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Daily production optimization of gas-lifted oil field with MPC framework

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Summary:

The continuous increase in energy demand requires alternative solutions and sustainable energy production from the existing sources. Thus, the existing mature oil fields require optimization and gas injection is one option for enhancing the reservoir's productivity.

A steady-state model within a Model Predictive Control structure for daily production optimization in gas-lifted oil fields has been developed to optimize the production from mature oil fields. The model is integrated with a dynamic reservoir. The reservoir model is based on the multiphase flow and dynamic pressure within the reservoir. Simulations were performed to study the uncertainty parameters such as reservoir pressure, productivity index (PI), and water cut (WC).

Two different reservoir models were considered for the DPO from the gas-lifted oil reservoir. A modified "Egg Model" and the SPE9 benchmark model were used to study the performance of well in terms of well. These two models were simulated with and without optimization. A constant gas lift rate is supplied for the non-optimized case. The simulation showed a dynamic gas injection rate is required to optimize the production process for both reservoir models.

The study further reveals that the effectiveness of the optimization strategy is influenced by the reservoir's geological characteristics and heterogeneity. The Egg model showed a more pronounced response to optimization compared to the SPE9 model due to its relatively homogeneous channelized structure. The developed model was able to optimize the production outcomes in the gas-lifted reservoirs.

Preface

This thesis is submitted as a partial fulfillment of the requirements for the master's degree program in Industrial IT and Automation at the University of South-Eastern Norway (USN), Porsgrunn. The research presented in this master thesis was a part of the DigiWell project, funded by The Norwegian Research Council, Equinor ASA, SINTEF, and USN. This thesis aims to develop a novel model to optimize daily production in gas-lifted oil fields. The model incorporates a robust model predictive control framework to address the inherent uncertainties in reservoir behavior.

I extend my heartfelt gratitude to my supervisor, Associate Professor Roshan Sharma, and co-supervisor Stein Krogstad, for their invaluable guidance, support, and insightful discussions throughout this research process. I am also grateful to all the individuals and organizations involved in the DigiWell project for providing me with this enriching opportunity to contribute to this research. The experience that I gained during this thesis work has been paramount, and I am confident that the knowledge and skills acquired will serve me well in my future endeavors.

Special thanks to my brother, Ramesh Timsina, for his constant support, guidance, and encouragement throughout my academic journey. Further, I would like to express my sincere gratitude to my family for their unconditional support, love, and encouragement. I am grateful to my friends and colleagues for their constant support throughout this journey.

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Mahesh Timsina

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Nomenclature

BHP	Bottom Hole Pressure
DPO	Daily Production Optimization
ESC	Extremum Seeking Control
ESP	Electric Submersible Pump
GOR	Gas to Oil Ratio
IEA	International Energy Agency
MATLAB	MATrix LABoratory
MPC	Model Predictive Control
NMPC	Non-linear Model Predictive Control
PI	Productivity Index
ROPA	Real-time Optimization with Persistent Adaptation
RTO	Real-Time Optimization
SOC	Self-Optimizing Control
TES	Total Energy Supply
USN	University of South-Eastern Norway
WC	Water Cut
WHP	Well Head Pressure

1 Introduction

1.1 Background

In today's ever-evolving energy landscape, efficient oil extraction remains paramount for ensuring global energy security. As a primary energy source, oil plays a fundamental role in fueling economies worldwide. Its extraction and refining processes are intricate and multifaceted, demanding meticulous planning and management to optimize the resource utilization [1].

According to the International Energy Agency (IEA) [2], the Total Energy Supply (TES) worldwide from 1990 to 2021 has been primarily based on oil, as illustrated in Figure 1-1. The figure shows approximately one-third of the total energy supply is attributed to oil. This statistic underscores the enduring significance of oil in meeting global energy demands. Considering this substantial contribution to the energy supply, it is evident that oil will continue to wield considerable influence in the world's energy landscape in the foreseeable future.

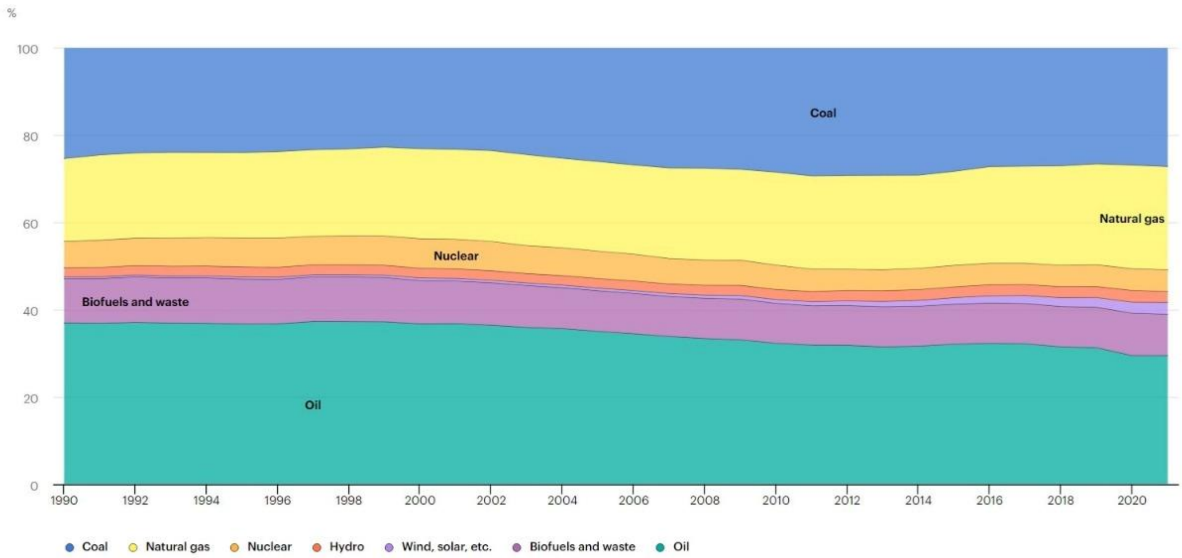


Figure 1-1: Total energy supply by source of the world from 1990 – 2021 [2]

As the energy demand continues to surge, oil production processes will require continuous optimization. Further, growing environmental concerns and finite resources make the oil and gas extraction process an overwhelmingly challenging task. Oil production rates gradually decline with an increase in production timeline. These fields are often called mature oil fields. Artificial gas is injected to improve the production from these mature or depleting oil fields. The injected gas reduces the density of the produced fluid which lowers the bottom hole pressure and increases the production flow rates.

Optimization of any process involves the most effective utilization of a resource. Optimization enhances productivity, minimizes operational costs, and contributes to minimizing environmental impacts. This ensures a long-term viability of oil production operations [3]. The optimization of oil and gas production involves different mathematical models and data-driven algorithms. The optimization of oil and gas production process involves reservoir management and well drilling to surface facility operations. These challenges associated in these different aspects of oil production can be studied and overcome with an optimized simulation model. These models can be fine-tuned to achieve optimal performance while adhering to safety and environmental standards [4].

The current study focuses on optimization of the gas lifted reservoir. The optimization of gas lifted systems presents some challenges. For example, excessive gas injection can lead to increased friction and reduced oil production. Therefore, an optimal gas injection rate for each well is crucial to maximizing production efficiency while minimizing operational costs. Additionally, real-world gas-lifted oil fields often operate under uncertainties such as reservoir variability and measurement errors. These uncertainties can significantly impact the optimal operating point, making it challenging to achieve maximum production solely based on deterministic optimization model. There are different optimization techniques available in the literature and they have resulted in better technology. These advancements have created different state-of-the-art techniques such as machine learning [5], model predictive control and real-time optimization (RTO) to address the complex challenges associated in oil and gas production [6, 7]. These technologies are being used for optimization, reservoir management, and process control [8].

Oil and gas production processes are complex that require decision-making within a certain time scale. A multi-level control hierarchy is used to make this decision-making simpler as shown in the Figure 1-2 [9]. This is like a team of experts that work together focusing on a specific task. This includes:

- **Asset management:** This team makes long-term decisions for investment and running of an entire oil field.

- **Reservoir management:** This team focuses on a particular oil field and its optimization to get the most oil out over a longer period of time.

- **Production optimization:** This is also known as real time optimization. RTO uses real-time data and models to assist in daily or hourly decision-making. For example, RTO can be used to evaluate the gas injection rates into wells [10, 11].

- **Control and automation:** This team deals with the equipment and systems that directly control the wells and facilities. These are automatic decisions based on a control algorithm and require only a few minutes to seconds to make the decisions.

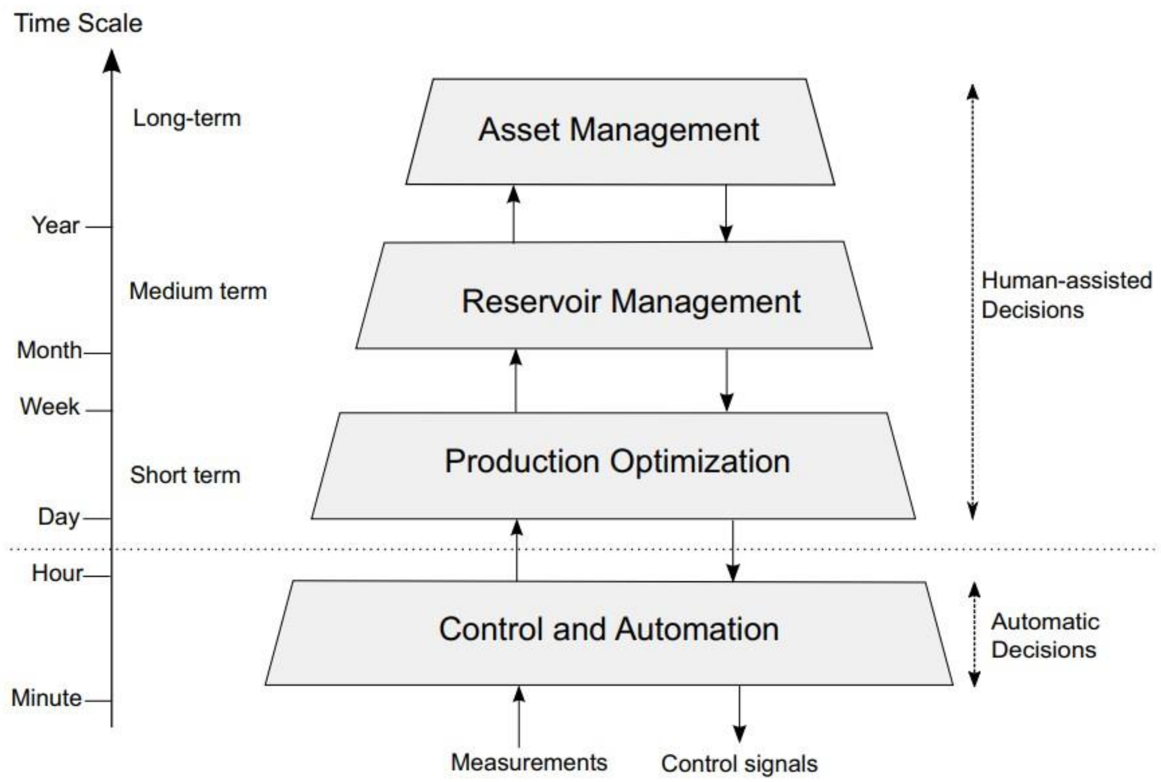


Figure 1-2. Typical multilevel control hierarchy in oil and gas operations [12]

This study focuses on RTO as this is crucial for decision making to get the most out of the gas lift production process. The gas lift rate can be adjusted based on current conditions to maximize oil production and minimize costs with RTO algorithm.

1.2 Previous works

The gas lifted oil field have been studied extensively by developing a mathematical model [13]. These models are based on the mass conservation principles within the well tubing and annulus region. However, these models often simplify complex real-world scenarios which may lead to potential inaccuracies and suboptimal solutions. Most of the models are often based only on steady-state (static models) optimization with simplified linear models, neglecting the dynamic behaviors which is highly critical to gas-lift systems [14, 15]. These models are based on limited set of parameters such as gas-to-oil ratio without considering the most important factors such as water cut and dynamic reservoir pressure [16]. This exclusion can lead to unrealistic results that are not applicable to the dynamic and uncertain nature of real-world gas-lift operations.

Recent research studies have developed mathematical model that are based on dynamic programming [16], piecewise linear formulation, and computational analysis [17]. However, a notable gap remains in robust procedures for addressing constrained optimization problems such as uncertainty, system dynamics, etc. Thus, daily production optimization have been implemented to incorporate uncertainty into the model [18, 19]. These models explicitly address short-term uncertainties while ensuring the efficient use of computational resources.

The optimization of offshore oil and gas production networks poses significant challenges [20]. Recent research and developments have developed various mathematical tools for easy decision-making in gas lifted reservoirs. However, these models are based on steady state models without taking consideration of uncertainties such as water cut, reservoir pressure and PI. These literature models do not have incorporates a reservoir model. Therefore, this study is based on the DPO with an incorporation of water cut, dynamic reservoir pressure and productivity index. This study also incorporates reservoir models for gas lifted production process. The research objective is presented in chapter 1.3.

1.3 Objective

This master thesis aims to fill a remaining gap by developing a steady-state optimization framework for gas-lifted systems that explicitly incorporates uncertainty. This approach helps to achieve computational efficiency while maintaining the realism afforded by direct reservoir coupling. The selected approach provides a balance between computational efficiency and model accuracy, leading to more effective and robust decision-making in the operation of gas-lifted oil fields. The lists of objectives are presented as follows:

1. Literature review on daily production optimization for gas lifted oil field.
2. Daily production optimization using MPC for gas lifted oil field.
3. Coupled the gas lifted oil field model against a more sophisticated reservoir model that represents the real process.
4. Perform a comprehensive review of the two different reservoir models namely ‘Egg model’ and ‘SPE9 model’ in steady state.
5. Analyze the comparison between with and without standard DPO for all the models. Study the key uncertainties parameters such as productivity index, water cut, and reservoir pressure for the two models.

1.4 Outline of thesis

The flow chart below gives an overview of the different chapters and how that information is used in subsequent sections to perform the tasks to fulfill the objectives.

Literature review: This section provides a comprehensive overview of existing research on gas-lift optimization, highlighting the challenges and opportunities in the field.

Model description and development: This section gives detailed development of a coupled well-reservoir model for gas-lifted systems, incorporating dynamic reservoir pressure and multiphase flow dynamics. This chapter also introduces the optimization framework and algorithm used in this study.

Case study: This section presents the two reservoir models ("Egg" and SPE9) that are used in simulations. Also, it provides the details of the simulation setup in the study.

Results and discussion: This section presents the results from the simulations. The two models were simulated to analyze the impact of varying simulation step sizes, prediction horizons, and optimization strategies on production outcomes.

Conclusion and future work: This section summarizes the key findings of this research, discusses their implications, and outlines potential directions for future research in gas-lift optimization scope.

2 Literature review

This chapter gives an overview of gas lift in an oil and gas production process, uncertainties associated with gas lifted process, different modelling approaches, and the optimization under these uncertainties for a gas lift technology.

2.1 Gas lift in oil and gas production

Gas lift is a commonly used method in many oil wells when the natural pressure in the reservoir is not enough to drive the reservoir fluids up to the production manifold. This artificial lift technique involves injecting compressed gas into the well to reduce the density of the fluid mixture. A typical gas-lifted oil field comprises numerous oil wells drawing lift gas from a common compressor. A gas lift choke valve and the gas metering in each gas injection well regulate the gas flow rate into the reservoir. Figure 2-1 shows a typical gas lift arrangement in an offshore oil production process. The lift gas enters the annulus of the well, which is the space between tubing and casing. Further, the lift gas enters the reservoir via the tubing section of the injection well.

The injection of gas into the reservoir has the following effects on the well [21]:

- **Aeration:** The injected gas is mixed with the produced fluids such as oil, water, and naturally occurring gas) which lowers their overall density. This reduces the hydrostatic pressure within the tubing which enhances production.
- **Gas expansion:** The lift gas tends to rise and expand inside the reservoir. This will further push the fluid above it which decreases the bottom-hole pressure.
- **Slug formation:** The lift gas is injected at a slower rate. Thus, the injected gas accumulates until pressure is sufficient to suddenly open the injection valve. This creates large gas bubbles that push a "slug" of liquid towards the production manifold.

Therefore, the gas injection makes a favorable process condition to increase oil production. The gas injection decreases the bottom-hole pressure which creates a higher-pressure difference between the reservoir and the production manifold. This differential pressure drives the reservoir fluid to the surface. However, excessive gas injection can cause more friction and slow down the production rate. Therefore, finding the right amount of gas to inject into each well is very important to optimize oil production while making sure too much gas is not used or exceeds production limits [22].

Orifice venturi valves are the common types of valves used for gas injection. These valves maintain a consistent gas injection rate regardless of tubing pressure fluctuations. The constant gas injection is crucial for preventing instability in the production process.

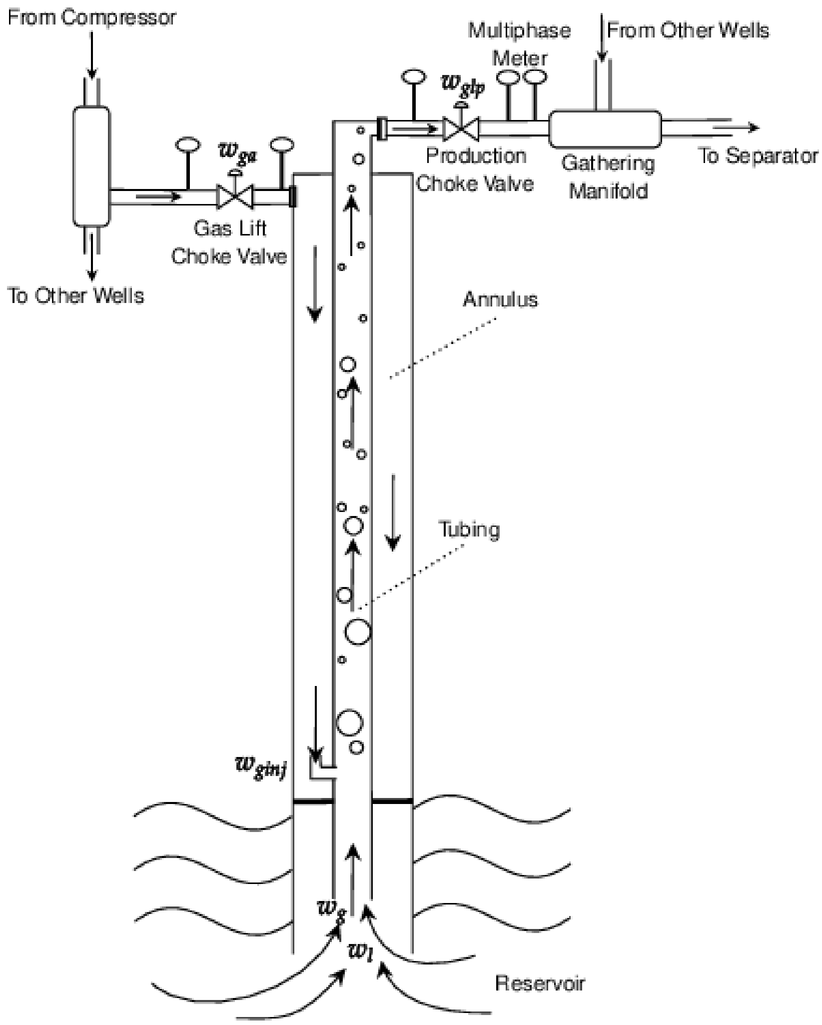


Figure 2-1: Schematic diagram of a single gas-lifted oil field

2.2 Uncertainty in gas-lifted oil fields

Uncertainty is an inherent characteristic of oil and gas production systems, that impacts optimal decision-making. Various uncertainties in a gas-lifted oil field are summarized below [23]:

- **Reservoir dynamics:** Reservoir pressure plays a vital role in the production process. Reservoir pressure depletion or fluctuations occur due to geological factors, production lifetime, etc.
- **Multiphase flow:** The simultaneous flow of oil, gas, and water within the wellbore introduces uncertainties related to phase behavior and flow patterns. The gas-to-oil ratio and water cut can vary over time.
- **Production parameters:** The productivity index is the measure of the well's ability to produce fluids. The PI can change due to factors like reservoir depletion or wellbore deposits. Uncertainty in productivity index estimation will give incorrect results.
- **Operational factors:** Different uncertainties related to operation include measurement noise, equipment inaccuracies, and unforeseen process disturbances.

Recognition of these uncertainties on gas-lift optimization process is crucial. The model developed for this study acknowledges these uncertainties such as dynamic reservoir pressure, water cut, and PI. This enhances the reliability and applicability of these mathematical models in solving real-world cases.

2.3 Modelling approaches

Uncertainties are inherent to gas-lifted oil fields is a challenge while developing a model to simulate the oil and gas production processes. These uncertainties include variations in reservoir pressure, multiphase flow behavior (GOR, WC), productivity index, and operational factors. Steady-state models offer efficiency; however, these simplified models may not fully capture reservoir complexities. Dynamic models offer high accuracy; however, these models often suffer from computational burdens particularly when uncertainties are involved. Self-optimizing control (SOC) and extremum-seeking control (ESC) have emerged as promising adaptive approaches, yet challenges remain in identifying suitable controlled variables and guaranteeing stability.

The different modelling optimization techniques available in the literature are summarized below:

2.3.1 Steady-state optimization

Steady state optimization technique optimizes the system's steady state operating point. This offers higher computational efficiency and makes it easy for real-time decision making. Steady state model relies on simplified models that can incorporate multiple phases (gas, oil, water, and solid particulates) encountered in oil production wells. This model can be combined with dynamic modeling in a hierarchical strategy [24]. Steady-state models, together with parameter estimation techniques, can further enhance the accuracy of real-time optimization [25].

In practical oilfield operations, it's essential to incorporate constraints beyond traditional process variables. Short-term production optimization should consider flow assurance constraints to prevent issues detrimental to operations. Additionally, the ability to accommodate different artificial lift methods, such as gas-lift systems with multiple valves, electric submersible pumps, or even dual completion, is crucial for maximizing production gains [26].

To address the challenges of real-time optimization, various strategies have been explored. One approach, "Hybrid RTO," combines dynamic models for parameter adaptation and steady-state models for computationally efficient optimization [27]. This allows the system to respond quickly to changing conditions while maintaining a focus on optimizing the steady-state operating point.

2.3.2 Dynamic optimization

Dynamic state optimization refers to the calculation based on the dynamic reservoir and well-state variables [28]. The optimized dynamic models give a detailed behavior of the real-world production process. Different advanced techniques directly couple reservoir simulators improve the accuracy of the dynamic simulators. Furthermore, mesh refining sequential methods accelerate convergence and improve the results quality within the dynamic optimization framework. These dynamic models together with multi-objective optimization results in oil production maximization against minimizing gas injection [29].

2.3.3 Self-optimizing control

Self-Optimizing Control automatically adapts to changing conditions, potentially offering robustness against uncertainty. The key idea is to identify a set of controlled variables (e.g., gas lift injection rates) and measured variables (e.g., production rates) that correlate with an economic objective function. The SOC algorithm iteratively adjusts the controlled variables to maintain the system near its optimal operating point, even under changing conditions [30]. This approach has a wide range of applications, demonstrated in areas as diverse as marathon running and economic optimization [31].

A significant challenge in designing SOC structures lies in identifying suitable controlled variables. Different methods such as brute-force approaches, local methods based on linearization, data-driven techniques, and strategies are available for finding optimal nonlinear controlled variables [30]. The SOC has been applied to optimizing the gas injection rate with a recycled gas-lift model in the oil and gas production industry [32]. Further, dynamic SOC models are being used to model the reservoir dynamic behavior. For example, a regression-based approach can be used to derive suitable controlled variables as combinations of measurements and manipulated inputs. A feedback control law can then be designed as a linear function of these controlled variables. This will give a near-optimal operational profit even in the presence of uncertainties [33].

2.3.4 Extremum-Seeking Control

Extremum-seeking control is an adaptive optimization technique that excels when an explicit system model is unavailable. The ESC model experimentally searches for the optimal operating point, making it suitable for systems where the dynamics or disturbances are poorly understood. This method is particularly valuable in scenarios where traditional model-based optimization methods become impractical.

ESC relies on introducing perturbations into the system to optimize steady-state performance. These perturbations help to estimate the gradient of the objective function, which represents the relationship between plant parameters and performance [34]. The estimated gradient is then used to adjust the plant parameters, which guide the system toward its optimal operating point. ESC methods fall into two broad categories [35]:

- perturbation-based - relies primarily on added perturbations
- model-based - Incorporates some degree of knowledge about the plant model structure

Several key considerations influence the successful implementation of ESC. Researchers have developed various strategies to enhance convergence rates and ensure asymptotic stability for plants that exhibits nonlinear dynamics [36]. In some cases, "self-driving" ESC allows the system to converge to the true optimum under specific conditions without the need for continuous perturbations [34]. Additionally, the coordination of perturbations can play a significant role in mitigating performance fluctuations and ensuring smoother operation [37].

However, ESC might face some challenges in highly nonlinear systems or the systems that are subjected to frequent disturbances [36, 38].

2.4 Optimization under uncertainty

Optimization in the real world almost invariably confronts uncertainty. Different sources of uncertainty in production systems include inaccurate measurements, manufacturing variations, environmental changes, modeling errors, and future demand fluctuations. Traditional optimization solutions primarily rely on nominal (expected or average) values. These setpoint can become severely infeasible or suboptimal even with a small perturbations [39]. Therefore, a robust model is required to incorporate uncertainties that may arise during the production process. The different approaches to address uncertainty in optimization are presented below:

2.4.1 Robust optimization

The robust optimization technique includes uncertain parameters to a bounded set without any specific probability distribution. The main focus is to find solutions that remain feasible for any realization of uncertainty within the specified boundary. The worst-case perspective prioritizes feasibility over potential performance gains. Robust optimization often leverages techniques from convex optimization [40].

2.4.2 Stochastic optimization:

The stochastic optimization technique defines uncertain parameters as random variables with known or estimated probability distributions. The goal is to optimize a performance metric over the distribution of uncertainty, such as expected value or risk measures. Stochastic programming and chance-constrained programming fall into this category [41].

2.4.3 Adaptive optimization

The adaptive optimization employs real-time measurements to continuously update model parameters and uncertainty estimations. This approach offers adaptability and computational efficiency but can face challenges for closed-loop stability.

2.5 Research focus at the University of South-Eastern Norway

The University of South-Eastern Norway has a focused research program on the optimization of oil fields for different artificial lift systems. Rohan Sharma have established foundational modeling and optimization techniques for gas-lifted oil fields [22]. The model employs nonlinear optimization within a dynamic model. This model have been extended to explore optimal control of electric submersible pump (ESP) systems [42].

The recent Ph.D. thesis by Nima Janatian has further contributed to this research scope. The thesis provides the importance of considering uncertainty in gas-lift systems, dynamic optimization techniques, etc. Further, the sensitivity analysis to classify uncertain parameters has been performed by Nima Janatian. The PhD thesis highlighted the challenges of computational cost and uncertainty within dynamic optimization for gas-lift systems [43]. Overall, the key research that have been performed at USN are summarized below:

- **Uncertainty handling:** USN research has prioritized addressing uncertainty in gas-lifted oil fields. This involves:
  - Variance-based sensitivity is being used to pinpoint critical uncertain parameters within the gas-lift model. This identification is essential for effective uncertainty handling in these models.
  - Robust optimization approach compares open-loop and closed-loop min-max MPC methods. This gives insights into tackling uncertainty in gas-lift systems.
  - Adaptive optimization approach offers potential computational advantages in handling uncertainty while maintaining performance.
  - Developing a novel constraint modification strategy to address limitations inherent in robust approaches. This minimizes excessive conservativeness while ensuring robust constraint satisfaction.

- **Computational efficiency:** Research at USN has also focused on enhancing computational efficiency for optimization techniques. For example, research by Nima Janatian has addressed the high computational demands of dynamic optimization for gas-lift systems. A study has been performed for ESP optimization in a steady-state model to reduce computational demands and facilitate easier real-time decision-making [43, 44].

Further, an optimization model based on uncertainty in an ESP-lifted oil field has been developed by Nima Janatian. This gives a scenario-based robust optimization framework for daily production optimization in ESP systems and explores the impact of uncertainty on ESP-specific optimizations. The model has been coupled together with a reservoir model [43] (Paper F).

Building upon this foundation, this master thesis aims to respect and acknowledge these achievements and addresses further challenges by introducing a steady-state optimization model coupled with a reservoir model for gas-lift systems.

3 Model description and development

3.1 Model background

This thesis builds upon and extends existing research on the performance of robust daily production optimization at the University of South-Eastern Norway. The developed model by Nima Janatian was a dynamic model for the gas-lifted system without coupling a reservoir model [45, 46, 47, 48]. Therefore, a dynamic reservoir model was developed and incorporated into the gas lift model. The gas lift model with reservoir coupling was simulated in this master study in steady state to study the well performances such as oil/water production rates, BHP, PI, water cut and cumulative profit for the production process. The developed model was used to optimize the oil and gas production from a gas injected reservoir. The fundamental principles used in this work are similar as those used in the other gas-lift modeling studies, however some modifications have been done to enhance modeling accuracy and investigate specific research questions. The major modifications in the developed model are:

- **Dynamic reservoir pressure:** A significant departure from Nima et al. models is the incorporation of dynamic reservoir pressure. This model reflects the real-world behavior of reservoirs, where pressure changes during the production process.
- **Multiphase reservoir:** The reservoir model realistically incorporates a multiphase mixture of crude oil, water, and gas, reflecting the complexity of production wells.
- **Simplified gas distribution:** The model represents the lift gas supply system with a focus on the mass flow rate of injected lift gas into the annulus as the primary control input. This streamlines the simulation compared to comprehensive gas distribution network modeling.

Assumptions: The following simplifying assumptions have been made for this study. These assumptions are consistent with the established practices in the gas-lift optimization researches [22, 43]:

- Constant liquid density
- Negligible frictional pressure losses within pipes
- Constant fluid temperatures
- Homogeneous multiphase fluid distribution within the tubing
- Absence of flashing phenomena

A significant contribution of this work is the development of a tailored well-reservoir model to simulate the gas lift injection into the oil and gas reservoir. The model incorporates dynamic reservoir pressure, providing a more rigorous and realistic representation of the oil production process compared steady-state models available in literature.

3.2 Governing equations

The gas-lifted oil field comprises of three oil wells interconnected by a shared gas distribution pipeline and a common gathering manifold. Each well, denoted by the superscript "i," is characterized by three primary states: the mass of lift gas in the annulus m_{ga}^{i}, the mass of the gas phase in the tubing above the injection point m_{gt}^{i}, and the mass of the liquid phase (a mixture of oil and water) in the tubing above the injection point m_{lt}^{i}. These states are governed by differential equations derived from the law of mass balance:

$$\dot{m}_{ga}^{i} = w_{ga}^{i} - w_{ginj}^{i} \tag{1}$$

$$\dot{m}_{gt}^{i} = w_{ginj}^{i} + w_{gr}^{i} - w_{gp}^{i} \tag{2}$$

$$\dot{m}_{lt}^{i} = w_{lr}^{i} - w_{lp}^{i} \tag{3}$$

Where, w_{ga}^{i} is the mass flow rate of injected lift gas into each well from the gas lift choke valve (the system input), w_{ginj}^{i} is the mass flow rate of gas injection from the annulus into the tubing, w_{gp}^{i} and w_{lp}^{i} is the mass flow rates of produced gas and liquid phase fluid from the production choke valve respectively. Further, w_{gr}^{i} is the gas mass flow rate from the reservoir into the well, w_{lr}^{i} is the liquid flow rate from the reservoir into the well, w_{or}^{i} is the oil flow rate from the reservoir into the well, w_{glp}^{i} represents the total mass flow rate of all phases from the production choke valve, and w_{op}^{i} is the oil compartment of w_{lp}^{i}.

The flow equations are defined as:

$$w_{ginj}^{i} = k^{i} y_{2}^{i} \sqrt{\rho_{ga}^{i} \max\left(p_{ainj}^{i} - p_{tinj}^{i}, 0\right)} \tag{4}$$

$$w_{gp}^{i} = \frac{m_{gt}^{i}}{m_{gt}^{i} + m_{lt}^{i}} w_{glp}^{i} \tag{5}$$

$$w_{lp}^{i} = \frac{m_{lt}^{i}}{m_{gt}^{i} + m_{lt}^{i}} w_{glp}^{i} \tag{6}$$

$$w_{lr}^{i} = PI^{i} \max\left(p_{r} - p_{wf}^{i}\right) \tag{7}$$

$$w_{or}^{i} = \frac{\rho_{0}}{\rho_{w}} \left(1 - WC^{i}\right) w_{lr}^{i} \tag{8}$$

$$w_{gr}^{i} = GOR^{i} w_{or}^{i} \tag{9}$$

$$w_{glp}^{i} = c_v y_3^i \sqrt{\rho_m^i \max\left(p_{wh}^i - p_s, 0\right)} \tag{10}$$

$$w_{op}^{i} = \frac{\rho_0}{\rho_w}\left(1 - WC^i\right) w_{lp}^{i} \tag{11}$$

The different pressures are calculated as:

$$P_a^i = \frac{z m_{ga}^i R T_a^i}{M A_a^i L_{a\_tl}} \tag{12}$$

$$P_{ainj}^i = P_a^i + \frac{m_{ga}^i}{A_a^i L_{a\_tl}^i} g L_{a\_vl}^i \tag{13}$$

$$P_{tinj}^i = \frac{z m_{gt}^i R T_t^i}{M V_G^i} + \frac{\rho_m^i g L_{t\_vl}^i}{2} \tag{14}$$

$$P_{wh}^i = \frac{z m_{gt}^i R T_t^i}{M V_G^i} - \frac{\rho_m^i g L_{t\_vl}^i}{2} \tag{15}$$

$$P_{bh}^i = P_{tinj}^i + \rho_l^i g L_{r\_vl}^i \tag{16}$$

Where, P_a^i is the pressure of lift gas in the annulus downstream the gas lift choke valve, P_{ainj}^i is the pressure upstream of the gas injection valve in the annulus, P_{tinj}^i denotes the pressure downstream of the gas injection valve in the tubing, P_{wh}^i and P_{bh}^i represent the wellhead and bottom hole pressure respectively.

The expression for densities and the algebraic variables are given by:

$$\rho_{ga}^i = \frac{M\left(P_a^i + P_{ainj}^i\right)}{2 z R T_a^i} \tag{17}$$

$$\rho_l^i = \rho_w WC^i + \rho_0\left(1 - WC^i\right) \tag{18}$$

$$\rho_m^i = \frac{m_{gt}^i + m_{lt}^i}{A_t^i L_{t\_tl}^i} \tag{19}$$

$$Y_2^i = 1 - \alpha_y \frac{P_{ainj}^i - P_{tinj}^i}{\max\left(P_{ainj}^i, P_{ainj}^{min}\right)} \tag{20}$$

$$Y_3^i = 1 - \alpha_y \frac{P_{wh}^i - P_s}{\max\left(P_{wh}^i, P_{wh}^{min}\right)} \tag{21}$$

$$V_G^i = A_t^i L_{t\_tl}^i - \frac{m_{lt}^i}{\rho_l^i} \tag{22}$$

Where ρ_{ga}^i is the average gas density in the annulus, ρ_l^i is the liquid phase density (oil and water), ρ_m^i is the average density of the multi-phase mixture in the tubing above the injection point, Y_2^i and Y_3^i are gas expandability factors for the gas passing through the gas injection valve and production choke valve, respectively. V_G^i symbolizes the gas volume in the tubing above the gas injection point, while c_v denotes the production choke valve characteristics.

The steady-state behavior of the developed model is achieved by equating the right-hand side of differential equations 1, 2, and 3 to zero.

$$w_{ga}^i - w_{ginj}^i = 0 \tag{23}$$

$$w_{ginj}^i + w_g^i - w_{gp}^i = 0 \tag{24}$$

$$w_{lr}^i - w_{lp}^i = 0 \tag{25}$$

The model can be represented by a system of algebraic equations, which can be expressed as:

$$\mathbf{F}(x, u, \theta) = 0 \tag{26}$$

In this representation, $x \in \mathbb{R}^{3n_w}$ represents the algebraic variables, $u \in \mathbb{R}^{1n_w}$ represents the system inputs, and $\theta \in \mathbb{R}^{3n_w}$ represents the uncertain parameters of the process. The variable n_w denotes the number of wells, and bold typeface indicates that the variable encompasses all wells.

$$x = \left[m_{ga} \;\; m_{gt} \;\; m_{lt}\right]^T \tag{27}$$

$$u = \left[w_{ga}\right]^T \tag{28}$$

$$\theta = [P_r \quad PI \quad WC]^T \tag{29}$$

3.3 Non-Linear Model Predictive Control

Nonlinear Model Predictive Control (NMPC) is a powerful optimization technique well-suited for controlling complex, dynamic systems with nonlinearities, such as gas-lifted oil reservoirs [49]. NMPC key features include:

- **Model-based predictions:** NMPC utilizes a mathematical model of the reservoir to predict its future behavior over a finite time horizon. This model captures the nonlinear dynamics characteristics in the gas-lifted production process.
- **Receding horizon:** At each time step, NMPC solves an optimization problem over a prediction horizon which is a several time steps into the future. NMPC determines the optimal sequence of control actions (e.g., gas injection rates) that maximize a desired objective (e.g., oil production) while respecting system constraints (e.g., maximum gas availability). However, only the first control action in this calculated sequence is implemented. The process repeats at the next time step.
- **Feedback mechanism:** The receding horizon and the use of current reservoir state information introduce a feedback mechanism. This allows NMPC to adapt the changes in the system or disturbances and correct for deviations from the predicted trajectories [50].

3.3.1 NMPC implementation in gas-lifted optimization

This study is based on the NMPC for a gas lifted oil production process. This includes:

1. **Problem formulation:** At each time step, the NMPC optimization problem is defined as the following three steps:
    - **Objective function:** This quantifies the desired goal by maximizing oil production or economic profit, considering gas costs and separation costs.
    - **Constraints:** This reflects operational limits like maximum gas injection rate, wellbore pressure limits, and total gas availability.
    - **Decision variables:** The gas lift injection rates for each well.
2. **Model-based optimization:** The NMPC solver uses the reservoir model and current state information to calculate the optimal control actions over the prediction horizon that maximize the objective function while adhering to the constraints.
3. **Implementation and recalculation:** Only the first control action from the calculated optimal sequence is applied to the real reservoir. The reservoir's new state is then measured or updated in the model. Subsequently, at the next time step, the whole NMPC process is repeated with this updated information.

3.3.2 Advantages of NMPC for gas-lift optimization

- **Handles complex dynamics:** NMPC effectively manages the nonlinear relationship between gas lift injection, reservoir pressure, and production rates.
- **Explicit constraint handling:** NMPC ensures that operational limits and safety constraints are respected, which are crucial for the safe and practical operation of a gas-lifted oil field.
- **Adaptability:** The feedback mechanism within NMPC makes it responsive to changing reservoir conditions and potential disturbances.

3.4 Standard DPO setup

This section presents standard optimization for a gas-lift system using a steady-state model over a finite prediction horizon. The plant is assumed to operate in a piecewise steady-state manner throughout the prediction horizon. The primary objective is to adjust the gas injection rates into the wells to optimize fluid production while considering operational constraints. The standard DPO approach is illustrated in Figure 3-1. The dynamic variables such as reservoir pressure, water cut, and productivity index are calculated at each sampling time. The true value of these variables is unknown to the controller however, these true values are calculated by adding a certain deviation to their actual values.

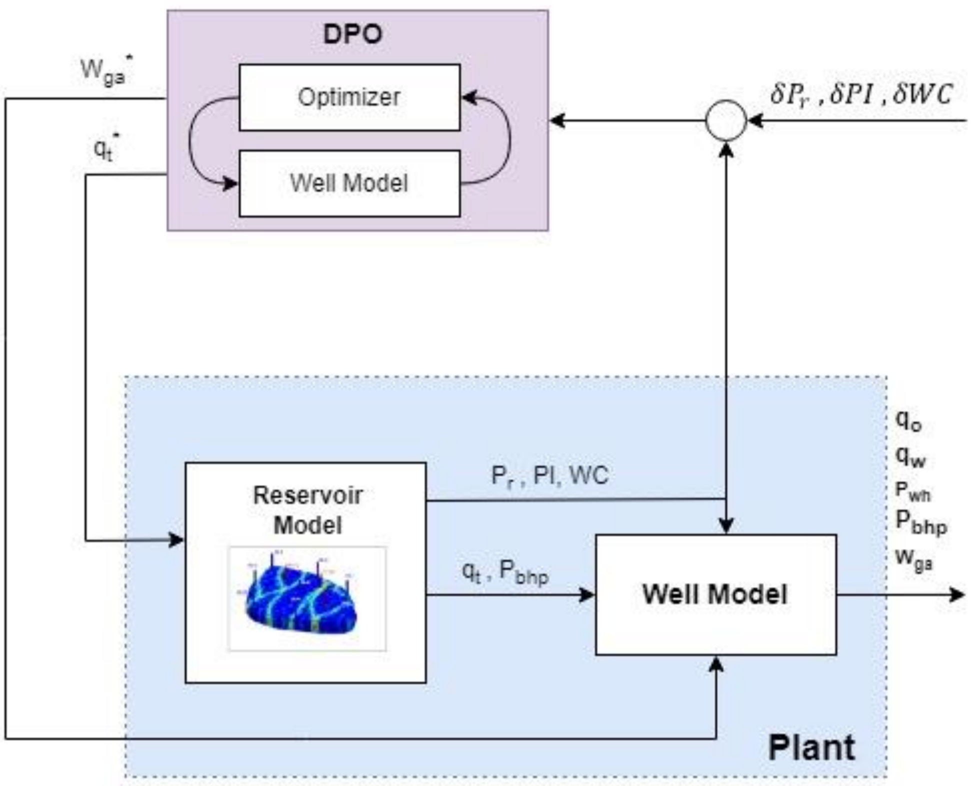


Figure 3-1: Block diagram of the coupled reservoir model with the DPO

The economic objective function includes the total income from selling the produced oil, while minimizing the costs associated with acquiring and injecting gas, and the operating costs associated with the separator.

Hence, the objective function over the prediction horizon $\mathcal{K}$ = {1, ..., Np} with the length Np is given by:

$$J_{eco} = \sum_{k=1}^{N_p}(-c_o \sum_{i=1}^{n_w} q_o^{i,k} + c_{sep} \sum_{i=1}^{n_w} q_w^{i,k} + c_{gas} \sum_{i=1}^{n_w} w_g^{i,k}) \tag{30}$$

Where c_o, c_{sep}, and c_{gas} represents the cost of oil, the cost of the separator, and the cost of gas injection respectively. Also, $q_o^{i,k}$, $q_w^{i,k}$ and $w_g^{i,k}$ represent the oil, water flow rates, and gas injection, from the well i at time step k.

The most important operational constraints are the separator capacity, gas-lift system limits, and well pressures. In particular, the total produced fluid should not exceed the separator capacity. Additionally, the gas injection rates must be maintained within a feasible range, and the bottom hole and wellhead pressures must stay within safe operational limits.

The optimal control problem formulation over the prediction horizon of the system is given by:

$$\min_{x,u} \; J_{\mathrm{eco}}(x,u,\theta) \tag{31}$$

$$s.t \; F(x_k, u_k, \theta_k) \; = \; 0 \qquad \forall \mathrm{k} \in \mathcal{K} \tag{32}$$

$$\sum_{i=1}^{n_w} q_t^{i,k} \; \leq Q_{sep}, \qquad \forall \mathrm{k} \in \mathcal{K} \tag{33}$$

$$w_{ga_{min}}^{i,k} \; \leq w_{ga}^{i,k} \leq w_{ga_{max}}^{i,k} \qquad \forall \mathrm{k} \in \mathcal{K} \tag{34}$$

$$P_{bh}^{min} \; \leq P_{bh}^{i,k} \; \leq P_{bh}^{max} \qquad \forall \mathrm{k} \in \mathcal{K} \tag{35}$$

$$P_{wh}^{min} \; \leq P_{wh}^{i,k} \; \leq P_{wh}^{max} \qquad \forall \mathrm{k} \in \mathcal{K} \tag{36}$$

In the context of steady-state DPO for gas-lifted wells, the equality constraint in Equation 32 represents the requirement for the system to maintain a balanced state at each segment of the prediction horizon. This ensures that the production rates, pressures, and other relevant variables are consistent with the steady-state model. The constraint on the total produced fluid (oil and water) is enforced in Equation 33, where Q_{sep} represents the maximum handling capacity of the separator. This ensures the physical limitations of the surface facilities are satisfied.

The safe operation of the gas-lift system is maintained within the allowable operating range ($w_{ga_{min}}^{i,k}$ to $w_{ga_{max}}^{i,k}$) of the gas lift rate. This range is determined by operational considerations and limitations of the gas-lift system. This limit is crucial to avoid excessive gas injection, which could lead to increased friction and reduced oil production. The lower and upper bounds on bottom hole pressure and wellhead pressure are implemented in Equation 35 and 36 respectively. These constraints ensure that the pressures within the well remain within safe operating limits, safeguarding the well's integrity and operation.

The optimization problem is solved in a receding horizon strategy. This means that at each time step, the optimization algorithm determines the optimal gas injection rates over the entire prediction horizon, but only the first control action is implemented. At the next time step, the model is updated with new information, and the optimization problem is solved again. This iterative process allows the system to adapt to changing reservoir conditions and uncertainties. Productivity index, reservoir pressure and water cut are treated as uncertain parameters for this study. This reflects the inherent uncertainties present in real-world oil fields. The optimization algorithm must take these uncertainties into account to ensure that the calculated gas lift rates remain robust and effective even under varying conditions.

3.5 Reservoir models

Two different reservoir models were used in this study. A brief description of these models is presented here.

3.5.1 Egg case model

This model presents a customized synthetic reservoir model drawing similar concept as that of "Egg model" [51]. The Egg case model simulates a channelized oil reservoir undergoing waterflooding. The model emphasizes the dynamic pressure evolution, multi-phase fluid behavior, and a realistic well configuration designed for optimization studies. The key feature of this model includes:

- **Channelized structure:** The reservoir model exhibits distinct high-permeability channels within a lower-permeability background, resembling fluvial depositional environments.
- **Dynamic pressure:** Reservoir pressure changes throughout the simulation, due to continuous fluid production and injection operations.
- **Multi-Phase flow:** The model simulates the flow of multiple fluid phases (oil, water, and potentially gas). The basic mass and energy balances govern the fluid properties and their interactions.
- **Well configuration:** The reservoir incorporates a network of four production and eight injection wells. This study focuses on three production wells as shown in the Figure 3-2.

- **Geological uncertainty:** This model includes subsurface geological parameters such as reservoir pressure, productivity index, and water cut.

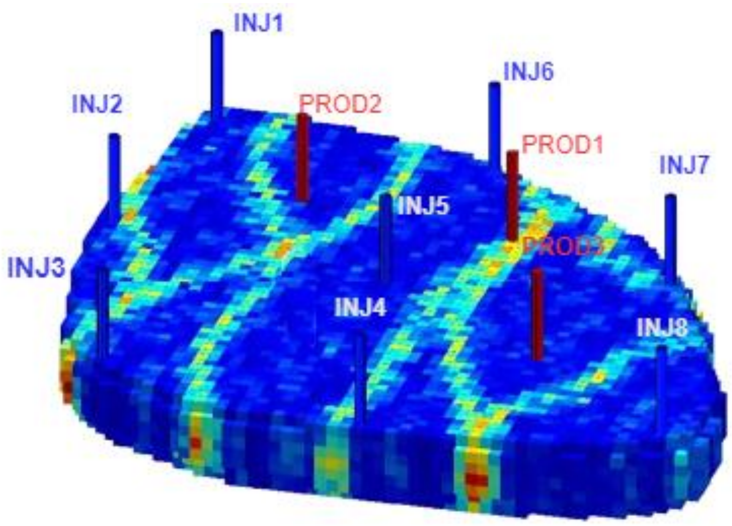


Figure 3-2: The egg case reservoir model modified with eight injectors and three producer wells

The existing Egg case model is modified for this study, and the modification are presented below:

- **Production optimization focus:** Well controls have been modified to prioritize total fluid production rates, which are directly determined by the optimization algorithm.
- **Realistic compressibility:** The model employs a slightly compressible oil phase (compressibility of 0.001) to better represent real-world reservoir behavior.
- **Injection strategy:** Waterflooding is the primary production mechanism. Injection rates are scaled to 505 m^3/d aligning with operational considerations and optimization goals.
- **Operational constraints:** The model operates within the potential constraints such as limits on injection pressure, maximum water cut, etc.

3.5.2 SPE9 model

This model is based on the SPE9 benchmark model available on MRST in MATLAB. The key characteristic of this model is presented here:

- **Heterogeneous reservoir:** A highly heterogeneous reservoir with anisotropic permeability (10x lower vertical permeability) is considered for this model. Waterflooding is the production mechanism in this model.

- **Well configuration:** The model incorporates three production wells for this study as shown in Figure 3-3.

- **Three-phase flow:** The black-oil model simulates the flow of oil, water, and gas phases.

- **Dynamic behavior:** The model captures the evolution of free gas as reservoir pressure falls below the bubble point, influencing relative permeabilities and fluid behavior.
- **Operational schedule:** Production wells undergo distinct control changes, transitioning from constant oil rate to pressure-limited modes during the simulation.

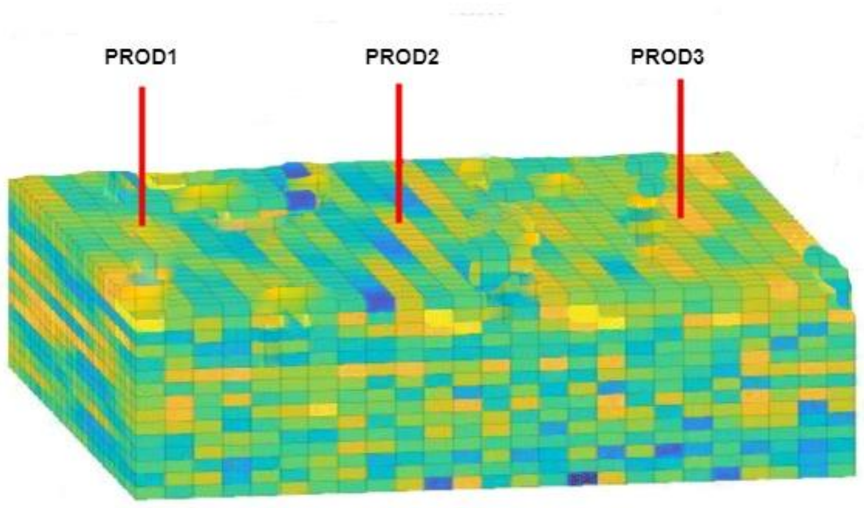


Figure 3-3: The SPE9 reservoir model with 3 producer wells

3.5.3 Simulation setup

The optimization for the simulation models was performed in CasADi v.3.6.4 in MATLAB R2023a. For reservoir simulation, MATLAB Reservoir Simulation Toolbox (MRST) was used. The IPOPT v3.14.1 solver has been used to solve the optimization problem on a 2.0 GHz processor laptop with 8 GB memory.

Table 1 provides detailed parameter values for the simulated wells. Table 2 provides the oil price and the costs related to separator and costs of gas. These cost parameters were used as a basis for the calculation in Equation 30.

Table 1: List of the parameters and their corresponding values

Parameters	Values	units
L_{a_tl} , L_{t_tl}	2758	[m]
L_{a_vl} , L_{t_vl}	2271	[m]
L_{r_vl}	114	[m]
A_t	0.0194	[m^2]
A_a	0.0174	[m^2]
K	68.43	[$\frac{\sqrt{\frac{kg*m^3}{bar}}}{hr}$]

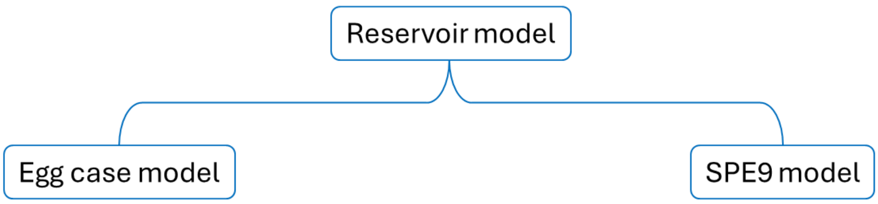
T_a , T_t	280	[K]
Z	1.3	[-]
ρ_w	1000	[kg/m^3]
ρ_o	800	[kg/m^3]
M	0.020	[kg/mol]
α_Y	0.66	[-]
p_s	30	[bar]
R	8.32	[J/K/mol]
GOR	0.08	[kg/kg]

Table 2: Price of oil, separator, and gas

Price	**Value**	**unit**
c_o	126	[\$/m^3]
c_{sep}	20	[\$/m^3]
c_{gas}	2	[\$/kg]

3.5.4 Simulated cases

The following six models were created to simulate the oil production rates, water production rates, bottom hole pressure, productivity index, water cut and cumulative profit. The list of different cases is presented below:



Cases	Simulation step
Case I	180 steps per year
Case II (no control)	12 hours
Case III (optimized)	12 hours

Cases	Simulation step
Case IV (no control)	12 hours
Case V (optimized)	12 hours
Case VI (optimized)	12 hours (1000 days)

4 Results and discussion

This chapter presents a comprehensive analysis of the simulation results obtained from two distinct gas-lifted reservoir models, i.e., Egg Case and SPE9 model. Daily production optimization was performed to investigate the impact of varying simulation steps, prediction horizons, and optimization strategies on model behavior. The models were used to investigate the well performances such as oil/water production rates, BHP, PI, water cut and cumulative profit for the production process.

4.1 Egg case model results

This section focuses on the results obtained from applying the gas-lift optimization model to a modified version of the egg reservoir as described in the sub-chapter 3.5.1. The results presented here are from three production wells as shown in the Figure 3-2.

4.1.1 Case I: Short simulation timestep with a 180 steps per year

The original Egg model consists of four production wells; however, this study focused on three producer wells. These producer wells are named as PROD1, PROD2 and PROD3 as shown in the Figure 3-2. Simulations were performed for 365 days of production with a timestep of approx. two days (180 steps per year). This simulation setup aimed to assess the model's sensitivity with respect to total liquid (oil and water) production rate from the reservoir.

Figure 4-1 shows the oil production rate for each well. As depicted in the figure, pronounced oscillations are observed in the oil production rate during the initial 50 days. The observed fluctuations could be due to the relatively coarse simulation time step taken for this model. Higher timesteps struggle to capture the rapid pressure-driven changes occurring in the reservoir's high-permeability areas. The magnitude of oscillations varied between the different producers, with PROD3 exhibiting the most pronounced fluctuations. The higher oscillations in PROD3 are likely due to its specific well location and surrounding reservoir properties.

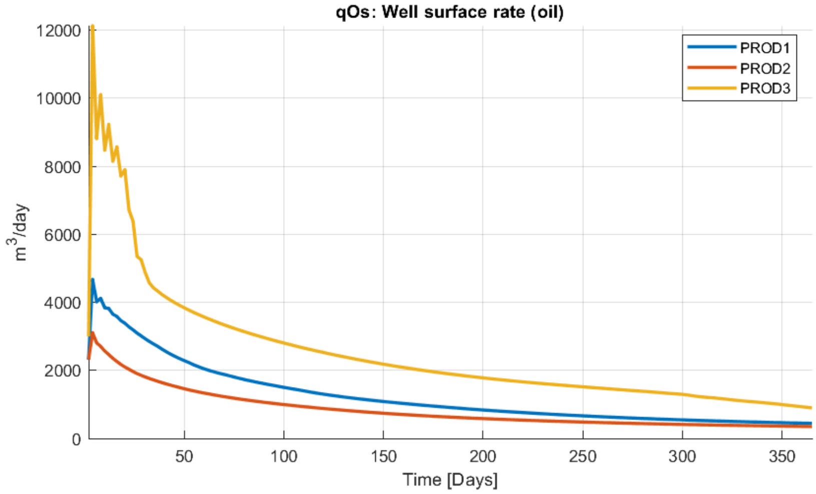


Figure 4-1: Oil production rate for each well in Egg model with 180 simulation steps per year

As the simulation progressed beyond 200 days, the oil production rate gradually stabilized. This suggests that the reservoir pressure dynamics become less volatile over time as the system approaches a near steady state condition. However, the initial highly transient behavior highlights the importance of choosing an appropriate time step to accurately capture the full range of the reservoir dynamics.

Figure 4-2 shows water production rates for PROD1, PROD2 and PROD3 producer wells. The water production rates exhibited an inverse relationship with the oil production rates. This result is consistent with the expected behavior in a waterflooding production scenario.

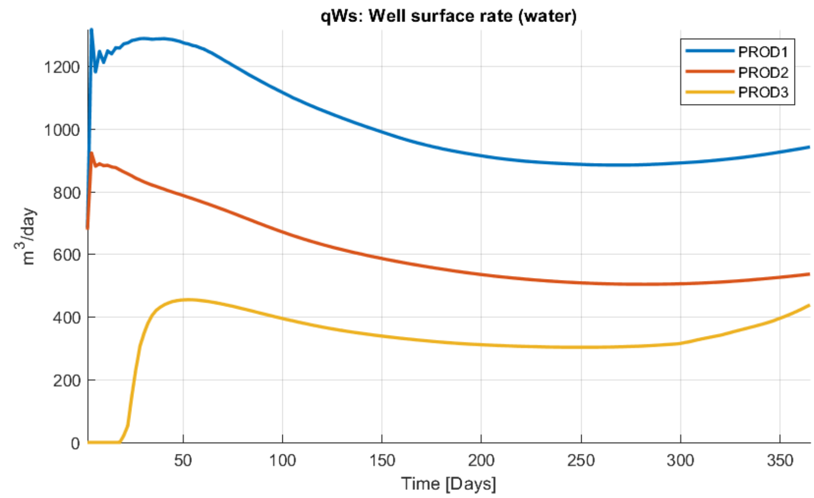


Figure 4-2: Water production rate for each well in Egg model with 180 simulation steps per year

Figure 4-3 shows a total liquid production rate from the separator. The total liquid production is dominated by oil production rate as compared to water production rate. Further, there is a gradual decline in oil production rate, however, water production rate is dynamic with production horizon. There is an increase in water production rate after the water breakthrough and the total water production rate gets decreased after around 50 days of production. Further, the water production rate increased after around 250 days of production. This result emphasizes the ongoing challenge of balancing oil recovery with water breakthrough in waterflooding operations. The oil production rate is 70.84% as that of total liquid production after 100 days of production. This ratio of oil production rate decreases with predicted horizon and reaches 46.78% as that of total liquid production after 365 days of production.

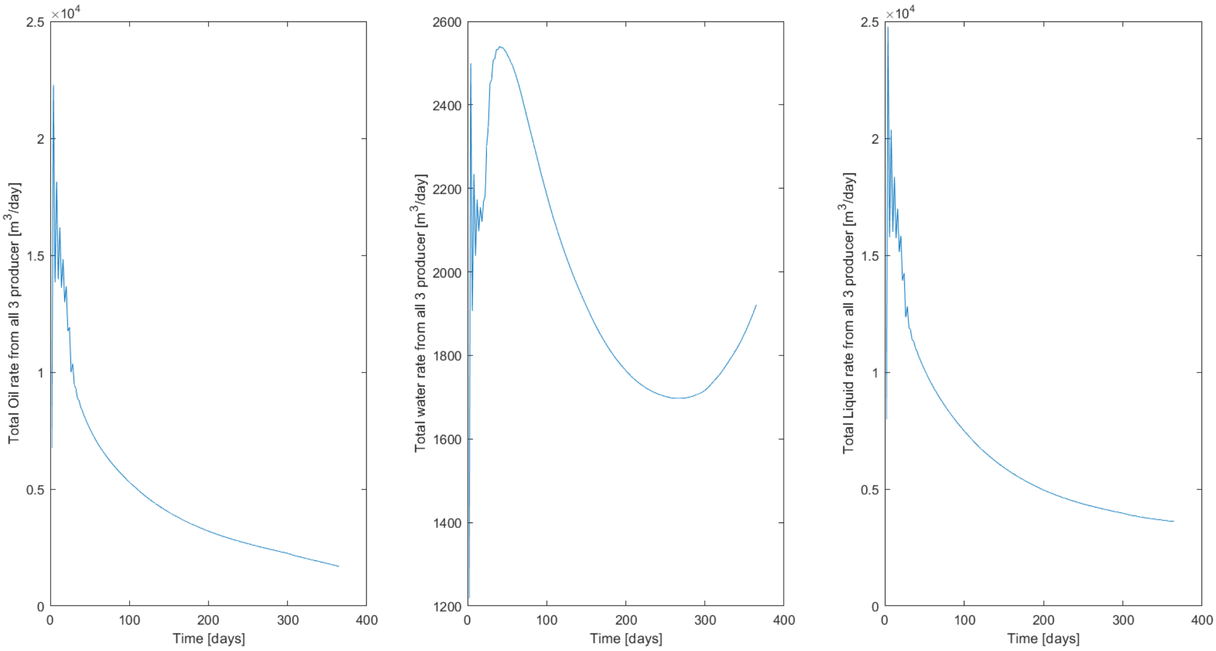


Figure 4-3: Total oil, water, and liquid production rates from the separator with 180 simulation steps per year

4.1.2 Case II: Refined simulation time step with no control

Simulations time step was reduced to 12 hours for further simulations to improve the resolution of transient behavior and mitigate the oscillations as observed in the sub-chapter 4.1.1. The refined model was used to investigate the well performances such as oil/water production rates, BHP, PI, water cut and cumulative profit for different optimization scenarios and prediction horizons. Simulations have been performed for 365 days of production. A constant gas lift rate of 4 kg/day is supplied into the reservoir. Figure 4-4 shows the oil production rates for the PROD1, PROD2 and PROD3 producer wells. As expected, this reduced time step successfully mitigated the initial oscillations as seen previously in Case I. Oil production rate gradually reaches a steady state approximately after 200 days of production, similar to that of Case I.

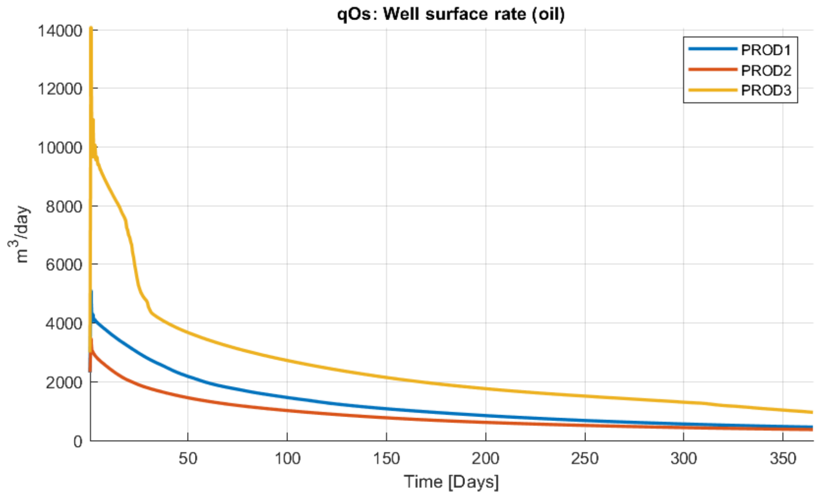


Figure 4-4: Oil production rate for each well in Egg model with no control with a 12-hour time step

Figure 4-5 provides insights into individual well performance metrics such as oil rates, water rates, BHP, productivity index, water cut and cumulative profit. As depicted in the figure, PROD3 has the highest oil production rates whereas PROD2 has the lowest oil production rate. Further, water production from PROD1 is highest and that of PROD3 is lowest. This suggests that the reservoir is heterogeneous and the surrounding reservoir properties affected the oil and water production rates. Bottom hole pressure for PROD2 is observed close to the set pressure of 60 bar whereas for PROD1 the bottom hole pressure is slightly higher than the set pressure. PROD3 shows a slight deviation in BHP initially and comes back to around set pressure after around 200 days of production.

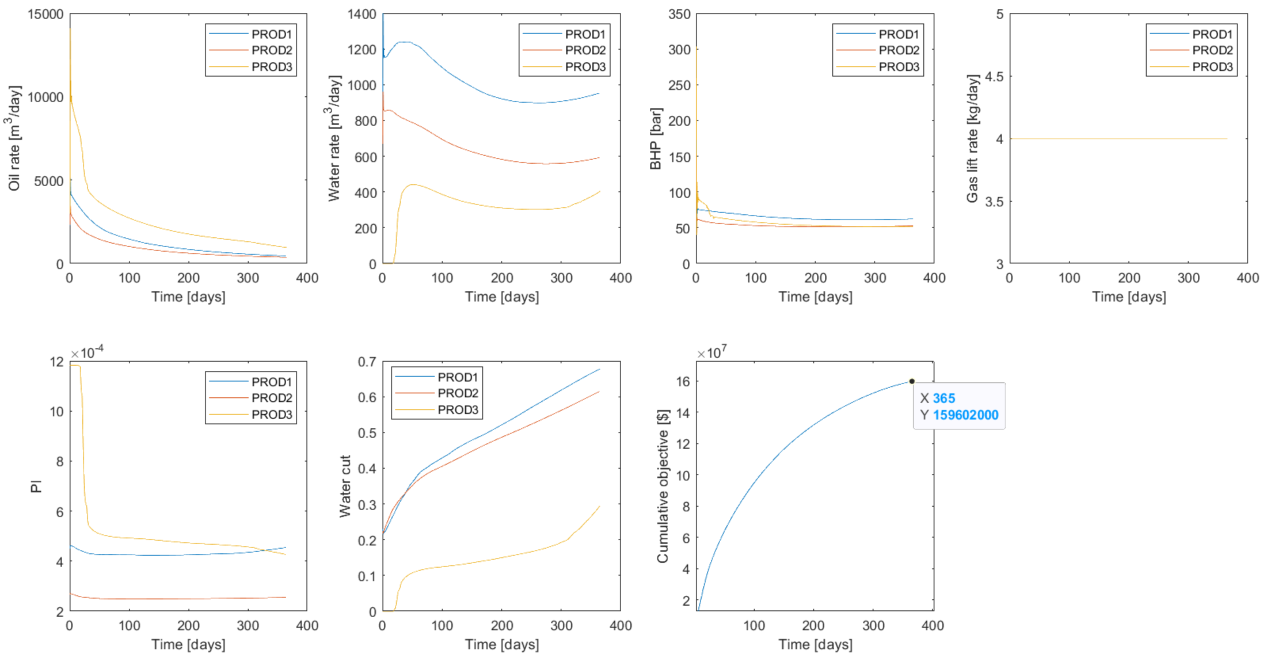


Figure 4-5: Individual well performance (oil/water rates, BHP, PI, water cut) and cumulative profit for Egg model with no control with a 12-hour time step

The higher the productivity index, the higher will be the oil production rate. This can be observed in the Figure 4-5. The lower oil production rate form PROD2 is due to the lowest PI for PROD2 as shown on this figure. Similarly, the higher the water cut, the higher would be the water production rate from the reservoir. For example, PROD1 has the highest water production rate due to its higher water cut. The cumulative profit for this model increases with an increase in production days. Initially the cumulative profit increased exponentially and increased gradually after around 200 days of production.

Figure 4-6 presents the total fluid production rates from the separator. The oil production rate reaches 1680.79 m3/day by day 365. The oil production rate decreases with increasing production days; however, the total water production rate increases initially and then decreases significantly. The water production increases again after around 250 days of production. The total liquid production rate decreases with increase in the production days. The ratio of oil and water production rate is similar to that of Case I.

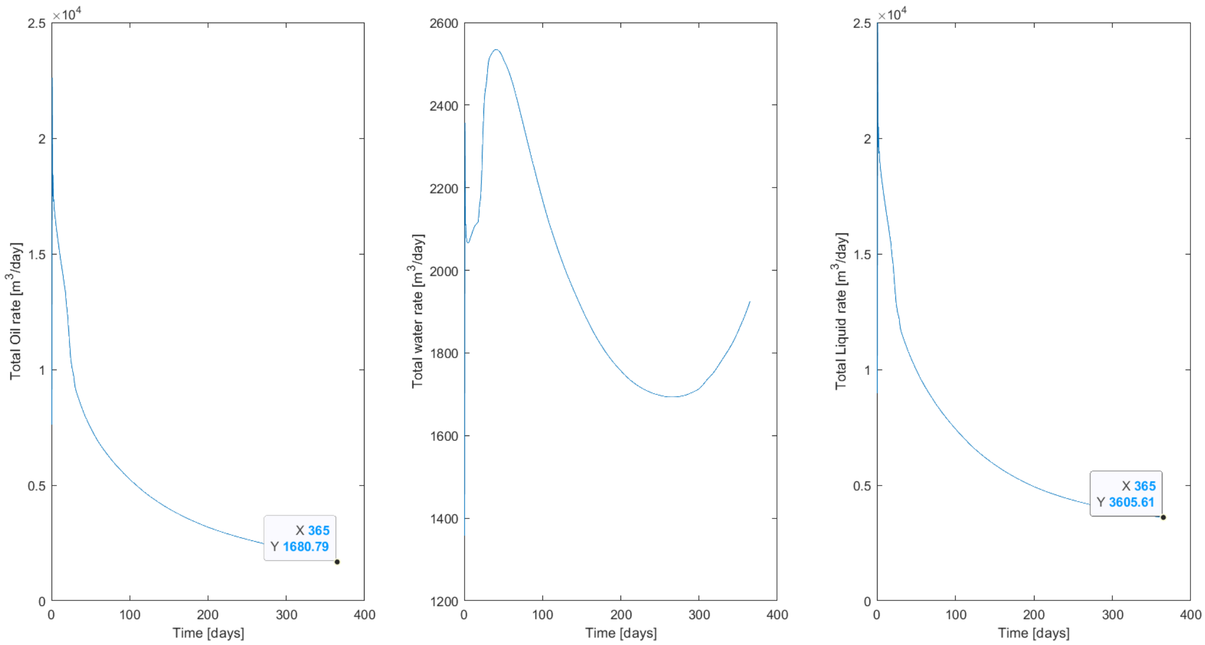


Figure 4-6: Total oil, water, and liquid production rates from the separator for Egg model with no control with a 12-hour time step

4.1.3 Case III: Refined simulation time step with an optimized DPO

A standard DPO algorithm is implemented in this case. The DPO algorithm dynamically adjusts gas lift rates for each well which leads to a significant increase in oil production. The results from the simulation for case III are presented in this sub-chapter. Simulations were performed for 365-day prediction horizon. Figure 4-7 shows the oil production rate from PROD1, PROD2 and PROD3 wells with a simulation time steps of 12 hours.

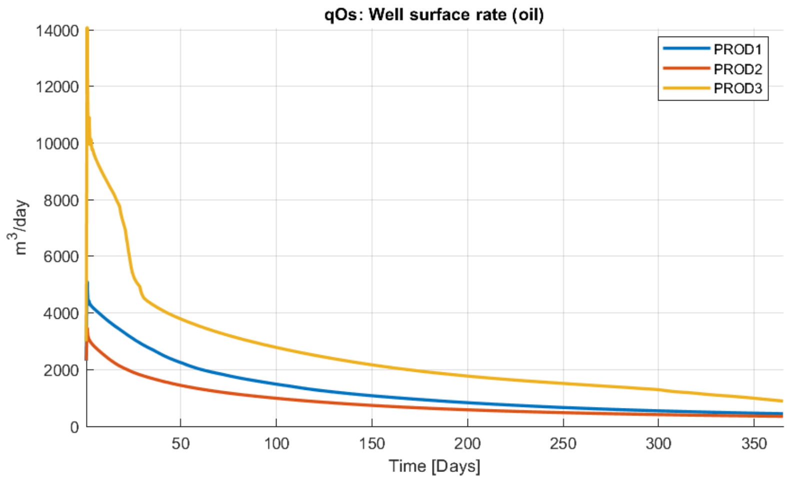


Figure 4-7: Oil production rate for each well in Egg model with optimized DPO with a 12-hour time step

As observed in previous simulations, the oil production from PROD3 has the higher oil production rate whereas PROD2 has the lower oil production rate. The oil production rate gets decreased gradually up to around 200 days of production and reaches a near steady state after 200 days of production.

Figure 4-8 shows the individual well performance metrics such as oil rates, water rates, BHP, productivity index, water cut and cumulative profit. The oil and water production rates as well as PI and water show a similar behavior as that of Case II. As the gas lift rate is dynamically adjusted by the model, the bottom hole pressure is comparatively closer to the set pressure.

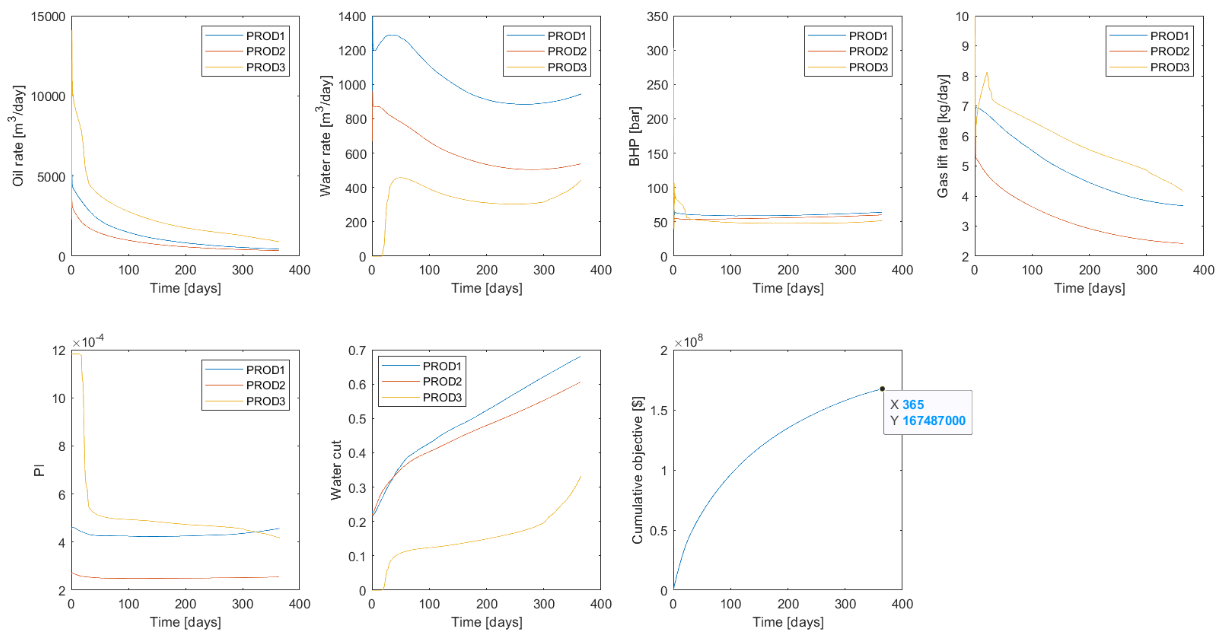


Figure 4-8: Individual well performance (oil/water rates, BHP, PI, water cut) and cumulative profit for Egg model with optimized DPO with a 12-hour time step

The cumulative profit increased by around 4% as compared to that of Case II. These findings highlight the effectiveness of DPO in enhancing both production and profitability in the gas-lift scenario.

Figure 4-9 shows the total liquid production rate from all the producers, i.e., PROD1, PROD2 and PROD3. The oil production rate reached 1782.08 m3/day on day 365, marking a substantial improvement in oil production rate as compared to Case II with no control.

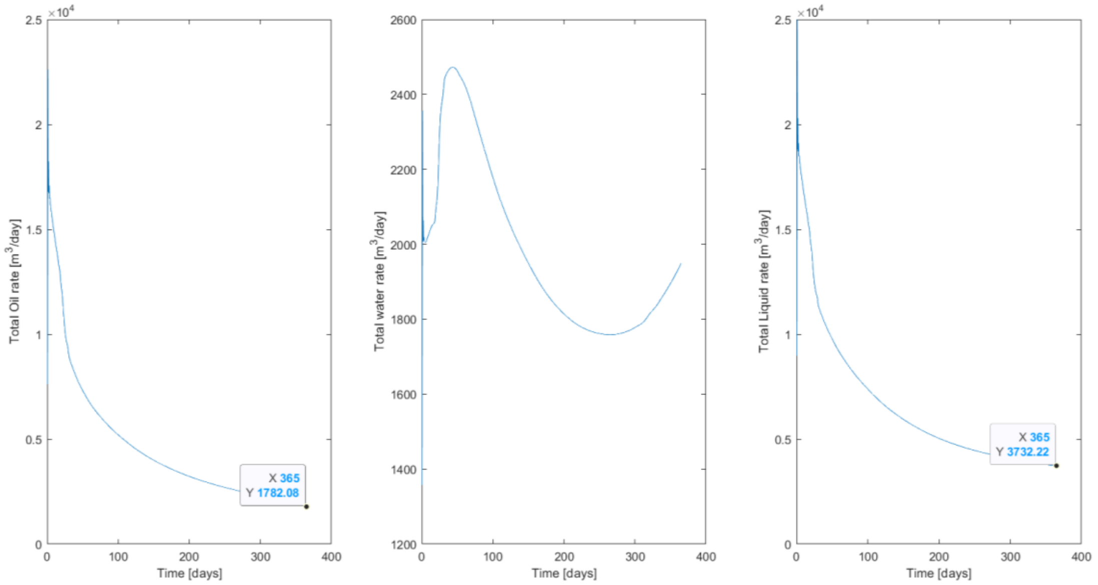


Figure 4-9: Total oil, water, and liquid production rates from the separator for Egg model with optimized DPO with a 12-hour time step

4.2 The SPE9 model results

This sub-chapter presents results obtained for the SPE9 reservoir model with a gas lifted production process. The results presented here are from three production wells, namely PROD1, PROD2 and PROD3.

4.2.1 Case IV: Refined simulation time step with no control

The performance of the gas-lifted systems was evaluated over a 365-day period with time step of 12 hours for this case. Figure 4-10 shows the oil production rate for each well in SPE9 model with no control. A gas constant lift rate of 1 kg/day for each well was used for this study. The oil production rate is highest from PROD2 and lowest from PROD3. The oil production rate reaches a steady state after around 150 days of production. This suggests that this model reaches a steady state earlier as compared to Egg case models.

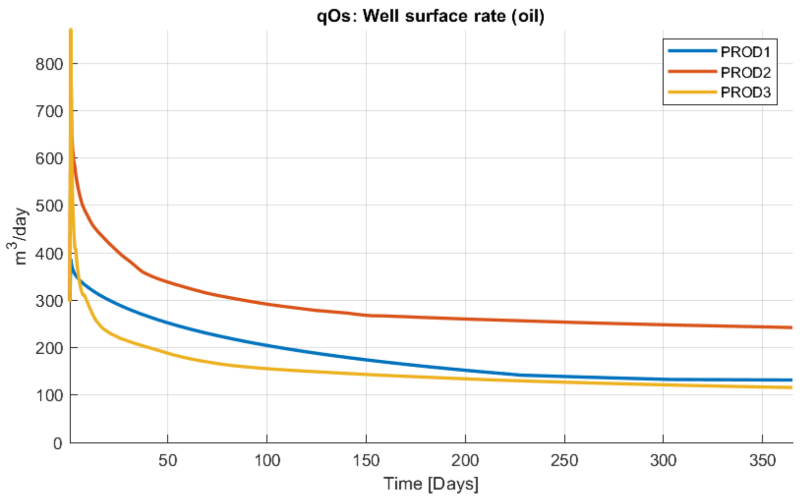


Figure 4-10: Oil production rate for each well in the SPE9 model with no control

Figure 4-11 provides a detailed performance characteristics for the individual well such as oil production rate, water production rate, bottom hole pressure, productivity index, water cut and cumulative profit. Oil production rate is higher for PROD2 due to its higher PI. Similarly, the oil production rate for PROD3 is lower due to its lower productivity index. The higher the water cut, the higher would be the water production rate which can be observed for PROD26. The water cut for PROD1 is near to zero which led to nearly zero water production rate from this producer.

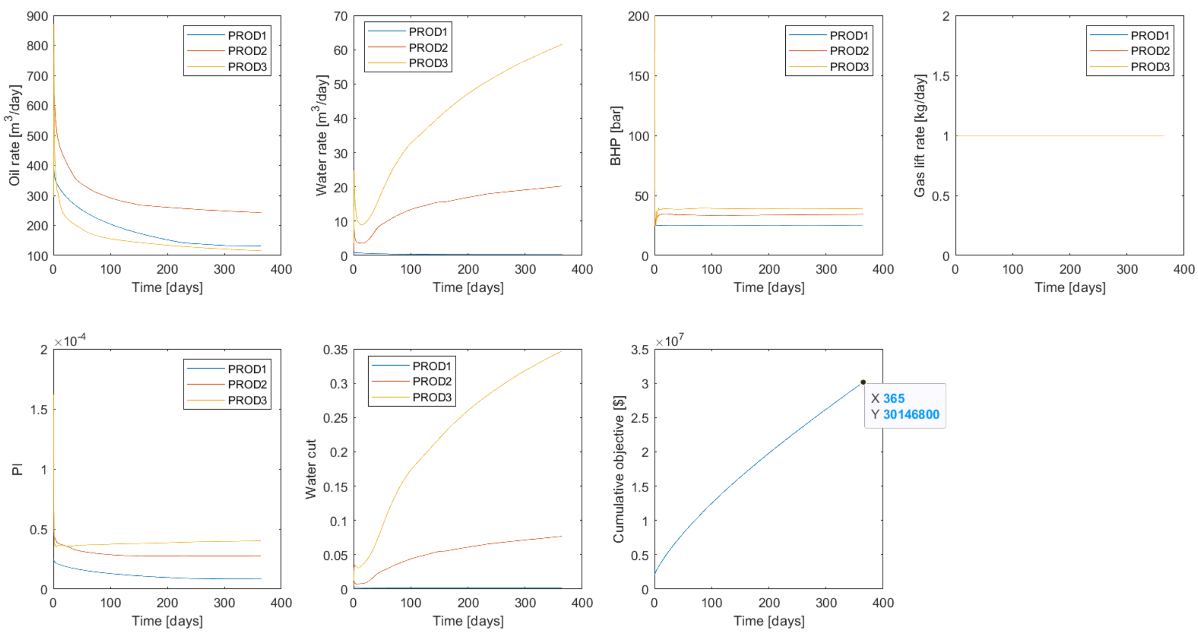


Figure 4-11: Individual well performance (oil/water rates, BHP, PI, water cut) and cumulative profit in the SPE9 model with no control

Bottom hole pressure for PROD1 is observed close to the set pressure of 30 bar whereas for PROD2 and PROD3 the bottom hole pressure is slightly higher than the set pressure. The initial fluctuations in bottom-hole pressure gets stabilized after around 10 days prediction horizon. The cumulative profit increased linearly as compared to exponential growth for Egg case models. This suggests that the constant gas lift rate might not be optimal for maintaining the reservoir pressure and maximizing production for this reservoir model.

Figure 4-12 shows the total oil production rate of 489.824 m3/day from the separator after 365 days of production. Oil production decreased with the start of production. Water production decreased initially and then increased continuously. However, water production is comparatively lower than oil production. Water production accounts for 14.34% after 365 days of production.

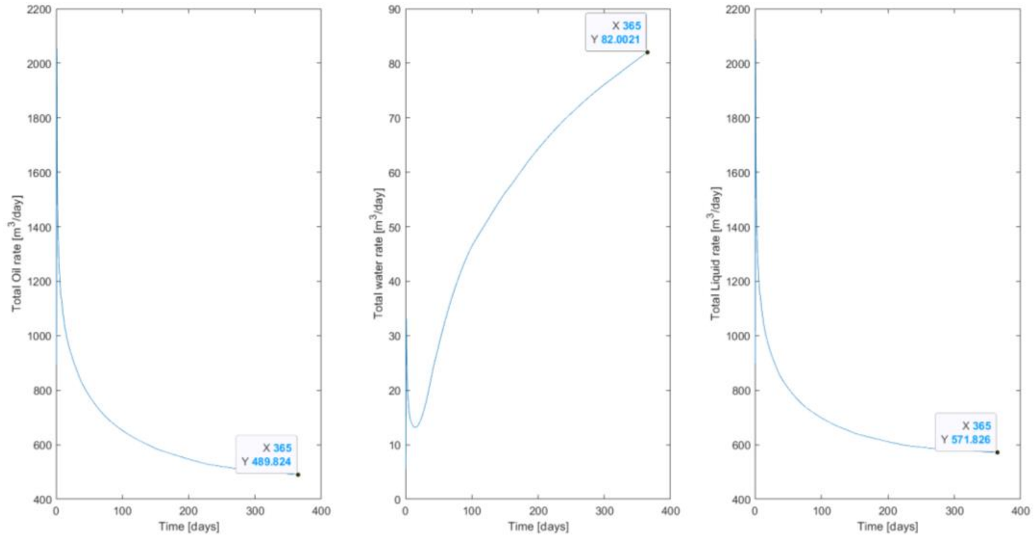


Figure 4-12: Total oil, water, and liquid production rates from the separator for the SPE9 model with no control

4.2.2 Case V: Refined simulation time step with an optimized DPO

Further, a DPO algorithm was implemented in the SPE9 model to study the well performance. The DPO algorithm dynamically adjusts the gas lift rate for each well. Simulations were performed for 365 days prediction horizons with 12 hours time step. Figure 4-13 shows the oil production rate for PROD1, PROD2 and PROD3 wells. Production form the PROD2 is comparatively higher than that of PROD1 and PROD3 wells. The oil production gets decreased initially and reaches saturation after around 150 days of production. The higher production rate from PROD2 is likely due to its specific well location and surrounding reservoir properties.

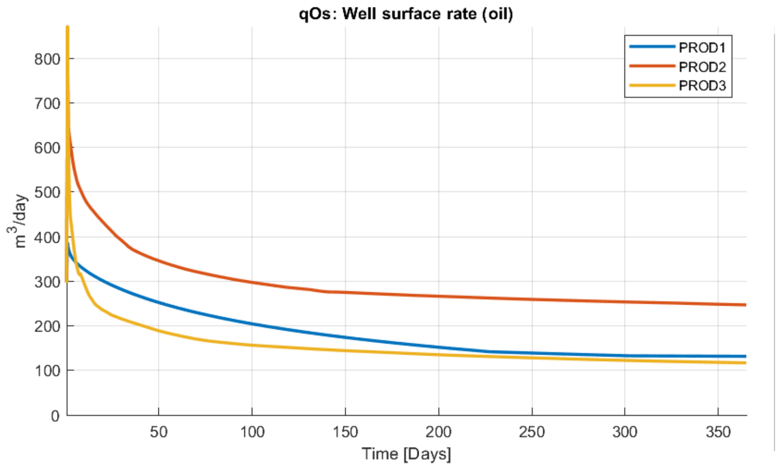


Figure 4-13: Oil production rate for each well in the SPE9 model with optimized DPO

Figure 4-14 illustrates the individual well performance metrics such as oil rates, water rates, bottom hole pressure, productivity index, water cut and cumulative profit. The results show similar characteristics as that of non-optimized model for the oil and water production profiles. However, due to the dynamic adjustment of gas lift rate for the individual well led to an increase in cumulative profit of 3% as that of Case IV. The dynamic adjustment of gas lift rates was able to better manage the reservoir pressure as illustrated by the bottom hole pressure plot. The dynamic gas lift into the reservoir exploited the reservoir heterogeneity leading to improved overall production and profitability for this model.

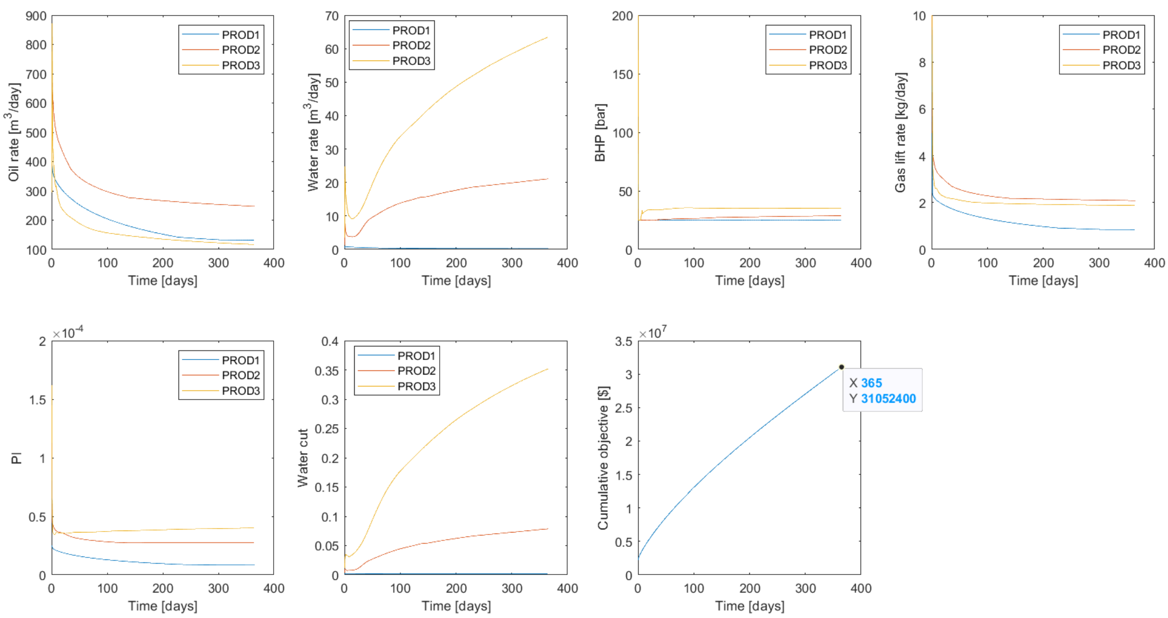


Figure 4-14: Individual well performance (oil/water rates, BHP, PI, water cut) and cumulative profit in the SPE9 model with optimized DPO

Figure 4-15 shows the total liquid production rates from the separator. This graph shows a notable increase in oil production, reaching 495.46 m3/day on day 365. This oil production rate is approximately 1.1% higher than that of Case IV with no control highlighting the potential benefits of optimization in the SPE9 reservoir model. The ratio of oil to water production rate for this model is 5.85 as there is no water flooding into the reservoir.

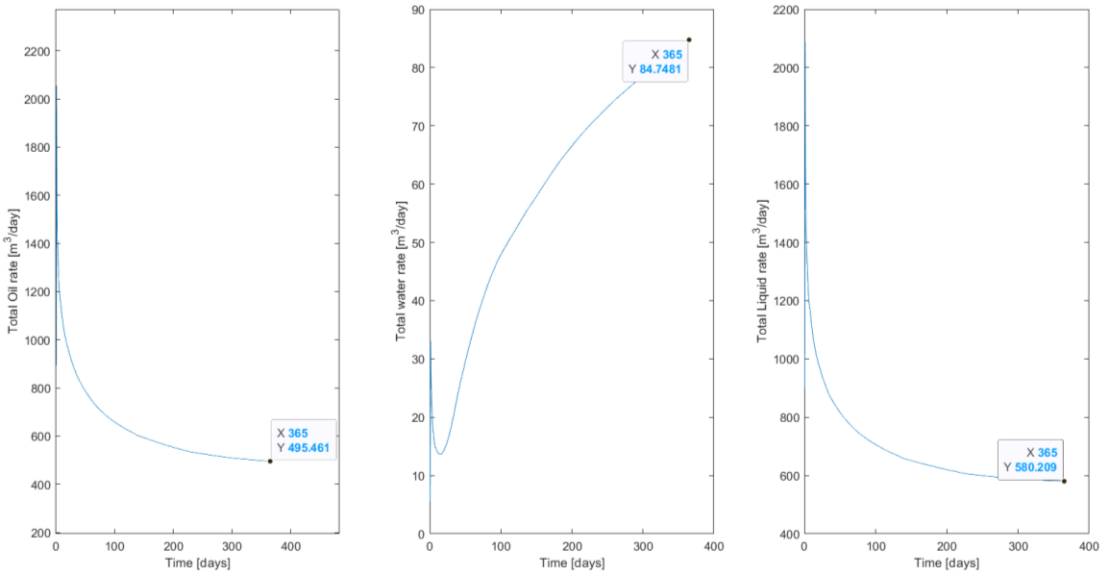


Figure 4-15: Total oil, water, and liquid production rates from the separator for the SPE9 model with optimized DPO

4.2.3 Case VI: Refined simulation time step with an optimized DPO (1000 Days)

A simulation with a longer prediction horizon was performed to investigate the long-term effects of the DPO strategy for the SPE9 reservoir model. This gives an overview of production performances for each well for a period of 1000 days. Simulation time step was taken as 12 hours for this simulation case. This model was chosen for the 1000-day prediction horizon due to its lower water cut in the reservoir as compared to the Egg case model.

Figure 4-16 shows the oil production rate for all three wells for the SPE9 reservoir model. The oil production decreased initially and stabilized after around 300 days for all the wells. This stabilization suggests that the DPO algorithm successfully maintained the reservoir pressure and fluid flow within a favorable regime for production.

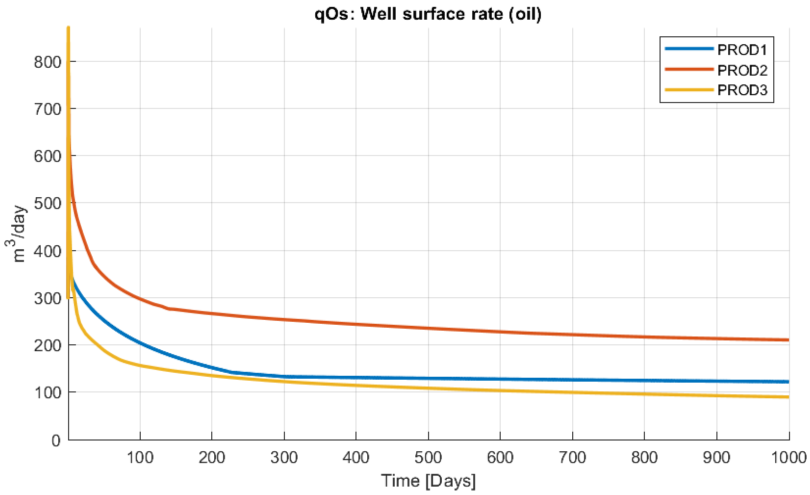


Figure 4-16: Oil production rate for each well in the SPE9 model with optimized DPO

Figure 4-17 shows the individual well performance metrics such as oil production rate, water production rate, BHP, productivity index, water cut and cumulative profit for optimized gas lift rate. The gas lift rate gets stabilized after around 200 days of production. The cumulative profit increased linearly for this model as the oil production rate is relatively constant throughout the prediction horizon. The bottom hole pressure remained steady throughout the prediction horizon except in the beginning for this case.

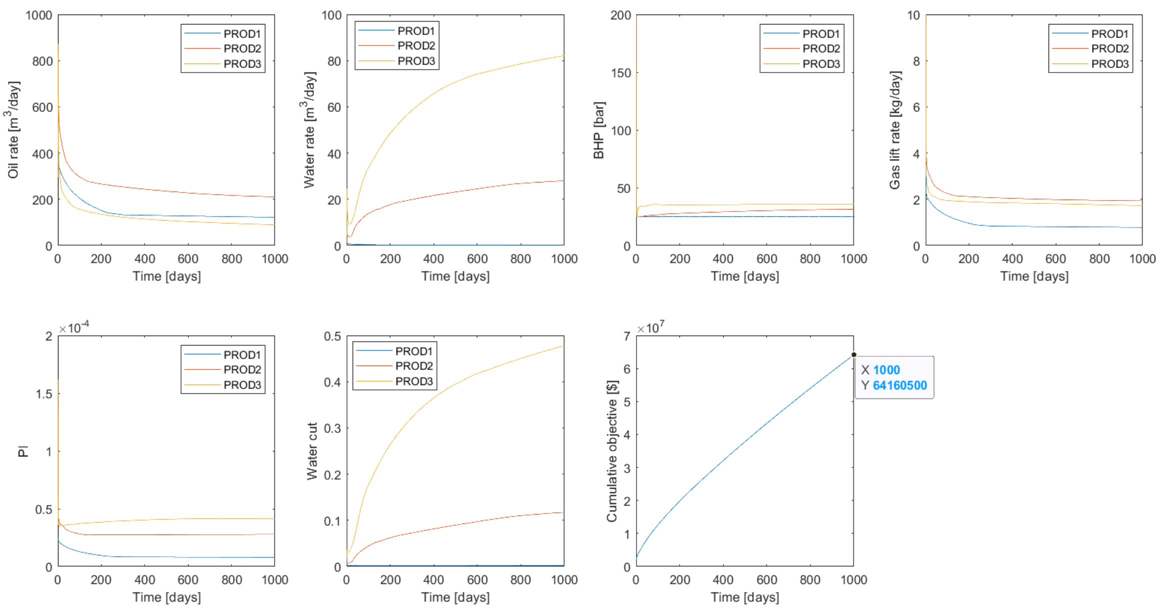


Figure 4-17: Individual well performance (oil/water rates, BHP, PI, water cut) and cumulative profit in the SPE9 model with optimized DPO

Figure 4-18 depicts the total liquid production rates from the separator. The oil production rate reaches 422.52 m3/day by day 1000. The oil production rate decreases with increasing production days; however, the total water production rate increases significantly after around 25 days of production. The water production rate as compared to oil production rate is around

26% after 1000 days of production. The total liquid production rate decreases with increase in the production days and gets almost stabilized after around 800 days of production.

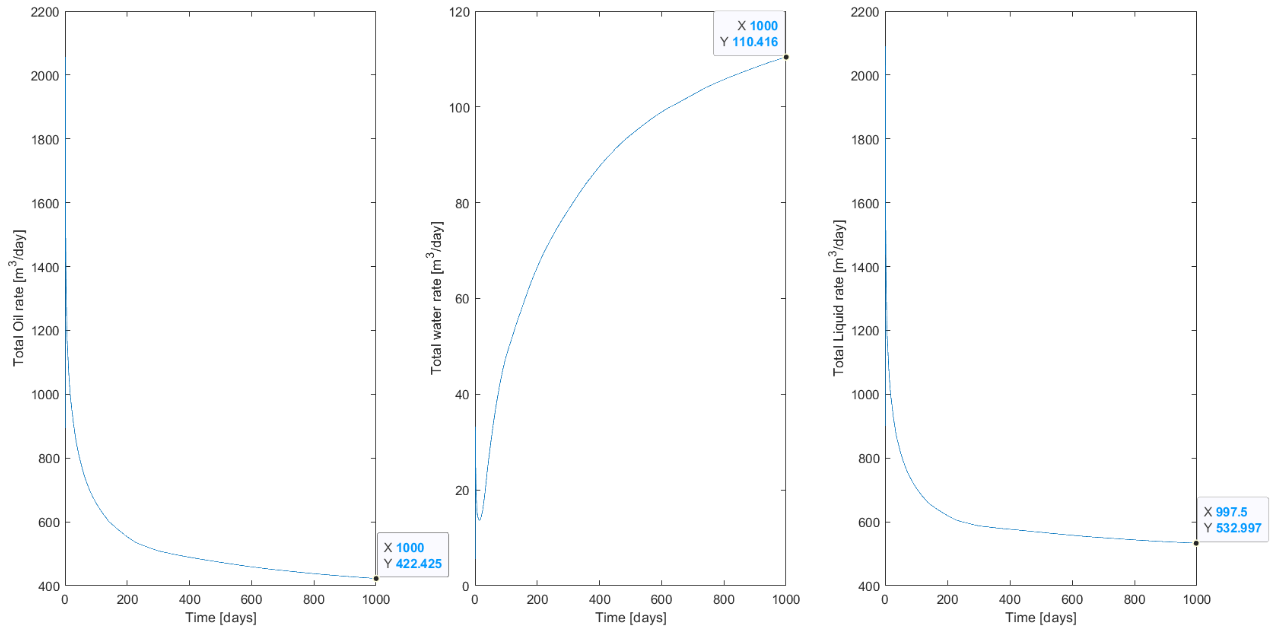


Figure 4-18: Total oil, water, and liquid production rates from the separator for the SPE9 model with optimized DPO

5 Conclusion and future work

5.1 Conclusion

This study investigated the application of gas-lift optimization strategies in two distinct reservoir models, i.e., "Egg model" and SPE9 model. A coupled well-reservoir model was developed, incorporating dynamic reservoir pressure and multi-phase flow dynamics to simulate realistic oil production scenarios. The study evaluated the impact of simulation steps, prediction horizons, and the use of a standard DPO algorithm on production outcomes. Individual well performance was calculated for three different wells for each of the reservoir models. The individual well performance included in this study were oil/water production rates, BHP, PI, water cut and cumulative profit.

The analysis showed several key findings which are summarized below:

1. **Importance of simulation time step:** Simulations with a coarse time step (180 steps per year) highlighted the importance of temporal resolution in accurately capturing transient reservoir dynamics. However, a refined time step of 12 hours mitigated oscillations in oil production, particularly in the early stages, and enabled a more precise representation of the reservoir model behavior.
2. **Effectiveness of DPO:** The standard DPO algorithm demonstrated its effectiveness in both the Egg and SPE9 models by significantly increasing oil production and cumulative profit compared to the "no control" scenarios. This gave a significant potential of gas-lift optimization to enhance the economic viability of oil production operations.
3. **Reservoir model sensitivity:** The gas-lift optimization strategies exhibited varying degrees of success in the two different reservoir models. The Egg model showed a more pronounced response to optimization, leading to a larger profit increase (4%) compared to the SPE9 model (3%). The egg model had relatively homogeneous channelized structure as compared to SPE9 model. This suggests that the effectiveness of gas-lift optimization may be influenced by the specific geological characteristics and heterogeneity of the reservoir.
4. **Profitability:** The SPE9 model’s profitability is linear whereas for the Egg case model, the initial profitability is exponential and gets linearized after a certain day of production. This gave a clear overview of profitability based on the reservoir properties.

5.2 Future work

The insights gained from this study open other different scopes for future research which are listed below:

1. **Advanced optimization algorithms:** Further simulations can be performed with more advanced optimization algorithms, such as machine learning or reinforcement learning to further enhance production and profitability.
2. **Uncertainty quantification:** These models can be further improved by quantifying the uncertainties associated with the reservoir parameters. This would improve the robustness and reliability of the optimization strategies.
3. **Field data validation:** The developed models can be validated against the real field data. Then the validated models can be used to optimize their applicability and effectiveness in real-world oil and gas productions.
4. **Economic evaluation:** A detailed comprehensive economic evaluation is needed to address the additional costs and factors, such as maintenance and operational expenses, to provide a more realistic assessment of the gas-lift optimization strategies.

The findings of this study together with these future works would develop a more advanced, robust, and efficient gas-lift optimization models that can be applied in a wider range of oil production processes.

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Appendices

Appendix A: Thesis task description

University of
South-Eastern Norway

Faculty of Technology, Natural Sciences and Maritime Sciences, Campus Porsgrunn

FMH606 Master's Thesis

Title: Daily production optimization of gas-lifted oil field with MPC framework

USN supervisors: Roshan Sharma (USN), Stein Krogstad (Sintef)

External partner: Digiwell, Sintef, Equinor

Task background:
In general, in an oil field, multiple oil wells are connected to a common gathering manifold. With production optimization, the task is to produce oil from different wells in such a manner that maximum profit is obtained. This has to be done while still satisfying various operational constraints. And with daily production optimization, the prediction horizon should be a relatively short time period, say a few days to a week. For achieving this an MPC framework can be potentially used for daily production optimization. In this thesis, the student should work on a Gas lifted oil field. The dynamic model of the system/process will be provided to the student.

Task description:
The following are the main tasks:

1. Literature review on daily production optimization for gas lifted oil field.
2. Daily production optimization using MPC for gas lifted oil field.
3. Couple the gas lifted oil field model with a more sophiscticated reservoir model.
4. Perform a comprehensive review of the two different reservoir models namely 'Egg model' and 'SPE9 model' by applying steady state optimization for oil production.
5. Analyze the comparision between these two coupled models (with and without standard DPO).
6. Document the work in a report. The report should be technically sound. Presentation of the work.

Student category: IIA students

Is the task suitable for online students (not present at the campus)? Yes

Practical arrangements: N/A

Supervision:
As a general rule, the student is entitled to 15-20 hours of supervision. This includes necessary time for the supervisor to prepare for supervision meetings (reading material to be discussed, etc).

Signatures:

Supervisor (date and signature): , Jan 25, 2024

Student (write clearly in all capitalized letters):Mahesh Timsina

Student (date and signature): , Jan 26, 2024

Appendix B: Lists of symbols used in the model

Table 3 and Table 4 give an overview of all the variable, parameters constants that are used in the model.

Table 3: All the variables and parameters of the model are listed below.

Symbol	**Type**	**Description**
m_{ga}	State	Mass of lift gas in the annulus
m_{gt}	State	Mass of gas in the tubing above the injection point
m_{lt}	State	Mass of liquid in the tubing above the injection point
w_{ga}	Input	Mass flow rate of gas injected into the annulus
w_{ginj}	Variable	Mass flow rate of gas injected from the annulus into the tubing
w_{gr}	Variable	Mass flow rate of gas from the reservoir into the well
w_{gp}	Variable	Mass flow rate of gas phase through the production choke valve
w_{lr}	Variable	Mass flow rate of liquid from reservoir into the well
w_{lp}	Variable	Mass flow rate of liquid phase through the production choke valve
w_{glp}	Variable	Total mass flow rate through the production choke valve
P_a	Variable	Pressure of gas in annulus downstream the gas lift choke valve
P_{ainj}	Variable	Pressure upstream of the gas injection valve in the annulus
P_{tinj}	variable	Pressure downstream of the gas injection valve in the tubing
P_{bh}	Variable	Bottom hole pressure
P_{wh}	Variable	Wellhead pressure
ρ_{ga}	Variable	Average density of gas in the annulus
ρ_m	Variable	Density of multiphase mixture in the tubing above the injection point
ρ_l	Variable	Average density of the liquid phase
V_G	Variable	Volume of the gas in the tubing above the gas injection point
Y_2	Variable	Gas expandability factor through the gas injection valve

Y_3	Variable	Gas expandability factor through the production choke valve

Table 4: List of the parameters and constants

Symbol	**Type**	**Description**
PI	Parameter	Productivity index
WC	Parameter	Water cut
GOR	Parameter	Gas to oil ratio
p_r	Parameter	Reservoir pressure
p_s	Parameter	Separator pressure
p_m	Parameter	Gathering manifold pressure
T_a	Parameter	Temperature in annulus
T_t	Parameter	Temperature in tubing
A_a	Parameter	Cross-section area of the annulus
A_t	Parameter	Cross-section area of the tubing
L_{a_tl}	Parameter	Total length of the annulus
L_{a_vl}	Parameter	Vertical length of the annulus
L_{t_tl}	Parameter	Total length of tubing above injection point
L_{t_vl}	parameter	Vertical length of tubing above injection point
L_{r_vl}	Parameter	Vertical length of tubing below injection point
C_v	Constant	Valve opening characteristic
K	Constant	Gas injection valve constant
α_Y	Constant	Constant
M	Constant	Molar mass
Z	Constant	Gas compressibility factor
R	Constant	Universal gas constant

g	Constant	Gravity
ρ_w	Constant	Density of water
ρ_o	Constant	Density of oil