AN INTEGRATED STOCHASTIC MULTI-OBJECTIVE UPSTREAM OIL & GAS SUPPLY CHAIN MODEL FOR TACTICAL DECISION MAKING

BY

AHMED MOHAMMED ALI ATTIA

A Dissertation Presented to the

DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the

Requirements for the Degree of

DOCTOR OF PHILOSOPHY

In

INDUSTRIAL AND SYSTEMS ENGINEERING

MAY 2017

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN- 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **AHMED MOHAMMED ALI ATTIA** under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **DOCTOR OF PHILOSOPHY IN INDUSTRIAL AND SYSTEMS ENGINEERING.**

Dr. Salih O. Duffuaa
(Advisor)

29/5/2017

Dr. Shokri Z. Selim
(Member)

28/5/2017

Dr. Muhammad Ben-Daya
(Member)

Dr. Hesham K. Al-Fares
(Member)

Dr. Sidqi A. Abu-Khamsin
(Member)

Dr. Hesham K. Al-Fares
Department Chairman

Dr. Salam A. Zummo
Dean of Graduate Studies

11/6/17

Date

عمادة الدراسات العليا
DEANSHIP OF GRADUATE STUDIES

Dedication

To My beloved

Mother, Wife and Sons

ACKNOWLEDGMENTS

First of all, the deep thanks for ALLAH for giving me the good health, courage and patience to complete this work. I would like to express the deepest gratitude and appreciation to my Advisor, Dr. Salih Duffuaa. You have been greatly supportive to me over the different stages of my thesis progress. You were always there to share me your rich knowledge and valuable experience. It was my pleasure that I completed my thesis under your supervision. Thank you for your time and your abundant effort.

In addition, I would like to thank my committee members, Dr. Shokri Selim, Dr. Muhammad Ben-Daya, Dr. Hesham Al-Fares and Dr. Sidqi Abu-Khamsin for their valuable comments and suggestions. It was honor for me that you were my committee members.

I acknowledge KFUPM for providing financial support and its excellent facilities. I express my gratitude to Dr. Hesham Al-Fares, Chairman of Systems Engineering Department, for providing an excellent environment of learning and research in the department.

Special thanks to my mother and my wife. I cannot express how grateful I am for everything you have made to encourage me to reach my goal. Your prayers always gave me the faith that I can sustain in the toughest moments.

Last but not least, I wish to thank Ahmed Ghaithan, my colleague, we work with each other we share the knowledge in all stages of the work.

TABLE OF CONTENTS

ACKNOWLEDGMENTS V

TABLE OF CONTENTS VI

LIST OF TABLES IX

LIST OF FIGURES X

LIST OF ABBREVIATIONS XII

ABSTRACT XV

ملخص الرسالة XVII

CHAPTER 1 INTRODUCTION 1

1.1 Hydrocarbon supply chain 1

1.2 Motivation behind this work 2

1.3 Objectives of this work 4

1.4 Theoretical background 5

1.4.1 Multi-objective optimization 5

1.4.2 Stochastic programming 6

1.4.3 Stochastic programming with risk 7

1.5 Contribution of this work 8

1.6 Dissertation organization 9

CHAPTER 2 LITERATURE REVIEW 10

2.1 Deterministic models 10

2.1.1 Deterministic upstream models 10

2.1.2 Deterministic downstream models 13

2.1.3 Deterministic integrated models 15

2.1.4 Deterministic gas models 16

2.2 Stochastic and risk management models 17

2.2.1 Stochastic upstream models 17

2.2.2 Stochastic downstream models 18

2.2.3 Stochastic integrated models 19

2.2.4 Stochastic gas models 21

2.3 Review papers 22

2.4 Conclusion 23

CHAPTER 3 MULTI-OBJECTIVE DETERMINISTIC MODEL 29

3.1 Network description 29

3.2 Deterministic model formulation 31

3.2.1 Deterministic model notations 31

3.2.2 Deterministic model constraints 36

3.2.3 Deterministic model objective functions 40

3.3 Saudi Arabia HCSC 42

3.4 Applied case study: MOD model 47

3.4.1 Numerical results of MOD 47

3.4.2 Sensitivity analysis of MOD 55

3.5 Conclusion 60

CHAPTER 4 MULTI-OBJECTIVE STOCHASTIC MODEL 62

4.1 Stochastic model formulation 63

4.1.1 Stochastic model notations 65

4.1.2 Stochastic model constraints 70

4.1.3 Stochastic model objective functions 75

4.2 Applied case study: MOS model 76

4.2.1 Numerical results of MOS 79

4.2.2 Sensitivity analysis of MOS 90

4.3 Conclusion 98

CHAPTER 5 MULTI-OBJECTIVE RISK MODEL 100

5.1 Risk model formulation 100

5.2 Applied case study: MOR model 102

5.2.1 Numerical results of MOR 102

5.2.2 Sensitivity analysis of MOR 111

5.3 Conclusion 117

CHAPTER 6 CONCLUSIONS AND FUTURE RESEARCH 120

6.1 Introduction 120

6.2 Conclusions 121

6.3 Future research 124

REFERENCES 126

APPENDIX A COLLECTED DATA 134

A.1 Oil and gas byproducts 134

A.2 Oil and gas production and processing plants 134

A.3 Distribution terminals 138

APPENDIX B IMPROVED AUGMENTED E-CONSTRAINED 140

VITAE 143

LIST OF TABLES

Table 1.1 HCSC entities and activities 1
Table 2.1 Summary of the reviewed papers........ 24
Table 3.1 Notations of the MOD model 31
Table 3.2 MOD model statistics 47
Table 3.3 Pay-off matrix of MOD model applying lexicographic optimization 48
Table 3.4 Sensitivity analysis for AUGMECON 2 resolution........ 49
Table 3.5 Preferred plan from the MOD model........ 53
Table 3.6 Utilization of oil and gas processing plants based on MOD model........ 55
Table 4.1 Notations of the MOS model 65
Table 4.2 Statistics regarding crude oil OPEC basket price 78
Table 4.3 MOS model statistics 79
Table 4.4 Pay-off matrix of MOS model applying lexicographic optimization 79
Table 4.5 Preferred plan from the MOS model 82
Table 4.6 Summary of the results from MOS per scenario 90
Table 4.7 Preferred plan for case II using MOS model 92
Table 4.8 Preferred plan for case III using MOS model........ 92
Table 5.1 MOR model statistics........ 103
Table 5.2 Pay-off matrix of MOR model applying lexicographic optimization........ 103
Table 5.3 Preferred plan from the MOR model 105
Table 5.4 Financial risk results of the MOR model........ 106
Table 5.5 VaR and CVaR values of cost function under different levels of α and β 113
Table 5.6 VaR and CVaR values of revenue function under different levels of α and β 114
Table 5.7 Preferred plan for three cases using MOR model........ 115
Table 6.1 Payoff matrix for MOD, MOS, and MOR models 122
Table 6.2 Breakeven production for MOD, MOS, and MOR models........ 122
Table 6.3 Preferred plans for MOD, MOS, and MOR models 123
Table A.1 Data about oil reservoirs and GOSPs........ 134
Table A.2 Data about oil sweetening plants. 135
Table A.3 Data about gas reservoirs and processing plants........ 136
Table A.4 Yield of gas byproducts at gas plants 136
Table A.5 Yield of gas byproducts at fractionation plants 138
Table A.6 Capacities and demands of distribution terminals 138
Table A.7 Prices at distribution terminals ($/bbl for oil and $/cft for gas)........ 139

LIST OF FIGURES

Figure 3.1 HCSC network entities, activities and echelons 30
Figure 3.2 Upstream crude oil supply chain network in Saudi Arabia 43
Figure 3.3 Natural gas supply chain network in Saudi Arabia 44
Figure 3.4 Efficient Pareto-optima surface of MOD model 50
Figure 3.5 Relation between oil production, gas production, and profit of MOD model. 51
Figure 3.6 Relation between crude oil production and total cost elements of MOD model........ 52
Figure 3.7 Relation between crude oil and natural gas productions with total cost of MOD model 53
Figure 3.8 Production profile from oil and gas reservoirs based on MOD model........ 54
Figure 3.9 Effect of OPEC quota on utilization of key processing plants 57
Figure 3.10 Effect of CO_2 emission limit 58
Figure 3.11 Effect of crude oil prices on oil and gas production levels 59
Figure 3.12 Effect of crude oil demand on oil and gas production levels 60
Figure 4.1 1st and 2nd stage decisions of the HCSC 64
Figure 4.2 SP formulation methods 71
Figure 4.3 Scenario construction for the MOS model 77
Figure 4.4 MOS network of Saudi Arabia HCSC........ 80
Figure 4.5 Efficient Pareto-optima surface of MOS model 81
Figure 4.6 Relation between oil production, gas production, and profit of MOS model . 82
Figure 4.7 Production profile from oil and gas reservoirs based on MOD & MOS........ 84
Figure 4.8 Total oil sent to local regions based on MOS & MOD 86
Figure 4.9 Total oil sent to international terminals based on MOS & MOD models........ 87
Figure 4.10 Total cost for oil and gas based on MOS & MOD models 89
Figure 4.11 Profit for oil and gas based on MOS & MOD models 90
Figure 4.12 Case II: Scenario construction for high price – low demand 91
Figure 4.13 Case III: Scenario construction for low price – high demand 91
Figure 4.14 Production profile for oil and gas reservoirs based on MOS model for the 3 cases 93
Figure 4.15 Total oil sent to local regions based on MOS model for the 3 cases........ 95
Figure 4.16 Total oil sent to international terminals based on MOS model for the 3 cases 96
Figure 4.17 Total cost for oil and gas based on MOS model for the 3 cases 97
Figure 4.18 Profit for oil and gas based on MOS model for the 3 cases 97
Figure 5.1 Definition of CVaR 101
Figure 5.2 Efficient Pareto-optima surface of MOR model 104
Figure 5.3 Relation between crude oil production and natural gas production of MOR model........ 104
Figure 5.4 Production profile for oil and gas reservoirs based on MOR model........ 107

Figure 5.5 Total oil sent to local regions based on MOR model 108
Figure 5.6 Total oil sent to international terminals based on MOR model 109
Figure 5.7 Total cost for oil and gas based on MOR model 110
Figure 5.8 Profit for oil and gas based on MOR model 111
Figure 5.9 Total cost and revenue values of MOR model under different values of α and β 113
Figure 5.10 Total cost for oil and gas based on MOR model for the 3 cases 116
Figure 5.11 Profit for oil and gas based on MOR model for the 3 cases 117

LIST OF ABBREVIATIONS

$	:	Dollar
AH	:	Arabian Heavy
AL	:	Arabian Light
AM	:	Arabian Medium
ARAMCO	:	Arabian American Oil Company
AXL	:	Arabian Extra Light
Bbbl	:	Billion Barrel
CCP	:	Chance-Constrained Programming
cftd	:	Cubic Feet per Day
CVaR	:	Conditional Value at Risk
HCSC	:	Hydrocarbon Supply Chain
GAMS	:	General Algebraic Modeling System
GOR	:	Gas-Oil Ratio
GOSP	:	Gas-Oil Separator plant
LNG	:	Liquefied Natural Gas
LP	:	Linear Programming
M	:	Million

MMbbld	:	Million Barrel per Day
MMcft	:	Million Cubic feet
MILP	:	Mixed-Integer Linear Programming
MINLP	:	Mixed-Integer Non-Linear Programming
MOD	:	Multi-Objective Deterministic
MOO	:	Multi-Objective Optimization
MOR	:	Multi-Objective Risk
MOS	:	Multi-Objective Stochastic
NGL	:	Natural Gas Liquid
NPV	:	Net Present Value
OPEC	:	Organization of Oil Exporting Countries
PHA	:	Progressive Hedging Algorithm
PSC	:	Petroleum Supply Chain
SAA	:	Sample Average Approximation
SC	:	Supply Chain
SCN	:	Supply Chain Network
SOO	:	Single Objective Optimization

SP	:	Stochastic Programming
TOPSIS	:	Technique for Order Preference by Similarity to Ideal Solution
VaR	:	Value at Risk

ABSTRACT

Full Name : Ahmed Mohammed Ali Attia

Thesis Title : An Integrated Stochastic Multi-Objective Upstream Oil & Gas Supply Chain Model for Tactical Decision Making

Major Field : Industrial and Systems Engineering

Date of Degree : May 2017

The supply chain of crude oil, natural gas, and their byproducts is known as the HCSC, which constitutes a major part of the world's energy sector. The economy of energy generating products is one of the most influential sectors in the world economy, and is known for its immense investments. Consequently, the strategic or tactical planning of the HCSC is an important research area. Planning decisions must include satisfying demand versus avoiding depletion of the natural resources, minimizing costs versus maximizing revenue, and achieving a high revenue versus maintaining a low levels of depletion rates.

The aim of this dissertation is to develop realistic and practical optimization models that considers the three echelons of the HCSC (e.g., production, processing, and distribution) and the production of oil and gas simultaneously. Three multi-objective mathematical programming models were formulated and their utility has been demonstrated using a real case study from Saudi Arabia HCSC: deterministic, stochastic, and financial risk management; for tactical planning decisions.

Objectives considered are: minimize the total costs, maximize the total revenue, and minimize the depletion rate (i.e., guarantee reserves sustainability). The deterministic model were formulated assuming certainty of model parameters. Whereas, the stochastic model considers different market situations of prices and demand as an uncertain parameters. Eventually, the stochastic model were modified to a financial risk management model by including CVaR as a risk measure in the objective function and reformulates the constraints. The purpose of risk model is to avoid developing a tactical plan with high total costs and low revenue.

The proposed models assesses various trade-offs among alternatives and guide decision makers for effective management of the HCSC. A real case study is provided to demonstrate the utility of the models and a sensitivity analysis is conducted to derive some managerial insights.

ملخص الرسالة

الاسم الكامل: أحمد محمد على عطيه

عنوان الرسالة: نموذج عشوائى متكامل متعدد الاهداف للمرحله العليا من سلاسل إمداد النفط و الغاز لصنع القرار التكتيكى.

التخصص: الهندسه الصناعيه و النظم

تاريخ الدرجة العلمية: مايو 2017م

سلاسل إمداد النفط ، الغاز الطبيعى، و مشتقاتهم تعرف بسلاسل إمداد الهيدروكربون HCSC، و هى تشكل جزءا رئيسيا من قطاع الطاقة في العالم. اقتصاد منتجات توليد الطاقة هو واحد من أكثر القطاعات تأثيرا في الاقتصاد العالمي، والمعروف باستثماراته الهائلة. وبالتالي، فإن التخطيط الاستراتيجي أو التكتيكي لسلاسل إمداد الهيدروكربون هو مجال بحث هام. التعارض بين قرارات التخطيط المختلفة هو بمثابة تحد، مثل: تلبية الطلب مقابل تجنب استنزاف الموارد الطبيعية، تقليل التكاليف مقابل زيادة الإيرادات، و تحقيق إيرادات عالية مقابل الحفاظ على مستويات منخفضة من معدلات نضوب الموارد الطبيعية.

تهدف هذه الرسالة الى تطوير نموذج واقعي وعملي للحل الأمثل لسلاسل إمداد الهيدروكربون حيث يأخذ فى الاعتبار المستويات الثلاثة (على سبيل المثال: الأنتاج, المعالجة و التوزيع) وإنتاج النفط والغاز في وقت واحد. وقد صيغت ثلاثة نماذج من البرمجة الرياضية متعددة الأهداف وتم تطبيقها على حالة واقعيه لسلاسل إمداد الهيدروكربون فى المملكة العربية السعودية: حتمية, عشوائية، و إدارة المخاطر المالية لأتخاذ قرارات التخطيط التكتيكي.

الأهداف التى أخذت فى الاعتبار هي: تقليل التكاليف الإجمالية، وتعظيم الإيرادات الإجمالية، وتقليل معدل النضوب (أى.، ضمان استدامة الاحتياطى). النموذج الحتمى تم صياغته بافتراض اليقين فى جميع معلمات النموذج. بينما، النموذج العشوائى يأخذ فى الاعتبار حالات مختلفه للسوق من حيث التغير العشوائى فى الأسعار و حجم الطلب.

أخيرا، تم تعديل النموذج العشوائى ليصبح نموذج إدارة المخاطر المالية باستخدام CVaR كمقياس للخطر في دالة الهدف بالإضافة الى إعادة صياغة القيود. الغرض من نموذج المخاطر هو تجنب وضع خطة تكتيكية يترتب عنها إجمالي تكاليف عالية و دخلا منخفض.

النماذج المقترحة تقوم بتقييم الأفضليه بين البدائل المختلفه وتوجيه صناع القرار للإدارة الفعالة لسلاسل إمداد الهيدروكربون. و تم تقديم دراسة لحالة واقعيه لأثبات عملية و كفاءة النماذج وقد بلغ عدد المتغيرات ١٠٩٤٦ و عدد القيود ١٢١٤٤. و قد و جد أن أفضل حالة للسوق و التى تحقق فيها المملكة العربية السعودية أعلى ربح هى عندما يكون سعر النفط مرتفع و الطلب عليه منخفض. و تم إجراء تحليل الحساسية لاستخلاص بعض التوجهات و الحلول الادارية.

CHAPTER 1

INTRODUCTION

1.1 Hydrocarbon supply chain

The supply chain of crude oil, natural gas, and their byproducts is known as the HCSC. The activities within the HCSC begin with exploration and production, followed by processing and refining, and finally end with distribution to the end customer. These activities usually are segmented as upstream, midstream, and downstream sectors. Sahebi et al. (2014) lists the entities and activities in each segment for the HCSC as listed in Table 1.1. Stewart and Arnold (2007) provides a detailed description of all activities and the associated surface facility (entity). The borders between the different streams are subjective. Several petroleum producers merge up- and mid-streams as one echelon, depending on the scope of the company.

Table 1.1 HCSC entities and activities

Segment	Entities	Activities
Upstream	Wellhead, well platform, production platform, and crude oil terminal.	Exploration, production (i.e. recovery and separation), and transportation to refineries.
Midstream	Refinery plant and petrochemical plant.	Transformation and production through refineries and petrochemicals
Downstream	Distribution center/depot, market, customer.	Transformation, including storage and distribution to customers

The HCSC starts from the oil well and well platforms up to customers. Through this journey the oil and gas pass through several stages of transformation generating different types of products in different forms. These products are transported using various modes all over the world. Managing the entities, information and logistics of this supply chain in an integrated fashion is an interesting challenging problems.

1.2 Motivation behind this work

Energy generating products are some of the world's most important commodities. Consequently, countries that have high levels of trading and reserves of energy resources, especially, crude oil and/or natural gas, represent a major amount of power in the world's economy. The supply of these products made available to the world market has an impact on energy prices.

Over the past years, crude oil prices have declined sharply, leading to considerable revenue shortfalls in producing countries. In addition, if these countries were to reduce their oil production, they would expect to lose market share and cut-off natural gas (i.e., associated gas) supply to their own industrial plants.

HCSC optimization includes many challenges for the academic sector. Optimization based on financial objectives includes many conflicting decisions such as minimizing total costs, maximizing revenues, and minimizing depletion rate. Based on the literature review on the next chapter, multi-objective optimization still not sufficiently utilized in HCSC optimization.

Tactical planning of the HCSC as a multi-product SC is another challenge. Crude oil and natural gas has dependency in production and overlapping exists in both networks. What increases the complexity of the problem is the transformation of oil and gas into different products within the network. Many of these products transforms into another products. Demand and prices of each product is uncertain in the market. As a result of uncertainty a risk of exceeding the budget or not covering the liabilities may occur.

As a summary, challenges in optimizing decisions in HCSC includes:

- Managing the HCSC in a multi-objective frame work.
- Planning the production of oil and gas (non-associated gas) simultaneously.
- Maintaining a sufficient reserves for future generations.
- Considering environment impact.
- Modelling different echelons of the network integrally.
- Formulating market uncertainty (e.g., price and demand)
- Mitigating the risks associated with market uncertainty.

The above challenges pose interesting and important problems for researchers and practitioners to address and optimize. This is the main motivation behind this dissertation.

1.3 Objectives of this work

The objective of this dissertation is to contribute the modelling, optimization, and managerial decision making of HCSC. As such several models are developed in this dissertation. Each one can be applied depending on the availability of data and the sophistication of the decision maker. The specific objectives of the dissertation:

- Develop a deterministic MOO model for HCSC.
- Extend the deterministic model to a stochastic MOO where two stage stochastic programming will be employed.
- Further, develop the stochastic model to consider risk.
- A real case study will be used to demonstrate the applicability of the models.

The multi-objective framework (i.e., study the trade-off among conflicting objectives) and tactical planning decision level (i.e., weekly or monthly planning period) had been embraced to model. Three objectives are considered in this dissertation. The first objective function aims to minimize the total costs of production, processing, transformation, transportation, distribution, and production above or below the demand. The second objective function ensures the organization or country has enough cash flow the cover total costs, pay other expenses and sustain development, through maximizing the total revenue. The third objective function minimizes the depletion rate of both oil and gas reserves to secure sufficient reserves for the coming generations.

The above three specific objectives are obtained after conducting a relevant and extensive literature review that indicated that the above types of models with multi-objective frame work have not be developed for HCSC optimization. Therefore, accomplishing the above objectives is expected to contribute in bridging the gap in the literature.

1.4 Theoretical background

1.4.1 Multi-objective optimization

MOO has no single optimal solution that optimizes all objective functions simultaneously, different in nature from SOO. Optimal solution is replaced with preferred solution and optimality replaced with Pareto-optimal. Mavrotas (2009) defined efficient Pareto-optimal as:" Pareto-optimal (or efficient, non-dominated, non-inferior) solutions are the solutions that cannot be improved in one objective function without deteriorating their performance in at least one of the rest".

Pareto-optimal may be weakly or strictly efficient, the solution is said to be weak if it is dominated by other solutions. Rational decision makers search for efficient solutions from all generated points. The generated solution form a Pareto-front, Pareto-curve, or Pareto-surface. The shape of Pareto-optimal represents the trade-off among different objectives.

Methods of solving MOO problems are classified based on the stage at which the decision maker interferes to select the preferred solution: priori methods, interactive methods, or posteriori methods, (Hwang and Masud, 2012). The main drawback of the first and second categories is that the decision maker does not have a whole picture about the trade-off before getting the Pareto set. To avoid the mentioned drawback we use an improved version of ε-constraint method (a posteriori method) proposed by Mavrotas and Florios (2013) to generate Pareto-surface, see Appendix B.

1.4.2 Stochastic programming

HCSCs contain several uncertain parameters such as price, demand, and yield. In such cases modeling HCSCs must consider uncertainty. One well-known approach for modeling situation under uncertainty is stochastic programming. In this approach, the decision maker is able to take some decisions at the start of the planning period based on the available information about certain parameters. As the values of the uncertain parameters became known he/she can take the rest of decisions. This process of staged decision making can be formulated using two stage stochastic programming, which cannot be formulated based on deterministic programming. SP can be of two or multi stage formulation based on the nature of the problem; in how many points of time all the uncertain parameters are realized.

In formulating SP models the values of uncertain parameters are represented as scenarios. If the scenarios of uncertain parameters are not known or the number is very high, the decision maker can use different formulations such as SAA (Tong et al., 2012; Oliveira and Hamacher, 2012) or CCP (Yang et al., 2010; Li et al., 2004). In this work we use a two stage SP base on the number of points over time that the uncertain parameters can be realized.

1.4.3 Stochastic programming with risk

In SP the decision maker take the decision based on optimizing the expected value of the objective function over all scenarios of the second stage decisions. The main drawback of optimization based on the expected value is the ignorance of the remaining parameters characterizing the distribution associated with uncertain parameters. In this situation, the optimization of the objective functions is risk neutral. For instance, the risk of exceeding a certain limit of costs (e.g., exceeding the budget limit) or not exceeding a desired levels of revenue (e.g., not enough cash flow) may occur. So, the SP model needs to be modified to achieve an economic objectives (i.e., total cost minimization and revenue maximization) and financial risk management, simultaneously.

To manage risk a term that measuring risk is included in the objective function to mitigate the effect of risks associated with uncertain parameters risk. Conejo et al. (2010) discussed many of the risk measures such as: variance, shortfall probability, expected shortage, VaR, and CVaR. In this work we use CVaR as a risk measure which proved to be a coherent risk measure (Conejo et al., 2010).

1.5 Contribution of this work

Based on the literature review in chapter 2, a considerable work has been done in the area of HCSC optimization; only Iakovou (2001) formulated a deterministic multi-objective model for the logistics of downstream segment. No multi-objective optimization model has been reported for an integrated HCSC. In addition, to the best of our knowledge, there are no papers considered oil and gas optimization simultaneously, although they highly dependent in reality.

Referring to the identified research gap from the literature review, this work provides several contributions. First, it formulates a multi-objective mathematical optimization model that integrates upstream HCSCs. Second, it optimizes the tactical decisions regarding the production and transportation quantities of crude oil and natural gas, simultaneously. Third it incorporates SP and risk management in modeling upstream HCSCs. Moreover, the environmental impact of HCSCs has been considered by limiting CO_2 emissions. The proposed model has been applied to a real case study from Saudi Arabia to verify its validity and practicability.

1.6 Dissertation organization

This dissertation consists of six chapters. **Chapter 2** presents an extensive and relevant literature review. The reviewed papers are classified based on certainty (deterministic or stochastic), product (oil- or gas-oriented) or by segment (upstream, downstream, or integrated); where the midstream segment have not been studied separately. **Chapter 3** describes the characteristics of the HCSC and the development of the deterministic MOO model. A real case study to demonstrate the use of the deterministic model and a sensitivity analysis to validate the behavior of the model is also provided in chapter 3.

Chapter 4 discuss the uncertain parameters in HCSC and construct scenarios that represent different situations of the uncertain parameters. Formulates a two stage stochastic programming model to address uncertainty and demonstrates its utility on a case from Saudi Arabia. Also the results of the stochastic programming and the deterministic model are compared in this chapter. **Chapter 5** explains different risks measures associated with taking decisions under uncertainty and modifies the stochastic model to account for risk. Sensitivity analysis based on different levels of risk has been applied. **Chapter 6** closes the dissertation by the conclusion and directions for further research.

CHAPTER 2

LITERATURE REVIEW

Several research papers have modeled the different segments of the HCSC, either in an integrated form or studied each segment separately. The literature can be classified by certainty level (deterministic or stochastic), by product (oil- or gas- oriented), or by segment (upstream, downstream, or integrated). It is noted that the midstream segment have not been studied separately. The reviews in this chapter covers deterministic, stochastic, and risk management models.

2.1 Deterministic models

2.1.1 Deterministic upstream models

Related to upstream oil-oriented deterministic modeling, Nygreen et al. (1998) reported an MILP that has been used by the Norwegian Petroleum Directorate for production and transportation planning. The aim of their research was to discuss a successful practical model that had been used for more than fifteen years and it was under continuous development. The model considered two objective functions that the user can choose between: minimizing a weighted sum of deviations from a given goal on production or resource usage, or maximizing the total net present value from all the projects.

Iyer et al. (1998) formulated an MILP model for facility allocation, production planning, and scheduling of offshore oil fields. The problem of investment planning was tackled by specifying the number and location of production platforms, well platforms, and wells to be drilled for production. For simplicity they linearized the reservoir behavior utilizing a piecewise linear function, which is a limitation in their model.

van den Heever and Grossmann (2000) discussed the same problem in Iyer et al. (1998) considering the same decisions but including the non-linear reservoir behavior as a constraint. The goal of their research was not to formulate a model rather than to develop an algorithm to solve MINLP models utilizing decomposition and aggregation/disaggregation techniques.

van den Heever et al. (2000) extended the model in van den Heever and Grossmann (2000) by including a more complex economic objectives. The model objective was to maximize the NPV of sales revenues, capital costs, operating costs, taxes, tariffs, and royalties. The study used the disjunctive formulation instead of the big-M approach. Consideration of the complex economic rules (e.g., tariff, tax, and royalty calculations) was found to be more profitable and yielding a completely different solution. The disjunctive approach applied tighter upper bounds that resulted in shorter solution time. Later on van den Heever et al. (2001) solved the same model in van den Heever et al. (2000) using the Lagrangean Decomposition and a heuristic to reduce the complexity of the model solution.

Carvalho and Pinto (2006a) formulated an MILP model for the assignment of well-platforms to well-heads in offshore oil fields as discrete decisions. In addition, the amount of production from each well was a continuous decision variable. They utilized the Bi-level decomposition approach to facilitate the solution of the large scale model with discrete and continuous variables. Carvalho and Pinto (2006b) extended the Carvalho and Pinto (2006a) model based on a realistic assumption regarding reservoir performance. They assumed that the pressure inside the reservoir changes globally with the extraction of oil or gas, independent of the pressure of other reservoirs in the same field; the pressure of all wells belonging to the same reservoir is therefore the same. Although their work focused on reservoir behavior, they ignored the change in pressure between the wells and platforms.

Ulstein et al. (2007) constructed an MILP model to maximize the net income from the offshore oil fields in Norway. Although the model was simple, it is generic and effective in production planning for medium terms (i.e., tactical planning). The model contains a set of constraints that keeps the performance of the reservoir at a desired level during the extraction.

Rocha et al. (2009) developed a model to generate a daily plan for shipping crude oil from the production site to the refineries. A heuristic inspired from the Branch-and-Bound algorithm called Local Branching was applied to expedite the solution procedure. Then, a local search procedure was used to increase the quality of the solution. As a limitation of their model a decomposition technique can be utilized to improve the solution quality, since, their model is naturally decomposed. For more details of the proposed model refer to Rocha (2010).

Gupta and Grossmann (2012) formulated the nonlinearity of the reservoir behavior as a third and a higher order polynomial. Aizemberg et al. (2014) tackled the transportation planning problem of crude oil from offshore facilities to the next processing units. First, they reviewed many models regarding the transportation planning problem and proposed new problems. Second, they solved the problems using a commercial software based on a Branch-and-Bound algorithm and to make the problem tractable a column generation based heuristic was utilized.

2.1.2 Deterministic downstream models

Sear (1993) addressed the problem of transportation cost minimization originating from refineries ending by customers. Persson and Göthe-Lundgren (2005) increased the complexity of the Sear (1993) problem by considering refinery scheduling optimization. The increased complexity affected the tractability and solution time of the model. Elkamel et al. (2008) focused on reducing CO_2 emissions from refineries.

Kuo and Chang (2008a and 2008b) modeled the operations inside the refinery as a detailed SCN. The model was able to coordinate the planning and scheduling decisions of the refining segment. However, both models ignored the nonlinearity in refining operations.

Al-Qahtani and Elkamel (2008 and 2009) formulated an MILP model to coordinate the operation of multi-refinery plants. The objective was to minimize the annualized operating and capital costs based on decisions regarding capacity expansion, production levels, and blending levels. Kim et al. (2008) tackled the same problem with an extra decision regarding facility relocation. However, capacity expansion decisions depend on market prices and demand and both parameters are uncertain. (Al-Qahtani and Elkamel 2008 and 2009; Kim et al. 2008) assumed that all parameters are deterministic. Therefore, sensitivity of the proposed models need to be examined against the variation in both demand and price.

Guyonnet et al. (2009) compared the effect of formulating a fully integrated model for crude oil unloading operation, production planning, and distribution process versus a non-integrated model for each operation. They concluded that, the integrated model achieved a significantly higher profit because of lower penalties of lost demand, safety stock, and unsatisfied demand. The model was tested using small problems with unreal (i.e., estimated) data.

(Fernandes et al. 2011 and 2013; Fiorencio et al., 2015) developed an MILP for strategic decisions related to depot locations, capacities (e.g., refinery, depot, retailer), transportation modes, and transportation routes. Kazemi and Szmerekovsky (2015) examined the effect of using different transportation modes (pipeline, waterway carriers, rail and truck) on the performance of the distribution network. They did not consider the possibility of disruption that may occurs to the transportation modes.

2.1.3 Deterministic integrated models

Related to integrated oil-oriented deterministic modeling, Neiro and Pinto (2004) constructed the network starting from oil fields to distribution terminals via refineries. Their model decisions include the amount of production of each entity that is transported through pipelines, refinery operational variables, and inventory and entities assignment.

Jiao et al. (2010) proposed an MILP model for Chinese PSC to decide how much to produce from each entity. They assumed unlimited capacity of entities and routes, and shortage is allowed and it is completely satisfied during the next period before the demand.

Chen et al. (2010) focused on minimizing transportation costs of imported crude oil within Chinese PSC. Cost elements include the transportation costs, operation cost in logistics centers, handling costs and domestic transportation cost.

2.1.4 Deterministic gas models

Related to gas-oriented HCSC (Al-Saleh et al., 1991; Duffuaa et al., 1992) formulated an LP model to study if Saudi Arabia was able to satisfy the industrial demand of methane and ethane from associated gas supplies only. The model considered a ceiling of 4.5 MMbbld as an OPEC quota and at that time the associated gas production could satisfy the industrial demand. The proposed model did not consider the effect of non-associated gas production or increasing the production levels on CO_2 emissions.

Hamedi et al. (2009) presented a case study considering the transmission and distribution planning of natural gas. An MINLP model has been developed to minimize the total costs of transportation and processing. The results need more verification whether by resolving the model by commercial software or developing a meta-heuristic to compare the results.

Grønhaug and Christiansen (2009) optimized the LNG downstream segment considering the activities related to liquefaction, transportation, storage, and regasification. The decision variables include the production quantities at each activity and quantities transported between activities to maximize the profit. Two formulations were presented based on arc-flow and route-flow. In case of using the route-flow formulation for large scale problem the optimizer ran out of memory.

2.2 Stochastic and risk management models

2.2.1 Stochastic upstream models

Jørnsten (1992) formulated an MILP model for investment planning of offshore petroleum fields considering many scenarios of future demand. Investment planning influences by uncertainty in demand and prices, the later was ignored by the author. Haugen (1996) tackled the problem of scheduling the production of oil or gas off-shore fields under the assumption of uncertain resources. Resources uncertainty has two reasons: advances in technology increases production and production reveals the physical structure of the reservoirs which changes the estimated reserves.

Jonsbråten (1998) proposed a model for maximizing the NPV of oil fields based on different scenarios of oil price. The PHA was used to decompose the model into scenario based sub-models which makes the proposed model applicable. Although the model focus on reservoir production uncertainty and non-linearity associated with reservoir performance was ignored. Aseeri et al. (2004) proposed a model similar to Iyer et al. (1998) by considering maximum budget and the potential for borrowing as constraints. They considered prices and productivity index as uncertain parameters. They utilized SAA to avoid the complexities of solving large scale stochastic models. VaR was used as a risk measure although its shortcomings, (Conejo et al., 2010).

Continue in the same line of research concerning investment planning of offshore fields, Tarhan et al. (2009) proposed a multi-stage stochastic programming model considering the uncertainties of initial maximum oil flow rate, recoverable oil volume, and water break through time of the reservoir. Solution algorithm need more improvement to reduce the solution time which is rather long.

2.2.2 Stochastic downstream models

The second set of stochastic models formulates the downstream segment of the HCSC. Li et al. (2004) compared the effect of two different objective functions on the planning of refinery operation utilizing CCP approach in formulation. The first objective was based on a confidence level (i.e., probability of satisfying customer demand) and the second was based on filling rate (i.e., proportion of satisfied demand). Neiro and Pinto (2005) incorporated the uncertainty of oil prices and demand on planning refinery operations.

(Khor, 2007; Khor et al., 2008) managed the risk from variation in price, demand, and yield by adding variance as a risk measure in the objective function. Although, the variance penalizes scenarios with profit less and more than the expected profit. Al-Qahtani and Elkamel (2010) extended the work proposed by Al-Qahtani and Elkamel (2008) by accounting for the uncertainty of quantity of imported products, product price, and demand employing SAA approach.

(Yang et al., 2010; Tong et al., 2012) utilized Markov chain to represent the fluctuation of product yield in refineries. The former used CCP in the formulation, whereas the later, used scenario based. Tong et al. (2012) incorporated CVaR as a risk measure in the objective function and the threshold value was estimated by SAA. They solved the model by a heuristic based on iterative algorithm integrating simulation framework. So, the optimum solution was not guaranteed.

Oliveira and Hamacher (2012) applied SP optimization to the downstream network in northern Brazil. They used SAA to avoid the existing large number of scenarios. As all strategic models, the first stage decisions are when and where to invest, while the second stage decisions are how much to produce. Fernandes et al. (2015) developed a stochastic MILP based on demand uncertainty using node-variable formulation to produce a compact model. Although, (Oliveira and Hamacher, 2012; Fernandes et al., 2015) optimized the downstream sector they ignored uncertainty associated with product price.

2.2.3 Stochastic integrated models

Related to integrated oil-oriented stochastic modeling, Escudero et al. (1999) developed a framework for scheduling transformation and transportation under uncertain price, cost, and demand. The results based on two objectives were compared: minimizing the penalties of non-sufficient resources and minimizing the total transformation and transportation costs.

In the same line, Dempster et al. (2000) formulated a model for depot and refinery optimization problem considering the uncertainty of prices and demands. Later on MirHassani (2008) tackled the same problem considering only demand as uncertain parameter. Al-Othman et al. (2008) showed that the plan based on stochastic models was more profitable than deterministic models.

Off-line the research direction that considers price and/or demand as uncertain parameters Ghatee and Hashemi (2009) considered uncertainty in daily production, daily exportation, refinery intake, capacity of pipelines, and capacity of storage tanks. Although, capacities of pipelines and storage tanks are fixed during the planning period.

Carneiro et al. (2010) formulated a two-stage scenario-based SP model incorporating CVaR as a risk measure. The model was able to manage the risk in the portfolio optimization because the objective was to maximize the expected portfolio return (i.e., the weighted mean of the individual returns).

Ribas et al. (2010) developed a two-stage SP model based on 27 scenario (i.e., 3 scenarios for uncertain parameter high, base, and low). MirHassani and Noori (2011) dealt with capacity expansion of the distribution systems (i.e., investment allocation). Capacity installments were the first stage decisions and quantities to be transported were the second stage decisions. Oliveira et al. (2013) tackled the same problem of investment allocation incorporating the expected shortage as a risk averse to avoid exceeding the budget. They considered demand uncertainty and ignored price uncertainty, although its effect on investment decisions.

Within the few research works that considered environmental legislation Liqiang and Guoxin (2015) proposed a model oriented around CO_2 emissions. The objective was to mitigate the carbon emissions to minimize the taxes from environment legislation. Although they optimized the production of different facilities they ignored uncertainty associated with demand.

2.2.4 Stochastic gas models

Few papers focused on optimizing gas-oriented models. (Goel and Grossmann, 2004; Goel et al., 2006) considered uncertainty in the amount of gas reserves. Amount of reserves estimated based on recoverable amount and maximum flow rate at any time. The first and second stage decisions was investments at the start of the project and production planning, respectively. The proposed models did not consider the financial risk from exceeding the budget allocated for investment.

Azadeh et al. (2015) presented uncertainty in demand, capacity, and costs as a fuzzy parameters to minimize the total costs including environmental costs. The model was solved through two steps first by getting the deterministic equivalent and second by converting the model into a single objective. They tested the proposed model on a small sized numerical example. The validity and practicability of the model require to be examined under real case models.

2.3 Review papers

(Bengtsson and Nonås, 2010; Leiras et al., 2011) conducted a literature review on the refining activities (i.e., a transformation activity in the HCSC). They concluded that (i) most of the existing models relaxes the non-linearity of the refining operation to reach optimal solution within an acceptable time, (ii) coordination between short term decisions (scheduling) and long term decisions (planning decisions) need more research, and (iii) environmental regulation gained more attention.

Hennig et al. (2011) conducted a review on the crude oil transportation especially tanker routing and scheduling. They highlighted that, the research area on solving the problem of fleet routing and scheduling needs efficient solving algorithms. Beforehand, Al-Yakoob (1997) pointed to the scarcity of research in the area of crude oil tanker routing and scheduling. Justified this shortage due to the trend of global economy which resulted in enlarging the supply chain.

(Sahebi, 2013; Sahebi et al., 2014) conducted a recent review on the applications of mathematical programming in PSC. Some of their recommendations for future research include (i) examining both strategic and tactical decisions in an integrated form, (ii) formulating nonlinearity of the refineries operations, (iii) exploring environmental impact of the PSC problems, (iv) modeling uncertainty features with multi-stage stochastic models, and (v) developing efficient solution techniques for multi-objective models.

2.4 Conclusion

Table 2.1 summarizes the reviewed papers according to product (oil and gas), segment (upstream and downstream), decision level (strategic and tactical), modelling approach (LP, MILP, NLP, and MNLP), level of uncertainty (deterministic, stochastic, and risk management), uncertain parameters, modelling approach in case of stochastic programming, and whether environmental aspects considered or not.

In a summary, a considerable work has been done in the area of HCSC optimization, but all of these models are either oil- or gas- oriented and considers a single objective. This work is an attempt to bridge the research gap by proposing a multi-objective and multi-product (i.e., oil and gas production simultaneously) stochastic optimization model for tactical decision making. It is worth to point out that, this is the first optimization model for doing so.

Table 2.1 Summary of the reviewed papers

Reference	Product	Segment	Decision levels	Modelling Approaches	Uncertain Parameters	Modeling approach	Environmental Aspects
Al-Saleh et al (1991)	O,G	DS	T	LP, SO			
Duffuaa et al (1992)	G	DS	T	LP, SO, D			
Jørnsten (1992)	O	US	S, T	MLP, SO, S	P, D	SV	
Sear (1993)	O	DS	S, T	LP, SO, D			
Haugen (1996)	G	US	T	MLP, SO, S	R		
Nygreen et al. (1998)	O	US, DS	S, T	MLP, SO, D			
Iyer et al. (1998)	O	US	S, T	MLP, SO, D			
Jonsbråten (1998)	O	US	S, T	MLP, SO, S	P	SV	
Escudero et al. (1999)	O	US, DS	T	LP, SO, S	P, D	SV	
van den Heever and Grossmann (2000)	O	US	S, T	MNLP, SO, D			
van den Heever et al. (2000)	O	US	S, T	MNLP, SO, D			
Dempster et al. (2000)	O	DS	T	LP, SO, S	P, D	SV	
van den Heever et al. (2001)	O	US	S, T	MNLP, SO, D			
Iakovou (2001)	O	DS	T	LP, MO, D			
Neiro and Pinto (2004)	O	US, DS	T	MNLP, SO, D			
Aseeri et al. (2004)	O	US	S, T	MLP, SO,S, RM	P, R	SAA	
Li et al. (2004)	O	DS	T	MLP, SO, S	P, D	CCP	

Goel and Grossmann (2004)	G	US	S, T	MLP, SO, S	R	SV	
Persson and Göthe-Lundgren (2005)	O	DS	T	MLP, SO, D			
Neiro and Pinto (2005)	O	DS	T	MNLP, SO, S	P, D	SV	
Carvalho and Pinto (2006a)	O	US	S, T	MLP, SO, D			
Carvalho and Pinto (2006b)	O	US	S, T	MLP, SO, D			
Goel et al. (2006)	G	US	S, T	MLP, SO, S	R	SV	
Ulstein et al. (2007)	G	US, DS	T	MLP, SO, D			CO_2
Elkamel et al. (2008)	O	DS	T	MNLP, SO, D			CO_2
Kuo and Chang (2008a, 2008b))	O	US, DS	T	MLP, SO, D			
Al-Qahtani and Elkamel (2008)	O	DS	S, T	MLP, SO, D			
Kim et al. (2008)	O	DS	S, T	MNLP, SO, D			
Khor et al. (2007, 2008)	O	DS	S, T	MLP, SO, S, RM	P, D, Y	SV	
MirHassani (2008)	O	DS	T	MLP, SO, D			
Al-Qahtani et al. (2008)	O	US, DS	S, T	MNLP, SO, S	P, D, Y		
Al-Othman et al. (2008)	O	US, DS	T	MLP, SO, S	P, D	SV	
Al-Qahtani et al. (2009)	O	DS	S, T	MLP, SO, D			
Rocha et al. (2009, 2010)	O	US, DS	T	MLP, SO, D			
Al-Qahtani and Elkamel (2009)	O	US, DS	S, T	MLP, SO, D			

Guyonnet et al. (2009)	O	DS	S, T	MLP, SO, D			
Hamedi et al (2009)	G	US, DS	T	MNLP, SO, D			
Grønhaug and Christiansen (2009)	G	DS	T	MLP, SO, D			
Tarhan et al. (2009)	O	US	S, T	MNLP, SO, S	R	SV	
Ghatee and Hashemi (2009)	O	US, DS	S, T	MLP, SO, D	D		
Jiao et al. (2010)	O	US, DS	T	LP, SO, S	P, D	SV	
Chen et al. (2010)	O	US, DS	S	MLP, SO, D			
Al-Qahtani and Elkamel (2010)	O	DS	S, T	LP, SO, S, RM	P, D	SAA	
Yang et al. (2010)	O	DS	T	MLP, SO, S, RM	Y	SV, CCP	
Leiras et al. (2010)	O	DS	S, T	MLP, SO,S,R	P, D		
Carneiro et al. (2010)	O	US, DS	S, T	MLP, SO, S, RM	P, D	SV	
Jian-ling et al. (2010)	O	US, DS	S, T	LP, SO, D			
Ribas et al. (2010)	O	US, DS	T	MLP, SO,S, R	P, D	SV	
Fernandes et al. (2011)	O	DS	S, T	MLP, SO, D			
Ribas et al. (2011)	O	US, DS	T	LP, SO, S	P, D		
Tong et al. (2011)	O	US, DS	T	MLP, SO, S	D, Y		
MirHassani and Noori (2011)	O	DS	T	MLP, SO, S	D	SV	
Gupta and Grossmann (2012)	O	US	S, T	MLNP, SO, D			

Tong et al. (2012)	O	US, DS	T	MLP, SO, S, RM	D, Y, R	SAA	
Oliveira and Hamacher (2012)	O	DS	S, T	MLP, SO, S	D	SAA	
Fernandes et al. (2013)	O	DS	S, T	MLP, SO, D			
Sahebi and Nickel (2013)	O	US, DS	S, T	MLP, SO, D			
Oliveira et al. (2013)	O	US, DS	S, T	MLP, SO, S	D	SV	
Fernandes et al. (2014)	O	DS	S, T	MLP, SO, D	D		
Cafaro and Grossmann (2014)	G	DS	S, T	MNLP, SO, D			
Azadeh and Raoofi (2014)	G	US, DS	T	LP, SO	D, R		
Aizemberg et al (2014)	O	US	T	MLP, SO, D			
Fiorencio et al (2015)	O	DS	S, T	MLP, SO, D			
Kazemi and Szmerekovsky (2015)	O	DS	S, T	MLP, SO, D			
Fernandes et al (2015)	O	DS	S, T	MLP, SO, S	D	NV	
Azadeh et al (2015)	G	US, DS	T	LP, MO, S	D		CO_2
Zaghian and Mostafaei (2015)	O	DS	T	MLP, SO, D			
Liqiang and Guoxin (2015)	O	US, DS	S, T	MLP, SO, S	P		CO_2
Proposed Work	O,G	US, DS	T	LP, MO, S, RM	P,D	NV	CO_2

[1] Product
- O = Oil
- G = Gas

[2] Segment and entities
- US = Upstream
- DS = Downstream

[3] Decision levels
- S = Strategic
- T = Tactical

[4] Modelling approaches and purposes
- LP = Linear Programming
- MLP = Mixed Integer Linear Programming
- NLP = Non-Linear Programming
- MNLP = Mixed Integer Non-Linear Programming
- SO = Single Objective
- MO = Multi Objective
- D = Deterministic
- S = Stochastic
- RM = Risk Management
- R = Robust

[5] Uncertain features
- P = Price
- D = Demand
- Y = Yield
- R = Recoverable amount

[7] Modeling approach
- NV = Node Variable
- SV = Scenario Variable
- SAA = Sample Average Approximation
- CCP = Chance Constrained Programming

[6] Environmental aspects
- CO_2 = Carbon Dioxide emission

CHAPTER 3

MULTI-OBJECTIVE DETERMINISTIC MODEL

This chapter presents the deterministic MOO model. Section 3.1 describe the HCSC followed by the model in section 3.2. The case study of Saudi Arabia is provided in section 3.3. The utility of the model is demonstrated using a real case study in section 3.4. The chapter ended with a conclusion in section 3.5.

3.1 Network description

Two SCNs define the HCSC, crude oil or natural gas. The two supply chains are formed from three echelon: production areas, processing plants, and demand terminals. An overlap exists between the two networks because the crude oil contains associated gas. A schematic representation of the network is depicted in Figure 3.1.

The SCN of crude oil starts from oil reservoirs, as production areas, subsequently the produced oil is transported to gas-oil separator plants (GOSPs) to separate the associated gas from the oil. Thereafter, oil streams from GOSPs are collected at the gathering centers, and then sent to oil processing plants for stabilization and sweetening (i.e., removal of hydrogen sulfide and other gases). Produced gas from gas reservoirs (i.e., non-associated gas) and associated gas from GOSPs are collected at the gas gathering centers, and then feed into gas processing plants. At the gas processing plants, hydrogen sulfide (used for sulfur production) and carbon dioxide are removed, and methane and natural gas liquid (NGL) are produced. Thereafter, NGL is fractionated to its gas components (e.g., ethane, butane, propane, and natural gasoline).

Finally, the sweetened crude oil and gas-byproducts are distributed to satisfy customer demand at different terminals (e.g., local, industrial, and international).

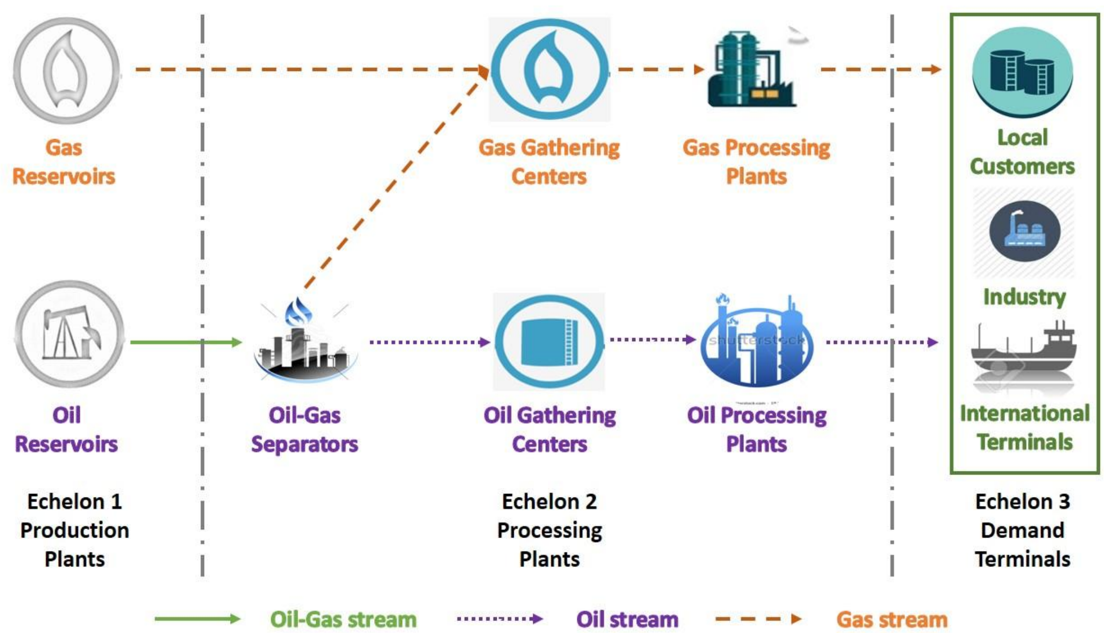


Figure 3.1 HCSC network entities, activities and echelons

3.2 Deterministic model formulation

The formulation of the MOD model begins by defining the adopted notations, then explaining the different sets of constraints, and finally the formulation of a three objective functions.

3.2.1 Deterministic model notations

Table 3.1 summarizes the notations used in the mathematical model.

Table 3.1 Notations of the MOD model

1. Sets/Indices:		
i, j	:	all nodes.
ro, rg	:	set of (oil, gas) reservoirs; i.e., production areas.
n	:	set of GOSPs.
go, gg	:	set of (oil, gas) gathering centers.
po, pg	:	set of (oil, gas) processing plants.
do, dg	:	set of (oil, gas) demand terminals.
$loco, locg$	:	subset of (do, dg); represents (oil, gas) local depots.

$indo, indg$: subset of (do, dg); represents (oil, gas) industrial complexes.

$into, intg$: subset of (do, dg); represents (oil, gas) international terminals.

t : set of time periods.

o : set of crude oil types; e.g., *AH, AM, AL, and AXL*.

g : set of natural gas byproducts; includes subsets: *gn* natural gas, *gp* gas byproducts produced at processing plants, H_2S and CO_2.

---

2. Decision Variables:

---

x_{ijt}^{o} : amount of crude oil of type *o* produced in time period *t* transported from node *i* to node *j*;

where $(i, j) \in (ro, n), (n, go), (go, po), (po, do)$.

y_{ijt}^{g} : amount of natural gas of type *g* produced in time period *t* transported from node *i* to node *j*;

where $(i, j) \in (rg, gg), (n, gg), (gg, pg), (pg, dg)$.

x_{jt}^{o+}, x_{jt}^{o-} : crude oil production of type *o* in time period *t* above and below the requirement at node *j*;

where $j \in go, do$.

y_{jt}^{g+}, y_{jt}^{g-} : natural gas production of byproduct *g* in time period *t* above and below the requirement at node *j*;

where $j \in gg, dg$.

D : deplition rate of crude oil and natural gas reserves.

3. Parameters:

3.1. Yield parameters:

GOR_{ijt}^{o} : Gas-oil ratio of crude oil type *o* produced during time period *t* from reservoir *i* linked to GOSP *j*; where $(i, j) \in (ro, n)$.

P_{ijt}^{o} : yield (composition) of crude oil of type *o* liberated during time period *t* at node *i* transported to node *j*; where $(i, j) \in (ro, n), (go, po)$.

P_{ijt}^{g} : yield of gas product *g* obtained during time period *t* at node *i* transported to node *j*; where $(i, j) \in (gg, pg)$.

3.2. Capacity parameters:

C_{j}^{o} : capacity of node *j* for crude oil *o*; where $j \in n, go, po, do$.

C_{j}^{g} : capacity of node *j* for gas product g; where $j \in gg, pg, dg$.

c_{ij}^{o} : capacity of the route linking node *i* to node *j* of crude oil *o*; where $(i, j) \in (ro, n), (n, go), (go, po), (po, do)$.

c_{ij}^{g} : capacity of the route linking node *i* to node *j* for gas product *g*; where $(i, j) \in (rg, gg), (n, gg), (gg, pg), (pg, dg)$.

3.3. Volume parameters:

R_i^o : amount of reserves in reservoir at node *i* for oil type *o*; where $i \in ro$.

R_i^g : amount of reserves in reservoir at node *i* for gas *g*; where $i \in rg$.

C_{max} : maximum amount of CO_2 to be emitted to the environment in time period *t*.

$OPECQ$: OPEC quota or market share per planning time period *t*.

3.4. Cost parameters:

ec_{ijt}^o : production cost per unit of stream x_{ijt}^o, at node *i* during time period *t*; where $(i,j) \in (ro,n)$.

ec_{ijt}^g : production cost per unit of stream y_{ijt}^g, at node *i* during time period *t*; where $(i,j) \in (rg,gg)$.

pc_{ijt}^o : processing cost per unit of stream x_{ijt}^o, at node *j* during time period *t*; where $(i,j) \in (ro,n),(go,po)$.

pc_{ijt}^g : processing cost per unit of stream y_{ijt}^g, at node *j* during time period *t*; where $(i,j) \in (gg,pg)$.

tc_{ijt}^o : transportation cost per unit of stream x_{ijt}^o, from node *i* to node *j* during time period *t*;

where $(i,j) \in (ro,n),(n,go),(go,po),(po,do)$.

tc_{ijt}^{g} : transportation cost per unit of stream y_{ijt}^{g}, from node *i* to node *j* during time period *t*;

where $(i,j) \in (rg, gg), (n, gg), \ (gg, pg), (pg, dg)$.

c_{jt}^{g} : cost per unit of emitting Carbon Dioxide to environment at plant *i* during time period *t*; where $j \in pg$

w_{jt}^{o+}, w_{jt}^{o-} : penalty cost per unit for producing oil of type *o* above or below the specified demand at node *j* during time period *t*; $where\ j \in go, do$.

w_{jt}^{g+}, w_{jt}^{g-} : penalty cost per unit for producing gas product *g* above or below the specified demand at node *j* during time period *t*; $where\ j \in gg, dg$.

3.5. Demand and prices parameters:

d_{jt}^{o} : demand at destination *j* for oil of type *o* in time period *t*; where $j \in do$.

d_{jt}^{g} : demand at destination *j* for gas byproduct *g* in time period *t*; where $j \in dg$.

pr_{jt}^{o} : selling price per unit of crude oil type *o* during time period *t* at demand node *j*; where $j \in do$.

pr_{jt}^{g} : selling price per unit of gas products *g* during time period *t* at demand node *j*; where $j \in dg$.

dr : discount rate per period *t*.

3.2.2 Deterministic model constraints

A set of linear constraints has been proposed to determine the feasible region of the model. They are grouped into eight types: material balance of the 2^{nd} echelon plants, plant capacity of the 2^{nd} and 3^{rd} echelon plants, capacity of the routes connecting all the plants, demand at 3^{rd} echelon plants, OPEC quota at international terminals, carbon dioxide emissions at gas processing plants, reserves sustainability of reservoirs 1^{st} echelon plants, and non-negativity constraints.

Material balance constraints: using the fact that the sum of incoming and outgoing streams at any plant must be equal; conservation of mass through the network. Eqs. (3.1) and (3.2) represents the mass balance for crude oil and associated gas separated at GOSPs (n), respectively, based on yield (p) and gas-oil ratio (GOR). The output streams transported to the oil and gas gathering centers (go, gg). Eq. (3.3) represents the mass balance at oil gathering centers (go), where the incoming stream plus inventory from the previous period (t-1) equals to the outgoing stream plus the end inventory at existing period (t). The outgoing stream from (go) sent to oil processing plants (po), where processed oil and hydrogen sulfide are produced based on their yields (p), Eqs. (3.4) and (3.5).

$$\sum_{i \in ro} P^{o}_{ijt}\, x^{o}_{ijt} = \sum_{i \in go} x^{o}_{jit} \qquad \forall o, \qquad \forall j \in n \tag{3.1}$$

$$\sum_{i \in ro} GOR^{o}_{ijt}\, x^{o}_{ijt} = \sum_{i \in gg} y^{g}_{jit} \qquad \forall o, \qquad \forall\, j \in n \tag{3.2}$$

$$\sum_{i \in n} x^{o}_{ijt} + x^{o+}_{jt-1} = \sum_{i \in po} x^{o}_{jit} + x^{o+}_{jt} \qquad \forall o, \qquad \forall j \in go \tag{3.3}$$

$$\sum_{i \in go} P^{o}_{ij}\, x^{o}_{ijt} = \sum_{i \in do} x^{o}_{jit} \qquad \forall o, \qquad \forall j \in po \tag{3.4}$$

$$\sum_{i \in go} P^{o}_{ij}\, x^{o}_{ijt} = \sum_{g \in H2S;\, i \in dg} y^{g}_{jit} \qquad \forall o, \qquad \forall j \in po \tag{3.5}$$

Regarding the natural gas network, associated gas from GOSPs (*n*) and non-associated gas from gas reservoirs (*rg*) are collected at the gas gathering centers (*gg*), Eq. (3.6). At (*gg*), the incoming streams from (*rg* and *n*) plus the end inventory from the previous period (*t-1*) should be equal to the outgoing stream plus the end inventory at period (*t*). Next, the outgoing stream sent to gas processing plants (*pg*), Eq. (3.7), to produce different gas byproducts based on the stream yield (*p*).

$$\sum_{i \in rg} y^{g}_{ijt} + \sum_{i \in n} y^{g}_{ijt} + y^{g+}_{jt-1} = \sum_{i \in pg} y^{g}_{jit} + y^{g+}_{jt} \qquad \forall g, \qquad \forall j \in gg \tag{3.6}$$

$$\sum_{i \in gg} P^{g}_{ijt} y^{g}_{ijt} = \sum_{i \in dg} y^{g}_{ijt} \qquad \forall g, \qquad \forall j \in pg \tag{3.7}$$

Plant capacity constraints: the formulation of plant capacity constraints depends on the purpose of the plant: processing or gathering and storing. Eqs. (3.8) and (3.9) and Eq. (3.12) represents the maximum processing capacity of processing plants for oil (*n* and *po*) and gas (*pg*), respectively. While, Eqs. (3.10) and (3.11), and Eqs. (3.13) and (3.14) account for gathering and storing plants (gathering centers and demand terminals) for both oil and gas.

Route capacity constraints: for all products and all routes in the proposed network are represented in Eqs. (3.15) and (3.16).

$$\sum_{i \in ro} p^{o}_{ijt} x^{o}_{ijt} \leq C^{o}_{j} \qquad \forall o, \qquad \forall\, j \in n \tag{3.8}$$

$$\sum_{i \in go} p^{o}_{ijt} x^{o}_{ijt} \leq C^{o}_{j} \qquad \forall o, \qquad \forall\, j \in po \tag{3.9}$$

$$\sum_{i \in n} x^{o}_{ijt} + x^{o+}_{jt-1} \leq C^{o}_{j} \qquad \forall o, \qquad \forall\, j \in go \tag{3.10}$$

$$\sum_{i \in po} x^{o}_{ijt} + x^{o+}_{jt-1} \leq C^{o}_{j} \qquad \forall o, \qquad \forall\, j \in do \tag{3.11}$$

$$\sum_{i \in gg} p^{g}_{ijt} y^{g}_{ijt} \leq C^{g}_{j} \qquad \forall g, \qquad \forall\, j \in pg \tag{3.12}$$

$$\sum_{i \in rg} y_{ijt}^{g} + \sum_{i \in n} y_{ijt}^{g} + y_{jt-1}^{g+} \leq C_j^g \qquad \forall g, \quad \forall j \in gg \tag{3.13}$$

$$\sum_{i \in pg} y_{ijt}^{g} + y_{jt-1}^{g+} \leq C_j^g \qquad \forall g, \quad \forall j \in dg \tag{3.14}$$

$$x_{ijt}^{o} \leq c_{ij}^{o} \qquad \forall o, \quad \forall i, \quad \forall j \tag{3.15}$$

$$y_{ijt}^{g} \leq c_{ij}^{g} \qquad \forall g, \quad \forall i, \quad \forall j \tag{3.16}$$

Demand constraints: the produced quantities of oil and gas byproducts from the processing plants used to satisfy demand at the terminals, as formulated in Eqs. (3.17) and (3.18). To avoid infeasibility, above production and below production decision variables are added to the constraints and the end inventory of the previous period subtracted from the demand. Whereas, ***OPEC quota*** constraint (3.19) specifies that the total amount of crude oil of all types at international terminals should not exceed the OPEC's quota or the market share. Emissions of carbon dioxide should be within the range established by ***environmental regulations***. Eq. (3.20) limits the carbon dioxide emissions. Oil and gas are natural resources, and deplete after certain time of consumption. Eqs. (3.21) and (3.22) are used as ***sustainability constraints***. Where *D* represents the depletion rate; it should be minimized to ensure longer lifetime for the reserves. Eventually, Eq. (3.23) represents the ***non-negativity constraint***.

$$\sum_{i \in po} x_{ijt}^{o} - x_{jt}^{o+} + x_{jt}^{o-} = d_{jt}^{o} - x_{jt-1}^{o+} \qquad \forall\, o, \qquad \forall j \in do \tag{3.17}$$

$$\sum_{i \in pg} y_{ijt}^{g} - y_{jt}^{g+} + y_{jt}^{g-} = d_{jt}^{g} - y_{jt-1}^{g+} \qquad \forall\, g, \qquad \forall j \in dg \tag{3.18}$$

$$\sum_{o;\, i \in po; j \in into} x_{ijt}^{o} + \sum_{o; j \in into} x_{jt-1}^{o+} \leq OPECQ \tag{3.19}$$

$$\sum_{g \in CO2; j \in pg} y_{jt}^{g} \leq C_{max} \tag{3.20}$$

$$\frac{\sum_{o; i \in ro; j \in n} x_{ijt}^{o}}{\sum_{o; i \in ro} R_{it}^{o}} \leq D \tag{3.21}$$

$$\frac{\sum_{g; i \in rg; j \in gg} y_{ijt}^{g}}{\sum_{g; i \in rg} R_{it}^{g}} \leq D \tag{3.22}$$

$$x_{ijt}^{o}, x_{jt}^{o+}, x_{jt}^{o-}, y_{ijt}^{g}, y_{jt}^{g+}, y_{jt}^{g-}, D \;\geq 0 \tag{3.23}$$

3.2.3 Deterministic model objective functions

The first objective considered is to ***minimize the total costs*** over the planning horizon, expressed in Eq. (3.24). Costs included cost of production from reservoirs in terms 1 and 2, cost of processing at each plant in terms 3 and 4, in terms 5 and 6 cost of transporting through all the existing routes, penalty cost of over- or under- the specified demand at terminals and inventory cost at gathering centers in terms 7 and 8, and the final term accounts for carbon dioxide emission cost. The total cost is discounted back to its present value based on the discount rate *dr* per planning period *t*.

$$Minimize\ Total\ Cost = \sum_{t} (1+dr)^{-(t-1)} \tag{3.24}$$

$$\left[\sum_{o,(i,j)\in(ro,n)} ec_{ijt}^{o}\, x_{ijt}^{o} + \sum_{g,(i,j)\in(rg,gg)} ec_{ijt}^{g}\ y_{ijt}^{g} \right.$$

$$+ \sum_{o,(i,j)\in(ro,n),(n,po)} pc_{ijt}^{o}\, x_{ijt}^{o} + \sum_{g,(i,j)\in(gg,pg)} pc_{ijt}^{g}\ y_{ijt}^{g}$$

$$+ \sum_{o,i,j} tc_{ijt}^{o}\, x_{ijt}^{o} + \sum_{g,i,j} tc_{ijt}^{g}\, y_{ijt}^{g}$$

$$+ \sum_{o,j\in(go,do)} \left(w_j^{o+} x_{jt}^{o+} + w_j^{o-} x_{jt}^{o-} \right) + \sum_{g,j\in(gg,dg)} \left(w_{lj}^{g+} y_{jt}^{g+} + w_j^{g-} y_{jt}^{g-} \right)$$

$$\left. + \sum_{g\in CD;j\in j} c_{jt}^{g} y_{it}^{g} \right]$$

The second objective is to ***maximize the total revenue*** obtained from selling crude oil and gas byproducts subtracting the over-production quantities, formulated in Eq. (3.25). Eq. (3.26) represents the third objective of ***minimizing rate of depletion*** of the reserves, and consequently maximizing the sustainability of the crude oil and natural gas reserves.

$$\text{maximize } Revenue = \tag{3.25}$$

$$\sum_{t}(1+dr)^{-(t-1)}\left[\sum_{o,(i,j)\in(po,do)} pr_{jt}^{o}\left(x_{ijt}^{o} - x_{jt}^{o+}\right) + \sum_{g,(i,j)\in(pg,dg)} pr_{jt}^{g}\left(y_{ijt}^{g} - y_{jt}^{g+}\right)\right]$$

$$\text{minimize } D \tag{3.26}$$

3.3 Saudi Arabia HCSC

In this section, a real HCSC from Saudi Arabia was chosen to elucidate the utility of the proposed MOO model, and the numerical results are analyzed. Also, sensitivity analysis is conducted to study the effect of key parameters of the model on planning decisions and to recommend some managerial insights. The network in the case study is depicted in Figure 3.2 and Figure 3.3; showing a representation of the figure in (McMurra, 2011). The network considers only the main production areas (high production reservoirs).

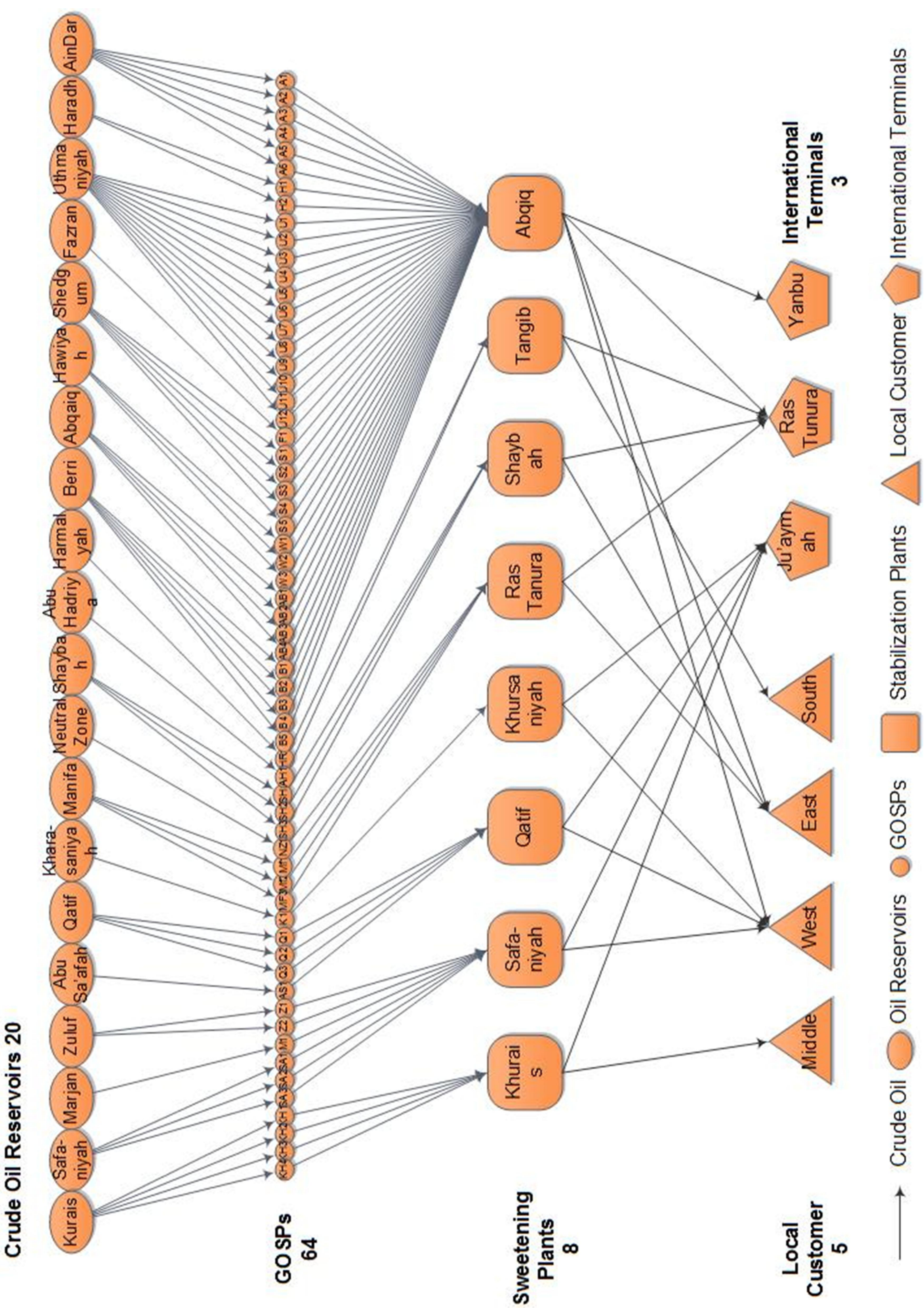


Figure 3.2 Upstream crude oil supply chain network in Saudi Arabia

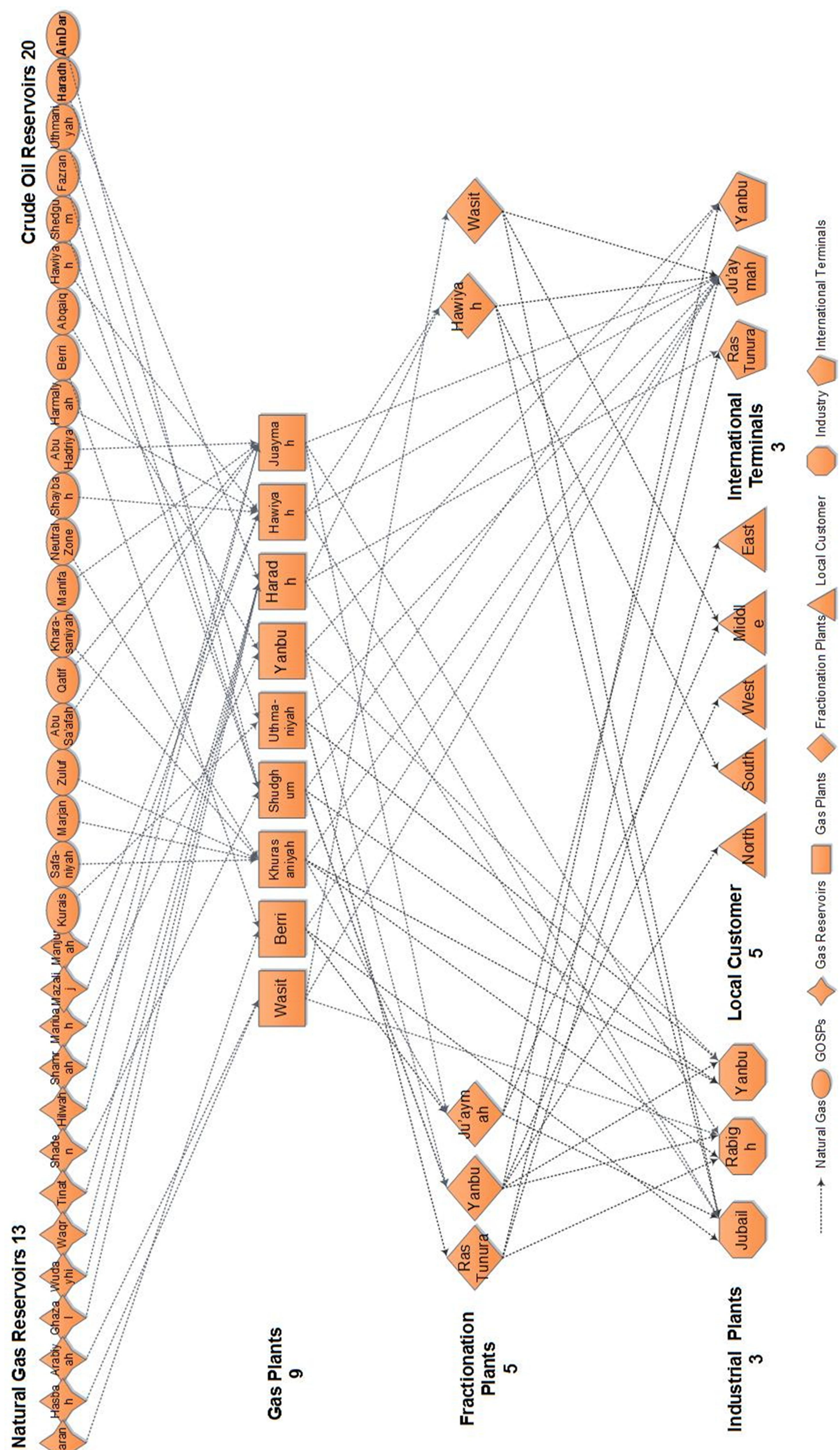


Figure 3.3 Natural gas supply chain network in Saudi Arabia

The network contains 20 oil reservoirs, connected to 64 GOSPs for separation of gases, water and salt from crude oil. The produced crude oil is transported to 8 stabilization and sweetening plants via pipelines.

The associated gas from GOSPs and the non-associated gas from 13 gas reservoirs are transported to 9 gas plants for impurities removal, and recovery of hydrogen-sulfide which converted to elemental sulfur. The obtained sweet-dry gas (e.g., methane) is used to satisfy industrial demand and feed stock, and the NGL and ethane are piped to 5 fractionation plants. The outputs from the fractionation plants are: ethane, butane, propane, and natural gasoline.

The produced crude oil (i.e., *AXL*, *AL*, *AM*, and *AH*) are used to satisfy the local demand of different refineries located in 4 regions in the Kingdom (i.e., East, West, Middle, and South regions), and satisfy the international demand as constrained by the OPEC quota. The total proven crude oil reserves in Saudi Arabia is 268 Bbbl with 17.33% *AXL*, 53.31% *AL*, 10.99% *AM*, and 18.36% *AH*. Whereas, the local demand of each type is 26.28% *AXL*, 44.11% *AL*, 2.99% *AM*, and 26.61% *AH*; and the international demand: 10.10% *AXL*, 56.56% *AL*, 22.22% *AM*, and 11.11% *AH*.

The gas byproducts are used as follows: methane and ethane are used to satisfy the industrial demand and thus ensure the survival of Saudi Arabia industry. NGL, propane, butane and natural gasoline are used to satisfy the international demand, and propane and butane are used for domestic supply.

The data required to run the model include the following, summarized in appendix A:

1) GOR corresponding to each crude oil type for different reservoir streams.
2) Crude oil composition; yield of main components (e.g., natural gas, hydrogen sulfide) at each entity.
3) Natural gas composition, for instance yield of carbon dioxide, hydrogen sulfide, methane, and ethane.
4) Demand of crude oil and gas byproducts by local customer, local industry and international customer and the corresponding selling prices.
5) International market share specified by the OPEC quota.
6) Capacity of each entity, capacity of routes connecting the entities and the transportation modes utilized through these routes.
7) Cost elements: production and processing costs at each entity, transportation costs, and penalty costs of producing above and below the demand. Penalty of producing above the required demand is the cost of holding the products and is estimated to be 25% of the international price. While, the below penalty is the international market price plus costs of delivering the product to the demand terminal (i.e., assuming that shortage is not allowed) and estimated to be 125% of the international price.

3.4 Applied case study: MOD model

The proposed model based on the available data was coded in GAMS 24.1.2 r40979 and solved with commercial solver CPLEX 12.5.1.0. The tactical planning horizon is 3 months with 1 month planning period and the model statistics are summarized in Table 3.2. The data in appendix A are on daily bases, the model was run for three months planning horizon (January, February, and March) with (31, 28, and 31) days, respectively.

Table 3.2 MOD model statistics

Blocks of Equations	95	Single Equations	1,833
Blocks of Variables	47	Single Variables	1,760
Non Zero Elements	8,433		

3.4.1 Numerical results of MOD

To generate the efficient Pareto-optima AUGMECON 2 (Improved Augmented ε-Constraint) algorithm proposed by (Mavrotas and Florios, 2013) based on the ε-constraint method was used, explained in appendix B.

The first step of the algorithm is to apply a lexicographic optimization, as follows. First, the model is optimized based on minimizing the total cost f_1 (11,487.61). Then, the total revenue is maximized f_2 (36,574.97) subject to f_1 value as an equality constraint and the other eight sets of constraints, subsequently, the depletion rate f_3 (0.001141) is minimized considering both f_1 and f_2 as equality constraints and the other sets of constraints. The procedure is repeated considering different orders of the objective functions; the results are listed in Table 3.3.

Table 3.3 Pay-off matrix of MOD model applying lexicographic optimization

	Total Cost (M$/month)	Total Revenue (M$/month)	Depletion Rate	Sustainability (Years)
Minimizing Total Cost	***11,487.61***	36,574.97	0.001141	73.01
Maximizing Total Revenue	11,673.71	***37,145.98***	0.001141	73.01
Minimizing Depletion Rate	34,774.49	19,299.20	***0.000578***	***144.20***

The obtained results are based on the assumption that all the demand should be satisfied. Consequently, the demand above the production (i.e., required extra quantities) has to be obtained from the international market and to be delivered to the customers. So, the penalties of producing below or above the required demand is estimated to be 125% and 25% from the international price, respectively.

The second step, is to pick out the efficient points from the pay-off matrix, by dividing the ranges of f2 and f3 equidistantly. A sensitivity analysis was conducted to specify the efficient resolution that provides a precise solutions. The analysis started by dividing the range of (f2, f3) by 25 equidistant segments (26 points) and keep increasing resolution by 25. As expected, the execution time increases and new efficient points were added. Values of (f1, f2, f3) were normalized on the range [0, 1], then, the Euclidean distance between the new points and the old points were calculated. The procedure was continued until the maximum Euclidean distance is less than 0.05; the results are shown in Table 3.4.

Table 3.4 Sensitivity analysis for AUGMECON 2 resolution

Resolution (segments)	Pareto Points	New Points	Maximum Euclidean distance
5	8	-	-
25	30	22	0.087
50	57	27	0.075
75	101	44	0.063
100	148	47	***0.049***
125	155	7	0.042
150	163	8	0.023
175	220	57	0.021
200	426	206	0.004

As a result, a systematic search based on dividing each interval into a 100 equidistant segment (i.e., 101x101 = 10201 possible points) was applied. Where, the coordination of the searched points (e_2, e_3) represents the right hand side of (f_2, f_3). In addition, to force the solver to minimize the surplus and slack, eps were chosen to be 10^{-3}, which is the highest value from the range, $eps \in [10^{-6}, 10^{-3}]$, proposed by Mavrotas and Florios (2013).

Eventually, the model were solved, where, efficient points provides a feasible solution and is only considered as a feasible plan (using the formulation (B.3) in appendix B to specify the efficient points).

The surface of the obtained Pareto-optima is depicted in Figure 3.4 with 148 efficient points obtained. As expected, the worst plan based on total cost and revenue M$ (34,774.49, 19,299.20) /3months occurred at a high reserves sustainability 144.20 years (i.e., low depletion rate). The total cost is at its highest levels because the production is very low, consequently, the penalty of producing less than the required demand is very high. Referring to Figure 3.5 this plan is non-profitable. On the other vertex of the Pareto-surface, low total cost and a high revenue cannot be achieved without affecting reserves sustainability. As a conclusion, to achieve the extreme of the sustainability of the natural resources, this affects the cash flow required for sustaining the development projects in the Kingdom. The break-even production of oil is 6.96 MMbbld and of gas 6,570.46 MMcftd, so, to achieve profit the kingdom should produce more of crude oil and less of natural gas.

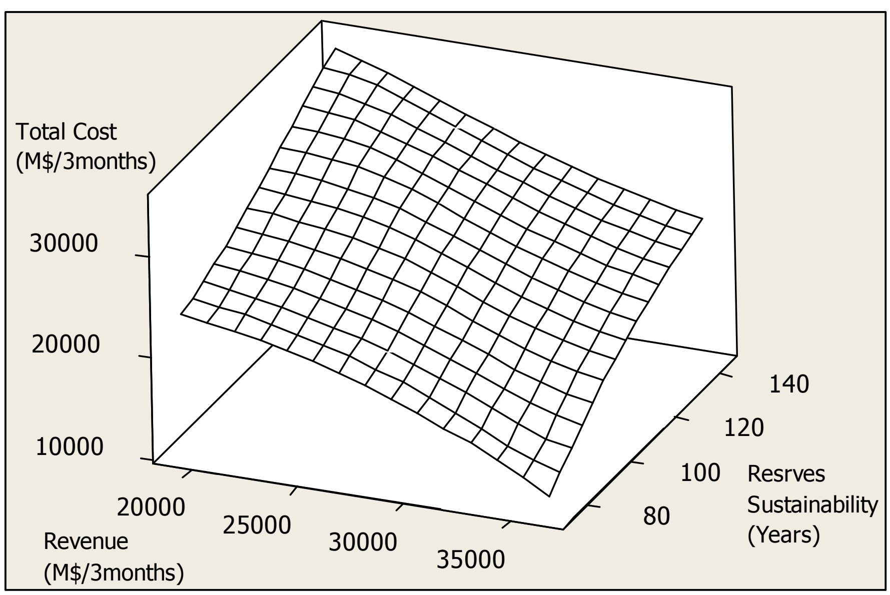


Figure 3.4 Efficient Pareto-optima surface of MOD model

Examining the relationship between crude oil and natural gas productions and their effect on profit. Figure 3.5 shows that oil production has an impact on gas production because part of the gas demand can be met from associated gas. Under high levels of oil production the Kingdom can reach the highest level of profit and keep sufficient amount of natural gas reserves to the coming generations. While, under this production level crude oil reserves will deplete within 73.01 years. To sustain oil reserves the Kingdom has a range of production until reaching the break-even point. At this case, gas production increases to compensate for the reduction in associated gas.

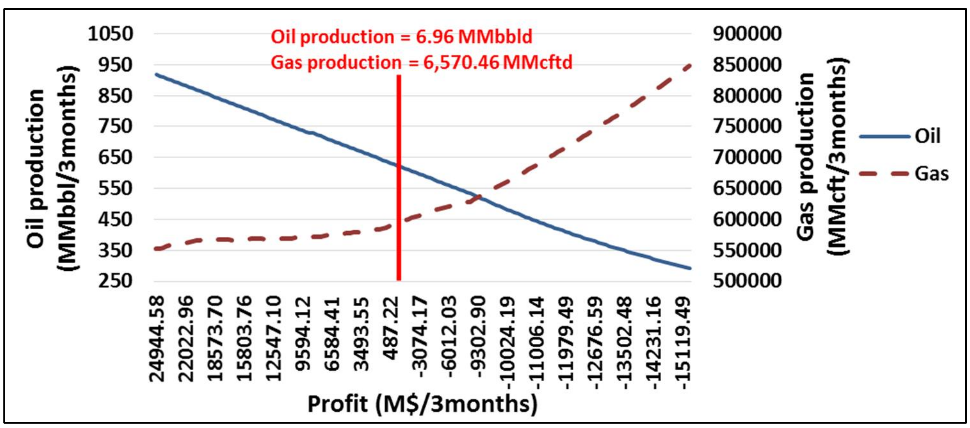


Figure 3.5 Relation between oil production, gas production, and profit of MOD model

The effect of oil production levels on the total cost elements (production, processing, and transportation costs, penalty of producing above the demand, and penalty of producing below the demand) is shown in Figure 3.6. As the oil production increase the costs of production, processing, and transportation increase. However the penalty of producing below the required demand decreases while the penalty of producing above demand is constant at zero (i.e., the solver forces the solution towards the minimum depletion).

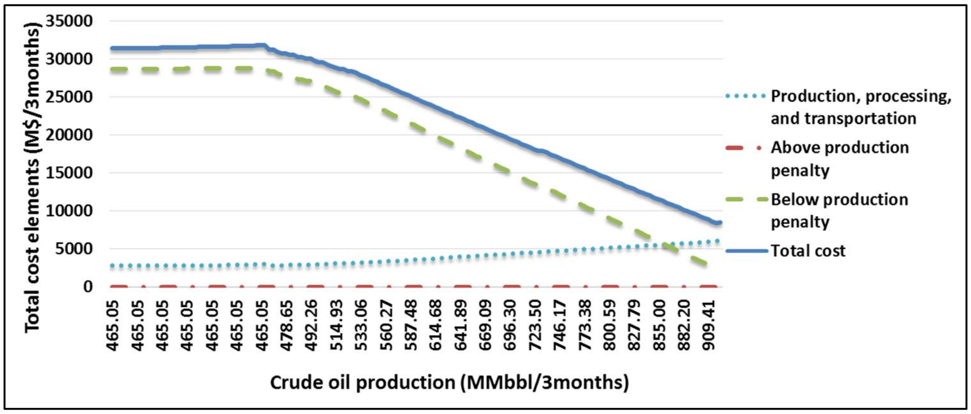


Figure 3.6 Relation between crude oil production and total cost elements of MOD model

Figure 3.7 demonstrates the effect of production levels of both oil and gas on the total cost. The total cost decreases as oil production levels increase, whether gas production is at high or low levels. In addition, the highest and lowest levels of total costs are related to the highest and lowest oil production levels, respectively. As the oil production increases and the gas production is at low levels, the total cost is low, because the demand for both oil and gas can be satisfied (from the associated gas). At the same time, the revenue from selling crude oil allows Saudi Arabia to cover the below production penalties of gas by-products. Whereas, the total cost is higher if oil production decreases and gas production is increased; and the penalty cost is higher because oil demand is not met in this case.

From the set of Pareto-optima the preferred tactical plan were chosen using TOPSIS technique based on equally weighted objectives. TOPSIS technique selects the nearest plan to the ideal one, (Clemen and Reilly, 2004). The values of the objective functions, quantity of oil production, and quantity of gas production are listed in Table 3.5.

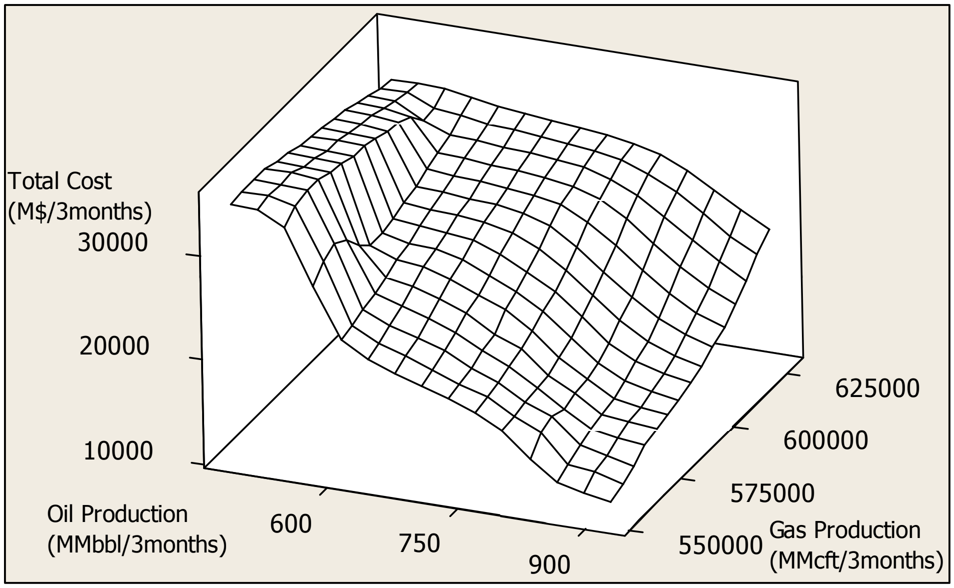
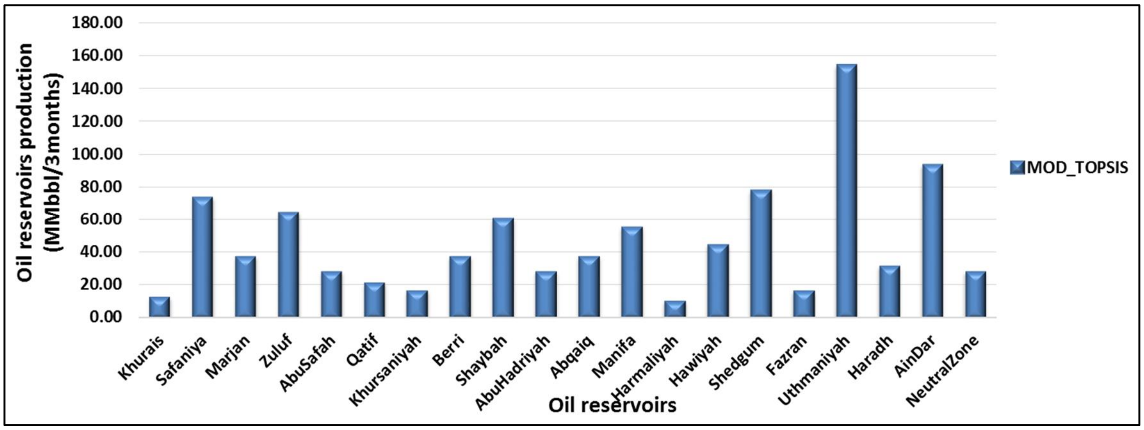


Figure 3.7 Relation between crude oil and natural gas productions with total cost of MOD model

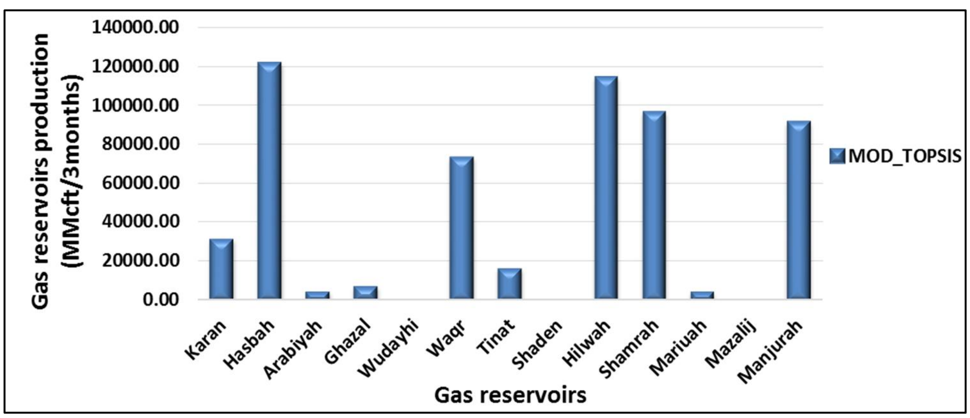
Table 3.5 Preferred plan from the MOD model

Total cost =	M$ 11,709.04/3months	Oil production =	913.94	MMbbl/3months
Revenue =	M$ 36,236.58/3months		10.15	MMbbld
Profit =	M$ 24,527.54/3months	Gas production =	553,251.39	MMcft/3months
Depletion rate =	0.00113568		6,147.24	MMcftd
Sustainability =	73.38 years			

Production profile for crude oil and natural gas reservoirs depicted in Figure 3.8 and the corresponding utilization of processing plant listed in Table 3.6. Utilization of Khurais sweetening plan is very low, because Khurais reservoir is the only source input to it as shown in Figure 3.2. The same case happened with Khursaniyah plant. The effect of saving natural gas reserves for the coming generations is clear on production profile where some of gas reservoir is suspended from production: Wudayhi, Shaden, and Mazalij. In addition, some reservoir have to produce very low quantities: Hasbah, Ghazal, and Mariuah. Suspending and decreasing gas production affects the utilization of some of processing plants: Hawiyah (6.76%) and Wasit (0.00%).



(a) Production profile for oil reservoirs



(b) Production profile for gas reservoirs

Figure 3.8 Production profile from oil and gas reservoirs based on MOD model

Table 3.6 Utilization of oil and gas processing plants based on MOD model

(a) Sweetening and stabilization plants			
Khurais =	08.77 %	RasTanura =	58.88 %
Safaniya =	65.39 %	Shaybah =	81.04 %
Qatif =	43.60 %	Tanajib =	80.22 %
Khursaniyah =	27.33 %	Abqaiq =	75.09 %
(b) Gas plants			
Berri =	88.96%	Haradh =	73.23%
Khursaniyah =	91.97%	Hawiyah =	76.18%
Shedgum =	72.84%	Juaymah =	100.00%
Uthmaniyah =	45.87%	Wasit =	54.75%
Yanbu =	71.94%		
(c) Fractionation plants			
RasTanura =	18.28%	Hawiyah =	6.76%
Yanbu =	41.00%	Wasit =	0.00%
Juaymah =	20.09%		

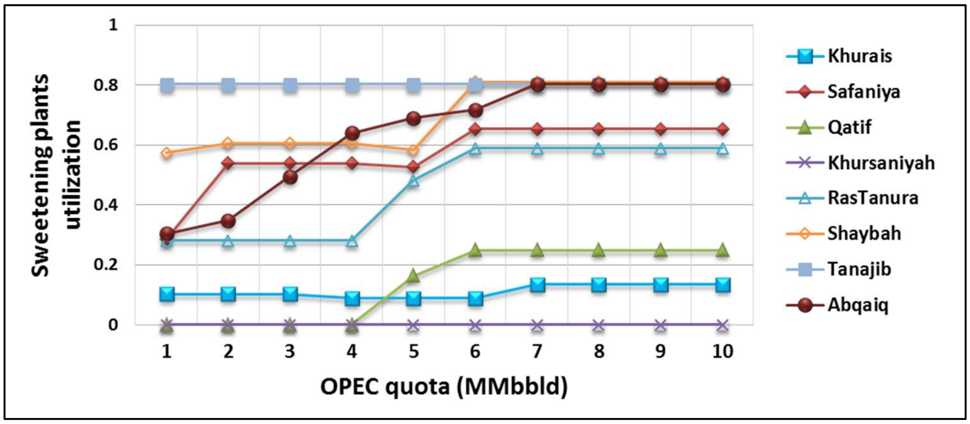
3.4.2 Sensitivity analysis of MOD

Model parameters classified into controlled or uncontrolled (certain or uncertain). The controlled parameters are those that can be handled by the decision maker (e.g., OPEC quota, GOR, CO_2 emission limit), while the uncontrolled parameters cannot be handled (e.g., yield) or change based on the market status (e.g., price and demand). In this section we examine the behavior of the model under different values of selected controlled parameters: OPEC quota and CO_2 emission limit. In addition, the model robustness was investigated against the change in an uncontrolled parameters: crude oil price and crude oil demand.

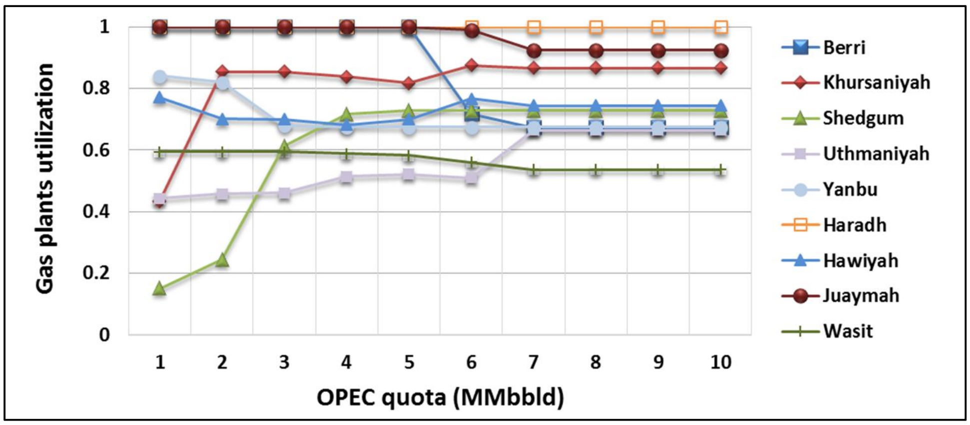
OPEC quota: To investigate the effect of changing OPEC quota on the utilization of the key processing plants, we evaluated the results based on ten levels of the quota; from 1 to 10 MMbbld incrementing by 1.

For the crude oil processing plants (sweetening and stabilization plants) the utilization is increasing as the quota increases until satisfying the demand or reaching the CO_2 emission limit and then becomes constant, as shown in Figure 3.9 (a). Except in Khursaniyah processing plant, which has a fixed utilization set at zero. Khursaniyah feeds oil to the west region and Ju'aymah international terminal. Where, the West region requirements are satisfied from Safaniya and Abqaiq plants, Ju'aymah demand is satisfied from Khurais, Safaniya, and Qatif plants.

Whereas, the utilization of gas plants does not necessarily increase (e.g., Berri gas plant), because as crude oil production increases with the quota, the Kingdom produces enough gas from the associated gas and therefore reduces the production of non-associated gas. However, some gas plants are not connected to GOSPs, therefore, the utilization of gas plants that process the non-associated gas decreases as OPEC quota for oil increases.



(a) Utilization of crude oil processing plants

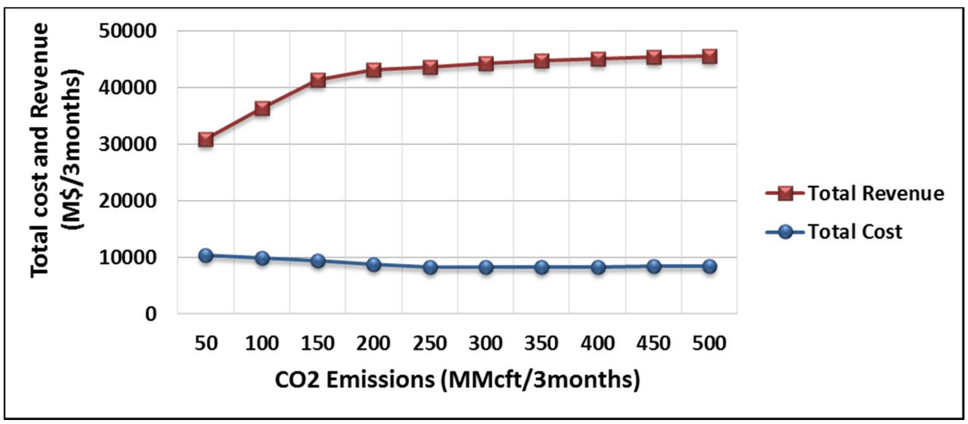


(b) Utilization of gas plants

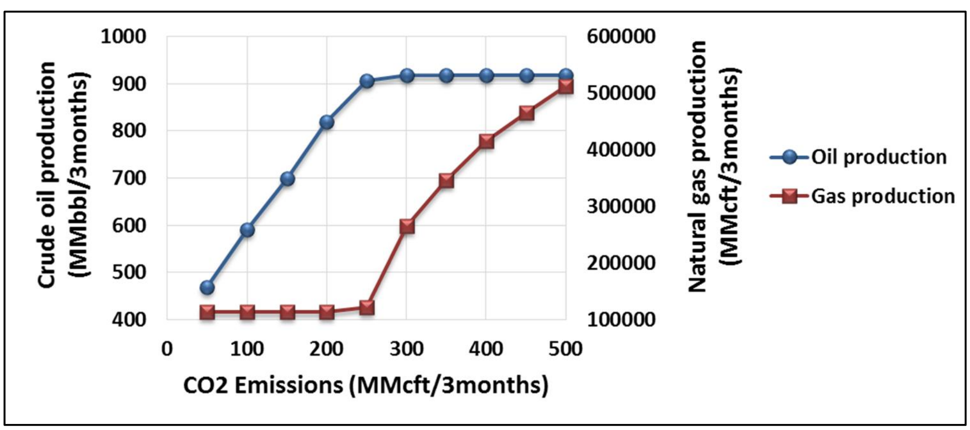
Figure 3.9 Effect of OPEC quota on utilization of key processing plants

CO_2 emission limit: The results obtained from solving the model based on different CO_2 emission limits are shown in Figure 3.10. Figure 3.10 (a) depicts that at low allowable emission levels we have to produce low quantities of both oil and gas. As the emission levels increases, more oil can be produced and hence satisfy gas from the associated gas. At a high levels, we can produce more from the non-associated gas to satisfy the demand within the maximum allowable emission levels.

Figure 3.10 (b) shows the trends of both total cost and total revenue under different CO_2 emission limits. At low emission limits and production (oil and gas) levels the total cost is reaching the highest point as a result of below production penalties. As the production increases penalties decrease and the revenue increases until satisfying the demand and both curves become stable. At 150 MMcft/month of allowable CO_2 emissions, Saudi Arabia can reach the break-even point, and at 250 MMcft/month reach the highest level of profit. At greater levels the increase in profit is almost insignificant.



(a) Oil and gas production levels



(b) total cost and total revenue

Figure 3.10 Effect of CO_2 emission limit

Crude oil price: As the international price increases, the solver increases the production (Figure 3.11) to satisfy the demand to: minimize the below production penalties and maximize the revenue. Intuitively, if the prices decreased, the solver decreases the production and satisfies the demand at under production penalties. Under production penalties, mean it is cheaper to get the products from the international market than producing it domestically; below production penalty less than production cost. But in real situations, the Kingdom have to satisfy the demand to avoid losing the market share even under low prices. ***Crude oil demand:*** The results obtained by altering crude oil demand on oil and gas production levels is shown in Figure 3.12. The dependency of natural gas production on crude oil production is clear, gas production should be increased if oil production is decreased to compensate for the reduction in associated gas supply.

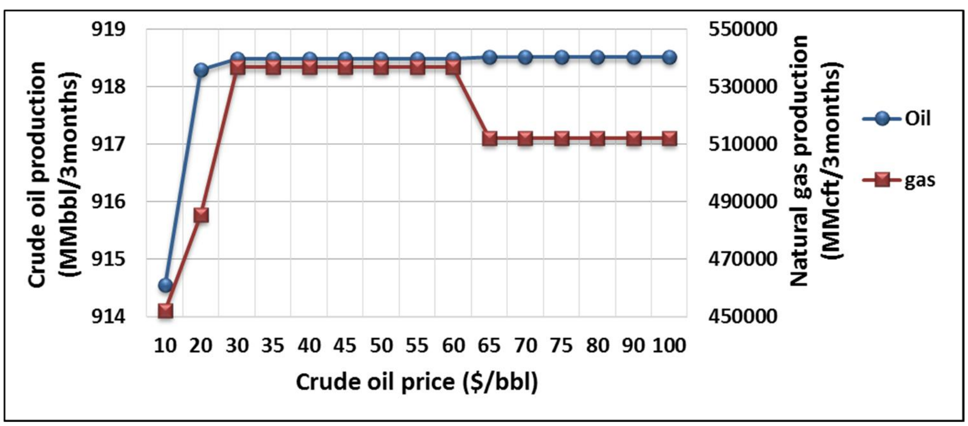


Figure 3.11 Effect of crude oil prices on oil and gas production levels

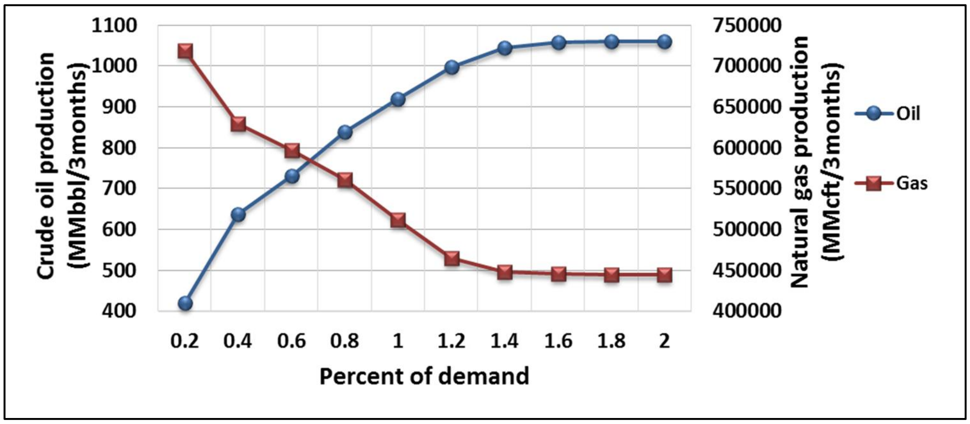


Figure 3.12 Effect of crude oil demand on oil and gas production levels

3.5 Conclusion

In this chapter a deterministic MOO model is presented for tactical planning of crude oil and natural gas products. The proposed model is an attempt to address a gap identified in the literature review. To the best of our knowledge, this work is the first attempt to optimize the HCSC in a multi-objective perspective and in an integrated framework (oil and gas simultaneously). Another aim of this chapter is to study the trade-off among different objectives for the Saudi Arabia HCSC.

The results show that, Saudi Arabia should produce crude oil in a rate higher than 6.96 MMbbld and a gas less than 6,570.46 MMcftd to achieve profit (break-even point). The preferred oil and gas production levels using TOPSIS technique are 10.15 MMbbld and 6,147.24 MMcftd, respectively. At these production levels and under the existing proved reserves the production can continue for 73.38 years. The selected plan costs the Kingdom M$ 11,709.04/3months and returns a cash flow M$ 36,236.58/3months. Regarding this plan, it is recommended for the Kingdom to stop production from the following gas reservoirs: Wudayhi, Shaden, and Mazalij. In addition to make a medium term contracts to compensate for the amount of quantities below the demand. Even with high costs of getting the extra oil or gas byproducts the plan still profitable and can cover all the costs.

Sensitivity analysis was conducted to study the model behavior under different levels of controlled and non-controlled parameters. Under controlled parameters the model perform as expected. While, under uncontrolled parameters the model is not robust against the change, so it is indispensable to use stochastic programming. Although the advantages of the proposed model it has some limitations such as: (1) ignoring the nonlinearity of the recoverable amount from reservoirs, (2) assuming a fixed transportation cost although transportation cost has a nonlinear relation with transported quantity, (3) considering all the transportation done using pipelines which is correct for Saudi Arabia, and (4) disregarding the uncertainty in market behavior. One of the richness of MOO it will provide Pareto-optima solution, known as the efficient set. However, the challenge is to select one solution from the efficient set.

The analysis in the previous section indicates that the model is practical and offers opportunities for deep analysis. Also the model can generate alternative plans and provide the decision maker to conduct a thorough sensitivity analysis in a small amount of time.

CHAPTER 4

MULTI-OBJECTIVE STOCHASTIC MODEL

Model parameters classified into controlled or uncontrolled parameters. Controlled parameters are those that can be handled by the decision maker (e.g., OPEC quota, GOR, CO_2 emission limit), while the uncontrolled parameters cannot be handled (e.g., yield) or change based on the market status (e.g., price and demand).

In real word situations the values of uncontrolled (uncertain) parameters are not known at the start of the planning period. Consequently, the decision maker can take some decisions based on the known values of controlled parameters, then, as the realization of some of uncontrolled parameters became clear, he/she can take a second batch of decisions (recourse decisions). This process continues, decide, realize, decide, realize and so on until all the parameters are realized and all the decisions are taken.

The previous process known as a multi-stage decision making and cannot be modelled by the deterministic formulation. So, SP formulation for the decision making became an appropriate optimization tool. In SP optimization, model parameters are classified based on the type as certain and uncertain parameters, and based on the time period that it became known as first, second, …, n-period. Uncertain parameters can be represented by a plausible number of scenarios (i.e., finite set of realizations) with a corresponding probabilities of occurrence. While the decision variables are classified into a first, second,

…, n-stage decisions sequentially arranged over time. Such that, the decision maker can take a here-and-now decisions (first-stage decisions) and after realizing the values of the uncertain parameters a recourse action can be taken to specify a wait-and-see decisions of subsequent stages.

4.1 Stochastic model formulation

In this study price and demand are considered as uncertain parameters and other parameters are fixed and known. Price is an objective function coefficient and demand is a right hand side of a constraints. The motivation behind price selection because of the dramatic changes happened in the prices of crude oil prices and petroleum by-products.

Over a one period of time all deterministic parameters are known at the beginning, while, uncertain parameters are realized subsequently (two-stage SP). Figure 4.1 depicts first and second stage decisions of the HCSC. Where, production from oil and gas reservoirs should start at the beginning to guaranty satisfying the demand on time. Produced oil and gas (associated and non-associated) are stored in the gathering centers. After that, market scenarios of both price and demand became known. So, sufficient quantities extracted from the gathering centers for further processing, transformation, and distribution. The extraction from gathering centers is known as a recourse or corrective action, where not all the produced quantities are sent for further activities (i.e., quantities as per need based on scenario values).

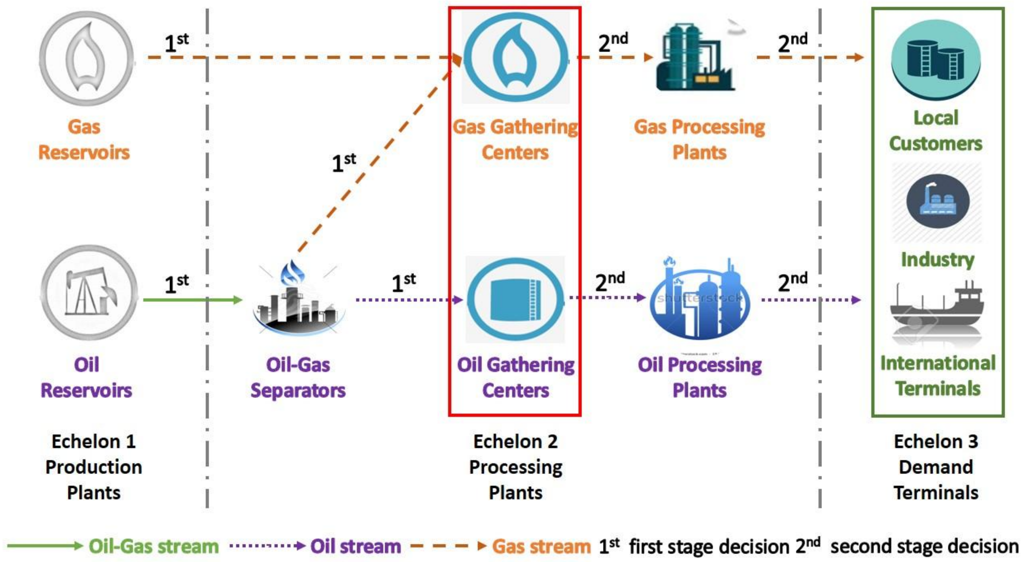


Figure 4.1 1st and 2nd stage decisions of the HCSC

The classical representation of the two stage SP model is as follows, first proposed by Dantzig (1955), the following formulation from Conejo et al. (2010):

$$Minimize_x \; z = c^T x + \varepsilon\{Q(\omega)\} \tag{4.1}$$

$$subject\ to \;\; Ax = b \tag{4.2}$$

$$x \in X \tag{4.3}$$

$$where$$

$$Q(\omega) = \{minimize_{y(\omega)} \; q(\omega)^T y(\omega) \tag{4.4}$$

$$subject\ to \;\; T(\omega)\, x + W(\omega) y(\omega) = h(\omega) \tag{4.5}$$

$$y(\omega) \in Y\}, \omega \in \Omega \tag{4.6}$$

Where x and $y(\omega)$ first- and second- stage decisions, ω scenario number, $\varepsilon\{Q(\omega)\}$ expected value of the second-stage decisions. The deterministic equivalent of the above formulation after a rearrangement is as follows:

$$Minimize_{x,y(\omega)}\ z = c^T x + \sum_{\omega \in \Omega} \pi(\omega) q(\omega)^T y(\omega) \tag{4.7}$$

$$subject\ to\ \ Ax = b \tag{4.8}$$

$$T(\omega)\,x + W(\omega) y(\omega) = h(\omega), \omega \in \Omega \tag{4.9}$$

$$x \in X, y(\omega) \in Y, \omega \in \Omega \tag{4.10}$$

4.1.1 Stochastic model notations

The same notations utilized in formulating the MOD are used in formulating the MOS with the addition of scenario data (number and probability of each scenario) and decision variables classification (first and second stage decisions). Table 4.1 list the notations used for formulating the MOS model.

Table 4.1 Notations of the MOS model

1. Sets/Indices:		
i, j	:	all nodes.
ro, rg	:	set of (oil, gas) reservoirs; i.e., production areas.

n : set of GOSPs.

go, gg : set of (oil, gas) gathering centers.

po, pg : set of (oil, gas) processing plants.

do, dg : set of (oil, gas) demand terminals.

$loco, locg$: subset of (do, dg); represents (oil, gas) local depots.

$indo, indg$: subset of (do, dg); represents (oil, gas) industrial complexes.

$into, intg$: subset of (do, dg); represents (oil, gas) international terminals.

t : set of time periods.

Ω : set of scenarios

ω : scenario number; scenario index

$\pi(\omega)$: probability of scenario ω

o : set of crude oil types; e.g., *AH, AM, AL, and AXL*.

g : set of natural gas byproducts; includes subsets: *gn* natural gas, *gp* gas byproducts produced at processing plants, H_2S and CO_2.

2. Decision Variables:

2.1. First stage decisions:

x_{ijt}^{1o}	:	amount of crude oil of type *o* produced in time period *t* transported from node *i* to node *j*; where $(i,j) \in (ro,n),(n,go)$.
y_{ijt}^{1g}	:	amount of natural gas of type *g* produced in time period *t* transported from node *i* to node *j*; where $(i,j) \in (rg,gg),(n,gg)$.
D	:	Depletion rate of the reserves (i.e., crude oil and gas)

2.2. Second stage decisions:

$x_{ij\omega t}^{2o}$	:	amount of crude oil of type *o* produced in time period *t* under scenario ω transported from node *i* to node *j*; where $(i,j) \in (go,po),(po,do)$.
$y_{ij\omega t}^{2g}$	:	amount of natural gas of type *g* produced in time period *t* under scenario ω transported from node *i* to node *j*; where $(i,j) \in (gg,pg),(pg,dg)$.
$x_{j\omega t}^{2o+}, x_{j\omega t}^{2o-}$	:	oil production of type *o* in time period *t* under scenario ω above and below the requirement at node *j*; where $j \in go, do$.
$y_{j\omega t}^{2g+}, y_{j\omega t}^{2g-}$	:	gas production of product g in time period *t* under scenario ω above and below the requirement at node *j*; where j $\in gg, dg$.

3. Parameters:

3.1. Yield parameters:

GOR_{ijt}^{o}	:	Gas-oil ratio of crude oil type *o* produced during time period *t* from reservoir *i* linked to GOSP *j*; where $(i,j) \in (ro,n)$.

P_{ijt}^{o} : yield of crude oil of type *o* liberated during time period *t* at node *i* transported to node *j*; where $(i,j) \in (ro,n),(go,po)$.

P_{ijt}^{g} : yield of gas product *g* obtained during time period *t* at node *i* transported to node *j*; where $(i,j) \in (gg,pg)$.

3.2. Capacity parameters:

C_j^o : capacity of node *j* for crude oil *o*; where $j \in n, go, po, do$.

C_j^g : capacity of node *j* for gas product g; where $j \in gg, pg, dg$.

c_{ij}^o : capacity of the route linking node *i* to node *j* of crude oil *o*;

where $(i,j) \in (ro,n),(n,go),(go,po),(po,do)$.

c_{ij}^g : capacity of the route linking node *i* to node *j* for gas product *g*;

where $(i,j) \in (rg,gg),(n,gg),(gg,pg),(pg,dg)$.

3.3. Volume parameters:

R_i^o : amount of reserves in reservoir at node *i* for oil type *o*; where $i \in ro$.

R_i^g : amount of reserves in reservoir at node *i* for gas *g*; where $i \in rg$.

C_{max} : maximum amount of CO_2 to be emitted to the environment in time period *t*.

$OPECQ$: OPEC quota or market share per planning time period *t*.

3.4. Cost parameters:

ec_{ijt}^{o} : production cost per unit of stream x_{ijt}^{1o}, at node *i* during time period *t*; where $(i,j) \in (ro,n)$.

ec_{ijt}^{g} : production cost per unit of stream y_{ijt}^{1g}, at node *i* during time period *t*; where $(i,j) \in (rg,gg)$.

pc_{ijt}^{o} : processing cost per unit of stream x_{ijt}^{1o} and $x_{ij\omega t}^{2o}$, at node *j* during time period *t*; where $(i,j) \in (ro,n),(go,po)$.

pc_{ijt}^{g} : processing cost per unit of stream y_{ijt}^{1g} and $y_{ij\omega t}^{2g}$, at node *j* during time period *t*; where $(i,j) \in (gg,pg)$.

tc_{ijt}^{o} : transportation cost per unit of stream x_{ijt}^{1o} and $x_{ij\omega t}^{2o}$, from node *i* to node *j* during time period *t*;

where $(i,j) \in (ro,n),(n,go),(go,po),(\mathrm{po},\mathrm{do})$.

tc_{ijt}^{g} : transportation cost per unit of stream y_{ijt}^{1g} and $y_{ij\omega t}^{2g}$, from node *i* to node *j* during time period *t*;

where $(i,j) \in (rg,gg),(n,gg),(gg,\ pg),(pg,dg)$.

c_{jt}^{g} : cost per unit of emitting Carbon Dioxide to environment at plant *i* during time period *t*; where $j \in pg$

$w_{j\omega t}^{o+}, w_{j\omega t}^{o-}$: penalty cost per unit for producing crude oil of type *o* above or below the specified demand at node *j* during time period *t*; $where\ j \in go, do$.

$w_{j\omega t}^{g+}, w_{j\omega t}^{g-}$: penalty cost per unit for producing gas product *g* above or below the specified demand at node *j* during time period *t*; $where\ j \in gg, dg$.

3.5. Demand and prices parameters:

$d_{j\omega t}^{o}$: demand at destination *j* for crude oil of type *o* under scenario ω in time period *t*; where $j \in do$.

$d_{j\omega t}^{g}$: demand at destination *j* for gas product *g* under scenario ω in time period *t*; where $j \in dg$.

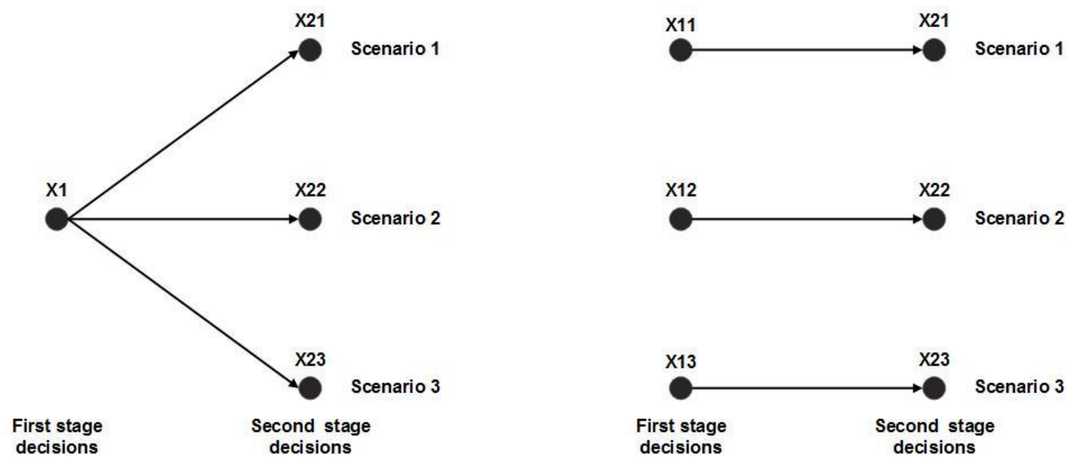
$pr_{j\omega t}^{o}$: selling price per unit of crude oil type *o* during time period *t* under scenario ω at demand node *j*; where $j \in do$.

$pr_{j\omega t}^{g}$: Selling price per unit of gas products *g* during time period *t* under scenario ω at demand node *j*; where $j \in dg$.

dr : Discount rate per period *t*.

4.1.2 Stochastic model constraints

Constraints and objective functions in SP are formulated mathematically based on node-variable formulation or scenario-variable formulation (Conejo et al., 2010), as represented in Figure 4.2. Number of decision variables depends on number of decision points in node-variable formulation and depends on number of scenarios in scenario-based formulation. Node-variable formulation generates a compact model and utilizes the recent advances in commercial software in solving optimization models without decomposition. While, scenario-based formulation generates a relatively larger models but the models are naturally decomposed. In this work node-variable formulation has been used.



(a) Node-variable formulation **(b) Scenario-variable formulation**

Figure 4.2 SP formulation methods

In formulating the MOS model same sets of linear constraints used in the MOD model has been considered. MOD model constraints was modified by considering scenarios of uncertain parameters and first- and second-stage decision variables. Set of constraints are: material balance, plant capacity, route capacity, demand, OPEC quota, carbon dioxide emission, sustainability, and non-negativity.

Material balance constraints: Eqs. (4.11) and (4.12) represents the mass balance for crude oil and associated-gas separated at GOSPs, respectively. The input and output streams are a first-stage decisions. The material balance at the processing plants for oil and gas represented by Eqs. (4.14) and (4.15), and Eq. (4.17) for oil and gas, respectively. While, Eqs. (4.13) and (4.16) balances the material at the gathering centers.

$$\sum_{i \in ro} P_{ijt}^{o}\, x_{ijt}^{1o} = \sum_{i \in go} x_{jit}^{1o} \qquad \forall o, \qquad \forall j \in n \tag{4.11}$$

$$\sum_{i \in ro} GOR_{ijt}^{o}\, x_{ijt}^{1o} = \sum_{i \in gg} y_{jit}^{1g} \qquad \forall o, \qquad \forall\, j \in n \tag{4.12}$$

$$\sum_{i \in n} x_{ijt}^{1o} + x_{j\omega t-1}^{2o+} = \sum_{i \in po} x_{ji\omega t}^{2o} + x_{j\omega t}^{2o+} \qquad \forall o, \qquad \forall j \in go, \qquad \forall \omega \tag{4.13}$$

$$\sum_{i \in go} P_{ij}^{o}\, x_{ij\omega t}^{2o} = \sum_{i \in do} x_{ji\omega t}^{2o} \qquad \forall o, \qquad \forall j \in po, \qquad \forall \omega \tag{4.14}$$

$$\sum_{i \in go} P_{ij}^{o}\, x_{ij\omega t}^{2o} = \sum_{g \in H2S;\, i \in dg} y_{ji\omega t}^{2g} \qquad \forall o, \qquad \forall j \in po, \qquad \forall \omega \tag{4.15}$$

$$\sum_{i \in rg} y_{ijt}^{1g} + \sum_{i \in n} y_{ijt}^{1g} + y_{j\omega t-1}^{2g+} = \sum_{i \in pg} y_{ji\omega t}^{2g} + y_{j\omega t}^{2g+} \qquad \forall g, \qquad \forall j \in gg, \qquad \forall \omega \tag{4.16}$$

$$\sum_{i \in gg} P_{ijt}^{g} y_{ij\omega t}^{2g} = \sum_{i \in dg} y_{ij\omega t}^{2g} \qquad \forall g, \qquad \forall j \in pg, \qquad \forall \omega \tag{4.17}$$

Plant capacity Constraints: Eqs. (4.18) - (4.21) represents the maximum processing capacity of oil plants: reservoirs, GOSPs, gathering centers, processing plants, and demand terminals, respectively. Eqs. (4.22), (4.23), and (4.24) models the capacity of gas plants. ***Route Capacity Constraints*** for all products and routes are represented in Eqs. (4.25) and (4.27) for first-stage decisions and Eqs. (4.26) and (4.28) for second-stage decisions.

$$\sum_{i \in ro} p^{o}_{ijt} x^{1o}_{ijt} \leq C^{o}_{j} \qquad \forall o, \qquad \forall\, j \in n \tag{4.18}$$

$$\sum_{i \in n} x^{1o}_{ijt} + x^{2o+}_{j\omega t-1} \leq C^{o}_{j} \qquad \forall o, \qquad \forall\, j \in go, \qquad \forall \omega \tag{4.19}$$

$$\sum_{i \in go} p^{o}_{ijt} x^{2o}_{ij\omega t} \leq C^{o}_{j} \qquad \forall o, \qquad \forall\, j \in po, \qquad \forall \omega \tag{4.20}$$

$$\sum_{i \in po} x^{2o}_{ij\omega t} + x^{2o+}_{j\omega t-1} \leq C^{o}_{j} \qquad \forall o, \qquad \forall\, j \in do, \qquad \forall \omega \tag{4.21}$$

$$\sum_{i \in rg} y^{1g}_{ijt} + \sum_{i \in n} y^{1g}_{ijt} + y^{2g+}_{j\omega t-1} \leq C^{g}_{j} \qquad \forall g, \qquad \forall\, j \in gg, \qquad \forall \omega \tag{4.22}$$

$$\sum_{i \in gg} p^{g}_{ijt} y^{2g}_{ij\omega t} \leq C^{g}_{j} \qquad \forall g, \qquad \forall\, j \in pg, \qquad \forall \omega \tag{4.23}$$

$$\sum_{i \in pg} y^{2g}_{ij\omega t} + y^{2g+}_{j\omega t-1} \leq C^{g}_{j} \qquad \forall g, \qquad \forall\, j \in dg, \qquad \forall \omega \tag{4.24}$$

$$x^{1o}_{ijt} \leq\ c^{o}_{ij} \qquad \forall\, o, \qquad \forall (i,j) \in (ro,n),(n,go) \tag{4.25}$$

$$x_{ij\omega t}^{2o} \leq c_{ij}^{o} \qquad \forall o, \qquad \forall (i,j) \in (go,po),(po,do), \qquad \forall \omega \tag{4.26}$$

$$y_{ijt}^{1g} \leq c_{ij}^{g} \qquad \forall g, \qquad \forall (i,j) \in (rg,gg) \tag{4.27}$$

$$y_{ij\omega t}^{2g} \leq c_{ij}^{g} \qquad \forall g, \qquad \forall (i,j) \in (gg,pg),(pg,dg), \qquad \forall \omega \tag{4.28}$$

Demand constraints: Eqs. (4.29) and (4.30). ***OPEC quota:*** Eq. (4.31), and ***environmental regulations constraints:*** Eq. (4.32) based on a second-stage decisions. ***Sustainability constraints:*** Eqs. (4.33) and (4.34) depends on first-stage decisions. Eventually, ***non-negativity constraints:*** Eqs. (4.35).

$$\sum_{i \in po} x_{ij\omega t}^{2o} - x_{j\omega t}^{2o+} + x_{j\omega t}^{2o-} = d_{j\omega t}^{o} - x_{j\omega t-1}^{2o+} \qquad \forall o, \qquad \forall j \in do, \qquad \forall \omega \tag{4.29}$$

$$\sum_{i \in pg} y_{ij\omega t}^{2g} - y_{j\omega t}^{2g+} + y_{j\omega t}^{2g-} = d_{j\omega t}^{g} - y_{j\omega t-1}^{2g+} \qquad \forall g, \qquad \forall j \in dg, \qquad \forall \omega \tag{4.30}$$

$$\sum_{o,i \in po,j \in into} x_{ij\omega t}^{2o} + \sum_{o;j \in into} x_{jt-1}^{o+} \leq OPECQ \qquad \forall \omega \tag{4.31}$$

$$\sum_{g \in CO2;j \in pg} y_{j\omega t}^{2g} \leq C_{max} \qquad \forall \omega \tag{4.32}$$

$$\frac{\sum_{i \in ro,j \in n} x_{ijt}^{1o}}{\sum_{c,i \in ro} R_{it}^{o}} \leq D \tag{4.33}$$

$$\frac{\sum_{i\in rg,j\in gg} y_{ijt}^{1g}}{\sum_{g,i\in rg} R_{it}^{g}} \leq D \tag{4.34}$$

$$x_{ijt}^{1o}, x_{ij\omega t}^{2o}, x_{j\omega t}^{2o+}, x_{j\omega t}^{2o-}, y_{ijt}^{2g}, y_{ij\omega t}^{2g}, y_{j\omega t}^{2g+}, y_{j\omega t}^{2g-}, D \geq 0 \tag{4.35}$$

4.1.3 Stochastic model objective functions

Applying the formulation of Eq. (4.7) to the objective functions Eqs. (3.24), (3.25), and (3.26) results stochastic objective functions Eqs. (4.36), (4.37), and (4.38).

$$Minimize\ Total\ Cost = \sum_{t}(1+dr)^{-(t-1)} \tag{4.36}$$

$$\left[\sum_{o,(i,j)\in(ro,n)} ec_{ijt}^{o}\, x_{ijt}^{1o} + \sum_{g,(i,j)\in(rg,gg)} ec_{ijt}^{g}\ y_{ijt}^{1g}\right.$$

$$+ \sum_{o,(i,j)\in(ro,n)} tc_{ijt}^{o}\, x_{ijt}^{1o} + \sum_{g,(i,j)\in(rg,gg)} tc_{ijt}^{g}\ y_{ijt}^{1g}$$

$$+ \sum_{o,(i,j)\in(ro,n)} pc_{ijt}^{o}\, x_{ijt}^{1o}$$

$$+ \sum_{\omega} \pi_{\omega} \left(\sum_{o,(i,j)\in(go,po)} pc_{ijt}^{o}\, x_{ij\omega t}^{2o} + \sum_{g,(i,j)\in(gg,pg)} pc_{ijt}^{g}\ y_{ij\omega t}^{2g} \right.$$

$$+\sum_{o,(i,j)\in(n,po),(po,do)} tc_{ijt}^{o}\, x_{ij\omega t}^{2o} + \sum_{g,(i,j)\in(gg,pg),(pg,dg)} tc_{ijt}^{g}\, y_{ij\omega t}^{2g}$$

$$+\sum_{o,j\in(go,do)} \left(w_{j\omega}^{o+} x_{j\omega t}^{2o+} + w_{j\omega}^{o-} x_{j\omega t}^{2o-}\right) + \sum_{g,j\in(gg,dg)} \left(w_{j\omega}^{g+} y_{j\omega t}^{2g+} + w_{j\omega}^{g-} y_{j\omega t}^{2g-}\right)$$

$$\left. \left. + \sum_{g\in CO2;\, j\in pg} c_{it}^{g} y_{j\omega t}^{2g} \right) \right]$$

maximize $Revenue =$ (4.37)

$$\sum_{t} (1+dr)^{-(t-1)} \left[\sum_{\omega} \pi_{\omega} \left(\sum_{o,(i,j)\in(po,do)} pr_{j\omega t}^{o} \left(x_{ij\omega t}^{2o} - x_{j\omega t}^{2o+}\right) \right. \right.$$

$$\left. \left. + \sum_{g,(i,j)\in(pg,dg)} pr_{j\omega t}^{g} \left(y_{ij\omega t}^{2g} - y_{j\omega t}^{2g+}\right) \right) \right]$$

minimize D (4.38)

4.2 Applied case study: MOS model

International prices and domestic demands are considered as uncertain parameters in optimizing Saudi Arabia HCSC. Three levels of each uncertain parameter was considered: high, base, and low with a corresponding probability for each level: 0.25, 0.50, and 0.25. Where, high and low are 1.20 and 0.80 of the base level. In scenarios construction, the combination between price and demand levels was considered, Figure 4.3 summarizes the scenario tree. Assuming independency between the realizations of the uncertain parameters to get the joint probability for the 9 scenarios.

Uncertain parameters were selected based on market behavior and consistency with the HCSC literature (see the 5th column of Table 2.1). The above assumptions of scenarios construction (i.e., probabilities and independency) are in the same line with the literature (Al-Othman et al., 2008; Khor et al., 2008; Ribas et al., 2010; Ribas et al., 2011).

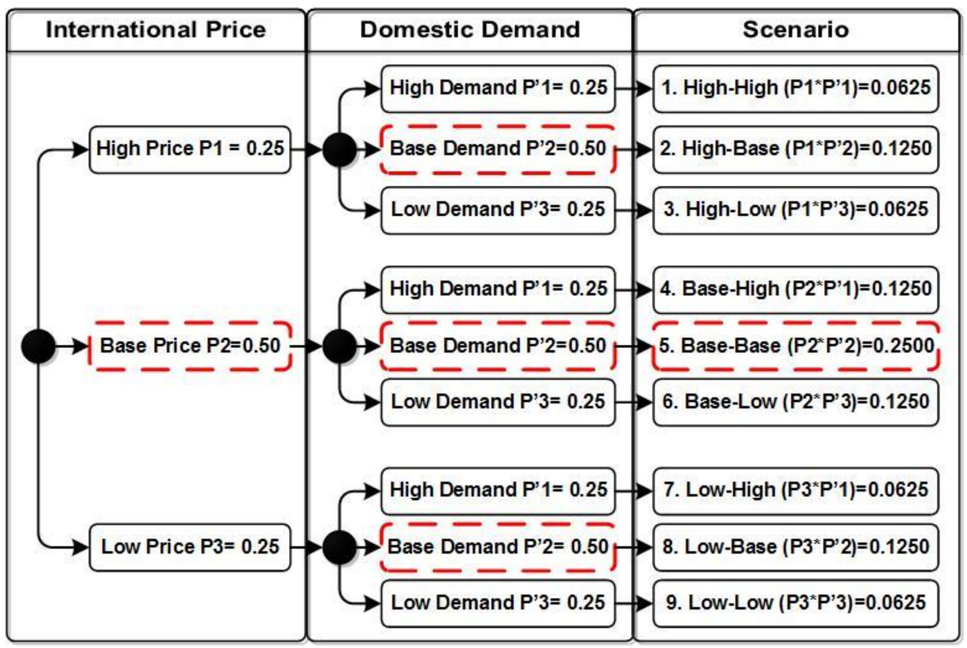


Figure 4.3 Scenario construction for the MOS model

Full dependency between scenarios during the planning period was assumed. In other words, if the first period was high price – high demand the subsequent periods will be same for short planning periods. This assumption has been validated using historical records of OPEC basket price of crude oil during 171 month starting from January 2003 to May 2017

("OPEC : OPEC Basket Price," n.d.). Table 4. 2 show that the average increase and decrease in oil price from month to the next are 3.97% and 3.38%, respectively, which less than 20% that assumed in scenario construction.

Table 4. 2 Statistics regarding crude oil OPEC basket price

Study period :	from 02//01/2003 to 11/05/2017
Total number of months:	171 months
Months with change over 20%:	8 months
Average change in oil price:	0.59 %
Average increase in oil price:	3.97 %
Average decrease in oil price:	-3.38 %

The decision variables are classified as a first- or second-stage decisions based on whether the decision has to be taken before or after the realization of the uncertainty (i.e., the recognition of the scenarios). First-stage decisions are the amount of production from oil and gas reservoirs, amount of production from GOSPs, and transported quantities to gathering centers (see Figure 4.1). Any decision other than the ones mentioned is a second stage. The existence of gathering centers assist in compensating for the differences between scenarios; help in taking a correction action for the second stage decisions. Figure 4.4 depicts the compliance between Figure 4.1 and the Kingdom network.

4.2.1 Numerical results of MOS

Table 4.3 summarizes the MOS model statistics result from using the same conditions that has been used for MOD model; program, solver, and number of planning periods. The payoff matrix listed in Table 4.4 show that the minimum total cost based on MOS higher than that of MOD, in the same line the maximum revenue is lesser. The worst case of sustainability of MOD is better than of MOS.

Table 4.3 MOS model statistics

Blocks of Equations	94	Single Equations	12,084
Blocks of Variables	47	Single Variables	10,880
Non Zero Elements	65,591		

Table 4.4 Pay-off matrix of MOS model applying lexicographic optimization

	Total Cost (M$/month)	Total Revenue (M$/month)	Depletion Rate	Sustainability (Years)
Minimizing Total Cost	***13,224.94***	35,215.28	0.0011825206	70.47
Maximizing Total Revenue	13,973.4	***35,656.8***	0.0011772191	70.79
Minimizing Depletion Rate	31,602.43	22,097.68	***0.0006752586***	***123.41***

Regarding the total cost, the solver produces quantities from reservoirs that compromises between production cost, processing cost, transportation cost, and penalty of producing above requirements (cost that increases with production) and penalty of below production (cost that decreases with production). According to scenarios, there are cases with above and below the base of prices and demand which increases the penalties (increases the expected total costs of scenario based terms).

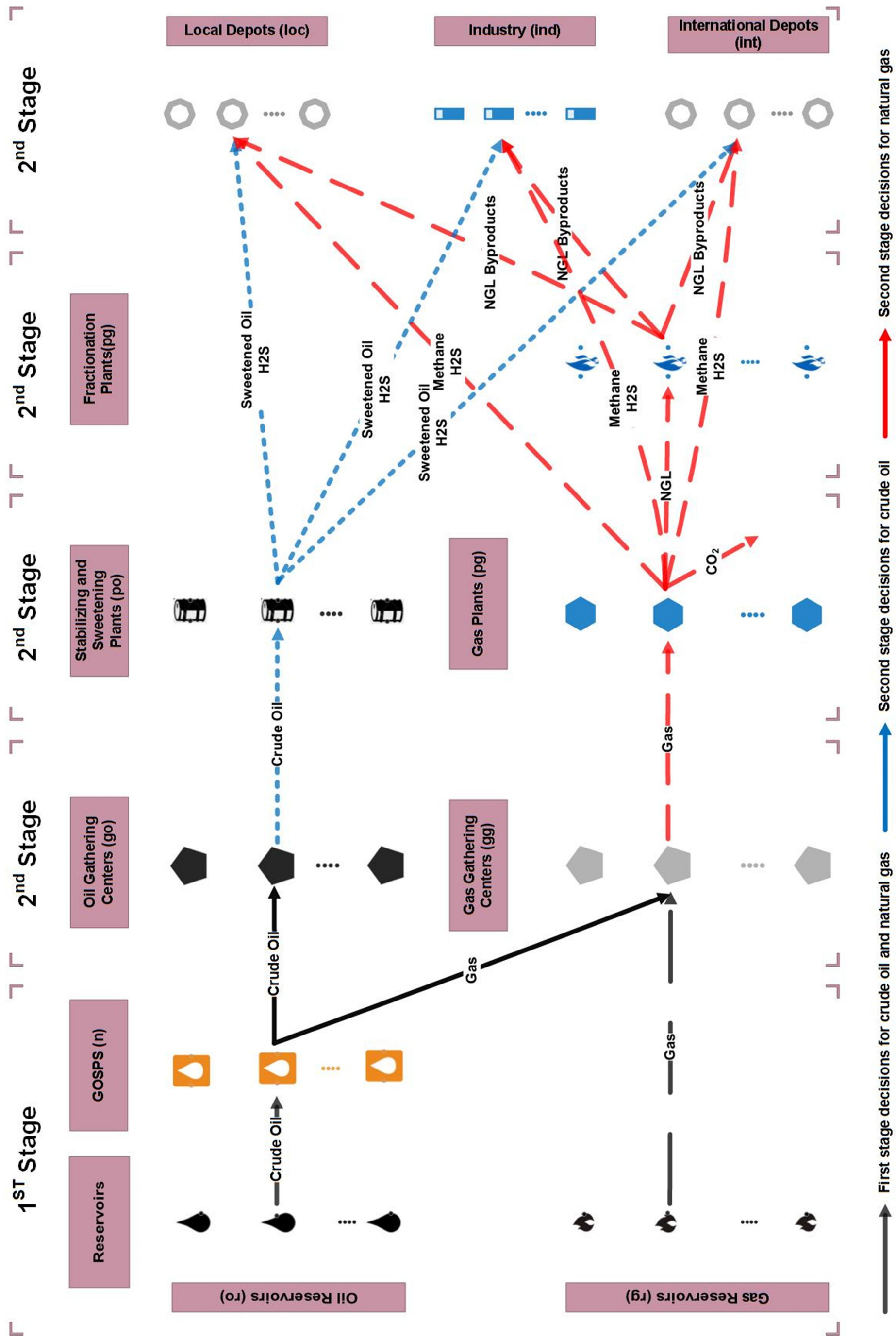


Figure 4.4 MOS network of Saudi Arabia HCSC

Clearly from Figure 4.5 Pareto-optima surface result from solving the stochastic model has the same topology as the one that produced from the deterministic model (see Figure 3.4). In other words, the trade-off between total cost, revenue, and depletion rate is same based on deterministic or stochastic models. Likewise, the correlation between crude oil and natural gas productions versus profit (Figure 4.6). The break-even production of oil is 7.23 MMbbld and of gas is 3,562.05 MMcftd. So, to achieve profit the kingdom should produce more of crude oil and less of natural gas than the break-even.

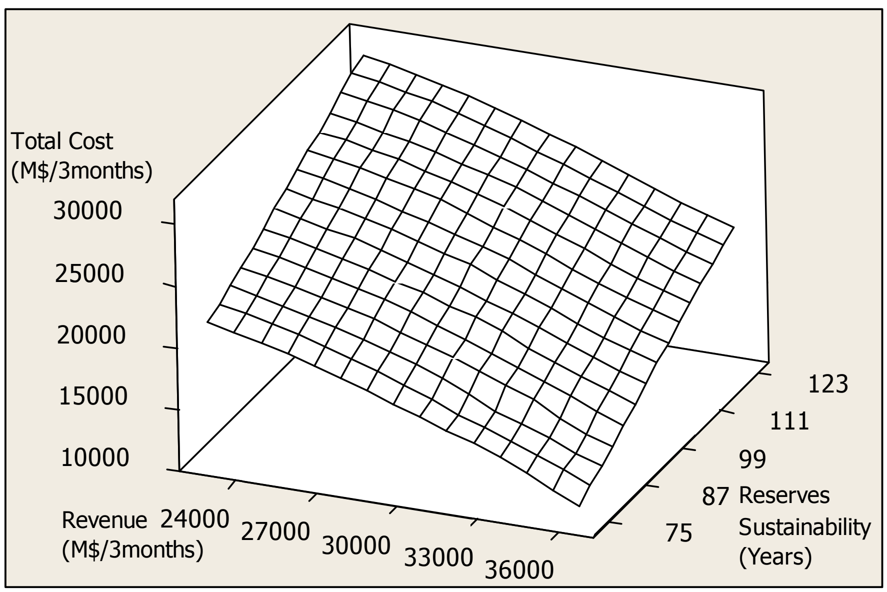


Figure 4.5 Efficient Pareto-optima surface of MOS model

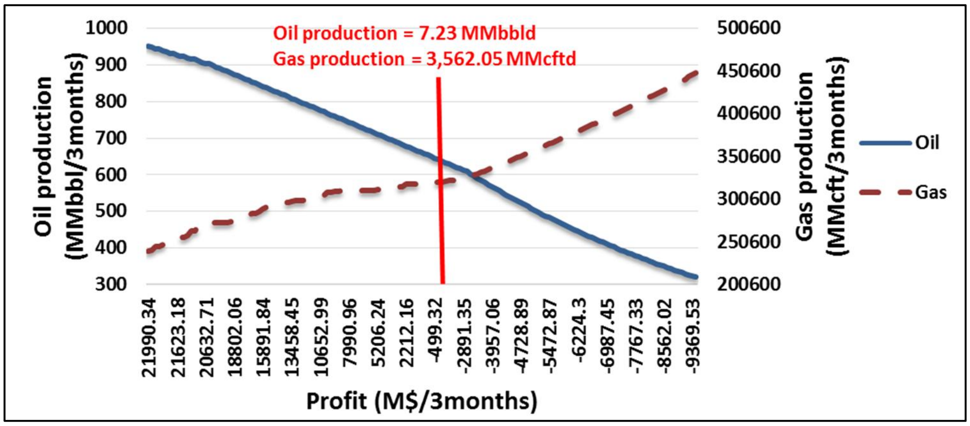


Figure 4.6 Relation between oil production, gas production, and profit of MOS model

From the set of Pareto-optima the preferred tactical plan were chosen using TOPSIS technique based on equally weighted objectives. The values of the objective functions, quantity of oil production, and quantity of gas production are listed in Table 4.5. Comparing MOD and MOS preferred plans, considering the uncertainty of market parameters require a decrease in oil production and a cut in gas production to almost the half. MOS model provide a plan with higher cost, lower revenue, and higher sustainability. The differences highlight that the deterministic models give misleading plans (i.e., different cost and cash flows).

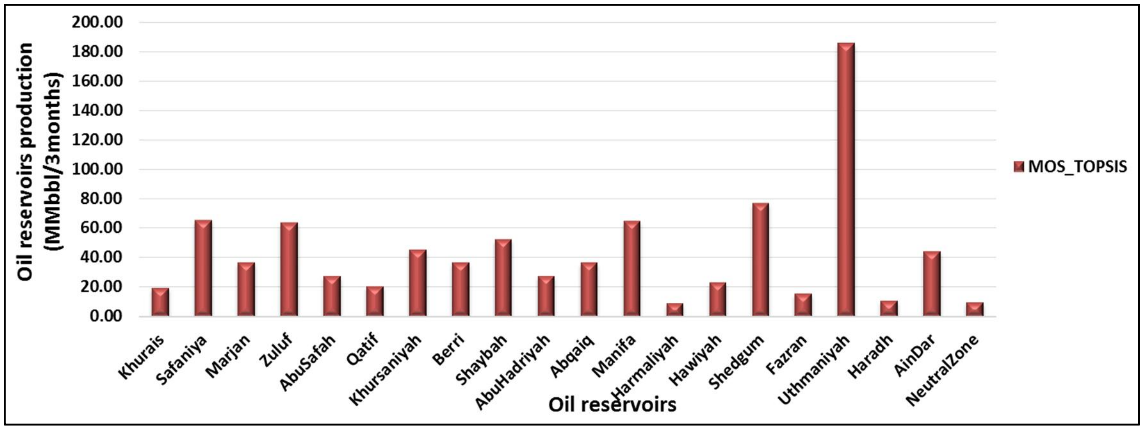
Table 4.5 Preferred plan from the MOS model

Total cost =	M$ 15,155.47/3months	Oil production =	869.99	MMbbl/3months
Revenue =	M$ 33,706.03/3months		9.67	MMbbld
Profit =	M$ 18,550.56/3months	Gas production =	275,062.99	MMcft/3months
Depletion rate =	0.00108107		3,056.26	MMcftd
Sustainability =	77.08 year			

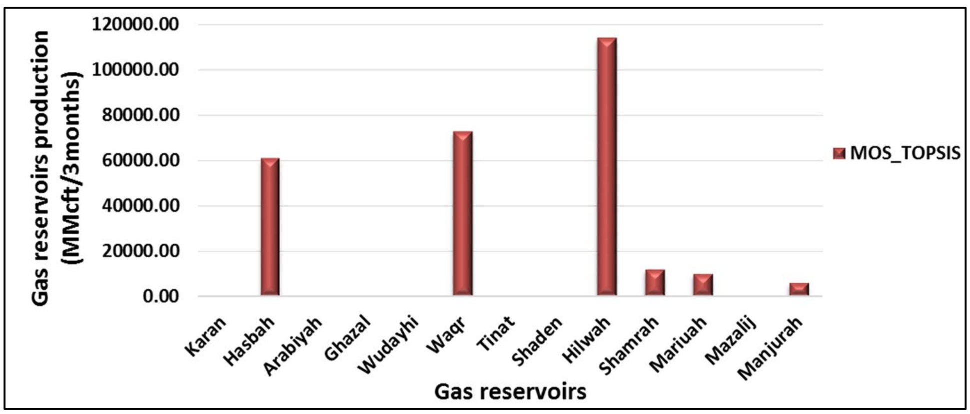
The presence of low demand scenarios reduces the production levels developed from the MOS model below MOD levels. The production profile of first stage decisions is shown in Figure 4.7 (a and b) for crude oil and natural gas reservoirs, respectively. Planning under the stochastic model keeps more reserves of natural gas for future generations. In other words, the Kingdom produce more oil to achieve high revenues and get the required gas from the international market. Crude oil production allocated to reservoirs with high amount of reserves; for instance, based on MOS model Uthmaniyah reservoir has 15.04% of reserves and constitutes 17.70% of total production. So, the production is allocated to reservoirs with high amount of reserves not the GOR.

To increase crude oil quantities the production from the following reservoirs should be increased (MMbbl/3months): Khurais (7.28), Khursaniyah (29.23), Manifa (10.19), and Uthmaniyah (31.65). In the same time, the production from the following reserviors should be decreased: Safaniya (7.81), Shaybah (7.68), Hawiyah (20.67), Haradh (20.40), AinDar (48.44), and NeutralZone (18.00).

To decrease natural gas quantities the production from the following reservoirs should be decreased (MMcft/3months): Karan (30,429.28), Hasbah (60,261.76), Arabiyah (3,518.34), Ghazal (5,981.41), Tinat (15,466.00), Shamrah (84,087.16), and Manjurah (84931.60). In addtition, the production from Mariuah reservior need to increase by 6,487.14 MMcft/3months.



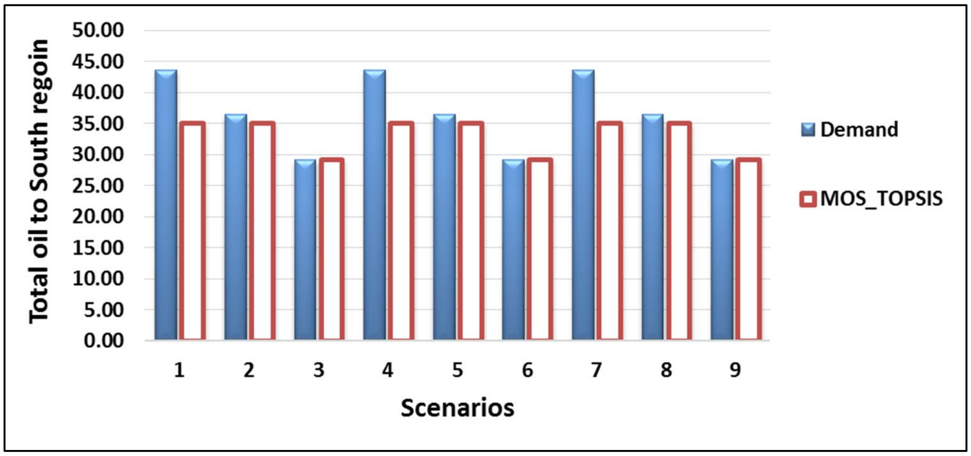
(a) Production profile for oil reservoirs



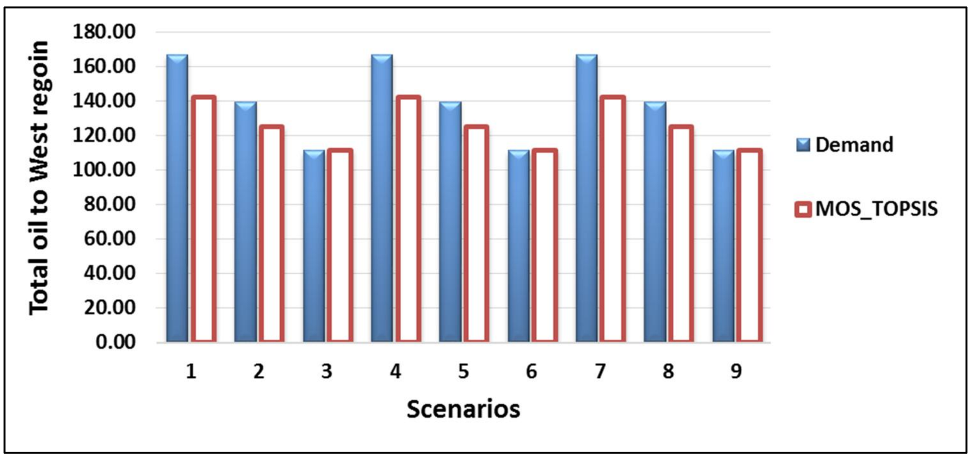
(b) Production profile for gas reservoirs

Figure 4.7 Production profile from oil and gas reservoirs based on MOD & MOS

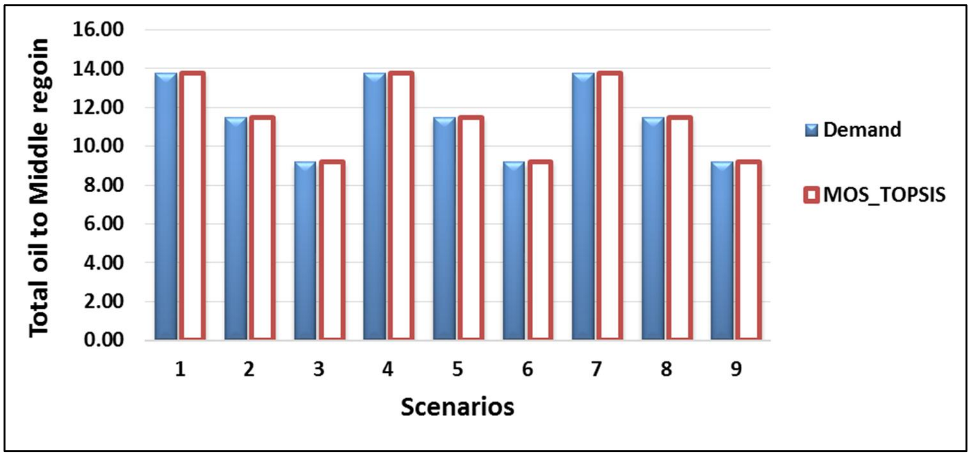
Analyzing the behavior of the proposed plan at the demand terminals, Figure 4.8 and Figure 4.9 depict the differences between solutions from MOD (applied for each scenario) and MOS models versus the demand per scenario at local and international terminals for crude oil, respectively. The production from reservoirs and the consumption at gathering centers cannot satisfy the demand of high and base demand scenarios at South, West, and East regions, Figure 4.8 (a, b, and d). Even if the amount of crude oil sent to the local regions is high for high demand scenarios. While all the demand can be satisfied at the Middle regions, Figure 4.8 (c). The reason behind this is the consideration of reserves sustainability.



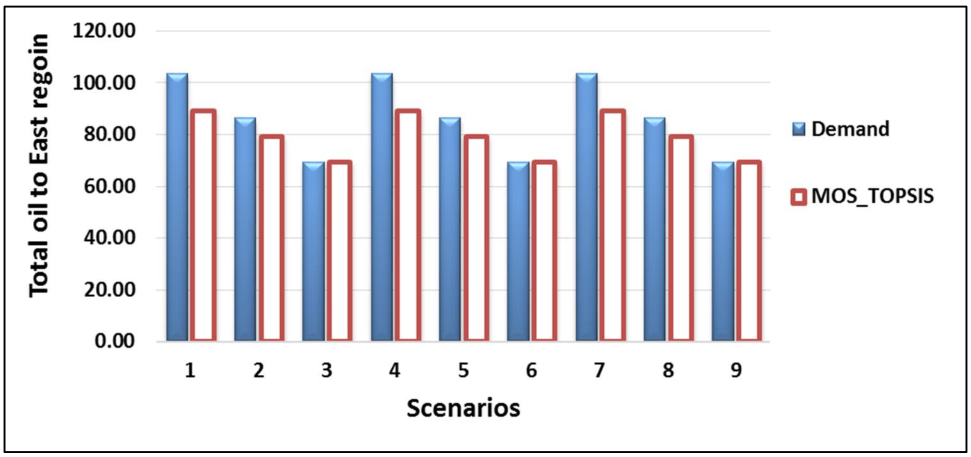
(a) Total oil sent to South region based on scenarios



(b) Total oil sent to West region based on scenarios



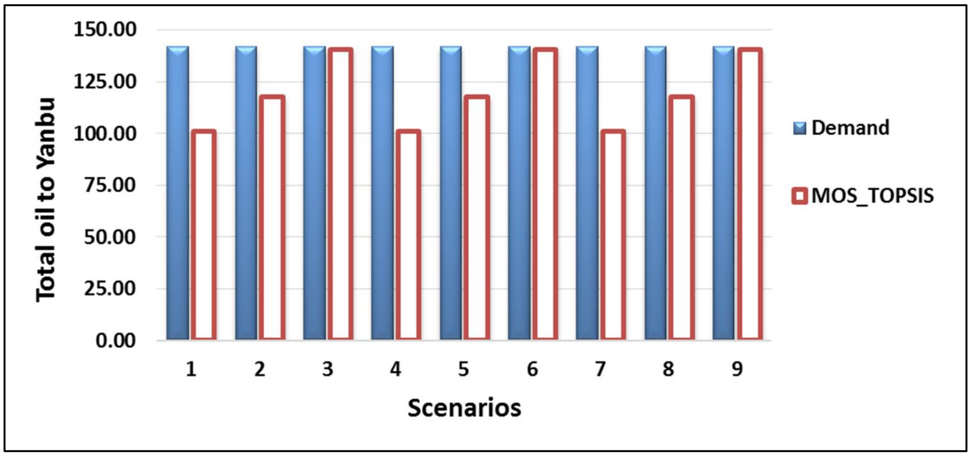
(c) Total oil sent to Middle region based on scenarios



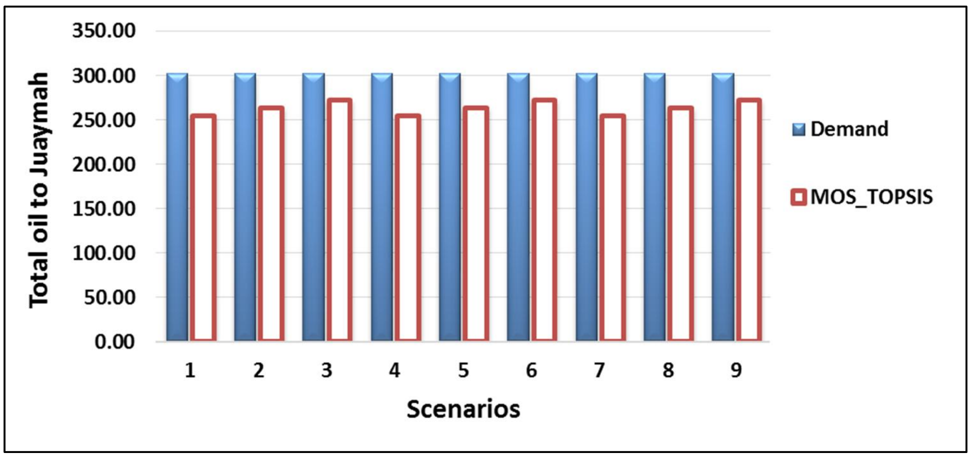
(d) Total oil sent to East region based on scenarios

Figure 4.8 Total oil sent to local regions based on MOS & MOD

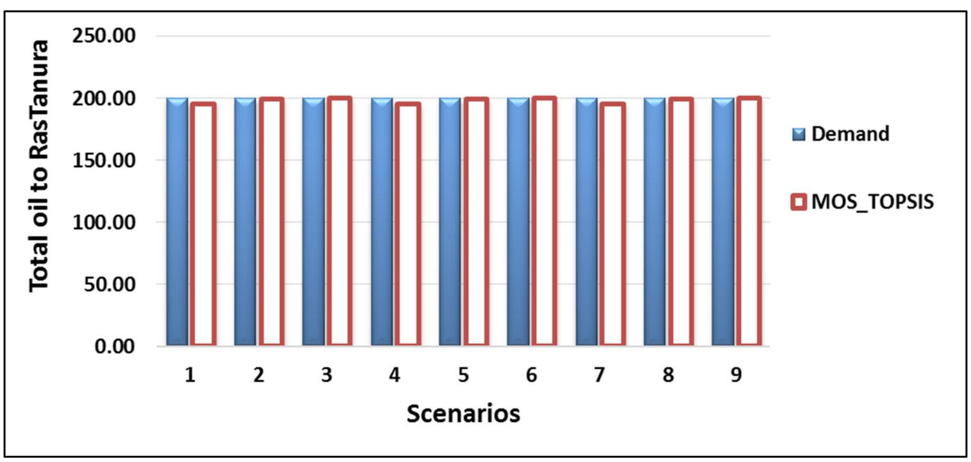
Although the demand is constant at international terminals, the received quantities are not constant because of the amount sent to local regions depends on demand level. It is clear that Yanbu is affected by this, Figure 4.9 (a). The Kingdom will face a below production during high and base demand scenarios. Below quantities should be satisfied from the international market at a 1.25% penalty of the international price. The effect decrease at Juaymah and disappear at RasTanura, Figure 4.9 (b) and (c).



(a) Total oil sent to Yanbu international terminal based on scenarios



(b) Total oil sent to Juaymah international terminal based on scenarios

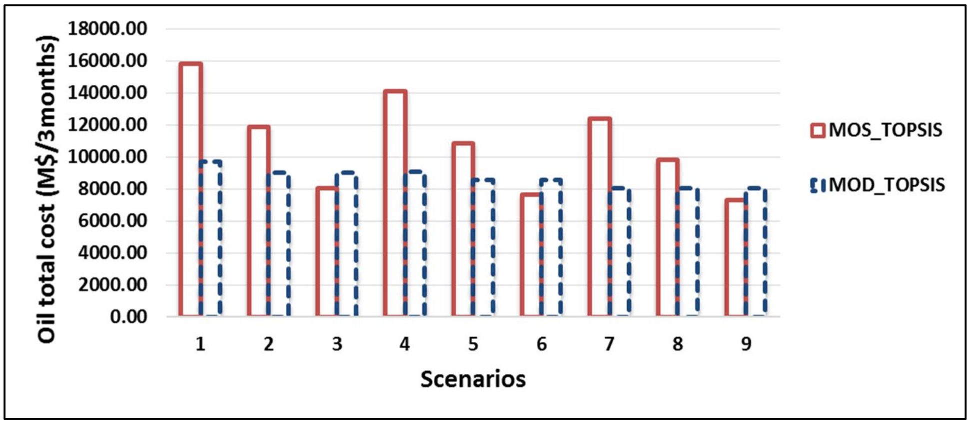


(c) Total oil sent to RasTanura international terminal based on scenarios

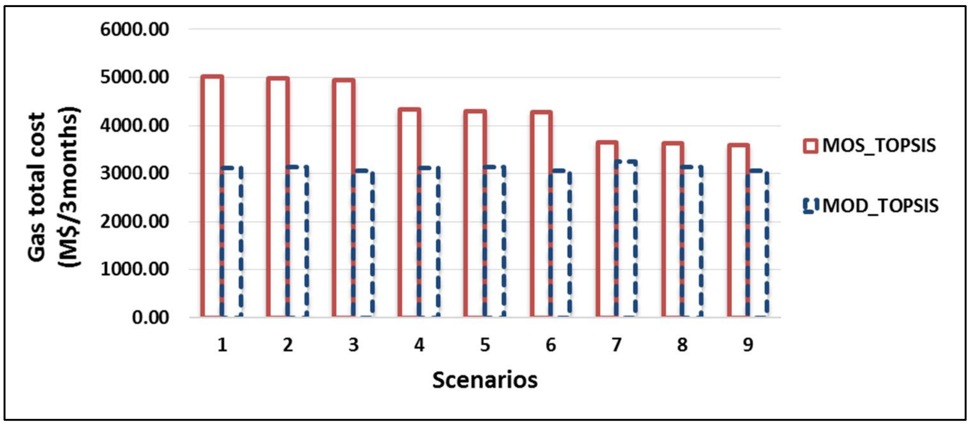
Figure 4.9 Total oil sent to international terminals based on MOS & MOD models

Not satisfying demand of crude oil during high and base scenarios at local and international terminals increases total costs as shown in Figure 4.10 (a). The same occurs with gas byproducts, Figure 4.10 (b). Also, the cut in gas production increases penalties of below production which affects the profit per scenario for both crude oil and natural gas byproducts. Figure 4.11 (a) and the summary in Table 4.6 show that, low demand with high price scenario is the highest profitable scenario for the Kingdom. During this scenario the whole demand can be satisfied. For the gas, all scenarios are not profitable, Figure 4.11 (b), but still the total profit for oil and gas is profitable, Table 3.5.

To get deeper insights, MOD model solved for each scenario individually and plotted in conjunction with results from MOS model in a dotted line, Figure 4.10 Figure 4.11. The deterministic model produce more crude oil per scenario. Consequently, total cost for scenarios with high and base demand is less for deterministic than stochastic, because of the reduction in penalty of producing less than the demand. While, scenarios with low demand situation is reversed because the cost of production, processing, and transportation associated with stochastic is less than that of deterministic. Again the highest profit can be achieved during high price – low demand scenario.

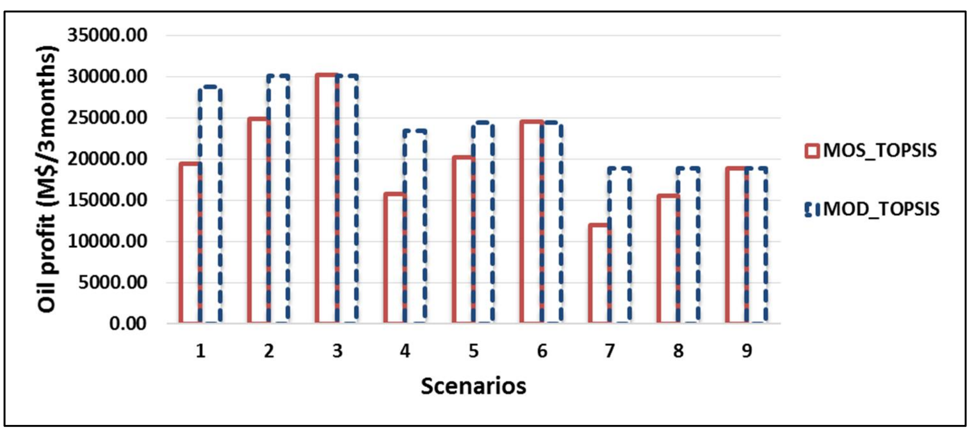


(a) Crude oil total cost over scenarios

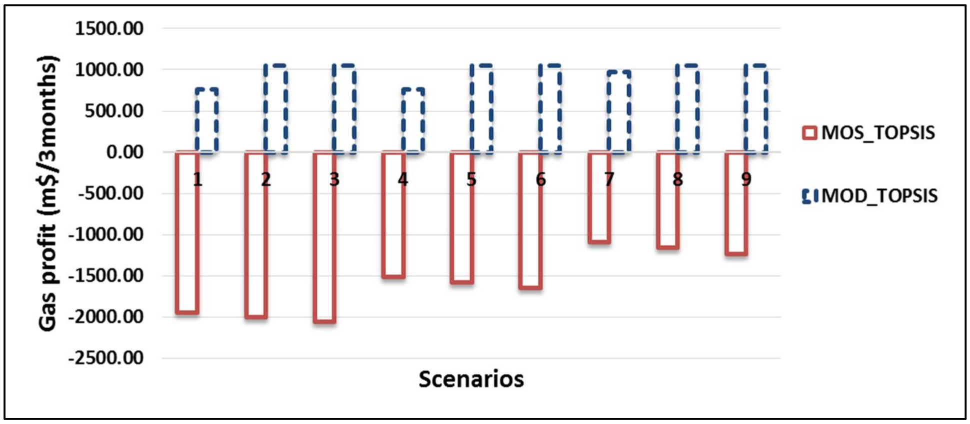


(b) Natural gas total cost over scenarios

Figure 4.10 Total cost for oil and gas based on MOS & MOD models



(a) Crude oil profit over scenarios



(b) Natural gas profit over scenarios

Figure 4.11 Profit for oil and gas based on MOS & MOD models

Table 4.6 Summary of the results from MOS per scenario

Scenario	1	2	3	4	5	6	7	8	9
Price	High	High	High	Base	Base	Base	Low	Low	Low
Demand	High	Base	Low	High	Base	Low	High	Base	Low
Oil total cost	15,819.8	11,866.0	8,032.6	14,113.5	10,829.7	7,655.6	12,407.2	9,793.5	7,278.6
Change from MOD	7,177.9	3,224.1	-609.3	5,471.6	2,187.8	-986.3	3,765.3	1,51.6	-1,363.3
Oil Profit	19,403.1	***24,810.7***	***30,167.1***	15,697.2	20,144.0	***24,534.8***	11,991.3	15,477.3	18,902.5
Change from MOD	-4,382.8	***1,024.7***	***6,381.1***	-8,088.7	-3,641.9	***748.8***	-11,794.7	-8,308.6	-4,883.4

4.2.2 Sensitivity analysis of MOS

In reality a correlation exists between product price and market demand (e.g., as price increase demand decrease). In this section more market scenarios are analyzed based on market statuses assuming a high probability for high price – low demand and low price –

high demand. Figure 4.12 and Figure 4.13 shows scenarios construction of the two cases with the corresponding probabilities and joint probability for each scenario, highlighting the scenario with high probability in dashed-red line.

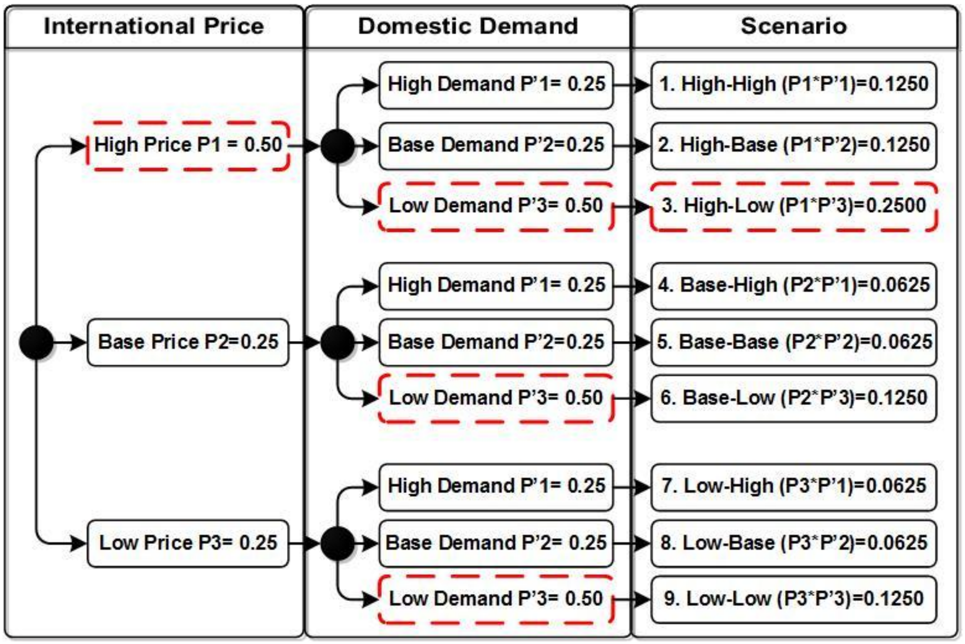


Figure 4.12 Case II: Scenario construction for high price – low demand

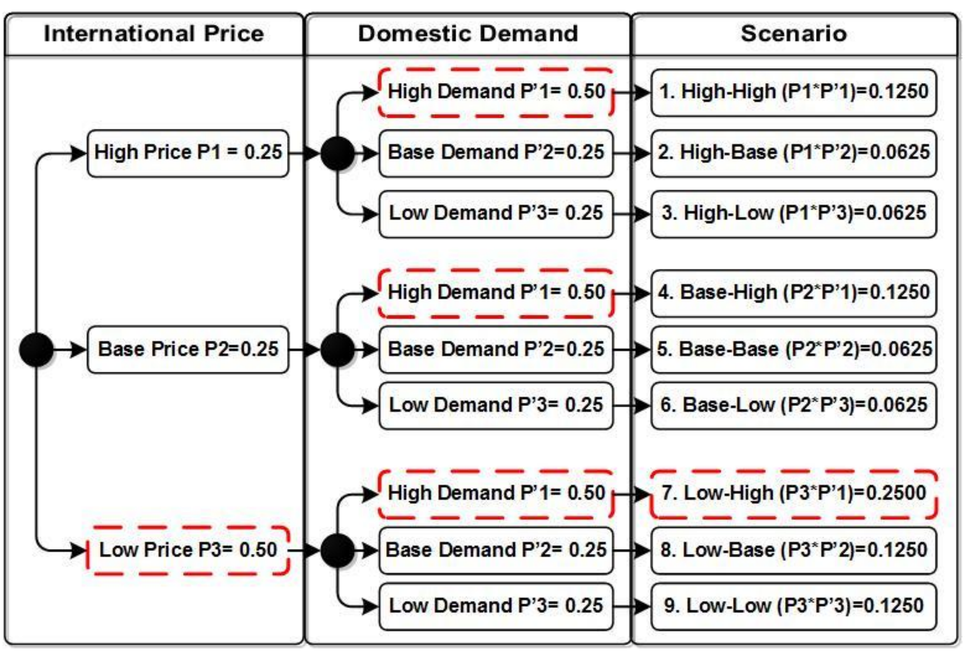


Figure 4.13 Case III: Scenario construction for low price – high demand

Table 4.7 and Table 4.8 summarizes the preferred plans based on the two cases. The main conclusion, assigning a high probability to high demand (case III in Table 4.8) increases crude oil production over the base case on the numerical example section and the case II. Increasing oil production decreases natural gas production and decreases the total costs as a result of decreasing penalty of producing below demand. High probability of low prices affects the revenue and hence decreases the profit.

Table 4.7 Preferred plan for case II using MOS model

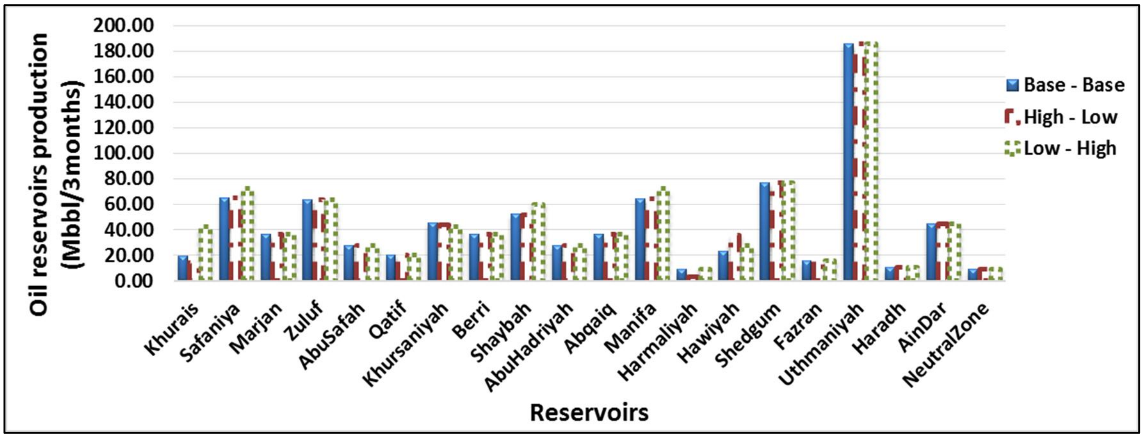
Total cost =	M$ 14,737.14/3months	Oil production =	869.99	MMbbl/3months
Revenue =	M$ 35,629.62/3months		9.67	MMbbld
Profit =	M$ 20892.48/3months	Gas production =	275,925.23	MMcft/3months
Depletion rate =	0.00108107		3,065.84	MMcftd
Sustainability =	77.08 year			

Table 4.8 Preferred plan for case III using MOS model

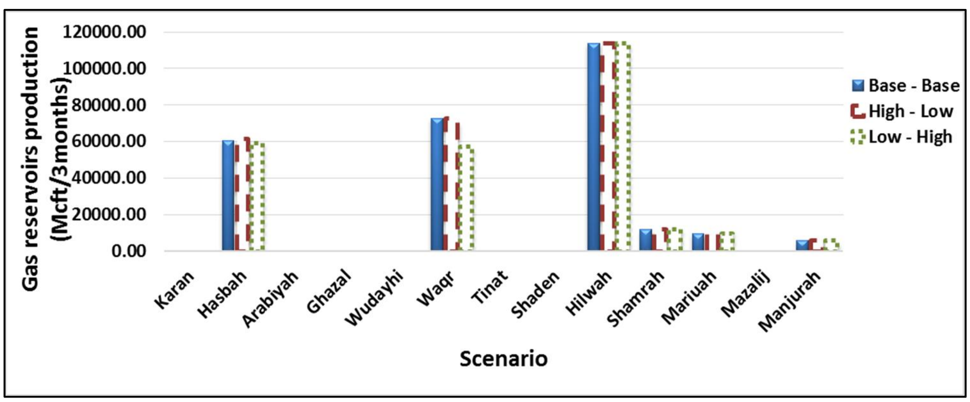
Total cost =	M$ 13,913.56/3months	Oil production =	918.98	MMbbl/3months
Revenue =	M$ 33,192.13/3months		10.21	MMbbld
Profit =	M$ 19,278.57/3months	Gas production =	257,711.18	MMcft/3months
Depletion rate =	0.00114194		2,863.46	MMcftd
Sustainability =	72.98 year			

Figure 4.14 shows that to increase crude oil production during case III scenarios the production from the following reservoirs should increase: Khurais, Safaniya, and Manifa.

In the same time, production from the following gas reservoirs should decrease: Hasbah and Waqr.



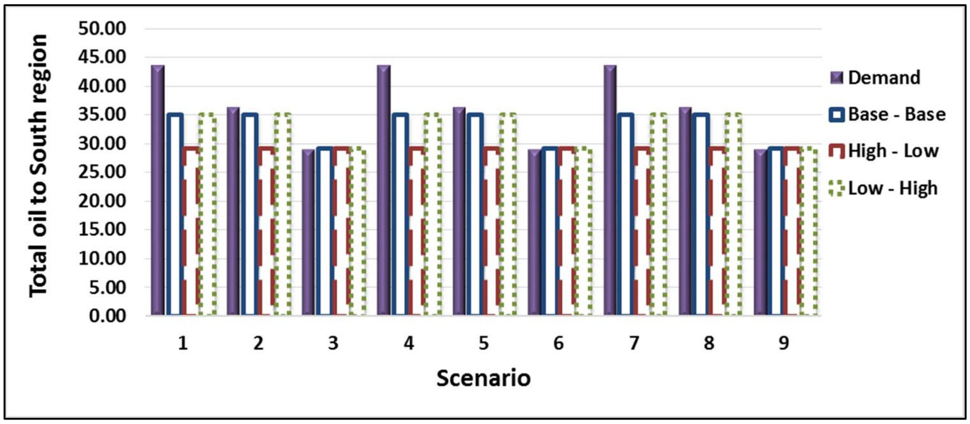
(a) Production profile for oil reservoirs



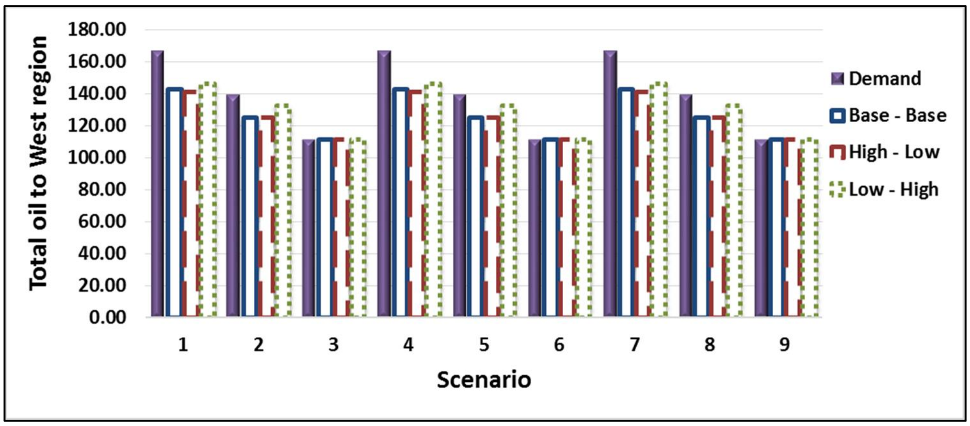
(b) Production profile for gas reservoirs

Figure 4.14 Production profile for oil and gas reservoirs based on MOS model for the 3 cases

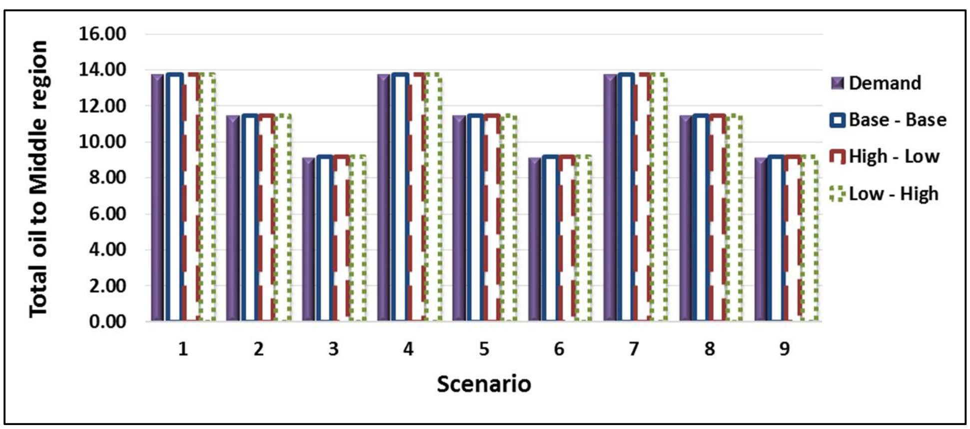
The effect of increasing crude oil production is clear on the amount of oil sent to satisfy the demand at South and East regions, Figure 4.15 (a and d). While, for the international terminals Yanbu receives the highest effect, Figure 4.16.



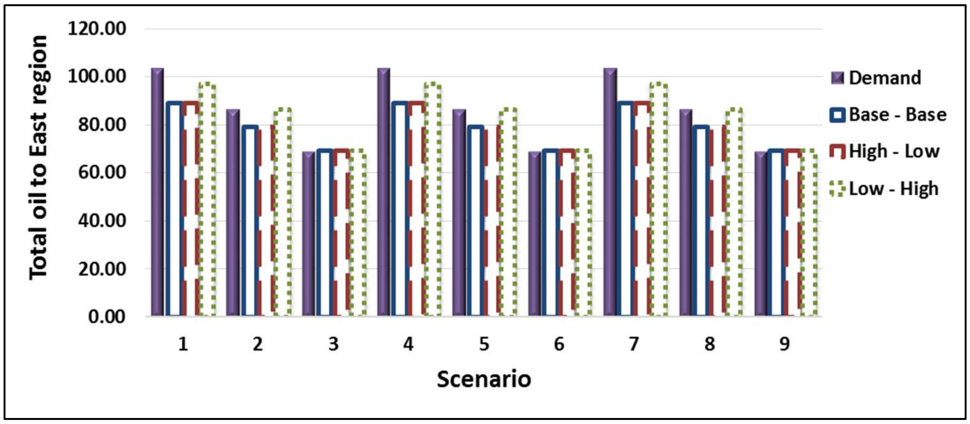
(a) Total oil sent to South region based on scenarios



(b) Total oil sent to West region based on scenarios

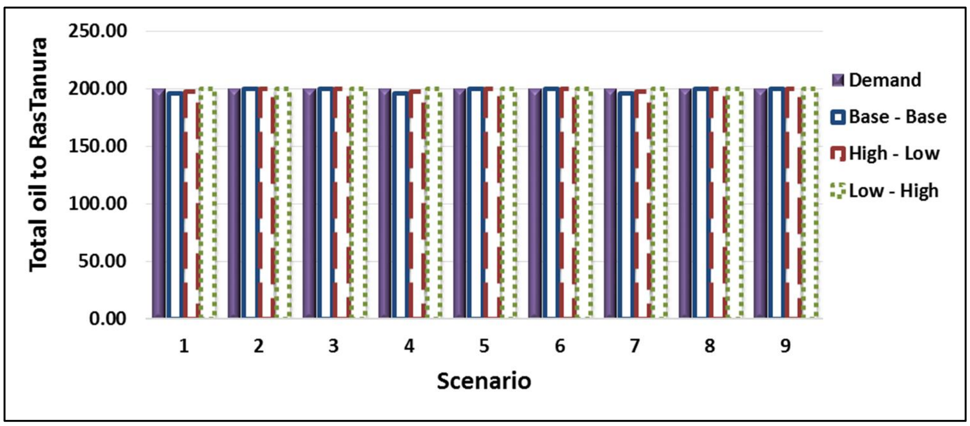


(c) Total oil sent to Middle region based on scenarios

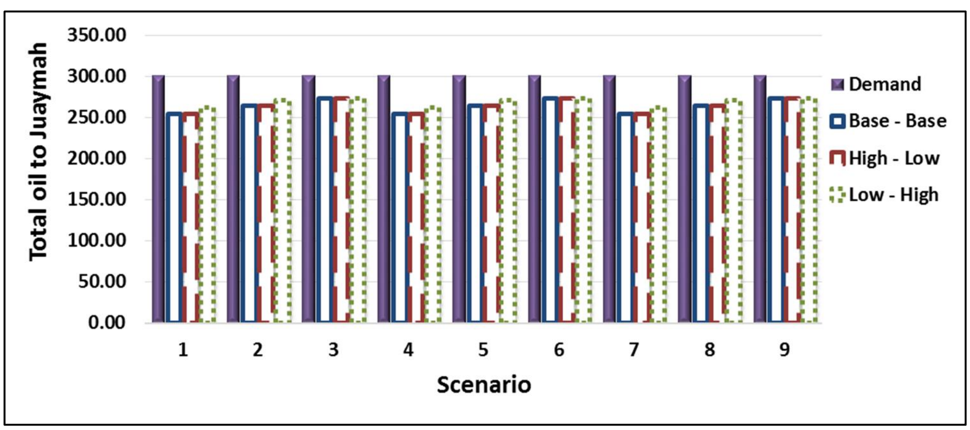


(d) Total oil sent to East region based on scenarios

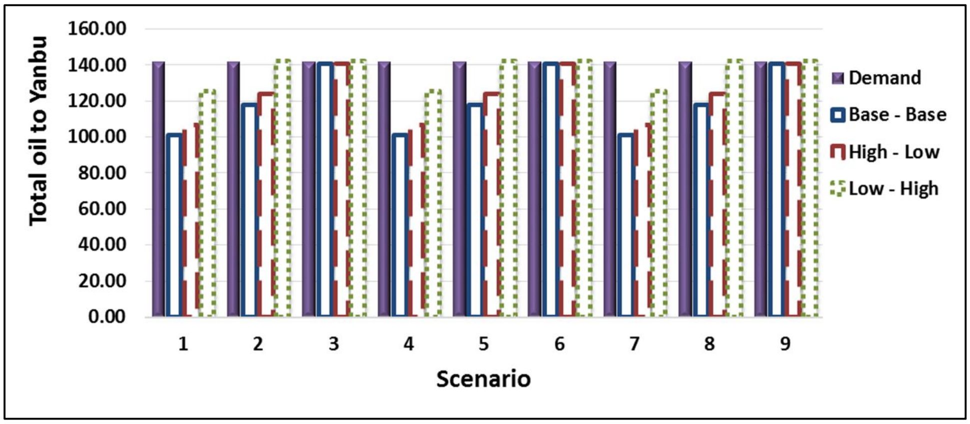
Figure 4.15 Total oil sent to local regions based on MOS model for the 3 cases



(a) Total oil sent to RasTanura international terminal based on scenarios



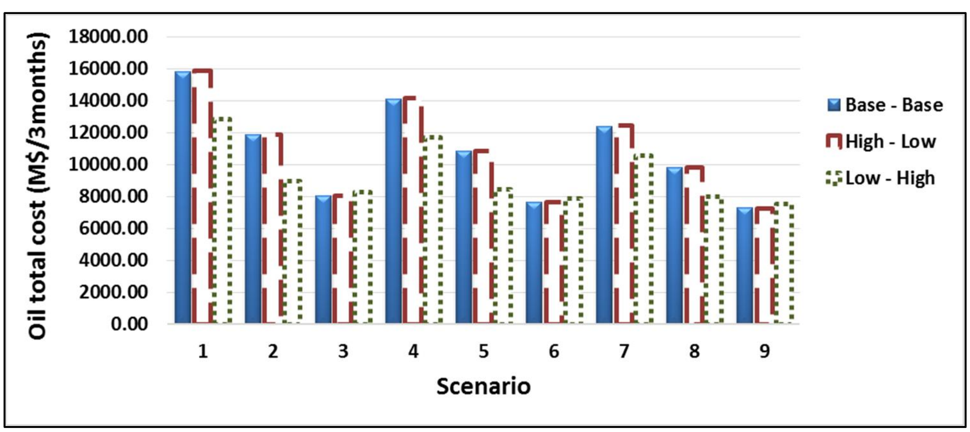
(b) Total oil sent to Juaymah international terminal based on scenarios



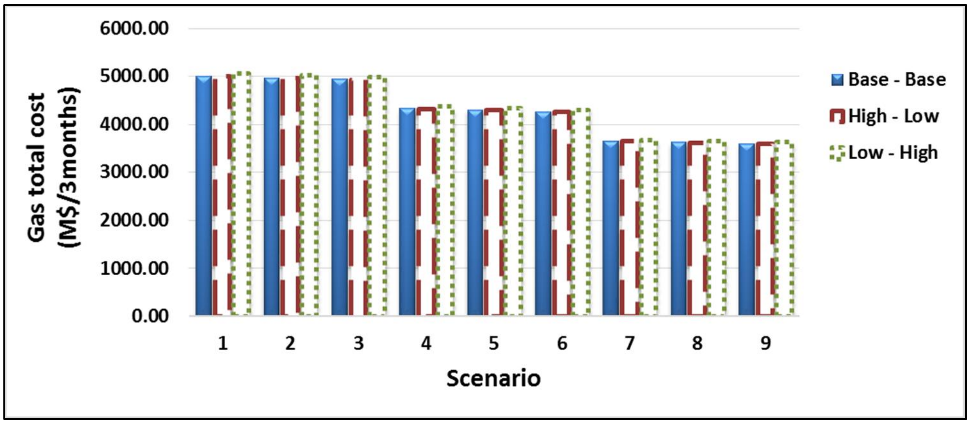
(c) Total oil sent to Yanbu international terminal based on scenarios

Figure 4.16 Total oil sent to international terminals based on MOS model for the 3 cases

As a result of the aforementioned conditions, total costs of the crude oil decreases during scenarios with high and base demand, as a result of increasing production and decreasing penalty of producing below demand, Figure 4.17 (a). Regarding the natural gas the total costs are the same over the three cases, Figure 4.17 (b). The overall effect on the profit is shown in Figure 4.18 (a and b) for both oil and gas, respectively. For oil high and based demand drives the production and profit to increase. On contrary, a decrease in gas production decreases the profit from gas for the same scenarios.

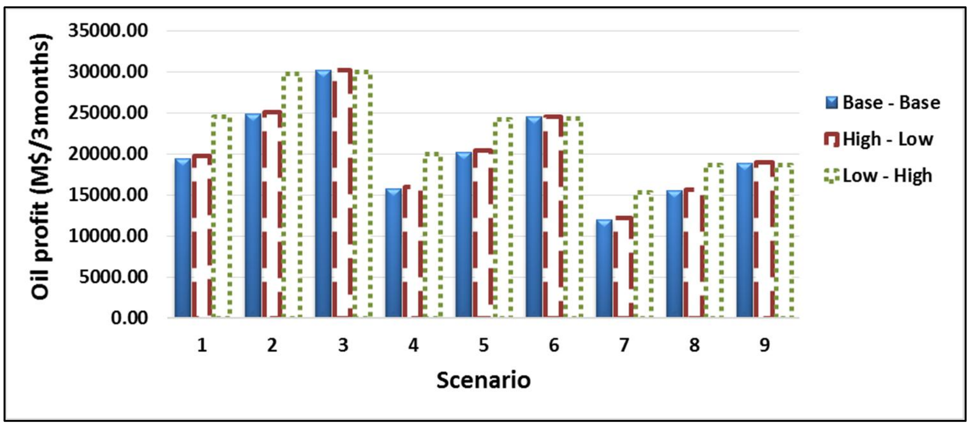


(a) Crude oil total cost over scenarios

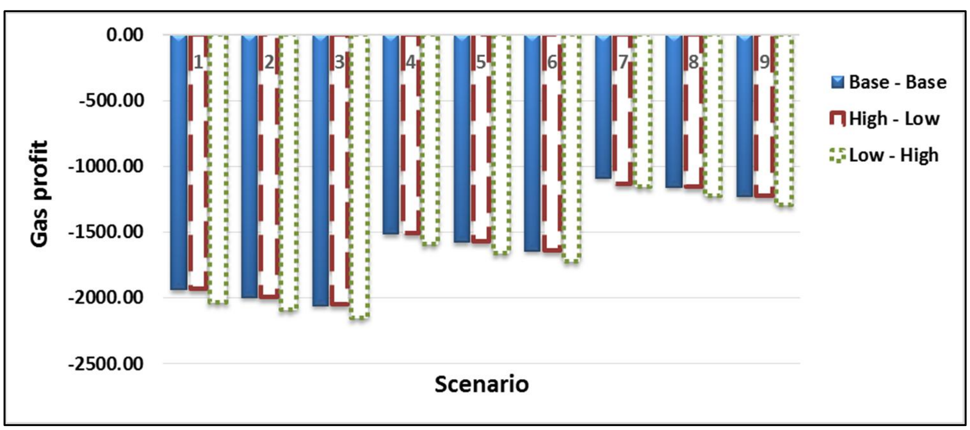


(b) Natural gas total cost over scenarios

Figure 4.17 Total cost for oil and gas based on MOS model for the 3 cases



(a) Crude oil profit over scenarios



(b) Natural gas profit over scenarios

Figure 4.18 Profit for oil and gas based on MOS model for the 3 cases

4.3 Conclusion

In this chapter a stochastic multi-objective optimization model was presented for tactical decisions planning of crude oil and natural gas by-products. The proposed model is an attempt to take decisions considering uncertainty that occurs on the market prices and demand. Uncertainty of market parameters represented as a finite set of scenarios and formulated as a two-stage SP model. The market was considered under a stable condition where price and demand at average levels.

The results show that, Saudi Arabia should produce crude oil in a rate higher than 7.23 MMbbld and a gas less than 3,562.05 MMcftd to achieve profit. The preferred oil and gas production levels using TOPSIS technique are 9.67 MMbbld and 3,056.26 MMcftd, respectively. At these production levels and under the existing proved reserves the production can continue for 77.08 years. The selected plan costs the Kingdom M$ 15,155.47/3months and returns a cash flow M$ 33,706.03/3months.

Comparing between plans provided using MOD and MOS models, break-even production for oil was increased by 0.27 MMbbld and for gas decreased by 3,008.41 MMcftd. For the preferred plan: oil production decreased by 0.48 MMbbld and gas production by 3,090.98 MMcftd. To achieve this plan crude oil production from the following reservoirs should be decreased: Safaniya, Shaybah, Hawiyah, Haradh, AinDar, and NeutralZone, and form following gas reservoirs: Karan, Hasbah, Arabiyah, Ghazal, Tinat, Shamrah, and Manjurah.

A sensitivity analysis was conducted to study the model behavior under two different market situations. The first situation assumes high probability for high prices and low demand. The second situation assumes a different case where low prices and high demand have high probability.

The assumptions of full dependency between scenarios and independency between uncertain parameters may lead limitations. Although it has been proven to be a valid assumption of scenario dependency more data and discussion with the stakeholders need to be conducted to examine the case of independency. Regarding uncertain parameters, in real life the values of prices and/or demand may not be independent. Price can take different values during the planning period (from period to another) and a dependency exist between these values and demand based on market conditions.

Eventually, after studying the three market situations, we found that the best situation (highest profit) for the Kingdom is during high price – low demand. Under this situation the Kingdom can reduce oil production and cuts gas production to a half. Demand over the production can be satisfied from the outside market by medium term contracts to satisfy customer needs and on the same time keep enough reserves to future generations.

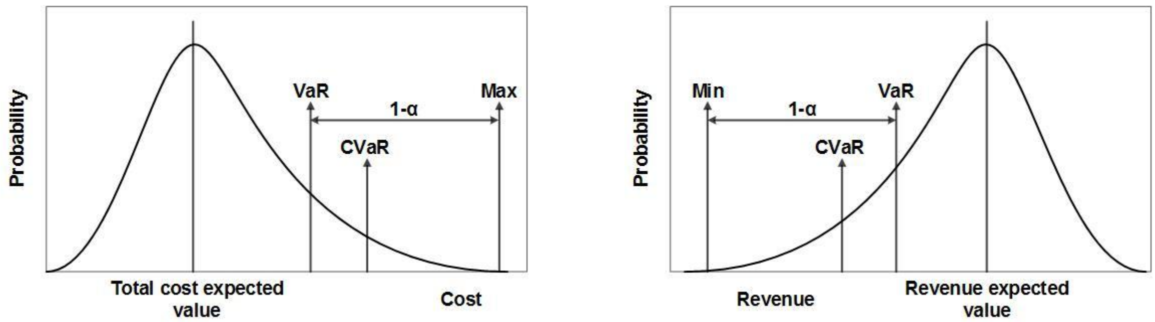
CHAPTER 5

MULTI-OBJECTIVE RISK MODEL

In SP formulation the objective functions are optimized by minimizing (maximizing) the expected value of the total costs (revenue) of the second stage decisions. In this situation, the optimization of the objective functions is a risk neutral. For instance, risk of exceeding a certain limit of costs (e.g., exceeding the budget limit) or risk of not exceeding a desired level of revenue (e.g., not enough cash flow) may occur. Consequently, the MOS model requires reformulation to achieve an economic objectives (i.e., total cost minimization and revenue maximization) and financial risk management, simultaneously.

5.1 Risk model formulation

For risk management *CVaR* utilized as a risk measure to eliminate or mitigate financial risks. *CVaR* is a widely used risk measure that has been proven to be a coherent risk measure (Conejo et al., 2010). Definition of *CVaR* is represented in Figure 5.1, where it is the expected value of the costs of scenarios that higher (smaller) than a threshold value that represents $(1 - \alpha)$ quantile of the cost (revenue) distribution. Two decision variables are introduced to manage the financial risk *VaR* and Φ_ω. Where, *VaR* is the lowest (largest) value ensuring that the probability of obtaining cost more (revenue less) than *VaR* is lower than $(1 - \alpha)$ quantile, and Φ_ω is the deviation between *Var* and scenario cost or revenue.



(a) For cost **(b) For revenue**

Figure 5.1 Definition of CVaR

Eqs. (5.1) - (5.4) formulates the above relations ($CVaR$, VaR, and Φ_ω) as linear constraints and added to the set of MOS model constraints. Based on $CVaR$ definition Eqs. (5.5) and (5.6) formulates total cost and revenue objective functions as proposed by Rockafellar and Uryasev (2000). The utilized formulation of CVaR is an acceptable approximation used in case of discrete distribution (i.e., representing uncertainty as a finite number of scenarios representing the density function), (Rockafellar and Uryasev, 2000; Rockafellar and Uryasev, 2002; Sarykalin et al., 2008). The first term represent economic objectives in Eqs. (4.36) and (4.37), and the second term represent $CVaR$. Where β is a weighting parameter between 0 and 1 used to materialize the value of the risk (i.e., represent the risk attitude of the decision maker).

$$Total\ Costs_\omega - VaR_{Cost} \leq \Phi Cost_\omega \qquad \forall\omega \qquad (5.1)$$

$$VaR_{Cost}, \Phi Cost_\omega \geq 0 \qquad \forall\omega \qquad (5.2)$$

$$VaR_{Revenue} - Revenue_\omega \leq \Phi \mathrm{Revenue}_\omega \qquad \forall\omega \qquad (5.3)$$

$$\Phi\text{Revenue}_{\omega} \geq 0 \qquad \forall\omega \tag{5.4}$$

$$\textit{Minimize Total Cost} = \tag{5.5}$$

$$(1-\beta)\ \textit{Total Cost Eq.}(4.36) + (\beta)\left(VaR_{Cost} + \frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi_{\omega}\,\Phi Cost_{\omega}\right)$$

$$\textit{Maximize Revenue} = \tag{5.6}$$

$$(1-\beta)\ \textit{Revenue Eq.}(4.37) + (\beta)\left(VaR_{Revenue} - \frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi_{\omega}\,\Phi\text{Revenue}_{\omega}\right)$$

5.2 Applied case study: MOR model

CVaR utilized to ensure that the expected value of scenarios having high costs (low revenue) lay within the 20% quantile ($1 - \alpha = 0.20$) of the cost (revenue) distribution. To materialize different terms of the objective functions equal weights ($\beta = 0.50$) is assigned to both the economic terms and financial risk terms.

5.2.1 Numerical results of MOR

Table 5.1 summarizes statistical results of the MOR model using the same conditions that has been used in MOD and MOS: program, solver, and number of planning periods. Payoff matrix in Table 5.2 show that the minimum total cost from MOR is higher than the minimum of MOD and MOS, the maximum revenue is lower, and the worst case of sustainability of MOD is better than of MOR.

Table 5.1 MOR model statistics

Blocks of Equations	99	Single Equations	12,144
Blocks of Variables	53	Single Variables	10,946
Non Zero Elements	80,162		

Table 5.2 Pay-off matrix of MOR model applying lexicographic optimization

	Total Cost (M$/month)	Total Revenue (M$/month)	Depletion Rate	Sustainability (Years)
Minimizing Total Cost	***14,068.12***	32,035.81	0.0011825206	70.47
Maximizing Total Revenue	15,075.65	***32,421.61***	0.0011554837	72.12
Minimizing Depletion Rate	34,901.3	20,155.19	***0.0006752586***	***123.41***

The generated Pareto-optima tested against the approximation, all the points deviated from the exact value with less than 1%. Clearly, from Figure 5.2 Pareto-optima surface results from solving the risk model has the same topology as that produced from the deterministic and stochastic models (see Figure 3.4 and Figure 4.5). Likewise, the correlation between crude oil and natural gas productions (Figure 3.5, Figure 4.6, and Figure 5.3). Break-even production of oil is 7.87 MMbbld and of gas is 3,472.18 MMcftd. So, to achieve profit the kingdom should produce more of crude oil and less of natural gas than the break-even production quantities.

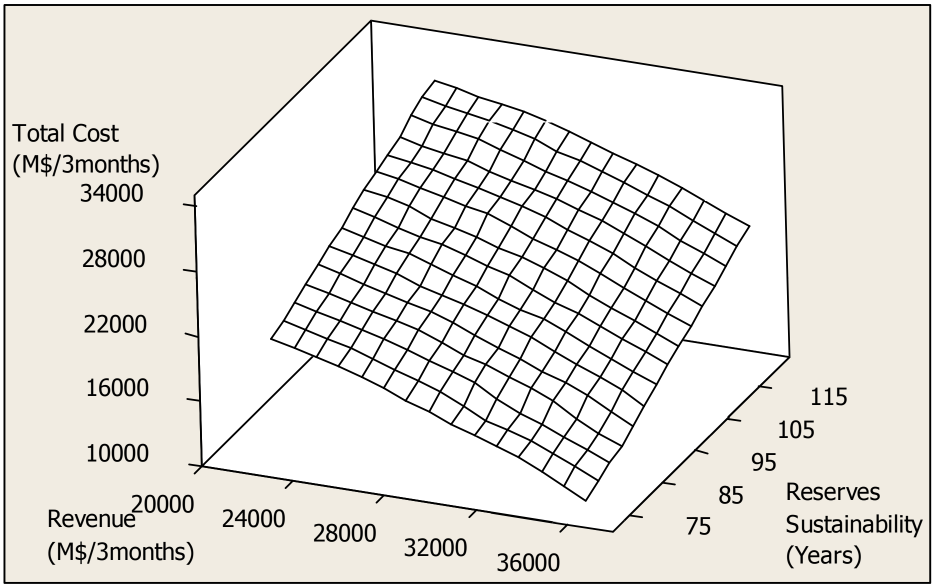


Figure 5.2 Efficient Pareto-optima surface of MOR model

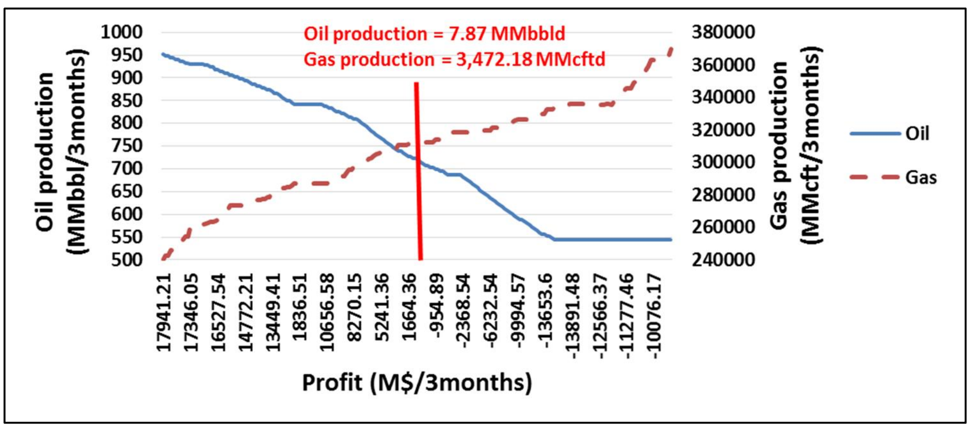


Figure 5.3 Relation between crude oil production and natural gas production of MOR model

From the set of Pareto-optima the preferred tactical plan were chosen using TOPSIS technique based on equally weighted objectives. The values of the objective functions, quantity of oil production, and quantity of gas production are listed in Table 5.3. Since, the purpose of using MOR is to reduce the risk of facing a high cost and low revenue associated with scenarios. The production based on risk model is higher than that from the stochastic model which reduces penalties from producing below demand (i.e., extra cost of getting shortage quantity from the outside market) and increases the revenue which achieve the objective of utilizing *CVaR*.

Based on the model parameters VaR_{Cost} value is M$ 14,875.39 /3months and the worst scenarios are 1st and 4th with deviation from VaR_{Cost} by M$ 3,907.40 and 1,941.27 /3months, respectively, Table 5.4. This means the probability of encountering scenarios with total costs higher than M$ 14,875.39 /3months is 0.20. While for the revenue objective $VaR_{Revenue}$ value is M$ 29,604.37 /3months and scenarios with revenue less than this value are 7th and 9th scenarios. In other words, with a probability of 0.20 the kingdom may encounter a scenarios with a revenue less than M$ 29,604.37 /3months.

The expected values of the worst scenarios for cost and revenue ($CVaR_{Cost}$, $CVaR_{Revenue}$) M$ (17,309.74 and 29,240.24) /3months. This means scenarios with (high and base price – *high demand*) are risky with respect to total costs. While regarding revenue, the risky scenarios associated with (*low price* – high and low demand).

Table 5.3 Preferred plan from the MOR model

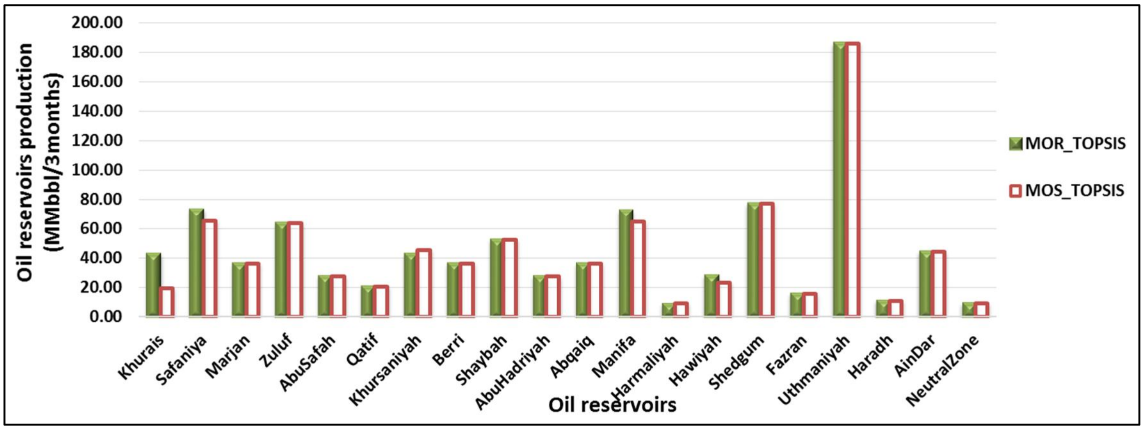
Total cost =	M$ 15,322.22/3months	Oil production =	910.81	MMbbl/3months
Revenue =	M$ 31,783.30/3months		10.12	MMbbld
Profit =	M$ 16,461.08/3months	Gas production =	270,096.81	MMcft/3months
Depletion rate =	0.00113179		3,001.08	MMcftd
Sustainability =	73.63 year			

Table 5.4 Financial risk results of the MOR model

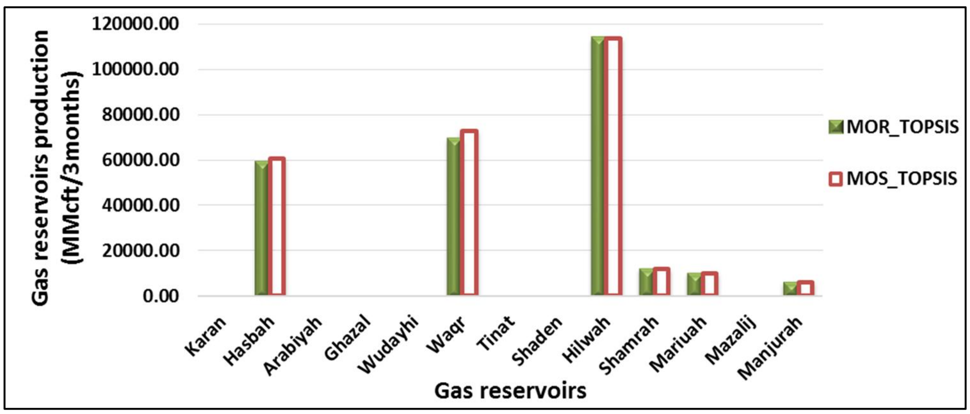
Objective function	*VaR*	*CVaR*	Risk value per scenario Φ_ω								
			1	2	3	4	5	6	7	8	9
Cost	14,875.39	17,309.74	3,907.40	0	0	1,941.27	0	0	0	0	0
Revenue	29,604.37	29,240.24	0	0	0	0	0	0	743.17	0	422.04

Oil production based on risk model is higher than that from stochastic model. To achieve this the production from the following reservoirs should increase (MMbbl/3months): Khurais (23.39), Safaniya (7.81), Manifa (7.81), and Hawiyah (4.55), as shown in Figure 5.4 (a). While, gas production remain the same. Figure 5.5 and Figure 5.6 depicts the amount of sweetened oil sent to local regions and international terminals. The increase in oil reservoirs production is clear in the amount sent to Eastern region Figure 5.5 (d) and Juaymah and Yanbu international terminals Figure 5.6 (c).

The eastern region receive more sweetened oil by 7.28 MMbbl/3months during high and base demand scenarios to compensate for high demand. While Juaymah receive an increase during high, base, and low demand scenarios by 39.87, 30.96, and 29.32 MMbbl/3months. Yanbu share of increase 16.85 MMbbl/3months in high demand scenarios.

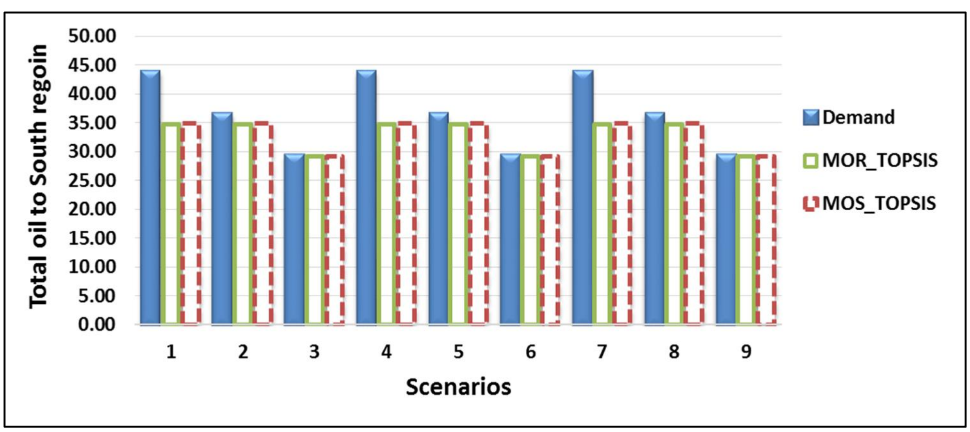


(a) Production profile for oil reservoirs

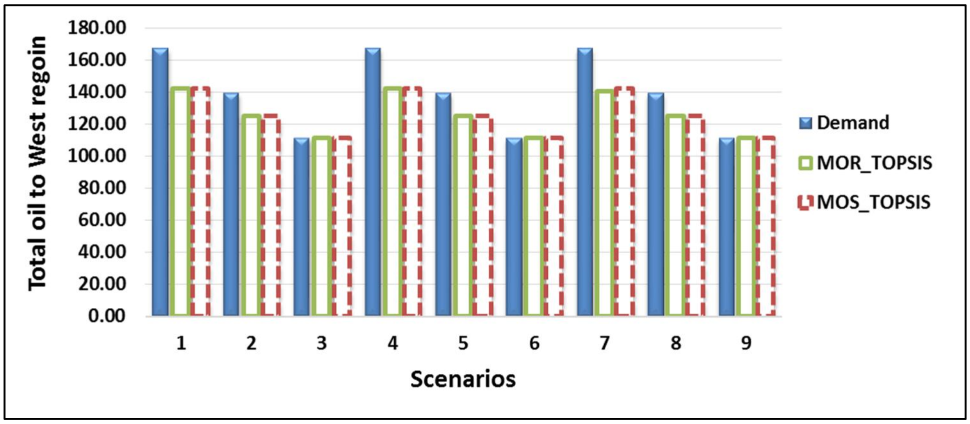


(b) Production profile for gas reservoirs

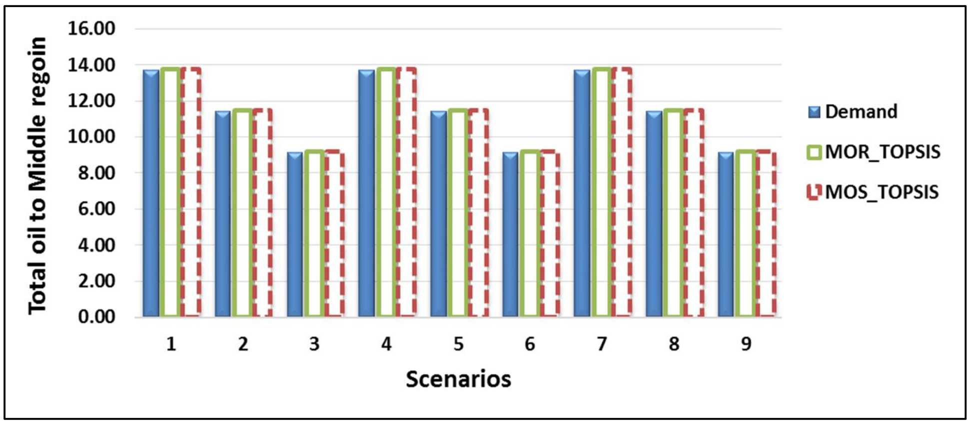
Figure 5.4 Production profile for oil and gas reservoirs based on MOR model



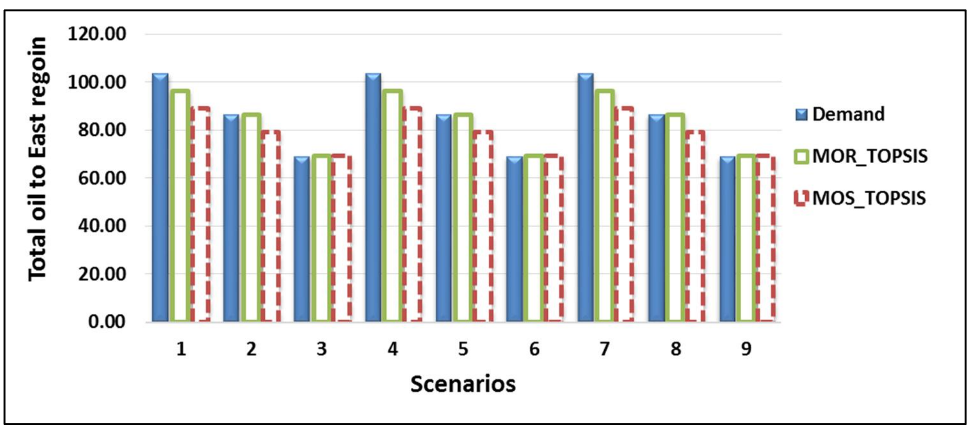
(a) Total oil sent to South region based on scenarios



(b) Total oil sent to West region based on scenarios

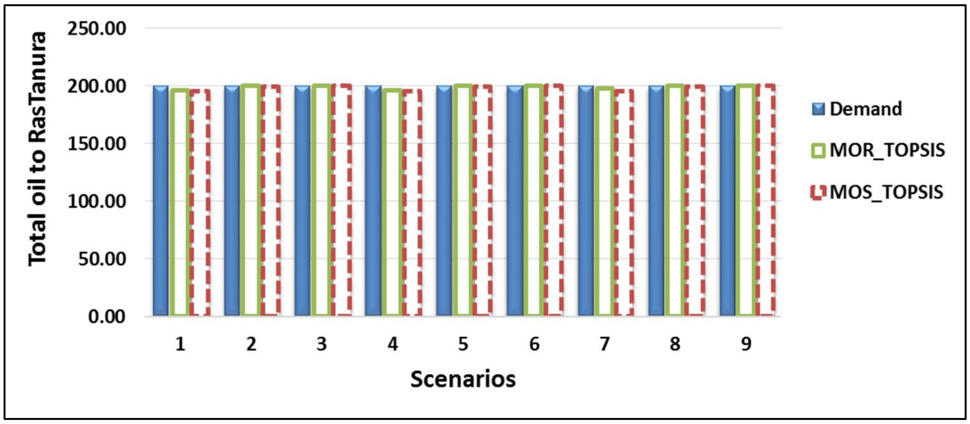


(c) Total oil sent to Middle region based on scenarios

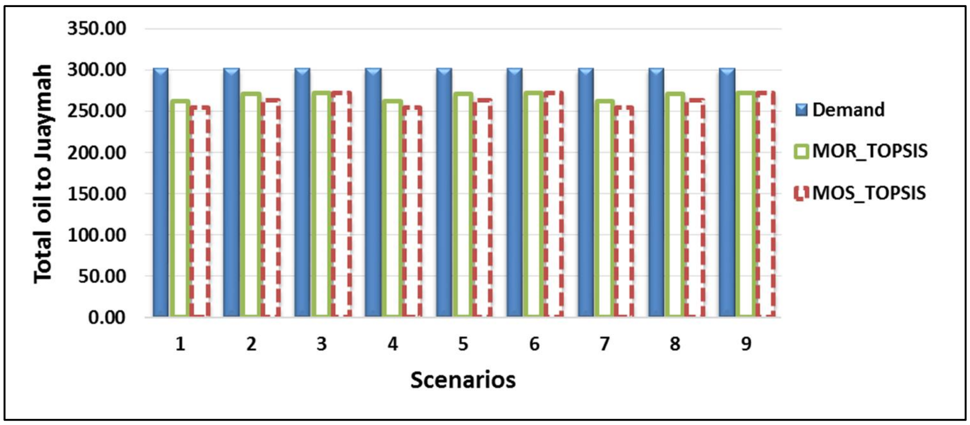


(d) Total oil sent to East region based on scenarios

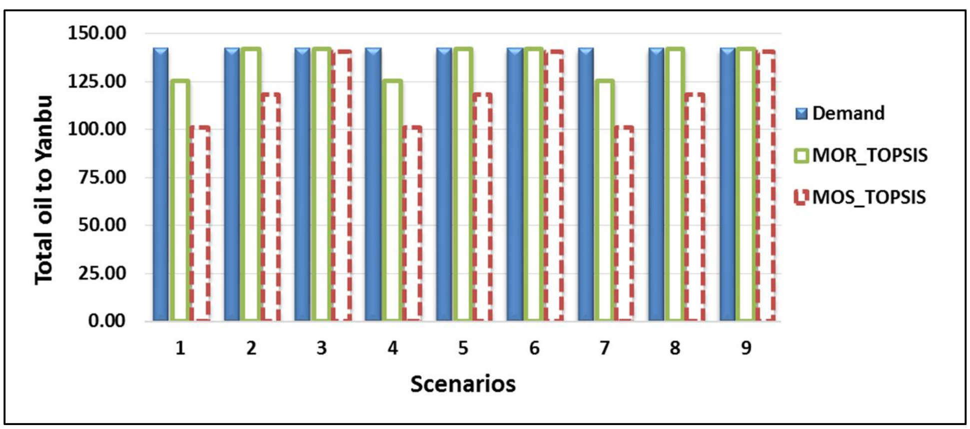
Figure 5.5 Total oil sent to local regions based on MOR model



(a) Total oil sent to RasTanura international terminal based on scenarios



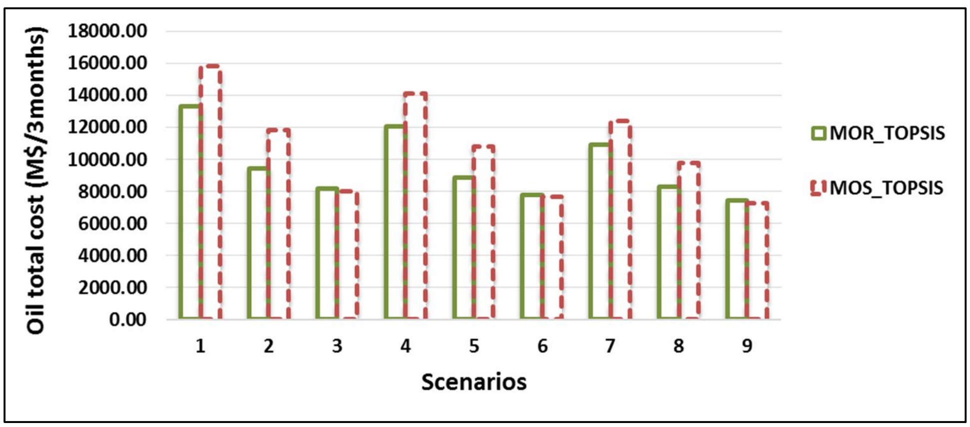
(b) Total oil sent to Juaymah international terminal based on scenarios



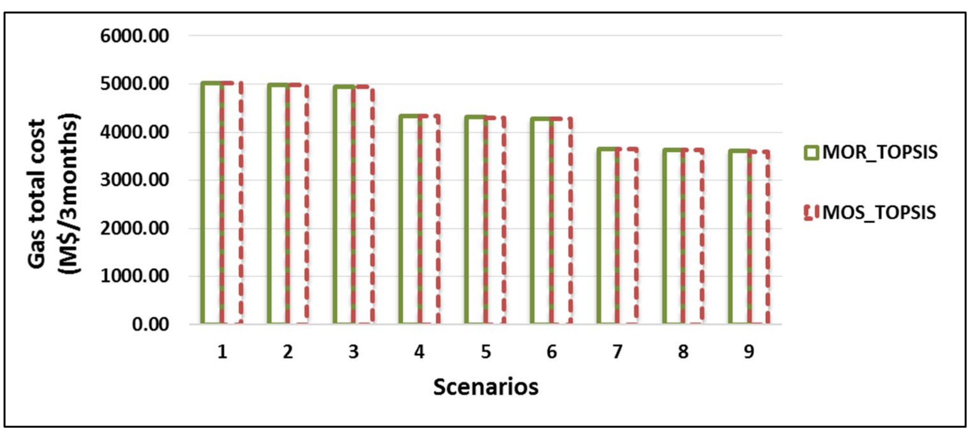
(c) Total oil sent to Yanbu international terminal based on scenarios

Figure 5.6 Total oil sent to international terminals based on MOR model

Figure 5.7 (a) shows the effect of changing the amount of production on the total cost per scenario. Where, the total costs per scenario for high risky scenarios (scenarios associated with high and base prices) decrease in values. Amount of saving in total costs for scenarios (1, 2, 4, 5, 7, 8): M$ (2489.25, 2412.90, 2016.16, 1947.76, 1495.59, 1482.57) /3months. Consequently, this result an increase in oil profit per scenario by M$ (4415.61, 4308.27, 3632.94, 3538.48, 2841.62, 2768.65) /3months, Figure 5.8 (a). While Figure 5.7 (b) and Figure 5.8 (b) highlights that planning under risk model does not affect the trend of natural gas total costs and revenue. Although, the plan is not profitable for natural gas it still profitable for the kingdom by M$ 16,461.08 /3months.

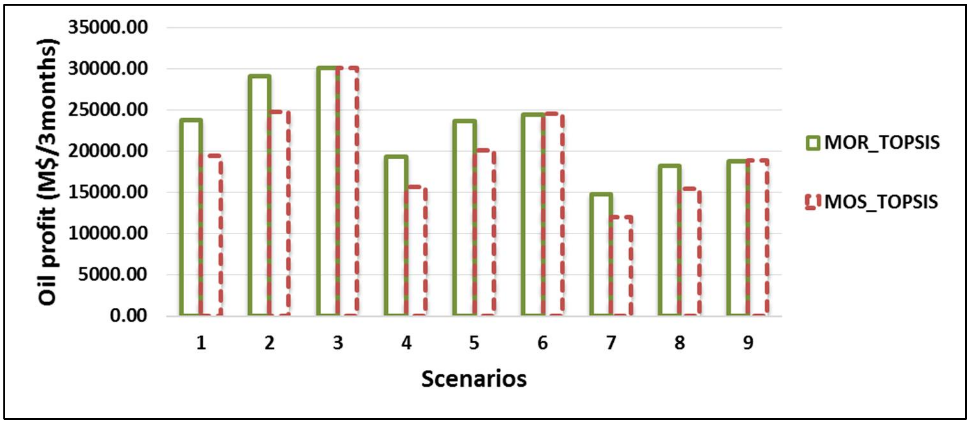


(a) Crude oil total cost over scenarios

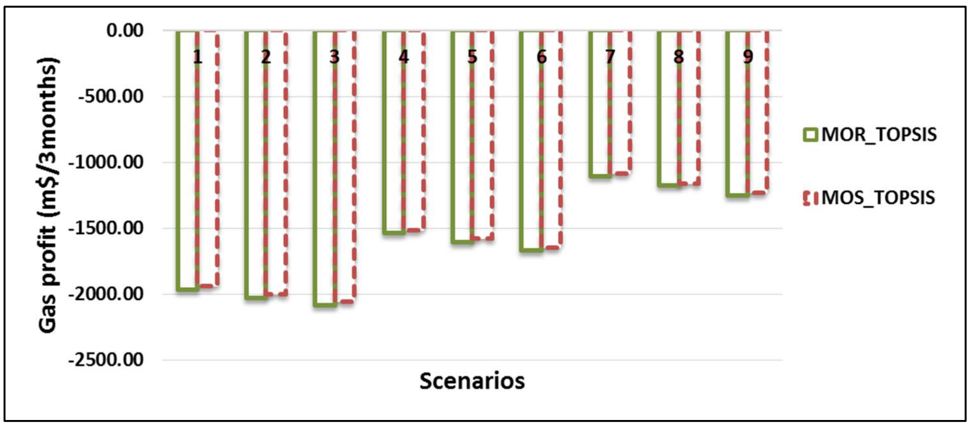


(b) Natural gas total cost over scenarios

Figure 5.7 Total cost for oil and gas based on MOR model



(a) Crude oil profit over scenarios



(b) Natural gas profit over scenarios

Figure 5.8 Profit for oil and gas based on MOR model

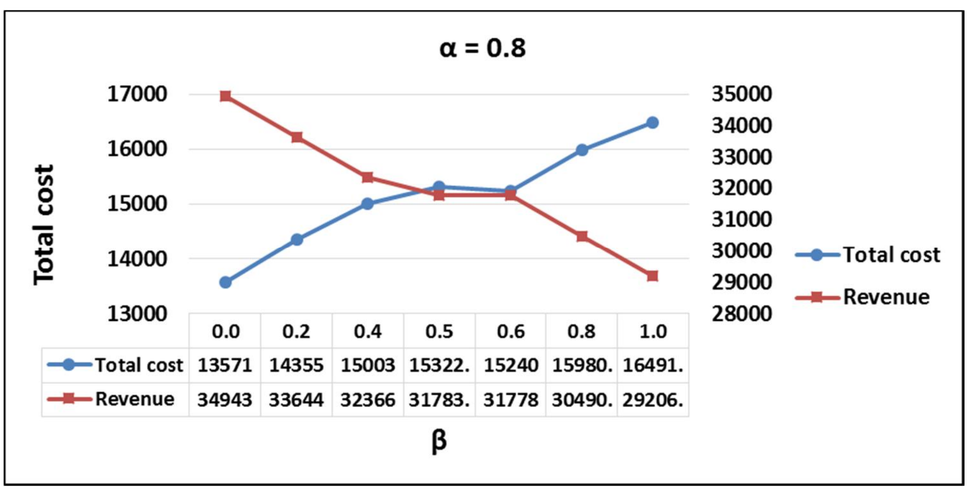
5.2.2 Sensitivity analysis of MOR

In this section a sensitivity analysis conducted to examine the consequences of planning under different levels of α and β. Another sensitivity analysis conducted to investigate the model tactical plans provided under different market situations. Two real situations are considered, where high probability assigned to (high price – low demand) and (low price

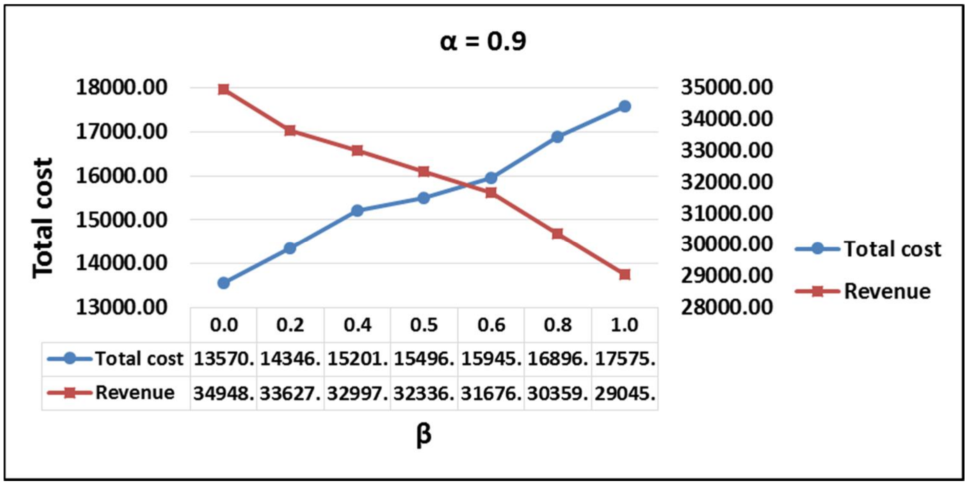
– high demand). The main purpose behind this analysis to get deeper insights to the decision making.

5.2.2.1 Different levels of α and β

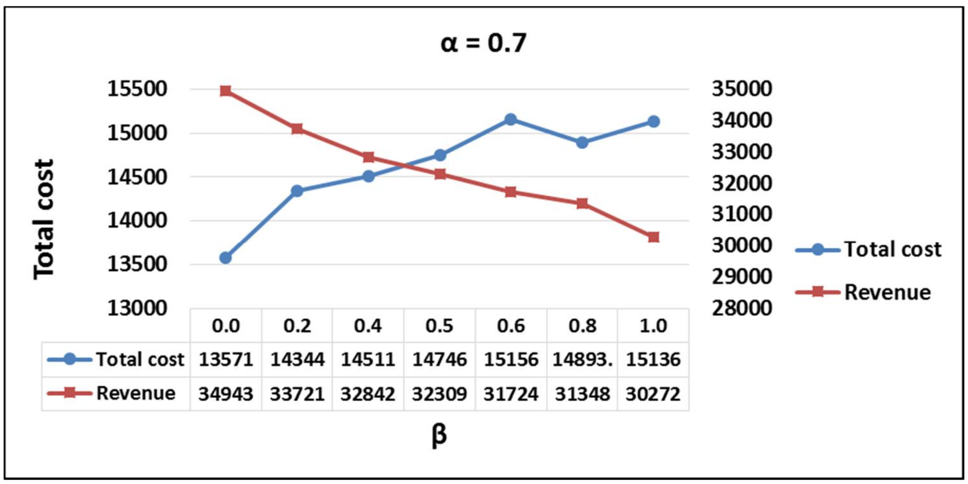
Referring to Figure 5.9 as the weight (β) of the risk term in cost (revenue) objective function increases the total value of the objective function increases (decreases). As the confidence level (α) increases the values of cost (revenue) function increases (decreases). The same aforementioned trade-off between (α, β) and objective functions exists between (α, β) and *VaR* and *CVaR*, the trade-off is listed in Table 5.5 and Table 5.6. Where *VaR* and *CVaR* of cost (revenue) equation has an inverse (direct) relation with α and β. These results are in the same line of risk model behavior on the literature.



(a) α = 0.8 and different levels of β



(b) α = 0.9 and different levels of β



(c) α = 0.7 and different levels of β

Figure 5.9 Total cost and revenue values of MOR model under different values of α and β

Table 5.5 VaR and CVaR values of cost function under different levels of α and β

β	α	*Var*	*CVaR*	Φ_1	Φ_2	Φ_3	Φ_4	Φ_5	Φ_6	Φ_7	Φ_8	Φ_9
0.0	0.7	0.0	46179.7	18533.2	14461.3	13400.2	16612.7	13230.8	12341.3	14692.3	12000.4	11282.4
0.2	0.7	14962.6	16676.5	4069.5	0.0	0.0	2056.6	0.0	0.0	43.7	0.0	0.0
0.4	0.7	14461.3	16254.2	4071.9	0.0	0.0	2151.5	0.0	0.0	231.1	0.0	0.0
0.5	0.7	14467.1	16255.2	4066.1	0.0	0.0	2145.7	0.0	0.0	225.3	0.0	0.0

0.6	0.7	14716.2	16466.3	4066.3	0.0	0.0	2100.1	0.0	0.0	133.9	0.0	0.0
0.8	0.7	14992.3	15475.8	1868.6	0.0	0.0	225.9	0.0	0.0	0.0	0.0	0.0
1.0	0.7	14999.2	15454.9	1778.8	0.0	0.0	204.4	0.0	0.0	0.0	0.0	0.0
0.0	0.8	0.0	69269.6	18533.2	14461.3	13400.2	16612.7	13230.8	12341.3	14692.3	12000.4	11282.4
0.2	0.8	14850.0	17307.8	3932.4	0.0	0.0	1966.2	0.0	0.0	0.0	0.0	0.0
0.4	0.8	14853.6	17308.1	3928.9	0.0	0.0	1962.7	0.0	0.0	0.0	0.0	0.0
0.5	0.8	14875.4	17309.7	3907.4	0.0	0.0	1941.3	0.0	0.0	0.0	0.0	0.0
0.6	0.8	15241.6	16535.6	2592.1	0.0	0.0	774.4	0.0	0.0	0.0	0.0	0.0
0.8	0.8	14946.2	16918.4	3375.4	0.0	0.0	1467.7	0.0	0.0	0.0	0.0	0.0
1.0	0.8	14960.9	16857.5	3252.1	0.0	0.0	1408.4	0.0	0.0	0.0	0.0	0.0
0.0	0.9	0.0	138539.2	18533.2	14461.3	13400.2	16612.7	13230.8	12341.3	14692.3	12000.4	11282.4
0.2	0.9	16612.7	17813.0	1920.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.4	0.9	16228.7	17394.4	1865.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.5	0.9	16222.4	17387.2	1863.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 5.6 VaR and CVaR values of revenue function under different levels of α and β

β	α	*Var*	*CVaR*	Φ_1	Φ_2	Φ_3	Φ_4	Φ_5	Φ_6	Φ_7	Φ_8	Φ_9
0.0	0.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.2	0.7	34733.4	30110.9	0.0	0.0	0.0	0.0	0.0	0.0	6113.7	5264.9	5544.6
0.4	0.7	35065.6	30294.5	0.0	0.0	0.0	0.0	0.0	0.0	6126.1	5434.4	5906.4
0.5	0.7	35065.6	30294.5	0.0	0.0	0.0	0.0	0.0	0.0	6126.1	5434.4	5906.4
0.6	0.7	34893.4	30227.8	0.0	0.0	0.0	0.0	0.0	0.0	6090.6	5296.6	5710.9
0.8	0.7	35910.4	30896.9	0.0	0.00	0.0	0.0	0.0	0.0	5596.2	5989.1	6490.1
1.0	0.7	35910.4	30896.9	0.0	0.00	0.0	0.0	0.0	0.0	5596.2	5989.1	6490.1
0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

0.2	0.8	29596.7	29219.2	0.0	0.0	0.0	0.0	0.0	0.0	793.9	0.0	414.3
0.4	0.8	29596.7	29203.3	0.0	0.0	0.0	0.0	0.0	0.0	793.9	0.0	465.1
0.5	0.8	29604.4	29240.2	0.0	0.0	0.0	0.0	0.0	0.0	743.2	0.00	422.0
0.6	0.8	30187.0	29805.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	224.4	772.8
0.8	0.8	30121.5	29808.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	151.6	699.9
1.0	0.8	30118.2	29808.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	148.0	696.3
0.0	0.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.2	0.9	29065.2	28979.5	0.0	0.0	0.0	0.0	0.0	0.0	125.6	0.0	11.4
0.4	0.9	29942.4	29629.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	500.9
0.5	0.9	29942.9	29629.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	500.9

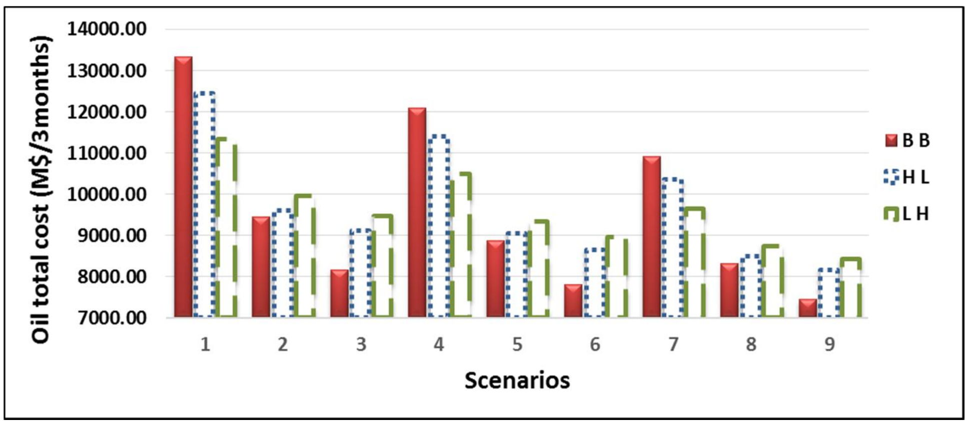
5.2.2.2 MOR model under different market conditions

Applying MOR model to the two cases represented in Figure 4.12 and Figure 4.13 to get more insights about different market scenarios. Increasing the probability of high price or high demand derives the reservoir production to increase. But, the power of demand to derive the production of crude oil is much higher than that of price, Table 5.7. Where from base to high prices crude oil production increase by 16.65 MMbbl/3months. While based on demand, change from base to high increase the production by 34.14 MMbbl/3months. As a result of the dependency between oil and gas productions an inverse relation exists between oil and gas production decreases.

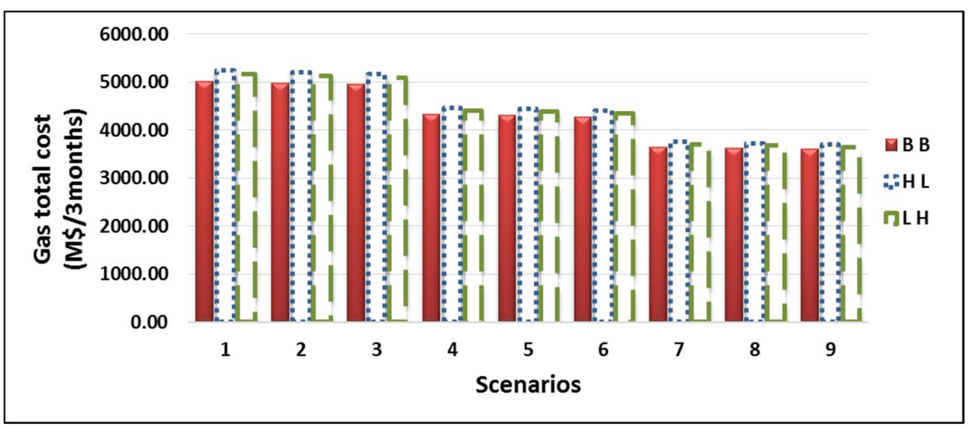
Table 5.7 Preferred plan for three cases using MOR model

Price	Demand	Total cost	Revenue	Profit	Depletion Rate	Years	Oil Prod	Gas Prod
Base	Base	15,322.22	31,783.30	16,461.08	0.00113179	73.63	910.81	270,096.81
High	Low	15,596.05	33,078.34	17,482.29	0.00115248	72.31	927.46	263,021.63
Low	High	14,983.13	31,582.87	16,599.74	0.00117421	70.97	944.95	260,613.04

The effect of increasing oil production is clear on the total costs per scenario, Figure 5.10. Where the total costs of scenarios with high and base demand is decreased, as a result of decreasing the quantity that brought from the outside market at a high penalty. While, the cost of scenarios with low demand is increased, as a results of increasing production, processing, and transportation costs. Figure 5.11 depicts the effect of the change in total cost per case on the profit per scenario for each case. Still the highest profit achieved if market demand is low and price is high.

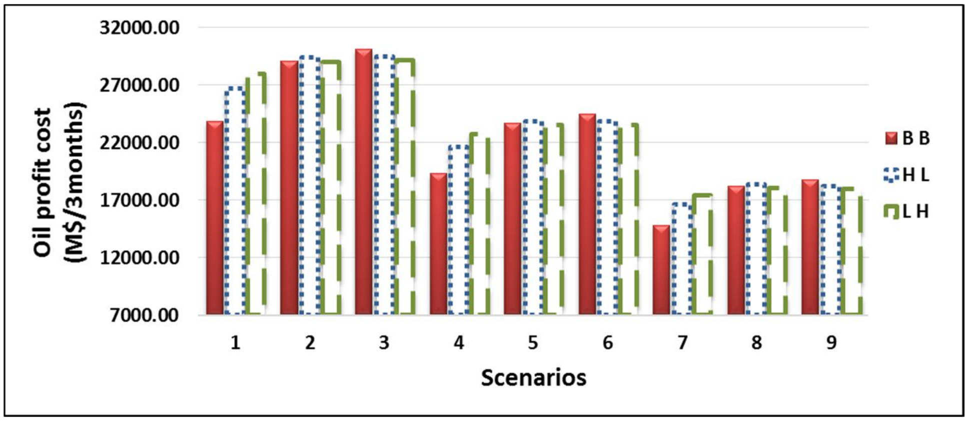


(a) Crude oil total cost based scenarios

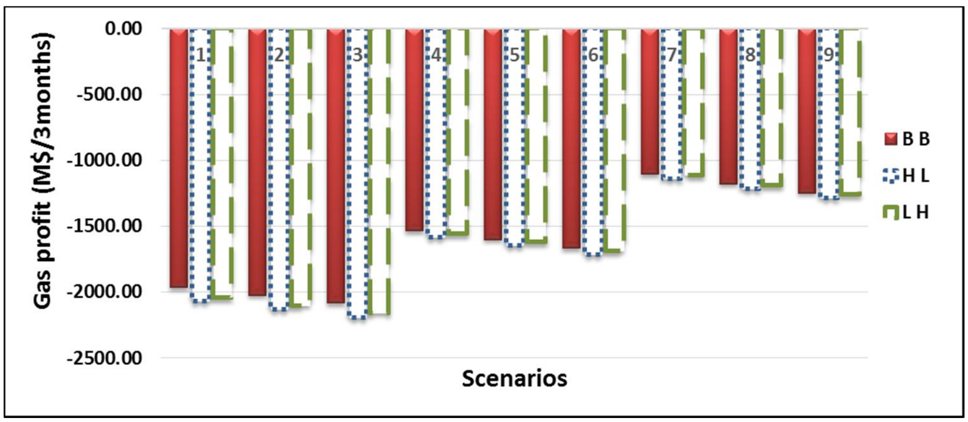


(b) Natural gas total cost based scenarios

Figure 5.10 Total cost for oil and gas based on MOR model for the 3 cases



(a) Crude oil profit based scenarios



(b) Natural gas profit based scenarios

Figure 5.11 Profit for oil and gas based on MOR model for the 3 cases

5.3 Conclusion

In this chapter a multi-objective optimization model for financial risk management is presented for the tactical decisions planning of crude oil and natural gas by-products. The proposed model utilize *CVaR* as a risk measure to eliminate or mitigate the risk effect of uncertainty on market prices and demand. The objective of risk averse decision making is to eliminate or mitigate the risks of exceeding a certain limits of budget or getting a returns below a desired level of cash flow that is required to cover all liabilities. In the proposed model the total costs (revenue) and the risk measure assigned equal weights $\beta = 0.50$ and the confidence level is considered to be 80 %.

Risk model reduced the total costs associated with scenarios (1, 2, 4, 5, 7, and 8). The common factor between these scenarios is the high or base level of demand. Production based on risk model is higher than that of stochastic model enables the Kingdom to reduce the quantities from the outside market. Consequently, the risk model achieves higher levels of profit per scenario than that of the stochastic model.

The results show that, Saudi Arabia should produce crude oil in a rate higher than 7.87 MMbbld and a gas less than 3,472.18 MMcftd to achieve profit. The preferred oil and gas production levels using TOPSIS technique are 10.12 MMbbld and 3,001.08 MMcftd, respectively. At these production levels and under the existing proved reserves the production can continue for 73.63 years. The selected plan costs the Kingdom M$ 15,322.22 /3months and returns a cash flow M$ 31,783.30 /3months.

A sensitivity analysis has been conducted to examine the trade-off between objective function and different levels of (α and β). A direct proportional relation exists between risk averse level β or confidence level α and total costs. While, they have an inverse relation with the revenue. Another analysis was conducted to investigate the effect of two real market situations where a high probability of occurrence was given to high price – low demand and low price – high demand.

The specific limitations of the prosed model are: (1) assumption of α and β values where the risk attitude level of the decision maker is not known precisely, and (2) approximation of CVaR equation used for continuous distribution to be applied to a discrete distribution.

Eventually, after studying three market situations we found that the best market situation (highest profit) for the Kingdom is under high price – low demand. During this situation the Kingdom can reduce oil and gas production. The demand over the production (shortage) satisfied from the outside market by medium term contracts to satisfy customer needs and on the same time keep enough reserves to future generations.

CHAPTER 6

CONCLUSIONS AND FUTURE RESEARCH

6.1 Introduction

As presented in the introduction, the purpose of this dissertation is to utilize the MOO framework in developing a realistic and practical model for tactical planning of HCSC. The first objective was to minimize the total costs associated with production, transportation, processing, inventory (holding), penalty of satisfying shortages, and penalty of emitting CO_2 to the environment. The second objective used to maximize the cash flow to maintain the development projects by maximizing the revenue. The third objective employed to keep a sufficient reserves of the natural resources for the coming generations by minimizing depletion rate.

The proposed model integrates crude oil and natural gas SCs considering the overlapping between both SCs. Different activities were considered starting from production areas and transportation go through processing plants and gathering centers end at demand terminals (domestic, industrial, and international).

An improved version of ε-constraint method utilized to generate set of efficient Pareto-optima. The preferred plan selected using TOPSIS technique which is the nearest point to the ideal solution.

Three different formulations were examined: deterministic, stochastic, and risk, based on different assumptions and considerations. The deterministic model assumes that the values of all the parameters are known for certainty. While, the stochastic model accounts for uncertainty associated with price and demand. The risk model mitigates the risks results from different market situations: high costs or low revenue.

6.2 Conclusions

Applying the proposed models to the HCSC of Saudi Arabia, we can conclude the following:

- Planning based on deterministic model provides misleading results regarding costs and revenue. Reformulating the deterministic model by considering uncertainty in market price and demand. Then, reformulating the stochastic model by including a risk measure in total cost and revenue objective functions. This results in increasing the minimum cost and decreasing the maximum revenue of the payoff matrix, Table 6.1. Where, the point with minimum total cost and maximum revenue represents a feasible plan. Applying this plan based on the deterministic model derives the kingdom into a misleading development plans.

Table 6.1 Payoff matrix for MOD, MOS, and MOR models

	Total Cost (M$/month)		Total Revenue (M$/month)		Sustainability (Years)	
	Min	Max	Min	Max	Min	Max
MOD	11,487.61	34,774.49	19,299.20	37,145.98	73.01	144.20
MOS	13,224.94	31,602.43	22,097.68	35,656.80	70.47	123.41
MOR	14,068.12	34,901.30	20,155.19	32,421.61	70.47	123.41

- The breakeven point is different for each model. As shown in Table 6.2, risk model provides highest crude oil production and lowest natural gas production. Consequently, the range of breakeven points for risk and deterministic models (6.96 to 7.87 MMbbld) is non-profitable for the Kingdom.

Table 6.2 Breakeven production for MOD, MOS, and MOR models

	MOD	MOS	MOR
Oil production (MMbbld)	6.96	7.23	7.87
Gas production (MMcftd)	6,570.46	3,562.05	3,472.18

- Table 6.3 lists the preferred plan based on the three models. It is clear that, for the Kingdom it is incorrect to build their future development plans based on the deterministic or stochastic models. Considering risk reduction, the true total cost is M$ 15,322.22 /3months which is higher than the other models. Also, the cash flow based on mitigating risk in revenue M$ 31,783.30 /3months.

Table 6.3 Preferred plans for MOD, MOS, and MOR models

	MOD	MOS	MOR
Total cost* =	11,709.04	15,155.47	15,322.22
Revenue* =	36,236.58	33,706.03	31,783.30
Profit* =	24,527.54	18,550.56	16,461.08
Depletion rate =	0.00113568	0.00108107	0.00113179
Sustainability** =	73.38	77.08	73.63
Oil production# =	913.94	869.99	910.81
##	10.15	9.67	10.12
Gas production~ =	553,251.39	275,062.99	270,096.81
~~	6,147.24	3,056.26	3,001.08

*: M$/3months; **: years; #: MMbbl/3months; ##: MMbbld; ~: MMcft/3months; ~:MMcftd

- In risk management formulation as the decision maker being more risk averse and increase the weight of the risk term in the objective function the total cost increases while the revenue decreases.

- After studying three market situations, we found that the best situation (highest profit) for the Kingdom is during: high price – low demand. Under this situation the Kingdom can reduce oil and gas production. The demand over the production (shortage) satisfied from the outside market by medium term contracts to satisfy customer needs and on the same time keep enough reserves to future generations.

6.3 Future research

There are some considerations that could not be investigated in this dissertation, but we believe their study would further improve the practicability of the proposed models. These topics are as follows:

- **Nonlinearity of existing activities:** reservoir behavior in reality is nonlinear which affects the recoverable amount of crude oil. Another nonlinearity araise from transportation activity, where transportation cost has a nonlinear relation with transported quantity.
- **Different transportation modes:** in this work we considered all the transportation is done using pipelines, which is correct for Saudi Arabia. For other HCSC different transportation modes may be used such as trucks, railways, and ships.
- **Dependency between scenario based parameters and multi-stage stochastic formulation:** in many real life situations the values of prices and/or demand are not independent. Price can take different values during the planning period (from period to another) and a dependency exist between these values based on market conditions. To investigate this case, we need historical information for the specified

planning period from the stakeholders, so we can construct a dependent scenario and applying a multi-stage stochastic formulation.

- **Robust programming optimization:** stochastic or risk programming optimization provides solutions that is feasible over all scenarios, whereas, robust optimization provides solutions that is feasible and robust for all scenarios. Examining the differences between the two solutions (robust & feasible versus feasible) is an important for the decision maker.
- **Ambiguity of risk attitude:** for the modeler it is not known the attitude of the decision maker or the correct probability distribution of scenario based parameters. Ben-Tal et al. (2010) and Wozabal (2012) proposed a framework for robust optimization under ambiguity in both risk attitude and probability distribution.
- Utilize the special structure of the models to develop efficient exact algorithms or heuristics.
- Integrate up- and down- streams in an integrated model.

References

[1] H. Sahebi, S. Nickel, and J. Ashayeri, “Strategic and tactical mathematical programming models within the crude oil supply chain context—A review,” *Comput. Chem. Eng.*, vol. 68, pp. 56–77, Sep. 2014.

[2] M. Stewart and K. E. Arnold, *Surface Production Operations, Volume 1, Third Edition: Design of Oil Handling Systems and Facilities*, 3 edition. Amsterdam ; Boston : Houston, Tex.? Gulf Professional Publishing, 2007.

[3] G. Mavrotas, “Effective implementation of the ε-constraint method in multi-objective mathematical programming problems,” *Appl. Math. Comput.*, vol. 213, no. 2, pp. 455–465, 2009.

[4] C.-L. Hwang and A. S. M. Masud, *Multiple objective decision making—methods and applications: a state-of-the-art survey*, vol. 164. Springer Science & Business Media, 2012.

[5] G. Mavrotas and K. Florios, “An improved version of the augmented ε-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems,” *Appl. Math. Comput.*, vol. 219, no. 18, pp. 9652–9669, May 2013.

[6] K. Tong, Y. Feng, and G. Rong, “Planning under Demand and Yield Uncertainties in an Oil Supply Chain,” *Ind. Eng. Chem. Res.*, vol. 51, no. 2, pp. 814–834, Jan. 2012.

[7] F. Oliveira and S. Hamacher, “Optimization of the petroleum product supply chain under uncertainty: A case study in northern brazil,” *Ind. Eng. Chem. Res.*, vol. 51, no. 11, pp. 4279–4287, 2012.

[8] J. Yang, H. Gu, and G. Rong, “Supply Chain Optimization for Refinery with Considerations of Operation Mode Changeover and Yield Fluctuations,” *Ind. Eng. Chem. Res.*, vol. 49, no. 1, pp. 276–287, Jan. 2010.

[9] W. Li, C.-W. Hui, P. Li, and A.-X. Li, “Refinery Planning under Uncertainty,” *Ind. Eng. Chem. Res.*, vol. 43, no. 21, pp. 6742–6755, Oct. 2004.

[10] A. J. Conejo, M. Carrión, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*, vol. 153. Boston, MA: Springer US, 2010.

[11] E. T. Iakovou, “An interactive multiobjective model for the strategic maritime transportation of petroleum products: risk analysis and routing,” *Saf. Sci.*, vol. 39, no. 1–2, pp. 19–29, Oct. 2001.

[12] B. Nygreen, M. Christiansen, K. Haugen, T. Bjørkvoll, and Ø. Kristiansen, “Modeling Norwegian petroleum productionand transportation,” *Ann. Oper. Res.*, vol. 82, no. 0, pp. 251–268, Aug. 1998.

[13] R. R. Iyer, I. E. Grossmann, S. Vasantharajan, and A. S. Cullick, “Optimal Planning and Scheduling of Offshore Oil Field Infrastructure Investment and Operations,” *Ind. Eng. Chem. Res.*, vol. 37, no. 4, pp. 1380–1397, Apr. 1998.

[14] S. A. van den Heever and I. E. Grossmann, “An Iterative Aggregation/Disaggregation Approach for the Solution of a Mixed-Integer Nonlinear Oilfield Infrastructure Planning Model,” *Ind. Eng. Chem. Res.*, vol. 39, no. 6, pp. 1955–1971, Jun. 2000.

[15] S. A. van den Heever, I. E. Grossmann, S. Vasantharajan, and K. Edwards, “Integrating complex economic objectives with the design and planning of offshore oilfield infrastructures,” *Comput. Chem. Eng.*, vol. 24, no. 2–7, pp. 1049–1055, Jul. 2000.

[16] S. A. van den Heever, I. E. Grossmann, S. Vasantharajan, and K. Edwards, “A Lagrangean Decomposition Heuristic for the Design and Planning of Offshore Hydrocarbon Field Infrastructures with Complex Economic Objectives,” *Ind. Eng. Chem. Res.*, vol. 40, no. 13, pp. 2857–2875, Jun. 2001.

[17] M. C. A. Carvalho and J. M. Pinto, “A bilevel decomposition technique for the optimal planning of offshore platforms,” *Braz. J. Chem. Eng.*, vol. 23, no. 1, pp. 67–82, Mar. 2006.

[18] M. C. A. Carvalho and J. M. Pinto, “An MILP model and solution technique for the planning of infrastructure in offshore oilfields,” *J. Pet. Sci. Eng.*, vol. 51, no. 1–2, pp. 97–110, Apr. 2006.

[19] N. L. Ulstein, B. Nygreen, and J. R. Sagli, “Tactical planning of offshore petroleum production,” *Eur. J. Oper. Res.*, vol. 176, no. 1, pp. 550–564, Jan. 2007.

[20] R. Rocha, I. E. Grossmann, and M. V. S. Poggi de Aragão, “Petroleum allocation at PETROBRAS: Mathematical model and a solution algorithm,” *Comput. Chem. Eng.*, vol. 33, no. 12, pp. 2123–2133, Dec. 2009.

[21] R. Rocha, “Petroleum supply planning: models, reformulations and algorithms,” Tese de doutorado, Departamento de Informática, PUC-Rio, 2010.

[22] V. Gupta and I. E. Grossmann, “An Efficient Multiperiod MINLP Model for Optimal Planning of Offshore Oil and Gas Field Infrastructure,” *Ind. Eng. Chem. Res.*, vol. 51, no. 19, pp. 6823–6840, May 2012.

[23] L. Aizemberg, H. H. Kramer, A. A. Pessoa, and E. Uchoa, “Formulations for a problem of petroleum transportation,” *Eur. J. Oper. Res.*, vol. 237, no. 1, pp. 82–90, Aug. 2014.

[24] T. N. Sear, “Logistics Planning in the Downstream Oil Industry,” *J. Oper. Res. Soc.*, vol. 44, no. 1, pp. 9–17, 1993.

[25] J. A. Persson and M. Göthe-Lundgren, “Shipment planning at oil refineries using column generation and valid inequalities,” *Eur. J. Oper. Res.*, vol. 163, no. 3, pp. 631–652, Jun. 2005.

[26] A. Elkamel, M. Ba-Shammakh, P. Douglas, and E. Croiset, “An Optimization Approach for Integrating Planning and CO2 Emission Reduction in the Petroleum Refining Industry,” *Ind. Eng. Chem. Res.*, vol. 47, no. 3, pp. 760–776, Feb. 2008.

[27] T.-H. Kuo and C.-T. Chang, “Application of a Mathematic Programming Model for Integrated Planning and Scheduling of Petroleum Supply Networks,” *Ind. Eng. Chem. Res.*, vol. 47, no. 6, pp. 1935–1954, Mar. 2008.

[28] T.-H. Kuo and C.-T. Chang, “Optimal planning strategy for the supply chains of light aromatic compounds in petrochemical industries,” *Comput. Chem. Eng.*, vol. 32, no. 6, pp. 1147–1166, Jun. 2008.

[29] K. Al-Qahtani and A. Elkamel, “Multisite facility network integration design and coordination: An application to the refining industry,” *Comput. Chem. Eng.*, vol. 32, no. 10, pp. 2189–2202, Oct. 2008.

[30] K. Al-Qahtani and A. Elkamel, “Multisite Refinery and Petrochemical Network Design: Optimal Integration and Coordination,” *Ind. Eng. Chem. Res.*, vol. 48, no. 2, pp. 814–826, Jan. 2009.

[31] Y. Kim, C. Yun, S. B. Park, S. Park, and L. T. Fan, “An integrated model of supply network and production planning for multiple fuel products of multi-site refineries,” *Comput. Chem. Eng.*, vol. 32, no. 11, pp. 2529–2535, Nov. 2008.

[32] P. Guyonnet, F. H. Grant, and M. J. Bagajewicz, “Integrated Model for Refinery Planning, Oil Procuring, and Product Distribution,” *Ind. Eng. Chem. Res.*, vol. 48, no. 1, pp. 463–482, Jan. 2009.

[33] L. J. Fernandes, S. Relvas, and A. Paula Barbosa-Póvoa, “Strategic Planning of Petroleum Supply Chains,” in *Computer Aided Chemical Engineering*, vol. 29, M. C. G. and A. C. K. E.N. Pistikopoulos, Ed. Elsevier, 2011, pp. 1738–1742.

[34] L. J. Fernandes, S. Relvas, and A. P. Barbosa-Póvoa, “Strategic network design of downstream petroleum supply chains: Single versus multi-entity participation,” *Chem. Eng. Res. Des.*, vol. 91, no. 8, pp. 1557–1587, Aug. 2013.

[35] L. Fiorencio, F. Oliveira, P. Nunes, and S. Hamacher, “Investment planning in the petroleum downstream infrastructure,” *Int. Trans. Oper. Res.*, vol. 22, no. 2, pp. 339–362, 2015.

[36] Y. Kazemi and J. Szmerekovsky, “Modeling downstream petroleum supply chain: The importance of multi-mode transportation to strategic planning,” *Transp. Res. Part E Logist. Transp. Rev.*, vol. 83, pp. 111–125, 2015.

[37] S. M. S. Neiro and J. M. Pinto, “A general modeling framework for the operational planning of petroleum supply chains,” *Comput. Chem. Eng.*, vol. 28, no. 6–7, pp. 871–896, Jun. 2004.

[38] J. l Jiao, J. l Zhang, and Y. s Tang, “A Model for the Optimization of the Petroleum Supply Chain in China and its Empirical Analysis,” in *2010 International Conference on E-Business and E-Government (ICEE)*, 2010, pp. 3327–3330.

[39] J. Chen, J. Lu, and S. Qi, “Transportation network optimization of import crude oil in China based on minimum logistics cost,” in *2010 IEEE International Conference on Emergency Management and Management Sciences (ICEMMS)*, 2010, pp. 335–338.

[40] M. A. Al-Saleh, S. O. Duffuaa, M. A. Al-Marhoun, and J. A. Al-Zayer, “Impact of crude oil production on the petrochemical industry in Saudi Arabia,” *Energy*, vol. 16, no. 8, pp. 1089–1099, 1991.

[41] S. O. Duffuaa, J. A. Al-Zayer, M. A. Al-Marhoun, and M. A. Al-Saleh, “A Linear Programming Model to Evaluate Gas Availability for Vital Industries in Saudi Arabia,” *J. Oper. Res. Soc.*, vol. 43, no. 11, pp. 1035–1045, 1992.

[42] M. Hamedi, R. Zanjirani Farahani, M. M. Husseini, and G. R. Esmaeilian, “A distribution planning model for natural gas supply chain: A case study,” *Energy Policy*, vol. 37, no. 3, pp. 799–812, Mar. 2009.

[43] R. Grønhaug and M. Christiansen, “Supply chain optimization for the liquefied natural gas business,” in *Innovations in distribution logistics*, Springer, 2009, pp. 195–218.

[44] K. O. Jørnsten, “Practical Combinatorial OptimizationSequencing offshore oil and gas fields under uncertainty,” *Eur. J. Oper. Res.*, vol. 58, no. 2, pp. 191–201, Apr. 1992.

[45] K. K. Haugen, "A Stochastic Dynamic Programming model for scheduling of offshore petroleum fields with resource uncertainty," *Eur. J. Oper. Res.*, vol. 88, no. 1, pp. 88–100, Jan. 1996.

[46] T. W. Jonsbråten, "Oil field optimization under price uncertainty," *J. Oper. Res. Soc.*, vol. 49, no. 8, pp. 811–818, Aug. 1998.

[47] A. Aseeri, P. Gorman, and M. J. Bagajewicz, "Financial Risk Management in Offshore Oil Infrastructure Planning and Scheduling," *Ind. Eng. Chem. Res.*, vol. 43, no. 12, pp. 3063–3072, Jun. 2004.

[48] B. Tarhan, I. E. Grossmann, and V. Goel, "Stochastic Programming Approach for the Planning of Offshore Oil or Gas Field Infrastructure under Decision-Dependent Uncertainty," *Ind. Eng. Chem. Res.*, vol. 48, no. 6, pp. 3078–3097, Mar. 2009.

[49] S. M. S. Neiro and J. M. Pinto, "Multiperiod Optimization for Production Planning of Petroleum Refineries," *Chem. Eng. Commun.*, vol. 192, no. 1, pp. 62–88, Jan. 2005.

[50] C. S. Khor, "A Hybrid of Stochastic Programming Approaches with Economic and Operational Risk Management for Petroleum Refinery Planning under Uncertainty," Jun. 2007.

[51] C. S. Khor, A. Elkamel, and P. L. Douglas, "Stochastic Refinery Planning with Risk Management," *Pet. Sci. Technol.*, vol. 26, no. 14, pp. 1726–1740, Sep. 2008.

[52] K. Al-Qahtani and A. Elkamel, "Robust planning of multisite refinery networks: Optimization under uncertainty," *Comput. Chem. Eng.*, vol. 34, no. 6, pp. 985–995, Jun. 2010.

[53] L. J. Fernandes, S. Relvas, and A. P. Barbosa-Póvoa, "Petroleum Supply Chain Network Design and Tactical Planning with Demand Uncertainty," in *Operations Research and Big Data*, Springer, 2015, pp. 59–66.

[54] L. F. Escudero, F. J. Quintana, and J. Salmerón, "CORO, a modeling and an algorithmic framework for oil supply, transformation and distribution optimization under uncertainty1," *Eur. J. Oper. Res.*, vol. 114, no. 3, pp. 638–656, May 1999.

[55] M. A. H. Dempster, N. H. Pedrón, E. A. Medova, J. E. Scott, and A. Sembos, "Planning Logistics Operations in the Oil Industry," *J. Oper. Res. Soc.*, vol. 51, no. 11, pp. 1271–1288, 2000.

[56] S. A. MirHassani, "An operational planning model for petroleum products logistics under uncertainty," *Appl. Math. Comput.*, vol. 196, no. 2, pp. 744–751, Mar. 2008.

[57] W. B. E. Al-Othman, H. M. S. Lababidi, I. M. Alatiqi, and K. Al-Shayji, “Supply chain optimization of petroleum organization under uncertainty in market demands and prices,” *Eur. J. Oper. Res.*, vol. 189, no. 3, pp. 822–840, Sep. 2008.

[58] M. Ghatee and S. M. Hashemi, “Optimal network design and storage management in petroleum distribution network under uncertainty,” *Eng. Appl. Artif. Intell.*, vol. 22, no. 4–5, pp. 796–807, Jun. 2009.

[59] M. C. Carneiro, G. P. Ribas, and S. Hamacher, “Risk management in the oil supply chain: a CVaR approach,” *Ind. Eng. Chem. Res.*, vol. 49, no. 7, pp. 3286–3294, 2010.

[60] G. P. Ribas, S. Hamacher, and A. Street, “Optimization under uncertainty of the integrated oil supply chain using stochastic and robust programming,” *Int. Trans. Oper. Res.*, vol. 17, no. 6, pp. 777–796, Nov. 2010.

[61] S. A. MirHassani and R. Noori, “Implications of capacity expansion under uncertainty in oil industry,” *J. Pet. Sci. Eng.*, vol. 77, no. 2, pp. 194–199, May 2011.

[62] F. Oliveira, V. Gupta, S. Hamacher, and I. E. Grossmann, “A Lagrangean decomposition approach for oil supply chain investment planning under uncertainty with risk considerations,” *Comput. Chem. Eng.*, vol. 50, pp. 184–195, Mar. 2013.

[63] H. Liqiang and W. Guoxin, “Two-stage Stochastic Model for Petroleum Supply Chain from the Perspective of Carbon Emission,” 2015.

[64] V. Goel and I. E. Grossmann, “A stochastic programming approach to planning of offshore gas field developments under uncertainty in reserves,” *Comput. Chem. Eng.*, vol. 28, no. 8, pp. 1409–1429, Jul. 2004.

[65] V. Goel, I. E. Grossmann, A. S. El-Bakry, and E. L. Mulkay, “A novel branch and bound algorithm for optimal development of gas fields under uncertainty in reserves,” *Comput. Chem. Eng.*, vol. 30, no. 6–7, pp. 1076–1092, May 2006.

[66] A. Azadeh, Z. Raoofi, and M. Zarrin, “A multi-objective fuzzy linear programming model for optimization of natural gas supply chain through a greenhouse gas reduction approach,” *J. Nat. Gas Sci. Eng.*, vol. 26, pp. 702–710, 2015.

[67] J. Bengtsson and S.-L. Nonås, “Refinery Planning and Scheduling: An Overview,” in *Energy, Natural Resources and Environmental Economics*, E. Bjørndal, M. Bjørndal, P. M. Pardalos, and M. Rönnqvist, Eds. Springer Berlin Heidelberg, 2010, pp. 115–130.

[68] A. Leiras, G. Ribas, S. Hamacher, and A. Elkamel, “Literature review of oil refineries planning under uncertainty,” *Int. J. Oil Gas Coal Technol.*, vol. 4, no. 2, pp. 156–173, 2011.

[69] F. Hennig, B. Nygreen, K. C. Furman, J. Song, and G. R. Kocis, “Crude oil tanker routing and scheduling,” *INFOR Inf. Syst. Oper. Res.*, vol. 49, no. 2, pp. 153–170, 2011.

[70] Al-Yakoob, M. S., “Mixed-Integer Mathematical Programming Optimization Models and Algorithms For An Oil Tanker Routing and Scheduling Problem,” Feb. 1997.

[71] H. Sahebi, “Strategic and Tactical Crude Oil Supply Chain: Mathematical Programming Models,” Karlsruhe, Karlsruher Institut für Technologie (KIT), Diss., 2013, 2013.

[72] S. McMurra, *Energy to the world: The story of Saudi ARAMCO volume 2*, First edition., vol. 2. Texas, USA: Aramco Services Company, Houston, 2011.

[73] R. T. Clemen and T. Reilly, *Making Hard Decisions with Decision Tools Suite Update Edition*, 1 edition. Pacific Grove, CA: Cengage Learning, 2004.

[74] G. B. Dantzig, “Linear programming under uncertainty,” *Manag. Sci.*, vol. 1, no. 3–4, pp. 197–206, 1955.

[75] G. Ribas, A. Leiras, and S. Hamacher, “Tactical planning of the oil supply chain: optimization under uncertainty,” *PRÉ-An. XLIIISBPO*, 2011.

[76] “OPEC : OPEC Basket Price.” [Online]. Available: http://www.opec.org/opec_web/en/data_graphs/40.htm. [Accessed: 14-May-2017].

[77] R. T. Rockafellar and S. Uryasev, “Optimization of conditional value-at-risk,” *J. Risk*, vol. 2, pp. 21–42, 2000.

[78] R. T. Rockafellar and S. Uryasev, “Conditional value-at-risk for general loss distributions,” *J. Bank. Finance*, vol. 26, no. 7, pp. 1443–1471, 2002.

[79] S. Sarykalin, G. Serraino, and S. Uryasev, “Value-at-risk vs. conditional value-at-risk in risk management and optimization,” in *State-of-the-Art Decision-Making Tools in the Information-Intensive Age*, Informs, 2008, pp. 270–294.

[80] A. Ben-Tal, D. Bertsimas, and D. B. Brown, “A soft robust model for optimization under ambiguity,” *Oper. Res.*, vol. 58, no. 4-NaN-2, pp. 1220–1234, 2010.

[81] D. Wozabal, “A framework for optimization under ambiguity,” *Ann. Oper. Res.*, vol. 193, no. 1, pp. 21–47, 2012.

APPENDIX A

COLLECTED DATA

A.1 Oil and gas byproducts

Crude oil products:

Arabian extra light (AXL), Arabian light (AL), Arabian medium (AM), and Arabian heavy (AH).

Natural gas byproducts:

Natural gas liquid (NGL), Methane (M), Ethane (E), Butane (B), Propane (P), and Natural gasoline (NG).

A.2 Oil and gas production and processing plants

Table A.1 Data about oil reservoirs and GOSPs.

Oil reservoirs	Crude type	Reserves MMbbl	GOSPs	GOSP capacity per day (MMbbld)	GOR
Khurais	AL	8500	4	0.30	274
Safaniya	AH	37000	5	0.24	177
Marjan	AM	10000	1	0.40	840
Zuluf	AM	12000	2	0.35	555

AbuSafah	AM	7500	1	0.30	64
Qatif	AL	10000	3	0.22	679
Khursaniyah	AL	10000	1	0.50	375
Berri	AXL	12000	5	0.08	756
Shaybah	AXL	12000	3	0.22	850
AbuHadriyah	AL	12500	1	0.30	267
Abqaiq	AXL	22500	4	0.10	846
Manifa	AH	11000	3	0.30	100
Harmaliyah	AL	2000	1	0.10	739
Hawiyah	AL	10080	3	0.17	400
Shedgum	AL	25210	5	0.17	543
Fazran	AL	840	1	0.17	448
Uthmaniyah	AL	40340	12	0.17	461
Haradh	AL	3360	2	0.17	400
AinDar	AL	20170	6	0.17	544
NeutralZone	AH	1250	1	0.30	160

Table A.2 Data about oil sweetening plants.

Sweetening plant	Oil type	Capacity (MMbbld)
Khurais	AL	1.47
Safaniya	AM, AH	2.81
Qatif	AL, AM	1.17
Khursaniyah	AL	0.61
RasTanura	AH	1.47
Shaybah	AX	0.81

Tanajib	AL	0.49
Abqaiq	AXL, AL	7.00

Table A.3 Data about gas reservoirs and processing plants.

Gas reservoirs	Reserves (MMcft)	Gas plant	Capacity (MMcftd)	Fractionation plant	Capacity (MMcftd)
Karan	31323005.88	Berri	600.00	RasTanura	1683.00
Hasbah	23489672.55	Khursaniyah	1000.00	Yanbu	729.30
Arabiyah	21923005.88	Shedgum	1500.00	Juaymah	2412.30
Ghazal	28189672.55	Uthmaniyah	1500.00	Hawiyah	2805.00
Wudayhi	23489672.55	Yanbu	520.00	Wasit	1346.40
Waqr	23489672.55	Haradh	1600.00		
Tinat	23489672.55	Hawiyah	2400.00		
Shaden	23489672.55	Juaymah	2400.00		
Hilwah	23489672.55	Wasit	2500.00		
Shamrah	23489672.55				
Mariuah	23489672.55				
Mazalij	23489672.55				
Manjurah	23489672.55				

Table A.4 Yield of gas byproducts at gas plants

Gas gathering centers	Gas plant	Hydrogen Sulfide	Carbon dioxide	Methane	Natural Gas Liquid
Khurais	Uthmaniyah	0.0023	0.0430	0.4096	0.5546
Safaniya	Khursaniyah	0.0000	0.0179	0.4871	0.4957
Marjan	Khursaniyah	0.0000	0.0124	0.8025	0.1874
Zuluf	Khursaniyah	0.0000	0.0095	0.7871	0.2045

AbuSafah	Juaymah	0.0224	0.0616	0.4824	0.4336
Qatif	Juaymah	0.1068	0.1408	0.3105	0.4420
Khursaniyah	Khursaniyah	0.0255	0.0517	0.4040	0.5189
Berri	Berri	0.0619	0.0642	0.5135	0.3603
Shaybah	Hawiyah	0.0100	0.0588	0.5542	0.3917
AbuHadriyah	Juaymah	0.0443	0.0338	0.3765	0.5455
Abqaiq	Yanbu	0.0148	0.0761	0.5886	0.3206
Manifa	Juaymah	0.0148	0.0179	0.4871	0.4957
Harmaliyah	Hawiyah	0.0437	0.0752	0.4576	0.4235
Hawiyah	Hawiyah	0.0130	0.0872	0.5452	0.3764
Shedgum	Shedgum	0.0072	0.0815	0.4764	0.4349
Fazran	Shedgum	0.0033	0.0598	0.5324	0.4044
Uthmaniyah	Uthmaniyah	0.0178	0.0828	0.4782	0.4412
Haradh	Haradh	0.0117	0.0762	0.5406	0.3895
AinDar	Shedgum	0.0141	0.0954	0.4359	0.4546
NeutralZone	Khursaniyah	0.0148	0.0179	0.4871	0.4957
Karan	Berri	0.0324	0.0574	0.6668	0.3604
Hasbah	Wasit	0.0935	0.0662	0.6445	0.2912
Arabiyah	Wasit	0.0464	0.0644	0.5749	0.3143
Ghazal	Haradh	0.0392	0.1142	0.4688	0.3778
Wudayhi	Haradh	0.0064	0.1301	0.4070	0.4852
Waqr	Haradh	0.0304	0.0262	0.7329	0.2104
Tinat	Haradh	0.0882	0.1234	0.5114	0.2770
Shaden	Shedgum	0.1136	0.0711	0.3463	0.4690
Hilwah	Juaymah	0.0562	0.0012	0.7462	0.1964
Shamrah	Juaymah	0.0059	0.0403	0.6384	0.3347

Mariuah	Yanbu	0.0869	0.0273	0.5937	0.2922
Mazalij	Hawiyah	0.0064	0.1301	0.4070	0.4189
Manjurah	Hawiyah	0.0304	0.0262	0.3900	0.3900

Table A.5 Yield of gas byproducts at fractionation plants

Gas plant	Fractionation plant	Ethane	Butane	Propane	Natural gasoline
Berri	Juaymah	0.4200	0.1100	0.2800	0.1900
Khursaniyah	Juaymah	0.4200	0.1100	0.2800	0.1900
Shedgum	Yanbu	0.4200	0.1100	0.2800	0.1900
Uthmaniyah	RasTanura	0.4200	0.1100	0.2800	0.1900
Yanbu	Yanbu	0.4200	0.1100	0.2800	0.1900
Haradh	Hawiyah	0.4200	0.1100	0.2800	0.1900
Hawiyah	Hawiyah	0.4200	0.1100	0.2800	0.1900
Juaymah	Juaymah	0.4200	0.1100	0.2800	0.1900
Wasit	Wasit	0.4200	0.1100	0.2800	0.1900

A.3 Distribution terminals

Table A.6 Capacities and demands of distribution terminals

		Crude oil (MMbbld)		Natural gas (MMcftd)	
		Capacity	Demand	Capacity	Demand
Domestic regions	North Region	0.00	0.00	45.08	30.05
	South Region	0.60	0.40	109.96	73.30
	West Region	2.30	1.53	268.48	178.99
	Middle Region	0.19	0.13	252.61	168.40

	East Region	1.43	0.95	120.37	80.25
Industrial cities	Jubail	0.00	0.00	4403.50	2935.67
	Rabigh	0.00	0.00	4403.50	2935.67
	Yanbu	0.00	0.00	4403.50	2935.67
International terminals	RasTanura	5.86	2.20	2017.13	1344.75
	Juaymah	6.25	3.32	2428.72	1619.15
	Yanbu	2.24	1.56	744.87	496.58

Table A.7 Prices at distribution terminals ($/bbl for oil and $/cft for gas)

Byproduct	Domestic	Industry	International
Arabian Extra Light	10		50
Arabian Light	10		50
Arabian Medium	10		50
Arabian Heavy	10		50
Hydrogen Sulfide			0.036944
Natural Gas Liquid			0.000820
Methane		0.002900	
Ethane		0.002626	
Butane	0.010278		0.020556
Propane	0.007625		0.015250
Natural Gasoline			0.010792

APPENDIX B

IMPROVED AUGMENTED ε-CONSTRAINED

AUGMECON method is a numerical technique used for generating the efficient Pareto-optimal solutions of the MOO.

Problem definition

Assume a MOO problem of p objective functions, *x* decision variables belongs to *S* feasible space.

$$\max\left(f_1(x), f_1(x), \dots, f_p(x)\right) \tag{B.1}$$

st

$x \ \in S$

In the usual ε-constraint method the objective function with the highest priority is optimized subject to the other objective functions as a constraints.

$$\max \ f_1(x) \tag{B.2}$$

st

$f_2(x) \geq e_2,$

$f_3(x) \geq e_3,$

...

$f_p(x) \geq e_p,$

$x \in S,$

where $e_1, e_2, \dots, and\ e_p$ are threshold values of the objective functions.

While the AUGMECON method optimizes the following model:

$$\max\left(f_1(x) + eps\ \left({}^{s_2}/_{r_2} + 10^{-1} \times {}^{s_3}/_{r_3} + \cdots + 10^{-(p-2)} \times {}^{s_p}/_{r_p}\right)\right) \tag{B.3}$$

st

$f_2(x) - s_2 = e_2,$

$f_3(x) - s_3 = e_3,$

...

$f_p(x) - s_p = e_p,$

$x \in S\ and\ s_i \in R^+$

Where $s_1, s_2, \ldots, and\ s_p$ are the slack or surplus variables, $r_1, r_2, \ldots, and\ r_p$ are the ranges of the objective functions, and $eps\ \in [10^{-6}, 10^{-3}]$.

Computational procedure for AUGMECON method

Step 1: Payoff table generation

The first step is to specify the range of each objective function applying a lexicographic optimization. Starting by optimizing the first objective function $f_1 = z_1^*$, then optimize the second objective function $(f_2 = z_2^*)$ adding $f_1 = z_1^*$ as a constraint. Thereafter, optimizing the third objective function $(f_3 = z_3^*)$ adding $f_1 = z_1^* and\ f_2 = z_2^*$ as a constraints and so on to finish all the objectives. Repeat the procedure starting from f_2 and continue until $f_{p.}$

Step 2: Efficient Pareto-optima generation

- Dividing the range of each objective function (i.e., equal intervals) to form a grid of possible Pareto points.
- Each point on the grid used as a right hand side of the (p-1) constrained objective functions. Then, solving the formulation (B.3), where the grid point that gives a feasible solution represents an efficient Pareto-optimal.

Vitae

Name : Ahmed Mohammed Ali Attia

Nationality : Egyptian

Date of Birth : 4/1/1981

Email : amattia@kfupm.edu.sa, am_attia@yahoo.com

Address : Dept. of Systems Engineering, KFUPM

Academic Background : Ahmed M. Attia is a lecturer-B of Industrial and Systems Engineering at the Department of Systems Engineering at King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia. He received his M.Sc. in Industrial Engineering 2011, Zagazig University, Egypt. Then Ph.D. in Industrial and Systems Engineering May 2017 at the Department of Systems Engineering KFUPM, Dhahran, Saudi Arabia. His research interests are in the areas of quality control, inventory control, supply chain management, operations research, and optimization. His work has appeared in journals such as International Journal of Production Research and Contemporary Engineering Sciences. He is an Editorial assistant of the Journal of Quality in Maintenance Engineering, published by Emerald in the United Kingdom. His contact details for KFUPM are: Email: amattia@kfupm.edu.sa and Mobile: 00966593068100.