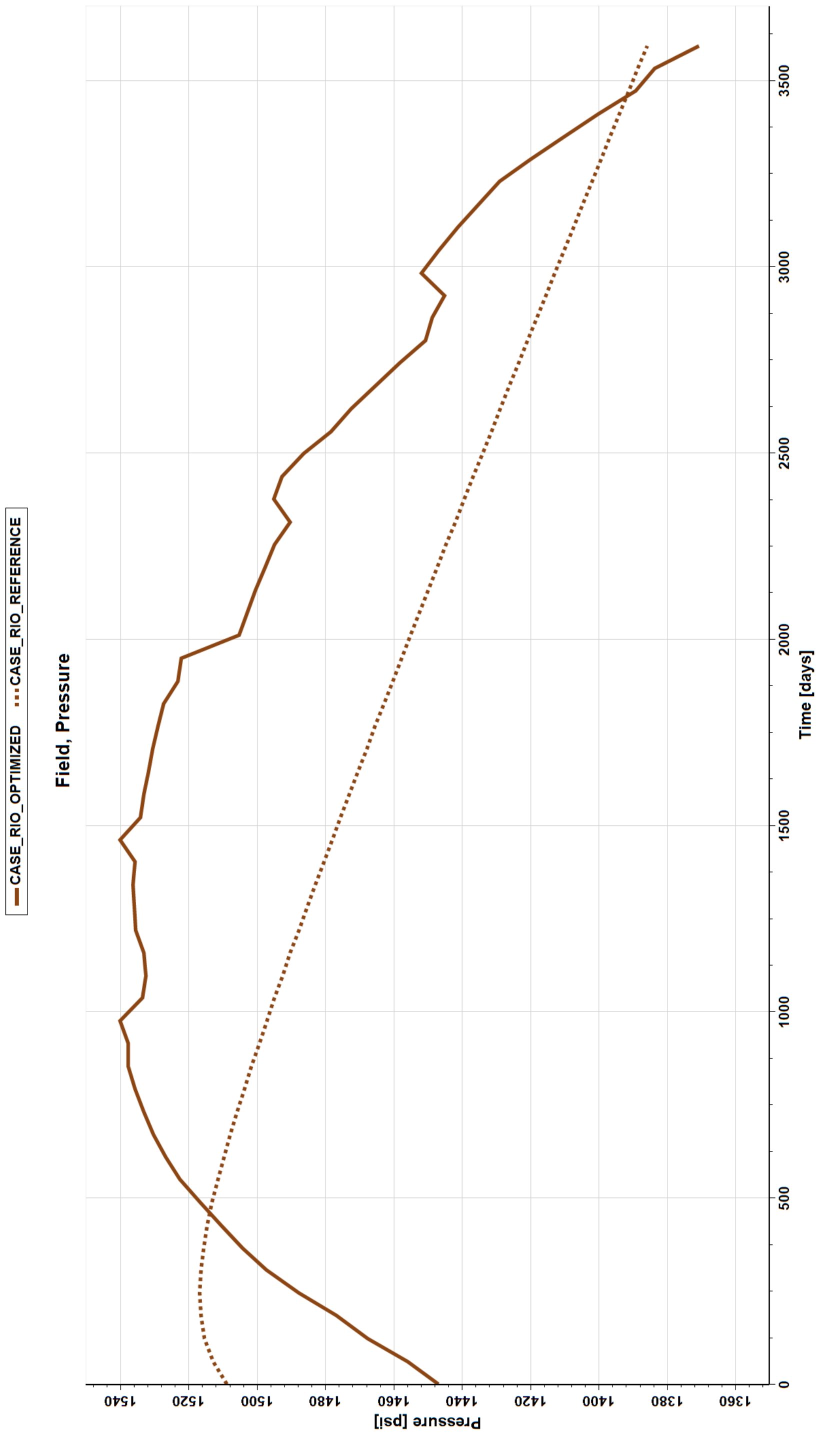


Figure 5.36: The comparison of average field pressure in the reference case and optimized case of Rio.

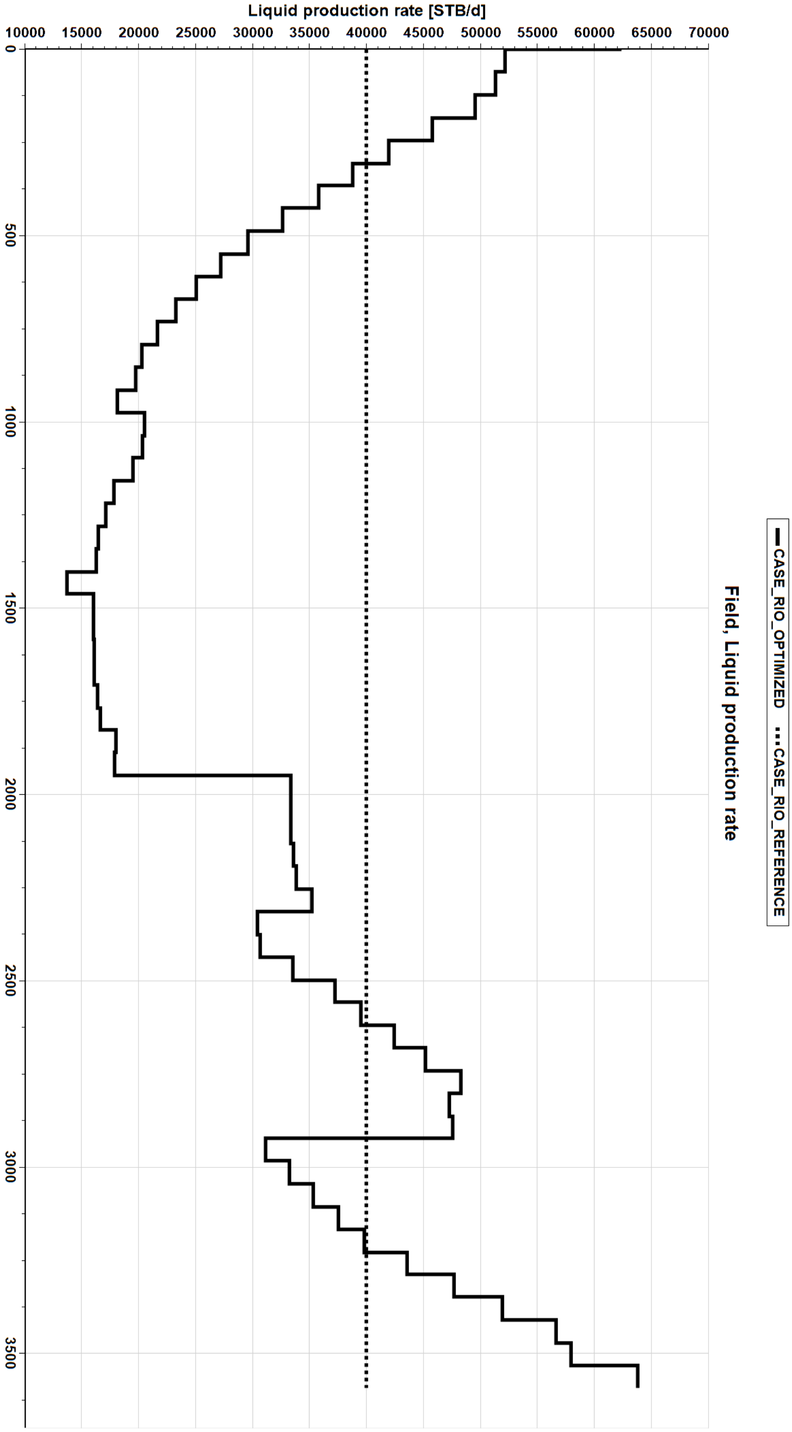


Figure 5.37: The comparison of field liquid production rate in the reference case and optimized case of Rio.

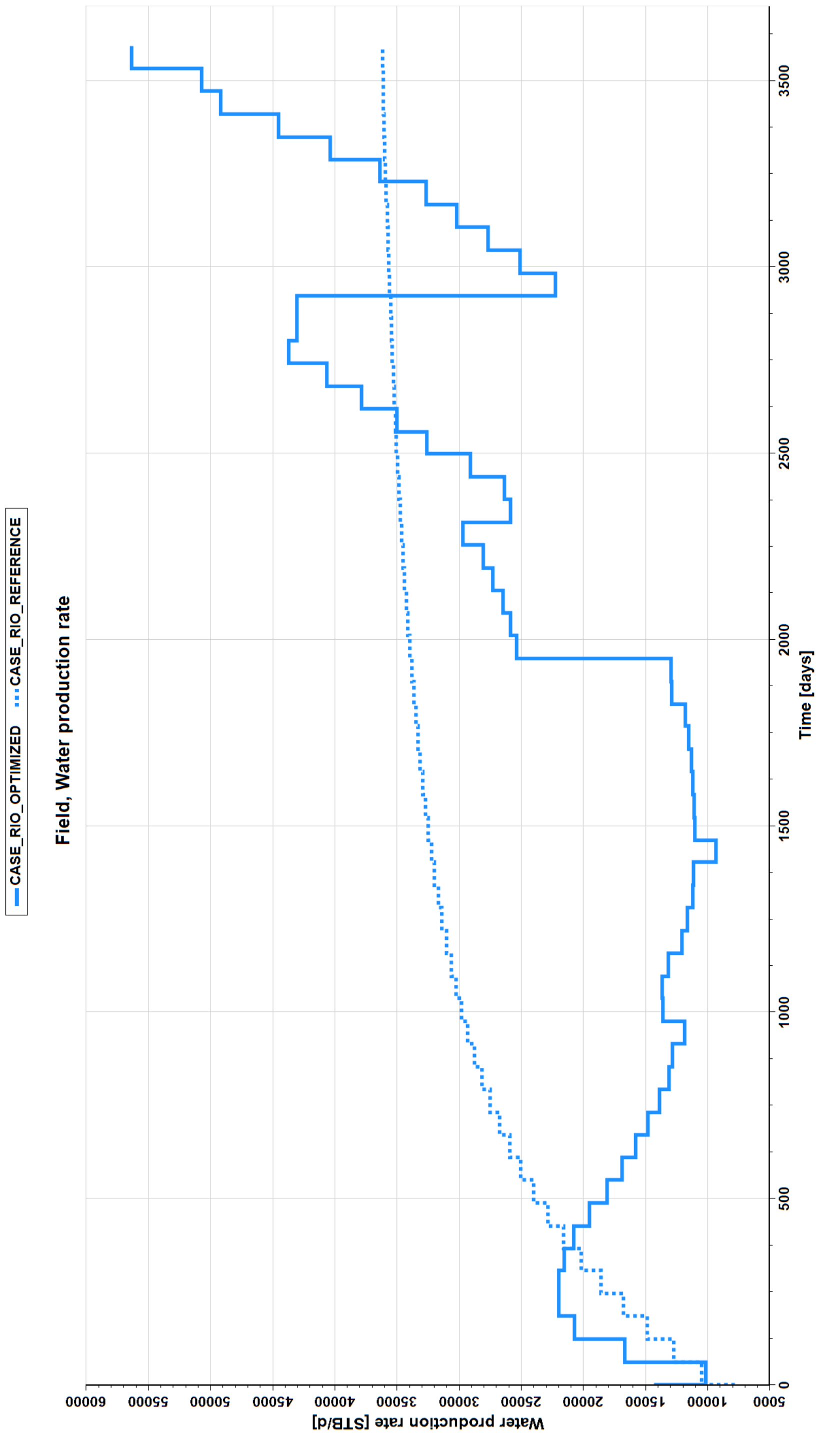


Figure 5.38: The comparison of field water production rate in the reference case and optimized case of Rio.

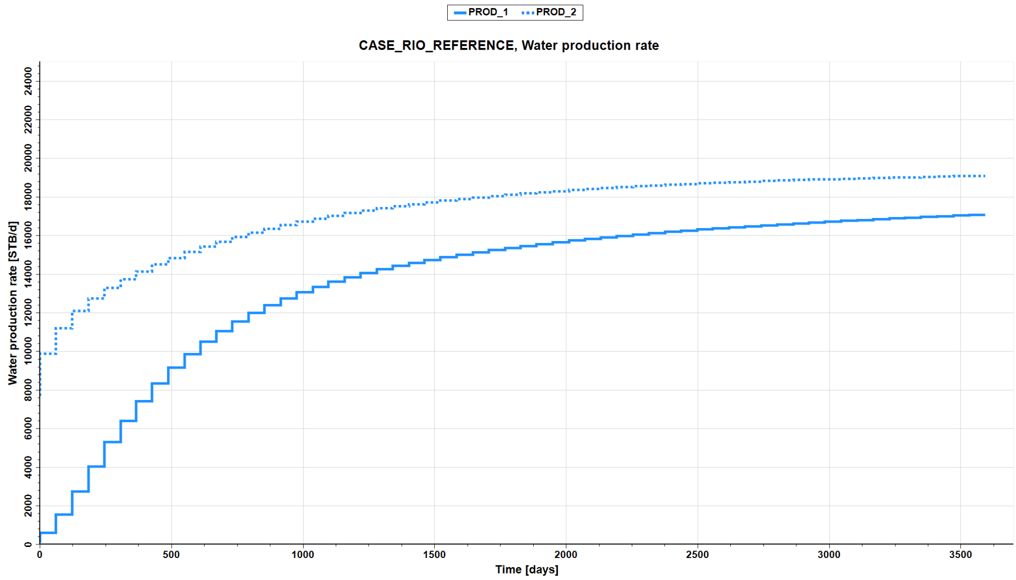


Figure 5.39: The comparison of wells water production rate in the reference case of Rio.

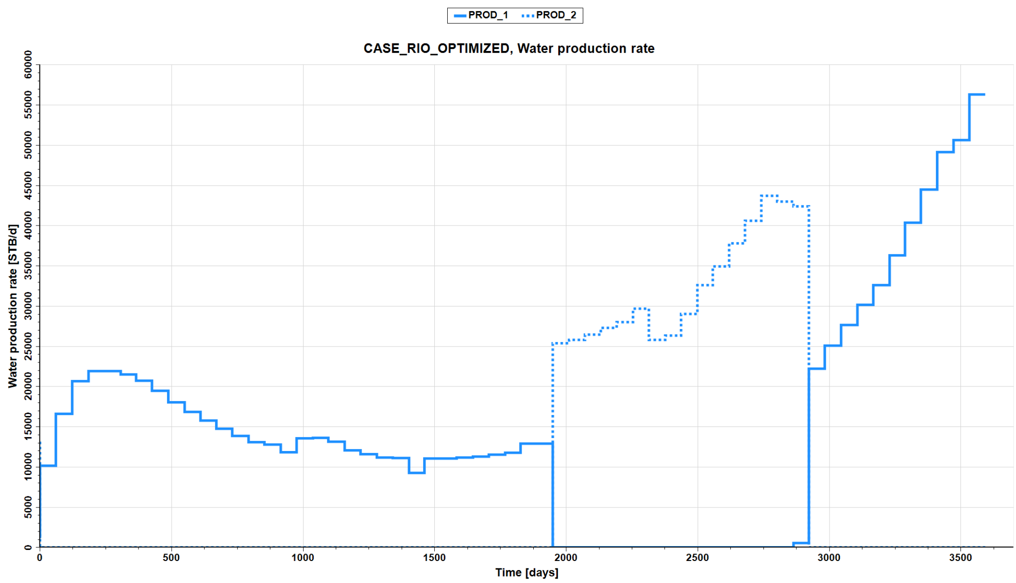


Figure 5.40: The comparison of wells water production rate in the optimized case of Rio.

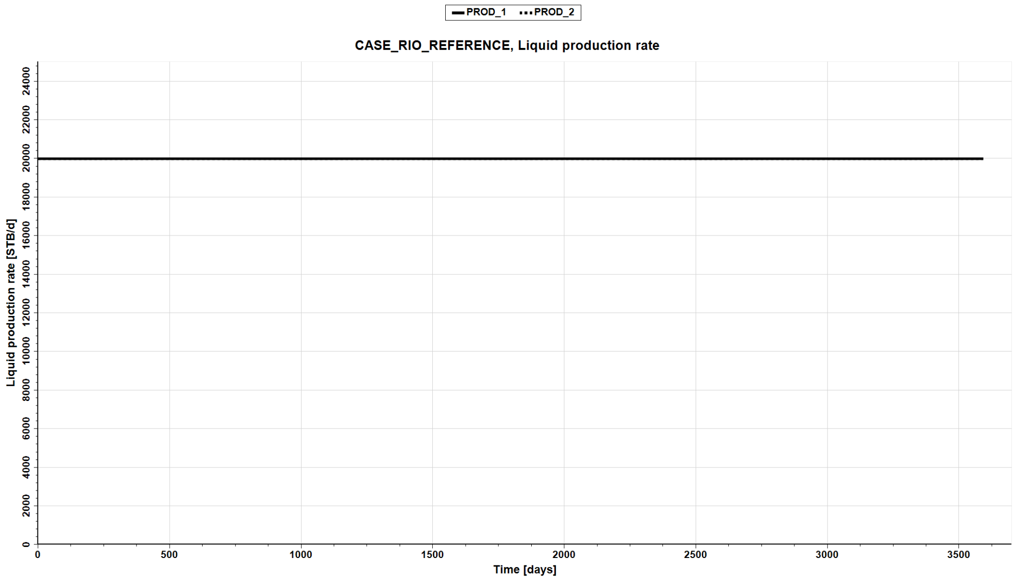


Figure 5.41: The comparison of wells liquid production rate in the reference case of Rio.

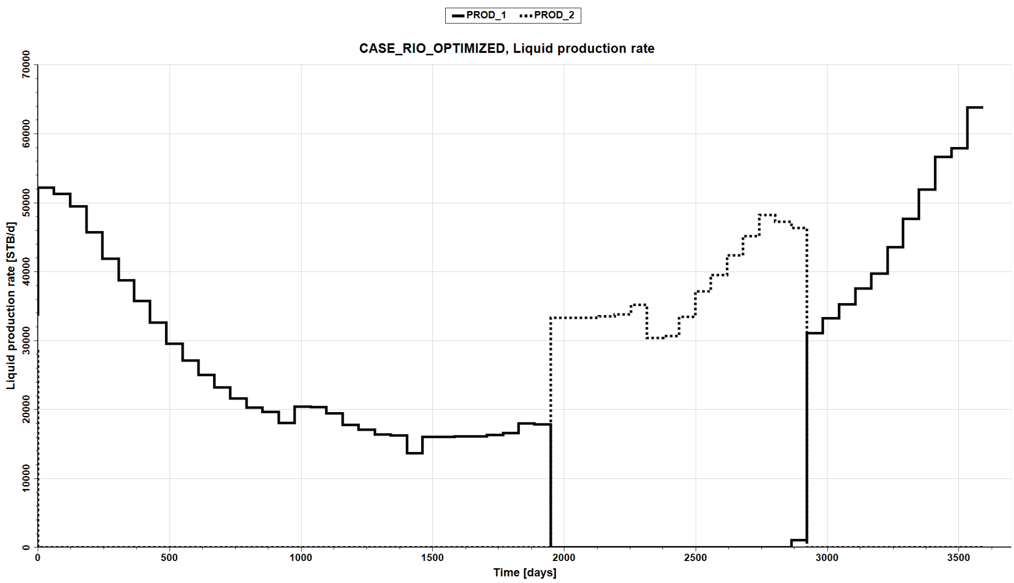


Figure 5.42: The comparison of wells liquid production rate in the optimized case of Rio.

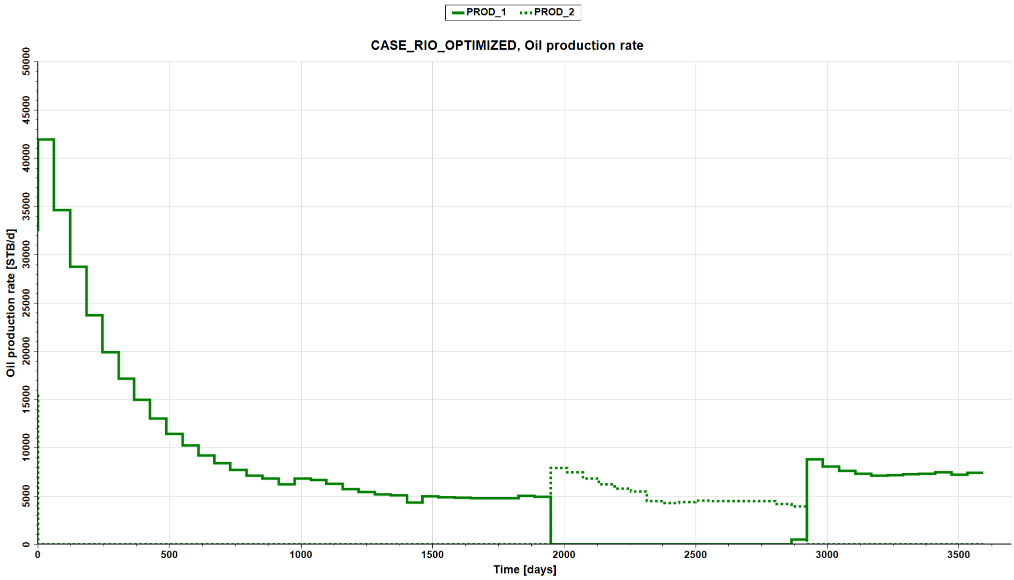


Figure 5.43: The comparison of wells oil production rate in the optimized case of Rio.

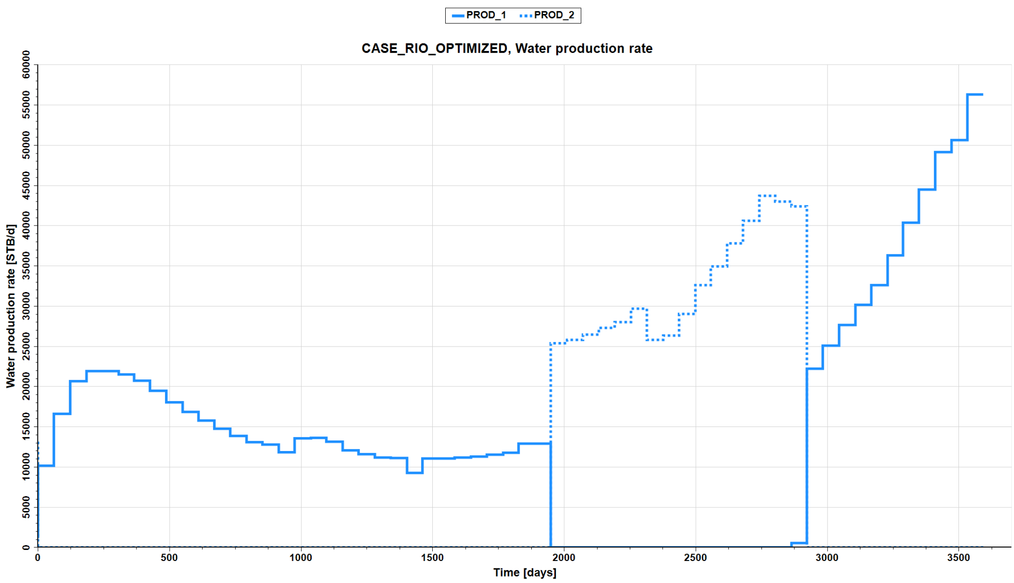


Figure 5.44: The comparison of wells water production rate in the optimized case of Rio.

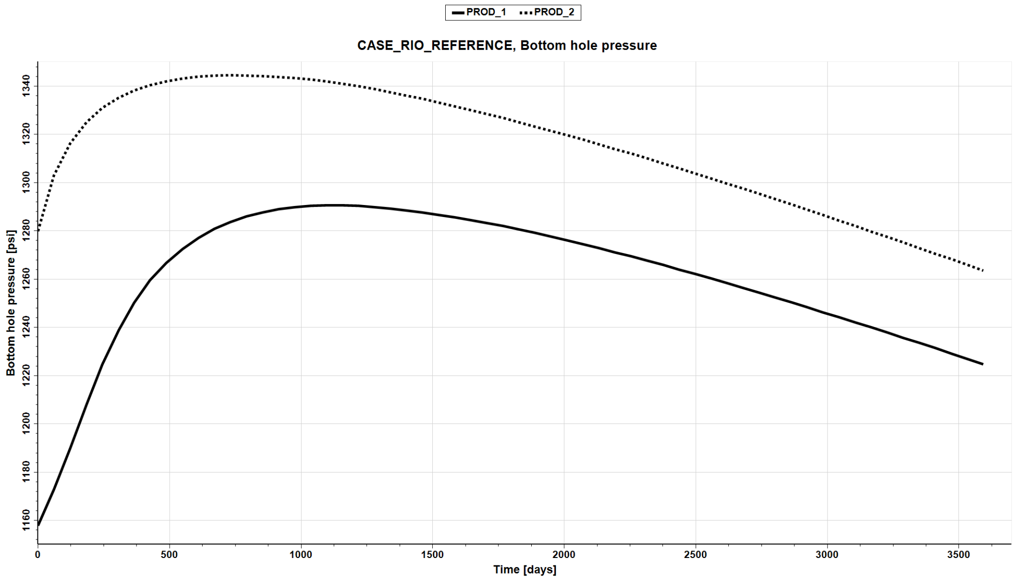


Figure 5.45: Wells bottom hole pressure in the reference case of Rio.

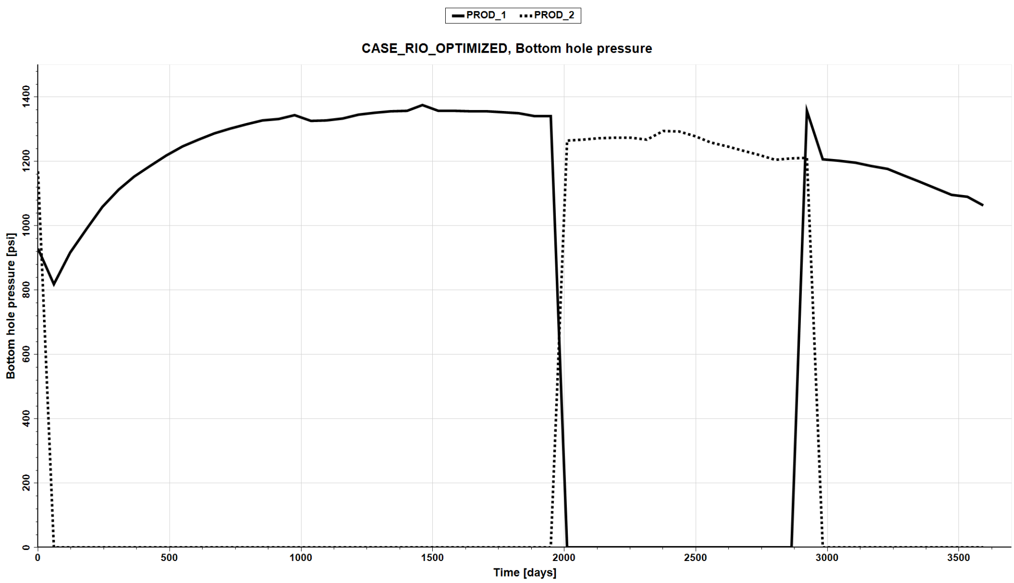


Figure 5.46: Wells bottom hole pressure in the optimized case of Rio.

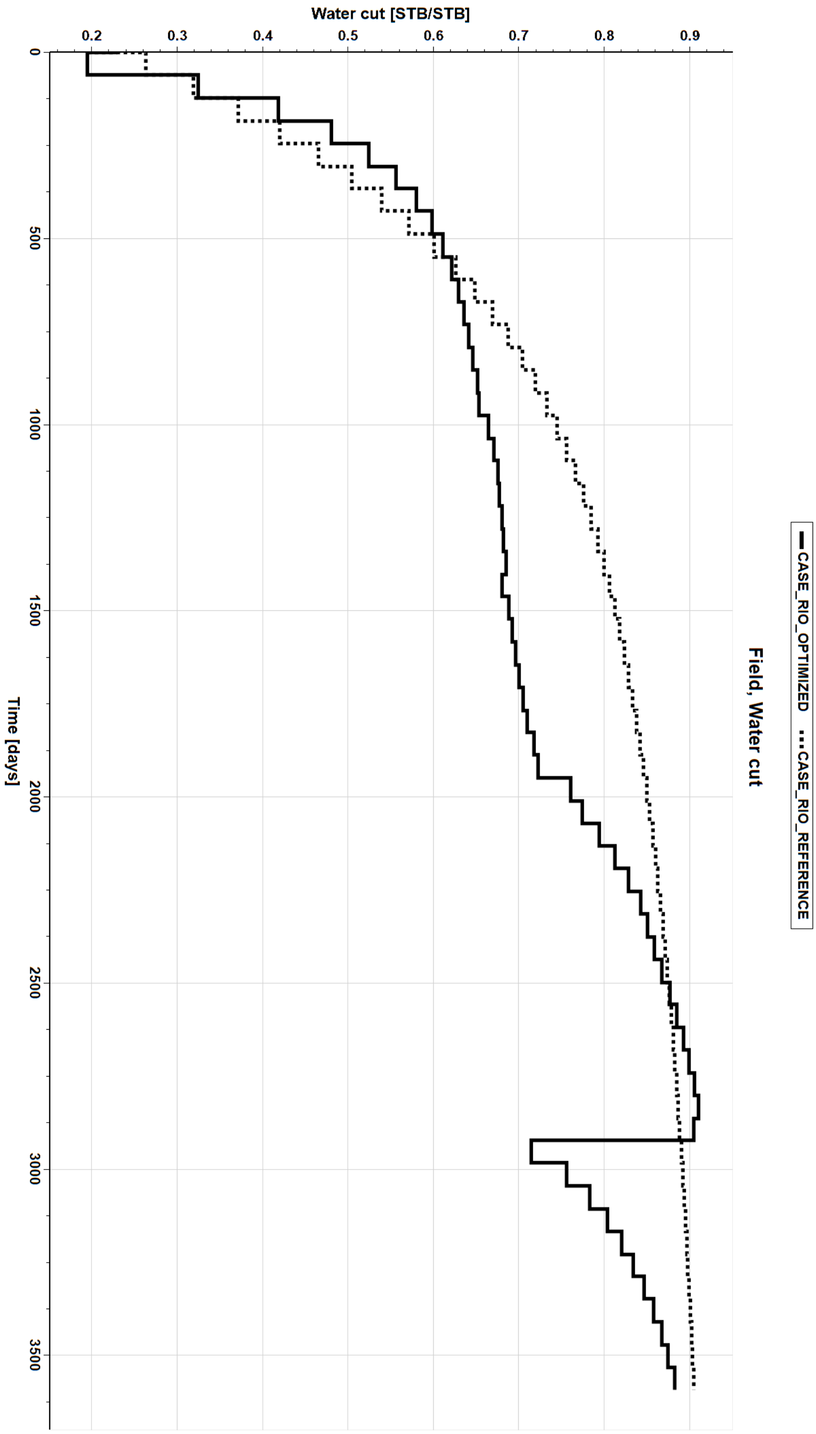


Figure 5.47: The water-cut of the Rio segment in the optimized case of Rio.

Chapter 6

Discussion

In this work, many different concepts and definitions of reservoir management have been reviewed and discussed. In the first chapter, we gave an overview of the importance of improving oil recovery from existing fields due to the increasing demand of energy. We observed that the discovery of marginal fields has stepped down and most of the currently producing fields are already at a mature stage of their lifetime.

In the second chapter, reservoir management was introduced. Here, we emphasized the integration of all available resources such as human, technological and financial resources since they are crucial to obtain a successful reservoir management. Because an important part of reservoir management is to have efficient tools to forecast the future performance of the reservoir, we started by defining reservoir simulation. We introduced the grid, flow equations and well models, which are essential parts to construct a reservoir model. In addition, the ability of reservoir models to forecast future production was also discussed. Although, there are several methods to decrease the uncertainty in the predictions, there is no guaranty that the simulated behavior is reliable. A relatively new concept that significantly reduces uncertainty is the closed-loop reservoir management. This method combines data assisted history matching and production optimization. The uncertainty in the models is minimized by integrating real-time data and continuously updating them. Production optimization algorithms use the updated models in order to find the best operating strategy. This implies that the algorithms will find the best state with respect to well placement, liquid injection and production rates or simply a valve setting. We introduced water-flooding, the most commonly used oil recovery method, and its displacement mechanisms. The most common well locations for water-flooding scenarios, pattern flooding, and peripheral flooding were reviewed. In addition, the pattern-flooding well setting was used in case 2.

In order to design new cases for production optimization, we used Brugge field. Brugge field is a synthetic field with typical North sea Brent type reservoir properties that has been implemented in several water-flooding optimization studies. Furthermore, smart well technology was introduced and reviewed. Smart wells are conventional wells equipped with new technologies that effectively allow the operator to react quickly to unexpected changes downhole and reduce costs by minimizing the well down-time. These wells respond to the industry's demand for cost reduction and increases oil production. They are also equipped with interval control valves that enable control of the zonal inflow and production from multiple zones using only one well. Smart wells technology remarkably improves reservoir management of highly heterogeneous reservoirs and can be used to control the water injection and production rates in order to obtain a better sweep in heterogeneous formations.

The mathematical background of the optimization theory was briefly introduced and discussed. In this section, the major classifications of optimization algorithms, stochastic and deterministic approaches were reviewed. We discussed what algorithm approach is appropriate given the type of optimization problem at hand and presented the properties of a proper optimization algorithm such as robustness, efficiency, and accuracy. The stochastic and deterministic approach were compared. Stochastic approach search in a wider span of solutions and hence has a larger chance of finding the global optima. However, the process is often ineffective since it typically evaluates a large number of functions and does not guarantee a monotonic and continuous improvement of the objective function. The deterministic approach, on the other hand, is more efficient compared to the stochastic optimization, but the chance to get trapped in the local optimum is large. It is divided into two methods: evaluation-only methods and gradient-based method. Reservoir optimization problems are often approached by deterministic gradient-based methods due to their efficiency to find the optimum. To approach the optimization problem in our study we used the steepest descent method implemented by the optimizer in Eclipse 300. This method is a deterministic gradient-based line-search method. Because deterministic approaches are initial guess dependent, one may lead the optimizer by giving a feasible initial guess in order to find the near optimal operating point. However, an efficient general procedure for finding a good initial guess is missing. The initial guess is usually a common sense one. For example, optimizing the NPV with considerably higher oil price compared to the water production and injection price with a substantial discount rate, one may choose to operate the wells on maximum allowed rate while honoring the pressure constraints. This is a reasonable strategy as the production of the maximum amount of oil may already yield a reasonably high NPV. Finally, the elements that defined the optimization problem were presented. The objective function, control parameters, and constraints were introduced for optimization. The workflow of the optimizer facility in Eclipse 300 was also presented.

In the next section, the basic theory and literature study of the production optimization was introduced. In this section, the reactive and proactive approaches in optimization were introduced and discussed. Reactive well controls are actions based on downhole events such as water or gas breakthrough. The proactive well control uses the acquired data and updated models to enhance decision-making in the long term. The entire life of the reservoir is subjected to optimization to find the optimal operating conditions. Both approaches lead to enhanced production, but the chance of reaching a suboptimal condition is larger in the reactive approach. Hence, all three cases developed in this study were subjected to proactive control. In the following section, the adjoint technique that is widely used in production optimization problems was presented. This approach is suited for problems with a large number of control parameters and which requires the gradient of the objective function, such as in reservoir optimization problems. Eclipse 300 also use this method to obtain the gradients of the objective function.

In chapter three, we respond one of the fundamental parts of this work which is to develop interesting and relevant petroleum cases for the purpose of the optimization. Three cases with different development strategies were developed in Petrel. The case development process included: (1) model conversion into an Eclipse 300 compatible model, (2) project conversion into Petrel, (3) case development and (4) optimization. In the case development process, several production scenarios were designed and run. The qualified cases were selected by analyzing parameters such as initial and final oil saturation, geological variations of the formation, different well settings, and various rate allocations between producers and injectors. These cases were run to test the performance of the reference production strategy.

As mentioned previously, a long-term proactive strategy was implemented in order to obtain the optimal state and maintain the constraints. In two cases, (1 and 2), water injectors were employed to increase the oil recovery. Hence, large and quick water production and rapid decline in the average field pressure resulted in high residual oil saturation in the field. In case 3, two production wells were completed in the field. There were no injection wells in this segment, however, a bottom water drive aquifer supported the field pressure. The production strategies implemented in all three cases resulted in high water production and poor oil recovery. In case 1, the objective was to maximize the NPV. In this optimization, the wells were on rate control mode. Three control approaches were tested: BHP, rate, and combination of the BHP and rate control. The combined optimization was tested because the injection well fell into pressure control mode and then selected as the control parameters for this case. Even though the injector fell into pressure control mode during the simulation, optimizing the water injection rate had a better response than the optimization of the BHP for this well, resulting in the highest NPV improvement for the rate optimization. In the optimized case, better sweep and pressure maintenance resulted in higher oil recovery and reduction in the produced and injected water. The field pressure was held almost constant due to the controlled water injection and liquid production. The reservoir volumes injected was higher than the volumes produced. In the base case, a rapid pressure decline is observed due to the higher volumes produced than injected into the reservoir. Note that in the optimized case, the reservoir volumes produced and injected were considerably lower than in the base case which leads to better sweep and a constant pressure in the segment in the optimized case. As a result, oil production increased by 22 %, water production reduced by 50 % and the water injection reduced by 23% whereas the objective function increased by 93 %. In the rate optimization, the objective function increased mainly during the four first iterations and almost stabilized after the fourth iteration. One might consider increasing the tolerance value in the objective function to avoid excessive time spent for optimization without a substantial increase in the objective function. In this case, the total time spent for optimization was approximately 10 minutes, however, this is not of great importance because, in the full field models where the time for a single simulation can be prohibitively long, the tolerance value must be selected carefully.

In case 2, the objective of the optimization was to maximize the ultimate cumulative oil production. Two control approaches (BHP and well rates) were tested as control parameters. The rate optimization responded best. The wells were on the liquid rate and therefore responded best to rate optimization even though some of the injectors fell into the pressure control mode for few time-steps. In the optimized case, the available water injection was employed to inject with the maximum allowed bottom hole pressure. The production wells bottom hole pressure were also higher (less liquid production) than the base case. Consequently, the field pressure was held almost constant. The controlled water injection and liquid production increased the sweep and maintained the reservoir pressure. The ultimate oil production increased by 100%, i.e., twice the total oil production in the base case whereas the total water injection increased by 52 % and the total water production increased by 30 %.

In case 3, the objective was to maximize the NPV of the segment. There were two production wells in the segment on rate control mode. The optimization responded best when the BHP pressures were selected as the control parameters. The reason was that both wells fell into pressure control mode. The objective function value increased by 12.7% due to the reduction in the field water production whereas the amount of oil production slightly decreased. The production constraint was respected during the optimization and field water-cut was maintained below the break-even value. In the optimized case, production well 1 performed better in terms of higher oil production and reduced water production compared to the production well 2. Production well 2 was shut-in long after field production started and produced only for a period of 1000 days. One might consider changing the well placement, the drilling schedule, or whether this well should be drilled. Production well 1 shuts-in when well 2 is producing, and well operations are possible to perform maintenance.

As it has been demonstrated, the optimization of the developed cases resulted in improved objective function value while the constraints were respected. In cases 1 and 2, controlling the water injection and liquid production resulted in optimized objective function value. In case 3, the variation of the bottom hole pressure of two production wells led to a reduction in water production and increased NPV.

Chapter 7

Conclusion and recommendations for future work

In this work, several concepts and definitions regarding reservoir management and optimization were introduced. The focus of this study was to develop interesting and relevant petroleum cases for the purpose of the optimization. Three cases were developed in Petrel and optimized by the built-in optimizer, in Eclipse. The combination of literature review and experimental work left the writer with valuable knowledge and experience about the topic, from which some of the most important points are summarized below:

- A successful reservoir management depends on the integration of all available resources such as human, technological, and financial resources. Reliable tools are essential to predict the future performance of the field. The uncertainty in the reservoir simulation models can be reduced by continuously updating the models with measured data (Closed-Loop approach) or by using several geological realizations to count different parameters of the formation. A combination of the methods can also be applied.

- Three cases for production optimization was developed. Parameters such as initial oil saturation, geological features, rapid petrophysical variations of the formation, different well placement, and rate allocations were taken into consideration in the development process. It is important to evaluate the model entirely and monitor all the components that constitute the model such as fluid models in order to avoid any unrealistic behavior.

- In production optimization studies, a long-term proactive approach has shown promising results to reach a near-optimal point while the chance to reach a sub-optimal point is large in the reactive approach. Thus, a long-term proactive approach was chosen to optimize the entire lifetime of the developed cases while respecting the constraints.

- As seen the implementation of the optimizer in E300 to the cases was successful. The optimization resulted in improved objective function value and respected the constraints. However, it is important to choose reasonable control parameters. The following should be considered when setting up the optimization problem:
  - Try the wells bottom hole pressure as the first control parameters due to wells dynamic behavior during the simulation. However, the control mode of the wells should determine the control parameters if no response were obtained by pressure optimization.
  - Since choosing the proper control parameters can be challenging and time-consuming for large models, initially run a single iteration and simulation (OPTDIMS keyword). In this way, one may perform sensitivity analysis and parameters screening to see whether the model responds to the selected control parameters.
  - Output frequency is important to obtain more accurate gradients. The rule of thumb is to request output report between 1 and 6 months.
- In the optimization of the developed cases, we observed that the performance of all three cases is improved.
  - In case 1, quick decline in the oil production, large water production and quick drop in the average field pressure resulted in poor recovery. The NPV of the segment was improved by controlling the water injection and liquid production rate. The production constraint in the field was the break even water-cut value which was respected. The field pressure was maintained constant during the production. The water injection rate and liquid production rate decreased compared to the based case, which resulted in better sweep and lower water production. The reservoir volumes injected were higher than the amount of liquid produced. These volumes were generally lower in comparison to the base case. This resulted in improved pressure maintenance in the reservoir. The total oil production increased by 22%, total water production decreased by 50%, total injection decreased by 23% and the NPV of the segment increased by 93%.
  - In case 2, the production strategy in the base case resulted in poor oil recovery and quick decline of the field pressure. The final oil recovery in the base case was only 10 %. The objective in this problem was to maximize the total oil production from the segment. The available water injection rate was employed to increase oil production by improving the sweep and maintaining the reservoir pressure. The production constraint was to limit the water production in the field and it was honored. The oil production increased by 100%, which is twice the base case. The final oil recovery from the segment was 20%, a 10% improvement.
  - In case 3, there were two production wells and a bottom drive aquifer that supported the segment with pressure support. In this case, the challenge was the large water production in the wells. The NPV of the segment was improved by controlling the bottom hole pressure of the producers in order to reduce

water production. Production well 2 was completed further down, closer to the aquifer. Production well 2 had the worst performance in terms of water-production and was shut-in for a long time to give the additional production potential to well 1 that had better performance in terms of oil production. About 2000 days after production start, well 2 started to produce. This well produced for approximately 1000 days and well 1 was shut-in during this period. The oil production in the segment slightly decreased but the water production reduced by 23.4 %. The total NPV of the segment increased by 12.7%.

In the future work of this study, it is recommended to create a new fluid model when using the developed cases for further studies. Since the keyword SWOF was not imported correctly, a new fluid model was generated in Petrel. The new fluid model was created by introducing fluid data from the original Brugge field. After all optimization cases were developed and run, it was discovered that water relative permeability is extremely small (in the order of 10^{-8}) compared to "regular" values. This has likely affected the magnitude of the rates computed by the simulator. However, this error is constant for all simulation runs performed in this study, and thus, the relative validity of the optimization results is maintained. For this reason, it is recommended to create a new fluid model when using these cases in further studies.

One may also equip the wells in these cases with "Smart completions". These wells improve the reservoir management process and enable to control the zonal fluid flow by internal control valves (ICV's). This gives the opportunity to optimize the cases by steering the zonal injection and production rate. For example, in the Half-dome structure, the permeability contrast between Schelde formation (high permeable) and Waal formation (low permeable) is huge. The initial oil saturation in these formations is large and by optimizing the injection and production rates one may obtain stable fluid front and improve the sweep efficiency. This can be an interesting petroleum case study for research and educational purpose.

References

A. Satter, J.E. Varnon, M. H., 1994. Integrated reservoir management. Society of Petroleum Engineers (SPE-22350-PA).

Addiego-Guevara, E., Jackson, M. D., Giddins, M. A., et al., 2008. Insurance value of intelligent well technology against reservoir uncertainty. In: SPE Symposium on Improved Oil Recovery. Society of Petroleum Engineers.

Ahmed, T., 2010. In Reservoir Engineering Handbook (Fourth Edition),. Gulf Professional Publishing.

Asadollahi, M., 2012. Waterflooding optimization for improved reservoir management. Ph.D. thesis, Ph. D. thesisNTNU, Norway.

Asadollahi, M., Naevdal, G., 2009. Waterflooding optimization using gradient based methods. In: SPE/EAGE Reservoir Characterization & Simulation Conference.

Asadollahi, M., Naevdal, G., et al., 2010. Selection of decision variables for large-scale production optimization problems applied to brugge field. In: SPE Russian Oil and Gas Conference and Exhibition. Society of Petroleum Engineers.

Asheim, H., 1987. Optimal control of water drive. Society of Petroleum Engineers.

Asheim, H., 1988. Maximization of Water Sweep Efficiency by Controlling Production and Injection RatesPaper SPE 18365 presented at the 1988 European Petroleum Conference, London, United Kingdom, 16-19 October.

Asheim, H., et al., 1985. Numerical optimization of production schemes for reservoirs under pressure depletion.

Aziz, K., Settari, A., 1979a. Petroleum Reservoir Simulation. Applied Science Publishers, New York, NY.

Aziz, K., Settari, A., 1979b. Petroleum reservoir simulation. Chapman & Hall.

Brouwer, D. R., 2004. Dynamic water flood optimization with smart wells using optimal control theory. Ph.D. thesis, Delft Technical university.

Brouwer, D. R., Jansen, J. D., 2004. Dynamic Optimization of Waterflooding With Smart Wells Using Optimal Control Theory. SPE Journal 9 (4), 391–402, SPE 78278.

Chavent, G., Jaffre, J., 1986. Mathematical models and finite elements for reservoir simulation. North Holland.

Craft, B. C., Hawkins, M. F., Terry, R. E., 1991. Applied petroleum reservoir engineering. Prentice-Hall Englewood Cliffs, NJ.

Craig, F., 1977. Optimized recovery through continuing interdisciplinary cooperation. Journal of Petroleum Technology.

Craig, F. F., 1993. The reservoir engineering aspects of waterflooding. Society of Petroleum Engineers (978-0-89520-202-4).

Ebadi, F., Davies, D., 2006. Should proactive or reactive control be chosen for intelligent well management? Society of Petroleum EngineersSPE 99929.

Essley, 1965. What is reservoir engineering? society of petroleum engineers. doi:10.2118/920-pa. Journal of Petroleum Technology.

Fanchi, J. R., 2005. Principles of Applied Reservoir Simulation, 3rd Edition. Gulf Professional Publishing.

Fathi, Z., Ramirez, F. W., et al., 1984. Optimal injection policies for enhanced oil recovery: part 2-surfactant flooding. Society of Petroleum Engineers Journal 24 (03).

F.Dilib, M, J. A. K., 2013. Field production optimization using closed-loop direct feedback control of intelligent wells: Application to the brugge model. Society of Petroleum Engineers.

G.A. Carvajal, I. Boisvert (Halliburton), S. K. H., 2014. A smart flow for smartwells: Reactive and proactive modes.

Harris, Hewitt, 1977. Synergism in reservoir management the geologic perspective. Journal of Petroleum Technology.

Jansen, J. D., Brouwer, D. R., Naevdal, G., van Kruijsdiik, C. P. J. W., Jan. 2005. Closed-loop Reservoir Management. First Break 23, 43–48.

Jansen, J. D., Douma, S. D., Brouwer, D. R., Van den Hof, P. M. J., Bosgra, O. H., Heemink, A. W., 2009. Closed Loop Reservoir ManagementPaper SPE 119098 presented at the 2009 SPE Reservoir Simulation Symposium, The Woodlands, Texas, 2-4 February.

Kalyanmoy Deb, Amrit Pratap, T. M., 1993. Constrained Test Problems for Multi-objective Evolutionary Optimization.

Lorentzen, R. J., Shafieirad, A., Naevdal, G., et al., 2009. Closed loop reservoir management using the ensemble kalman filter and sequential quadratic programming. In: SPE Reservoir Simulation Symposium. Society of Petroleum Engineers.

Maghsoudi, B., 2015. Study of optimization routines for improved water flooding using eclipse optimizer module.

Muggeridge, A., Cockin, A., Webb, K., Frampton, H., Collins, I., Moulds, T., Salino, P., 2013. Recovery rates, enhanced oil recovery and technological limits. Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences.

Naevdal, G., J. L. M. A. S. I. . V. E. H., mar 2005. Reservoir monitoring and continuous model updating using ensemble kalman filter. Society of Petroleum Engineers.

Nocedal, J., Wright, S. J., 2006. Numerical Optimization. Springer, 2nd Edition.

Passaro, A., Starita, A., 2008. Particle swarm optimization for multimodal functions: A clustering approach,. Journal of Artificial Evolution and Applications.

Peaceman, D., 1977. Fundamentals of numerical reservoir simulationelsevier scientific.

Peaceman, D. W., Jun. 1978. Interpretation of Well-Block Pressures in Numerical Reservoir Simulation. SPE Journal 18 (3), 183–194, SPE 6893.

Peaceman., D. W., 1991. Fundamentals of Numerical Reservoir Simulation. Elsevier Science Inc., New York, NY, USA,.

Peters, L., Arts, R., Brouwer, G., Geel, C., Cullick, S., Lorentzen, R. J., Chen, Y., Dunlop, N., Vossepoel, F. C., Xu, R., et al., 2010. Results of the brugge benchmark study for flooding optimization and history matching. SPE Reservoir Evaluation & Engineering 13 (03), 391–405.

Rijswijk, S. I. E. A., 1996. A review of the adjoint-state method for computing the gradient of a functional with geophysical applications.

Sarma, P., Aziz, K., Durlofsky, L. J., 2005. Implementation of Adjoint Solution for Optimal Control of Smart Wells. In: Proceeding of the SPE Reservoir Simulation Symposium. Houston, TX, SPE 92864.

Sarma, P., Chen, W. H., 2008. Efficient Well Placement Optimization with Gradient-based Algorithm and Adjoint Models. In: Proceedings of the SPE Intelligent Energy Conference and Exhibition. Amsterdam, The Netherlands, SPE 112257.

Schlumberger, 2012a. ECLIPSE Reference Manual.

Schlumberger, 2012b. ECLIPSE Technical Description.

Sethi, S. P., 2006. Deterministic and stochastic optimization of a dynamic advertising model.

Steihaug, T., 1983. The conjugate gradient method and trust regions in large scale optimization. SIAM Journal on Numerical Analysis.

Stephens, F., 1960. Peripheral and line-drive water-injection projects. Society of Petroleum Engineers.

Stetter, H. J., 1973. Analysis of discretization methods for ordinary differential equations. Vol. 23. Berlin-Heidelberg-New York: Springer,.

Stratton, J., 2002. Overview: Smart wells. Journal of Petroleum Technology (SPE-0902-0062-JPT).

van Essen, G., Jansen, J.-D., Van den Hof, P., 2011. Hierarchical Long Term and Short Term Production Optimization. SPE Journal, 191–199.

Van Essen, G., Zandvliet, M., den Hof, P. V., Bosgra, O., Jansen, J.-D., 2009. Robust Waterflooding Optimization of Multiple Geological Scenarios. SPE Journal 14 (1).

Vanderplaats, G. N., 2007. Multidiscipline Design Optimization.

Vlemmix, S., Joosten, G. J., Brouwer, R., Jansen, J.-D., 2009. Adjoint-Based Well Trajectory Optimization. In: EUROPEC/EAGE Conference and Exhibition. Amsterdam, The Netherlands, SPE 121891.

Wang, C., Li, G., Reynolds, A. C., 2007. Optimal Well Placement for Production Optimization. In: Proceedings of the SPE Eastern Regional Meeting. Lexington, KY, SPE 111154.

Well-dynamics, 2011. intellignet completions.

Willhite, G Paul, G. D. W., 1998. Enhanced oil recovery; Henry L. Doherty Memorial Fund of AIME.

Yan Chen, D. S. O., 2010. Ensemble-based closed-loop optimization applied to brugge field. Society of Petroleum Engineers.

Yeten, B., Durlofsky, L. J., Aziz, K., 2003. Optimization of Nonconventional Well Type, Location, and Trajectory. SPE Journal 8 (9), 200–210, SPE 86880.

Yuqing Chang, Andreas S. Stordal, R. V., 2016. Integrated work flow of preserving facies realism in history matching: Application to the brugge field. Society of Petroleum Engineers.

Zandvliet, M., Handels, M., van Essen, G., Brouwer, R., Jansen, J.-D., Dec. 2008. Adjoint-based Well-placement Optimization under Production Constraints. SPE Journal 13 (4), 392–399, SPE 105797.

Zhang, K., Li, G., Reynolds, A. C., Yao, J., Zhang, L., Sep. 2010. Optimal Well Placement using an Adjoint Gradient. Journal of Petroleum Science and Engineering 73 (34), 220–226.

Appendix A

Appendix

A.1 Work-flow to design different optimization cases

Designing new cases for optimization is not a trivial task and takes several steps to finalize. As mentioned, the built-in optimizer of Eclipse is only implemented in the E300 version. The provided model, Brugge field is an E100 model must be converted into an E300 model to be compatible with the optimizer. The model was then imported and converted into a Petrel Re project in order to be able to carve-out the grid, design horizontal wells, and define new development strategies. The developed cases were then exported and optimized using Eclipse 300. In this chapter, the case development process and optimization workflow are presented.

A.1.1 Step 1: Model conversion from E100 to E300

The provided model for simulation was an E100 model. The aim is to make an Eclipse 300 model of Brugge field and create a Petrel project. E300 is capable of running in black oil *and* compositional mode. Many keywords in E100 is not supported in the E300 version. In the following, the conversion process is described step-wise.

- Running the E100 model in E300 simulator for debugging purpose
- 3 phases: Oil/Water/Gas must be specified - In the provided model there exist two phase: water and oil
- By specifying the third phase(gas), its PVT properties must also be specified in the ”PROPS” section. The PVT properties of the ”SPE Comparative Study 1” is used which is a three-phase model.
- For initialization of the pressure in the model, ”Values” in an include file for each cell were not accepted. Therefore, the keyword ”EQUIL” were used to initiate the

simulation. The input of EQUIL keyword is ”Datum depth”,”Datum pressure”, ”OWC depth”, ”OWC pcow”, ”GOC depth”, ”GOC PCOG” were approximately read from the original E100 model.

- In the original model, there exist no free gas and in such cases, Eclipse manual recommends to set the ”GOC depth” above the top of the reservoir.
- Some keywords are not supported in E300 simulator. These were either deactivated or changed. For example, summary output keywords such as WWPR, WWCT, WWIR etc were not supported, or PVCDO (Dead oil PVT properties). These particular keywords were defined in the ”old” PROPS section but were replaced.
- Since we only needed the Brugge field grid and its fluids in place, the original wells and simulation events (SCHEDULE section) were deactivated to simplify the model.

After these modifications, the model was running successfully in the Eclipse 300 model. In the table below, a summary of the modified keyword are listed:

Section in data file	Modification
RUNSPEC	Add FULLIMP, HWELLS
PROPS	Entire section changed
SOLUTION	EQUIL keyword and data added
SUMMRAY	Entire section from the E100 model deactivated
SCHEDULE	Entire section from the E100 model deactivated

After running the modified E300 model and comparing the initial conditions to the original Brugge field, the following were observed:

- An alteration of the initial oil saturation in the transition zone of the oil-water contact.
- A sharper transition zone is obtained. The crossing between oil and water zone is occurring very rapidly without a ”transition” as observed in Brugge field.
- Oil saturation has a constant value of 0.88 throughout the oil zone.
- The number of active cell properties has decreased. E100 model has 44,550 active cells but the E300 model has ”shrunk” and have 31,662 active cells

Even though the model is modified, it is a sufficient approach for the purpose of optimization. This is due to comparing the optimized results with a base case originating from the same model.

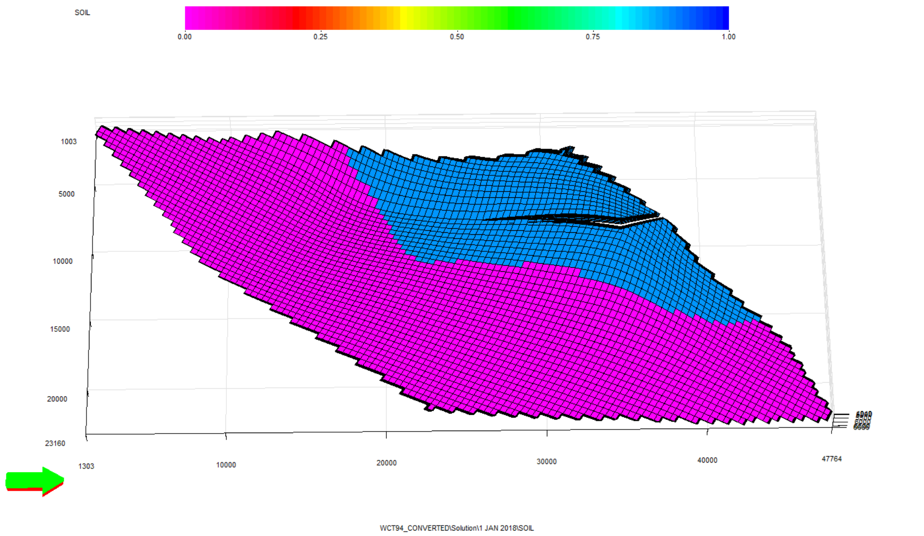


Figure A.1: Initial oil saturation per 1. Jan 2018 in the modified E300 model.

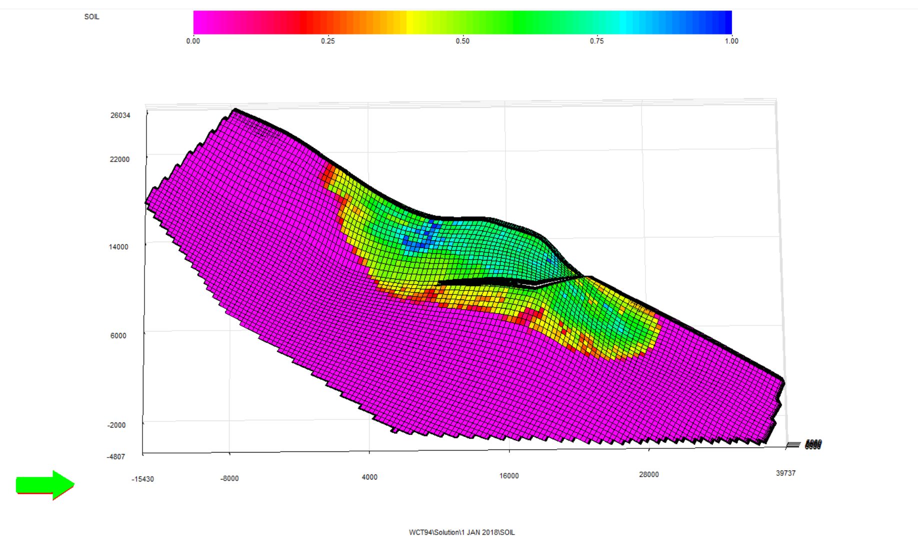


Figure A.2: Initial oil saturation per 1. Jan 2018 in the provided E100 model.

A.1.2 Step 2: E300 Eclipse deck conversion to a Petrel project

After successfully running the modified Brugge model in Eclipse 300, it had to be converted into a Petrel project in order to be able to develop cases. The case development is considerably more convenient in Petrel due to its graphical user interface. The process of converting the Eclipse deck to a Petrel project is not a click-and-convert process. The following steps were taken to create a Petrel project:

1. Run the Eclipse 300 model to get the simulation output results (INIT file is necessary for initialization of the Petrel project).

2. Import simulation data such as .DATA,. INIT, .GRID files. Make sure the ACTNUM property is generated. Go to ”simulation” tab →, ”import” and in this window, untick ”Automate handling of import setting” → ”Advance” → tick ”Using ACTNUM in the grid file”. See Figure A.3

3. Convert the project to a Petrel case - Pop-outs appears: Change the coordinate system in the Petrel project (otherwise import fails), choose OK for grid orientation.

4. Run simulation of imported case, define simulation case, → press Run, → simulation errors appears in the log.

5. The errors were fixed by comparing the original data file with the converted project. In Petrel, right click on the converted case, choose ”Editor” and compare to the Eclipse data file. The data for following keywords were not imported correctly: NOGGF, WELLDIMS, OIL, TABDIMS, SWOF. It’s more systematic to have the same keywords order in the editor window.

6. Since the keyword SWOF was not imported correctly, a new fluid model was created in Petrel. The new fluid model was created by introducing fluid data from the original Brugge field. After all optimization cases were developed and run, it was discovered that water relative permeability values are extremely small (in the order of 10^{-8}) compared to ”regular” values. This has likely affected the magnitude of the rates computed by the simulator. However, this error is constant for all simulation runs performed in this study, and thus, the relative validity of the optimization results is maintained. For this reason, it is recommended to create a new fluid model when using these cases in further studies.

7. After successfully running the converted project from the Petrel platform, load the results from the Eclipse deck and Petrel project. Comparing the results such as injection and production rates, the cumulative production gives a good indication of the success of model conversion. This is one way to ensure the validity of the model as well.

A.1.3 Step 3: Case development

The procedure of case development in Petrel RE will be introduced in this section. Various cases were carved-out from different regions of the Brugge field. New wells were constructed and for each case, a development strategy was defined. In one of the cases, an aquifer was introduced.

This section introduces the step-by-step method to perform these modifications and develop the cases.

Carving Brugge field into new reservoir shape

- Make a copy of 'ACTNUM from grid file' property: new property 'ACTNUM from grid file - Case 1'.
- Make a visual filter that can be will be used for carving.
  1. Go to "Model pane" → right click on "properties" → "filter" → mark "Index filter" and choose the coordinates of the desired part of the field → "Apply".
  2. Mark "invert total filter" - selecting the blocks to be inactive. See Figure A.4.
- Right click on the copy of the Actnum property → choose "Calculator".
- Choose "General discrete" or "Boolean" template.
- Mark "Use filter" → choose the Actnum property from the variables and set it equal to zero. See Figure A.5
- Return to "Properties" in the model pane. Un-mark "Invert total filter" and only active cells are visible. See Figure A.6
- Make a new simulation case and right click on that case → "Define simulation case" and add a new row for "Active cell flag [ACTNUM]". The simulation will only take into account active cells defined in the new ACTNUM property.

Designing new well trajectory and completion

There are several methods to construct new well trajectories in Petrel. One of the most common and simple work-flows is the following:

- Choose 'Well Engineering' pane → under the 'Well path' choose 'Digitize Well'
- Choose 'Add design points'
- Use the 'Property Player' to explore layers
- Create wells by clicking on the desired cells
- To create well completions → choose 'Automated design/Well completion design'
- Operation: 'Create simple completions'
- Select and introduce well in 'Wells'
- 'Create casing: Whole well' marked in gray

- ’Create perforations: Whole well’
- press ’Run’

Manual aquifer design in Eclipse

In Case 3, an aquifer was defined in order to offer pressure support in the segment. The following workflow is applied:

- Identify a water zone.
- Define a ”Box” for the water zone in the ”Grid” section.
- Use the pore volume multiplier keyword ”MULTPV” and increase the pore volume of the box by a factor a multiplier. This leads to increased water encroachment during the production and acts as an aquifer in the segment.

```
Aquifer design example:
Define box - The grid numbers
I = 96 - 113
J = 21 - 22
k = 8 - 9

In ”grid” section in data file:
Grid
BOX
i1 - i2, j1 - j2, k1 - k2
96 113 21 22 8 9
- -72 cells

MULTPV
72*1E3
```

Schedule setup / Development strategy

- Under the ”Well Engineering” pane choose ”Development strategy”
- Insert wells into ’Wells folder’
- Setup group: ’Groups folder/Field/Group 1’
- Add rules for injection wells/ production wells and limits

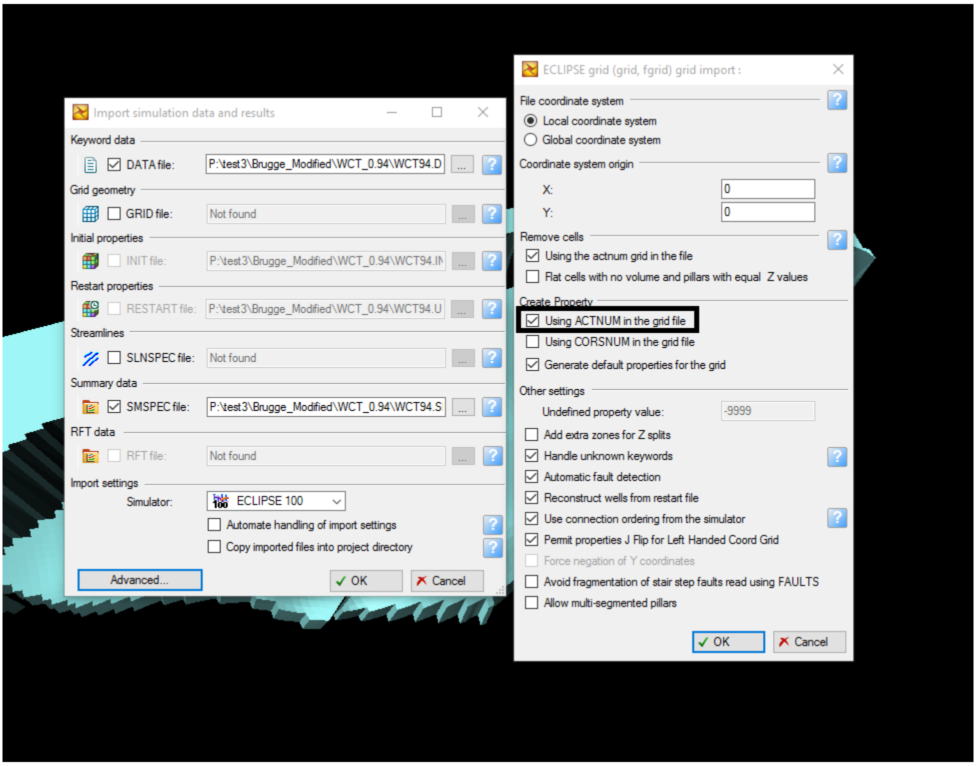


Figure A.3: Tick on "Using ACTNUM in the grid file" in order to create a property for active cells in the grid.

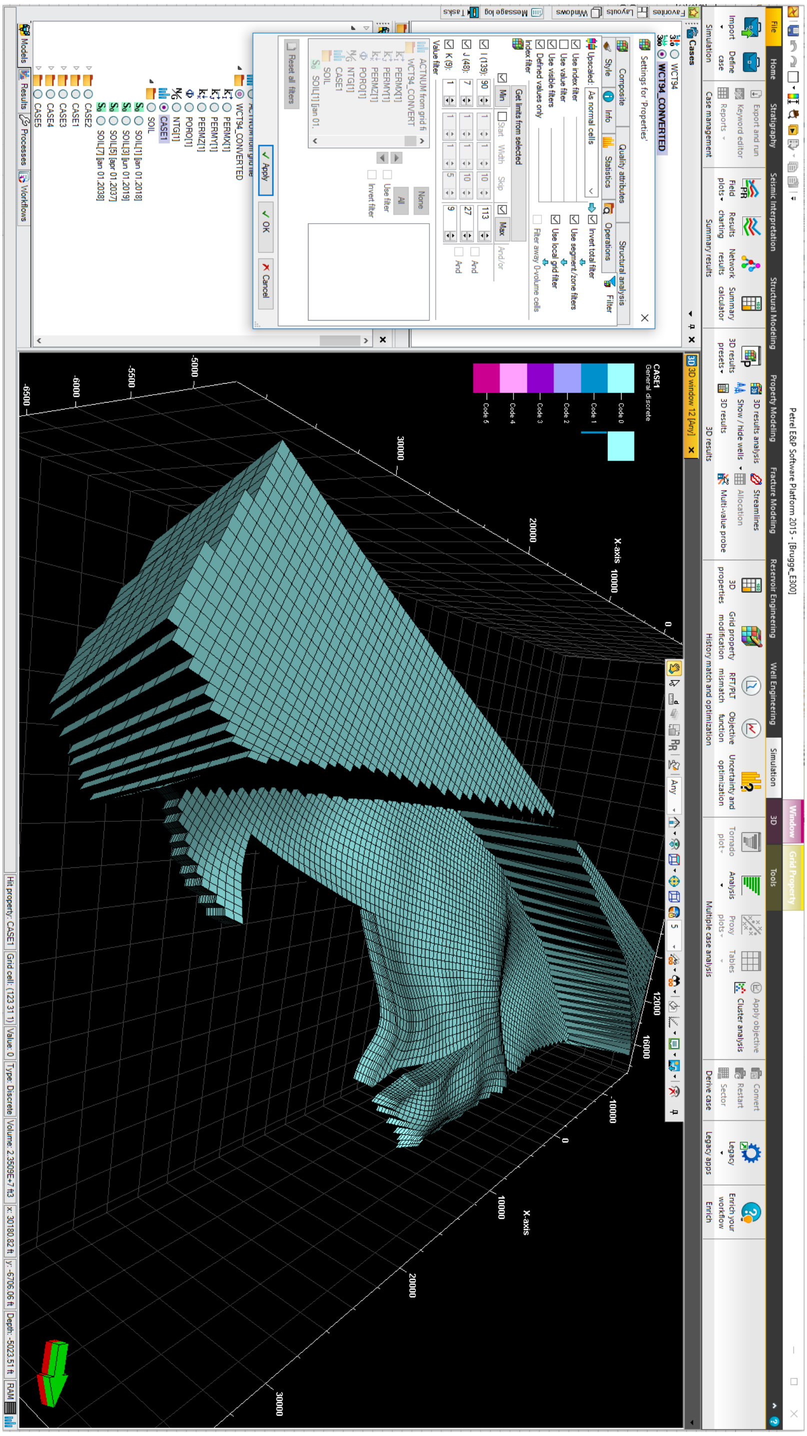


Figure A.4: The figure shows the cells that are set to be inactive. This is only a visual filter. This filter is used in the calculator for deactivating the cells.

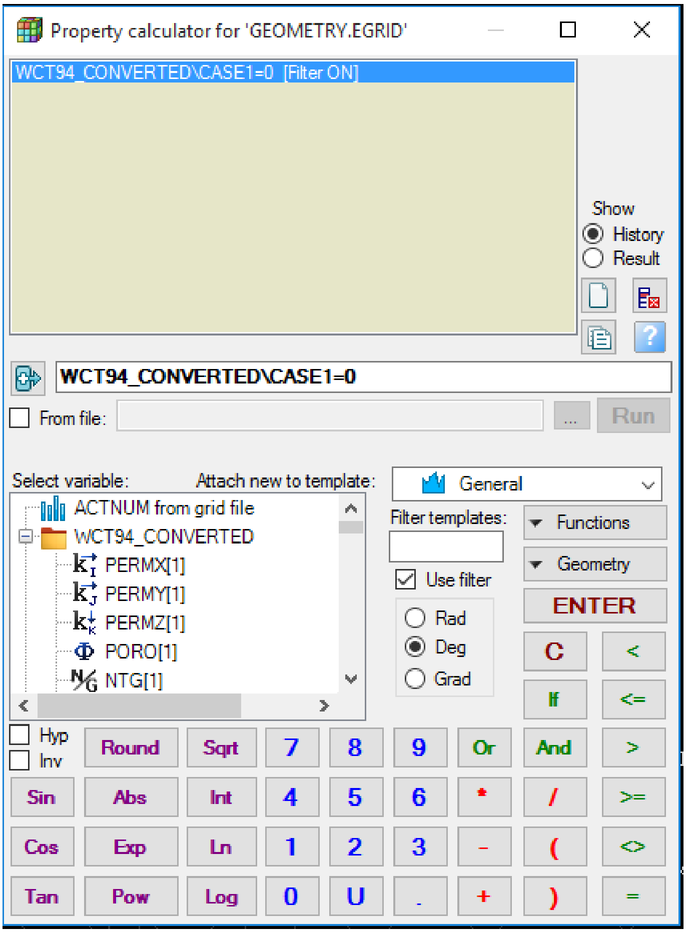


Figure A.5: The calculator is used to deactivate the cells. The new ACTNUM value is set equal to 0 with the filter on. This method deactivates the grid cells that are visualized in Figure A.4. The non-visualized cells remains active.

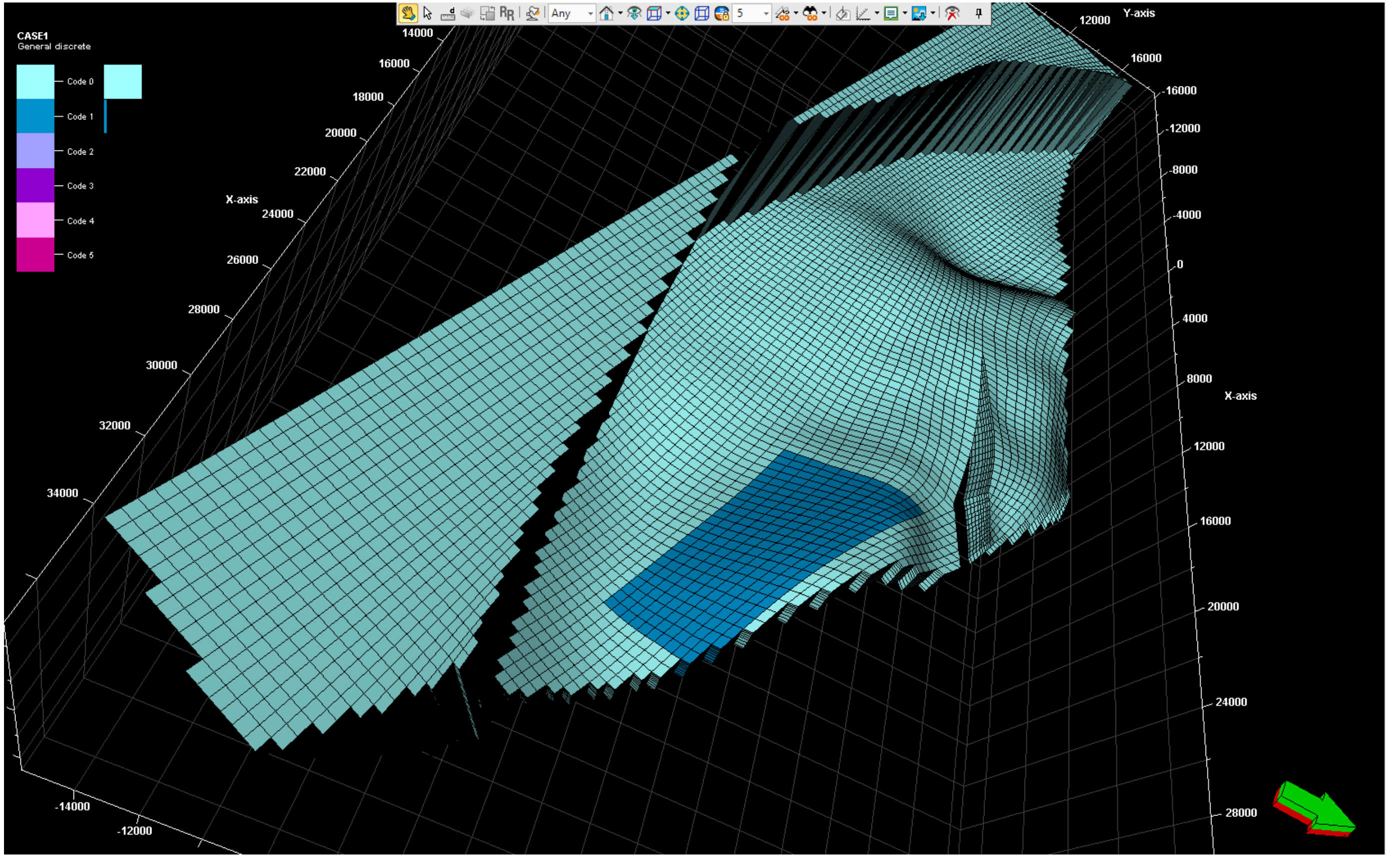


Figure A.6: The active cells are marked with the dark green on the grid.

A.1.4 Step 4: Optimization

The developed cases for production optimization were exported from Petrel Re. These cases were exported for defining the optimization problem manually in the data file. The procedure to define an optimization problem and considerations for improved optimization performance is described in Appendix A.2.

In this part, we will implement the optimization problem of the Half-dome structure - Production strategy 1 that was defined in Subsection 4.1.1.

’OPTIMIZE’ section is a distinct section and not a part of the ”Schedule” section. The ’Optimize’ section is initiated by the keyword ’RESOPT’ in the ’RUNSPEC’ section. The data in the optimize section is defined by particular keywords as seen in the example below. In the example on the next page, the optimization problem of the Half-dome structure - Production strategy 1 is defined. This problem contains one horizontal injector and one horizontal producer. The objective of this optimization problem was to maximize the NPV of the segment. This section is started with specifying the report output of the reservoir optimization results which is requested to be separated. ’SEPARATE’ option output separates summary and restart files for each optimization iteration. The next mnemonic is ’OPTUNE’ which is used to specify optimization tuning parameters. This keyword defines the values such as the initial constraint tolerance, the constraint tolerance, and objective function convergence tolerance. ’OPTFUNC’ is used to specify the objective function of the optimization problem. In the optimization problem defined in the next page, the objective function is NPV with the economic values of 50 $/stb for oil, and the cost of water production 5 $/stb and water injection is 5 $/stb. These values are specified as the weighting coefficient of each parameter. ’OPTDIMS’ defines the optimization dimensions as mean of the maximum number of iterations and the maximum number of simulations permitted to find the optimum point. In this case, the maximum number of iterations is 20 and the maximum number of simulations are 100. The production constraints is defined by the keyword ’OPTCONS’. In this case, the constraint is the break-even water-cut of the field and this value should not exceed the value of 0.91. In the end, the control parameters of the optimization problem are defined by the keyword ’OPTPARS’. The control parameters, in this case are the well liquid production rate for the producer and the well water injection rate in the injector. The available range for rate variations is between 0-20,000 stb/d.

```
------------------------------------------------

OPTIMIZE

------------------------------------------------


RPTOPT                     -- Optimization report output

'SEPARATE' /

OPTTUNE                    -- Optimization tuning

0.05 1* 20 /


OPTFUNC                    -- To specify the objective function: NPV = FOPT*50-FWPT*5-FWIT*5

-- O.F.              O.F.              Weighting
-- Component         Domain             Coefficient

   FOPT              Field                 50/
   FWPT              Field                 -5/
   FWIT              Field                 -5/

/


OPTDIMS                                  -- Optimization dimensions

-- Max no.           Max no.
-- Iterations        Simulations

   20                  100 /

/

OPTCONS                                  -- To specify the production constraints

-- Constraint        Constraint        Constraint    Value
-- Mnemonic           Domain             Type

  FWCT                 Field              '<'          0.91 /

/

OPTPARS                                    -- To specify the control parameters

-- Parameter       Parameter       Lower     Upper
-- Mnemonic       Domain          Limit      Limit

    WLPR        HD1_PROD        0          20000/   -- Producer
    WWIR        HD1_INJ          0          20000/   -- Injector
```

A.2 How to use the built-in optimizer in Eclipse simulator for production optimization?

The optimization facility in Eclipse 300 is controlled by keywords in the ”OPTIMIZE” section. This is initiated by ”RESOPT” in the ”RUNSPEC” section of the data file. ”RESOPT” activates the ”OPTIMIZE” section of a data-set where the objective function, parameters and constraints related to the optimization task is specified.

There are several keywords for defining the optimization problem. The objective function is specified using the ”OPTFUNC” keyword. The domain for optimization can be the field, group or well scale. The control parameters are defined using the keyword ”OPTPARS”. The available control parameters in reservoir optimization problems are well bottom hole pressures, liquid production rates, or liquid injection rates, or segment cross-sectional area. The constraints, that are the limitation in the optimization problem are specified using the keyword ”OPTCONS”. The oil, water, gas production rates, water and gas injection rates, water-cuts and gas oil ratio can for example be chosen as the constraints.

There are also other keywords such as ”OPTDIMS” to specify parameters the dimension of the optimization(the maximum number of iterations, and simulation), and ”OPTTUNE” where the tuning of the optimization problem (tolerances) is defined. After defining the objective function, specifying the control variables and the constraints on these variables, the file is ready to run. The output file is written for each iteration of the optimization procedure and contains the following:

- Objective function value
- Parameters values
- Constraint values
- A list of search direction which are currently active
- Optimizer search direction
- Line search details

There are some considerations to be made during an optimization problem. The model should be compatible with the optimization facility in Eclipse 300, meaning that it should be fully implicit, and should have a frequent reporting step output. The features that may not be included is

- Parallel optimization
- fast restarts
- Local grid refinement
- Grid coarsening
- Sector model

- Thermal option
- AIM, IMPES, IMPSAT formulations
- Well control keywords against the optimizer ACTION, WECON, CECON
- Optimization should be started from feasible region

As the number of variables in the objective function large, the most proper way to find the gradients is using the adjoint method. The adjoint method uses the report steps to calculate the required gradients in Eclipse thus choosing report steps too far from each will reduce the accuracy, and should be avoided (Schlumberger, 2012b). Therefore, there should be a reasonable frequent output and the optimization should start from a feasible region. In the optimizer facility of E300, two search direction methods are available, steepest descent method and conjugate gradient method. The default option in the optimizer is the steepest descent method, but can be modified by the "OPTOPT" keyword. The steepest descent method uses the first derivatives in the current iteration to determine the search direction. The advantage of this search method is the lower computational memory. Conjugate gradient method also uses the first derivative, but the information is used from the current and previous iteration to determine the search direction. The advantage of this method is that it might perform faster than the steepest descent method. However conjugate gradient method performs slightly faster than the steepest descent method, the performance of both methods depends strongly on choosing a proper initial guess.

The study done by Asadollahi and Naevdal (2009) concluded that however conjugate gradient method performs slightly faster than the steepest descent method, the performance of both methods depends strongly on choosing a proper initial guess. However, an efficient general procedure for finding a good initial guess is missing, the initial guess is usually a common sense one. For example, optimizing the NPV with considerably higher oil price compared to the water production and injection rates and a substantial discount rate, one may choose to operate the wells on maximum allowed rate while respecting the pressure constraints. This is a reasonable strategy as the production of the maximum amount of oil may already yield a reasonably high NPV.

In Schlumberger (2012b), it is recommended that from the available control parameters, the bottom hole pressures should be tried first in production optimization problems. This is due to the insensitivity of production rates to well target rates whenever the wells fall into the bottom hole pressure control. Asadollahi and Naevdal (2009) applied bottom hole pressures as the control parameters in their optimization problem but could not observe any improvements after several iterations. Improvements were observed first when the optimization parameters were changed from BHP to the well liquid rates.

The reason was that most of the wells in their model (Brugge field) were under liquid control thus these variables should be chosen as the control parameters to maximize the objective function. It can be concluded that not always using the BHP as the control parameter may yield optimum results. Since choosing the proper control parameters can be challenging and time-consuming for large models, initially run a single iteration and simulation (OPTDIMS keyword). In this way, one may perform sensitivity analysis and parameters screening to see whether the model responds to the selected control parameters. By choosing realistic parameter bounds for the optimization, one may prevent unphysical and unacceptable values and also prevent the simulator from entering tricky convergence regions. It is also important to set a reasonable optimizer tolerance, if the default option is not used. (Maghsoudi, 2015)