University of Bahrain

College of Engineering

Department of Mechanical Engineering

Plan Portfolio Optimization for Upstream Petroleum Companies in a Volatile Oil Price Environment

A Thesis Submitted in Partial Fulfilment of the Requirements for the Master of Science Degree in Engineering Management

Submitted by:

Mohamed Mansoor Ahmed Hasan

ID: 20040070

Supervised by:

Dr. Mohamed Bin Shams

Associate professor

University of Bahrain

Kingdom of Bahrain

January 2023

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University of Bahrain
Deanship of Graduate Studies
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جامعة البحرين
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Thesis Discussion Committee Decision

Student Name: MOHAMED MANSOOR AHMED	Student ID: 20040070
Department: **Mechanical Engineering**	College: **Engineering**
Program: **Masters in Engineering Management**	
Thesis Title: **Plan Portfolio Optimization for Upstream Petroleum Companies in a Volatile Oil Price Environment**	
Supervisor Name: **Dr. Mohamed Bin Shams**	Student GPA: **3.74**

The Discussion Committee met on 19-Jan-23 In Virtual Microsoft Teams. Upon discussing the student whose details are stated above in public, the discussion committee recommends the following:

The student is awarded a grade A in the thesis subject.

☐ Without making any changes to the thesis.

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Discussion Committee Members Approval:

Name		Signature
1. Dr. Mohamed Bin Shams	(Advisor)	Click here to enter text.
2. Prof. Hatem Masri	(Internal Examiner)	Click here to enter text.
3. Dr. Munawar Abdul SHAIK	(External Examiner)	Click here to enter text.

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Abstract

The health of global economy is directly and indirectly impacted by the petroleum industry performance. Unfortunately, this vital natural resource is non-renewable and eventually depletes over time. As a result, massive capitals are continually invested to meet rising worldwide demand. Regrettably, this substantial investment capital is coupled with a number of technical, operational, commercial, and geopolitical uncertainties. These uncertainties; however, are commonly disregarded in economic evaluations by petroleum firms, such as the one under study, that generate their annual business plans by using traditional deterministic excel models and ranking projects manually. Therefore, while making an investment decision, an effective assessment of the spectrum of uncertainties is crucial for improved decision making.

This study uses a two-stage stochastic programming with recourse approach as an alternate way for business program selection to assist oil and gas companies in making a better investment decision under uncertainty. To simplify the approach, we looked at Company A' portfolio and picked development drilling program for optimization under future oil price uncertainty.

Among several investment opportunities accessible, Company A decision makers have concerns in maximizing the Expected Net Present Value (ENPV) by drilling an optimal collection of development wells from a variety of formations and trajectory options considering several constraints. Furthermore, in light of future oil price volatility, the company would like to plan the optimum drilling rigs number, which can be adapted as part of annual operation strategy. This operational decision does not have to be made at the time the plan is being prepared; rather, it can be decided later when new information on actual oil prices is available. As a result, this becomes a sequential decision problem, and modelling the information structure of such a problem becomes crucial.

A representative mathematical Mixed Integer Linear Programming (MILP) model was formulated, coded in GAMS, verified, and solved for Company A's oil development drilling program problem. After investigating the stochastic model's outcomes value over the deterministic model, the stochastic model was used to propose an optimal Annual Work Program and Budget (AWPB) and 5 years plan. Although, the Expected Value of Perfect Information (EVPI) is found 1.3% and less than 1 % of the calculated portfolio value, which equates to over $9.8 million and $33.6 million for AWPB and 5 years plan, respectively. These figures indicate the motivating fact that even a small improvement in portfolio value measured in percentage represents a significant money. Furthermore, the optimized plan increased the ENPV by $67 million, or 9.3 %, over Company A's AWPB original plan. In addition, the model revealed the potential of new facility investment.

Dedication

This work is dedicated to my dear parents, who have always loved, encouraged, and believed in me over the years.

To my dear wife and little daughter, for their unconditional love and patience.

Finally, to my family members and loved ones.

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First and foremost, I would really like to convey my gratitude to my supervisor, Dr. Mohamed Bin Shams, for his guidance, support, and encouragement during the various stages of this research.

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Abbreviations

EIA	Energy Information Administration
IEA	International Energy Agency
TOC	Total Organic Carbon
Bbl	Barrels of oil
USD	Dollar of United States of America
$/bbl	Dollar per barrel of oil
BOPD	Barrels of Oil per Day
BWPD	Barrels of Water per Day
CAPEX	Capital Expenditure, USD
OPEX	Operation Expenditure, USD
Mscf	Thousand standard cubic feet
Mscf/d	Thousand standard cubic feet per day
NPV	Net Present Value
ENPV	Expected Net Present Value
NCF	Net Cash Flow
E&P	Exploration and Production
R&D	Research and Development
IOR	Improved Oil Recovery
EOR	Enhanced Oil Recovery
DCF	Discounted Cash Flow
%	Percentage
EMV	Expected Monetary Value
$ M	Thousand dollars
$ MM	Million dollars
M bbl	Thousands barrels oil
MM bbl	Million barrels oil
M BOPD	Thousands Barrels Oil per Day
No.	Number
BP	Business Plan
DP	Depletion Plan
AWPB	Annual Work Program and Budget
5Yrs BP	Five Years Business Plan
SP	Stochastic Programming
BoD	Board of Directors
IRR	Internal Rate of Return
VaR	Value at Risk
MOP	Method of Production
ABC	Activity Based Costing

WMF	Well Manifold
TB	Tank Battery
VAT	Value Added Tax
DCA	Decline Curve Analysis
WC	Water Cut
GOR	Gas Oil Ratio
GAMS	General Algebraic Modelling System
GDX	GAMS Data Exchange
MIP	Mixed Integer Programming
MILP	Mixed Integer Linear Programming
EVPI	Expected Value of Perfect Information
WTI	West Texas Intermediate

CHAPTER 1

INTRODUCTION

1.1 An Overview of Upstream Petroleum Sector Characteristics and Investment Challenges
1.2 Problem Statement
1.3 Motivation and Objectives
1.4 Methodology
1.5 Thesis Structure

CHAPTER 1 Introduction

The health of global economy is directly and indirectly influenced by the petroleum industry performance; because simply the oil and gas supply over half of the world's energy consumption. It has been the most essential energy resource for the world's daily activities since the 1950s. It is being utilized basically in different sectors as it supplies fuels for transportation, electricity generation, and large variety of hydrocarbons end products. This explains why the world pays close attention to petroleum companies' activities such as discoveries, supply and demand, prices forecast, investment portfolios, projects' risks, uncertainties and so on.

In fact, even with lofty goals of reducing greenhouse gas emissions which contributes to global warming, petroleum resource is projected to continue dominating the energy supply by over 50% till 2050 according to Energy Information Administration (EIA) forecast (EIA website, 2022). Today, there is no ripe alternative or competitor energy resource for the oil and gas. All the renewable energy choices are exorbitant and unreliable at present. Unfortunately, this crucial natural resource is non-renewable and depleting over time due to rising demand to assure global industrial growth. As a result, massive capitals are being continually invested in this vital sector. The International Energy Agency (IEA website, 2022) estimated global upstream oil and gas investment of USD 505 billion in 2019, with an increase of 6% comparing to previous year, which makes the upstream petroleum industry's investments one of the most capital intensives comparing to other sectors. Unfortunately, this large investment capital

is coupled with several technical, operational, commercial, and geopolitical challenges and uncertainties.

Considering the capital intensiveness of the oil and gas business, as well as the wide range of risks and uncertainties associated with the petroleum projects, investment decision makers must carefully select portfolios of projects as part of Annual Work Program and Budget (AWPB) and long-term plans in order to achieve their strategic goals through projects execution. Therefore, Planners and economists must use robust methodologies in order to propose an optimal subgroup of projects that increase the company's value while sticking to company's limited resources and maintaining an acceptable risk level. These methods must count for potential risks and uncertainties, and guarantee immediate response to any unforeseen conditions or deviation from the original plan.

To achieve the goal of maximizing the value of an asset for any corporation, portfolio optimization techniques are usually utilized. The main objective of portfolio optimization is to translate the strategies into an optimum business program that meets the company's portfolio goals. The optimization process is an iterative procedure that necessitates thousands of simulations runs to reach an optimal solution.

1.1 An Overview of Upstream Petroleum Sector Characteristics and Investment Challenges

Upstream, midstream, and downstream are the three segments of the petroleum industry. The upstream sector includes Exploration and Production (E&P) activities from exploring the promising hydrocarbon field till producing commercial oil and gas and selling it to customers including downstream sector enterprises. The downstream sector, on the other hand, is in charge of refining the crude oil and further processing the gas into end products. The bridge connects

the upstream and downstream sectors is called midstream sector, which includes activities such as storage and transportation.

Any typical oil and gas field in the upstream industry must go through five stages of field maturity, beginning with exploration, appraisal, development, production and ending with abandonment as indicated in Figure 1.1.

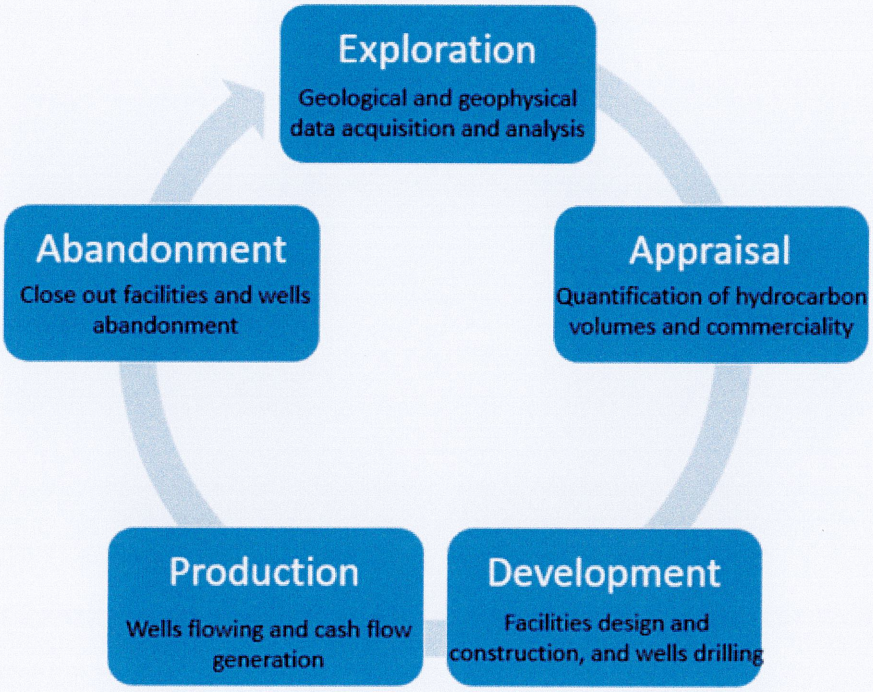


Figure 1.1 Life cycle of petroleum fields (Johnston, 2003 with modification)

- **Exploration phase:** It is the first step of detecting a potential presence of a petroleum asset. This phase entails collecting and interpretation of geological, geophysical and geotechnical data utilizing advanced technologies such as 3D seismic. It is a very cost intensive and high-risk phase in which a successful exploration wells may lead to verification of acceptable percentage of Total Organic Carbon (TOC) or hydrocarbons volumes.
- **Appraisal phase:** Drilling more wells and gathering more static and dynamic data are critical in this phase to establish the size of the field and the amount of hydrocarbon volumes. It also assesses whether a product is

commercially viable and whether an investment decision should be made to halt at this stage or proceed on to the next development phase.

- **Development phase:** The development phase entails a more thorough plan and the execution for facilities engineering and construction, pipeline networks and storage tanks, as well as drilling wells scheduling and operations. This phase requires an intensive investment of capital to prepare the field for production.
- **Production phase:** Oil or gas start flowing in this phase, and corporations begin to generate cash flows. Once the reservoirs have lost their natural energy, the hydrocarbon reserves are depleted, and extra costs of production enhancement are added over time to produce the difficult oil or gas through Improved Oil Recovery (IOR) and Enhanced Oil Recovery (EOR) processes.
- **Abandonment phase:** Once the recoverable reserves have already been produced, the field reaches the point when it is no longer economically viable to continue producing, resulting in field abandonment.

Each of five stages listed above has its own set characteristics, uncertainties, challenges, as well as opportunities. However, despite all of these individual stage challenges, the painful fact is that the hydrocarbon reserves is non-renewable and is depleting as a result of continuous production. Since there is no other competitive alternative source at large scale available today or in the near future, oil and gas will remain the primary source of energy supply with the world economic growth. This is, also, linked to the fact that easy oil has already been produced, and the industry turning to more complex oil and gas assets. As a result, the production technologies will play a critical role in the commerciality of oil production and will dominate the market prices.

One of the main challenges lies in the upstream petroleum projects is that they are dealing with underground product, which could carry many uncertainties

about the volume of movable oil, how much oil and gas can be produced, and what is are the technologies required. As a result, this creates some challenges in funding these intensive capital projects considering its high risk and uncertain investment environment. Furthermore, there are always geopolitical considerations, which typically have an impact on stability of energy supply. In addition, due to global plan to attain net zero emissions by 2050, there are environmental concerns related to hydrocarbon usage, which may impact the level of investments in developing petroleum fields. Moreover, with the rising of energy consumption, as well as the rapid depletion of reservoirs and the deterioration of infrastructures, massive investments are continually required in order to maintain present levels of production and to ensure additional production capacity.

On top of the aforementioned challenges, the upstream petroleum industry in nature is exposed to numerous risks and uncertainties associated with its projects investment. These uncertainties can be categorized in four dimensions, which are technical (reserves, decline, initial rate, and enhanced oil recovery response), operational (downtime, drilling schedule, Workover schedule, and time to market), commercial (CAPEX, OPEX, and oil price), and external (social, environmental, and supply chain process).

The challenges and uncertainties in the upstream petroleum business are numerous, and they are not confined to those related technical or commercial issues. For example, the world experienced the consequence of the COVID 19 pandemic being spared in 2020 and beyond, which restricted people's movements and harmed the logistics sector, mostly through reduced productivity and imbalanced supply chain management. As a result, there has been a significant increase in oil price volatility, as well as a shrinkage in the economy of several countries. Therefore, unforeseen pandemics or natural catastrophes are usually viewed as a threat.

Due to combination of the abovementioned challenges and different uncertainties, investment decisions in the petroleum industry have become more complex, as they have a direct impact on investment decision making and the likelihood of projects success. Hence, before committing any resources, it is critical to conduct a proper economics evaluation for each investment, taking into consideration these key factors. This necessitates thorough grasp of both individual and portfolio projects' spectrum of uncertainties, as well as a well-represented economic model to better guide decision makers on the best and most optimal investment portfolio scenario for the business plan.

1.2 Problem Statement

Profit maximization is a common objective for all corporates in different industries, including oil and gas enterprises. Among several investment opportunities accessible, petroleum organizations' executives are concerned about which is the best business program to pursue in order to satisfy the organization's goals of growth and maximization of owned assets. Investment decisions are routinely made in a high-risk and high-uncertainty context. If the decision-making process does not include a thorough assessment of the risks and uncertainties, it may result in underperformance, missed opportunities, increased risk exposure, and share market losses. Unfortunately, these uncertainties are frequently overlooked in economic evaluations, either due to a lack of information about how to effectively address them or simply underestimating their true impact on investment and projects performance.

In today's market, our experience has shown that company business planning is frequently hampered by a lack of direction and integration. Failure to adapt organizational planning techniques to reflect projects uncertainties and investment conditions change could lead to produce un-realistic business program, as well as could give rise to a number of unexpected consequences. Oil and gas corporations have their own methods and models for evaluating E&P

projects economically. Those models were either built in house or customized through third party service providers. Many small, medium, and perhaps big organizations, including the case under study, construct their annual business plans using spreadsheets deterministic models and ranking projects manually. Although the deterministic approach is extensively used to assess feasibility of petroleum projects, it has significant limitations in terms of its capacity to be employed in real industrial problems and particularly assessing investments involving uncertainties. The issue with the traditional deterministic assessment techniques is that they are no longer flexible or intelligent enough to react to dynamic changes in the business world and the input parameters are assumed to be perfectly known. The output, as a result, which is based on ideal knowledge of all parameters values, is definitely unrepresentative of real industrial problems and could lead to poor investment decisions. With such techniques, business plans would become isolated from the firm's day to day actuality, and will lose its value as a road to desired outcomes.

To overcome the challenge of applying suitable assessment for investment under uncertainty, as well as to provide top Management better guidance for good decision making, several mathematical programming methods have been introduced in the literature. This thesis focuses on establishing a better technique for business program selection to assist oil and gas corporations in making investment decisions under uncertainty. To simplify the approach, we will look at a business program for a case study in which we will use a development drilling program to apply the two-stage stochastic methodology by introducing oil price as an uncertain parameter.

The problem we want to solve is this: Company A wishes to maximize the Net Present Value (NPV) by drilling an optimal collection of development wells in a variety of formations and trajectory options from an inventory of development wells available for drilling considering some constraints. In

addition, in light of future oil price uncertainties, the company would like to plan drilling rigs requirement as part of its AWPB and 5-year business plan, with flexibility to be adapted in react to volatile oil price as part of operation strategy. This operational decision does not have to be taken at the time the plan is being produced; instead, it can be decided later when more information on actual oil prices becomes available. As a result, the problem becomes a sequential decision problem, and modelling the information structure of such a problem becomes critical. The concept is that rather than making a perfect development plan "right now," future decisions might be adjusted based on updated information. The main problem is determining which information is available at the time when judgments must be made. As a result, when modelling decision-making under uncertainty, a two-stage model is often considered sufficient. Two-stage models have proven to be beneficial as planning models in situations when the first stage decisions must be made immediately, but the second stage decisions can be made after the uncertainty has been resolved. The first stage decisions may represent the plan; however, the second stage decisions (e.g., number of rigs and well mix) are allowed to be influenced by observable random elements. Typically, such issues are modelled as recourse problems.

1.3 Motivation and Objectives

Since the 1980s, there has been a substantial theoretical and empirical literature on oil and gas investment portfolio optimization and decision making under uncertainty. Despite the fact that oil and gas business investment has expanded dramatically since then, with greater challenges and uncertainties, the flow of new research has been significantly reduced during the last decade. Furthermore, it appears that there is a disconnection between academic research and real-world investment assessment practices in upstream petroleum companies like the one we are looking at in this research. "Despite the importance and economic significance of project portfolio selection and the existence of

- Demonstrate the significance of quantifying petroleum projects uncertainties on portfolios optimization taking into account the range of uncertainties of individual projects.
- Develop a robust optimization model that can guide for a better investment decision in a volatile oil price environment.
- Develop a portfolio optimization model that can be expanded to incorporate more key uncertain parameters.

1.4 Methodology

Any problem analysis should have the purpose of providing comprehensive and reliable information to decision makers so that they can make the best decision possible. In this research, we followed a standard decision analysis framework refers to (Matheson and Howard, 1968) as shown in Figure 1.2, in order to solve our optimization problem.

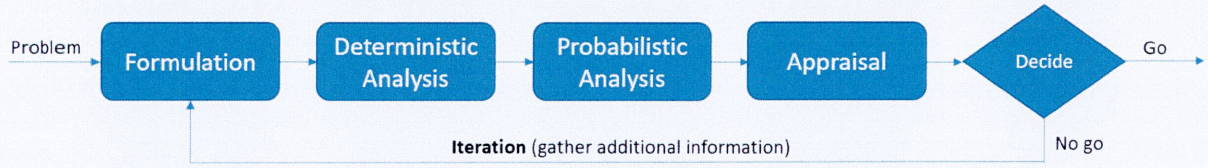


Figure 1.2 Decision analysis cycle

The four steps of the standard decision analysis cycle are as follows:

- **Formulation:** Mathematical frame model represents the decision problem with its constraints and point out alternatives and uncertainties. It is crucial step as it establishes the foundation for all the other following steps.
- **Deterministic Analysis:** Assess sensitive parameters and approximately quantify critical uncertainties.
- **Probabilistic Analysis:** Examine the relevant uncertainty's probability distribution and evaluate risk tolerance.

- **Appraisal:** Assess sensitivity of uncertain parameters with their likelihood of occurring to determine the impact on the optimal decision. If high confidence still not achieved, then assess the value of obtaining more data.

Since the decision is not an event rather than it is an iterative procedure, it is subjected for further evaluation by gathering additional data which should lead to a better decision. Otherwise, decision should be taken on ready projects.

This research follows a quantitative approach, in which a representative mathematical model for a problem case study was formulated and solved. As an upstream oil and gas industry representative, the case study analysis has been completed for an oil and gas company. The proposed optimization problem solving procedure aims to offer a better methodology for overcoming the challenge of preparing an optimal AWPB while taking into account a large number of projects' uncertain parameters and limited resources constraints.

First and foremost, a thorough review of the literature we conducted to gain a better understanding of the nature of petroleum projects and the challenges they face. In addition, we dug deeper to try to understand how petroleum businesses make decisions in the presence of a variety of uncertainties, particularly oil price uncertainty. Then, we reviewed optimization methods available in the literature and identified the strengths and deficiencies of each approach in order to choose the best methodology that fits our problem case and fill the current practice gap in evaluating business programs in order to propose an optimal collection of projects as part of AWPB.

Next, we formulated our optimization problem into a mathematical model with an objective function, constraints and decision variables. Following that, we began collecting real data from the national petroleum firm about its business plans, such as individual project's CAPEX and OPEX costs, production, reserves, projects' associated risks and other dependencies inputs. These data were

meticulously processed in order to address and quantify the various uncertainty ranges. Some sensitivity tests were also run to find key sensitive parameters to be considered in optimization modelling.

Then, as part of portfolio optimization, a two-stage stochastic model was built to account for individual projects' technical, operational, and commercial uncertainties, as well as corporate's resources constraints such as capital budget limits, facility capacity, and many other internal or external constraints. After comparing the stochastic model's outcomes value over the deterministic model, the stochastic model was used to propose an optimal AWPB.

Finally, since our scope of work was limited by personnel capability and a specific time frame, we suggested ways to improve this work for future research.

The methodology applied to formulate and solve the problem can be summarized as follows:

1. Recognize the challenges in making investment decisions in the upstream petroleum sector due to a wide range of projects and market uncertainty.
2. Review of the literature.
3. Select a case study to assess current practice and gaps in the project's evaluation and selection approach.
4. Formulate a representative mathematical optimization model for the problem under study.
5. Field data collection for the case study.
6. Build and run model for best projects selection using deterministic approach.
7. Build and run two stage stochastic model considering key uncertain parameters.
8. Compare the findings of deterministic approach versus stochastic approach.

9. Generate an optimum annual work business plan proposal.
10. Summarize the study's findings and recommend future work improvement.

1.5 Thesis Structure

The thesis is presented into eight chapters. In chapter 1, we introduced the investment characteristics and challenges of the upstream petroleum business. Furthermore, we defined the scope and objectives of this research before explaining the methodology for achieving these objectives. The rest of this research paper is structured as follows:

Chapter 2 presents a review of relevant literature on the uncertainties associated with upstream petroleum projects. The relationship between investment and uncertainty in general, as well as investment and oil price uncertainty in particular, is then discussed. In addition, we introduce the available techniques of portfolio optimization under uncertainty with an emphasis on two stage stochastic programming with recourse methodology, which is applied in this study.

Chapter 3 introduces the case study (Company A) by providing an overview on present practices and gaps in assessing its annual and five years business programs.

Chapter 4 is basically formulating the optimization problem mathematically, in which we identify the decision variables, objective function and problem constraints.

Chapter 5 and 6 show coding of previous chapter formulation using an optimization software and testing the model, respectively. In these two chapters, we address the challenges of model development, as well as verifying the functionality of the model by applying several cases.

Chapter 7 is the core of this study, in which a model application using real case field data is used to highlight and compare the outcomes of both deterministic and stochastic techniques.

Chapter 8 rolls up the study's findings and conclusions, as well as sets recommendations for future research.

Finally, Appendix (A) that includes the GAMS model elements is attached as a supplement to this report.

CHAPTER 2

LITERATURE REVIEW

2.1 Petroleum Projects Uncertainties
2.2 Investment and Uncertainty Relationship
2.3 Investment under oil price uncertainty
2.4 Portfolio Optimization under Uncertainty Methods
2.5 Two Stage Stochastic Programming with Recourse Methodology

CHAPTER 2 Literature Review

The uncertainties associated with the projects, as well as the volatility of crude oil prices, play a significant role in any strategic investment decision in the upstream petroleum sector. Although there has been major work on portfolio optimization problems, there are very few researches exist at the precise level required, particularly on Stochastic Programming (SP) problems in the upstream petroleum sector.

This chapter presents a review of accessible literature on upstream petroleum portfolio projects optimization under investment uncertainty. After reviewing the previous forty years of researches relevant to our problem statement under study, we structured this chapter into five sections. Section 2.1 includes a review of uncertainties associated with petroleum projects. The second and third sections discuss the relationship between investment and uncertainty in general, and between investment and specifically oil price uncertainty, respectively. Section 2.4 provides a literature review on the techniques of portfolio optimization under uncertainty. Finally, Section 2.5 introduces two stage stochastic programming with recourse methodology applied in this research.

2.1 Petroleum Projects Uncertainties

It is critical to understand the characteristics of petroleum projects, as well as the various risks and uncertainties associated with them, in order to assess their commercial viability and make smart investment decision.

Risk and uncertainty have become as synonymous in the petroleum sector as per (Caldwell and Heather, 2001). "Indeed, the pioneering work on the subject by (Newendorp, 1975), did not draw a distinction between the two terms. Since that time, it has become generally accepted that the term "risk" is associated with the probability of total loss, while "uncertainty" is associated with the description of the range of possible outcomes".

Based on time horizon, uncertainty can be classified as short term, midterm, and long term as per to (Li, 2004). Daily, weekly, and monthly variances in production rates, prices, and equipment downtimes all are examples of short term uncertainty involves. Long-term uncertainties, on the other hand, can be expressed in 5 years plus and may include long-term net cash flow and demand. The midterm uncertainty is somewhere in between short and long uncertainties, and it might include parameters from.

The uncertainties, also, can be split into internal and external uncertainties based on their position from the process or "asset" according to (Wendt et al., 2002). (Jonsbraten, 1998) used exogenous and endogenous terms to represent external and internal uncertainty, respectively. External uncertainties are those elements that have an impact on the process operations and comes from outside source such as market condition, society, environment, and politics. Internal uncertainties, on the other hand, are those occur due to lack of full knowledge of the process like expected production, scheduling and cost estimation.

Measurement inaccuracy, insufficient data, computational approximation, and stochastic system are the four sources of uncertainty identified by (Caldwell and Heather, 2001). The measurement inaccuracy might be caused by either human error or inadequate instrument calibration. The insufficient or incomplete data, which is a result of the charge of data collection, is another source of uncertainty. Because of high cost of advanced data collection, some assumptions are made based on personal experience and judgment, which raises questions

about the accuracy of these assumptions. The third source of uncertainty is the computational approximation, which results from applying empirical correlations without taking into account the scatter of the original experimental measurement data. The final source of uncertainty is the stochastic parameters, which are not subject to engineering estimation or control but have a major impact on the investment evaluations, such as the stochastic nature of the crude oil price volatility.

Several uncertainties exist while dealing with petroleum projects. (Grab, 1988) classified the uncertainties involved in evaluating of the Exploration and Production (E&P) projects into three categories: technical, economic, and political. The technical uncertainties are those uncertainties have to do with the accuracy of estimating the unground hydrocarbon volumes and the recoverable amounts within a given time frame. In fact, the technical uncertainty can be also extended to cover uncertainties associated with activities such as drilling operation and facility construction scheduling. The economic uncertainties, on the other hand, are related to product price forecasting, capital investment, operating expenses, inflation, and market conditions. Finally, international political instability, operational restrictions, limits, and taxation projections are all linked to the political uncertainties.

"Today's petroleum industry is operating in an ever-changing technical, economical, and political environment" according to (Mian, 2002). He listed several "factors affecting decision making include technology advancements, new products and techniques, uncertainty of oil and gas prices, operating costs, equipment costs, inflation, market conditions, political risks, environmental threats, reliability of the aging production facilities, capital availability constraints, scarcity of good prospects, and governmental regulations".

In fact, each of the five stages of petroleum field life cycle (see Section 1.1) has its own challenges and uncertainties. According to (Kokolis *et al.*, 1999),

the level of uncertainty is highest at early stage of Exploration and Production (E&P) projects. This is largely true since decisions must be made with minimum information available. While in the late of the production stage, and due to a wealth of historical data, technical uncertainties decrease as reservoir production and depletion increase.

Economic uncertainty impacts the petroleum industry's investments almost as much as technical uncertainty (Stermole, F. and Stermole J., 1996). Economic uncertainty does not reduce over the life of reservoir depletion like the technical uncertainty. For companies contemplating development options, oil and gas prices forecast is a significant source of economic uncertainty. Price forecast, according to (Campbell et al., 2001), is the main source of project assessment errors than any other parameter. Although we can't completely ignore uncertainty, we can better represent it in investment assessment model to help us make better decisions.

2.2 Investment and Uncertainty Relationship

The relationship between the investment and uncertainty has always been motivating topic for both theorists and empirical researches. The results of researches on the relationship between investment and uncertainty are equivocal.

Many studies for the investment decision under uncertainty dating back to the early of 1980s suggested postponing investment with increasing uncertainty of future profitability until new options such as technology and cost reduction opportunities appear (Cukierman,1980), (Bernanke, 1983), and other studies. These studies refer to the theory of irreversible investment and real waiting option. This irreversibility gives businesses a genuine choice to postpone investment. The value of this waiting option increases with the increasing in future profitability uncertainty, which suggesting a negative investment reaction to rising uncertainty.

On the one hand, (Goldberg, 1993) found that there is a weak link between investment and exchange rate uncertainty. Several studies, on the other hand, found that uncertainty has a significant negative impact on the firm's investment decisions. (Dixit and Pindyck, 1994) pointed out that if investments are irreversible, uncertainty reduces the level of firms' investments. Furthermore, (Leahy and Whited,1996) discovered a negative link between investment and various uncertainties for United States manufacturing enterprises. Moreover, (Ogawa and Suzuki, 2000) found that uncertainty has a negative impact on Japanese firm's investment decisions. (Bulan, 2005) investigated the influence of stock return uncertainty (volatility) on investment in United State companies and discovered that uncertainty had a detrimental impact on investment level in these firms. (Baum et al., 2010) investigated the direct and indirect effects of uncertainty on investment via cash flow and discovered a negative association. According to (Wang et al., 2014), when economic policy and market are highly uncertain, firms prefer to lower the investment levels, which has a negative impact also on Research and Development (R&D) spending.

While the standard irreversible investment and real waiting option theory argues that investment and uncertainty have a negative connection, the strategic investment theory suggests that investment under uncertainty also entails a potential reward of future development opportunities through the value of acquisition. Oil and gas investments are extremely pertinent to the concept of irreversible investment, which involve sequences of waiting options. This irreversible nature of investment expenditure is clearly in exploratory activities; once a well has been spudded, there is no going back. However, for strategic reasons, the possible prize of new discovery is justifying the investment decision under high uncertainty.

The uncertainties are not always a threat, they can also be an opportunity reward and a positive link between investment and uncertainty may exist. Risk

can act as a stimulus for investment, according to (Abel, 1983), as long as enterprises can adapt after the uncertainty is resolved. Due to the possible benefits from acquisition future development opportunities, a positive correlation between the investment decision and high uncertainty was also emphasized by (Sarkar, 2000). Furthermore, for some corporations in the United States, (Shaanan, 2005) discovers a positive relationship between the investment decision and stock market uncertainty. This could be explained by the fact that investing in uncertain situation increases the worth of genuine options and accelerates the acquisition of prospective rewards for long term growth opportunities (Smit and Trigeorgis, 2004).

Based on a survey of 494 professionals in the oil and gas industry, (Bickel and Bratvold, 2008) published a study that assessed the sources of uncertainty in petroleum projects. Respondents were asked to rate the impact of several sources of uncertainty (scale: 1= Minor Impact till 5=Significant Impact) on investment decision-making, as well as the importance or significance of these uncertainties on investment performance. The findings of the ranking of uncertainty are shown in Figure 2.1 below.

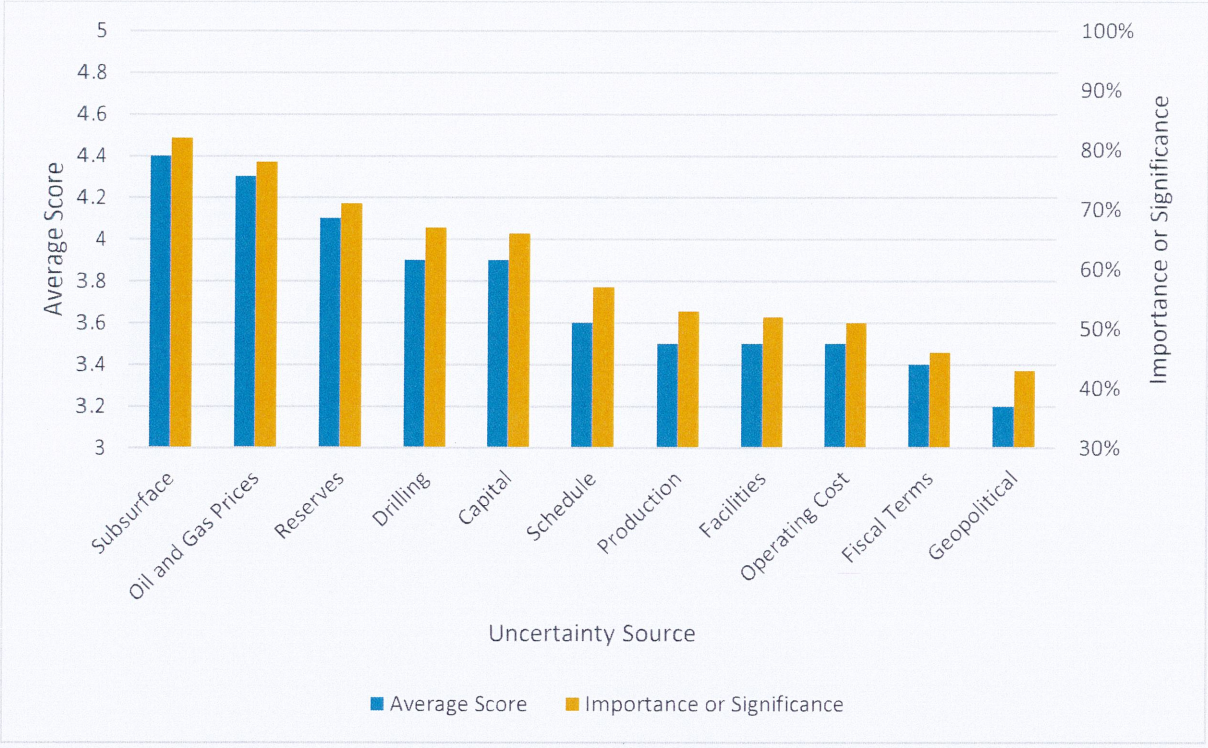


Figure 2.1 Ranking of sources of uncertainty on impact on investment decision and performance in oil and gas industry (Bickel and Bratvold, 2008)

As clearly shown in above figure, majority of professionals responded to the survey believe that subsurface and hydrocarbon prices uncertainties have the most significant impact on investment decision and performance.

Since the impact of oil price volatility on investment decisions is our primary concern in this study, the next section will briefly review relevant literature.

2.3 Investment under Oil Price Uncertainty

Natural resource price volatility is becoming a more important research issue as natural resources such as oil and gas become more important in the global economy in general and in corporate investment decisions in particular. The volatility of oil prices is a key consideration for petroleum firms when making investment decisions. According to (McMichael, 1999), oil and gas prices are critical components in economic and reserve assessments, and they have at least

same influence of technical uncertainties impact on projects. This section examines the link between oil price volatility and investment decisions.

The low or volatile oil price has an impact not only on petroleum corporations' investment decisions, but also on government decisions, particularly in countries that rely heavily on oil and gas exports or imports. In contrast, for non- petroleum industries, rising oil price leads an increase in business expenditure and ultimately a drop in profit (Sadorsky, 2008).

The "shocks" in oil prices might be caused by supply-demand imponderables or geopolitical events. Historically, however, such shocks or peaks in oil price volatility have only lasted a short time. As a result, it should be viewed a temporary circumstance. This viewpoint was backed up by modern approach of strategic investment (Smit and Trigeorgis, 2004).

In the previous literatures, many published studies have looked at the influence of oil price volatility on investment decisions, and the majority of these papers have concluded that oil price volatility has significant negative impact on investment. To better comprehend the prior result, it is worth to mention that most of these researches were limited to the developed countries. (Bernanke, 1983) investigated the impact of oil price volatility on investment decisions, concluding that as future oil price uncertainty increases, it is preferable to postpone investment expenditure. In their study on impact of uncertainty on the period between discovery and development using field data from 53 oil fields in the United Kingdom region, (Favero et al.,1992) observed a negative relationship between oil price volatility and investment in the oil and gas sector. However, one interesting study for (Hurn and Wright, 1993) explored the relationship between investment and oil and gas price uncertainty in the United Kingdom, concluding that oil price fluctuation has a minor impact on petroleum investment decisions. In china, according to (Fan and Zhu, 2008) uncertainties such as oil price volatility and exchange rate affect the oil investment decisions. (Mohn and

Misund, 2009) observed that the oil price volatility decreases the investment in long term in the oil and gas industry. (Henriques and Sadorsky, 2011) examined the influence of oil price uncertainty on corporates investment in United States and observed a U-shaped trend links the two parameters. Recently, (Phan et al., 2019) studied the effects of oil price shocks on corporate investment in 54 countries and found that high price volatility has a minimal influence on firms' investment, but they emphasised that oil price uncertainty negatively affects the investment.

The relationship between oil price and investment is even more sensitive in the oil and gas exploration activities. Oil and gas corporations adapt their portfolio exploration investment based on the performance of the market (Reiss, 1990). Oil price volatility, in addition to the quality of prospective exploration opportunities, has had a significant effect in exploration activity levels over the years. The productivity of the exploratory process is directly affected by oil price fluctuations (Iledare and Pulsipher, 1999). In general, increasing the price of oil stimulates more exploration drilling activities. By focusing on capital and labour, the exploratory behaviour was empirically explored by (Dahl and Duggan, 1998). Based on collective drilling data from the Norwegian area from 1965 to 2004, (Mohn and Osmundsen, 2007) indicted a negative correlation between investment and volatile oil price by using an empirical model on exploration appraisal drilling. The cost of capital and labour is supposed to be funded from a standby capacity; therefore, it is subjected to change from year to year depending on the availability of prospective exploration opportunities, accumulated technical experience, and regulatory constraints.

As aforementioned, most studies in the literature have established that there is a negative investment-uncertainty relationship. As a result, these uncertainties must be taken into account and appropriately represented in any approach of portfolio optimization which will be addressed in the next section.

2.4 Portfolio Optimization under Uncertainty Methods

The necessity for investment decision techniques in the context of high uncertainty has always attracted researchers' interest. During the 1980s and 1990s, the effect of uncertainty on investment modelling has become more appealing to researchers (Carruth et al., 2000).

In industry, there are usually more proposed projects than funding can be secured. Therefore, senior management should select the best portfolio of projects to fulfil the corporate goals while operating within the budget and other resources limitation. This objective can be achieved by utilizing portfolio optimization techniques, which provide decision makers the tool to determine the optimum varied business program which increase the company value at acceptable risk.

The problem of portfolio projects selection is a prevalent one that has been extensively researched in the literature. Several Operations Research models were established, with the objective function of maximization or minimization of a value considering some technical and resource constraints.

Traditional approaches such as NPV, profit, and Internal Rate of Return (IRR) have been used to investigate this issue. These methods can still be used to make good selections of projects if they are employed correctly, especially with considering uncertainties that are exist in real life projects.

The optimal portfolio is the one that incorporates numerous projects and achieves a perfect balance of value and risk. An efficient traditional portfolio theory based on the mean variance efficient was developed by (Markowitz, 1952, 1959). His portfolio optimization methodology educates the investors to account not only the maximum on aiming to maximize predicated return, but also the risks and uncertainties associated with the investment while making decisions. This can be achieved by calculating standard deviation of the expected value of returns to consider the overall risk-reward instead of the best value.

In their study about investment appraisal "Three Problems in Rationing Capital", (Lorie & Savage,1955) questioned the projects selection criteria based on IRR versus NPV. This valid question paved the way for future studies considering a selection criterion based on a multi-objective integer linear programing such as (Bebed-Dov, 1965) and techniques (Ringuest and Graves, 1990).

Additional components of the project selection problem were considered over time, such as the use of multi-criteria approach including qualitative aspects of the problem, such as the one applied by (Nowak, 2005).

(Linton et al., 2002) conduct a review of current project portfolio methods and divide them into three categories. The first group includes procedures that use NPV computations, the second group includes scoring systems, and the third group includes other decision analysis techniques.

Several mathematical optimization algorithms have been developed for petroleum industry's portfolio projects optimization by (Davidson and Davies, 1995), (Orman and Duggan, 1998), and (Fichter, 2000). To improve portfolio optimization of petroleum industry projects and to better guide decision makers, uncertainty inputs were introduced extensively into a multi-objective programming by (Kalu, 1999), portfolio optimization based on projects values with considering probabilistic risk analysis by (Walls, 2004), and semi-variance algorithms (Hightower and David, 1991), (Sira, 2006) and (Jorge A. et al., 2017).

The modern portfolio theory developed later to a large extent is based on the concepts outlined in Markowitz's model such as risk-reward, investor utility, investments return heterogeneity and efficient frontier. Although the mean-variance efficiency theory, which assumes that portfolio returns are normally distributed, is still widely utilized in the industry for portfolio selection, new data and reports from the industry reveals that actual portfolio returns are not normally

distributed and have been found to be extremely unstable practically (McVean, 2000) and (April et al., 2003).

Recently, considering complex situations and combination of uncertainties, mathematical problems cannot be analysed or solved by traditional techniques like trial and errors. Today, the problem's mathematical model can be solved quickly and efficiently by using incredibly powerful optimization algorithms help to direct simulation tools to produce high quality solutions for the unstructured mathematical problems (Pichitlamken and Nelson, 2001).

Most of real projects portfolio optimization problems involve uncertain parameters. While the uncertainty cannot be avoided in any investment assessment, it can be properly quantified in economics evaluation models to aid better decision making. "Quantifying uncertainty allows companies to better evaluate the risks associated with individual projects and, at the portfolio level, to make the best choices from an array of uncertain investment opportunities" (Faryibi, 2006). However, quantifying uncertainty adds no benefit in and of itself. Rather, the goal is to make a smart decision, which may necessitate uncertainty evaluation. (Bickel and Bratvold, 2008) emphasized that "Uncertainty quantification creates value only to the extent that it holds the possibility of changing a decision that would otherwise be made differently".

A number of methodologies for quantifying economic uncertainty were highlighted by (Holmes et al., 2003), including Monte Carlo simulation, bootstrap, Value at Risk (VaR), and fuzzy logic techniques. The Monte Carlo simulation is the system capable of producing thousands of randomized sampling values for each variable through the input distributions. The bootstrap methodology, on the other hand, is a statistical approach for generating scenarios based on the historical data by sampling with replacement to make the desired probability density function. Furthermore, the VaR approach is an extension of Monte Carlo simulation that quantifies the difference between expected value of

an economic parameter from the Monte Carlo cumulative density function and the value at a given low probability. The fourth method is the fuzzy method, which is based on subjective probability used to characterise the uncertainty in the absence of historical data.

Sensitivity analysis, scenario analysis, probability approaches and computer simulation are four approaches being applied in the petroleum industry for dealing with uncertainty in capital investment decisions outlined by (Mian, 2002). The sensitivity analysis technique is used to determine how the profitability of a project changes when specific input is changed while other variables remain constant. The second approach is scenario analysis, which takes into account sensitivity of profitability changes considering three scenarios (worst case scenario, most likely case scenario, and best case scenario). The probability technique, on the other hand, employs the expected value for each alternative in conjunction with risk measurement. The last method is the computer simulation, which can generate a combination of multi-uncertain variables that are derived from individual variable' probability distribution curves. This technique, also known today as risk analysis was originally developed by (Herz, 1979), is capable to generate thousands of profitability scenarios based random combinations.

The investment valuation models, which are quantitative techniques for assessing effect of uncertainties on projects, are developed in three stages according to (Brennan and Trigeorgis, 2000). The first stage, static models are described by Discounted Cash Flow (DCF) method with no management flexibility. The second phase, dynamic modelling techniques, which count uncertainty associated with investment decisions. Examples of dynamic modelling are decision tree analysis, mathematical programming, stochastic programming, and real options analysis. The third stage is called option games, which takes into consideration both uncertainties and reactions of the competitors throughout the investment decision process.

In the next section, we will look at two stage stochastic modelling with recourse, which is the approach applied in this study.

2.5 Two Stage Stochastic Programming with Recourse Methodology

Among all the techniques developed for incorporating uncertainty in resolving the planning optimization problems, the most commonly applied is stochastic programming (Birge, and Louveaux, 1997). In any stochastic model, the uncertain parameters, which are also called random variables, their probability distributions are assumed to be known. Like any other optimization model, SP is modelled with an objective function that minimizes or maximizes an expected value based on some decision variables considering some constraints.

According to (Sahinidis, 2004), stochastic programming is mainly including two forms of techniques: programming with recourse (also known "here" and "now") and probabilistic programming (also called chanced constrained). The recourse approach idea is built on describing process uncertainty using a probability distribution function with the goal of minimizing expected recourse costs, whereas the probabilistic approach focuses on reliability of the system by ensuring the probability of satisfying constraints is higher than the required level.

The SP, also, involves two main groups of methods: Two stage and multi stage models. The two-stage stochastic model, which a special case of multistage SP, is the most commonly researched SP models. In this type of problems, investment decision is taken at the start of the first stage even though the values of the random parameters are uncertain. After making observations about the uncertain parameters, a recourse decision can be taken to adjust or mitigate the first stage action at the start of the second stage, which is usually an operational decision. The planning decisions are taken "here-and-now" prior to the resolution of uncertainty in this bi-level decision-making framework, while the operation

decisions are deferred to a "wait-and-see" mode (Gupta and Maranas, 2000). The best decision is taken in the first stage given the possible realizations of the random parameters, and the best recourse action in the second stage for every possible realization, make up the optimum solution for a two-stage model. For instance, (Eppen et al., 1989), applied two stage stochastic recourse model concept, in which the first stage decision is the capacity of a plant, while the recourse decision is the production quantity.

The first recourse linear model in which the solution might be modified in response to occurrence of a random event was proposed by (Dantzig, 1955). From then on, the SP domain has matured into a valuable tool in operations research field for optimizing in uncertain conditions. Researchers have developed a considerable number of advanced algorithms, which are documented in (Birge and Louveaux, 2011) textbook. The L-shaped decomposition method introduced by (Van Slyke and Wets, 1969) is the most widely recognized method for dealing with two-stage recourse problems. This approach is a particular variant of Benders decomposition method (Benders, 1962) that works with programs that have continuous variables. Decomposition methods in stochastic programming were comprehensively explained by (Ruszczyhski, 1997). With the maturation of mathematical and computational techniques, SP has been used to a wide range of problems in different fields such as financial planning, supply chain management, process systems, climate change mitigation, electricity generation, and others according to (Wallace and Ziemba, 2005). Notable references on the basics and applications of two stage program with fixed recourse can be found in (Kall and Wallace, 1994), and (Birge and Louveaux , 1997).

CHAPTER 3

Presentation of the case study

3.1 Case Study Overview
3.2 Evaluation of Current Business Plan Practices

CHAPTER 3 Presentation of the Case Study

The case under study employed in this thesis will be for a corporation called (Company A). The company's real name was hided based on the corporation request, in which a confidentiality agreement pledge was signed.

This chapter provides an overview of Petroleum Company A as a case study, as well as an evaluation to its current practices for generating the Annual Work Program and Budget (AWPB) and Five Years Business Plan (5 Yrs BP).

3.1 Case Study Overview

The case study is about an oil and gas company that has taken over the responsibility of management and development of a mature field since last decade only. This petroleum firm is owned entirely by the country's government. It is a substantial contributor to the country's economic growth and is regarded as the primary source of income. The corporation A is not only supporting the current economic growth by supplying the required energy fuel and main income to the country, but also is considered the backbone of achieving the country's economic growth vision for next decade. As a result, this corporation has significant impact on citizens' and residents' living standards, as well as on the country's social prosperity.

The company's primary business includes oil and gas exploration, development, and operations, as wells as gas distribution and sales to the local market.

The Company's principal objective is to enhance the oil and gas production in order to meet the country's present and future energy demands. The Company

employs the most cutting-edge enhanced oil recovery technologies to carry out its purpose of developing the field resources to maximize value for its stakeholders and support the country's economic growth.

The corporation oversees one of the region's most mature field, which is and still being explored and developed. There are seventeen oil and three gas producing stacked reservoirs in the field. The field has already hit its production peak before fifty years and is declining alarmingly.

While business activities are growing to meet the increase in energy demand, Company A employs the newest technologies for exploration and development activities, not only to overcome the technical challenges, reduce operating costs, and maintain the oil and gas production, but also to sustain high standards of safety and healthy work environment.

Over the last twelve years of Company A establishment, it spent massive capitals to maintain and increase the oil and production rates. These capital investments are expected to rise in order to meet the country's growing energy needs and to support its economy flourish. Furthermore, the recent announcement of a large oil and gas discovery in the offshore area will necessitate significant investments to assess the commerciality of this new resource and to exploit it accordingly.

In one hand, with the announcement of new resource discovery, exploration activities have been increased dramatically. As a result, large expenditure has been expedited to confirm the resource commerciality by executing several appraisals to assess these new assets.

On the other hand, the continuous development activities such as drilling development drilling and workover existing underperforming wells have been also greatly increased to at least keep maintain current production rate.

Several IOR and EOR processes trials have been ongoing in various reservoirs, on top primary production efforts, in order to unlock the more difficult oil, which resulting in significant expenditure on expanding the existing facilities fluid handling and processing capacities. This was associated with large investments in field modernization and establishment of a solid infrastructure to satisfy current and future improvement needs.

Despite the fact that current fluctuated oil price, with the intensive investment on latest technologies and services to expedite the new discovered resource assessment as well as the increasing of development activities, the cost per barrel has increased as a result.

All of the aforementioned huge expenditures are accompanied by significant risks and uncertainties. Apart from the high level of uncertainty in exploration activities, given the rapid depletion of the existing developed field and geological complexity, many projects have proven to be challenging. Each formation has its own set of difficulties and unknowns, and each well producing from the same formation may perform differently.

The preceding mentioned challenges and uncertainties are not only exclusively associated with the subsurface target, but also to the surface in terms of wells performance, wells' failure rate due to leakage, facilities maintenance and activities scheduling. There are also additional uncertainties when it comes to economics assessment such as capitals cost estimation and operating costs per barrel.

These challenges are also extended to those relevant to company's system. Despite the fact that the Company A is handling an old petroleum field, it has only been in charge of this field operation for about one decade. As a result, many processes and workflows are not robust yet and are still being optimized. One of these important processes is the Business Plan (BP) process, which generates the

AWPB and 5Yrs BP. In the following section, we will assess Company A's current process for preparing the business plan.

3.2 Evaluation of Current Business Plan Practices

The main goal of the business plan is to provide decision makers a better understanding of the field's commercial potential as well as the range of uncertainties associated with the proposed development plans. The BP aims to achieve the following:

- Maximize the company's assets value
- Maximize the recovery of oil and gas reserves
- Optimize the production rates
- Optimize development expenditures

Company A, like most petroleum corporations, bases it decision to invest in a particular petroleum project on economic models created in Microsoft Excel by the company's internal economists based on data input from several professionals. Existing economic models employ deterministic approach in assessing the commerciality of these projects. In most cases, these models are distinguished by uncertain inputs and hence inaccurate outputs.

As part of its investment portfolio configuration, Company A is basically applying traditional methodology for projects selection. To accept the proposed project, Company A relies on positive Net NPV, Internal Rate of Return (IRR) greater than 10, and pay out within 5 years as economic indicators. These techniques, when properly applied, can still lead to appropriate projects selection decision; however, deterministic approach ignores a large range of uncertainties associated with the inputs of individual projects' economics assessment.

Although Reservoir Management Team provides Integrated Planning Department with low, medium and high production profiles for each project, the economist uses the medium oil profile only and applies a fixed risk factor. This

risk factor is not even based on solid data; rather, it is based on personnel's conservative judgment applying to the initial excepted oil production rate. This practice completely disregards several uncertainties, like the wells' decline, which is affected by number of factors including facility shutdowns, well and facility optimization problems, and reservoir static and dynamic uncertainties. Not only that, it also hides the upside potential of the production on decision makers, which closing the door of additional investment opportunities. Furthermore, it ignores the impact of uncertain associated fluid (water and gas) volumes on facility capacity.

On the other side, when it comes to cost estimates, economists simply apply a contingency percentage with no solid basis other than being assumed with a default percentage or as information given by focal point who may not have solid experience or data to support his assumption, especially for special or unique projects. This practice, once again, equalizes cost estimation uncertainty across all projects, as well as misrepresent the risk of overspending or could lead to loss of some opportunities by allocating excess budget for a specific project and limiting fund for more appealing initiatives due to budget constraints.

Other unpredictable aspects such as drilling operation challenges and rig unproductive time, and their impact on activities scheduling, are also ignored in current practice. Furthermore, current practice eliminates the uncertainty of time to market, which is the time from a well's completion to its production. By specifying this timeframe per formation, which overlooks the real reasons for any potential delay in producing a new well and, as a result, delay generation of positive cash flow.

Although the economics of petroleum projects are very sensitive to the volatility of the oil price parameter, the annual plan and budget is being generated using a single oil price value issued by an authorized governmental entity. This ignores the fact that oil price fluctuation on a daily basis owing to supply-demand

imbalances, inflation, geopolitical and unforeseen events like the current COVID-19 pandemic.

Current practices have flaws not only in economic evaluation inputs, but also in selecting the best proposals. Drilling and workover activities, as an example, are the main activities in any petroleum firm to increase the oil and gas production. Unfortunately, the mix wells used to feed drilling and workover rigs' schedules are not determined by supported data or solid criteria, rather than by a directive from field development representatives to use a specific wells mixture and schedule them based on personnel judgments. Not only that, but instead of looking at individual well economics, the drilling and workover economic evaluation is being done for the entire programs. This approach has always created a significant gap in optimal mix wells selection; thus, it is threatening the optimality of resources utilization and lead to missing up better investment opportunities.

Another major gap is that there is no reliable basis for determining the optimal number of rigs by reacting to oil price market fluctuations rather than following top management's instructions or simply looking at the available wells inventory and production target as drivers for the required number of rigs. An instance, given the low oil price in 2020-2021 due the impact of COVID 19 pandemic restrictions, the Company A has operated 6 drilling rigs for oil and gas production development and exploration activities for the first time in the corporation's history. Moreover, it used on an average of 7 Workover rigs to maintain base oil production, which the highest number of rigs used comparing to other periods that oil price exceeded 100 dollars. However, in 2022, when oil prices have surpassed $120/bbl, Company A has decided to release 2 oil drilling rigs and operate only one oil rig for the rest of the year. In addition, it intends to drop 2 Workover rigs by end of the year.

The most significant flaw in existing practices is that the budgeted rigs and well mix differs from what is actually implemented, in most cases, due to realization of some factors such as oil price, wells performance, and strategy changes. Unfortunately, because the economic model assumes perfect information, these changes were not taken into account or reflected in the economic assessment during the planning phase. As a result, there is a significant difference between projected and actual NPV, making it difficult for decision makers to validate investment outcomes.

To sum up, what Company A's planners are practising actually is merely allocating capital to justify the required budget instead of plan optimization. Figure 3.1 summarizes the main practices gaps discussed above for the process of proposing the AWPB and 5 Yrs.

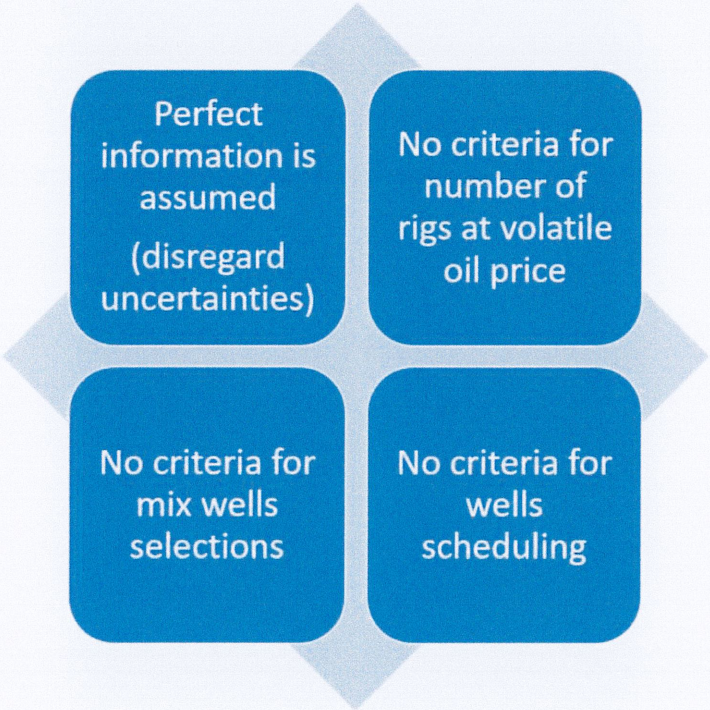


Figure 3.1 Company A main practises gaps for AWPB and 5 Yrs plan proposals

Given the current level of activity, the potential for additional capital investment growth and the high projects' uncertainties, as well as current practices gaps, a more robust economic evaluation approach than the current

deterministic method is required for assessing business programs that meet the company's growth goals.

The proposed two stages stochastic method in this research is an alternative approach based on a data-driven for quantifying projects uncertainties, understanding project risks, and forecasting outcomes. This aids in the creation of a more realistic budget and plan by providing objective information for a better investment decision making.

In this research, although the focus will be on optimizing drilling oil development program, the model and proposed method we provide are applicable to other oil and gas development and exploration portfolios. In fact, we built our model in such a way that by changing a few inputs, it can be used to optimize any other program.

CHAPTER 4

Mathematical Model Formulation

4.1 Problem Background
4.2 Problem Analysis
4.3 Decision Variables
4.4 Objective Function
4.5 Constraints
4.6 Mathematical Model Formulation Summary

CHAPTER 4 Mathematical Model Formulation

Optimization modelling is an area of mathematics that aims to identify the best solution to a problem in order to maximize or minimize its objective function for a given constraints. Any mathematical model formulation must incorporate four key components in order to be representative, namely, decision variables, objective function, constraints, and parameters. These components are considered as the skeleton of any problem formulation. The model key elements are depicted in Figure 4.1.

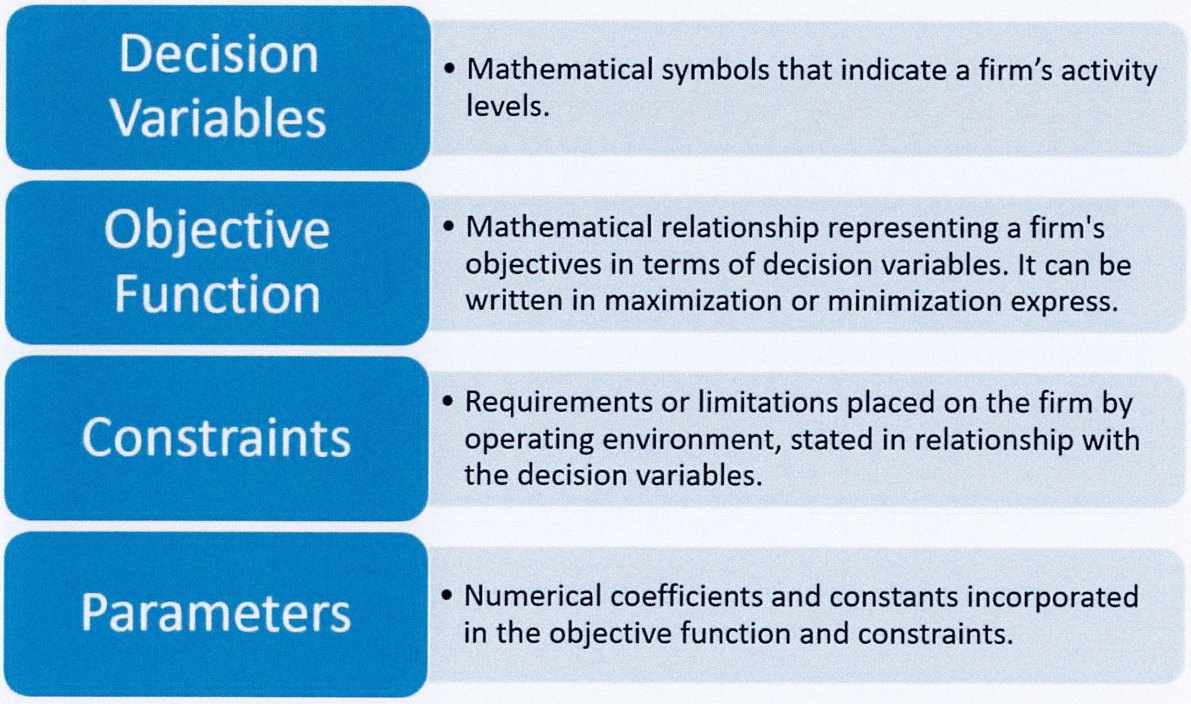


Figure 4.1 Main components of mathematical models

In this chapter, we are going to formulate an optimization problem related to a portfolio of Company A. Among Company A's capital programs, we formulate the oil drilling program as a two-stage stochastic problem. However, this stochastic formulation concept is also applicable to other programs within

Company A's portfolio. We have, also, included base oil production program in our problem formulation as it is considered the baseline of the company portfolio.

The size and complexity of the stochastic programming models increases exponentially with the number of input parameters, which is a major shortcoming. As a result, actual examples of stochastic programs are large scale optimization models, which necessitate the development of efficient solution algorithms such as the Benders and Lagrangean decompositions (Li and Grossmann, 2021). Therefore, to simplify our problem solution, we will consider only one uncertain parameter, which is the oil price; because it is the most sensitive parameter in our case.

This chapter is structured to give first a background on problem case, followed by individual section for the model's main components, which will be thoroughly detailed.

4.1 Problem Background

The concerned problem is about determining the optimal number of drilling rigs and development wells mix producing from a set of geological formations and is designed to be drilled as vertical/ deviated or horizontal (well type), in order to maximize the Net Present Value (NPV). Maximizing the NPV is subjected to several constraints such budget, number of rigs, production target, reserves, wells mix inventory, minimum drilling needs, wells economic production cut offs and facilities capacity constraints. Figure 4.2 shows a schematic of the problem formulation components for the case under study.

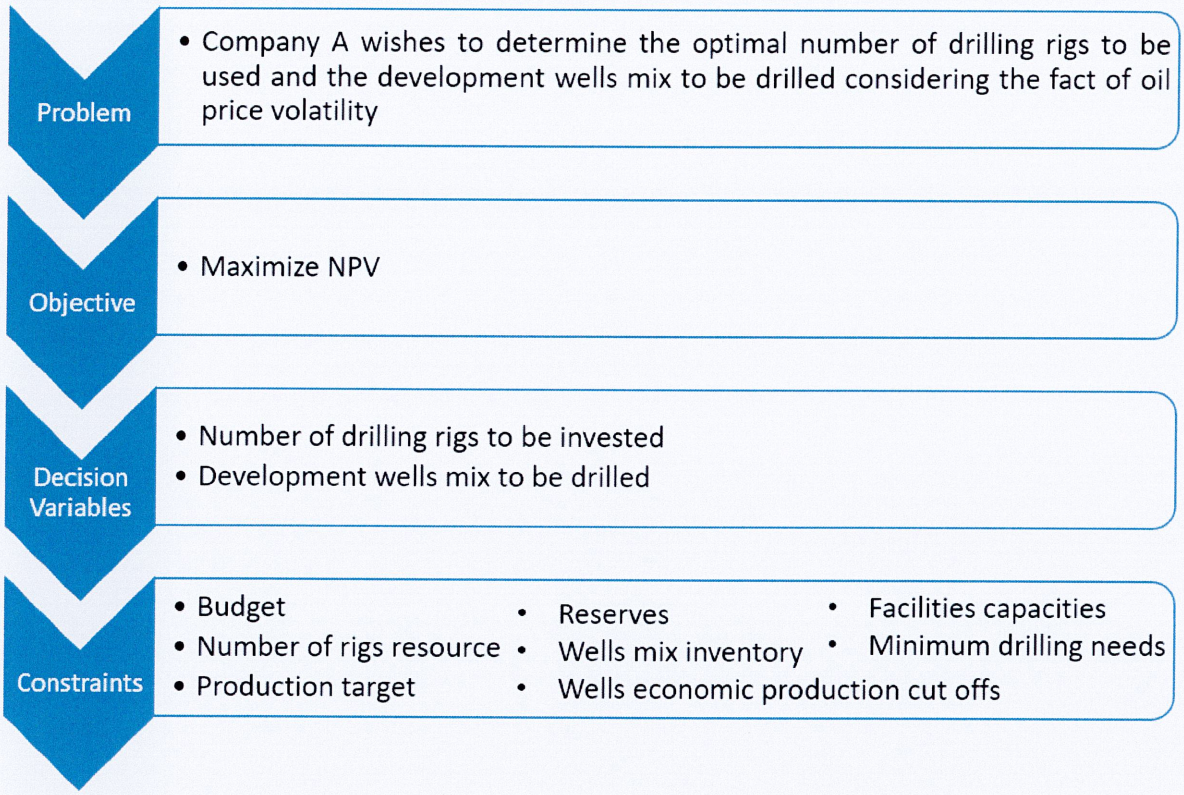


Figure 4.2 Components of the problem formulation

The Mixed Integer Linear Programming (MILP) model formulation that will be applied in this study is an extension of the deterministic formulation given by (Khonji and Suliman, 2020). In our case, we used a two-stage stochastic mixed integer linear programming with recourse approach to formulate our problem, under uncertain oil price.

It is worth to mentioning that we have not employ oil grade vector as in Khonji's formulation; because heavy oil production in our case accounts for less than 1% of the total oil production.

It is also worthy to note that there are no taxes considered in the case under study as the local oil business is free of taxes, with exception of a negligible Value Added Tax (VAT) which is applied on few items purchased from abroad. Therefore, Taxes are left out of the formulation.

4.2 Problem Analysis

Primarily, our optimization problem involves products mix and scheduling, which necessitates high level decisions on development wells collection, wells scheduling, required rigs number, and the potential of new facility investment. Decision taken at the required number of rigs has a significant effect on wells mix and scheduling, whereas scheduling determines the viability of fulfilling company's targets such as oil production target, considering limited resources available. Therefore, the integration of planning, scheduling, and operational constraints improves not only the performance of the concerned drilling program but also the overall Company's portfolio by assuring the most efficient use of company resources.

Taking into account Company A's resources constraints, the model will be formulated to give answers on to the following questions:

- What is the optimal number of drilling rigs to be used?
- How many wells can be drilled?
- What is the optimal mix of development wells to consider?
- What is the optimal drilling wells scheduling?
- What is expected oil production rate?
- How is the Net Cash Flow (NCF) profile will look like?
- What is the expected NPV?
- What is the impact of the oil price volatility or any other potential uncertain parameter on original plan?
- What are the corrections to operation strategy to be implemented after uncertainty is realized?

Given a fluctuating future oil price and concerns of limited resource availability and wells inventory, the primary aim is to design an optimal feasible operating plan that maximizes NPV over a particular period of time. However,

the plan is adjustable, and some decision variables can be made at later stage when additional information on actual oil prices becomes available. As a result, the problem formulation must be structured in a sequential decision manner.

We emphasized on portfolio optimization techniques under uncertainty in Section 2.1, and concentrated on two stage stochastic programming with recourse method in Section 2.5. This is due to the fact that conventional deterministic optimization models are inefficient for uncertain conditions such as the volatile oil price market, because accurate information is not always available when decision makers need to make decisions related to next stages.

In stochastic programming, the uncertain parameters' probability distributions are supposed to be known. As an approximation to the actual probability distribution, the uncertainties can be described by some discrete values of the uncertain parameters. For instance, the realizations of future oil price can assume three different levels, for example low, medium, and high scenarios of oil price. The stochastic programming aims to maximize or minimize the expected value of an objective function (in our case maximizing NPV) among all possible scenarios.

To hedge against the uncertainties in oil prices, a special mathematical framework known as two-stage stochastic programming will be applied to solve our problem. As the term implies, decisions are taken in two stages: 'now' and 'future'. Before the realization of the uncertainty, stage one decisions must be determined. In contrast, decision makers have the option to revise their decisions in light with the new available information in stage two. Stage two decisions, also called recourse decisions, are considered as corrective actions to stage one.

According to (AlQahtani, and Elkamel, 2010), the two-stage with recourse problem's objective function is standardly formulated as:

$$Max\ c^T x + \mathrm{E}[Q(x, \xi(\omega))] \qquad (4.1)$$

Subject to $Ax = b, x \geq 0$ (4.2)

Where $Q(x, \xi(\omega))$ is the second stage's optimal value:

$Max\ q^T y$ (4.3)

Subject to $Tx + Wy = h, y \geq 0$ (4.4)

Where,

x: Vectors of the first stage decision variables

y: Vectors of the second stage decision variables or recourse decisions

$\xi(\omega)$: The probability distribution of the random variable

ω: The uncertain parameter

In order to represent the uncertainty in our formulation in a simple form, we choose to apply the scenario-based approach (discrete events) with a finite number of possible scenarios (S) of future oil price parameter corresponds to the probability of each scenario (P^S). Therefore, the Equations 4.1 and 4.3 can be expressed as an equivalent deterministic problem and displayed as follows:

$Max\ c^T x + \sum_{s=1}^{S} P^S q_s^T y_s$ (4.5)

Subject to $Ax = b, x \geq 0$ (4.6)

$T_s x + W_s y_s = h_s,$ $s=1, 2, ..., S$ (4.7)

$x \geq 0, y_s \geq 0$ $s=1, 2, ..., S$ (4.8)

We applied an approximation method known as the Sample Average Approximation (SAA) since future oil prices forecast accuracy is challenging and no way to weight the probability of each scenario. In addition, this method is used to avoid the exponential increase in sample size by introducing more random variables in the model. Thus, the equation 4.1 can be expressed as:

$Max\ c^T x + \frac{1}{N} \sum_{s \epsilon N} q_s^T y_s$ (4.9)

4.3 Decision Variables

Basically, our problem can be briefed as the following: There must be two stages of decision making under uncertain oil prices. The first stage decision, which is normally made during the planning phase, is to determine the optimal number of drilling rigs per year and development wells mix given a certain information. The second stage decision, also known as the recourse decision, is usually an operational decision on the actual number of drilling rigs to be employed and, as a result, the wells mix to be drilled. When the plan is in the execution phase, the second stage decision can be updated when the actual oil price become known.

The model is formulated as to determine the optimal number of rigs per year a firm should utilize to drill an optimal mix of development wells from various formations with specific trajectory (vertical/deviated or horizontal). The following decision variables are defined based on two stochastic stages (G), with 1, 2 denoting stage one and stage two decision variables, respectively.

$X_{GTFi,s}$: Number of development wells of type (T) from formation (F) to be drilled at month (i) for stage (G), (in wells units)

$RN_{Gi,s}$: Number of drilling rigs to be operated at month (i) for stage (G), (in rigs units)

4.4 Objective Function

The objective of this optimization model is to maximize NPV, which is the sum of Net Cash Flow (NCF) over a given period when a given discount or interest rate (r) is used to reflect the change in money value over time. We present Probability Scenario (P^S) of oil price in the below formulation as discrete event for now, which will be assumed equal for all scenarios of oil price. The objective function and its constituents are written as follows:

$$\text{Maximize } NPV = \sum_{i=0}^{i=I} \frac{NCF_i}{(1+r)^i} = \sum_{i=0}^{i=I} \frac{NCF_{1i}}{(1+r)^i} + \sum_{i=0}^{i=I} \sum_{s=1}^{S} P^S * \frac{NCF_{2i,s}}{(1+r)^i} \quad (4.10)$$

$$NCF_i = (Revenue_1 - Cost_1) + \sum_{s=1}^{S} P^S * (Revenue_{2,s} - Cost_{2,s}) \quad (4.11)$$

Where,

NPV: Net present value, $

NCF_i: Net cash flow at month (i), $

r: Discount rate, fraction

i: Time, month

I: Total intervals or number of months, month

P^S: Probability of scenario, fraction

1,2: Denotes stage number relevant parameters

As indicated earlier, the NCF is about cost subtracted from revenue; accordingly, revenue and cost components are discussed further below.

4.4.1 Revenue Components

The revenue is derived mathematically by a multiplying the total monthly produced oil for both development and base wells by oil price at each month. More elaboration on the Revenue components formulation is discussed below.

4.4.1.1 Oil Price Forecast

The crude oil prices have historically been so volatile due to the reasons mentioned in Section 3.2. They are frequently the most significant factor in stochastic analysis. Because the price of oil prediction is a difficult, accurately forecast is even more challenging task. Investors in the petroleum sector must live with the fact that there is no perfect information on the price of oil forecast. "The real challenge is not trying to make forecasts more accurate through technical advances; rather, it is to shift focus to developing better ways to use forecast and

to develop planning mechanisms that help to anticipate and prepare for contingent developments" (Mendjoge, 2003). The projection and modelling of future oil prices is beyond the scope of this research, but we will look at how the NPV could be maximized given number of future pricing scenarios.

$P_{oi,s}$: Oil price of wells at month i, $/bbl

4.4.1.2 Oil Production Forecast

The Decline Curve Analysis (DCA) is the most common method for predicting well production performance. These empirical equations, established by (Arps, 1945), rely on historical production data quality and can generate more accurate production forecasts for a reservoir or a well under the do-nothing scenario. The historical production trend is primarily influenced by reservoir drive mechanisms and well's methods of production. The DCA equations involve three types of declines (exponential, hyperbolic, and harmonic), each of which describes the link between time and the semi log production rate decline pattern.

Based on historical data and analysis for our case study, the wells are experiencing exponential decline; thus, the Arps exponential decline equation has been used for both development and base wells.

Development Wells

A well's average daily oil production rate of type (T) from formation (F) at month (i) is formulated using Arps exponential decline equation. Due to uncertainty in data recording and interpretation, heterogeneity of formation properties, dynamic reservoir energies, facilities constraints, operation instability, and suboptimal lifting, both initial production and decline rates forecast are potentially uncertain parameters that vary from well to well and from formation to formation and within the formation itself.

$$Q_{OTFi} = Q_{OTF0} e^{-(\frac{D_{OTF}}{12})*(i-1)} \quad (4.12)$$

Where,

Q_{OTFi}: Average daily oil rate of development wells of type (T) from formation (F) at month i, BOPD

Q_{OTFO}: Initial average daily oil rate of development wells of type (T) from formation (F) at month zero, BOPD

D_{OTF}: Annual oil exponential decline rate for development well of type (T) from formation (F), fraction

And therefore, total oil production forecast for all development wells at month i, should be equal to the sum of individual well production from various formations and well types multiplied by the number of development wells. The number of development wells of type (T) from formation (F) will be examined in both stages one and two because it is a decision variable that is influenced by oil price volatility.

$$TQ_{Oi,s} = \sum_{i=1}^{i=I} X_{1TFi} * Q_{OTFi} + \sum_{i=0}^{i=I} \sum_{s=1}^{S} P^S * X_{2TFi,s} * Q_{OTFi} \qquad (4.13)$$

Where,

$TQ_{Oi,s}$: Total daily oil rate of all development wells at month i, BOPD

Base Wells

The base wells oil production forecast from Formation (F) at month i can be also formulated by using Arps Exponential Decline Equation. Unlike new development wells, base wells have historical production, which should be useful to predict the wells' future performance more accurately. However, base wells forecast still have a certain range of uncertainty similar to development wells, which mainly comes from future well's decline. Eq. 4.14 can be used to compute the oil production forecast for base wells.

$$Q_{BOFi} = Q_{BOF0} e^{-(\frac{D_{BOF}}{12})*(i-1)} \quad (4.14)$$

Where,

Q_{BOFi}: Average daily oil rate of base wells from formation (F) at month i, BOPD

Q_{BOF0}: Initial average daily oil rate of base wells from formation (F) at month zero, BOPD

D_{BOF}: Annual oil base wells exponential decline rate for formation (F), fraction

Since base wells production is considered an OPEX activity, it is unaffected by decision variable optimization. As a result, the total base wells oil production forecast for month (i) can be determined using the equation below.

$$TQ_{BOi} = \sum_{j=1}^{j=F} Q_{BOFij} \quad (4.15)$$

Where,

TQ_{BOi}: Total daily oil rate of base wells at month i, BOPD

As a result, the aforementioned equations can be used to calculate revenue, which is simply total production from base and development wells at a given month (i) multiplied by the month's expected oil price.

$$Revenue = \sum_{i=1}^{I}(TQ_{Oi} + TQ_{BOi}) * P_{oi} + \sum_{i=1}^{I}\sum_{s=1}^{S} P^S * \left(TQ_{Oi,s} + TQ_{BOi}\right) * P_{oi,s} \quad (4.16)$$

4.4.2 Cost Components

The cost of development wells includes three elements: CAPEX, OPEX and rig standby costs; however, for base wells it is only OPEX cost. All costs aspects are coupled with uncertainties related to estimation or even allocation, which will be explained thoroughly below.

It is worth noting that no taxes are taken into account; because, for the case under study, the taxes are not applied on petroleum products, with the exception

of negligible Value Added Tax (VAT) applied on limited items. Therefore, no taxes are considered in the below formulation.

4.4.2.1 Total Capital Cost (CAPEX)

The capital cost, which is a onetime payment, for a development well includes three components: drilling, completion, and facilities hook up and site preparation costs. Detailed explanation of these three cost elements are given below.

1. Drilling cost

A well's drilling cost includes all costs related to utilizing a rig to drill the well. It covers costs of rig's operation, crew, drilling materials and variety of other services. Therefore, a Daily Rig Rate (DRR) is commonly used as a unit cost to estimate the cost of a rental rig's daily drilling operation.

The cost of drilling a well is determined by the number of drilling days required. The number of drilling days required per well depends on the target Formation (F) depth and well Type (T), which are both variable. Furthermore, the wells are scheduled using a typical number of drilling days per well, per formation, and per type, which in reality is coupled with some uncertainties difficult to precisely anticipate. If drilling goes smooth, performance of drilling can be improved over time and hence less days are required for drilling a well. In many situations, however, drilling wells are delayed owing to a variety of factors such as operation failures, drilling fluid (Mud) losses, fishing issues, and so on. These factors could result in an increase in the number of days required to complete the well. The following equation can be used to determine the cost of drilling a well.

$$CCD_{TF} = NDD_{TF} * DRR \qquad (4.17)$$

Where,

CCD_{TF}: Capital drilling cost of a development well of type (T) for target formation (F), $

NDD_{TF}: No. of drilling days of a development well of type (T) for target formation (F), days

DRR: Drilling Rig Rate, $/day

2. Completion cost

Once the drilling operation is over, the well must be secured and prepared for production, which is known as well completion. Completion costs involve perforating the target interval, stimulation treatment, Method of Production (MOP) components, and completion material, which varies depending on well trajectory or type and target formation depth. There are many uncertainties in the cost estimation of the above items, hence a typical cost based on historical jobs is normally used during the budgeting stage. The capital completion cost of a well, per well type and target formation, is represented as:

CCC_{TF}: Capital completion cost of a development well of type (T) for target formation (F), $

3. Facilities hook up and site preparation costs

The surface facilities cost involves two cost items, the site preparation and well hook up. Prior to drilling a well, the well location must be levelled in order to provide easy and safe access for drilling rig equipment, as well for the well to be safely drilled. The site preparation cost depends on the site levelling nature and target drilling depth. More expense is incurred when the topography becomes more complex. Also, deeper wells will also necessitate a larger rig, necessitating the preparation of a larger site.

The cost of hooking up a well is determined by the distance between the well and a nearby facility with sufficient fluid handling capacity. Furthermore, it is dependent on how smooth the route is; otherwise, pipeline re-routing costs are to be added.

As a result of the foregoing, we can infer that facility hook-up and well site preparation remain uncertain during the budget planning phase until a definite target location is identified, at which point more precise cost estimates can be made. The single well's capital facilities cost per target formation is symbolized as:

CCFS: Facilities hook up and site preparation capital cost, $

Therefore, the overall capital cost for development wells is equal to the sum of the above three capital components cost per well multiplied by the number of development wells of each formation and type to be drilled at each month, as expressed in the equation below.

$$DCC_{i,s} = \sum_{j=1}^{j=T} \sum_{k=1}^{k=F} X_{1TFi} * (CCD_{TF} + CCC_{TF} + CCFS) + \sum_{j=1}^{j=T} \sum_{k=1}^{k=F} \sum_{s=1}^{S} P^S * X_{2TFi,s} * (CCD_{TF,s} + CCC_{TF,s} + CCFS) \quad (4.18)$$

Where,

$DCC_{i,s}$: Total capital cost of development wells to be drilled at month i, $

4.4.2.2 Operating Expenditure Cost (OPEX)

The operating expenditure (OPEX) cost is the routine cost associated with producing the oil which involves expenditure such as fuel gas, chemicals treatment, electricity, equipment rental, wells maintenance, manpower, and variety of other costs related to contract labour, supplies and so on.

The cost of operation is determined by how easy it is to produce oil, and it differs from one petroleum field to another. Primary production methods are often

far less expensive than IOR or EOR production methods, which require additional costs for injecting and processing both injected and produced fluid. For example, to produce heavier oil, additional costs for steam generation, injection compression, data acquisition, additional maintenance, and possibly some processing costs should be added to the baseline cost. As a result, the OPEX of producing a barrel of oil using the steam process might be at least twice that of primary production methods.

In petroleum upstream sector, the Activity Based Costing (ABC) is usually done by allocating operation cost per produced oil in barrel or produced gas in million cubic feet. However, the accuracy of allocation cost per barrel is a challenge task in general. As oil is produced from several formations with varying degrees of complexity in production techniques, employing a single operation cost per barrel does not accurately reflect our case under study and is associated with several uncertainties.

The overall OPEX cost for a given month is calculated using the sum of both development and base wells' production rates multiplied by operating cost unit (per barrel of oil), which is estimated using Company A's OPEX model.

$$CO_{i,s} = \sum_{i=1}^{i}(TQ_{Oi,s} + TQ_{BOi}) * CPB_O \qquad (4.19)$$

Where,

$CO_{i,s}$: Total operating expenditure of all wells producing at month i, $

$TQ_{Oi,s}$: Total daily oil rate of development wells at month i, BOPD

TQ_{BOi}: Total daily oil rate of base wells at month i, BOPD

CPB_O: Operation cost per oil barrel, $/bbl

4.4.2.3 Rig Standby Cost

The rig standby cost is considered to count for the rig cost during the idle days with no drilling operations, as the company should still pay a rental charge even if there are no drilling activities. Those standby costs are usually not allocated directly to the development wells, but they must be factored into the budget. Furthermore, due to equipment failures, a drilling rig cannot be operated efficiently for the entire year, and there must be some unproductive periods and unanticipated repair work. Those unproductive periods must be subtracted from the rig days available for drilling. After subtracting the projected unproductive days due to failure or maintenance, the rig days available for drilling at a certain month (RDA_i) are the days within each month for a set of rigs that are available for drilling wells.

To figure out the monthly standby cost, subtract the rig drilling days (RDD_i) from the rig available days after discounting the unproductive days, then multiply by the drilling rig rate (DRR). It's worth noting that, two parameters, the unproductive time (UPT_i) and the number of drilling days per formation per well type (NDD_{TF}), are sometimes uncertain. The rig standby cost is calculated using the equations below.

$$CS_{i,s} = \left(RDA_{i,s} - RDD_{i,s}\right) * DRR \quad (4.20)$$

$$RDA_{i,s} = RN_{1i} * 30.417 * (1 - UPT_i) + \sum_{s=1}^{S} P^S * RN_{2i,s} * 30.417 * (1 - UPT_i) \quad (4.21)$$

$$RDD_{i,s} = \sum_{j=1}^{j=T} \sum_{k=1}^{k=F} X_{1TFi} * NDD_{TF} + \sum_{j=1}^{j=T} \sum_{k=1}^{k=F} \sum_{s=1}^{S} P^S * X_{2TFi,s} * NDD_{TF} \quad (4.22)$$

Where,

$CS_{i,s}$: Rig standby cost at month (i), $

$RDA_{i,s}$: Rig days available at month i, days

$RN_{Gi,s}$: Number of drilling rigs to be operated at month (i) for stage (G), (in rigs units)

UPT_i: Unproductive rig time at month (i), fraction

DRR: Drilling rig rate, $/day/rig

$RDD_{i,s}$: Rig drilling days at month i, days

NDD_{TF}: Drilling days of well of type (T) target formation (F), days/well

30.417: Time conversion factor, days/month

Thence, the Total Cost (TC_i) for base and development programs at month (i) is calculated by:

$$TC_{i,s} = DCC_{i,s} + CO_{i,s} + CS_{i,s} \quad (4.23)$$

In addition, the maximization of the objective function (i.e., NPV) must be subject to specific constraints, which to be presented next.

4.5 Constraints

The objective function, discussed in previous section, is subjected to several constraints due limitations in resources. In addition to the constraints listed by (Khonji and Suliman, 2020) such as annual budget, oil production target, remaining reserves, maximum wells or wells inventory, number of drilling rigs and Facilities liquid and gas handling capacities, we will be adding extra constrains like minimum number of wells required to be drilled per formation per type and economic cut offs for development wells as will be explained next.

4.5.1 Annual Budget

The approved AWPB budget by the company's Board of Directors (BoD) is a limited resource; hence, expenditures must be kept within that budget. Thus, the

total expenditure in a given year must not exceed the budgeted amount for that year. The budget constraint is formulated as follows.

$$TC_{Y,S} \leq AB_Y$$

(4.24)

$$TC_{Y,S} = \sum_{i=12*Y-11}^{12*Y} TC_{i,S} \quad (4.25)$$

Where,

$TC_{Y,S}$: Total cost at year (Y), $

AB_Y: Annual budget approved for year (Y), $

4.5.2 Oil Production Target

To meet stakeholders' expectations and to meet its financial commitments, the operating company must produce minimum oil production target. Thus, a year's average oil production must be equal or exceed the minimum expected average oil target for that year as stated in the equations below.

$$AQ_{OY,S} \geq MAQ_{OY} \quad (4.26)$$

$$AQ_{OY,S} = \sum_{y=12*Y-11}^{y=12*Y} \frac{(TQ_{Oi,S}+TQ_{BOi})}{12} \quad (4.27)$$

Where,

MAQ_{OY}: Minimum average daily average oil production for year (Y), BOPD

$AQ_{OY,S}$: Average daily oil production for year (Y), BOPD

4.5.3 Remaining Oil Reserves

Each formation has a specific Original Oil In Place (OOIP) and it is the role of reservoir engineers to advise the best strategy for extracting as much oil as feasible from it. This volumetric oil gets depleted over years as a result producing oil, and hence depleting the formation's energy. Unfortunately, even with the most advanced technologies, not all OOIP can be produced, owing to capillary

pressures forces and the inefficiency of oil sweeping. The recoverable oil amount varies from one formation to another due to many factors including formation rock properties, geology complex, drive mechanisms, and fit technology availability.

The cumulative predicted production from a given formation must not exceed the remaining oil amount left in that formation. In other words, the cumulative production prediction from each formation's base and development wells should not exceed the remaining recoverable oil reserves (ROR_F).

$$CQ_{OTFi,s} \leq ROR_{Fi} \quad (4.28)$$

The remaining recoverable oil in a certain formation that can be produced by development drilling is computed by subtracting the sum of historical produced oil and expected oil to be produced through base wells from expected recoverable oil in that formation, as per below formulas:

$$ROR_{Fi} = (OOIP_F * RF_F) - (NP_F + C_{BOFi}) \quad (4.29)$$

$$C_{BOFi} = 30.417 * \sum_{j=1}^{j=i} TQ_{BOi} \quad (4.30)$$

$$CQ_{OTFi,s} = 30.417 * \sum_{j=1}^{j=i} TQ_{Oi,s} \quad (4.31)$$

Where,

ROR_F: Remaining oil reserves can be produced from formation (F) at time (i), bbl

$OOIP_F$: Original oil in place of formation (F), bbl

RF_F: Recovery factor of formation (F), fraction

NP_F: Cumulative oil produced from the reserves of formation (F) at time zero, bbl

C_{BOFi}: Cumulative oil recovery expected to be produced from base wells by do nothing from the reserves of formation (F) at month (i), bbl

$CQ_{OTFi,s}$: Cumulative of expected average daily oil rate of development wells of type (T) from formation (F) at month (i), BOPD

4.5.4 Inventory of Development Wells

Due to specific size of each formation, limited oil resource, surface accessible area constraint, and wells safe spacing to avoid production interference, there is a limited inventory or numbers of wells per formation per well type available for drilling. Therefore, technical experts like reservoir engineers and geologists should advise on the maximum number of wells for each formation. The number of wells available per formation per well should not be less than the number of chosen wells for drilling by the optimization model.

$$X_{TF,s} \leq I_{TF} \tag{4.32}$$

$$X_{TF,s} = \sum_{i=1}^{T} X_{1TFi} + \sum_{i=1}^{T} \sum_{s=1}^{S} P^{S} * X_{2TFi,s} \tag{4.33}$$

Where,

$X_{TF,s}$: Total number of development wells of type (T) from formation (F), wells

I_{TF}: Maximum inventory of number of development wells of type (T) from formation (F), (in wells units)

4.5.5 Minimum Drilling Needs

For strategic reasons and regardless of wells productivity, the corporation may choose to drill a set of wells from different formations without considering the economic factor in order to explore the formations' boundaries and minimize uncertainties compromising any future opportunities for utilizing these assets. Therefore, there should be a minimum number of wells in each formation to be drilled within a given year as per the below formula.

$$X_{TF,S} \geq M_{TF} \quad (4.34)$$

Where,

M_{TF}: Minimum number of development wells of type (T) from formation (F) to be drilled, (in wells units)

4.5.6 Number of Drilling Rigs

Drilling rigs are critical resource that influence the optimum wells mix and ultimately the NPV. Each rig provides a specific number of days available to be used for drilling, which in turn constraining the maximum wells that can be drilled according to specific mix of wells (refer to equations 4.21 and 4.22). The number of rigs constraint is formulated as:

$$RDD_{i,s} \leq RDA_{i,s} \quad (4.35)$$

Where,

$RDA_{i,s}$: Rig days available for drilling at month i, days

$RDD_{i,s}$: Rig drilling days at month i, days

4.5.7 Facilities Capacity

Water and gas are associated fluids that produce with oil, and their rates vary from well to well and even within the same formation due to formation heterogeneity and dynamism of fluid flow regimes.

All fluids are processed at surface utilizing discrete handling facilities according to the well location before those are assigned to their eventual destination. All producing wells, whether they are current or planned, use the same fluid handling facility called Well Manifold (WMF). The WMF is a set of equipment used to separate liquid from gas as first step of separation, followed by the separation of oil from water in a separate process inside Tank Battery (TB)

facility. Figure 4.3 depicts a typical fluid handling facility block diagram for an oil field.

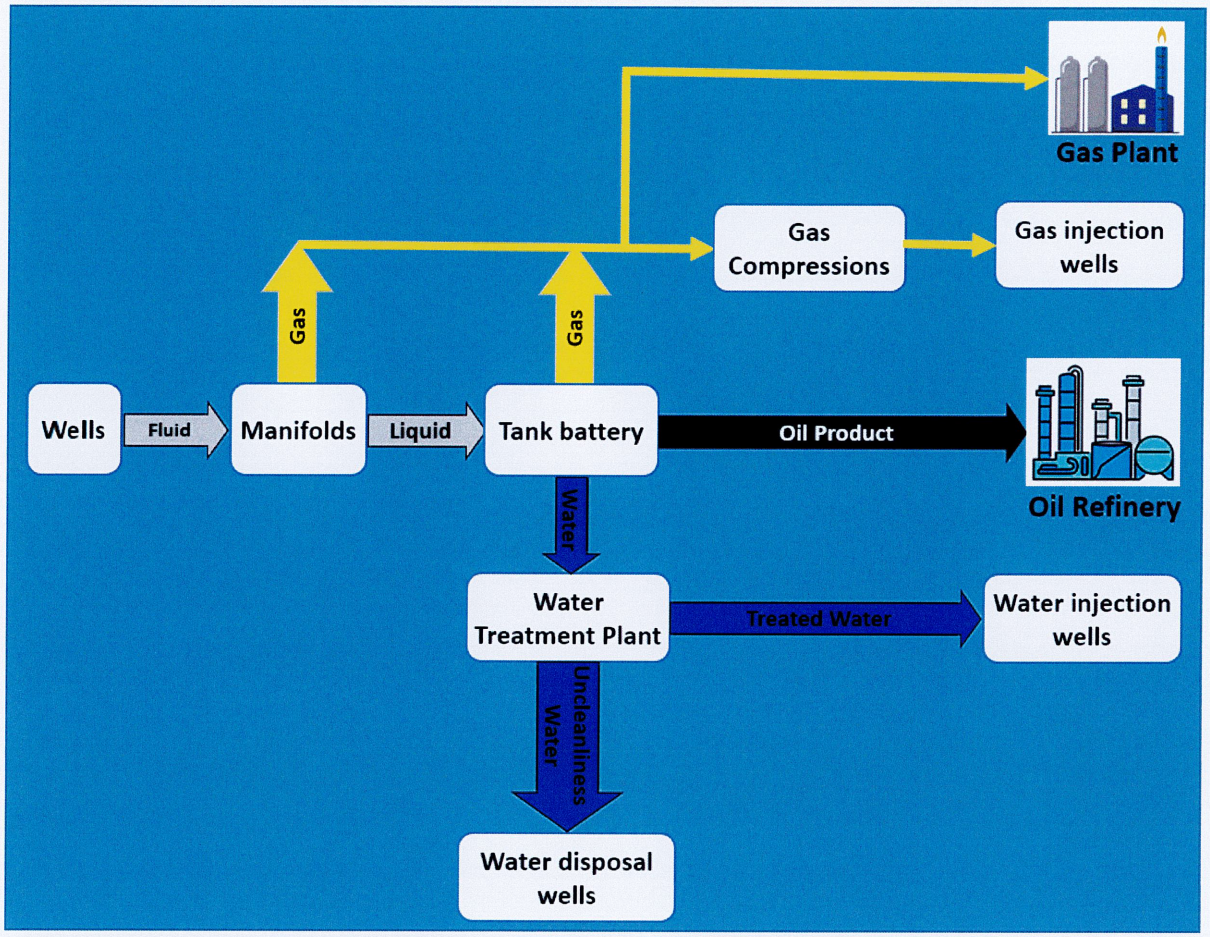


Figure 4.3 Oil field facilities block diagram

If a new well is added to the production system, there must be enough room in the facilities to accommodate the additional expected fluid production; otherwise, existing wells may be forced to shut down in order to connect the new well, which could lead to loss oil from the base production. Therefore, to drill the planned development wells, their expected production rates must be counted, taking into account the limited WMFs capacity after discounting the existing base wells production. If it is economically feasible and aligns with the company's future growth objectives, the corporation can still invest in increasing the fluid handling facilities to maximize its value.

Due to uncertainty of planned wells' location and hook up plans during the budget planning phase, we decided to consider the overall field liquid and gas handling capacities instead of localized WMFs capacities. The formulas for both liquid and gas handling capacity constraints are discussed below.

Liquid Capacity:

For our case study, the liquid capacity is filled mainly by water, as oil accounting for less than 10% of total liquid production; nevertheless, both oil and water rates have been counted in the below formulation for the liquid (oil and water) capacity constraint.

Arps exponential decline equation can be applied for water rate in the same way it can be used for oil rate formulation. The following equation can be used to calculate the water rate for a single development well of type (T) producing from a certain formation (F).

$$Q_{WTFi} = Q_{WTF0} e^{-(\frac{DWTF}{12})*(i-1)} \quad (4.36)$$

Thus, the liquid production rate for all development wells at a given month is calculated by:

$$TQ_L = \sum_{i=1}^{i} X_{1TFi} * (Q_{WTFi} + Q_{OTFi}) + \sum_{i=1}^{i} \sum_{s=1}^{S} P^S * X_{2TFi,s} * (Q_{WTFi} + Q_{OTFi}) \quad (4.37)$$

The water production forecast of all base wells, on the other hand, can be calculated using the below Arps exponential decline equation:

$$Q_{BWFi} = Q_{BWF0} e^{-(\frac{D_{BWF}}{12})*(i-1)} \quad (4.38)$$

Therefore, facilities overall liquid handling capacity constraint is formulated as following:

$$TQ_L + \sum_{i=1}^{i} (Q_{BWFi} + Q_{BOFi}) \leq TQ_{LAC} \quad (4.39)$$

Where,

Q_{WTFi}: Average daily Water rate of development wells of type (T) from formation (F) at month i, BWPD

Q_{WTF0}: Initial average daily Water rate of development wells of type (T) from formation (F) at month zero, BWPD

D_{WTF}: Annual exponential decline of water rate for development well type (T) from formation (F), fraction

Q_{BWFi}: Average daily water rate of base wells from formation (F) at month i, BWPD

Q_{BWF0}: Initial average daily water rate of base wells from formation (F) at month zero, BWPD

D_{BWF}: Annual water base wells exponential decline rate for formation (F), fraction

$TQ_{Li,s}$: Total liquid rate for all development wells at month i, BLPD

TQ_{LACi}: Total WMFs capacity available for liquid at month i, BLPD

Gas Capacity:

For a single development well, Arps exponential decline equation for gas is:

$$Q_{GTFi} = Q_{GTF0} e^{-(\frac{D_{GTF}}{12})*(i-1)} \quad (4.40)$$

The total gas rate for total development wells is then calculated as follows for a given month:

$$TQ_G = \sum_{i=1}^{i} X_{1TFi} * Q_{GTFi} + \sum_{i=1}^{i} \sum_{s=1}^{S} P^S * X_{2TFi,s} * Q_{GTFi} \quad (4.41)$$

On the other side, the following is a forecast of gas production for all base wells using Arps exponential decline:

$$Q_{BGFi} = Q_{BGF0} e^{-(\frac{D_{BGF}}{12})*(i-1)} \quad (4.42)$$

Thus, overall gas handling capacity constraint is formulated as:

$$TQ_G + \sum_{i=1}^{i} Q_{BGFi} \leq TQ_{QAC} \quad (4.43)$$

Where,

Q_{GTFi}: Average daily gas rate of development wells of type (T) from formation (F) at month i, MSCFD

Q_{GTF0}: Initial average daily gas rate of development wells of type (T) from formation (F) at month zero, MSCFD

D_{GTF}: Annual exponential decline gas rate for development well of type (T) from formation (F), fraction

Q_{BGFi}: Average daily gas rate of base wells from formation (F) at month i, MSCFD

Q_{BGF0}: Initial average daily gas rate of base wells from formation (F) at month zero, MSCFD

D_{BGF}: Annual exponential decline gas rate for base wells for formation (F), fraction

$TQ_{Gi,S}$: Total gas rate for all development wells at month i, MSCFD

TQ_{QACi}: Total WMFs capacity available for gas at month i, MSCDF

4.5.8 Economics Cut offs per Well

Logic dictates that each well have a marginal economic rate in order to justify to keep it on production; otherwise, the Net Cash Flow (NCF) for that well will

be negative. The only rationale to keep an unprofitable well running is for strategic reasons related to reservoir management strategy.

The economic cut offs could be directly connected to the oil rate or to the ratios of water and gas to oil. A complicated OPEX model for assigning costs to wells and thus estimating marginal economics per well is employed to calculate these cut offs. Different economic cut offs may exist for each formation, well's Method of Production (MOP), or project. However, for the sake of simplicity, we will assume fixed economic limits for all wells, regardless of production method or target reservoir. Oil, Water Cut (WC), and Gas Oil Ratio (GOR) equations and constraints are listed below.

The well should be kept on production as long as it is producing above economic oil rate; thus, economic oil rate cut off constraint is:

$$Q_{OTFi} \geq Q_{OEW} \tag{4.44}$$

Also, if a well's WC is less than the economic WC ratio, it should be open; thus, the water cut economic cut off constraint is defined as:

$$WC_{TFi} \leq WC_{EW} \tag{4.45}$$

Where water cut is defined as the ratio of water rate to liquid rate as shown in the equation below:

$$WC_{TFi} = \frac{Q_{WTFi}}{(Q_{WTFi}+Q_{OTFi})} \tag{4.46}$$

Another constraint is the GOR economic cut off, which states that a well should not be shut down until its GOR hits the marginal economical GOR ratio. The GOR constraint is written as follows:

$$GOR_{TFi} \leq GOR_{EW} \tag{4.47}$$

Where the gas oil ratio is computed by dividing the gas rate by the oil rate, as shown in the equation below:

$$GOR_{TFi} = \frac{Q_{GTFi}}{Q_{OTFi}} \quad (4.48)$$

Where,

Q_{OEW}: Oil rate economic cut off per well, BOPD

WC_{EW} : Water cut economic cut off per well, BWPD

GOR_{EW}: Gas oil ratio economic cut off per well, MCF/Bbl

WC_{TFi}: Average daily water cut of a well of type (T) from formation (F) at month i, fraction

GOR_{TFi}: Average daily gas oil ratio of a well of type (T) from formation (F) at month i, MCF/Bbl

4.5.9 Integer Decision Variable

For decision variables, while the number of wells per type per formation at month (i), $X_{GTFi,S}$, must be an integer, the number of rigs per year; however, can be a fraction number because the drilling rig can be released at any time during the year if the oil price or drilled wells performance not justifying continuing the drilling activities at any time during the year.

All $X_{GTFi,S}$ are integers,

For X, T, F, i = 0, 1, 2 ,... (4.49)

Also, all variables are non-negative, except for NCF and NPV,

$X_{GTFi,S}$, $RN_{Gi,S}$, all variables (except NCF and NPV) ≥ 0.

4.6 Mathematical Model Formulation Summary

Below is a summary of the aforementioned mathematical formulation.

Decision variables:

$X_{GTFi,s}$: Number of development wells of type (T) from formation (F) to be drilled at month (i) for stage (G), wells

$RN_{Gi,s}$: Number of drilling rigs to be operated at month (i) for stage (G), (in rigs units)

Objective function:

Maximize $NPV = \sum_{i=0}^{i=I} \frac{NCF_{i,s}}{(1+r)^i} = \sum_{i=0}^{i=I} \frac{NCF_{1i}}{(1+r)^i} + \sum_{i=0}^{i=I} \sum_{s=1}^{S} P^S * \frac{NCF_{2i,s}}{(1+r)^i}$

$$= \sum_{i=0}^{i=I} \frac{[(TQ_{Oi}+TQ_{BOi})*P_{oi}-(DCC_i+CO_i+CS_i)]}{(1+r)^i} + \sum_{i=0}^{i=I} \sum_{s=1}^{S} P^S * \frac{[(TQ_{Oi,s}+TQ_{BOi})*P_{oi,s}-(DCC_{i,s}+CO_{i,s}+CS_{i,s})]}{(1+r)^i} \quad (4.50)$$

Subject to:

1. Annual budget

$$TC_{Y,s} \leq AB_Y \quad (4.24)$$

2. Oil production target

$$AQ_{OY.s} \geq MAQ_{OY} \quad (4.26)$$

3. Remaining oil reserves

$$CQ_{OTFi,s} \leq ROR_F \quad (4.28)$$

4. Inventory of development wells per formation

$$X_{TF,s} \leq I_{TF} \quad (4.32)$$

5. Min. wells to be drilled per formation per type

$$X_{TF,s} \geq M_{TF} \quad (4.34)$$

6. Number of drilling rigs

$$RDD_{i,s} \leq RDA_{i,s} \quad (4.35)$$

7. liquid and gas facilities handling capacities

$$TQ_{Li,s} + \sum_{i=1}^{i}(Q_{BWFi} + Q_{BOFi}) \leq TQ_{LACi} \quad (4.39)$$

$$TQ_{Gi,s} + \sum_{i=1}^{i} Q_{BGFi} \leq TQ_{QACi} \quad (4.43)$$

8. Economics cut offs per well

$$Q_{OTFi} \geq Q_{OEW} \quad (4.44)$$

$$WC_{TFi} \leq WC_{EW} \quad (4.45)$$

$$GOR_{TFi} \leq GOR_{EW} \quad (4.47)$$

9. Integer decision variable

$X_{GTFi,s}$ is an integer for X, T, F, i = 0, 1, 2 ,... (4.49)

$X_{GTFi,s}$ $RN_{Gi,s}$: all variables (except *NCF* and *NPV*) ≥ 0

CHAPTER 5

Model Development in GAMS

5.1 Introduction to GAMS
5.2 Model development and challenges
5.3 Model Structure

CHAPTER 5 Model Development in GAMS

Among all research stages, coding and solving model is the most difficult task. In order to code the previous chapter formulation, a sophisticated software was required to solve this vast number of equations with big data set inputs and scenarios. The General Algebraic Modelling System (GAMS) was chosen to execute and run the model after an evaluation of available tools.

In this chapter, we will introduce GAMS and justify why we used it. In addition, we are going to demonstrate the stages of model development as well as obstacles. Furthermore, we will be explaining the model's structure in more depth.

5.1 Introduction to GAMS

GAMS is not only a powerful tool for resolving complicated mathematical formulations, but also it is extremely simple to use, especially for persons with no prior programming and coding skills. Large scale optimization models can be easily created and solved rapidly and effectively in GAMS (GAMS User's Guide, 2022). The software features a library of templates in a variety of scientific fields, as well as options for mathematical optimization algorithms. This can save significant time when it comes to building and developing a model.

GAMS is an optimization modelling system that contains input, process, and output just like any other system. Data and statement coding could be included in the input. While the process is the use of numerical models as well as the use of optimizer to solve problems. The output, on the other hand, is about a full report, containing equations and solutions. In Figure 5.1, (Grossmann, 1991) simplified the aforementioned modelling system.

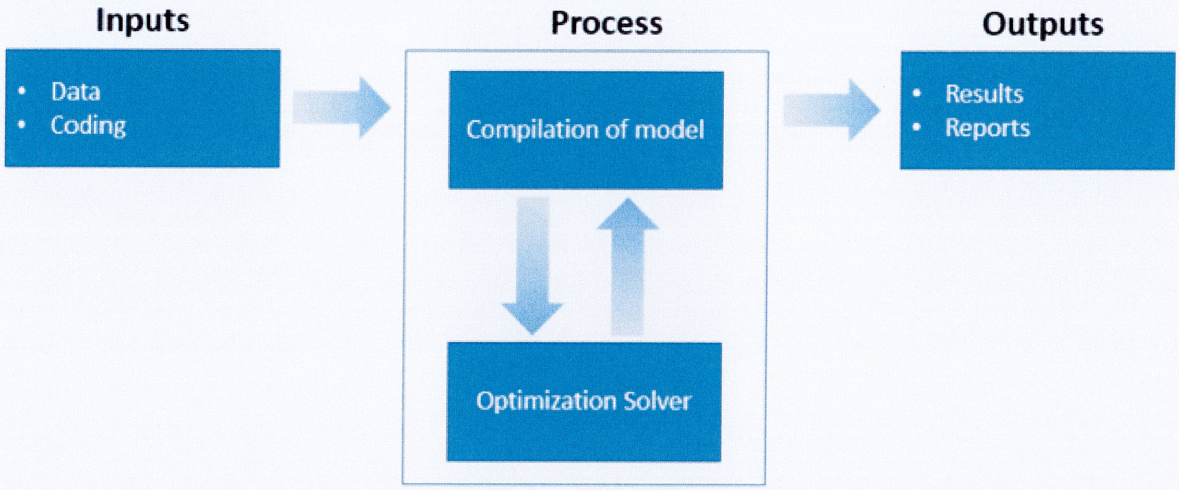


Figure 5.1 GAMS modelling system

Due to its significant advantages, GAMS was chosen to execute and run our model. The following are some of these advantages:

- GAMS' mathematical expressions are relatively close to the problem formulation; as a result, new users can be easily familiar with it in short period.
- It has variety of powerful solvers options for solving linear, nonlinear, integer, and mix integer problems optimization. With no additional coding, the same problem formulation can be solved by switching from one solver to another with only minor adjustments.
- GAMS is a more specialized mathematical programming language for solving optimization problems. It has been widely utilized in stochastic programming.
- GAMS is fully integrated with a variety of packages, including Excel, allowing users to import, process and exporting data comfortably.
- By simple modifying the inputs, the same model formulation can be used to generate thousands of scenarios for both small and large datasets.

- Other modelling software, such as LINDO and MATLAB, can be connected to GAMS. Furthermore, data import and export between Microsoft office and GAMS is smooth.
- Continuous performance improvements and new algorithms and features are added rapidly and frequently.
- GAMS firm and expert users provide excellent support, along with easy access to the models' library, which includes a large database and algorithms collection.

GAMS makes setup for optimization problem solving easy for users through identifying variables, equations, data input, and picking a suitable solver, which is usually suggested by default in GAMS. GAMS Manual contains further information on GAMS's history, capabilities, and modelling techniques (*GAMS User's Guide*, 2022).

Because of advantages stated above, the stochastic model was performed in GAMS. To run the model, we used a machine with an Intel Core i7-1165G7 @ 2.8 GHz processor (CPU), 64-bit operating system, and 16 MB RAM memory. The model was executed using GAMS 35.1and ILOG CPLEX 20.1 MILP solver. The GAMS Community license, which provides more features and capacity than the demo license, was used. It was provided free of charge by GAMS sales for non-commercial use for one-year period, with and a limit of 5,000 variables and 5,000 constraints for solving linear models and up to 2,500 variables and 2,500 constraints for solving other types of models.

5.2 Model Development Stages and Challenges

Several obstacles were encountered in translating the previous chapter formulation into GAMS codes as a new user with no prior knowledge in coding. It is not just because of the large number of complex errors to resolve, but also

because of how to deal with restricted license capacity while dealing with a large number of variables.

This model passed through numerous stages and challenges during its development. Figure 5.2 highlights the main difficulties encountered during the development of the GAMS model.

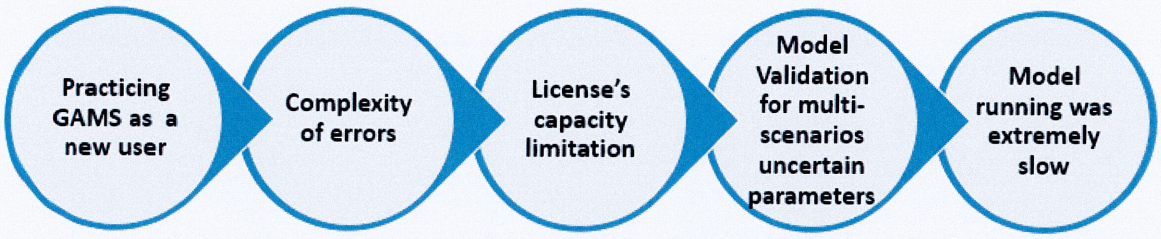


Figure 5.2 GAMS model development challenges

The first barrier was to become comfortable with the GAMS tool via self-learning and practicing its coding language. In fact, the lack of coding experience led to another challenge, which is resolving massive number of coding errors. Reason for such a large number of complex errors is mainly due to not adhering to the GAMS language's standard coding guidelines. As a result, we have decided to adjust our modelling approach by simplifying the model for the start rather of running all equations at once. To achieve the simplification strategy, we dealt with the model as of its all variables are known. This is to ensure that the model can accurately read and display each parameter, as well as solving individual equation correctly.

A major challenge was faced when variables were incorporated into the model. Even by decreasing number of equations require solver engine, as well as reducing scope of inputs such as number of years, formations and well types; the demo license capacity limitation was a barrier to successfully run the model. Because of the limited license capacity, the model was needed restructuring to reduce the number of equations that required the solver.

Although, the preceding procedure enabled us to run the model with a limited scope; it was not going to serve us run the model with requisite scope, nor it was going to support any plan for model expansion. Therefore, a matrix concept was introduced to allow all calculations to be done outside of the solver loop independently from the decision variables and limiting equations in the solver to those dependent on decision variables. We were able to develop a model with a matrix principle, and we were able to validate the results by comparing them to previous model outputs.

Although the new model concept has many advantages such as requiring much less running time, being expandable with no issue regard to license limitations, and its outcomes can be validated easily with any other software; after receiving a new license (community license) with larger capacity from GAMS firm based on our request, we decided not to use the model with matrix concept for this thesis scope and will keep it for future work. The above justification for continuing to use the normal model formulation rather than matrix concept is to keep GAMS formulation as similar to original mathematical formulation as possible, so that the reader can easily link both problem formulations with software coding.

The model challenges were not halted at this point. We moved on to building the stochastic model by introducing several uncertain parameters after we had high confidence in the deterministic model. The incorporation of multiple uncertain parameters, on the other hand, adds to the difficulty of validating and explaining the model outputs. As a result, we decided to conduct sensitivity model and focusing on the most sensitive parameter impacting the objective function.

Finally, it appears that when the model was expanded, a more powerful computer was required to perform the model much faster. For the larger scope with stochastic runs, the model running was extremely slow. This may be

acceptable for offline runs for research purposes, but not for practical use, as large amounts of uncertain data to be processed and multiple development scenarios must be computed; therefore, solver tolerance was adjusted to perform runs faster.

5.3 Model Structure

The created GAMS model is based on the concept formulation presented in previous chapter. However, the equations must be rearranged to be compatible with GAMS language.

The GAMS model was structured in a way to make it easier to spot any faults and to expand it further in the future. Therefore, it is worth to note that our focus during construction of this model was not only on creating a model that would fulfil the needs of this research only, but also on ensuring that it would be ready for any future growth for practical usage. For instance, instead of a single uncertain parameter, such as the price of oil in this research, the coding considers set of uncertain parameters that follow specific distribution functions. This is to ensure more representation for the real field problem and projects uncertainties.

The model is divided into two main sections to reflect the two-stage stochastic approach of solving the problem. The deterministic section, or first stage, begins with the definition of the model's parameters and determining their input values. Variables are also introduced as well as the equations that are solved by the solver, then the final results may be displayed. The second stage is basically building on the deterministic section by introducing some uncertain parameters and defining the variables are affected by those uncertain parameters. The framework structure of GAMS stochastic model is shown in Figure 5.3.

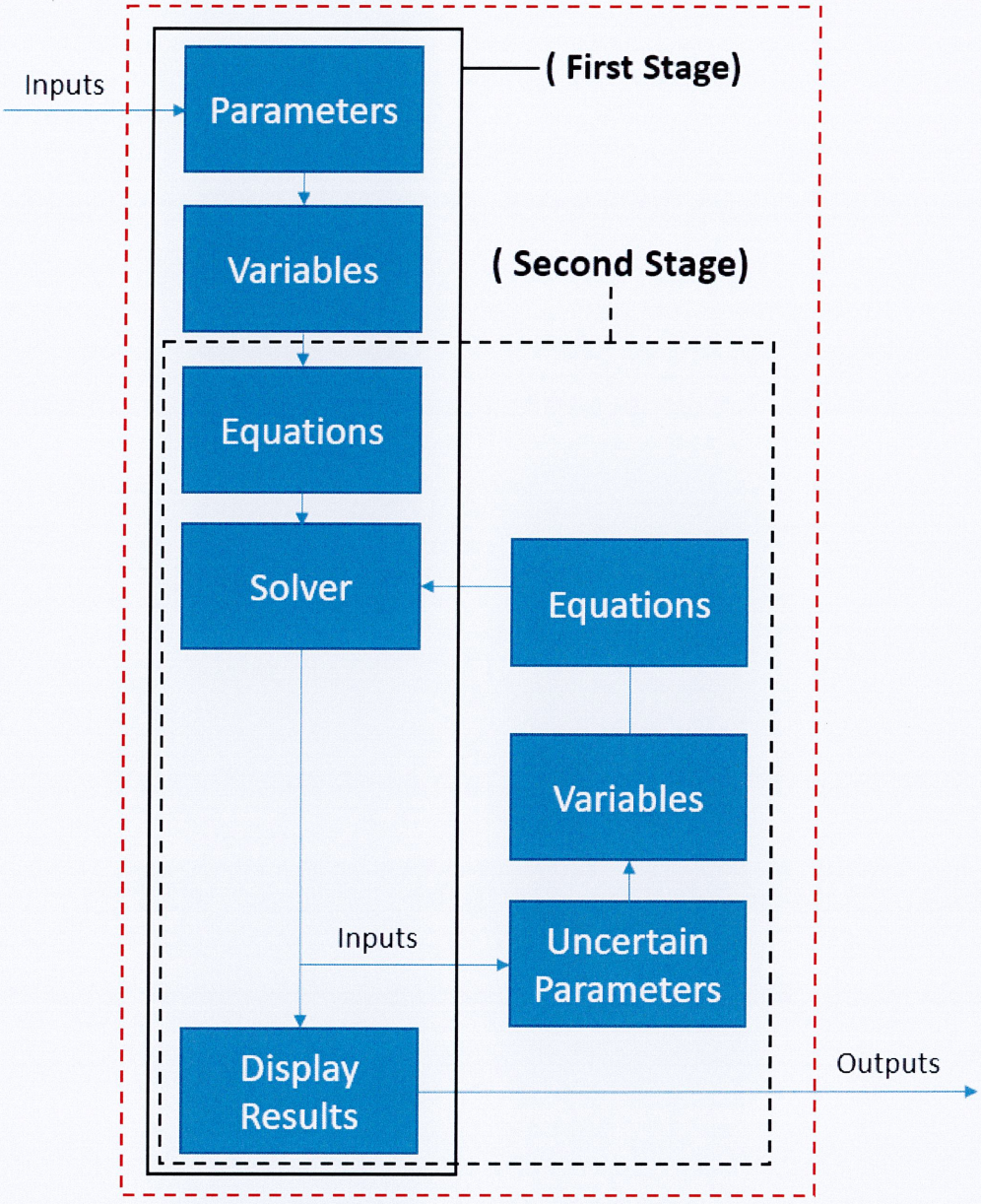


Figure 5.3 GAMS stochastic model main structure

We will go over the components of both stages in further details in the following two subsections.

5.3.1 First Stage Model Construction

The objective of this model is to determine the optimal number of drilling rigs and development well mix that give the maximum NPV under specific constraints. In this model, we shall assume perfect information are available, which means no uncertain parameters in this model.

5.3.1.1 Model Components

The first stage model or the deterministic part is made up of five elements. As indicated in Figure 5. 4, these are parameters, variables, equations, solver, and display results.

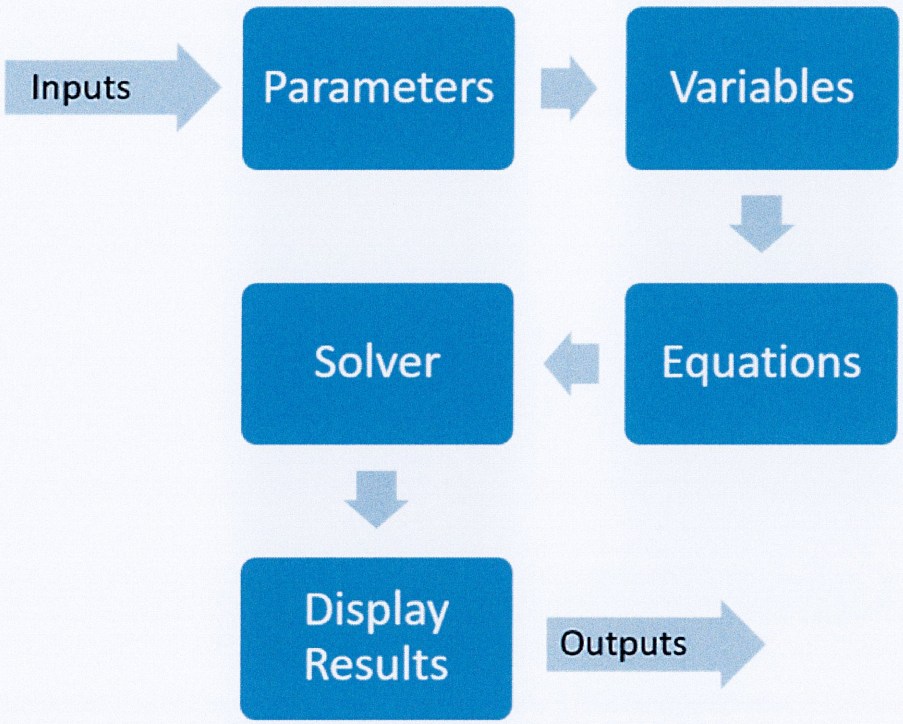


Figure 5.4 First stage model elements

Each element of the first stage model, as well as the notation that go with it, will be defined and discussed below. The GAMS code of each element can be found in Appendix (A).

5.3.1.2 Parameters and Inputs

The model is configured to directly enter all of the parameters' input into the GAMS model. This is to make it easier for adjusting inputs as needed and also to prevent links breaking issues when changing the model file from one location to another.

The data inputs were classified into four categories. All unclassified and independent parameters or inputs are included in the first batch of data. Table A.1 presents these general data inputs.

The second set of data is for those parameters that are based on a periodic or annual based input such as budget, production target, and allocated resources. The annual based inputs are shown in Table A.2.

The formations and wells type relevant data are included in the third category of inputs, such as initial production rates, declines, cost, and wells inventory. Table A.3 shows the data input regarding to formations and wells type.

The data that only dedicated to the formation, such as oil volume, base current production rates, and declines, are grouped together in the fourth category of inputs, as displayed in Table A.4.

There are some parameters in the model that have indirect inputs, which means they must be calculated using the above inputs from the preceding four categories of data or parameters. These calculated parameters represent the fifth group of model inputs, which are listed in the Table A.5.

5.3.1.3 Variables

The first stage model's variables that are dependent on decision variables, are divided into three groups: positives, free and integers, as described and categorized in Table A.6.

5.3.1.4 Equations

During coding and in order to reduce the number of iterations owing to software license capacity limitations, we tried to trim equations in the solver loop to those contain decision variables only. The other equations, which didn't include any decision variables, were already solved outside the loop as part of

parameters equations outlined earlier. The model's variables and constraints equations are listed in Table A.7.

5.3.1.5 Solver

GAMS offers a number of options to solve a problem. Because the model's objective function and constraint equations do not include non-linear variables, and the decision variables are mixed integer, the model was solved using a linear Mixed Integer Programming (MIP) solver.

We used CPLEX Mixed Integer Linear Programming (MILP), which is a powerful solver and widely used as a default solver for solving linear programming problems. Its algorithm was developed based on the interior point method developed by (Karmarkar, 1984).

5.3.1.6 Display Results and Outputs

This model's final segment is simply to validate some constraints. In addition, it was coded to display some variables and equations solution.

5.3.2 Second Stage Model Construction

In this part of model, we will incorporate several uncertain parameters; however, the analysis of outcomes will be discussed in Chapters 6 and 7, which will focus just on oil price uncertainty while fixing all the other uncertain factors.

Several uncertain parameters were introduced into the model to convert the deterministic model to a stochastic one, including:

- Oil price
- Initial oil, water, and gas production rates for development wells
- Oil, water, and gas decline rates for development wells and formation base production

- Costs including OPEX and some components of CAPEX such as completion cost per well type per formation and facilities hook up cost.
- Drilling days per well type per formation

The additional components included into the deterministic model to convert it into a two-stage stochastic model will be outlined in the following subsections.

5.3.2.1 Stochastic Parameters and Inputs

For now, the introduced uncertain parameters were assumed to follow a certain probability distribution function. For instance, we applied a normal distribution for oil price, initial production rates, oil decline and costs; however, for the number of drilling days we chose to apply a triangular distribution function. When it comes to real case application, a solid justification and support basis are essential for those assumptions. As our interest in this research is the oil price, and due to its volatility nature based on historical data, we shall defend the employment of a normal distribution function for this uncertain parameter in Section 7.1.

To run the model with random oil price input scenarios, we employed the looping concept. The first draw was compelled to use deterministic case data input to ensure the looping concept is working properly.

Table A.8 summarizes the additional input parameters introduced in the second stage of the model.

5.3.2.2 Variables

The stage two model's variables that include decision variables and other dependent variables, are shown in Table A.9.

5.3.2.3 Display Results and Outputs

One of GAMS's limitations is that necessitated the use of other software tools to visualize the results. Therefore, to display the results, we unloaded data

into a GAMS Data Exchange (GDX) file while the model was running and then displayed final selective results into Excel. To analyse the results, additional calculations and formatting were done in Excel.

In next chapter, we will run several tests on the model to ensure its reliability for a real field data application as part of the Company A's portfolio optimization.

CHAPTER 6

Model Testing

6.1 Sensitivity Analysis
6.2 Model Functionality Tests

CHAPTER 6 Model Testing

The objective of this chapter is to test the model's functionality by examining several cases. This chapter presents a small-scale application on the stochastic GAMS model discussed in the previous chapter. Before using real case data in the next chapter, a demo data will be used to run the various verification cases.

Unfortunately, Khonji's model could not be used to validate the model results, at least for the deterministic part; because of the enhancements that were included in our model, as well as the gaps that were observed in Khonji's model, such as:

- The time value of money was not taken into account in the model. Although the discounted rate was considered during the formulation, it was assumed to be zero during model testing and real application.
- Although the standby cost was considered in the formulation; however, in the real application it was not accounted.
- Revenue and OPEX results were observed to be inaccurate. Monthly production rates were used to calculate revenue and OPEX; however, these parameters must be multiplied by the number of days per month in order to be calculated accurately.

6.1 Sensitivity Analysis

It was necessary to understand the most sensitive parameters affecting the objective function value before proceeding with the stochastic application of the model. This is required to achieve model simplification by concentrating solely

on significant uncertainties in order to fully understand and analyse model outcomes. The stochastic part of the GAMS formulation was built after identifying those uncertain parameters using sensitivity analysis.

Number of sensitivities were tested in this model. The objective is to determine the most sensitive uncertain parameter that effects NPV and use it for stochastic modelling. Out of 16 potential uncertain parameters in our model, we picked 6 parameters to run the sensitivities on. Individual parameters were changed one at a time, while the rest of the parameters remaining unchanged. Step changes of 20% up to +/-60% were used in the sensitivity test for the following uncertain parameters:

- Oil Price
- OPEX
- Facilities hook-up and site preparation cost
- Completion cost
- Initial oil production rate for the development wells
- Decline oil rate for the development wells

To visualize the sensitivity analysis, two common techniques were utilized to represent the influence of each parameter on NPV. Those techniques are Spider graph and Tornado chart, which are shown in Figure 6.1 and Figure 6.2, respectively.

The slope of the lines in Figure 6.1 reflects the degree of sensitivity of each parameter to NPV. The steeper line slope, the greater influence on NPV. Figure 6.1 indicates clearly that the most sensitive parameter influencing NPV is the price of oil.

The results of the Spider graph analysis are confirmed by the Tornado chart (Figure 6.2), which shows that oil price is the most sensitive parameter on NPV. Any change in oil price by +/-20% affecting NPV by +/- $84MM (+/- 29.6%).

The second most sensitive parameter is the initial oil production for the development wells. The NPV could be impacted by +/- $44MM (or +/- 15.4) in case of any change in initial oil production by +/- 20%. The third most sensitive parameter is OPEX, which is impacting NPV by +/-6.6% in case of any deviation by +/-20%. All other parameters, on the other hand, have a minor impact on NPV of less than +/- 1%.

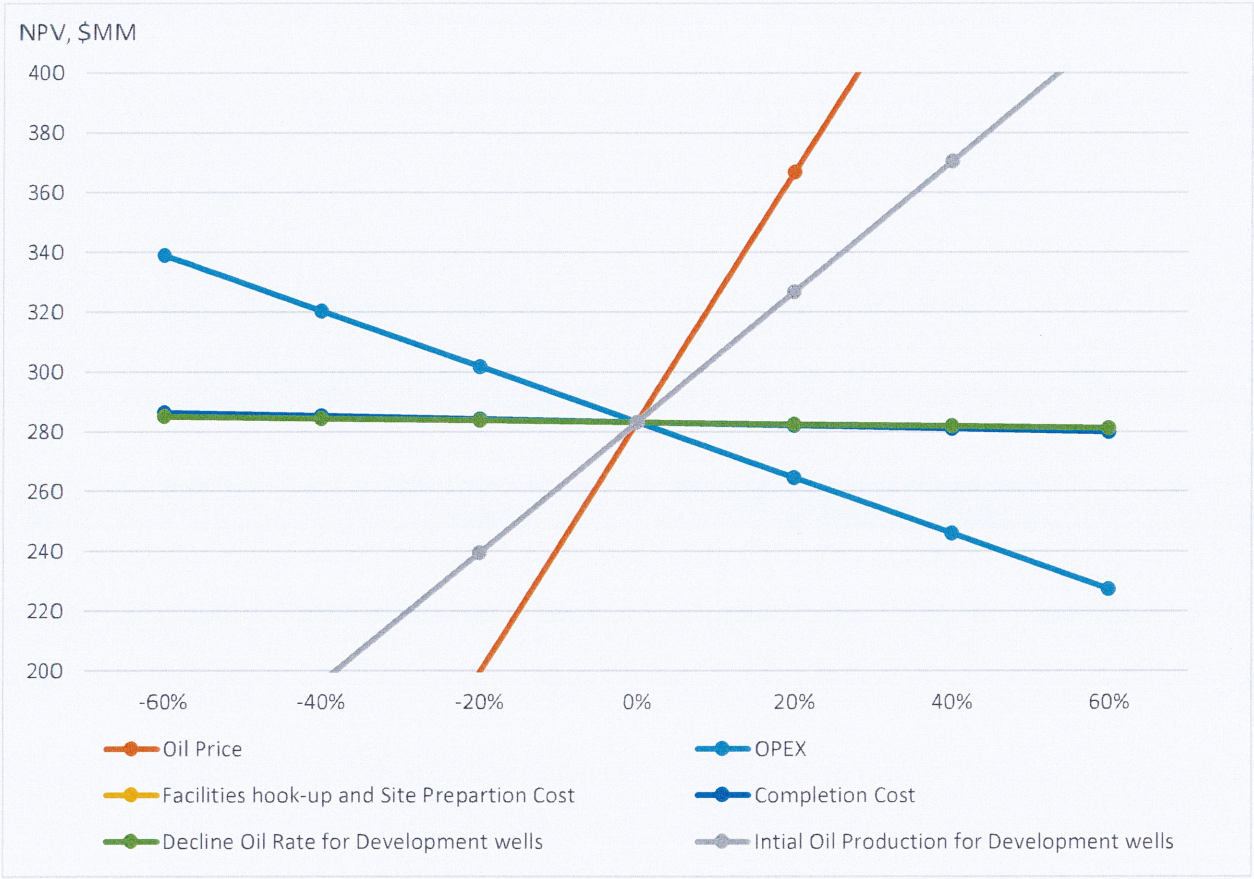


Figure 6.1 Spider graph analysis

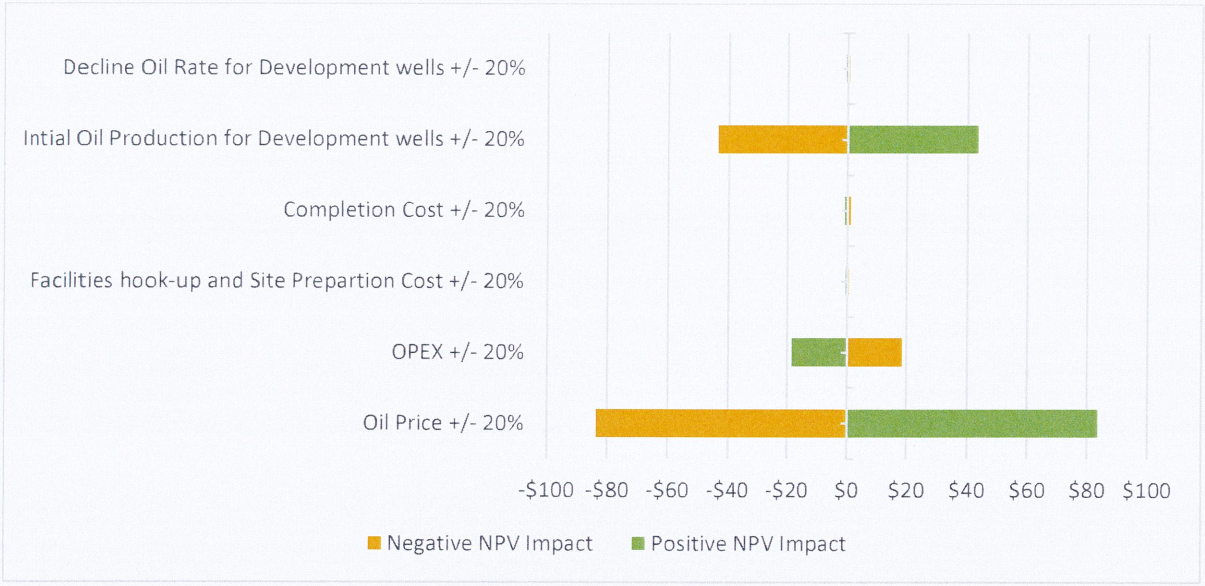


Figure 6.2 Tornado chart

Because the price of oil is the most uncertain sensitive parameter influencing the NPV, it was taken into account in the two-stage stochastic model formulation and application.

6.2 Model Functionality Tests

In this section, three cases will be run and reported to test the functionality of the GAMS model. Case 1 tests scalability of the model. Case 2 examines how key constraints affect the model's solution. Case 3 looks at other uncertain parameters besides than the oil price.

6.2.1 Case 1: Model Scalability

The aim of this subsection is to verify the scalability of the model by gradually expanding the scope of the model in four steps. In the first case, the model will be run without including the base program. In the second case, the base program will be included along with the development program. The third and fourth cases assume that there are more options for the wells inventory and that a longer time period than one year is to be examined, respectively.

6.2.1.1 Case 1.1 Base case (development program)

As previously stated, our model includes two programs a part of Company A's portfolio. We will consider development program only in this case to simplify with the optimization run. Furthermore, the run scope will be limited to 1 year timeframe, 2 formation options, and 1 well trajectory option. Table 6.1 summarizes the input parameters used.

Table 6.1 Case 1.1 input parameters

Formation (F)

Index	Formation Name
1	Formation A
2	Formation B

Well Type(T)

Index	Well Type
1	Vertical

Price and OPEX

Index	Oil Price ($)	Opex Cost ($/bbl)
1	Norm (60, 20%)	8

Plan per Year

Year No.	Budget ($)	Min. Oil rate (BOPD)	Rigs NO.
1	175,000,000	12,000	N/A

Reservoir and Base production Parameter

F	Oil In Place (Bbls)	Recovery Factor ()	Cumulative Oil Produced (Bbls)	Current Production Oil (BOPD)	Current Production Water (BWPD)	Current Production Gas (Mscf/d)	Oil Decline Rate (D) ()	Water Decline Rate (D) ()	Gas Decline Rate (D) ()
1	170,000,000	0.25	17,000,000						
2	1,230,000,000	0.3	98,400,000						

Other inputs

Paramter	Value
Rig Daily Rate ($)	120,000
Unproductive rig time at month i ()	0.03
Site Preparation & Hook-up Cost ($) per well	180,000
Discount rate ()	0.10
Liquid Capacity (Bbls)	800,000
Gas Capacity (MSCF)	400,000

Development Wells

Ref	F	T	IP (BOPD)	IP (BWPD)	IP (MSCFD)	Annual Oil Decline Rate (D) ()	Annual Water Decline Rate (D) ()	Annual Gas Decline Rate (D) ()	Drilling Days	Completion Cost ($)	CAPEX,$	Max No. of Wells	Min No. of Wells
1	1	1	60	240	600	0.1	-0.02	-0.02	3	100,000	640,000	180	0
2	2	1	60	90	600	0.08	-0.01	-0.01	3	120,000	660,000	150	0

The model was run with 1000 different oil price input scenarios, according to normal distribution with a mean of $60 per bbl and a standard deviation of 20%. The model suggests an average rig number of 2.1, when no constraint on the number of rigs is applied. Accordingly, out of an inventory of 330 wells belong to 2 different formations, the model scheduled an optimal average number of 194 wells to be drilled mainly from formation 1. This gives maximum expected NPV value of $ -6,745,678. The negative NPV could be due to the limited unattractive options for drilling. As we will see in Case 1.3, introducing more drilling options improved the NPV substantially.

6.2.1.2 Case 1.2 Adding base program

In this case, we will include both the base and development programs. This means that company resources (i.e. budget, fluid handling capacity, ...etc) will be split between the two programs. Due to the fact that the base program only includes OPEX, the optimization will primarily focus on the capital development program. We will use the same input listed in Table 6.1, but with adding base program's relevant data input. The inputs used in Case 1.2 are listed in Table 6.2.

Table 6.2 Case 1.2 input parameters

Formation (F)

Index	Formation Name
1	Formation A
2	Formation B

Well Type(T)

Index	Well Type
1	Vertical

Price and OPEX

Index	Oil Price ($)	Opex Cost ($/bbl)
1	Norm (60, 20%)	8

Plan per Year

Year No.	Budget ($)	Min. Oil rate (BOPD)	Rigs NO.
1	175,000,000	12,000	N/A

Reservoir and Base production Parameter

F	Oil In Place (Bbls)	Recovery Factor ()	Cumulative Oil Produced (Bbls)	Current Production Oil (BOPD)	Current Production Water (BWPD)	Current Production Gas (Mscf/d)	Oil Decline Rate (D) ()	Water Decline Rate (D) ()	Gas Decline Rate (D) ()
1	170,000,000	0.25	17,000,000	500	4,000	8,000	0.2	-0.02	-0.02
2	1,230,000,000	0.3	98,400,000	5,000	35,000	10,000	0.25	-0.01	-0.01

Other inputs

Paramter	Value
Rig Daily Rate ($)	120,000
Unproductive rig time at month i ()	0.03
Site Preparation & Hook-up Cost ($) per well	180,000
Discount rate ()	0.10
Liquid Capacity (Bbls)	800,000
Gas Capacity (MSCF)	400,000

Development Wells

Ref	F	T	IP (BOPD)	IP (BWPD)	IP (MSCFD)	Annual Oil Decline Rate (D) ()	Annual Water Decline Rate (D) ()	Annual Gas Decline Rate (D) ()	Drilling Days	Completion Cost ($)	CAPEX,$	Max No. of Wells	Min No. of Wells
1	1	1	60	240	600	0.1	-0.02	-0.02	3	100,000	640,000	180	0
2	2	1	60	90	600	0.08	-0.01	-0.01	3	120,000	660,000	150	0

By adding the base program there was no noticeable effect on decision variables optimal solution was seen in case 1.1. The model suggested an average of 2 drilling rigs to be used. Moreover, the model scheduled an optimal average number of 188 wells to be drilled, primarily from formation 1, which is nearly identical to the preceding case's optimal solution. This can be explained by the fact that optimization of decision variables has nothing to do with base OPEX program. The model, however, gives a maximum expected NPV of $ 81,225,642, which is a substantial positive increase over the previous case, owing to the high profitability of base program, which solely includes OPEX.

6.2.1.3 Case 1.3 Expanding inventory of wells mix

In this case, the model's scope will be enlarged by taking into account a bigger number of wells options. The number of formations has been increased to 3 formations, with adding 2 type of wells for formation 3. The inputs employed in this case are listed in Table 6.3.

Table 6.3 Case 1.3 input parameters

Formation (F)

Index	Formation Name
1	Formation A
2	Formation B
3	Formation C

Well Type(T)

Index	Well Type
1	Vertical
2	Horizontal

Price and OPEX

Index	Oil Price ($)	Opex Cost ($/bbl)
1	Norm (60, 20%)	8

Plan per Year

Year No.	Budget ($)	Min. Oil rate (BOPD)	Rigs NO.
1	175,000,000	12,000	N/A

Reservoir and Base production Parameter

F	Oil In Place (Bbls)	Recovery Factor ()	Cumulative Oil Produced (Bbls)	Current Production Oil (BOPD)	Current Production Water (BWPD)	Current Production Gas (Mscf/d)	Oil Decline Rate (D) ()	Water Decline Rate (D) ()	Gas Decline Rate (D) ()
1	170,000,000	0.25	17,000,000	500	4,000	8,000	0.2	-0.02	-0.02
2	1,230,000,000	0.3	98,400,000	5,000	35,000	10,000	0.25	-0.01	-0.01
3	800,000,000	0.35	120,000,000	4,000	25,000	20,000	0.3	-0.01	-0.01

Other inputs

Paramter	Value
Rig Daily Rate ($)	120,000
Unproductive rig time at month i ()	0.03
Site Preparation & Hook-up Cost ($) per well	180,000
Discount rate ()	0.10
Liquid Capacity (Bbls)	800,000
Gas Capacity (MSCF)	400,000

Development Wells

Ref	F	T	IP (BOPD)	IP (BWPD)	IP (MSCFD)	Annual Oil Decline Rate (D) ()	Annual Water Decline Rate (D) ()	Annual Gas Decline Rate (D) ()	Drilling Days	Completion Cost ($)	CAPEX,$	Max No. of Wells	Min No. of Wells
1	1	1	60	240	600	0.1	-0.02	-0.02	3	100,000	640,000	180	0
2	2	1	60	90	600	0.08	-0.01	-0.01	3	120,000	660,000	150	0
3	3	1	80	120	800	0.15	-0.01	-0.01	3.5	130,000	730,000	400	1
4	3	2	120	200	1200	0.15	-0.01	-0.01	5	200,000	980,000	200	0

By introducing extra options for drilling, the model gives an optimal number of rigs of 1.7. This allows for drilling an average of 103 wells, practically all of which are from formation 3 type 2, as it provides double oil production at 50% additional cost that of other options. The suggested optimal mix of wells gives NPV of $ 182,784,222, which is significantly higher than the NPV from Case 1.2 because better alternatives were offered.

6.2.1.4 Case 1.4 Expanding time frame

In this case, we will build on Case 1.3 data input and expand the timeframe to 2 years instead of 1 year. Case 1.4 inputs are shown in Table 6.4.

Table 6.4 Case 1.4 input parameters

Formation (F)	
Index	Formation Name
1	Formation A
2	Formation B
3	Formation C

Well Type(T)	
Index	Well Type
1	Vertical
2	Horizontal

Price and OPEX		
Index	Oil Price ($)	Opex Cost ($/bbl)
1	Norm (60, 20%)	8
2	Norm (70, 20%)	9

Plan per Year			
Year No.	Budget ($)	Min. Oil rate (BOPD)	Rigs NO.
1	175,000,000	12,000	N/A
2	250,000,000	10,000	N/A

Reservoir and Base production Parameter									
F	Oil In Place (Bbls)	Recovery Factor ()	Cumulative Oil Produced (Bbls)	Current Production Oil (BOPD)	Current Production Water (BWPD)	Current Production Gas (Mscf/d)	Oil Decline Rate (D) ()	Water Decline Rate (D) ()	Gas Decline Rate (D) ()
1	170,000,000	0.25	17,000,000	500	4,000	8,000	0.2	-0.02	-0.02
2	1,230,000,000	0.3	98,400,000	5,000	35,000	10,000	0.25	-0.01	-0.01
3	800,000,000	0.35	120,000,000	4,000	25,000	20,000	0.3	-0.01	-0.01

Other inputs	
Paramter	Value
Rig Daily Rate ($)	120,000
Unproductive rig time at month i ()	0.03
Site Preparation & Hook-up Cost ($) per well	180,000
Discount rate ()	0.10
Liquid Capacity (Bbls)	800,000
Gas Capacity (MSCF)	400,000

Development Wells													
Ref	F	T	IP (BOPD)	IP (BWPD)	IP (MSCFD)	Annual Oil Decline Rate (D) ()	Annual Water Decline Rate (D) ()	Annual Gas Decline Rate (D) ()	Drilling Days	Completion Cost ($)	CAPEX,$	Max No. of Wells	Min No. of Wells
1	1	1	60	240	600	0.1	-0.02	-0.02	3	100,000	640,000	180	0
2	2	1	60	90	600	0.08	-0.01	-0.01	3	120,000	660,000	150	0
3	3	1	80	120	800	0.15	-0.01	-0.01	3.5	130,000	730,000	400	1
4	3	2	120	200	1200	0.15	-0.01	-0.01	5	200,000	980,000	200	0

The solution suggested 1.8 and 2.1 rigs for Year 1 and Year 2, respectively. The overall number of wells to be drilled is 266 wells over 2 years, with nearly all of them to be drilled from formation 3 type 2 for the reasons stated above. Taking into account the second year's production, as well as continuing drilling, maximize the NPV to $ 607,369,300.

6.2.2 Case 2: Constraints Sensitivity

In this subset of cases, we will assess the impact of three key constraints on model outcomes by adjusting constraints values by +/- 20% and observe the impact on NPV. The annual budget, production target, and fluid handling capacity are the three constraints that will be tested. During the various runs, the other constraints will remain constant.

6.2.2.1 Case 2.1 Relaxing constraints

In this case, we are going to relax annual budget, production target and fluid handling constraints before measuring the influence of each constraint on objective function in the next three subsections. The inputs employed in Case 2.1 are listed in Table 6.5.

Table 6.5 Case 2.1 input parameters

Formation (F)

Index	Formation Name
1	Formation A
2	Formation B

Well Type(T)

Index	Well Type
1	Vertical

Price and OPEX

Index	Oil Price ($)	Opex Cost ($/bbl)
1	Norm (60, 20%)	8

Plan per Year

Year No.	Budget ($)	Min. Oil rate (BOPD)	Rigs NO.
1	1,000,000,000	0	N/A

Reservoir and Base production Parameter

F	Oil In Place (Bbls)	Recovery Factor ()	Cumulative Oil Produced (Bbls)	Current Production Oil (BOPD)	Current Production Water (BWPD)	Current Production Gas (Mscf/d)	Oil Decline Rate (D) ()	Water Decline Rate (D) ()	Gas Decline Rate (D) ()
1	170,000,000	0.25	17,000,000	500	4,000	8,000	0.2	-0.02	-0.02
2	1,230,000,000	0.3	98,400,000	5,000	35,000	10,000	0.25	-0.01	-0.01

Other inputs

Paramter	Value
Rig Daily Rate ($)	120,000
Unproductive rig time at month i ()	0.03
Site Preparation & Hook-up Cost ($) per well	180,000
Discount rate ()	0.10
Liquid Capacity (Bbls)	1,000,000
Gas Capacity (MSCF)	1,000,000

Development Wells

Ref	F	T	IP (BOPD)	IP (BWPD)	IP (MSCFD)	Annual Oil Decline Rate (D) ()	Annual Water Decline Rate (D) ()	Annual Gas Decline Rate (D) ()	Drilling Days	Completion Cost ($)	CAPEX,$	Max No. of Wells	Min No. of Wells
1	1	1	60	240	600	0.2	-0.02	-0.02	3	100,000	640,000	180	0
2	2	1	60	90	600	0.25	-0.01	-0.01	3	120,000	660,000	150	2

The model shows NPV of $ 98,644,290. Despite the relaxation of three constraints, the solution is still constrained by others, such as the limitation of wells inventory. The model suggests drilling limited number of wells just to satisfy some other constraints such drilling minimum number of wells per formation in order to arrest the base wells decline.

6.2.2.2 Case 2.2 Annual Budget

We will start with a base case, in which the results will be compared with +/- 20% change in a specific constraint, while fixing the remaining constraints. The annual budget, production target, and fluid handling capacity constraints in the base case are $175,000,000, 9000 BOPD, 120,000 LBOPD, and 120,000 MSCFD, respectively. Table 6.6 summarizes the input parameters for the base case.

Table 6.6 Case 2.2 base case input parameters

Formation (F)

Index	Formation Name
1	Formation A
2	Formation B

Well Type(T)

Index	Well Type
1	Vertical

Price and OPEX

Index	Oil Price ($)	Opex Cost ($/bbl)
1	Norm (60, 20%)	8

Plan per Year

Year No.	Budget ($)	Min. Oil rate (BOPD)	Rigs NO.
1	175,000,000	9,000	N/A

Reservoir and Base production Parameter

F	Oil In Place (Bbls)	Recovery Factor ()	Cumulative Oil Produced (Bbls)	Current Production Oil (BOPD)	Current Production Water (BWPD)	Current Production Gas (Mscf/d)	Oil Decline Rate (D) ()	Water Decline Rate (D) ()	Gas Decline Rate (D) ()
1	170,000,000	0.25	17,000,000	500	4,000	8,000	0.2	-0.02	-0.02
2	1,230,000,000	0.3	98,400,000	5,000	35,000	10,000	0.25	-0.01	-0.01

Other inputs

Paramter	Value
Rig Daily Rate ($)	120,000
Unproductive rig time at month i ()	0.08
Site Preparation & Hook-up Cost ($) per well	180,000
Discount rate ()	0.10
Liquid Capacity (Bbls)	120,000
Gas Capacity (MSCF)	120,000

Development Wells

Ref	F	T	IP (BOPD)	IP (BWPD)	IP (MSCFD)	Annual Oil Decline Rate (D) ()	Annual Water Decline Rate (D) ()	Annual Gas Decline Rate (D) ()	Drilling Days	Completion Cost ($)	CAPEX,$	Max No. of Wells	Min No. of Wells
1	1	1	60	240	600	0.2	-0.02	-0.02	3	100,000	640,000	180	0
2	2	1	60	90	600	0.25	-0.01	-0.01	3	120,000	660,000	150	2

The model gives NPV of $83,999,550. By applying the above base case constraints on annual budget, production target and fluid handling capacity, the NPV was reduced by $14,644,740 (or around -15%) compared to previous case.

In this case, we looked at how changing the budget limit affected the NPV. By increasing and decreasing the annual budget within +/-20%, there was no significant change in NPV result (less than 1%).

6.2.2.3 Case 2.3 Oil Production Target

In this case, we'll see how a +/-20 variation in production target affects the NPV. When changing the production target by +/-20, the model indicates up to 5.5% change in NPV when compared to the base case.

6.2.2.4 Case 2.4 Fluid Handling Capacity

In last case, changes in liquid and gas handling capacity within +/-20 had a small influence on NPV (less than 1.7%).

6.2.3 Case 3: Other Parameters Uncertainty

In this subgroup of cases, we will run the stochastic model with introducing more uncertain variables. Initial oil production rate for the development wells, OPEX, and completion cost are the additional uncertain parameters to be examined individually, along with volatile oil price, before considering a combination of uncertainty scenario. For upcoming cases, we will use the base case input parameters listed in Table 6.6.

6.2.3.1 Case 3.1 Initial oil production rate for the development wells

In this case, we will assume that initial oil production for development is a random variable distributed normally with a mean per formation per well type, stated in Table 6.6, and a standard deviation of 20%.

By introducing the initial oil production for development wells as uncertain parameter along with uncertain oil price, the model suggests an optimal number of wells of 135, which is just 4 wells higher than Case 2.2 optimal solution. However, the optimal mix of wells suggested by the model gives NPV of $ 93,590,308, which is $9,590,758 greater than NPV from Case 2.2, owing to higher year average production by 720 BOPD. This backs up the sensitivity analysis discussed in Section 6.1 that shows initial oil production rate for development comes as a second most sensitive parameter affecting the NPV after the oil price.

6.2.3.2 Case 3.2 OPEX

In this case, we will introduce OPEX as uncertain parameter with normal distribution of a 20% standard deviation.

The model calculates an NPV of $ 84,042,777, which is nearly identical to case 2.2 solution in terms of the number of rigs and optimal wells mix. This is logical, given that the model was created solely to optimize capital projects. NPV

is less sensitive to OPEX than initial production rate for development wells, as seen in Figure 6.2.

6.2.3.3 Case 3.3 Completion cost

According to the sensitivity run for deterministic model discussed in Section 6.1, we pick a parameter that has a negligible impact on NPV optimization in this scenario. The idea is to put the model's results to the test in conjunction with a highly sensitive parameter, such as the price of oil. When completion cost is treated as an uncertain parameter distributed normally with a standard deviation of 20%, the model yields NPV of $84,358,016, confirming the negligibility impact of completion cost on NPV as well as and the weak link between oil price and completion cost.

6.2.3.4 Case 3.4 Combination of uncertainty

Finally, in addition to oil price, we will test the model by combining the three uncertain parameters stated in previous cases: initial oil production for development wells per formation per type, OPEX, and completion cost. The objective is to see how a set of uncertain parameters affects NPV results. Therefore, we will compare the results fairly by using similar inputs as in previous cases.

The model yields an optimal number of wells of 136 with an NPV of $ 93,783,554, which is nearly identical to the results of Case 3.1. This backs up the sensitivity analysis stated in Section 6.1, which shows that the impact on NPV is dominated by the initial oil production rate for development, as compared to OPEX and completion cost.

6.2.4 Conclusion

A summary table of the model's NPV outcomes for the different cases is shown in Table 6.7.

Table 6.7 Summary of the model's NPV outcomes for all cases

Case	NPV		
Case 1 Model Scalability			
Case 1.1 Base case (development program)	$-6,745,678		
Case 1.2 Adding base program	$ 81,225,642		
Case 1.3 Expanding inventory of wells mix	$182,784,222		
Case 1.4 Expanding time frame	$ 607,369,300		
Case 2: Constraints Sensitivity	**-20%**	**Base Case**	**20%**
Case 2.1 Relaxing Constraints	N/A	$98,644,290	N/A
Case 2.2 Annual Budget	$83,204,110	$83,999,550	$83,999,550
Case 2.3 Production Target	$88,526,660	$83,999,550	$79,337,920
Case 2.4 Fluid Handling Capacity	$82,577,790	$83,999,550	$84,656,230
Case 3 Other Parameters Uncertainty			
Case 3.1 Initial oil production rate for the development wells	$ 93,590,308		
Case 3.2 OPEX	$ 84,042,777		
Case 3.3 Completion cost	$84,358,016		
Case 3.4 Combination of uncertainty	$93,783,554		

By expanding scope gradually, the model produced logical results. The addition of the base program not only helped to lower development wells CAPEX, but also contributed significantly to meet the target production. In addition, by adding a second year period, the NPV increased dramatically due to higher positive cash flow generation from both base and development wells drilled in Year1. Furthermore, the more drilling alternatives available, the higher the NPV value is observed.

Secondly, the influence on NPV was disparate based on selective resources sensitivity testing. Increasing one resource while keeping the others constant did not result in a significant increase in NPV. To have a significant influence on NPV, raising the budget must be coupled with expanding fluid handling capacity, for example.

Finally, the sensitivity of the NPV to inputs varies, and the more sensitive the parameter, the greater the impact on the NPV. Adding unnecessary uncertain parameters to the model will not improve the NPV.

To conclude, based on above testing results, the model now is ready for a real field application, which will be discussed in next chapter.

CHAPTER 7

Case Study
Real Field Application

7.1 Model Inputs
7.2 Model Results and Analysis
7.3 Conclusions

CHAPTER 7 Case Study: Real Field Application

In the previous chapter, we assessed the model with limited scope to ensure its functionality. We can now trust the model in a real case application. In this chapter, data inputs from Company A were used in the model and results were consolidated at portfolio level and presented graphically.

In Section 7.1, we will introduce Company A's data inputs and will justify oil price specifically as the key concern input. In Section 7.2, we are going to propose both AWPB and 5 years business plans, in which a comparison of deterministic and stochastic outcomes will be discussed, as well as a comparison of the model optimized plan compared to Company A's AWPB original plan. In Section 7.3, we will look at two scenarios at which an additional fluid handling capacity is invested. In Section 7.4, we will run the model considering a combination of uncertain parameters and discuss the outcomes.

7.1 Model Inputs

The model was developed to gather and convert various relevant data into useful information for decision-making. The model was designed to reflect selective key uncertain parameters and to display, in numbers and graphs, the impact of these uncertainties on oil production, capital and operational expenses, and NPV.

The model's inputs come from various departments at the Company A. Most likely case data were provided by multidisciplinary experts supported by a range of uncertainty for some input parameters based on historical data. Table 7.1 lists the AWPB and 5 Yrs plan inputs.

Table 7.1 The AWPB and 5 Yrs plan inputs

Formation (F)	
Index	Formation Name
1	Formation A
2	Formation B
3	Formation C
4	Formation D
5	Formation E
6	Formation F

Well Type(T)	
Index	Well Type
1	Vertical
2	Horizontal

Price and OPEX		
Index	Oil Price ($)	Opex Cost ($/bbl)
1	Norm (67, 23%)	9
2	Norm (59, 23%)	9
3	Norm (64, 23%)	10
4	Norm (65, 23%)	10
5	Norm (66, 23%)	10

Plan per Year			
Year No.	Budget ($)	Min. Oil rate (BOPD)	Rigs NO.
1	300,000,000	40,000	N/A
2	320,000,000	36,000	N/A
3	340,000,000	32,000	N/A
4	360,000,000	28,000	N/A
5	380,000,000	24,000	N/A

Reservoir and Base production Parameter								
F	Oil In Place (Bbls)	Recovery Factor ()	Cumulative Oil Produced (Bbls)	Current Production Oil (BOPD)	Current Production Water (BWPD)	Current Production Gas (Mscf/d)	Oil Decline Rate (D) ()	Water Decline Rate (D) ()	Gas Decline Rate (D) ()
1	580,000,000	0.10	5,000,000	600	3,000	2,000	0.16	-0.03	-0.01
2	1,145,000,000	0.15	24,000,000	3,500	18,000	12,000	0.25	-0.01	-0.02
3	563,000,000	0.20	75,000,000	6,000	28,000	26,000	0.20	-0.03	-0.03
4	2,240,000,000	0.40	730,000,000	25,000	312,000	480,000	0.18	-0.02	-0.02
5	273,000,000	0.15	10,000,000	2,000	7,000	4,000	0.12	-0.01	-0.01
6	268,000,000	0.25	51,000,000	400	12,000	8,000	0.30	-0.04	-0.04

Other inputs	
Paramter	Value
Rig Daily Rate ($)	110,000
Unproductive rig time at month i ()	0.03
Site Preparation & Hook-up Cost ($) per	160,000
Discount rate ()	0.10
Liquid Capacity (Bbls)	600,000
Gas Capacity (MSCF)	900,000

Development Wells												
Ref	F	T	IP (BOPD)	IP (BWPD)	IP (MSCFD)	Annual Oil Decline Rate (D) ()	Annual Water Decline Rate (D) ()	Annual Gas Decline Rate (D) ()	Drilling Days	Completion Cost ($)	CAPEX,$	Max No. of Wells	Min No. of Wells
1	1	1	60	240	150	0.12	-0.03	-0.01	3.5	220,000	765,000	50	0
2	1	2	100	400	200	0.12	-0.03	-0.01	7.5	250,000	1,235,000	100	0
3	2	1	60	90	180	0.20	-0.01	-0.02	3.5	190,000	735,000	200	0
4	2	2	120	180	300	0.20	-0.01	-0.02	5.5	200,000	965,000	100	0
5	3	1	80	120	320	0.16	-0.03	-0.03	3.5	120,000	665,000	180	0
6	3	2	140	210	520	0.16	-0.03	-0.03	6	180,000	1,000,000	150	0
7	4	1	90	90	1400	0.12	-0.02	-0.02	4	150,000	750,000	300	0
8	5	1	70	50	140	0.10	-0.01	-0.01	9	150,000	1,300,000	80	1
9	5	2	110	80	220	0.10	-0.01	-0.01	12	220,000	1,700,000	20	0
10	6	1	120	480	900	0.20	-0.04	-0.03	13	200,000	1,790,000	20	0
11	6	2	230	920	1000	0.20	-0.04	-0.03	19	260,000	2,510,000	10	0

Although Company A permitted full data access for the model inputs, some of the critical data had to be adjusted due to the data's confidentiality.

In the following subsection, we will look over oil price input as a key uncertain element in our research.

7.1.1 Oil Price Forecast and Uncertainty Quantification

The oil price is primarily influenced by supply-demand, inflation, and geopolitical events, all of which are difficult to predict. Unfortunately, even few months ahead, oil price forecast cannot be accurately predicted. The decision makers must make their investment decisions without having a perfect information about market price. However, to reduce any gaps in stakeholders' expectations, planners should reflect the uncertainty of oil price forecast in BP assessments.

As an illustration of the current gap in BP practices in Company A, when it comes to reflecting the most sensitive variable, oil price, in the AWPB and 5 Yrs Plan. Figure 7.1 depicts actual historical daily oil prices during the last five

years, as well as monthly and annual average actual prices. However, when the 2017 BP was generated 5 years ago, a single value for oil price for each year was used based on an input from an authorized governmental entity, which definitely gave the stakeholders unrealistic picture to what they should expect as income for their investment.

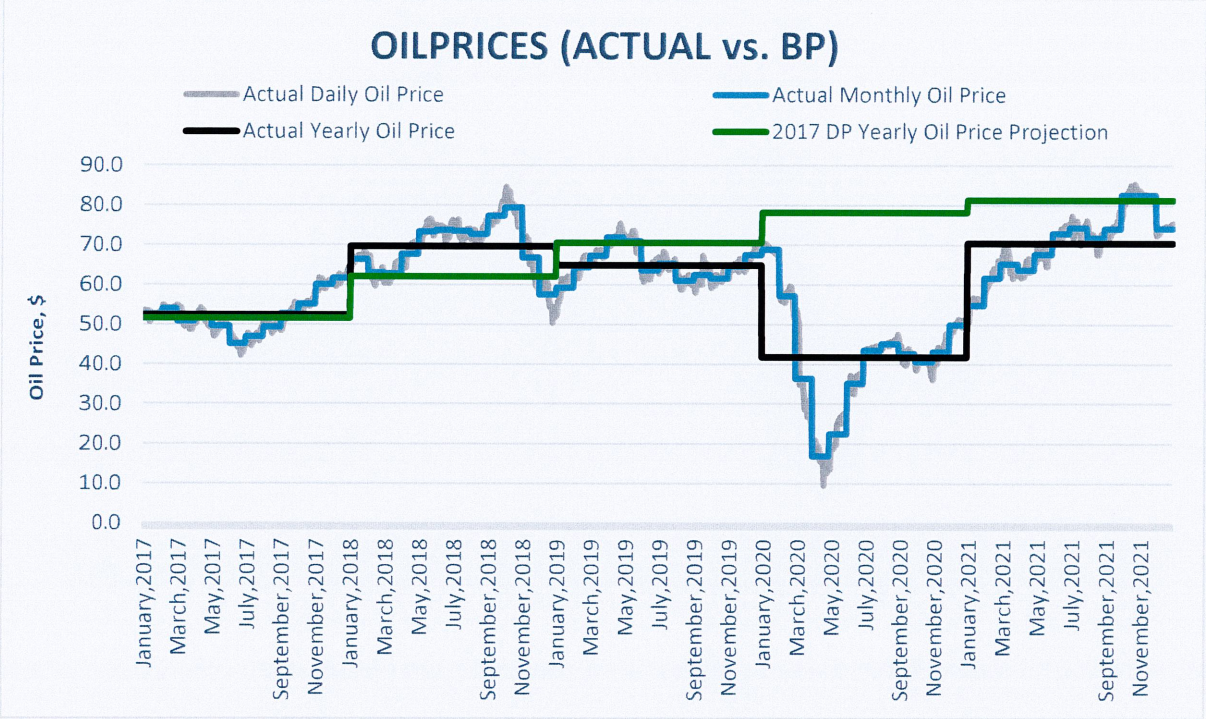


Figure 7.1 Actual historical oil prices for Company A in the last five years

We have no control over oil price fluctuations, and we know that exact forecasting is impossible; but we can examine multiple future oil price possibilities to better depict volatility in our model and its impact on expected outcomes.

Several correlations have been developed in the literature based on historical oil prices in attempt to forecast future prices on a credible basis. However, in this study, we are more interested in representing the uncertainty associated with a certain oil price forecast scenario rather than developing our correlation to predict future prices.

Since the tariff of oil prices is typically determined based on the API gravity of the produced crude oil; we will apply "West Texas Intermediate (WTI) Spot" forecast prices for our case study because API is fairly close to WTI. The five-year projection for oil prices will be taken from the (EIA website, 2022), which is widely used as a reference. Figure 7.2 shows WTI crude oil prices projection for next 5 years by EIA. Although these prices appear conservative comparing to today's prices; however, assessing forecast basis is out of this study scope and prices will be used as per the reference.

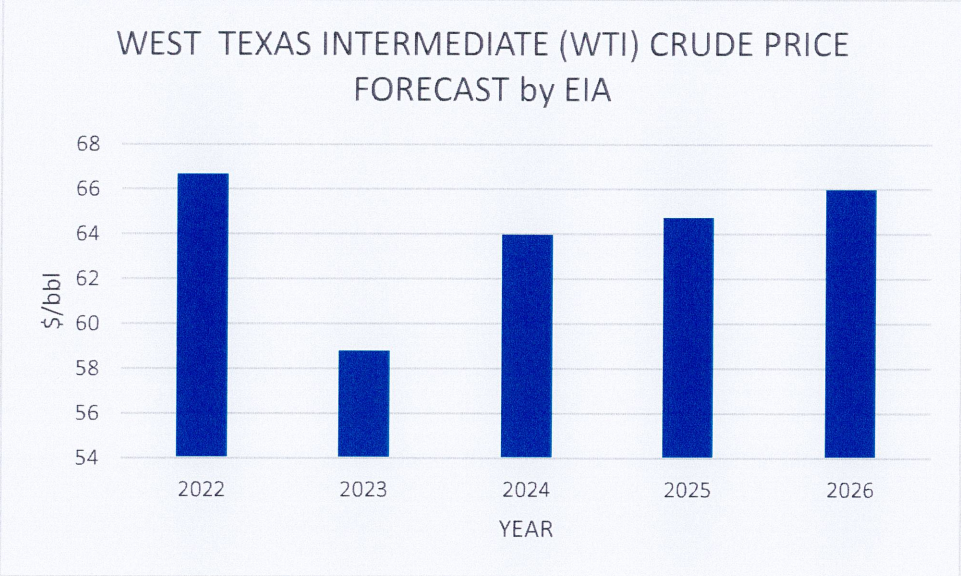


Figure 7.2 Five Years WTI crude oil prices forecast by EIA

To estimate the range of volatility in oil prices in this study, Company A's historical daily oil prices data are analysed and considered indicative for next 5 years production planning activities. The main justification is that oil prices volatility is stochastic and cyclic in nature and usually follow a repetitive pattern. By analysing petroleum business activity level from 1960 to 2000, (Solomon et al., 2001) found cyclical investment patterns in E&P due to the cyclical nature of oil prices. (Caldwell, 1995) observed that oil prices behave like they have been normally distributed 94 % of the time.

We used actual historical prices for Company A in order to detect a pattern in these historical data and to determine the uncertainty range that may be applied to future pricing. Crude oil prices have been available for research since January 2017 only. These daily oil prices, which were earlier displayed in Figure 7.1, indicate the oil price volatility, and show the actual prices fluctuation. Over 1,800 daily prices were grouped into a number of bins with computed frequency and presented in a histogram. Although the data appears left-skewed distribution to the right as seen in Figure 7.3; however, by eliminating around 6% of the data, which represented oil prices less than $38/bbl for few days during COVID-19 pandemic lockdowns, the data seemed to be normally distributed.

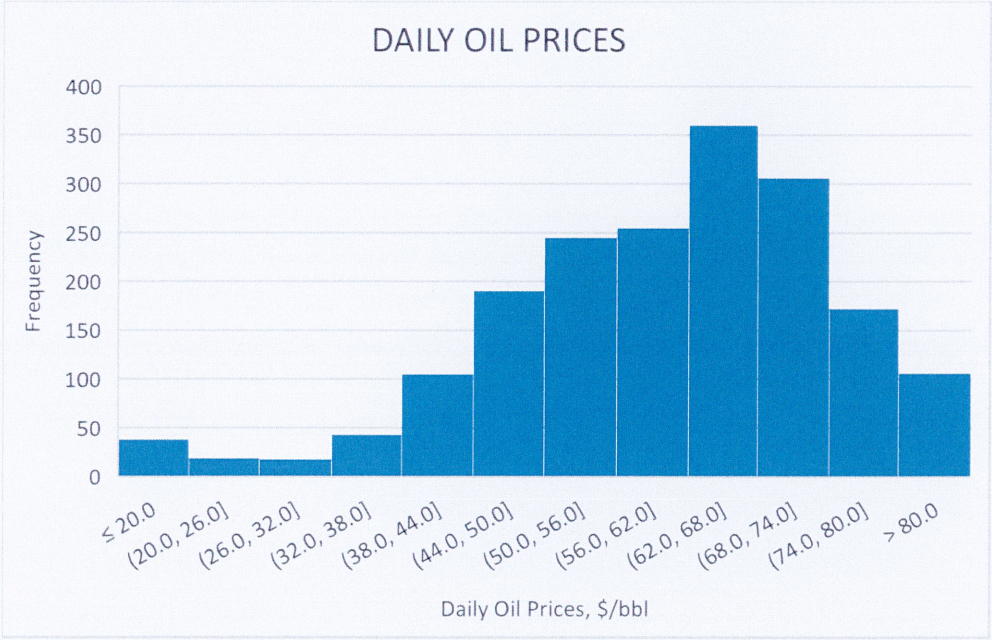


Figure 7.3 Company A's five years historical oil prices distribution

From the 5 years historical oil prices data, the mean price is $60 per barrel. The price uncertainty is determined by standard deviation, which quantifies how far values are spread from the mean. The dataset has standard deviation of $13.8 per barrel, which represents +/- 23% deviation from the mean.

As a result, the oil price input in our model is assumed to follow a normal distribution, with various mean values each year according to EIA predictions, and a standard deviation of +/- 23%.

Although we introduce two discrete input options for the oil price in the model; however, in the real application we are going to generate multi-scenarios randomly according to a specific density distribution function. It was taken into consideration that traditional techniques of quantifying uncertainties, such as using discrete values including low, medium, and high scenarios to establish uncertainty ranges, may fail to detect the peaks of variables by narrowing down the historical data. In addition, identical probability value for each scenario is assumed, as no reference to weight the probability of each scenario.

7.2 Model Results and Analysis

In this section, the results of deterministic and stochastic modelling will be compared using the AWPB and 5 Yrs plan scopes. In addition, we will compare AWPB optimized plan with Company A's original program (current practice).

It is worth to highlight that due to the huge number of variables and equations and in order to reduce running time, all runs were automatically cut by solver tolerance of 0.8%. Economic cut off constraints were also disabled because no well should hit its economic cut off within 5 years given constant initial production rates and declines.

7.2.1 AWPB Proposal

The GAMS model is run with the input parameters specified in Table 7.1 for a one-year scope. Section 7.2.1.1 discusses the model AWPB outputs in terms of both deterministic and stochastic solutions. In addition, AWPB optimized plan based on stochastic model is compared with Company A's AWPB original plan in Section 7.2.1.2.

7.2.1.1 AWPB Stochastic Versus Deterministic Outcomes

Among 1210 wells, represent Company A's wells inventory, we need to pick a set of wells for drilling, taking into account some financial and operational constraints. In addition, the number of optimal rigs that should be used must be

determined. The model is run with oil price that sampled randomly from a normal probability distribution considering 1000 scenarios based a mean of $67/bbl and a standard deviation of +/- 23%. The model solution is reported and analysed in terms of expected NPV, NCF, oil production, oil prices input, and optimal decision variables.

- **Decision Variables:**

The optimal number of rigs, according to the deterministic model, is 2.64, while the stochastic model yields an average of 2.55 rigs, a difference of 33 drilling days between the two outputs. On the other hand, the optimum number of wells to be drilled based on deterministic solution is 134 wells, while the average of 1000 scenarios are 129 wells. As a result, the development wells mix varies between deterministic and stochastic solutions. Figure 7.4 depicts the optimal development wells mix based on the deterministic model solution, whereas Figure 7.5 depicts the stochastic model solution. The two-stage stochastic approach allows decision makers to adjust the original plan of the number of drilling rigs to be operated and the mix of development wells to be drilled in response to actual price volatility without deviating from the expected value of NPV.

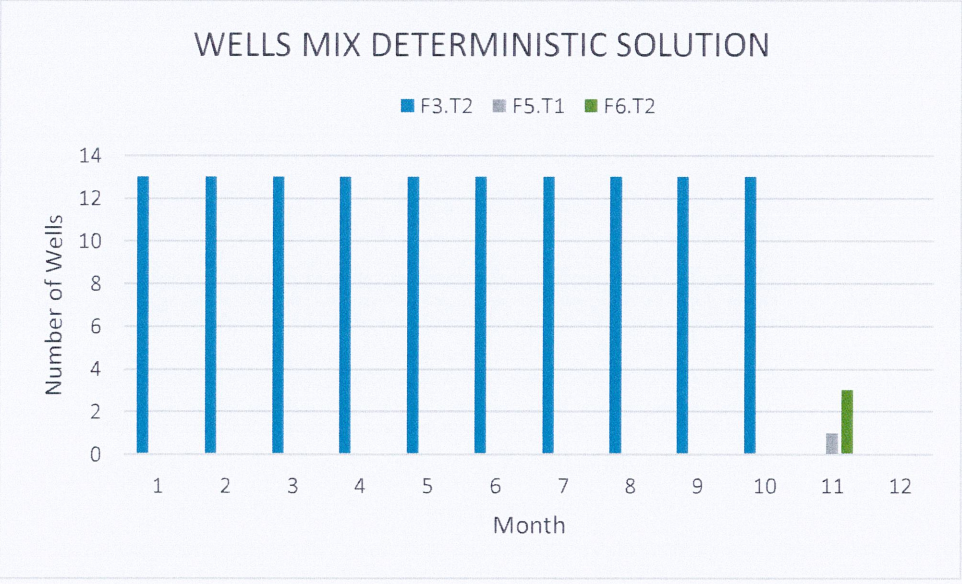


Figure 7.4 Optimal development wells mix based on deterministic model solution

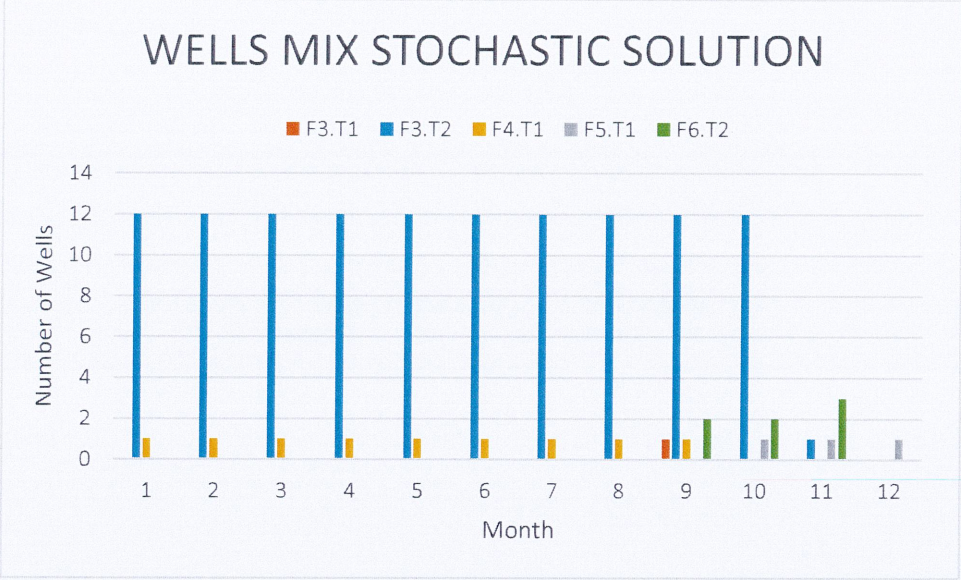


Figure 7.5 Optimal development wells mix based on stochastic model solution

It is worth noting that the stochastic average solution was simplified by converting it to an integer value in Figure 7.5. Also, because the data were from 1000 scenarios, summing the average wells per formation per type does not represent the total optimal number of wells to be drilled.

- **Oil Production:**

The GAMS stochastic model generates 1000 oil production profiles based on different scenarios for development wells mix and number of rigs. It was difficult to plot more than 250 profiles due to Excel plot limitations. As a result, to simplify the results, we chose to exhibit the minimum and maximum production profiles, which are represented in P99 and P01 in Figure 7.6, respectively. P10, P50, and P90 production profiles were also highlighted. It is clear that oil production is influenced indirectly by oil price uncertainty, in which production gap increases overtime, as shown in Figure 7.6. When compared to stochastic outputs, the deterministic production profile is a bit optimistic comparing to P50 profile as presented in Figure 7.6.

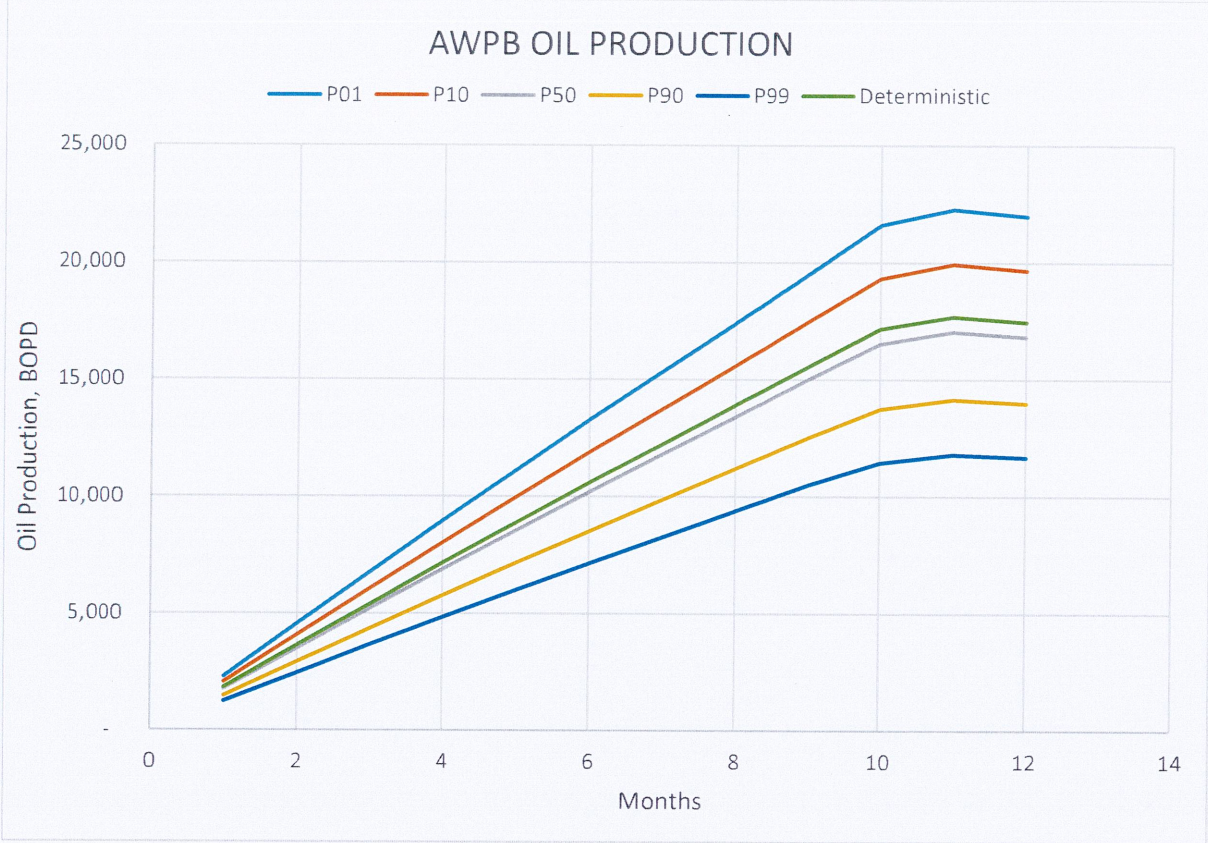


Figure 7.6 AWPB model's oil production profiles

The stochastic model predicts a year average production range of 7,359 to 13,743 BOPD for development wells. The P50 year average oil production is 10,551 BOPD, whereas deterministic year average production is 10,947 BOPD.

Considering the P50 scenario, company A should be able to exceed its year average production target of 40,000 BOPD by 5,017 BOPD by combining both base and development wells' production.

- **NCF:**

Figure 7.7 depicts the monthly average NCF over a year. It has been positive for all months, due to the base wells' contribution, which account for 76.6% of production while requiring no capital expenditures. The stochastic NCF year average is $68.5MM, comparing to $67.7MM for deterministic NCF.

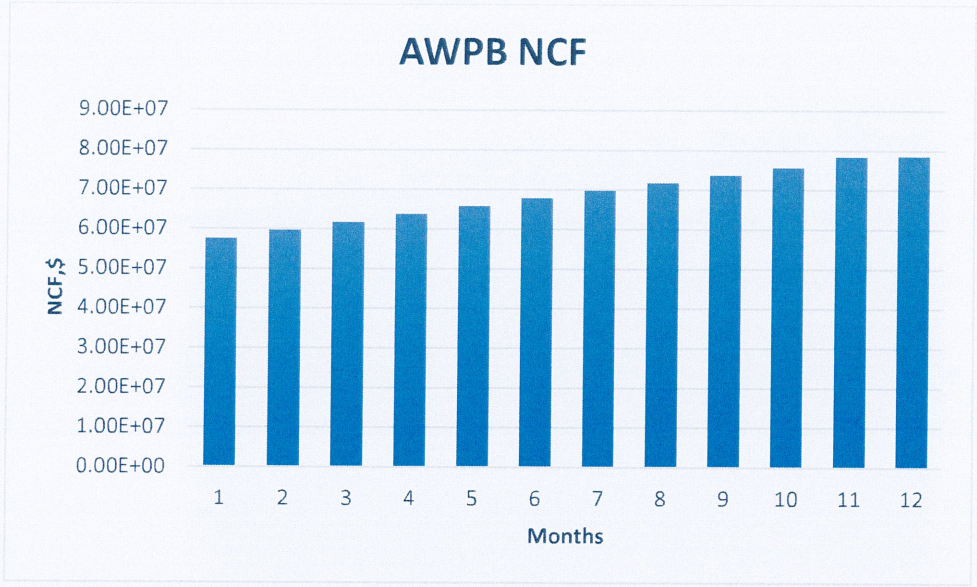


Figure 7.7 AWPB monthly average NCF

- **NPV:**

The AWPB NPV stochastic outcomes are shown in Figure 7.8. P10, P50, and P90 are valued at $1,094MM, $783MM, and $471MM, respectively. In contrast, the deterministic model gives NPV of $773MM.

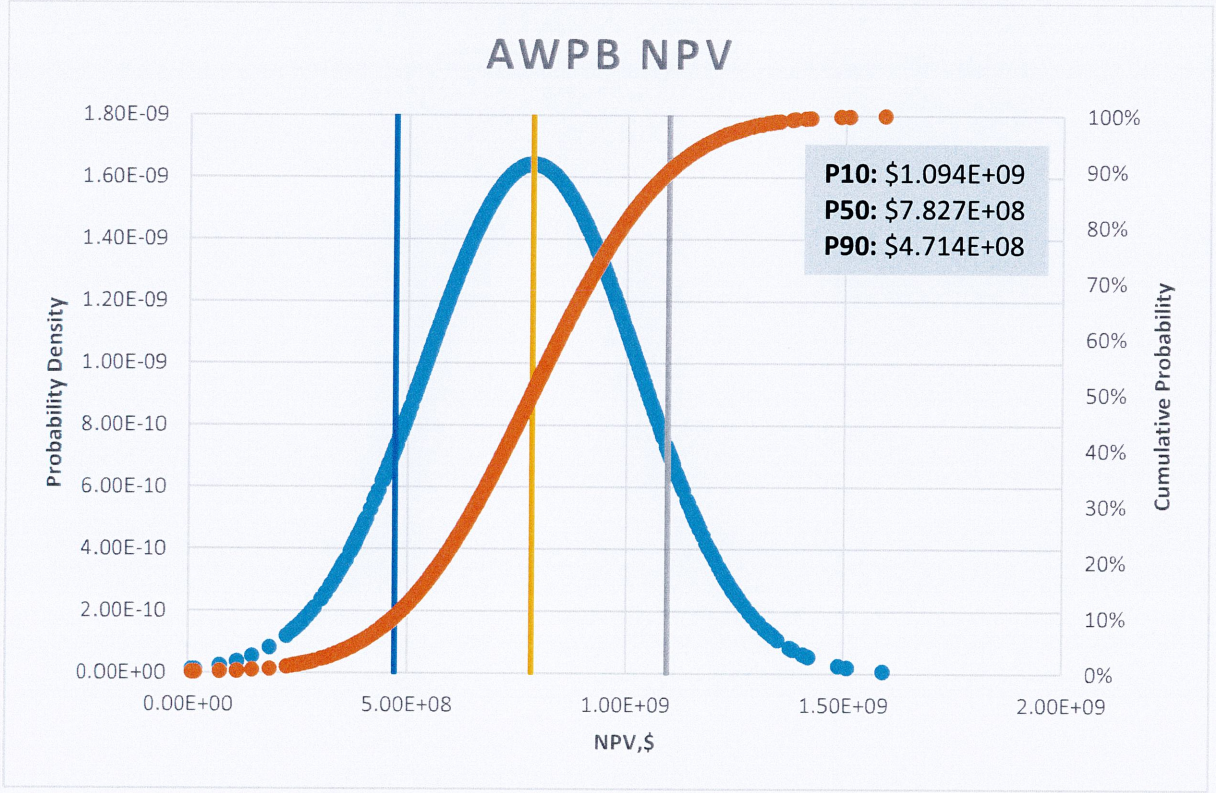


Figure 7.8 AWPB NPV

The price a decision maker would be likely to give for perfect information on all variables that impact investment decision is known as the Expected Value of Perfect Information (EVPI). In other words, it is the monetary value of eliminating all uncertainty. EVPI is defined as the difference between stage one "here and now" and stage two "wait and see" solution. Based on the above model results, the EVPI is estimated to be $9.8MM, or 1.3% of the total NPV.

7.2.1.2 AWPB Original Plan versus Optimized Plan Comparison

As thoroughly discussed in Chapter 3, Company A's current practices for proposing AWPB have several shortcomings, including the lack of systematic optimization approach to select the best development wells mix and to determine the optimal number of rigs to be used for drilling. As a result, un-optimized plan is usually proposed, which we will call it the original plan next.

In this section, we will use the same GAMS model inputs as in Figure 7.1, but we will fix the number of rigs and the wells mix according to Company A's original plan. For the sake of consistency, we will use the same oil price inputs, which are assumed to follow a normal distribution, instead of using single values as Company A usually does.

- **Original Plan Input:**

The original plan, according to the Company A's AWPB, assumed the use of 2.1 drilling rigs, with the development wells mix scheduling given in Figure 7.9.

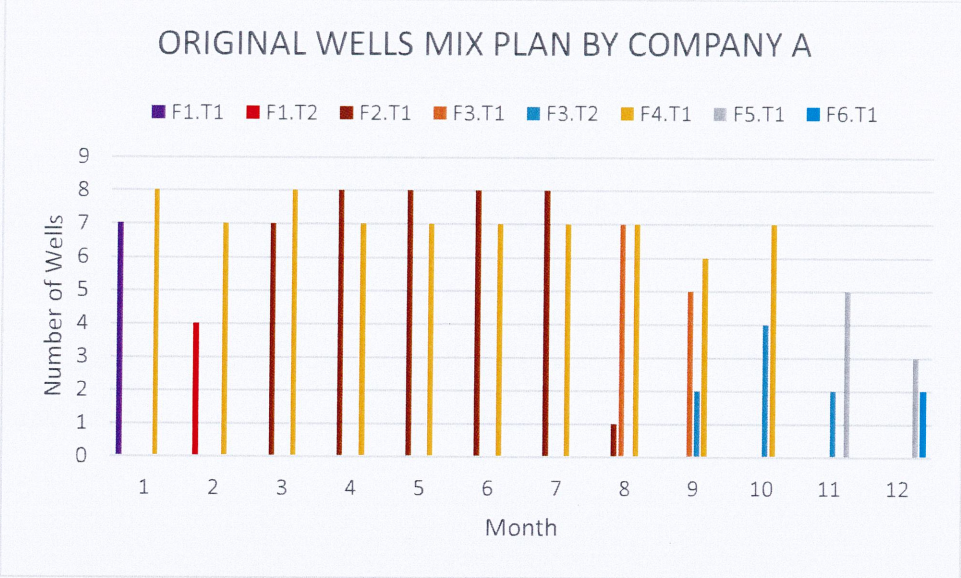


Figure 7.9 Company A's original plan wells mix inputs

- **Oil Production:**

Because the oil production profile for the original plan is based on a constant mix of development wells and rigs number, it is unaffected by oil price volatility. As a result, all 1000 oil price scenarios generated the same oil production profile.

Figure 7.10 shows both optimized and original plans' oil production profiles for development wells. By picking P50 case, the optimized plan displays a higher oil production profile than the original plan's production profile. The production gap between both plans increases over time, reaching 5,149 BOPD by end of the year.

The optimized plan's year average production for development wells using the P50 profile is 10,550 BOPD, compared to 6,881 BOPD for the original plan.

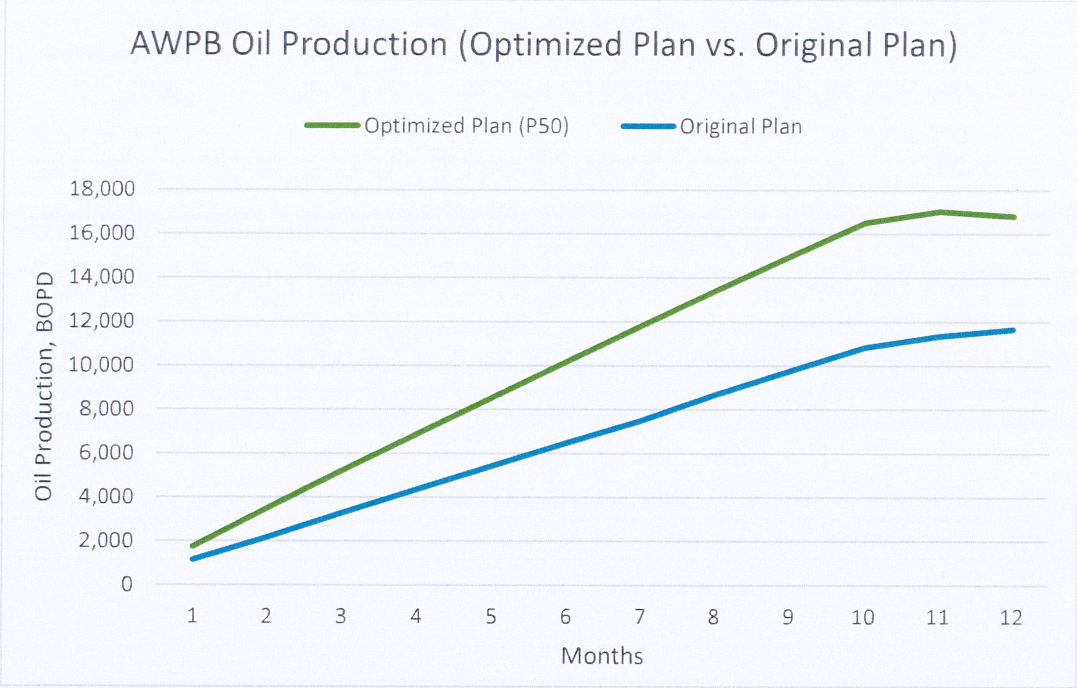


Figure 7.10 AWPB oil production profiles (optimized plan vs original plan)

- **NCF:**

Figure 7.11 illustrates that both the optimized and original plans have positive NCF. However, the optimized plan generates greater NCF, and the difference grows over time. The optimized plan's NCF year average is $68.5MM, compared to $62.7MM for the original plan.

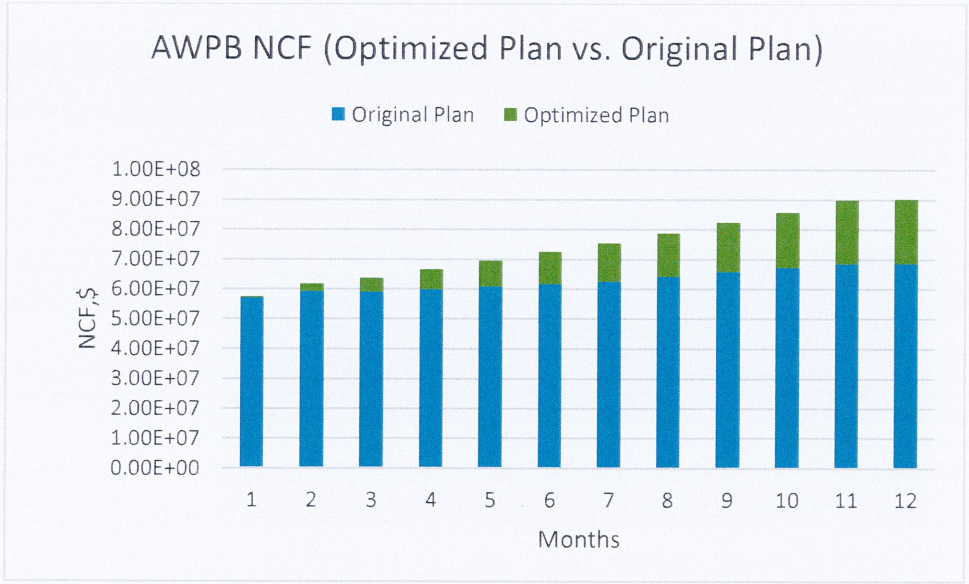


Figure 7.11 AWPB monthly average NCF (optimized plan vs original plan)

- **NPV:**

The optimized and original P50 NPVs are $783 million and $716 million, respectively. In comparison to Company A's original plan, the optimized plan increased the ENPV by 9.3%. The NPV distribution function of both optimized and original plans is shown in Figure7.12, with the optimized plan indicating a larger NPV.

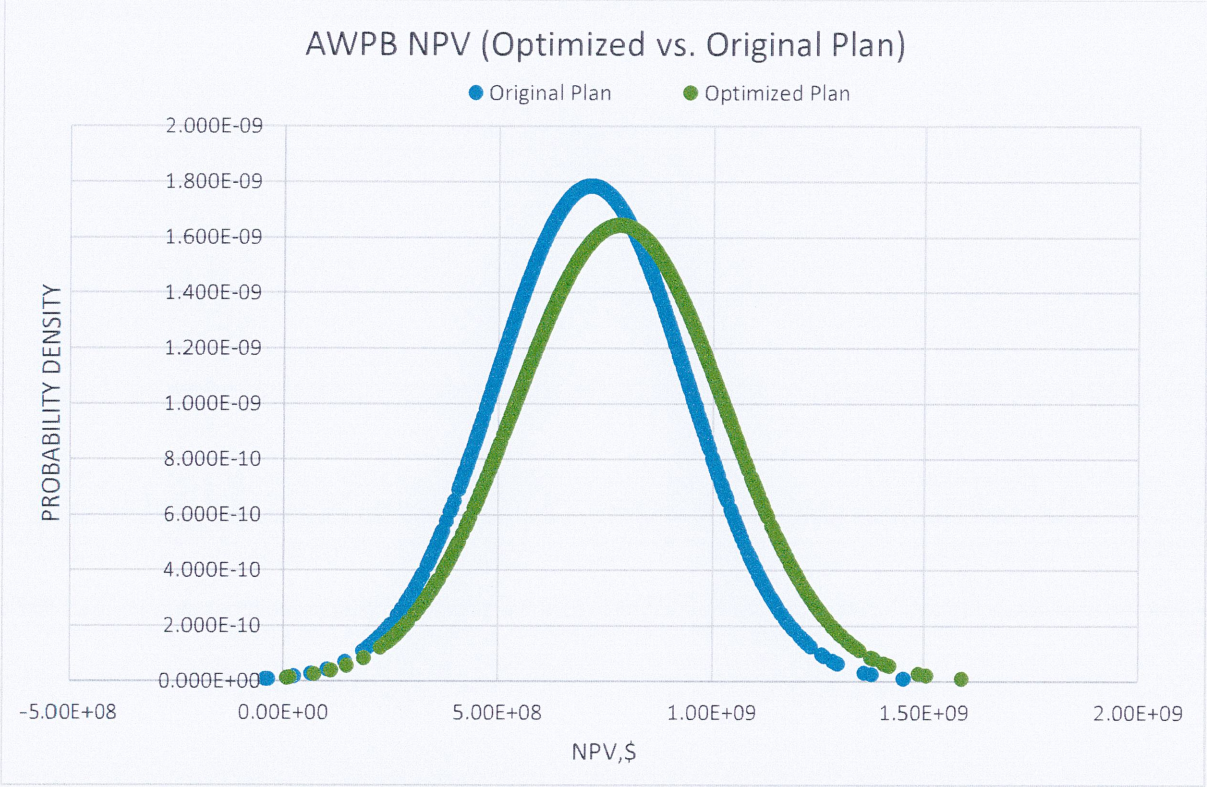


Figure 7.12 AWPB NPV (optimized plan vs original plan)

7.2.2 5 Years Plan Proposal

The same model that is used to generate AWPB proposal is used with a longer span of 5 years proposal. The GAMS model is run over a five-year period with the input parameters listed in Table 7.1. This section discusses the 5 years stochastic proposal compared to deterministic findings.

- **Decision Variables:**

The optimum solution of the GAMS deterministic model suggested a total of 593 wells to be drilled over five years using an average of 1.85 rigs. The

stochastic model optimal solution, on the other hand, predicted a total of 575 wells to be drilled over five years employing 1.91 rigs. As a result, the development wells mix indicated differences between deterministic and stochastic solutions. Figure 7.13 compares the optimal number of rigs based on the deterministic model versus the stochastic model solution for individual year.

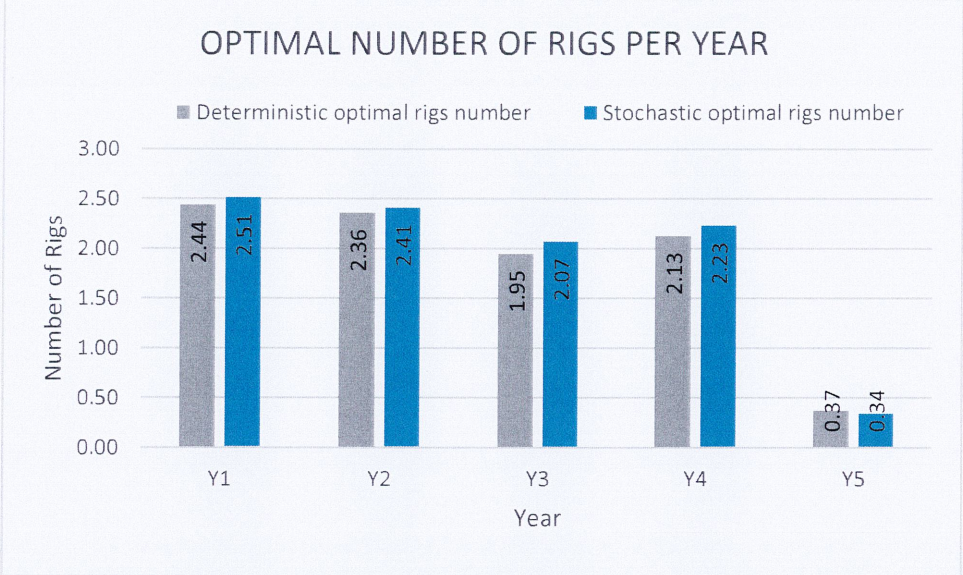


Figure 7.13 5 Yrs optimal number of rigs based on deterministic and stochastic models' solution

- **Oil Production:**

Figure 7.14 compares deterministic and stochastic oil production profiles for development wells over a five-year period. The stochastic model predicts a 5 years average oil production range of 28,827 to 33,109 BOPD for development wells. The 5 years average based on P50 is 30,968 BOPD, whereas deterministic average is 31,463 BOPD.

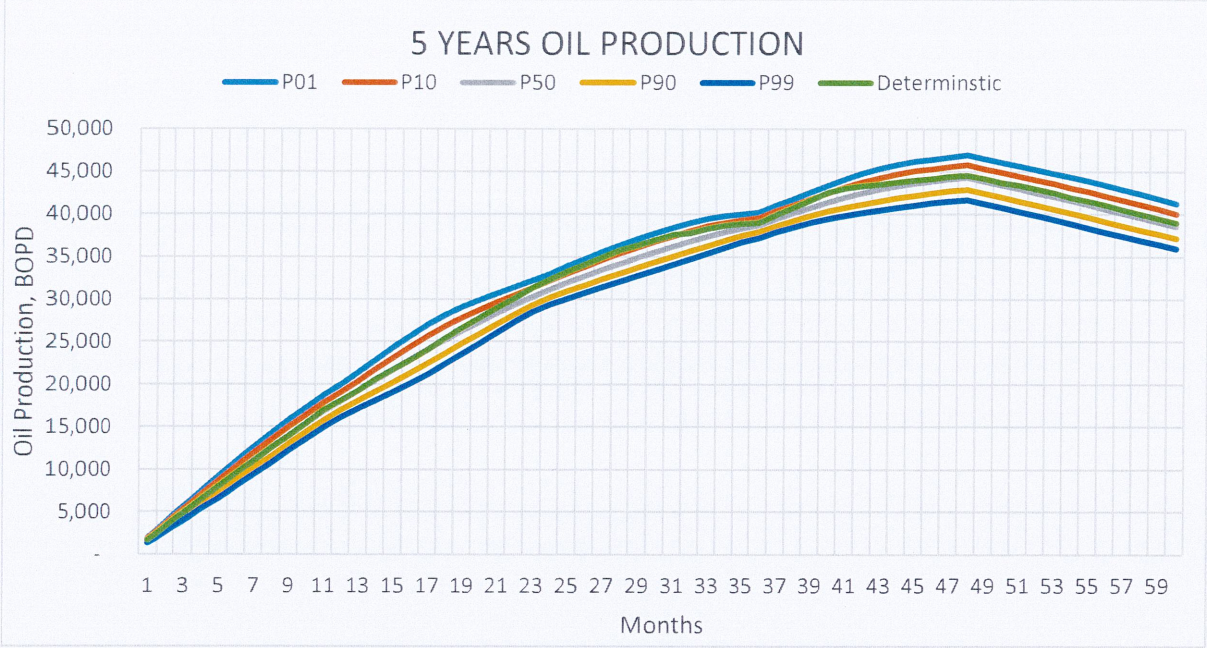


Figure 7.14 5 Yrs oil production profiles

- **NCF:**

Figure 7.15 shows 5 years NCF profile. 5 years stochastic NCF year average is $82.9MM, whereas for deterministic NCF it is $83.6MM.

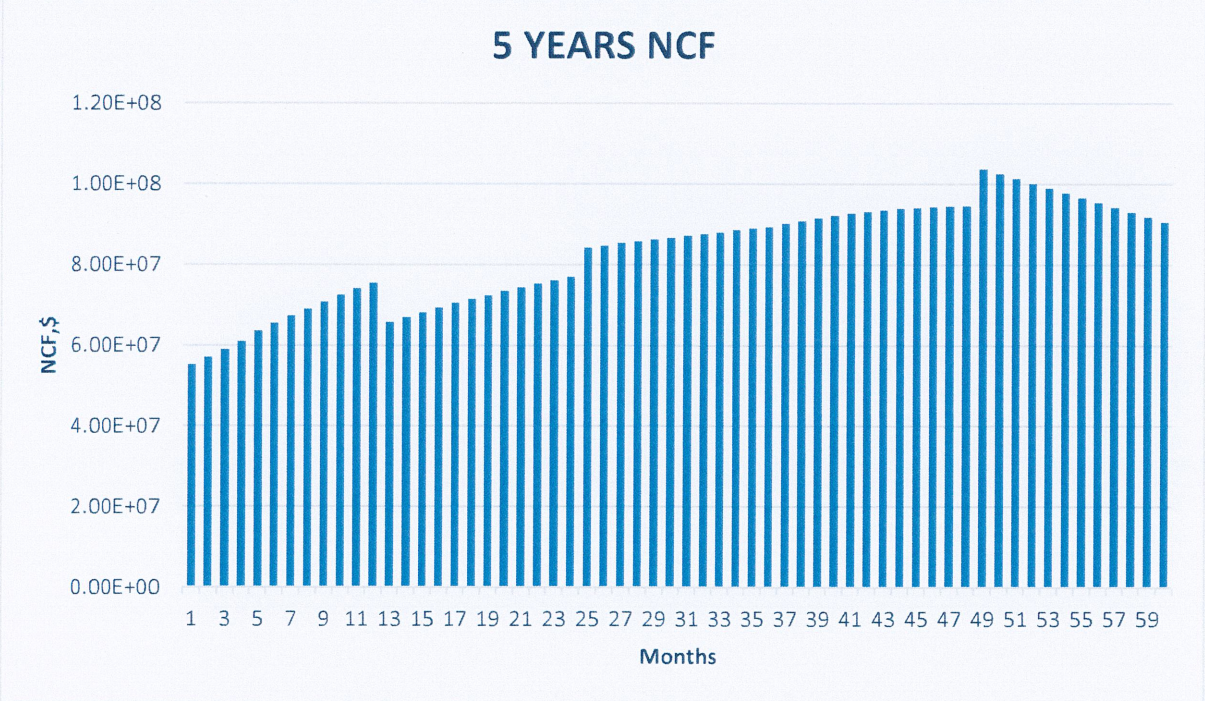


Figure 7.15 5 Yrs monthly average NCF

- **NPV:**

Based on model results, NPV is expected to be \$4,525MM, \$3,875MM, and \$3,226MM for P10, P50, and P90, respectively. The deterministic NPV result, on the other hand, is \$3,909MM. As a result, the estimated EVPI or the added value of considering the uncertainty in oil price while planning the 5 Yrs is \$33.6MM, or 0.9% of the overall NPV. The NPV distribution function for 5 years is shown in Figure 7.16.

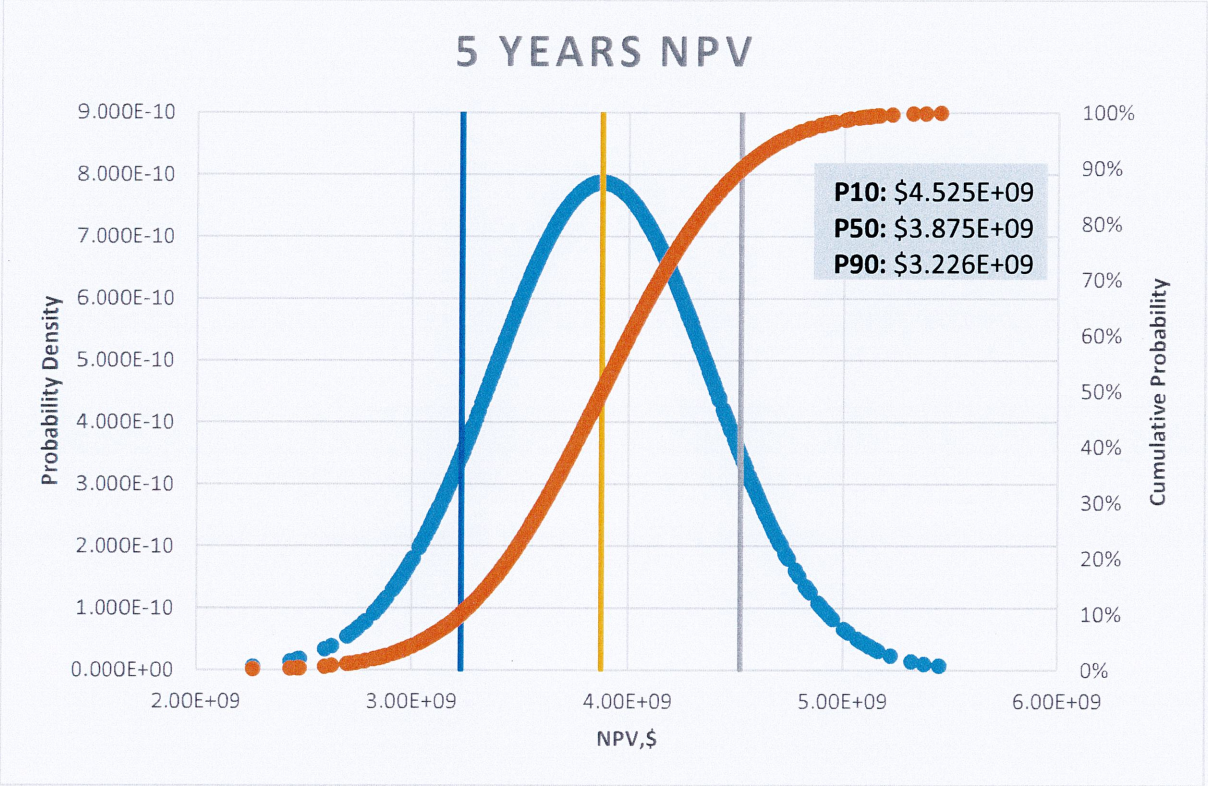


Figure 7.16 5 Yrs NPV

7.2.2.1 Potential of New Facility Investment

The model's advantage is that it could be used not only to identify optimal decision variables that maximize NPV, but also to optimize the Company's resources. In this section, we will look at an example of utilization of this model.

When the model was run for a 5 years period, the results indicated a bottleneck in gas capacity. Therefore, we run the model to estimate the potential prize of installing an extra 200MM SCFD of gas capacity. Based on model solution, an

additional of about $130MM can be earned over 5 years based on NPV P50 case compared to optimum plan. The NPV distribution function of both optimized and potential of new Facility investment is shown in Figure7.17.

It is important to highlight that we have not accounted the additional required capital to build the proposed new facility. Therefore, Company A is compelled to investigate the economics of such a proposal.

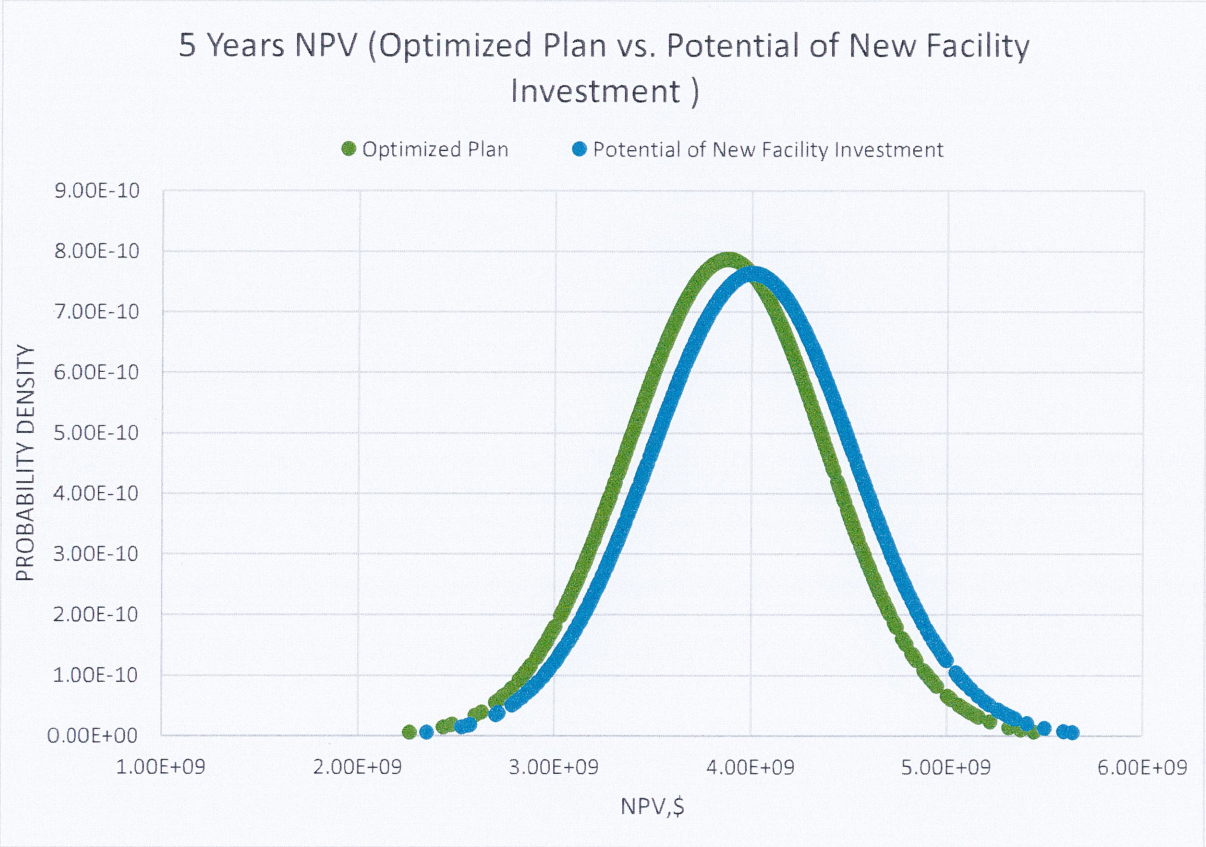


Figure 7.17 5 Yrs NPV (optimized plan vs potential of new Facility investment)

7.3 Conclusion

As seen in Section 6.2, the model is expandable either by increasing the time scope or by adding more uncertainties and constraints. This model can also be expanded to include additional programs within a company's portfolio.

Uncertainty is not always a negative factor; it can sometimes be a positive thing. By including two more uncertain parameters, initial oil production for

development wells and OPEX, the 5 years model generates a $318MM larger NPV than if only oil prices were uncertain.

The stochastic model yielded very promising results. When compared to the original Company A's AWPB, the optimized plan provides an additional ENPV of $67MM, or 9.3 %. Furthermore, the calculated EVPI demonstrates a substantial value for stochastic modelling over deterministic modelling of $9.8MM (1.3%) and $33.6MM (0.9%) for AWPB and 5 years plan, respectively. In addition, the model revealed the potential of new facility investment.

CHAPTER 8

Conclusion, Limitations, and Future Research

8.1 Conclusion
8.2 Limitations of the Study
8.3 Recommendations for the Future Research

CHAPTER 8 Conclusion, Limitations, and Future Research

The execution of massive capital projects coupled with many uncertainties and risks in the upstream oil and gas industry necessitates enhancing the practice of investments evaluation techniques. Organizations that effectively appraise their business program have a considerably greater chance of achieving stakeholders' expectations and thereby maximizing these firms' asset value.

This thesis looked at the problem of how to properly assess investment in the upstream petroleum business when there is uncertainty. The purpose of this research was to guide decision makers to choose an optimal portfolio of projects as part of AWPB and 5 years business plan considering a volatile oil price environment with numerous other key uncertainties. Therefore, we picked the development drilling program from Company A's portfolio to optimize the number of drilling rigs to be invested as well as scheduling development wells mix to be drilled while keeping several constraints in mind. A two-stage stochastic with recourse model was formulated and built in GAMS, in which the deterministic and stochastic results were compared beside each other, as well as with Company A's initial plan. The main conclusions, limitations, and future research considerations are discussed below.

8.1 Conclusion

To sum up the findings of this study, they are as follows:

- There is a significant gap between the industrial practices represented by the case under investigation and the best practice techniques are available in the literature for portfolio projects optimization.

- When comparing distribution output provided by a stochastic model for an individual program, the single point deterministic model outcomes bias is obvious because projects uncertainties are neglected. When a portfolio is assessed, this effect is amplified.
- When dealing with problems including uncertainties, two-stage stochastic programming with recourse is an appropriate optimization method, as recourse actions are already taken into account during the investment evaluation.
- The methodology provided in this thesis allows identifying the most sensitive elements that influence project economics, allowing efforts to be focused on areas where optimization can be made.
- The model design is proven that it is flexible and expandable based on future needs.
- The optimized plan increased the ENPV by $67 million, or 9.3 %, over Company A's AWPB original plan.
- The calculated EVPI indicates significant value for stochastic modelling over the deterministic modelling of $9.8 million and $33.6 million for AWPB and 5 years plan, respectively.
- A potential for new facility investment was observed using the model.

8.2 Limitations of the Study

The scope of this project is constrained by the efforts and time allocated for this research. The following are some limitations to recognize:

- While Company A's portfolio includes multiple programs that require integrated assessment, the research focus was limited to optimizing development drilling program only.

- For the sake of simplicity, we focused the analysis on oil price as a key uncertainty, rather than covering in more depth with other operational, technological, and subsurface geological uncertainties variables.
- With such a large scope and a large number of variables and scenarios, validating model outputs was difficult. Unfortunately, due to time constraints, we were unable to use another tool to validate optimal decision variables.

8.3 Recommendations for the Future Research

The following recommendations are to be left for future research in order to overcome the above limitations and achieve a more comprehensive scope.

- In addition to NPV, multiple selection criteria should be considered.
- To use a different optimization tool to validate the model's outputs.
- To expand the model by introducing and analysing more uncertainties, adding more constraints, and optimizing multiple programs.

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APPENDIX A - Model Elements in GAMS

Table 8.1 General data

Table 8.2 Annual based data

Table 8.3 Formations and wells type data

Table 8.4 Formations data

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Table A.1 General data input

Symbol	Definition	Unit
i	Time	month
Y	Time	year
T	Well Type	type
F	Formation	formation
r	Discounted rate (annual)	fraction
DRR	Drilling rig rate	USD/day
CCFS	Capital Facilities hook-up and site preparation costs	USD
TQGACi	Total WMFs available gas capacity at month i	MSCFD
TQLACi	Total WMFs available liquid capacity at month i	BLPD
UPTi	Unproductive rig time at month i	fraction
ALPHA	To include/ exclude base equations [ALPHA = 1 (base is included)], [ALPHA = 0 (base is excluded)]	Integer
XTFi	Total no. of scheduled wells of type (T) from formation (F) to be drilled at month (i)	Wells

Table A.2 Annual based data input

Symbol	Definition	Unit
PO	Oil Price at Year (Y)	USD
CPBO	Operating cost per oil barrel at Year (Y)	USD/BBL
QOEw	Oil rate economic cut off per development well at Year (Y)	BOPD
WCEw	Water Cut rate economic cut off per development well at Year (Y)	fraction
GOREw	Gas Oil Ratio economic cut off per development well at Year (Y)	MSCF/BBL
AB	Annual budget limit at Year (Y)	USD
MAQOY	Minimum average oil production of Year (Y)	BOPD
RNY	Number of drilling rigs at Year (Y)	Rigs

Table A.3 Formations and wells type data input

Symbol	Definition	Unit
QOTF0	Initial average oil rate of development wells of type (T) from Formation (F) at month zero	BOPD
QWTF0	Initial average water rate of development wells of type (T) from Formation (F) at month zero	BWPD
QGTF0	Initial average gas rate of development wells of type (T) from Formation (F) at month zero	MSCFD
DOTF	Annual exponential oil decline rate for development well of type (T) from Formation (F)	fraction
DWTF	Annual exponential water decline rate for development well of type (T) from Formation (F)	fraction
DGTF	Annual exponential gas decline rate for development well of type (T) from Formation (F)	fraction
NDDTF	Drilling days of development well of type (T) for target Formation (F)	Days/well
CCCTF	Capital completion cost of development well of type (T) for target Formation (F)	USD
ITF	Maximum inventory of number of wells of Type (T) from Formation (F)	wells
MTF	Minimum number of wells of Type (T) from Formation (F)	wells

Table A.4 Formations data input

Symbol	Definition	Unit
OOIPF	Original oil in place of Formation (F)	MMBO
RFF	Expected Recovery factor of Formation (F)	fraction
NPF	Cumulative oil produced from the reserves of Formation (F) at time zero	MMBO
QBOF0	Initial average oil rate of base wells from Formation (F) at month zero	BOPD
QBWF0	Initial average water rate of base wells from Formation (F) at month zero	BWPD
QBGF0	Initial average gas rate of base wells from Formation (F) at month zero	MSCFD
DBOF	Annual exponential oil decline rate for base wells from Formation (F)	fraction
DBWF	Annual exponential water decline rate for base wells from Formation (F)	fraction
DBGF	Annual exponential gas decline rate for base wells from Formation (F)	fraction

Table A.5 Model's calculated parameters

Symbol	Definition	Unit
rm	Discounted rate (monthly)	fraction
QOTFi	Average daily oil rate of development wells of type (T) from Formation(F) at month (i)	BOPD
QOTitime	Average daily oil rate of development wells of type (T) from Formation(F) at scheduled month (i)	BOPD
QBOFi	Average daily oil rate of base wells from Formation(F) at month (i)	BOPD
TQBOi	Total daily oil rate of base wells at month (i)	BOPD
CCDTF	Capital drilling cost of development well of type(T) for target formation(F)	USD
RDAi	Rig days available at month(i)	Days
CBOF	Cumulative oil expected from base wells per formation (F)	BO
RORF	Remaining oil reserves from a formation (F)	BO
QWTFi	Average daily water rate of development wells of Type (T) from Formation(F) at month (i)	BWPD
QBWFi	Average daily water rate of base wells from Formation(F) at month (i)	BWPD
TQBWi	Total daily water rate of base wells at month (i)	BWPD
QGTFi	Average daily gas rate of development wells of Type (T) from Formation(F) at month (i)	MSCFD
QBGFi	Average daily gas rate of base wells from Formation(F) at month (i)	MSCFD
TQBGi	Total daily gas rate of base wells from all Formation at month (i)	MSCFD
XTF	Total no. of wells of type(T) from formation(F) at month i	Wells
AQOY	Total year average oil production	BOPD
RDAimopt	Rig days available at Year (Y)	Days

Table A.6 First stage model's variables

Symbol	Definition	Unit	Variables Type
TQOFi	Total daily oil rate of all development wells at month (i) per Formation (F)	BOPD	Positive
TQOi	Total daily oil rate of all development wells at month (i)	BOPD	Positive
CCTFi	Total capital cost of development wells of Type (T) for Formation (F) to be drilled at month (i)	USD	Positive
COt	Total operating cost expenditure of producing wells at month(i)	USD	Positive
RDDi	Rig drilling days required at month(i)	Days	Positive
CSi	Rig standby cost at month(i)	USD	Positive
TCi	Total cost of development wells at month (i)	USD	Positive
TCY	Total annual cost of development wells at year (Y)	USD	Positive
CQOTF	Cumulative oil expected from development wells per Formation (F)	BO	Positive
TQWi	Total water production rate from development wells at month (i)	BWPD	Positive
TQLi	Total liquid production rate from development wells at month (i)	BLPD	Positive
TQGi	Total gas production rate from development wells at month (i)	MSCFD	Positive
NCF	Net Cash Flow at month (i)	USD	Free
NPV	Net Present Value at end of period	USD	Free
Yrig	No. of drilling rigs per Year (Y)	Rigs	Positive
Xopt	Total no. of development wells of type (T) from formation (F) at month (i)	Wells	Integer

Table A.7 Model's equations

Equation Number	Equation Definition
eqn_e02	Total daily oil rate of all development wells per formation at month i
eqn_e03	Total daily oil rate of all development wells at month i
eqn_e08	Total capital cost of development wells of type (T) for formation (F) to be drilled at month i
eqn_e09	Total operating expenditure of all wells producing at month i
eqn_e12	Rig standby cost at month i
eqn_e12b	Maximum drilling rigs constraint
eqn_e13	Total cost at month i
eqn_e14	Net cash flow at month i
eqn_e15	Net present value
eqn_e16	Budget constraint
eqn_e17	Oil production target constraint
eqn_e22	The remaining oil reserves constraint per from formation
eqn_e24a	Maximum number of wells constraint
eqn_e24b	Minimum number of wells constraint
eqn_e33	Facilities liquid handling capacity constraint
eqn_e39	Facilities gas handling capacity constraint

Table A.8 Second stage model's parameters input

Symbol	Definition	Unit
d	Number of draws or scenarios	N/A
Price_stc	Stochastic Oil Price	USD
CPBOi_stc	OPEX	USD/BBL
QOTF0_stc	Initial average oil rate of development wells of type (T) from Formation (F) at month zero	BOPD
DOTF_stc	Annual exponential oil decline rate for development well of type (T) from Formation (F)	fraction
QWTF0_stc	Initial average water rate of development wells of type (T) from Formation (F) at month zero	BWPD
DWTF_stc	Annual exponential water decline rate for development well of type (T) from Formation (F)	fraction
QGTF0_stc	Initial average gas rate of base wells from Formation (F) at month zero	MSCFD
DGTF_stc	Annual exponential gas decline rate for base wells from Formation (F)	fraction
NDDTF_stc	Drilling days of development well of type (T) for target Formation (F)	Days/well
CCCTF_stc	Capital completion cost of development well of type (T) for target Formation (F)	USD
CCFS_stc	Capital Facilities hook-up and site preparation costs	USD
probprice_stc	Probability of stochastic Oil Price using 3 scenarios (low, medium, high) for the oil price.	fraction

Table A.9 Second stage model's variables

Symbol	Definition	Unit
NPV_stc	Net Present Value (based on random variable generation option)	USD
NPV_prob	Average of Net Present Value considering a specific number of "d".	USD
NCF_stc	Net Cash Flow at month (i)	USD
XTFi_stc	Total number of wells	Wells
TQOi_stc	Total daily oil rate of all development wells at month (i)	BOPD
QOTFi_stc	Average daily oil rate of development wells of type (T) from Formation(F) at month (i)	BOPD
QWTFi_stc	Average daily water rate of development wells of Type (T) from Formation(F) at month (i)	BWPD
QGTFi_stc	Average daily gas rate of development wells of Type (T) from Formation(F) at month (i)	MSCFD
Yrig_stc	No. of drilling rigs per Year (Y)	Rigs
Xopt_stc	Total no. of development wells of type (T) from formation (F) at month (i)	Wells

ملخص الدراسة

تتأثر صحة الاقتصاد العالمي بشكل مباشر وغير مباشر بأداء قطاع صناعة البترول. لسوء الحظ ، هذا المورد الطبيعي الحيوي غير متجدد ويستنفد في نهاية المطاف بمرور الوقت. نتيجة لذلك ، يتم استثمار رؤوس أموال ضخمة باستمرار لتلبية الطلب العالمي المتزايد. للأسف ، يقترن رأس المال الاستثماري الكبير هذا بعدد من حالات عدم اليقين أو الشكوك الفنية والتشغيلية والتجارية والجيوسياسية. على الرغم من حالات عدم اليقين هذه، يتم تجاهلها غالباً في التقييمات الاقتصادية من قبل شركات البترول ، كالشركة موضع هذه الدراسة ، والتي تضع خطط أعمالها السنوية باستخدام نماذج تقليدية حتمية باستخدام برنامج الاكسل (Excel) مع تصنيف المشاريع يدويًا. لذلك ، أثناء اتخاذ قرار الاستثمار ، فإن التقييم الفعال لمجموعة أوجه عدم اليقين أمر بالغ الأهمية لتحسين عملية اتخاذ القرار.

تستخدم هذه الدراسة الطريقة العشوائية ذات المرحلتين مع التصحيح كطريقة بديلة لاختيار برنامج الأعمال لمساعدة شركات النفط والغاز في اتخاذ قرارات استثمارية أفضل في ظل حالة عدم اليقين. لتبسيط النهج ، نظرنا في محفظة الشركة "أ" واخترنا برنامج حفر التطوير لتحسينه في ظل حالة عدم اليقين في أسعار النفط في المستقبل.

من بين العديد من فرص الاستثمار التي يمكن الوصول إليها ، يهتم صناع القرار في الشركة أ بتعظيم صافي القيمة الحالية المتوقعة (ENPV) عن طريق حفر مجموعة مثالية من آبار التطوير من مجموعة متنوعة من الخزانات وخيارات المسار مع مراعاة العديد من القيود. علاوة على ذلك ، في ضوء تقلب أسعار النفط في المستقبل ، ترغب الشركة في التخطيط الأمثل لتوريد الحفارة ، والذي يمكن مراجعته كجزء من إستراتيجية التشغيل السنوية. لا يلزم اتخاذ هذا القرار التشغيلي في وقت إعداد الخطة ؛ بدلاً من ذلك ، يمكن تحديده لاحقًا عند توفر معلومات جديدة عن أسعار النفط الفعلية. نتيجة لذلك ، تصبح المشكلة مشكلة قرار تسلسلي ، وتصبح نمذجة بنية المعلومات لمثل هذه المشكلة أمرًا بالغ الأهمية.

تمت صياغة نموذج رياضي خطي مختلط (MILP)، وترميزه باستخدام برنامج GAMS ، والتحقق منه ، و حله لمشكلة برنامج الحفر التطويري للنفط لشركة "أ". بعد التحقق من قيمة نتائج النموذج العشوائي مقارنة بالنموذج الحتمي ، تم استخدام النموذج العشوائي لاقتراح برنامج العمل والميزانية السنوية المثالي (AWPB) والخطة الخمسية. على الرغم من أن القيمة المتوقعة للمعلومات المثالية (EVPI) تم تقديرها ب 1.3٪ وأقل من 1٪ من القيمة المحسوبة للمحفظة ، والتي تعادل أكثر من 9.8 مليون دولار و 33.6 مليون دولار لخطة AWPB وخطة 5 سنوات ، على التوالي. تشير هذه الأرقام إلى الحقيقة المحفزة أنه حتى مع التحسين الطفيف في قيمة المحفظة المقاسة بالنسبة المئوية إلا أنها تمثل قيمة مالية كبيرة. من ناحية أخرى، استطاعت الخطة المحسّنة زيادة ENPV بمقدار 67 مليون دولار ، أو 9.3٪ ، مقارنة بخطة AWPB الأصلية للشركة "أ". بالإضافة إلى ذلك ، كشف النموذج عن إمكانية الاستثمار في منشأة جديدة.

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خطة تحسين المحفظة لشركات إنتاج البترول في بيئة أسعار النفط المتقلبة

بحث لاستكمال متطلبات الحصول على درجة الماجستير في برنامج الإدارة الهندسية

إعداد

محمد منصور أحمد حسن

الرقم الجامعي: ٢٠٠٤٠٠٧٠

إشراف

د. محمد بن شمس

أستاذ مشارك

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