

Model-based Optimisation of the Operation of Integrated Natural Gas Production, Processing & Supply Networks

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Abstract

Gathering significant volumes of natural gas involves connecting to wells in different oil and/or gas fields that are usually spread across large geographical areas. Supplying processed gas and associated liquids, such as liquefied petroleum gas (LPG) and natural gas liquids (NGL) to the consumers often requires an extensive network of degassing stations, compressor stations, pipelines and gas processing plants, as well as storage and shipping facilities for the liquids. The operation of such natural gas networks involves many degrees of freedom impacting profitability, efficiency and environmental performance, which creates significant scope for optimisation.

This work presents novel methodologies making use of detailed models for optimizing integrated production, processing and supply chain operations of natural gas networks. Despite the underlying complexity of the system, the application of rigorous mathematical optimisation to detailed models of an entire gas network is now computationally tractable and can ensure that the solution obtained meets all constraints.

Using the vast natural gas network of Basrah Gas Company (a Shell Joint-venture in Iraq) as a case study, optimisation approaches to find optima to profitability, production and flexibility problems of natural gas networks have been developed. The magnitudes of the resulting improvements in optimised operations are significant.

A Gradient Ranking method has been developed and tested for determining the significance of the decision variables to the objective function and thereby reducing problem complexity. Methods have also been developed to assess the relative economic impact of the different products (dry gas, propane, butane and natural gasoline) in relation to optimal profitability with varying market prices.

Finally, a multiperiod optimisation (MPO) approach has also been developed to maximise the overall profit for multiple periods by varying, in each period, the process operating variables, sales rates and inventory levels. The results show that the MPO approach results in significantly improved profitability compared with that achieved via the sequential single-period optimisation approach.

Declaration of Originality

I declare that this thesis and the work contained herein is my own. I spent a considerable amount of time in the oil and gas fields of Iraq where I collected data, developed models, performed validations and carried out analysis for this work. All results and inputs from other sources have been appropriately referenced.

Daniel Elaigwu Aluma

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Not much could have been accomplished without the loving support of my mother Veronica, my wife Amira, my daughter Lara Ene and my son Daniel Akogwu. I will now focus on optimising my time with all of you.

To the memory of my Father, Pius Akogwu Aluma. A brilliant son of Idoma land in Nigeria

Contents

Abstract	2
Acknowledgments.....	6
PART I: INTRODUCTION AND BACKGROUND	18
Chapter 1. Introduction.....	19
1.1 Growing Importance of Natural Gas.....	19
1.2 Natural Gas Network Challenges	20
1.3 Approaches to Supply Network Optimisation	21
1.4 Case Study: Iraq Natural Gas Network	23
1.5 Benefits of Optimising Natural Gas Networks	25
1.6 Research Objectives.....	26
1.7 Thesis Outline.....	28
Chapter 2. Literature Review	30
2.1 Optimisation: Classification and Methods	30
2.2 Nonlinear Optimisation of Large Systems	33
2.2.1 Sequential Quadratic Programming (SQP)	36
2.2.2 Merit Functions and Line Search.....	38
2.3 Optimal Solution of Non-Convex Problems.....	39
2.3.1 Spatial Branch and Bound Methods	40
2.3.2 Convex Relaxation/ Underestimators	41
2.4 Optimisation of Natural Gas Systems	43

2.5	Integrated Network Optimisation	46
2.6	Supply Chain Optimisation.....	47
2.6.1	Planning Models and Frameworks.....	49
2.7	Current Work.....	51
PART II: NATURAL GAS NETWORK		52
Chapter 3. The BGC Gas Network.....		53
3.1	Degassing Stations	57
3.2	Compressor Stations.....	61
3.3	North Rumaila (NR) NGL Plant.....	68
3.4	Khor Az Zubair (KAZ) NGL/ LPG Plant.....	71
3.5	Pipeline Network.....	76
3.6	Um Qasr Terminal (Storage and Marine)	78
3.7	Gas Transmission Unit (GTU)	80
3.8	Typical Natural Gas Network	80
Chapter 4. Detailed Gas Network Modelling.....		82
4.1	Compressor Station Modelling.....	85
4.2	Pipeline Modelling.....	86
4.3	NGL Plant Modelling.....	88
4.3.1	Slug Catchers	89
4.3.2	Liquid Stripper Units.....	89
4.3.3	Booster Units.....	89
4.3.4	Cooling Loops and Low-Temperature Separator	89

4.3.5	De-ethanizers.....	90
4.4	LPG Plant Modelling.....	91
4.4.1	De-propanizer	92
4.4.2	De-butanizer	92
4.5	Model Initialization	93
4.6	Conclusion.....	94
Chapter 5.	Model Validation.....	95
5.1	Thermodynamics & Property Models Validation	95
5.2	Network Model Validation	97
5.2.1	Compressors Model Validation	98
5.2.2	Pipeline Model Validation	98
5.2.3	NGL Plant Model Validation.....	100
5.2.4	LPG Plant Model Validation.....	100
5.3	Conclusion.....	101
PART III:	NETWORK OPTIMISATIONS.....	102
Chapter 6.	Optimisation Solution Approach	103
6.1	Optimisation Solvers	104
6.1.1	NLP Solver	104
6.1.2	MINLP Solver	106
6.2	Scaling of Variables	107
6.3	Initial Step Length.....	108
6.4	Conclusion.....	109

Chapter 7.	Optimisation of Gas Network Profitability	110
7.1	Objective Function: Maximise Profit	111
7.2	Solution Approach	112
7.2.1	Decision Variables, Constraints and Input Parameters	113
7.3	Comparison of Solution Algorithms	115
7.4	Effect of Variable Scaling	116
7.5	Effect of Initial Step Length.....	118
7.6	Optimal Profit versus Base Operational Profit.....	119
7.7	Network Bottlenecks	120
7.8	Significance of Decision Variables to Optimum Profitability: The Gradient Ranking Method.....	121
7.9	Test of Gradient Ranking Method for Variable Significance	126
7.10	Sensitivity of Optimal Profit Improvement to Market Prices	128
7.11	Relative Economic Impact of Products with Varying Prices	131
7.11.1	Results.....	132
7.12	Conclusion.....	135
Chapter 8.	Operational Optimisation.....	136
8.1	Maximise Total Production	137
8.1.1	Results.....	137
8.1.2	Significance of Decision Variables	138
8.2	Maximise Product Yields	140
8.2.1	Results.....	141

8.2.2	Significance of Decision Variables to Maximum Yield.....	142
8.3	Mimimise Flaring.....	144
8.3.1	Results.....	144
8.3.2	Significance of Decision Variables	145
8.4	Abnormal Operating Scenarios.....	147
8.4.1	Equipment Failure	147
8.4.2	Field Decline.....	149
8.5	Conclusion.....	150
Chapter 9.	Multi-Period Optimisation of Network Profitability.....	151
9.1	Mathematical formulation.....	152
9.2	Implementation of MPO in gPROMS.....	155
9.3	A Two-Period Optimisation Case study.....	156
9.3.1	Optimisation Decision Variables.....	157
9.3.2	Constraints	157
9.3.3	Prices and Costs	158
9.4	Case Study Results	159
9.5	Comparison of MPO with multiple Single-Period Optimisations.....	162
9.6	Conclusions.....	164
Chapter 10.	Conclusions.....	165
10.1	Key Conclusions from this Work.....	165
10.2	Recommendations for Further Research.....	169
References		171

Glossary of Acronyms.....	177
Publications from this Thesis.....	179
Appendix A: NLPSQP Algorithm in gPROMS.....	180
Appendix B: Decision Variables for Single-Period Profitability Optimisation (Scaling =0)	184
Appendix C: Constrained Variables for Single-Period Profitability Optimisation.....	186
Appendix D: gPROMS Equation Based Language for Gas Network Model	188
Appendix E: Gradient of Decision Variables near Optimal Profit point.....	206
Appendix F: Constrained Variables for Profit Optimisation with Increased Propane Prices.....	209
Appendix G: Constrained Variables for Profit Optimisation with Increased Butane Prices	210
Appendix H: Optimum Variables for Propane Yield Optimisation	211
Appendix I: Optimum Decision Variables for Flare Minimisation	212
Appendix J: Constrained Variables for Flare Minimisation.....	213
Appendix K: Optimum Decision Variable Values for MPO	214
Appendix L: gPROMS Language for Multiperiod Hierarchical Model for Profit Optimisation	215

List of Figures

Figure 1: Map of Iraq showing the major Oil Fields in Basrah Province.....	24
Figure 2: Locations of BGC facilities in the Basrah province (Credit: South Oil Company).....	55
Figure 3: BGC Asset Network.....	56
Figure 4: Typical Degassing station (coloured units) and Compressor Station.	60
Figure 5: Head Curves for North Rumaila K3 (3 rd stage Feed Gas) Compressors.....	62
Figure 6: Head Curves for North Rumaila K4 (2 nd stage Feed Gas) Compressors	63
Figure 7: NR NGL Plant Block Diagram.....	68
Figure 8 KAZ NGL/ LPG Plant Block Diagram	75
Figure 9: Um Qasr Receiving, Storage and Marine Terminals (Red Units are 3 rd Party facilities) 79	
Figure 10: Natural Gas Production, Processing and Supply Network.....	81
Figure 11: BGC network model topology in gPROMS ProcessBuilder.....	84
Figure 12: gPROMS topology of 3-train compressor station model	86
Figure 13: gPROMS topology of sections of the pipeline systems in the network	87
Figure 14: gPROMS topology of NGL model showing cooling cycles, low-temperature separator and de-ethanizer	91
Figure 15: gPROMS topology of LPG plant model showing de-propanizer and de-butanizer....	93
Figure 16: Multi-period optimisation	152
Figure 17: Composite Model of Multi-Period Operation.....	156

List of Tables

Table 1: Degassing Station Gas Temperatures and Pressure	58
Table 2: Compressor Stations and Specifications	61
Table 3: Gas Compositions for West Qurna Stations	64
Table 4: Gas Compositions for North Rumaila Stations	65
Table 5: Gas Compositions for South Rumaila Stations	66
Table 6: Gas Compositions for Zubair Stations	67
Table 7: NR NGL Plant Train Capacities	69
Table 8: Liquid Stripping Column Specifications	70
Table 9: De-ethanizer Column Specifications	71
Table 10: De-propanizer Column Specifications	73
Table 11: De-butanizer Column Specifications.....	74
Table 12: Pipelines Parameters	76
Table 13: Um Qasr Refrigeration and Storage Capacities.....	80
Table 14: Low Pressure Validation Case	96
Table 15: High Pressure, High Temperature Validation Case	96
Table 16: Sour Gas Validation Case.....	97
Table 17: Validation using Compressor Power Consumption Data	98
Table 18: Validation of Pipeline models.....	98
Table 19: Validation of NGL Plant Model Using North Rumaila Operations Data.....	100
Table 20: Validation of LPG Plant Model Using KAZ Operations Data.....	101
Table 21: Optimisation Tolerances applied to the NLP Problem.....	106
Table 22: Optimisation decision variables.....	114
Table 23: Constraint types and numbers.....	114
Table 24: Cost and price data.....	115

Table 25: Comparison between optimisation approaches	116
Table 26: Comparison of Scaling Strategies.....	117
Table 27: Varying Initial StepLength	119
Table 28: Optimum Profit versus Design Operational Profit.....	120
Table 29: Gradient Ranking of Profit Optimisation for different Scaling Strategies.....	124
Table 30: Test of Significance of Decision Variables	127
Table 31: Product Prices Varied for Profit Optimisation	128
Table 32: Price Sensitivity of Profit Optimisation [Product Prices Varied Separately]	129
Table 33: Top-5 Gradient Ranking of Variable Significance for Profit Optimisation at higher propane prices	130
Table 34: Price Sensitivity of Profit Optimisation [All Product Prices Varied Together].....	131
Table 35: Economic Impact of Varying Product Prices on Optimal Production Rates	133
Table 36: Optimum Total Production vs Design Operational Production	138
Table 37: Top-20 Gradient Ranking of Variable Significance for Total Production Optimisation	139
Table 38: Optimum Yield Cases for Various Products.....	141
Table 39: Top-20 Gradient Ranking of Variable Significance for Maximum Propane Yield.....	143
Table 40: Optimised Flaring vs Default Operational Flaring.....	145
Table 41: Top-15 Gradient Ranking of Variable Significance for Flare minimisation.....	146
Table 42: Total Production Under Equipment (KAZ 11.2 Train) Failure: Optimum vs Default Operation	148
Table 43: Total Production Under Field Decline: Optimum vs Default Operation	150
Table 44: Decision Variable types and number of degrees of freedom per Period	157
Table 45: Multi-Period Constraint Type and Number.....	158
Table 46: Cost and Price Data	159
Table 47: Optimum Multi-Period Profit	160

List of Tables

Table 48: Initial and Optimal values of Variables for Commercial Planning	161
Table 49: Profitability over 2-period operation	163
Table 50: Computational Statistics (Sequential Single-Periods vs Simultaneous MPO)	163

PART I: INTRODUCTION AND BACKGROUND

Chapter 1. Introduction

1.1 Growing Importance of Natural Gas

Natural gas is increasingly becoming the fuel of choice to power the future of the global economy. With improvements in seismic, drilling and production technology, the proved reserves of natural gas in the world are now estimated at around 6973 trillion cubic feet. This is a 35% increase from the proved global reserves recorded 15 years earlier (U.S. EIA, 2015).

Once considered to be in imminent danger of depletion, the US natural gas resource base is now widely agreed to be sufficient to last 100 years at current rates of consumption (IHS CERA, 2014). U.S. net electricity generation from natural gas went from 20% in 2010 to over 30% in 2015 (U.S. Energy Information Administration, 2015).

Around the world, proved natural gas reserves are expected to further increase significantly in the coming years as shale gas technology and experience from the United States is applied in Argentina, China, South Africa, United Kingdom, Poland and several other countries. Abundance of natural gas based feedstock is also underpinning a revival in the chemical industry and spurring manufacturing. This, in turn, creates jobs and stokes economic growth.

Furthermore, natural gas has gained a new role as a key enabler for the deployment of renewable energy. Gas-fired generation can quickly swing into action when the wind dies down and the sun does not shine. In contrast, the coal and nuclear steam turbines that form the backbone of most electricity systems today are very slow to turn up and down and become much less efficient when running at less than full power (Kitasei, 2010).

Compared to other primary sources of energy, natural gas emits less CO₂, sulphur oxides (SO_x), nitrogen oxides (NO_x) and particulate matter. Natural gas is also cheaper than other fossil fuels on an energy parity basis.

From the foregoing, it is evident that guaranteeing natural gas and natural gas liquids supply is critical to energy security, economic growth and reduction of CO₂ emissions.

1.2 Natural Gas Network Challenges

Gathering significant volumes of natural gas usually involves connecting to wells in different oil and/or gas fields that can be spread across large geographical areas. Supplying processed gas and associated liquids such as liquefied petroleum gas (LPG) and natural gas liquids (NGL) to the consumers often requires an extensive network of degassing stations, compressor stations, pipelines and gas processing plants, as well as storage facilities and shipping terminals for the liquids.

Natural gas networks have peculiar characteristics which complicate supply chain management. Complexity partly arises from the fact that natural gas is sourced from geographically different fields with different compositions and is processed in different and diverse units to produce a mixed product slate for multiple markets. Moreover, as there is usually no intermediates storage capacity, it is generally not possible to curtail well production of associated natural gas as this leads to loss of oil revenue. Therefore, a reduction in consumer gas demand or an outage in the gas network typically results directly in significant gas flaring. The penalty for a constrained or inefficient gas network is environmentally and economically severe, more so than for liquids- or solids-based process networks.

A supply chain network indicates connections of facilities, such as production plants, storage and distribution facilities, in a supply chain. It has been suggested that a successful network structure should achieve some of the following objectives: locating new facilities in the supply chain, retrofitting existing facilities, sourcing materials or services for facilities and allocating facilities to form production routines. (Geoffrion & Powers, 1995)

At the strategic planning level for natural gas network of processing units, decisions have to be taken on feed gas intake, utilisation of processing capacities, utilisation of liquids storage capacity and demand allocation. Existing capacities as well as new capacities may be considered.

Since natural gas/NGL supply chains usually comprise extensive networks of compressor stations pipelines processing units and other facilities. Their operation involves many degrees of freedom impacting profitability, efficiency and environmental performance, which leads to the need for model-based optimisation.

1.3 Approaches to Supply Network Optimisation

Historically, only subsystems of the oil and gas supply chain have been studied at a high level of detail i.e. using detailed property equation models. This is because complexity increases significantly when different parts of the oil and gas chain are put together within the same model. Less advanced technologies in the past, like inefficient optimisation algorithms, slow CPU and shortage of computer memory limited the optimisation of large integrated natural gas networks.

Enterprise wide optimisation (EWO) is an equivalent term to supply chain management but with emphasis on the planning, scheduling and control of manufacturing facilities which often requires the use of nonlinear process models. In his seminal paper, Grossmann explained that achieving EWO in the process industry will require a new generation of computational tools for which the

following major challenges must be addressed: (a) the modeling challenge; (b) the multiscale optimisation challenge; (c) the uncertainty challenge; (d) the algorithmic and computational challenge. (Grossmann, 2005)

Conventional approaches to the optimisation of large supply networks usually tend to rely on rather simple models of the individual nodes (e.g. production facilities and processing plants) in the networks, often taking the form of simple (mostly linear) relations between the flowrates of the various materials entering and leaving each node. Whilst this greatly simplifies the solution of the underlying mathematical optimisation problem, it may be problematic in some important ways. In particular, the resulting solutions may be unimplementable in practice as they exceed the real plant capabilities. This problem may be addressed by performing the optimisation calculations in a conservative manner, for example by introducing safety margins which ensure that the solution stays away from any critical constraints. Alternatively, some appropriate adjustments may be applied – often at the local level of individual processing plants - *a posteriori* to the “optimal” solution to restore feasibility of any constraints that it violates. However, such pragmatic adjustments almost always lead to sub-optimal solutions which, given the very substantial money flows in such large networks, may translate into significant loss of opportunity.

An alternative approach to natural gas supply chain optimisation is to use a higher level of physical detail in describing the operation of the individual production and processing nodes, thereby ensuring that any solution obtained satisfies all important constraints on the operation of plant equipment.

Until recently, this approach was considered to be impractical because of two significant obstacles. First, the construction of detailed models for the individual plants is a non-trivial exercise. Secondly, the resulting optimisation problem was often beyond the capabilities of existing numerical solvers.

However, detailed mathematical modeling is increasingly being used for the simulation and optimisation of individual plants, which means that the required plant models are already available in many cases. And the continual evolution of computer hardware and process modeling technology is now bringing the solution of models of the required size within the scope of the available tools.

A key development in this context has been the significant development over the past decade of equation-oriented process modeling frameworks (Pantelides, et al., 2015). These now allow large-scale models, comprising fairly detailed models of individual equipment items within wide system envelopes, to be constructed and solved reliably with minimal user intervention. Moreover, coupling these models with rigorous mathematical optimisation solvers allows the effective and efficient exploration of decision spaces spanning large numbers of decision variables. In practical terms, it is now possible to perform optimisation of models comprising several hundreds of thousands of nonlinear equations subject to many tens of decision variables.

The technological developments outlined above, coupled with improving process knowledge and developments in the global natural gas industry, are now driving rapid innovation in natural gas/NGL supply chain modeling and optimisation. This research focuses on using detailed models of such networks to optimise the profitability, as well as other business objectives, in order to create significant economic benefit without the need for additional capital expenditure.

1.4 Case Study: Iraq Natural Gas Network

Iraq is one of the largest hydrocarbon resource holders in the world with estimated proven hydrocarbon volumes of about 110 billion barrels (bbls) of oil and about 110 trillion cubic feet (Tcf) of natural gas contained in about 70 discovered fields. The bulk of these fields are located in South Iraq and some 70% of the proven gas is associated gas. Approximately 1,400 million cubic

feet per day (MMscfd) of natural gas is currently being produced in south Iraq with a large proportion of this being flared off. The flaring is a result of ageing equipment, network inefficiencies, and absence of comprehensive utilisation plans. Iraq however has ambitions to reduce gas flaring and increase gas production by improving the performance of its vast natural gas infrastructure.

The natural gas network of Basrah Gas Company (BGC) in Iraq is used as a case study for this research. BGC is a Joint-venture between Royal Dutch Shell company and the Iraqi government. The BGC gas network spans oil and gas fields in Southern Iraq as shown in Figure 1.

In general, BGC processes and supplies natural gas for power generation, fertiliser production and domestic consumption in Iraq. The company also produces liquefied petroleum gas (LPG i.e. propane and butane) and C5+ condensate (natural gasoline) for domestic consumption. These liquid products are also exported once local demand is satisfied.

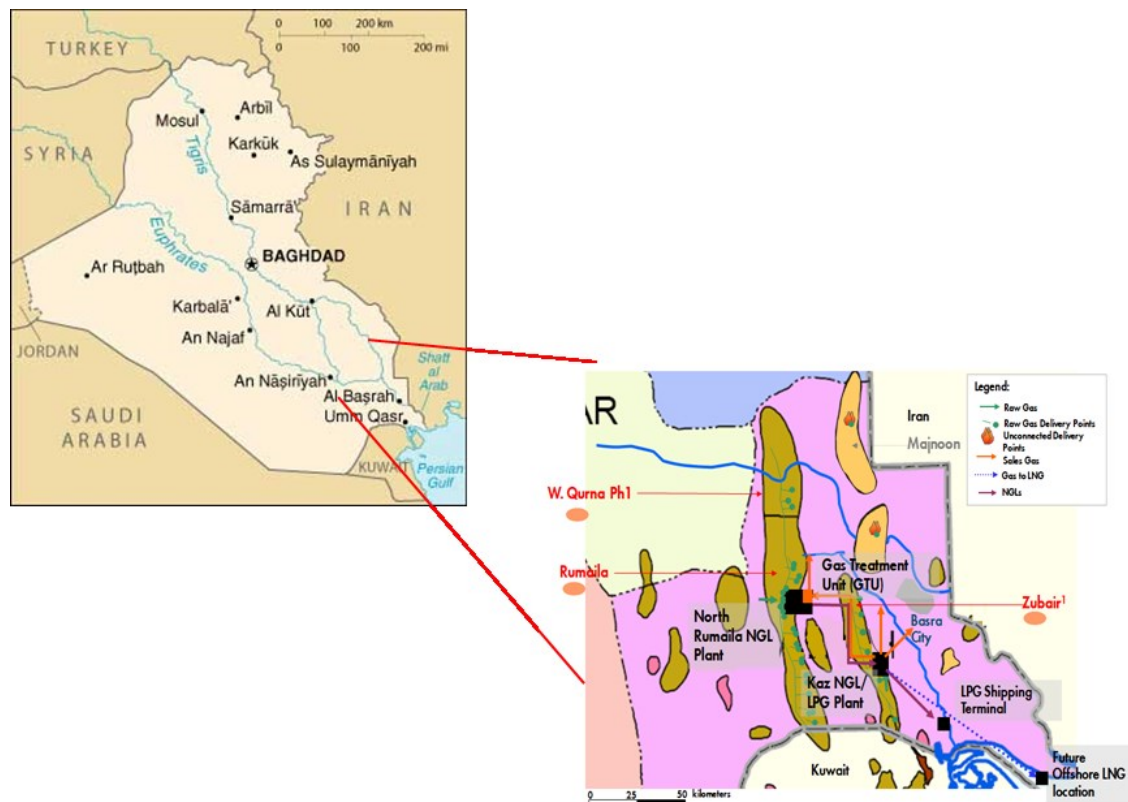


Figure 1: Map of Iraq showing the major Oil Fields in Basrah Province

BGC's network processes associated natural gas from four oilfields situated in West Qurna, North and South Rumaila, and Zubair respectively. At each oilfield, gas is received at different pressures following its separation from oil. It is then compressed at a total of 16 degassing and compressor stations, and transported via an extensive pipeline network (total length of over 650 km) to an NGL processing plant at North Rumaila and NGL/LPG plants at Khor al Zubair. An important characteristic of the network is that gas from the South Rumaila field may be sent to either of the two processing locations, which provides an additional degree of overall operational flexibility. Moreover, the two processing facilities are coupled via a broadcut liquid stream, comprising propane, butane and gasoline, being sent from the North Rumaila plant to the Khor al Zubair plant for further processing. Dry gas from both plants is introduced into the domestic Iraqi network via a gas transmission unit (GTU) while liquid products from Khor al Zubair are sent to the Um Qasr storage and marine terminals for export.

Overall, the BGC natural gas/NGL network represents an elaborate example of large natural gas/NGL networks in general.

1.5 Benefits of Optimising Natural Gas Networks

The use of network modeling and optimisation technologies for strategic decision-making yields substantial benefits not only in economic and environmental terms but also in improved understanding of the interaction between the various components of the process and the overall business (Thijssen, 2004).

Potential benefits from the application of systematic optimisation to natural gas networks include:

- Increased profitability: Given the current tight oil and gas market conditions, even small improvements in the gas supply chain can have an impact on profitability, and could be critical to long-term business viability.
- Improved reliability: Network optimisation provides a tool that can be used, for example, to rapidly reallocate production on equipment failure in order to satisfy customers and honour contractual delivery commitments.
- Investment planning: Comprehensive network models can be used to gain insights into network bottlenecks, and enable planning for debottlenecking or expansion projects.
- Flare reduction: Network optimisation techniques can be used to minimise the environmental and economic penalties from inefficient operations.

The benefits may be even higher by considering the simultaneous optimisation of production, sales and inventory over multiple consecutive time periods, with demands, prices and costs varying across periods.

1.6 Research Objectives

To the author's knowledge, to date no work has been reported in the open literature on combining detailed property-based¹ process models with optimisation of integrated production, processing and supply chain operations for large natural gas & NGL production networks.

To fill the research gap, this work is aimed at developing a detailed property-based model of natural gas/NGL networks and finding suitable optimisation methods to study the operational

¹ Property-based models are detailed models based on first-principles and incorporating thermodynamic properties.

profitability, flexibility, and environmental performance of such large networks and underlying facilities over single and multiple time horizons.

Specifically, four main objectives are defined for this work:

1. Using real-world data, develop and validate a property-based (detailed) model for a region-wide natural gas/NGL network involving gathering, transport, processing and sales of natural gas and associated liquids.
2. Examine holistic single and multi-period optimisation approaches to solve the large nonlinear problem of region-wide natural gas/NGL supply chain model:
 - i. Method to find optimal solutions to the single-period optimisation problems.
 - ii. Method to find optimal solutions to the multi-period optimisation problems.
 - iii. Comparative analysis of multi-period optimisation vs sequential single-period optimisations.
3. Develop objective functions and determine parameters for optimisation and analysis of natural gas network problems of profitability, operational flexibility and environmental performance, with particular emphasis on the following aspects:
 - i. Effect of the optimisation parameters and problem structure on the optimal solutions
 - ii. Profitability Analysis of the network:
 - a. Optimal solution to profit optimisation.
 - b. Significance of decision variables to the objective function
 - c. Sensitivity of optimal profit improvement to market prices
 - d. Relative economic impact of the different products with varying prices
 - iii. Flexibility of the network in response to changes:

- a. Feasibility and benefit of yield optimisation for specific products relative to total product slate.
 - b. Feasibility and benefit of production optimisation under the scenario of equipment failure or restriction in the capacity of certain facilities.
 - c. Feasibility and benefit of production optimisation under scenario of changing feed gas composition and/or feed gas rates (e.g. with field decline)
 - d. Identification of bottlenecks (e.g hardware constraints) in the network.
- iv. Environmental performance:
 - a. Feasibility and benefit of optimisation to minimise gas flaring, leading to reduced hydrocarbon losses and CO₂ emissions in the network.
- 4. Study the impact of applying model-based optimisation to the operations and profitability of natural gas networks.
 - i. Quantifying the value of optimised operations relative to un-optimised operations
 - ii. Determining the significance of operating variables to desired operational or commercial objectives.

1.7 Thesis Outline

The literature that is relevant to this work is reviewed in Chapter 2. The literature review covers optimisation in general, and specifically gives background on nonlinear optimisation of large nonlinear systems. It also covers global optimal solutions, optimisation of natural gas systems and supply chain optimisation.

Chapter 3 describes the BGC gas network that is used as a case study and representative of natural gas networks in general. It covers description of degassing stations, compressor stations, NGL

plants, LPG plants, pipelines and storage terminals. Gas compositions and equipment capacity data are also provided.

The detailed modelling of the gas network of the case study is described in Chapter 4. This covers the modelling of the unit operations and equipment in the gas processing network.

In order to establish a reliable basis for the optimisation studies, the network model was validated with real-world operating data from the BGC network. Chapter 5 outlines the results of the network model validations.

The algorithmic aspects relating to optimisation solvers and parameters used in this work are presented in Chapter 6.

A single-period formulation for the gas network profit optimisation problem has been set-up. The optimal solutions and related network profitability studies are given in Chapter 7.

Chapter 8 presents formulations for operational optimisation problems related to production, product yields, flaring and abnormal operating scenarios. The optimal solutions and related network analysis for these problems have also been presented.

A multi-period optimisation formulation (MPO approach) for the gas network multi-period profit problem has been set-up in Chapter 9. The optimal solutions and comparative analysis vis-à-vis sequential single periods is also presented.

This thesis is summed up in Chapter 10 which outlines the contributions of this work and offers recommendations for future research.

Chapter 2. Literature Review

Several variables influence the operation of natural gas processing networks. Examples of these variables are feed gas rates, compressor speeds, reboiler temperatures in the distillation columns etc. With all these variables affecting the production and profitability of the network, there is need to find the optimal point in every given operational scenario. Exploring the interaction of numerous variables on the system performance requires rigorous mathematical techniques for optimisation.

While there is extensive literature on supply chain management and optimisation of process systems, the area of gas network optimisation has not received significant research coverage. Gas networks have peculiar challenges that are not sufficiently addressed by existing supply chain planning methods. Other works have addressed stand-alone optimisation of gas production or optimisation of gas processing or optimisation of gas supply. This work, however, considers optimisation of the integrated production, processing and supply chain operations.

Firstly, this chapter presents a generic background of optimisation and then optimisation algorithms suited to nonlinear and large systems are discussed. This chapter also reviews the literature on natural gas systems optimisation, integrated network optimisation and supply chain optimisation.

2.1 Optimisation: Classification and Methods

Optimisation problems can be classified along different lines. For example,

- Degree of rigour: Deterministic methods or Stochastic methods

- Stochastic methods use algorithms and acceptance probabilities based on the generation of random points in the domain of the objective function. Fabio Schoen made a survey of stochastic algorithms for global optimisation. (Schoen, 1991).
- Deterministic methods have the advantage that they can provide rigorous guarantee of global optimality of the solution but require some assumptions about the mathematical structure of the model (Quesada & Grossmann, 1995).
- Function Linearity: Linear or Nonlinear
 - Nonlinear Convexity: Convex or Nonconvex
- Variable Type: Discrete or Continuous
- Constraints: Constrained or unconstrained
- Objective function: Single objective or Multi-objective
- Time-dependency: Dynamic or Steady-state

A problem is linear when the relationship between the objective function and the decision variables is linear and when all constraints are also linear. Linear optimisation problems can be solved using well-established methods such as simplex, interior-point methods etc.

Most process systems are however nonlinear. For nonlinear problems (NLP), a further distinction is whether the problem is convex or nonconvex. For a convex function defined over a certain region, the optimum is always global while nonconvex functions may result in multiple local optima.

A lot of research has been undertaken in the area of nonlinear optimisation and several optimisation methods have been developed for different types and structures of optimisation problems.

In their paper on '*Future perspective on optimisation*', Grossmann and Biegler discuss strategies and methodologies that can be applied to a broad class of optimisation problems (Grossmann &

Biegler, 2004). They concluded that “due to the increased scope of decision-making in engineering and business applications, optimisation problems will always increase in size and complexity. Thus large-scale optimisation remains a challenging research area for NLP and MINLP applications”.

There is a wide range of optimisation algorithms for the solution of NLPs, including the following:

- CONOPT: Generalised Reduced Gradient (Drud, 1994)
- IPOPT: Advanced primal-dual interior-point algorithm (Wachter & Biegler, 2006)
- NPSOL: Dense solver
- MINOS (Modular In-core Nonlinear Optimisation System): For sparse NLP. No elastic bounds, but still widely used.
- Sequential [or Successive] Quadratic programming. More on this in section 2.2.1 below.

Several problems in engineering design and supply chain planning require the application of nonlinear optimisation algorithms that can handle both continuous and integer variables, especially of the 0-1 type. These problems are called Mixed Integer Nonlinear Programming (MINLP) problems. Grossmann and Kravanja have presented an overview of different general-purpose algorithms for MINLP including the following (Grossmann & Kravanja, 1995):

- Branch and Bound
- Generalised Benders Decomposition
- Outer-Approximation/ Equality-Relaxation method: (Viswanathan & Grossmann, 1990) proposed an improved outer-approximation algorithm for MINLP optimisation which is aimed at the solution of problems where convexity conditions may not hold. The algorithm starts by solving the NLP relaxation. If an integer solution is not found, a sequence of iterations consisting of NLP subproblems and mixed-integer linear programming (MILP) master problems is solved. The MILP master problem is based on the outer-approximation/equality-relaxation algorithm and features an exact penalty function that

allows violations of linearisations of nonconvex constraints. The search proceeds until no improvement is found in the NLP subproblems. This Outer Approximation/Equality Relaxation/ Augmented Penalty (OAERAP) algorithm is applied for a MINLP problem that is presented later in this work.

For this work, the focus is largely on nonlinear problems. The next section provides some background on this class of problems.

2.2 Nonlinear Optimisation of Large Systems

Many of the systems involved in the production and processing of natural gas cannot be described by linear equations.

Nonlinear optimisation problems are generally of the form:

$$\text{Minimize } f(x) \tag{1}$$

over $x \in \mathbb{R}^n$; Subject to:

$$h(x) = 0 \tag{2}$$

$$g(x) \leq 0 \tag{3}$$

Where $f(x): \mathbb{R}^n \rightarrow \mathbb{R}$ is the objective function; $h(x): \mathbb{R}^n \rightarrow \mathbb{R}^m$ are the equality constraints that describe the performance of the systems (e.g. mass and energy balances etc); $g(x): \mathbb{R}^n \rightarrow \mathbb{R}^p$ are the inequality constraints (e.g. system capacities, contractual limitations etc).

To resolve NLP problems with inequality constraints, auxiliary variables called Lagrange multipliers are introduced and the Lagrangian $\mathcal{L}: \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{C}$ is defined as:

$$\mathcal{L}(x, \lambda, \mu) := f(x) + \lambda^T h(x) + \mu^T g(x) \quad (4)$$

Where λ^T is the Lagrange multiplier vector corresponding to the equality constraint; μ^T is the Lagrange multiplier vector corresponding to the inequality constraint.

A solution to this NLP is derived when a stationary point x^* is found that corresponds to the minimum or maximum of the function over a certain domain. It should be noted however that not all stationary points yield a solution to the optimisation problem hence other conditions must also be satisfied.

In their seminal paper on NonLinear Programming, Kuhn and Tucker (Kuhn & Tucker, 1951) showed that for x^* to be a solution of the NLP, it is necessary that certain conditions are satisfied [William Karush independently established the same theorem in 1939 but did not publish]. The Karush-Kuhn-Tucker (KKT) conditions for a stationary point x^* , are:

- a. First Order Necessary Optimality Conditions: There exists optimal multiplier vectors λ^* and μ^* such that:

$$\nabla_x \mathcal{L}(x^*, \lambda^*, \mu^*) = 0 \quad (5)$$

$$\mu^* \geq 0 \quad (6)$$

- b. Complementarity condition: guarantees that the optimal multiplier vectors λ^* and μ^* are unique:

$$g_i(x^*)\mu_i^* = 0 \quad , \quad 1 \leq i \leq p \quad (7)$$

$$\mu_i^* > 0, i \in I(x^*) \quad (8)$$

Where I is the set of active constraints at x defined as:

$$I(x) = \{i \in \{1, \dots, p\} \mid g_i(x) = 0\} \quad (9)$$

- c. Linear independence constraint qualification: Below gradients must be linearly independent:

$$\nabla h_i(x^*) \quad , \quad i = 1, \dots, m \quad (10)$$

$$\nabla g_i(x^*) \quad , \quad i \in I \quad (11)$$

- d. Second order sufficient condition: the Hessian of the Lagrangian function (i.e. $\nabla_{xx}\mathcal{L}(x^*, \lambda, \mu)$ or $H\mathcal{L}^*$) with respect to x is positive definite [i.e. $\mathcal{L}^*$ is convex meaning that all its eigenvalues are positive] on the tangent space to the equality and active inequality constraints at x i.e.

$$d^T H\mathcal{L}^* d > 0 \quad (12)$$

For every $d \neq 0$ that satisfies:

$$\nabla g_i(x^*)^T d = 0 \quad , \quad i \in \{i \in I: \mu_i > 0\} \quad (13)$$

$$\nabla g_i(x^*)^T d \leq 0, \quad i \in \{i \in I: \mu_i = 0\} \quad (14)$$

$$\nabla h_i(x^*)^T d = 0, \quad i = 1, \dots, m \quad (15)$$

The second order sufficient optimality conditions guarantee that the Lagrange multipliers λ and μ are uniquely determined.

It can be shown that if the above conditions are satisfied, then x^* is a strict local optimum of the NLP problem.

2.2.1 Sequential Quadratic Programming (SQP)

Sequential quadratic programming is one of the most successful methods for the numerical solution of constrained nonlinear optimisation problems and has been shown to require the fewest function evaluations to solve NLPs. The SQP algorithm essentially replaces the objective function with a quadratic approximation subject to a linearization of the constraints. Biegler & Grossman defined SQP as an iterative procedure which models the NLP by a Quadratic programming (QP) sub-problem and applying the equivalent of a newton step to the KKT conditions of the NLP problem. This leads to a fast convergence (Biegler & Grossmann, 2004).

The Newton method which is the foundation for the SQP algorithms, uses iterations for finding the roots of a twice-differentiable function. Given an iterate point x^k , the objective function in equation (1) can be replaced by its quadratic Taylor series approximation:

$$f(x) \approx f(x^k) + \nabla f(x^k)(x - x^k) + \frac{1}{2}(x - x^k)^T H f(x^k)(x - x^k) \quad (16)$$

Where $Hf(x^k)$ is the Hessian matrix.

The constraint functions can be replaced by their local linear approximations:

$$h(x) \approx h(x^k) + \nabla h(x^k)(x - x^k) \quad (17)$$

$$g(x) \approx g(x^k) + \nabla g(x^k)(x - x^k) \quad (18)$$

Setting

$$d(x) := x - x^k \quad (19)$$

leads to the following QP form of the original problem around iterate point k [The term $f(x^k)$ in equation (16) is dropped from the QP objective function since it is a constant with respect to $d(x)$ and hence plays no role in the optimisation step]:

$$\text{Minimize } \nabla f(x^k)d_x + \frac{1}{2}d_x^T Hf(x^k)d_x \quad (20)$$

over $x \in \mathbb{R}^n$; Subject to:

$$h(x^k) + \nabla h(x^k)d_x = 0 \quad (21)$$

$$g(x^k) + \nabla g(x^k)d_x \leq 0 \quad (22)$$

The QP problem is solved by computing the increment d_x in the above system of equations which is then used to take the step:

$$x^{k+1} = x^k + d_x \quad (23)$$

This is followed by applying the KKT conditions for optimality. If the first order necessary conditions and the second order sufficient conditions are not satisfied, then another iteration is made starting at the updated iterate point. Boggs and Tolle (Boggs & Tolle, 1995) examined the underlying theory behind the SQP method and described different SQP algorithms. Common algorithms for solving the QP sub-problems include interior-point-convex, Trust-region-reflective and Active-set.

2.2.2 Merit Functions and Line Search

To ensure that the NLP algorithm converges to a local optimum from any remote starting point, a merit function ϕ is built into the algorithm. The idea behind merit functions is to measure progress towards the solution of the NLP by only accepting iteration steps that correspond to a decrease in the merit function. A reduction in the merit function implies that an acceptable step has been taken.

As explained by Boggs & Tolle (Boggs & Tolle, 1995) “a line search procedure is used to modify the length of the step d_x so that the step from x^k to x^{k+1} reduce the value of ϕ ”.

A coefficient α , known as the Step length can be introduced for $d(x)$ in equations (20)-(23). The line search procedure iteratively calculates α so that:

$$\phi(x^k + \alpha d_x) < \phi(x^k) \quad (24)$$

Boggs & Tolle also (Boggs & Tolle, 1995) presented an overview of properties and types of merit functions that can be applied to SQP algorithms.

2.3 Optimal Solution of Non-Convex Problems

Several chemical process phenomena depend on non-convex functions. For example, multiphase equilibria calculation based on the equality of chemical potentials is non-convex (Nichita, et al., 2004). Gas pressure and flow relationships are also non-convex. A nonlinear problem is non-convex if the Hessian of the Lagrangian is a negative-definite matrix i.e. all its eigenvalues² are negative over the entire variables space.

One of the major limitations of most NLP methods is that they are not guaranteed to find the global optimum in nonconvex problems (Grossmann & Biegler, 2004). Specifically, SQP methods can only find local solutions of the NLP.

The KKT conditions reviewed in the section 2.2 are sufficient for the global optimality of a convex NLP. For nonconvex problems, the KKT conditions can only satisfy local optimality but not global optimality. More rigorous search procedures are therefore required to find the global solution of nonconvex problems.

Methods for global optimisation can broadly be classified in 2 groups: Stochastic or Deterministic.

Stochastic methods use algorithms and acceptance probabilities based on the generation of random points in the domain of the objective function. Fabio Schoen made a survey of stochastic algorithms for global optimisation. (Schoen, 1991). A disadvantage of stochastic methods is that they ‘are not rigorous, and tend to have difficulty in handling complex constrained problems’ (Grossmann & Biegler, 2004).

Deterministic methods have the advantage that they can provide rigorous guarantee of global optimality of the solution but require some assumptions about the mathematical structure of the

² The eigenvalues of the Hessian matrix allow classification of the critical point. If the Hessian has both positive and negative eigenvalues then x is a saddle point for the function.

model (Quesada & Grossmann, 1995). As noted by Grossman and Biegler, several deterministic methods have been developed for nonconvex optimisation including:

- a. Lipschitzian methods
- b. Branch and Bound
- c. Cutting Plane
- d. Outer-approximation
- e. Primal-dual
- f. Reformulation-linearization
- g. Interval methods.

Branch and bound is by far the most widely used tool for solving large scale *NP*-hard (i.e. non-convex and nonlinear) optimisation problems (Clausen, 1999).

2.3.1 Spatial Branch and Bound Methods

The branch and bound algorithm solves a sequence of problems in each of which the objective function takes a convex form. These problems correspond to successive partitions of the feasible set (Falk & Soland, 1969). Each of these problems restricts each variable x_i to a suitable subinterval of $[x_i^L, x_i^U]$ and replaces each function by its convex envelope over the subinterval (Soland, 1971). For a function $f(x)$ defined on a set R , Soland defined the convex envelope of $f(x)$ taken over R as the ‘highest’ convex function that fits below $f(x)$.

The branch and bound method can be described as an algorithm that “divides the feasible region of continuous variables and compares lower bound and upper bound for fathoming each subregion. The subregion that contains the optimal solution is found by eliminating subregions that are proved not to contain the optimal solution.” (Grossmann & Biegler, 2004). At each

iteration of the branch and bound tree algorithm, the node with the best lower bound gets selected, and the lower-bounding problem gets updated per its bounds and then optimised.

Algorithms for the branch and bound methods also consist of a set of rules for refining the partitions [i.e. branching rules], and procedures for upper and lower bounding.

Several Branch and Bound methodologies have been developed and reported in the literature. The various branch and bound methods are mainly distinguished by the form of the convex underestimators [or convex envelope] and by how the branching is performed on the variables.

The applicability of branch and bound methods depend on the generation of rigorous upper and lower bounds for the objective function over any given variable subdomain. The generation of the upper bound is relatively simple as any feasible point of the NLP acts as an upper bound on the objective function value at the global optimum. To determine a rigorous/tight lower bound, the most common method is the minimization of a convex relaxation (underestimator) of the original problem (Smith & Pantelides, 1999).

2.3.2 Convex Relaxation/ Underestimators

Specific tight convex relaxations have been developed for several classes of functions and algebraic forms such as linear fractional terms, bilinear terms, trilinear terms, signomial terms etc. For example, Quesada and Grossman formulated convex underestimator functions for nonconvex NLP in which the nonlinearities arise from linear fractional and/or bilinear terms (Quesada & Grossmann, 1995).

For an arbitrary nonconvex function or in cases where the tight convex envelope does not exist, a general approach for the convex relaxation/underestimation of the NLP can be used. Maranas and Floudas showed that by adding a defined quadratic term, the nonconvex characteristics of the original function can be overpowered (Maranas & Floudas, 1994). A function Z can be defined

which acts as a convex-underestimator of a twice differentiable function $f(x)$ defined over a region X :

$$Z(x) = f(x) + \alpha \sum_{i=1}^n (x_i^L - x_i)(x_i^U - x_i) \quad (25)$$

Where x^L and x^U corresponds to the lower and upper bounds on x . While α is a nonnegative parameter which must be greater or equal to the negative half of the minimum eigenvalue of $f(x)$ over $x^L \leq x \leq x^U$ i.e.

$$\alpha \geq \max \left\{ 0, -\frac{1}{2} \min_{k, x^L \leq x \leq x^U} \lambda_k(x) \right\} \quad (26)$$

Where $\lambda_k(x)$ are the eigenvalues of the function $f(x)$. Exploiting the fact that α depends on the second-order characteristics of the original function, Adjiman and Floudas proposed the α BB method which uses the interval Hessian matrix technique to determine the smallest eigenvalues, λ_{min} , for the convex underestimation (Adjiman & Floudas, 1996).

Several variants of the α BB for general nonconvex functions have been developed. Examples are: piecewise α BB, nondiagonal α BB, Brauer α BB and the moment method. Guzman, Faruque-Hasan and Floudas (Guzman, et al., 2016) compared the performance of the original α BB method against competing variants and found that the classical α BB formulation was consistently among the fastest [for root node execution time] while producing identical tightness to the other methods.

Smith and Pantelides have argued that “if it is possible to construct a convex relaxation of simple terms corresponding to binary and unary operations, then it must, in principle, also be possible to construct convex relaxations of any algebraic expression” (Smith & Pantelides, 1999). They presented an algorithm that employs a symbolic reformulation that brings the original problem to

an equivalent standard form for which tight convex relaxations can be constructed. This reformulation/ spatial branch and bound algorithm was implemented in gPROMS.

2.4 Optimisation of Natural Gas Systems

With the emerging profile of natural gas in the global energy mix, the application of optimisation methods to natural gas systems is gaining more interest in both academia and industry. Four groups of natural gas systems are usually considered: gathering, transmission, processing and distribution. The research emphasis has mostly been on gathering and transmission. This work takes an integrated approach of integrating the different natural gas systems that make up the network [from well production to distribution to end users] and applying a holistic optimisation approach to the natural gas network.

Mathematical optimisation of gas systems is difficult due to the nonlinearities in the physical phenomena underlying the behavior of the unit operation e.g. compression, pipeline transport, distillation etc.

In one of the earliest works in the area, Wong and Larson showed that the steady-state optimisation of a single-source, tree-structured, natural gas transmission network can be decomposed into the sequential solution of one-dimensional linear programming problems (Wong & Larson, 1968).

More recently, a number of works have been carried out.

Schmidt et al presented stationary NLP type models that include detailed nonlinear physics for the minimization of the variable operating cost (fuel consumption and electricity cost) for a natural gas transmission system (Schmidt, et al., 2015). Their work considered detailed compressor models and flow models incorporating gas quality parameters and uncontrolled mixing of different gas types.

Alem Demissie studied multi-objective optimisation for natural gas pipeline optimisation. Conflicting objectives (fuel cost minimisation and throughput maximisation) were considered in finding the optimal operating conditions for different pipeline configurations. The multi-objective optimisation was carried out using NSGA-II (a stochastic method that uses evolutionary algorithms) which resulted in a set of Pareto optimal solutions. It was noted that selecting a specific solution from the Pareto front is critical (Demissie, 2016). Kashani and Molai carried out a similar study using similar methods but included minimization of CO₂ emissions cost in the multi-objective optimisation (Kashani & Molaei, 2014).

Some works have concentrated on optimal design of gas networks. Mahdavi et al showed how the gas flow cost in a town distribution network can be minimised by using minimum spanning tree with an LP solver (Mahdavi, et al., 2010).

Uster and Dilaveroglu considered the problem of designing a new natural gas transmission system while minimizing the total investment and operating costs (Uster & Dilaveroglu, 2014). A mixed-integer nonlinear optimisation model was set up to determine numbers, capacities and installation timings of facilities (pipelines and compressor stations) in a multi-period planning horizon. The model also considered natural gas purchase and steady-state flow decisions for each period. The impact of varying period lengths and varying network sizes was analysed. The optimisation problem was solved using the online Bonmin solver which provides a heuristic solution for non-convex MINLPs.

To support the decision of regulatory authorities in selecting optimal design for a natural gas transmission network, Alves et al proposed a multi-objective optimisation formulation for the minimization of the transportation costs and the maximisation of gas volume. Given the conflicting objectives, a Pareto front was generated i.e. a set containing the best solutions. The ϵ -constraint method was used to identify the Pareto front, whereby each point of the Pareto front

is determined from a mono-objective optimisation problem. The solutions to the mono-objective problems were obtained using the CONOPT solver (Alves, et al., 2016).

Al-Sobhi and Elkamel presented a simulation-optimisation framework for natural gas processing network including utilization processes such as LNG and GTL. The network profit was optimised using an LP model (Al-Sobhi & Elkamel, 2015).

A stochastic programming model for integrated design and operation of natural gas production networks under uncertainty has been proposed (Li & Li, 2017). The multi-scenario formulation considers uncertainties on which facilities are to be developed and on operating conditions for different scenarios. The objective of optimisation is to determine the system network structure that maximises the expected NPV of the system over its life span. The problem is solved using a modified nonconvex generalized Benders decomposition (NGBD) method called multi-loop NGBD. In the multi-loop NGBD, each primal subproblem (which is an operation subproblem) is solved using GBD rather than using a global optimisation solver directly, and it is faster than the standard single-loop NGBD by at least an order of magnitude.

Zhang et al have studied optimal operational strategy and planning for a natural gas refining complex in South China. The objective was to obtain maximum profit for a given planning period. (Zhang, et al., 2017). The bilinear and exponential items in their model made it nonconvex. Reformulation techniques (logarithmic and factorization) were therefore introduced to reduce the nonconvex terms in the MINLP model. For example, the nonlinear constraint used to calculate the vapour-liquid phase equilibrium ratios for the chemical components is nonconvex as verified by eigenvalue calculation. This phase equilibrium constraint was reformulated by applying logarithmic operators. The resulting overall model for the natural gas complex consisted 136 binary variables and 2461 continuous variables and was solved using ANTIGONE and LINDOGLOBAL global optimisation solvers. Their computational results indicate a profit

increase of about 10% compared to normal operations. It should be noted that upstream compression systems and pipelines were not considered in the study.

A comprehensive review of natural gas transmission systems has been presented by Rios-Mercado and Borraz-Sanchez. Their paper (Rios-Mercado & Borraz-Sanchez, 2015) covers works on the optimisation areas of interest in transmission systems namely: short-term storage (line-packing problem), pipeline resistance, gas quality satisfaction (pooling problem), and fuel cost minimisation (compressor station modeling).

2.5 Integrated Network Optimisation

When dealing with continuous processes which involve several interconnected process units, it has been suggested that in order to enhance operational feasibility and model accuracy, the optimisation should be executed directly in a site-wide fashion and employing rigorous process representations. Cheung went further to say “simultaneous optimisation of all units and nodes in the network is the most straightforward way to explore benefits from mathematical programming techniques (Cheung, 2008).

Instead of optimising individual elements and sub-systems, a holistic optimisation of production networks in an integrated manner is becoming increasingly important in the oil and gas industry. With integrated network analysis, it is possible to evaluate the impact of all individual changes on the entire network. Thijssen et al described a network planning tool developed by Shell which solved Mixed Integer type problems by using piecewise linear modeling which prevented the problem from becoming nonlinear. The tool was applied to a network from the wellhead platforms to the oil/gas export facilities. The simplified network structure presented consisted of: Demand module, Supply module, Production module, and Pipeline module (Thijssen, et al., 2008). Process modeling was done on a separate stand-alone simulation tool and the results were inputted to the

network optimisation tool hence allowing the Network optimisation to proceed as a mixed integer programming (MIP) problem. The results indicated that a >10% increase in oil production and >5% increase in gas production over a 15-year period could be achieved with network optimisation.

2.6 Supply Chain Optimisation

A lot of work has been carried out on supply chain modeling and optimisation by industry and diverse academic fields such Operations Research, Process Engineering, Industrial Engineering etc. According to Shapiro, a company's supply chain is comprised of geographically dispersed facilities where raw materials, intermediate products, or finished products are acquired, transformed, stored, or sold, and transportation links connecting facilities along which products flow (Shapiro, 2001). Supply chain management has been defined as *“the coordination of production, inventory, location, and transportation among the participants in the supply chain to achieve the best mix of responsiveness and efficiency for the market being served”* (Hugos, 2003).

Lasschuit and Thijssen have made a case for using supply chain planning in the oil and chemical industry. They also outlined the core requirements for an integrated supply chain toolset which include: modularity, scalability and complete horizontal integration (Lasschuit & Thijssen, 2004).

In his review of process industry supply chains, Shah (Shah, 2005) divided supply chain problems into three categories: (i) supply chain infrastructure (network) design; (ii) supply chain analysis and policy formulation; (iii) supply chain planning and scheduling. He stated that “Supply chain planning considers a fixed infrastructure over a short- to medium-term, and seeks to identify how best to use the production, distribution and storage resources in the chain to respond to orders and demand forecasts in an economically efficient manner”. The review highlighted that representation of the production process used in the supply chain modeling could be either recipe-

based or property-based. Whereas recipe-based representation is more desirable for batch processes, continuous processes are more suited to the 'property-based' representation. Furthermore, it was stated that 'to study precisely the effects of condition variations on continuous processes, the process model should consider material physical properties directly'.

This present research work incorporates elements of the third problem i.e. property-based supply chain planning.

To fully realise the potential of modern information technology tools, Grossmann explained that the development of sophisticated deterministic and stochastic linear/nonlinear optimisation models and algorithms is needed to explore and analyse alternatives of the supply chain to yield overall optimum economic performance. (Grossmann, 2005)

This present research work concerns the development of sophisticated deterministic nonlinear optimisation models to analyse the natural gas supply chain.

Papageorgiou presented an extensive review of works carried out in supply chain modeling and optimisation for process industries. The paper highlighted the presence of uncertainties within supply chains and applicable frameworks were discussed. He concluded that "most of the existing frameworks are suitable for two-stage problems while there is a need for appropriate multi-stage, multi-period optimisation frameworks for supply chain management". He also indicated that an "emerging research area is the systematic incorporation of environmental impact indicators within supply chain management systems". (Papageorgiou, 2009)

This present research work develops a framework for supply chain optimisation over multi-periods and considers environmental impact of the supply chain.

The production aspect of the supply chain has been covered in the previous sections of this literature review.

In their work on multi-site planning Sousa *et al* suggested that there are cases where supply chain design and strategic planning should not be performed separately from short term scheduling, or the adopted solution may prove inefficient at the operational level. They concluded that “Resource capacity manipulation provides a natural, organized way of distributing production operation by all available resources rather than centralising them in a single one, which would make scheduling more difficult for the local planner” (Sousa, et al., 2008).

2.6.1 Planning Models and Frameworks

Grossmann provided an overview of mathematical programming frameworks for enterprise wide optimisation. This includes an overview of mixed-integer linear and nonlinear optimisation methods, as well as decomposition methods and stochastic modeling systems. (Grossmann, 2012)

According to Wilkinson et al, the short-term scheduling problem can often be expressed as a multiperiod mixed integer linear programming (MILP) formulation in which the planning horizon is discretised into equally spaced time intervals. A set of discrete and continuous decision variables describe the resource levels and the activities being performed in each time interval. An objective function is optimised (e.g. profit is maximised) subject to certain constraints such as material balances and capacity constraints. (Wilkinson, et al., 1995)

Scheduling problems arising in multi-product and multi-purpose chemical plants have been represented using a state-task network (Kondili, et al., 1993). The novel feature of this representation is that both the individual operations (“tasks”) and the feedstocks, intermediate and final products (“states”) are included explicitly as network nodes.

Wilkinson et al described the Resource-Task Network formulation [originally presented by CC Pantelides] in which all resources (raw materials, equipment items, storage capacity, utilities etc.) are treated uniformly. With the Resource-Task Network representation, the process is described

by a formulation employing a uniform, discrete representation of time such that all events occur on time interval boundaries. It was shown that the aggregate formulation automatically generated can be solved in considerably less computational time and often gives a tight upper bound on the solution to the original formulation (Wilkinson, et al., 1995).

(Wassick, 2009) used a Resource-Task Network (RTN) for enterprise-wide optimisation. They show how the site is composed of sub-systems, called envelopes, which involve the production of a basic chemical and its downstream derivatives or comprise a network of units that provide an important utility. Several planning and operational challenges in these envelopes are shown to be excellent optimisation opportunities. For example, a Resource-Task network model was presented as a solution to the waste treatment scheduling problem. A comparison to the incumbent scheduling process showed that the RTN proposed schedules with significantly lower cost under certain operating conditions.

(Neiro & Pinto, 2004) proposed a general framework for modeling petroleum supply chains. Particular frameworks are proposed for the refineries, storage tanks and pipelines. Nodes of the chain are considered as grouped elementary entities that are interconnected by intermediate streams. The complex topology is then built by connecting the nodes representing refineries, terminals and pipeline networks. Decision variables include stream flow rates, properties, operational variables, inventory and facilities assignment. The resulting multiperiod model is a large-scale MINLP.

(Perea-Lopez, et al., 2003) described a model predictive control strategy to find the optimal decision variables to maximise profit in supply chains with multiproduct, multiechelon distribution networks with multiproduct plants. The paper compares the behavior of a supply chain under centralized and decentralized management approaches, and shows that the former yields better results.

(Jung, et al., 2004) proposed the use of deterministic planning and scheduling models which incorporate safety stock levels as a means of accommodating demand uncertainties in routine operation.

(Rocha, et al., 2009) described how mathematical programming is used to solve the petroleum allocation problem. They proposed a mixed-integer linear programming formulation of the problem that relies on a time/space discretisation network. As the model cannot be solved for the industrial size instances of the problem, and not even a feasible solution can be found after 15 days of computation, they implemented an algorithm based on a heuristic to find a feasible solution and on a local search procedure based on optimisation to improve it.

2.7 Current Work

This present work uses region-wide network optimisation as the tool for tactical level (medium-term) supply chain planning. It plans the usage of resources including production, storage and distribution over a planning period, and considers variable product pricing to meet forecasted demands efficiently and economically. The objective function is the maximisation of a profit function involving the value of the products, and the cost of raw materials, utilities and inventory.

Unlike previous works, this research work concerns the development of sophisticated deterministic nonlinear optimisation models to analyse the natural gas supply chain using actual data from an operating natural gas network. This work also develops novel methods to reduce the complexity of the enterprise wide optimisation to make it more amenable to optimise operations in real-time with a smaller set of decision variables. Furthermore, a novel multiperiod optimisation approach is presented to demonstrate the feasibility and benefit of applying multiperiod optimisation to large natural gas networks.

PART II: NATURAL GAS NETWORK

Chapter 3. The BGC Gas Network

The Basrah Gas Company's production network presents an opportunity to implement, test and assess the optimisation methodology developed in this work. This gas network, located in the South of Iraq, is quite representative of complex gas networks in general.

Significant time was spent in the oil and gas fields of Southern Iraq collecting data and clarifying information with staff of Basrah Gas Company and with the personnel of the upstream oil producing companies. This approach was endorsed by the management of Basrah Gas Company with a view to benefit from possible operational and investment insights that could be derived from this optimisation study.

The gas from Iraq's Basrah province is primarily produced as associated gas from crude oil production and is separated from oil in the Degassing stations. The upstream oil production facilities are operated by the South Oil Company (SOC) in partnership with major international oil companies for the respective fields: ExxonMobil in West Qurna field, BP in Rumaila (North & South) fields and ENI in Zubair field.

The custody transfer of the associated gas from SOC to BGC takes place at the gas outlets of the gas-oil separators in the degassing stations. The gas from these degassing stations is either flared or collected and transported through the BGC gas network systems. Currently, a significant percentage of the gas production is flared as a result of downstream equipment failure [which limits the capacity to receive the gas and/or condensate] and network inefficiencies.

The gas received from SOC is compressed and processed by BGC to produce domestic gas (mainly used for power generation and as industrial feedstock), LPG and gasoline products.

The system originally gathered gas from the Zubair, North and South Rumaila fields through fourteen gathering stations (see Figure 2 and Figure 3). In 2015, the West Qurna field was connected to the gas network when two additional gathering stations (WQ 7 & WQ 8) were commissioned. The recovered gas is processed in the two gas processing plants, namely North Rumaila (NR) NGL plant and the KAZ NGL. The natural gas liquids (NGL) from the processing plants is further processed at the KAZ LPG plant. The NR NGL plant, the Gas Transmission Unit (GTU), and the KAZ NGL/LPG plants are the primary elements of gas treatment and processing in South Iraq. The LPG and gasoline products are stored at Um Qasr terminal from where they are exported by sea.

The following sections describe BGC's gas production, processing and export facilities in further detail.



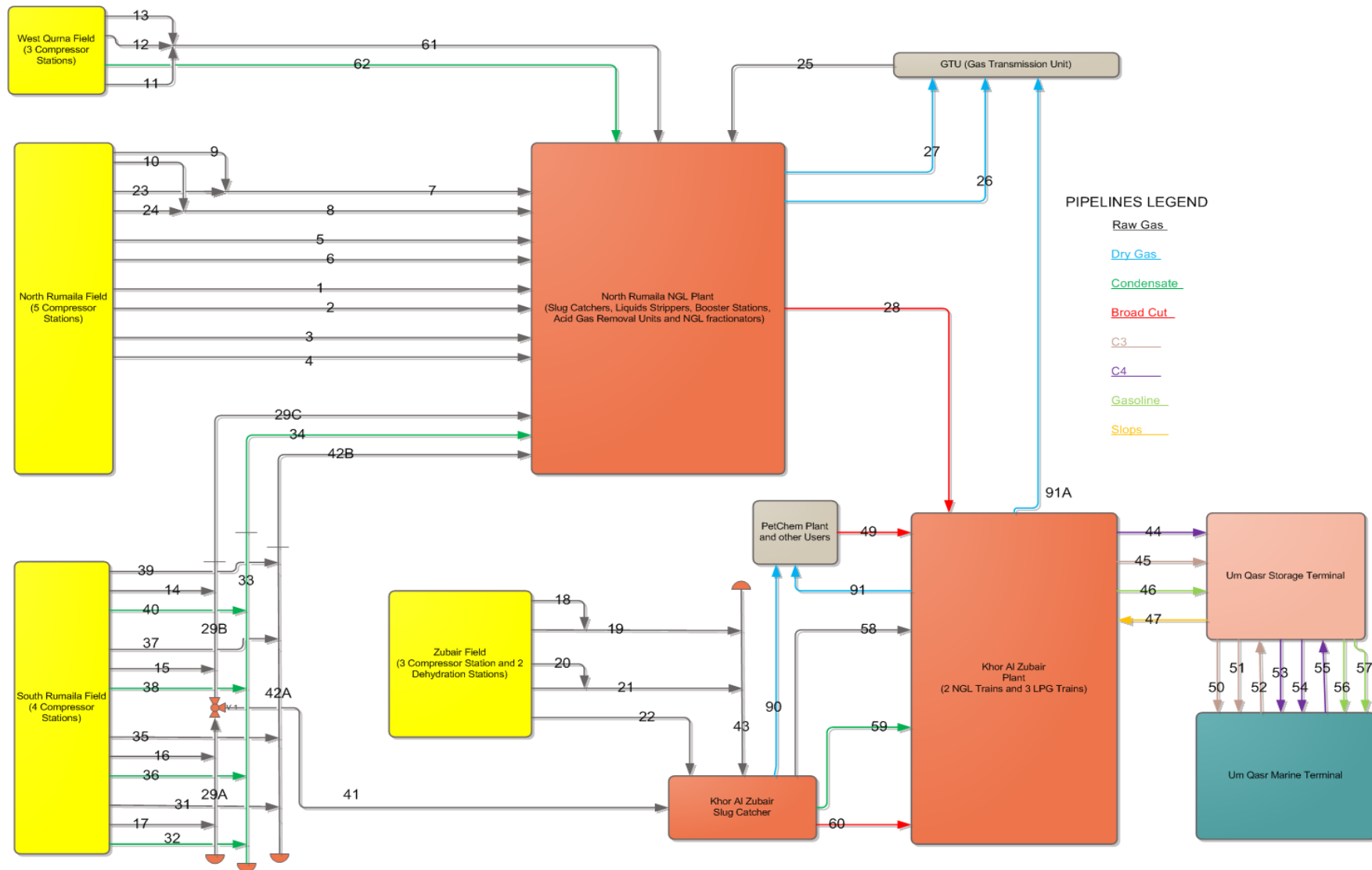


Figure 3: BGC Asset Network

3.1 Degassing Stations

Figure 4 shows a typical degassing station (DS) and compressor station (CS) in North Rumaila. The crude oil produced from the wells is routed to the DS to be stabilised via a series of gas-oil separators. The DS consist of a number of separation banks/trains, each bank consisting of up to 5 stages of separations, including the final flow tank from which crude oil is exported. West Qurna degassing stations have 3 stages of separation. Each separation stage operates at a lower pressure than the preceding stage i.e. 3rd stage separator vessels operate at a lower pressure than 2nd stage separator vessel. This allows for deeper vapour-liquid separation through the separator stages.

The gas stream produced from each stage of gas-oil separation and each bank is unique due to the difference in flowrate, pressure, temperature and compositions. The following characteristics are also notable:

- The gas-oil separators in each field operate at a set of fixed stage pressures. However, in some banks, the 1st stage separator has been operating at a lower than process design pressure, presumably to sustain oil production.
- The temperature from each stage changes due to seasonal and day/night variation. Due to the seasonal change, gas produced in summer has more heavy hydrocarbons, i.e. higher molecular weight.

The gas produced from the corresponding separation stages in all banks is gathered into a common header and sent to the compressor stations. In most cases, there is a dedicated compressor station to receive gas from a degassing station. There are exceptional cases, in which several degassing stations share the same compressor stations or have the flexibility to divert the oil produced to other compressor stations for further gas-oil separation. For e.g., in NR the gas liberated from the 1st stage separator in NIDS (an auxiliary degassing station) is routed to CS4 whilst the oil can be routed to DS1 or DS4 for further separation.

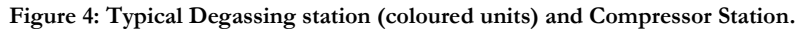
The gas streams from the degassing stations is the source gas feeding into the BGC Network and Table 1 shows the condition of the feed gas streams to the network. Depending on the pressures, the feed gas is sent to the neighbouring compressor stations and pressurised for transport to the processing plants. Table 1 gives an overview of the gas pressures and temperatures for the separator trains/strings in respective degassing stations. The gas from the 1st Stage HP (High Pressure) string is of high enough pressure to flow freely to the gas processing plants without compression. The 1st stage LP (Low Pressure) string and the 2nd, 3rd and 4th stage gases all need to be boosted in pressure before being transported for further processing in the NGL plants.

The West Qurna 6 (WQ 6) degassing station is not yet connected to the BGC Network and hence it will not be considered in this study.

Table 1: Degassing Station Gas Temperatures and Pressure

Degassing Station		1 st HP	1 st LP	2 nd	3 rd	4 th	Flow Tank
NR 1	Temp (°C)	60	45	44	42	40	40
	Pressure (barg)	28	12.5	7	1.9	0.4	0
NR 2	Temp (°C)	54	50	50	48	45	42
	Pressure (barg)	27.4	14	7	1.9	0.4	0
NR 3	Temp (°C)	50	50	49	48	47	45
	Pressure (barg)	28	12	7	1.9	0.4	0
NR 4	Temp (°C)	60	50	58	55	54	50
	Pressure (barg)	28	14	7	1.9	0.35	0
NR 5	Temp (°C)	55	50	54	52	48	45
	Pressure (barg)	28	14	7	1.9	0.4	0
SR Central (Markazia)	Temp (°C)	60	60	60	60	60	60
	Pressure (barg)	34	14	7	1.9	0.8	0

SR Janubia	Temp (°C)	60	60	60	60	60	60
	Pressure (barg)	34	14	7	1.9	0.85	0
SR Shamiyah	Temp (°C)	60	60	60	60	60	60
	Pressure (barg)	35	14	7	1.9	0.85	0
SR Qurainat	Temp (°C)	60	60	60	60	60	60
	Pressure (barg)	34	13	7	1.9	0.85	0
ZU Central (Zubair)	Temp (°C)	60	45	44	42	40	40
	Pressure (barg)	43	12.5	9	1.9	0.8	0
ZU Mishrif	Temp (°C)	54	50	50	48	45	42
	Pressure (barg)	43	12.5	9	1.9	0.8	0
ZU Hammar	Temp (°C)	60	50	58	55	54	50
	Pressure (barg)	43	12	9	3	1	0
ZU Hammar Mishrif	Temp (°C)	55	50	54	52	48	45
	Pressure (barg)	42	12	9	1.9	0.8	0
ZU Rafidiyah	Temp (°C)	50	50	49	48	47	45
	Pressure (barg)	42	12	9	1.9	0.8	0
				1st	2nd	3rd	Tank
WQ 6	Temp (°C)			60	45	44	42
	Pressure (barg)			12.5	2.1	0.35	0
WQ 7	Temp (°C)			54	50	50	48
	Pressure (barg)			12.5	2.1	0.35	0
WQ 8	Temp (°C)			60	50	58	55
	Pressure (barg)			12.5	2.1	0.35	0



3.2 Compressor Stations

The gas produced from the gas-oil separators in the degassing stations is piped to the compressor stations (CS). The gas is compressed and dehydrated to the pipeline specifications for delivery to the gas processing plants. The compressor stations in the network can be classified into 1-train, 2-trains, 3-trains and 4-trains stations. Each compressor train has multiple compression stages as typified in Figure 4. Before arrival at the compressor stations, the gas from the different banks/strings in the degassing stations is combined on basis of common pressures.

The compressors stations in the network are outlined in Table 2. The South and North Rumaila compressor stations are driven by fixed-speed electric motors. The electric motor is coupled to the compressor via a gearbox through which the speed (rpm) of the compressors is set.

Table 2: Compressor Stations and Specifications

Compressor Station	No of Trains	Stages /Train	Type	Driver	Rated Power (MW)	Shaft Type	Speed (rpm)
NR CS1	3	2	Centrifugal	Electric	4.93	Common	11178
NR CS2	1	2	Centrifugal	Electric	3.3	Common	11222
NR CS3	2	2	Centrifugal	Electric	2.9	Common	11222
NR CS4	2	2	Centrifugal	Electric	4.93	Common	11178
NR CS5	2	2	Centrifugal	Electric	3.3	Common	11222
SR Shamiya	2	3	Centrifugal	Electric	6.1	Common	8600
SR Qurainat	2	3	Centrifugal	Electric	4.35/ 6.1	Separate	6300/ 8600
SR Janubiya	2	3	Centrifugal	Electric	5.9	Common	8600
SR Markaziya	4	3	Centrifugal	Electric	5.9	Common	8600
Zubair	4	2	Reciprocating	Gas Engine	1.1	Piston	1200

Zubair Mishrif	N/A						
Hammar	N/A						
Ham-Mishrif	4	2	Reciprocating	Gas Engine	1.1	Piston	1200
Rafidiyah	2	2	Reciprocating	Gas Engine	1.1	Piston	1200
WQ 7	N/A						
WQ 8	N/A						

For most stations, all the compressors stages in a compressor train are on a single shaft with a common driver. The exception is the Qurainat stations where the first and second compressor stages are on the same shaft while the third stage is on a different shaft with a different drive motor.

The compressor curve is a characteristic of the compressor and is provided by the original equipment manufacturer (OEM). Figure 5 and Figure 6 show the compressor curves for some of the North Rumaila compressors.

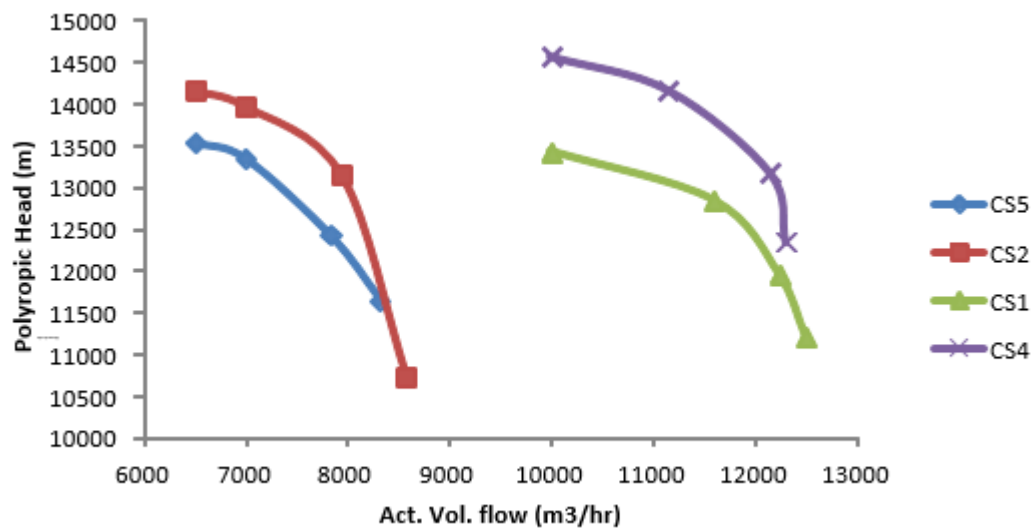


Figure 5: Head Curves for North Rumaila K3 (3rd stage Feed Gas) Compressors

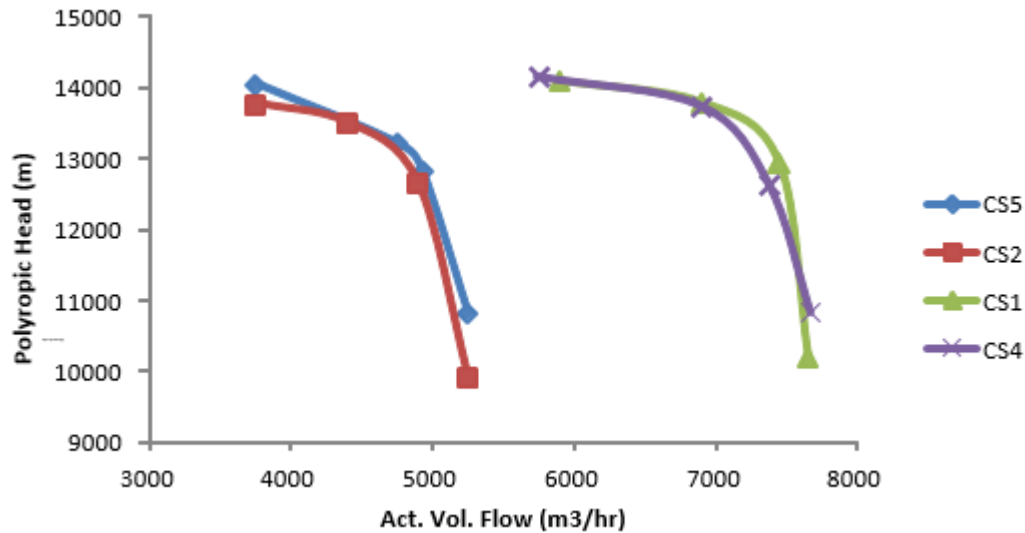


Figure 6: Head Curves for North Rumaila K4 (2nd stage Feed Gas) Compressors

A centrifugal compressor's polytropic head relates the suction and discharge pressures. With the help of compressor (Head) curves, the polytropic head can be used to determine the gas flow rate that can be handled by the compressor. Conversely, with a given gas flow rate, the compressor curves can be used to determine polytropic head. For a given suction pressure and polytropic head, the discharge pressure can be determined if the gas composition is known. Typical feed gas compositions [on a dry basis] for the respective compressor stations in all the oilfields in the network are given in Table 3 to Table 6.

Table 3: Gas Compositions for West Qurna Stations

Station	WQ 6			WQ 7			WQ 8		
Mol%	1st stage	2nd stage	3rd stage	1st stage	2nd stage	3rd stage	1st stage	2nd stage	3rd stage
H ₂ S	0.1%	0.2%	0.3%	0.1%	0.3%	0.4%	0.1%	0.1%	0.3%
CO ₂	2.0%	1.8%	1.0%	1.9%	1.7%	1.5%	2.2%	1.9%	1.7%
N ₂	0.7%	0.3%	0.1%	0.6%	0.6%	0.4%	0.7%	0.6%	0.4%
C ₁	68.7%	39.1%	12.9%	67.8%	51.1%	38.2%	67.2%	51.6%	38.9%
C ₂	16.0%	24.8%	27.7%	16.6%	20.2%	20.4%	15.6%	18.9%	20.0%
C ₃	8.0%	19.8%	32.0%	8.3%	14.6%	19.6%	9.1%	13.4%	19.5%
iC ₄	0.9%	2.6%	4.7%	0.9%	2.1%	3.3%	1.0%	2.2%	3.1%
nC ₄	2.1%	6.6%	12.4%	2.1%	5.4%	9.2%	2.4%	5.9%	8.7%
iC ₅	0.5%	1.4%	2.8%	0.5%	1.3%	2.3%	0.6%	1.6%	2.4%
nC ₅	0.5%	1.5%	3.0%	0.5%	1.3%	2.4%	0.6%	1.7%	2.5%
C ₆	0.4%	1.1%	2.2%	0.4%	1.1%	1.7%	0.4%	1.5%	1.8%
C ₇	0.2%	0.5%	0.7%	0.2%	0.4%	0.6%	0.2%	0.5%	0.6%
C ₈	0.1%	0.1%	0.2%	0.0%	0.1%	0.2%	0.0%	0.1%	0.2%

Table 4: Gas Compositions for North Rumaila Stations

Station	NR 1			NR 2				NR 3				NR 4				NR 5			
Mol%	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage
H ₂ S	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
CO ₂	2.2%	1.6%	1.3%	1.4%	1.4%	1.5%	1.2%	2.5%	1.8%	2.2%	2.3%	2.0%	1.4%	1.8%	1.5%	2.4%	1.6%	2.0%	1.7%
N ₂	0.7%	0.2%	0.1%	0.7%	0.7%	0.2%	0.0%	0.9%	1.1%	0.5%	0.4%	0.9%	0.7%	0.4%	0.2%	0.6%	0.7%	0.3%	0.1%
C ₁	70.7%	46.6%	20.1%	69.9%	69.9%	44.1%	20.1%	77.1%	71.1%	58.2%	24.1%	72.1%	69.9%	52.3%	22.9%	72.5%	70.2%	51.7%	19.6%
C ₂	14.7%	25.8%	32.5%	16.3%	16.3%	27.1%	33.0%	11.5%	15.2%	21.3%	30.4%	14.2%	16.3%	22.9%	29.8%	13.9%	15.9%	23.5%	31.2%
C ₃	7.0%	15.8%	26.0%	7.2%	7.2%	16.7%	25.8%	4.7%	6.7%	11.1%	26.8%	6.7%	7.2%	13.7%	25.8%	6.4%	7.1%	13.6%	27.5%
iC ₄	0.9%	1.9%	3.1%	0.9%	0.9%	2.0%	3.1%	0.5%	0.8%	1.3%	2.9%	0.8%	0.9%	1.6%	3.0%	0.8%	0.9%	1.6%	3.2%
nC ₄	2.2%	3.8%	8.9%	1.7%	1.7%	3.9%	8.7%	1.4%	2.0%	3.3%	7.9%	2.1%	1.7%	3.7%	8.8%	2.1%	1.8%	3.8%	9.3%
iC ₅	0.5%	1.0%	2.2%	0.4%	0.4%	1.0%	2.3%	0.3%	0.5%	0.7%	1.7%	0.4%	0.4%	0.9%	2.2%	0.5%	0.4%	0.9%	2.2%
nC ₅	0.6%	1.3%	2.9%	0.6%	0.6%	1.4%	3.0%	0.4%	0.5%	0.8%	1.8%	0.5%	0.6%	1.2%	2.7%	0.5%	0.6%	1.1%	2.7%
C ₆	0.4%	1.2%	2.1%	0.6%	0.6%	1.3%	2.2%	0.4%	0.3%	0.5%	1.3%	0.3%	0.6%	0.9%	2.2%	0.3%	0.5%	0.9%	1.9%
C ₇	0.1%	0.7%	0.7%	0.3%	0.3%	0.8%	0.7%	0.2%	0.1%	0.1%	0.4%	0.1%	0.3%	0.5%	0.6%	0.1%	0.2%	0.4%	0.5%
C ₈	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%

Table 5: Gas Compositions for South Rumaila Stations

Station	SR Central (Markazia)				SR Janubia				SR Shamiyah				SR Qurainat			
Mol%	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage
H ₂ S	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
CO ₂	2.0%	2.0%	1.5%	1.2%	1.9%	2.0%	2.0%	1.3%	1.9%	1.9%	1.7%	1.4%	2.1%	2.0%	1.8%	1.5%
N ₂	0.7%	0.7%	0.2%	0.0%	0.9%	1.0%	0.7%	0.6%	1.0%	0.7%	0.3%	0.1%	0.7%	0.7%	0.5%	0.4%
C ₁	74.4%	74.4%	44.1%	20.1%	71.4%	64.1%	50.5%	16.2%	72.2%	73.8%	51.6%	18.1%	72.8%	74.4%	51.4%	15.5%
C ₂	13.7%	13.7%	27.1%	33.0%	14.2%	16.5%	21.1%	25.5%	13.5%	14.0%	22.9%	28.9%	13.9%	13.7%	22.2%	27.2%
C ₃	5.9%	5.9%	16.7%	25.8%	6.6%	9.4%	14.0%	27.8%	6.1%	6.1%	13.3%	27.1%	6.3%	5.9%	13.6%	29.0%
iC ₄	0.7%	0.7%	2.0%	3.1%	0.8%	1.1%	1.8%	3.9%	0.8%	0.7%	1.7%	3.5%	0.8%	0.7%	1.7%	4.0%
nC ₄	1.6%	1.6%	3.9%	8.7%	2.3%	3.3%	5.2%	13.1%	2.2%	1.7%	4.1%	10.9%	2.1%	1.6%	4.8%	12.2%
iC ₅	0.3%	0.3%	1.0%	2.3%	0.5%	0.8%	1.3%	3.1%	0.5%	0.3%	1.1%	2.7%	0.5%	0.3%	1.2%	3.0%
nC ₅	0.4%	0.4%	1.4%	3.0%	0.6%	1.0%	1.6%	3.8%	0.7%	0.4%	1.4%	3.4%	0.6%	0.4%	1.4%	3.6%
C ₆	0.3%	0.3%	1.3%	2.2%	0.5%	0.7%	1.3%	3.3%	0.6%	0.3%	1.3%	2.7%	0.4%	0.3%	1.1%	2.9%
C ₇	0.1%	0.1%	0.8%	0.7%	0.2%	0.2%	0.4%	1.4%	0.3%	0.1%	0.5%	1.1%	0.0%	0.1%	0.4%	0.8%
C ₈	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%

Table 6: Gas Compositions for Zubair Stations

Station	ZU Central				ZU Mishrif				ZU Hammar				Zu Hammar Mishrif				ZU Rafidiyah			
Mol%	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage	1st HP	1st LP	2nd stage	3rd stage
H ₂ S	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
CO ₂	1.7%	1.2%	1.6%	1.4%	1.8%	0.7%	0.6%	0.5%	1.6%	0.6%	1.5%	1.4%	1.7%	1.2%	1.4%	1.3%	1.2%	1.6%	1.6%	1.3%
N ₂	0.4%	0.7%	0.3%	0.1%	0.6%	0.9%	0.5%	0.2%	0.3%	0.9%	0.3%	0.1%	0.9%	0.9%	0.6%	0.4%	0.5%	0.4%	0.2%	0.1%
C ₁	77.2%	71.6%	59.3%	34.9%	81.3%	69.4%	49.2%	22.8%	78.2%	72.1%	59.6%	32.1%	78.9%	69.6%	58.9%	38.4%	73.5%	76.9%	56.8%	26.2%
C ₂	10.2%	14.8%	20.5%	26.1%	9.6%	16.1%	25.9%	30.3%	11.8%	15.2%	20.9%	27.2%	11.8%	15.9%	21.2%	25.6%	16.3%	11.1%	20.0%	24.6%
C ₃	5.3%	7.3%	11.0%	22.9%	4.5%	7.9%	14.6%	27.0%	5.0%	6.9%	10.9%	23.8%	4.5%	7.7%	11.2%	21.8%	5.8%	5.4%	12.0%	26.5%
iC ₄	0.9%	0.8%	1.3%	2.5%	0.5%	0.9%	1.6%	3.3%	0.6%	0.8%	1.3%	2.7%	0.5%	0.9%	1.3%	2.2%	0.5%	0.8%	1.6%	3.3%
nC ₄	2.1%	2.2%	3.4%	6.9%	1.1%	2.4%	4.6%	9.5%	1.5%	2.1%	3.2%	7.2%	1.2%	2.3%	3.2%	6.0%	1.6%	1.9%	4.1%	8.7%
iC ₅	0.6%	0.5%	0.8%	1.6%	0.2%	0.5%	1.1%	2.2%	0.3%	0.5%	0.7%	1.6%	0.2%	0.5%	0.7%	1.3%	0.3%	0.5%	0.9%	2.2%
nC ₅	0.7%	0.5%	0.9%	1.8%	0.3%	0.6%	1.3%	2.7%	0.4%	0.5%	0.8%	1.8%	0.3%	0.6%	0.8%	1.5%	0.4%	0.6%	1.0%	2.5%
C ₆	0.7%	0.4%	0.7%	1.4%	0.1%	0.4%	0.5%	1.0%	0.3%	0.4%	0.6%	1.6%	0.2%	0.4%	0.5%	1.2%	0.3%	0.6%	0.7%	1.9%
C ₇	0.2%	0.1%	0.2%	0.4%	0.0%	0.1%	0.2%	0.3%	0.1%	0.1%	0.2%	0.4%	0.0%	0.1%	0.1%	0.3%	0.1%	0.2%	0.3%	0.7%
C ₈	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.3%

3.3 North Rumaila (NR) NGL Plant

The compressed gas from the Rumaila (North and South) compressor stations flows to the North Rumaila (NR) NGL plant for further processing. Uncompressed high-pressure 1st stage gas from the North Rumaila and West Qurna degassing stations also free-flows to NR NGL plant. The plant has a total processing capacity of 680 MMscfd. Figure 7 shows the block diagram of the existing NR NGL plant. The plant processes gas from the NR and WQ fields to produce sales gas to the grid network and broadcast NGLs (i.e. C3+ hydrocarbon components) for further fractionation in the KAZ LPG plant to produce C3 (propane), C4 (butane) and C5+ (gasoline) products.

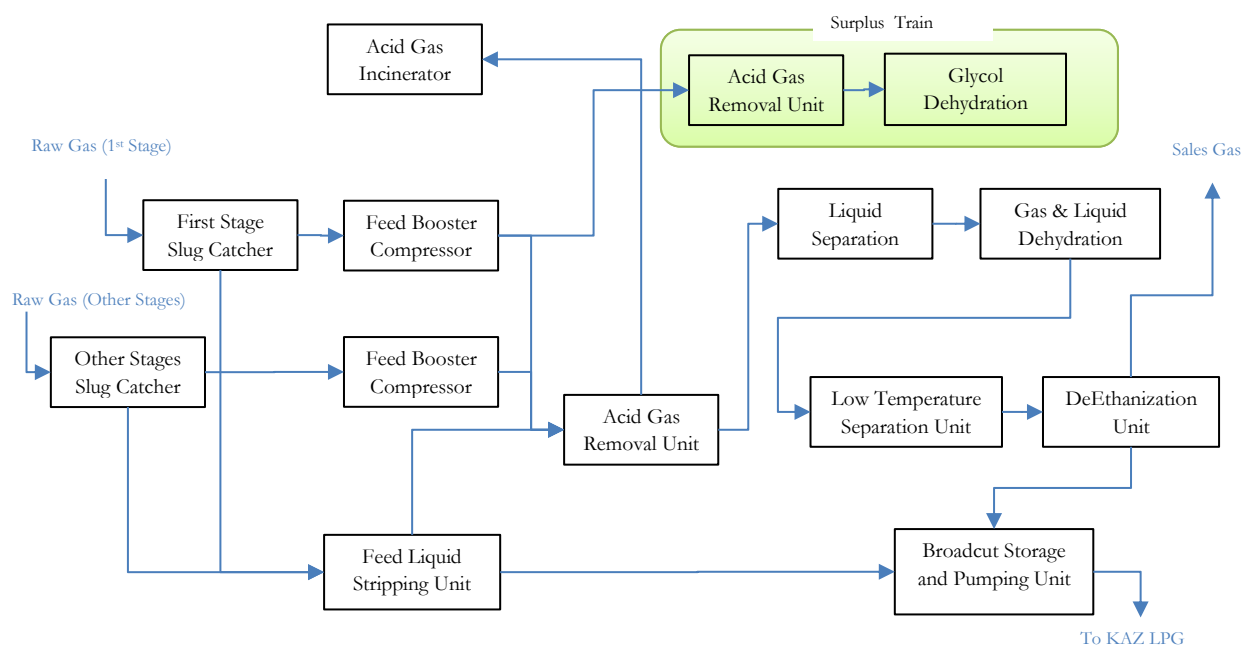


Figure 7: NR NGL Plant Block Diagram.

There are two primary processing trains in NR NGL plant, namely the NGL train and the surplus gas train. Both trains include acid gas treating and dehydration facilities.

Table 7: NR NGL Plant Train Capacities

Train	1 st stage gas (MMscfd)	Other stages gas (MMscfd)
NGL	110	240
Surplus	-	330

The gas from the upstream fields arrives into the slug catcher of the NR NGL plant. A slug catcher removes the slugs and condensed liquids that form during transportation in the pipeline. NR NGL plant has two slug catcher systems: one for the uncompressed 1st stage gas and the other for the compressed ‘other stages’ gas. It is important to segregate these two gas streams as the compressed gas stream usually has a higher level of heavier hydrocarbons and hence a higher likelihood of slug formation in the pipeline. From the slug catcher, the gas goes through booster compressors to increase the pressure to the level required for NGL processing.

The **NGL plant** comprises the following operations:

- Feed Liquid Stripping: The function of the liquids strippers is to desorb any residual gas from the liquids and the condensate recovered from the slug catcher, using the process of reboiling stripping. This increases gas recovery while stabilising the resulting liquid stream. The gas removed overhead is added back to the bulk vapour stream after compression. The recovered liquid is pumped to the broadcut (C3+) storage after being mixed with the liquid product from the deethanizer. The liquid stripper unit comprises a trayed column with a reboiler. The specification of the liquid stripping column is given in Table 8.
- Acid Gas Removal (MD-1): CO₂ and H₂S are removed in order to protect downstream equipment and also to meet the regulatory and customer specification for sales gas.

- Gas & Liquid Dehydration (MD-2): Water is removed to prevent freeze-out in the downstream cryogenic systems. Such H₂O freeze-out events can damage equipment and negatively impact on operations.
- Low-Temperature Separation: The gas is flashed and goes through a series of heat exchangers within a refrigerant propane cycle to lower the temperature to -36 °C before it flows to the fractionation column.
- De-ethanizer units: These are cryogenic fractionation columns to recover broadcut NGL from the gas. The unit recovers approximately 97% of all propane and heavier components into the broadcut NGL. The specification of the de-ethanizer column is given in Table 9.

The **surplus gas train** comprises Acid Gas Removal (MD-3) and Glycol Dehydration (MD-4) units to remove H₂S and CO₂ and water from the gas before entering the network. The acid gas is subsequently incinerated in the Acid Gas Incinerator (MD-9).

There is an interconnection downstream of the booster compressors between the NGL and surplus gas trains, to allow part of the 1st stage gas from the latter train to be transferred into the former train for processing.

Table 8: Liquid Stripping Column Specifications

	Value	Unit	Remarks
Number of Trays	21		Bubble cap trays
Column Height	18.0	m	
Column Diameter	3.3	m	
Design Pressure	24	barg	
Feed Trays	1		
Overhead Compressor Duty	2.68	MW	Centrifugal, electric motor

Reboiler Type	Horizontal Kettle type		
Reboiler Medium	Hot Oil		Tube side
Reboiler Duty	10×10^6	kcal/h	

Table 9: De-ethanizer Column Specifications

	Value	Unit	Remarks
Number of Trays	36		Ballast trays
Column Height	32.58	m	
Column Diameter	5.1	m	
Design Pressure	30	barg	
Feed Trays	2		Trays 10 & 19
Reboiler Type	Horizontal Kettle type		
Reboiler Medium	Hot Oil		Tube side
Reboiler Oil Temperature	220	°C	
Condenser Type	Horizontal Kettle type		
Condenser Medium	Refrigerant Propane		Shell side
Condenser Duty	6.3×10^6	kcal/h	

3.4 Khor Az Zubair (KAZ) NGL/ LPG Plant

The KAZ NGL/ LPG plant, located approximately 50 km south of the NR NGL plant, is the largest gas processing facility in Iraq. The plant receives associated gas from the degassing and compressor stations in South Rumaila (SR) and Zubair fields.

The KAZ plant consists of two main processes: NGL extraction and LPG fractionation. The NGL plant has two NGL extraction trains with 350 MMscfd capacities each. The units can achieve more than 98 mol% LPG recovery into the broadcut (i.e. C3+) NGL. The LPG plant consists of 3 fractionation trains, each with a capacity of 4,400 t/d of LPG. The block diagram of the KAZ NGL/LPG plant is shown in figure 8.

KAZ NGL plant was not designed with sweetening facilities because associated gas from the South Rumaila and Zubair fields contains only trace amounts of H₂S. The rest of the KAZ NGL plant is similar to the North Rumaila NGL plant. The de-ethanizer column in KAZ plant has similar specification to that of NR NGL plant.

The broadcut NGLs (i.e. C3+ hydrocarbon components) from the KAZ de-ethanizer is combined with the broadcut which flows 52 km from the NR NGL plant. Both broadcut streams are combined in the LPG feed storage tanks. The combined broadcut is then pumped to the 3 parallel LPG trains. The broadcut first enters the de-propanizer column where propane is distilled out from the top of the column while the heavier components (C4+ hydrocarbons) flow out from the column bottoms. The specification of the de-propanizer is given in Table 10. The stream from the de-propanizer bottoms then flows to the de-butanizer column where butane is distilled out from the top of the column while the heavier components (C5+ hydrocarbons) flow out from the column bottoms. The specification of the de-butanizer is given in Table 11. The stream from the de-butanizer bottoms (mainly C5+ hydrocarbons) then flows to the gasoline rectification and sweetening units where mercaptans are removed by the Merox process to produce natural gasoline which can be blended into high-octane gasoline for use as vehicle fuel.

Overall, the four main products from the KAZ plant are dry sales gas (C1+C2), propane, butane and C5+ hydrocarbons, the latter being commercially referred to as “natural gasoline”. The three liquid products (C3, C4, and C5+ hydrocarbons) are delivered by pipeline to the Um Qasr storage terminal while sales gas goes to both the NR gas transmission unit (GTU) export pipelines system

to supply power plants, and to the local gas pipeline system for delivery to domestic gas customers such as fertilizer plants.

Table 10: De-propanizer Column Specifications

	Value	Unit	Remarks
Number of Trays	48		4-pass valve trays
Column Height	37.6	m	
Column Diameter	5.1	m	
Design Pressure	24.6	barg	
Feed Trays	2		Trays 20 & 28
Reboiler Type	Horizontal Kettle type		
Reboiler Medium	Hot Oil		Tube side
Reboiler Oil Temperature	220	°C	
Reboiler Diameter	1.27 / 2.48	m	
Reboiler Length (TL-TL)	12.2	m	
Condenser Type	Air-cooler		Forced draft
Condenser Dimension	12.2(L) × 2.9(W) × 0.7(H)	m	Bundle

Table 11: De-butanizer Column Specifications

	Value	Unit	Remarks
Number of Trays	30		2-pass valve trays
Column Height	24.7	m	
Column Diameter	3.7	m	
Design Pressure	9.4	barg	
Feed Trays	1		Tray 15
Reboiler Type	Horizontal Kettle type		
Reboiler Medium	Hot Oil		Tube side
Reboiler Oil Temperature	220	°C	
Reboiler Diameter	1.25 / 2.27	m	
Reboiler Length (TL-TL)	6.1	m	
Condenser Type	Air-cooler		Forced draft
Condenser Dimension	12.2(L) × 2.9(W) × 0.8(H)	m	Bundle



3.5 Pipeline Network

As shown in Figure 3, BGC has an extensive network of pipelines that transport gas and liquids between different facilities in the network. Some of the main pipeline clusters are:

- Gas pipelines from the stations in North Rumaila and West Qurna fields to the NR NGL plant.
- Gas pipelines from the stations in South Rumaila field to the NR NGL plant.
- Liquid pipeline carrying broadcut (C3+ hydrocarbons) from the NR NGL plant to the KAZ plant.
- Gas pipelines from the stations in South Rumaila field to the KAZ NGL plant.
- Gas pipelines from the stations in Zubair field to the KAZ NGL plant.
- Liquid pipelines carrying propane, butane and C5+ condensates from KAZ plant to the Um Qasr storage terminal.
- Liquid pipelines carrying propane, butane and C5+ condensates from the Um Qasr storage terminal to the Um Qasr marine terminal.

The parameters for the pipelines included in the scope of this project are shown in Table 12.

Pipelines 91 and 90 (Refer to Figure 3) are not part of the BGC's assets and hence are not included in this table. Most of the pipelines are buried to depths of about 1.5 m in soil with clay characteristics.

Table 12: Pipelines Parameters

Line No (Ref Figure 3)	Diameter (inch)	Length (km)
1	12	0.6
2	16	0.6
3	20	7.9
4	12	7.9
5	14	2.3

6	12	2.3
7	32	5.2
8	24	5.2
9	22	7.5
10	18	7.5
11	Not in use	
12	16	1.0
13	16	0.8
14	30	10
15	20	0.05
16	30	10
17	20	0.05
18	8	0.6
19	12	0.2
20	12	1.4
21	12	0.1
22	12	5.5
23	22	0.05
24	16	0.05
25	24	1.5
26	18	2.1
27	20	2.1
28	10	52.1
29A	24	52.3
29B	40	52.3
29C	30	52.3
30	30	2.1
31	18	0.05
32	6	1.5
33	18	0.05
34	12	23.0
35	24	1.5
36	6	1.5
37	20	1.5
38	6	1.5
39	20	1.5
40	6	1.5
41	48	35.2
42A	36	50
42B	32	50
43	24	34.0
44	8	22.2
45	12	22.2
46	8	22.4

47	6	22.2
49	8	5.1
50	20	7.4
51	20	7.4
52	24	7.4
53	20	7.4
54	20	7.4
55	24	7.4
56	20	7.4
57	20	7.4
58	48	3.3
59	12	3.3
60	3.5	3.3
61	40	50.0
62	8	52.0
63	12	52
64	14	17

3.6 Um Qasr Terminal (Storage and Marine)

BGC has custody of the Um Qasr terminal. The terminal is the main LPG and gasoline export facility in Southern Iraq. Figure 9 provides an overview of the terminal showing the LPG and gasoline products from the KAZ LPG plant and Nassariya (non-BGC facilities in North Iraq) piped to the receiving terminal, after which the products are refrigerated and stored in the storage tanks from where the products are transported 7.5 km to the marine terminal and loaded on ships for export.

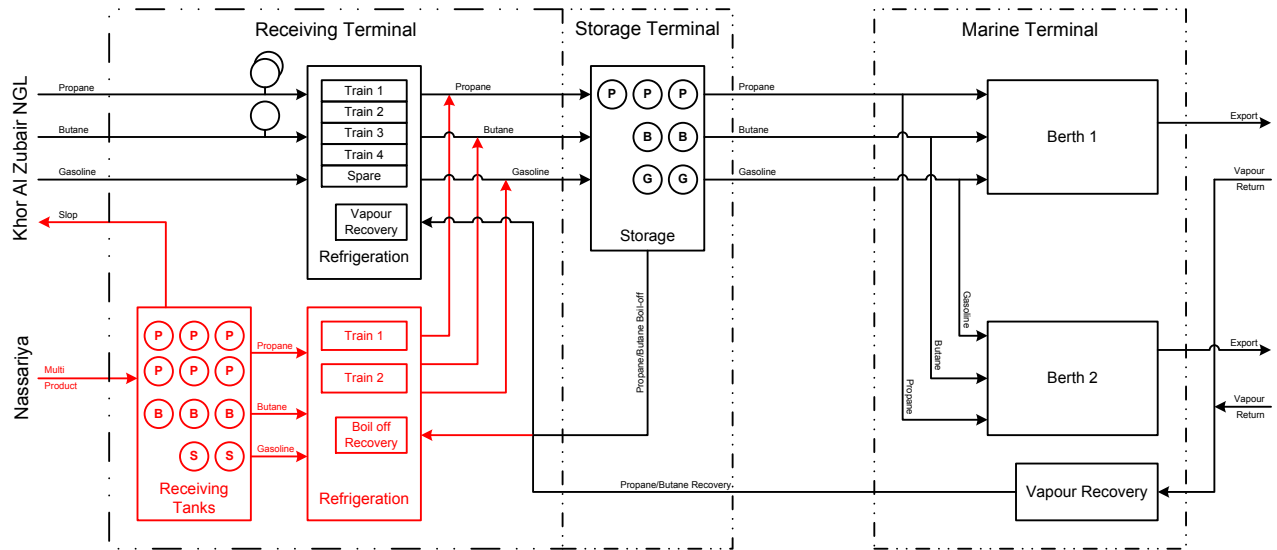


Figure 9: Um Qasr Receiving, Storage and Marine Terminals (Red Units are 3rd Party facilities)

Three pipelines take products from the KAZ plant. Propane and butane product streams are transported to refrigerated storage facilities and the C5+ hydrocarbons stream is piped to atmospheric storage facilities. The storage facilities are connected to the Umm Qasr shipping terminal by dedicated pipelines for the different products.

The Um Qasr terminal operational processes have not been modelled in detail in this work as they are considered a demand node. The capacities of the storage tanks are, however, important as they result in inventory constraints that need to be taken into account for the multi-period supply chain optimisation.

Table 13: Um Qasr Refrigeration and Storage Capacities

	Capacity/ Unit	No. Of Units	UOM
Refrigeration			
Propane	1795	5 (4+1 spare)	t/d
Butane	1059	5 (4+1 spare)	t/d
Gasoline	1041	5 (4+1 spare)	t/d
Storage Tanks			
Propane	80,000	3	m ³
Butane	71,200	2	m ³
Gasoline	65,000	2	m ³

3.7 Gas Transmission Unit (GTU)

The dry gas from NR NGL and KAZ NGL plants goes to the GTU. This is a system of trunk lines which supply power plants and industrial consumers across Southern Iraq. The GTU is not a part of BGC's assets. In this work, it is modelled simply as a demand node in the network.

3.8 Typical Natural Gas Network

The facilities presented in this chapter are representative of the nodes in a typical gas network as shown conceptually in Figure 10. The network is comprised of five levels of facilities or types of nodes. Material flows from the wells (gas source) to the gathering (or compressor) stations, gathering stations to NGL plants, NGL plants to product outlets and to LPG plants, and LPG plants to product outlets. In general, a natural gas network may be comprised of an arbitrary number of levels or sub-facilities and involve different spatial and temporal scales. The temporal scales may correspond to different price regimes.

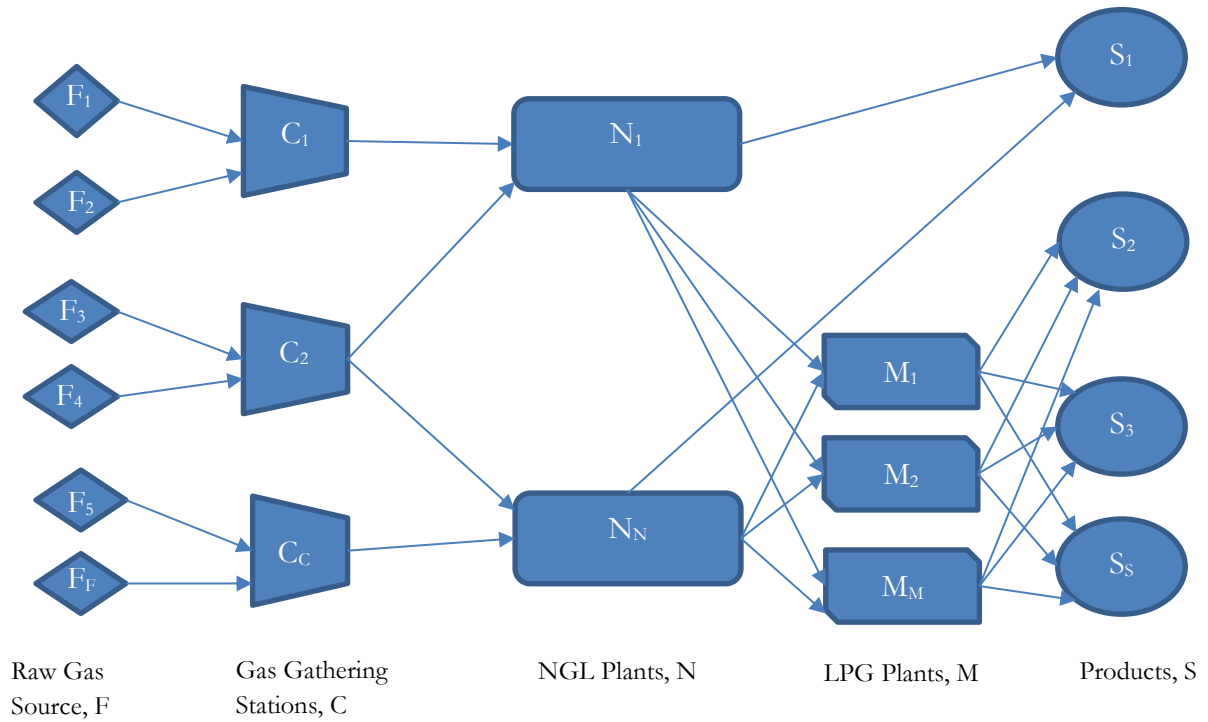


Figure 10: Natural Gas Production, Processing and Supply Network

The case study gas network for this work consists of several facilities as shown in Figure 3. The detailed modelling of the underlying facilities in the network is presented in the next chapter.

Chapter 4. Detailed Gas Network

Modelling

The BGC gas network described in the previous chapter has been modelled in the gPROMS[®] ProcessBuilder. This advanced modelling platform combines the power of equation-oriented and object-oriented modelling. Figure 11 shows the topology of BGC network as set-up in gPROMS.

The network modelling was done on a Windows 7 personal computer (64-bit OS) with a 2.90 GHz dual-core processor (AMD A6-5350M APU with Radeon™ HD Graphics) and 8GB RAM.

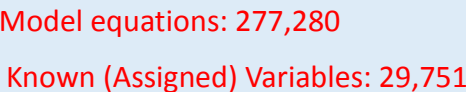
In order to provide the fidelity required for meaningful optimisation calculations, detailed pipeline models, compressor models with performance curves and multicomponent vapour-liquid-equilibrium (VLE) models for the NGL and LPG distillation column calculations were used throughout.

Component and mixture properties were supplied by the built-in Multiflash physical property package, using the Peng-Robinson equation of state to describe the pressure-volume-temperature (PVT) properties of the natural gas system. The Multiflash physical property package is interfaced with the Network model in gPROMS as a foreign object. Multiflash performs Pressure-Volume-Temperature (PVT) and Equation of State (EOS) modeling and provides the property data dynamically to the gPROMS model. All the component molecules in the system are inputted in Multiflash along with the selected equation of state. The Multiflash configuration file is then generated and imported into gPROMS. During runs, the configuration file is loaded into the Multiflash engine which performs the physical property calculations requested by gPROMS.

Mass and energy balance equations are solved in the models for the respective unit operations. Material information is transferred between adjacent units through material connectors that are basically equality relations between variables in these units.

The network model shown in Figure 11 is composed of sub-models which are the blocks shown in the figure.

The following sections describe how the different process systems and sub-models in the BGC gas network are modelled in gPROMS.



4.1 Compressor Station Modelling

Detailed steady-state models have been developed for the compressor stations. The compressor model relates the energy consumption to the pressure rise provided by compression. The actual compressor performance curves have been built into the models for each compressor station. Interpolation methods on the flow data are used to determine polytropic head and efficiency. Given the polytropic head, the discharge pressure is calculated using the equation:

$$Head_{poly} = \left(\frac{n}{n-1} \right) \frac{Z_a R T_1}{MW} \left[\left(\frac{P_2}{P_1} \right)^{\left(\frac{n-1}{n} \right)} - 1 \right] \quad (27)$$

where P_1 is suction pressure, P_2 discharge pressure, T_1 the suction temperature, Z_a average gas compressibility factor, MW the gas molecular weight, R the gas constant, and n the polytropic exponent.

To represent all the types of compressor stations available in the network, six different compressor station models have been developed representing different compressor types, configurations and number of compressor trains per station. Refer to Table 2 for more information.

The compressor station models also contain models for air-cooled heat exchangers, vapour-liquid separators and a tri-ethylene glycol (TEG) dehydration unit used to meet the pipeline specification for H_2O . The TEG unit has been modelled as a simple component splitter to remove water from the compressed gas.

Figure 12 shows a screen shot of the gPROMS topology for a 3-train compressor station.

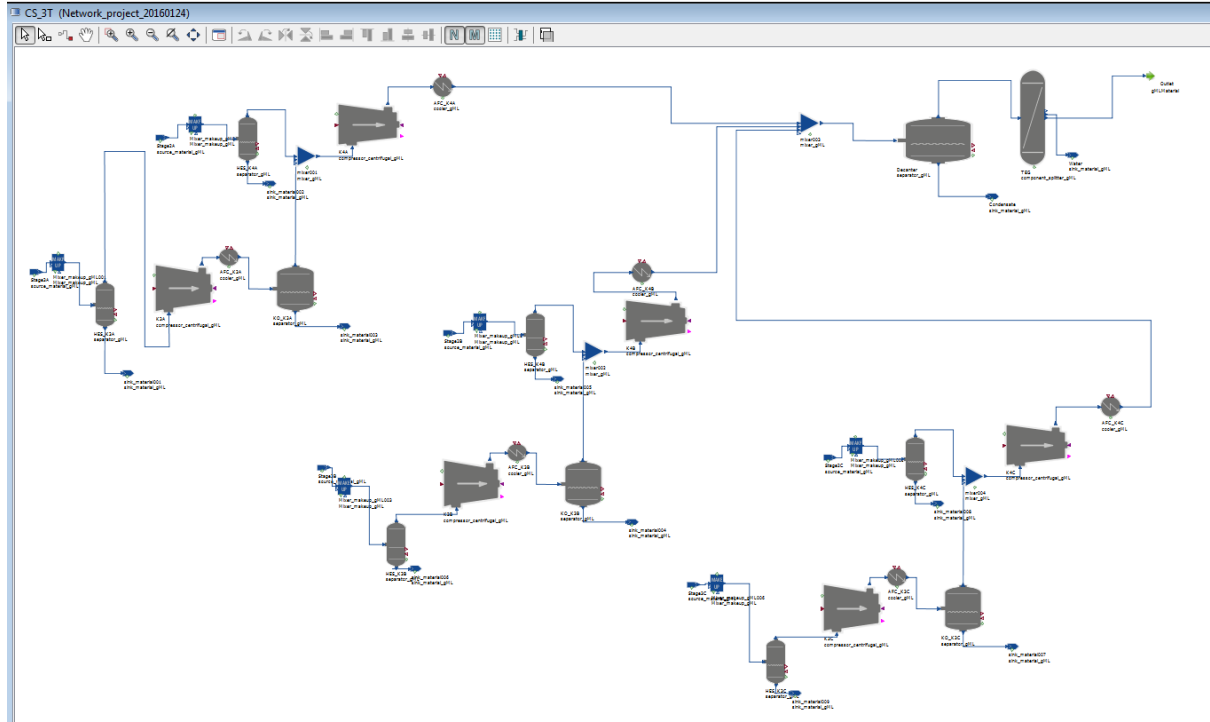


Figure 12: gPROMS topology of 3-train compressor station model

4.2 Pipeline Modelling

The pipelines in the network have been modelled using a distributed model to describe pressure drop in the line and heat transfer to surroundings. The model uses a pressure-flow relationship that describes how the gas flows are dependent on the pressures in pipelines. It should be noted that only pipelines greater than 1 km have been included in the network model. This reduces the number of equations and size of the network model. It can be expected that the pressure drop in very short pipelines (< 1 km) is relatively negligible.

Pressure drop is calculated with the following equation:

$$\Delta p = f \frac{L}{D} \frac{\rho V^2}{2} \quad (28)$$

where Δp is pressure drop, f the Darcy friction factor, L the length of pipe, D pipe diameter, ρ fluid density and V average velocity.

Initially, the pipelines were modelled using a smooth pipe approximation for the Darcy friction factor. It was however observed that this approach underestimates pressure drop by about 30%. The Haaland correlation was then implemented. This is applicable to both laminar and turbulent flow regimes, and takes the form:

$$\frac{1}{\sqrt{f}} = -1.8 \log_{10} \left[\left(\frac{\varepsilon/D}{3.7} \right)^{1.11} + \frac{6.9}{Re} \right] \quad (29)$$

where ε/D is the relative roughness of the pipe and Re the Reynolds number.

Some of the fluid in the pipelines of interest to this model may involve mixtures of vapour and liquid i.e. multiphase flow. However, comparison between Haaland correlation and Beggs and Brill correlation for multiphase flow did not show significant difference in the pressure drop results. To correct for pipeline bends and elevations, the friction factor obtained from the Haaland correlation is multiplied by a pressure drop correction factor. [See section 5.2.2 for more details on model validation]

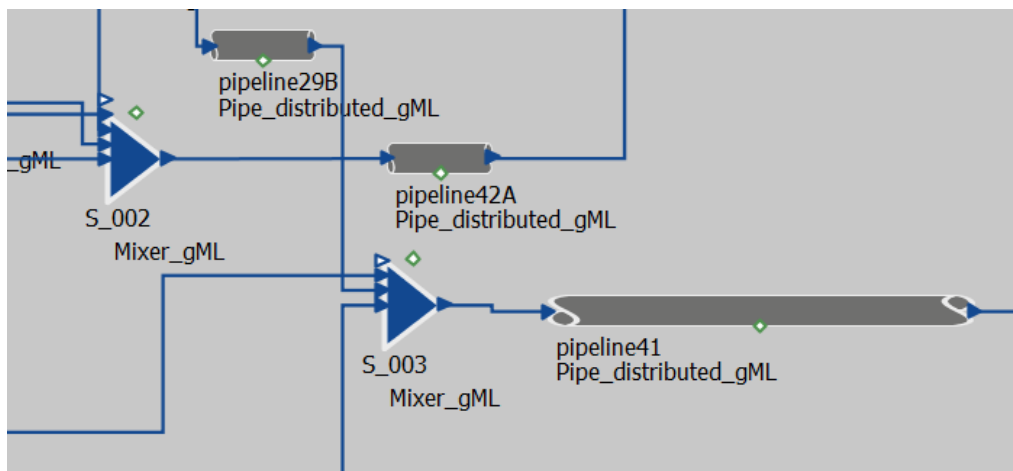


Figure 13: gPROMS topology of sections of the pipeline systems in the network

It is important to ensure that the natural gas flow in the pipeline is not choked. Fluid flow in a pipe is choked when the fluid velocity reaches the speed of sound in that medium i.e the fluid has a Mach number M of 1. Choked flow impacts operations and controllability of the flow in the pipelines. For two-phase flow [where condensates are present], choked flow could lead to cavitation which can damage the pipeline and associated equipment.

The Mach number is the ratio of relative velocity of a fluid to the speed of sound in that medium i.e.

$$M = \frac{V}{V_s} \quad (30)$$

where V_s is the speed of sound.

To maintain subsonic speeds and prevent choked flow in the pipelines, the following inequality constraint has been applied to the optimisation problems in this work:

$$M \leq 0.8 \quad (31)$$

4.3 NGL Plant Modelling

The NGL plant consists of slug catchers, gas booster units, acid gas removal unit (AGRU), cooling loops, low-temperature separator and de-ethanizer.

Detailed models for the cooling loops, low-temperature separator and de-ethanizer have been developed. The AGRU is not modeled because its function of ensuring that H_2S composition in product meets specifications, does not significantly affect overall network flowrates and production.

The NR NGL plant is modelled with the design process conditions given in section 3.3 and 3.4.

Figure 14 shows the topology of the NGL plant modelled in gPROMS.

4.3.1 Slug Catchers

The slug catcher removes the transient slugs that develop in the pipeline and normalizes gas flow to the NGL plant. In a gas pipeline, the gas flow usually includes both gas and liquid phases and there may be mass transfer between the two phases. The liquids that form in the pipeline as a result of friction losses and ambient cooling are also removed in the slug catcher.

The slug catcher has been modelled as a flash vessel incorporating vapour-liquid phase equilibria.

4.3.2 Liquid Stripper Units

The liquid stripper unit comprises a trayed-column with a reboiler. The model has been developed on the basis of the column specification outlined in Table 8. The trays have been modeled as a set of equilibrium stages modelled using detailed phase equilibria.

4.3.3 Booster Units

Due to friction losses and the long pipeline distances, the gas arriving at the NGL plant has insufficient pressure for processing. Booster compressors are therefore installed to raise the pressure of the gas inlet.

The booster unit compressors are modeled as mass and energy balance models with outlet pressure specifications.

4.3.4 Cooling Loops and Low-Temperature Separator

The gas cooling cycle has been modeled in detail. The cooling cycle is represented by a number of recycle loops comprising chillers and heat exchangers-for heat integration between the inlet and

outlet streams of the low-temperature separator (LTS). Recycle breakers have been included in the gPROMS model to aid with initialization of the cooling loop.

The propane refrigeration cycle is not modelled in detail as this can be considered to be a utility not affecting the process in steady-state mode. All the chillers in the cooling cycle are modeled as coolers with steady-state temperatures per the actual cooling cycle.

After cooling to about -30°C , the fluid goes into the LTS where it is flashed. The gas phase is dry gas (mostly methane) which goes to the export grid after it is used to cool the inlet stream. The liquid phase from the LTS is passed through a heat exchanger to cool down the inlet streams before flowing to the de-ethanizer fractionator.

4.3.5 De-ethanizers

Dry gas (methane and ethane) is extracted from the top of the de-ethanizer distillation column while the broadcut (C_3+) is drawn from the bottom.

A rigorous distillation model together with applicable thermodynamic properties is used to describe vapour-liquid equilibria of each tray (equilibrium stage) of the column assuming a tray efficiency of 100%. The actual number of trays in the column is specified. Reboiler and condenser performance data is also specified. The model has been developed on the basis of the column specification outlined in Table 9.

An important constraint during network optimisation is the avoidance of flooding in the various columns. Failure to take proper account of this may result in significant over-estimation of the plant's processing capacity. Our optimisation calculations required the actual vapour velocity not to exceed the flooding velocity as determined via the Fair correlation:

$$v_{flood} = C_{Fair} \left(\frac{\sigma}{20} \right)^{0.2} \sqrt{\frac{\rho_L - \rho_V}{\rho_V}} \quad (32)$$

where ρ_L is density of the liquid phase, ρ_V the density of the vapour phase, σ the surface tension (in dynes/cm), and C_{Fair} the Fair capacity factor obtained from the correlation:

$$C_{Fair} = 0.04232 + 0.1674T_s + (0.0063 - 0.2686T_s)F_{LV} \\ + (0.1448T_s - 0.008)F_{LV}^2 \quad (33)$$

where T_s is tray spacing and F_{LV} a dimensionless group defined as $F_{LV} \equiv \left(\frac{L}{V} \right) \sqrt{\frac{\rho_V}{\rho_L}}$.

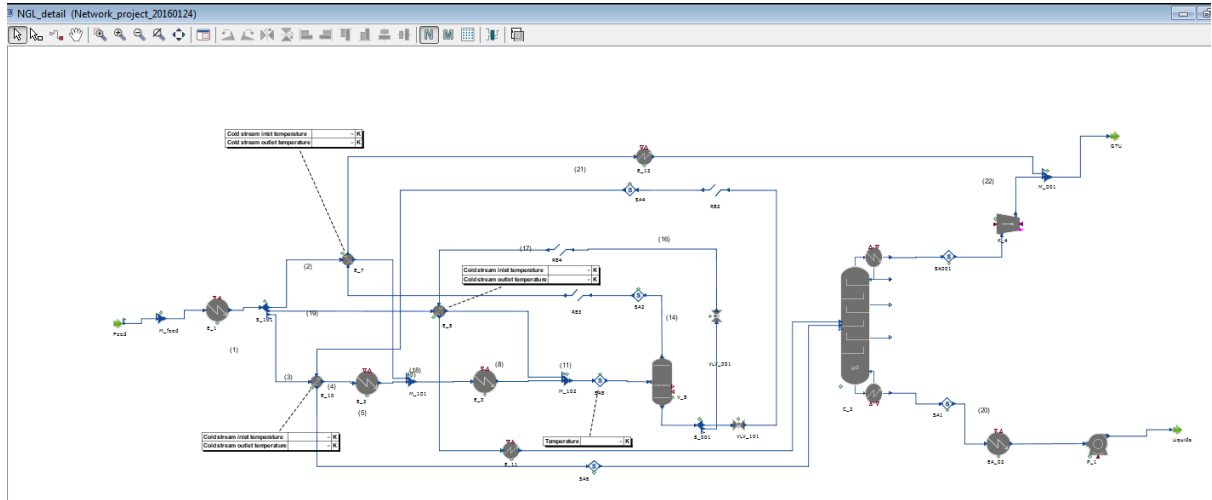


Figure 14: gPROMS topology of NGL model showing cooling cycles, low-temperature separator and de-ethanizer

4.4 LPG Plant Modelling

The case-study network of BGC includes 3 LPG trains, each consisting of a de-propanizer column and a de-butanizer column. Figure 15 shows the topology of the LPG plant as modelled in gPROMS.

A rigorous distillation model together with applicable thermodynamic properties is used to describe vapour-liquid equilibria of each tray (equilibrium stage) of the de-propaniser and de-butaniser columns. The actual number of trays in each column is specified. Reboiler and condenser performance data is also specified.

Flooding calculations as described for the de-ethanizer in section 4.3.5 are implemented for the de-propaniser and de-butaniser column models as well.

4.4.1 De-propanizer

The de-propanizer model has been developed on the basis of the column specification outlined in Table 10. Each depropanizer receives two feeds (preheated and non-preheated) of C3+ components from the NGL trains. There are no column side-draws. A totally condensed propane-rich stream is extracted from the top of the column while the C4+ components are drawn from the bottom.

The top products from the de-propanizers in all 3 LPG trains are combined using a mixer model to form the propane product stream.

4.4.2 De-butanizer

The de-butanizer model has been developed on the basis of the column specification outlined in Table 11. A butane-rich stream is extracted from the top of the column while natural gasoline stream (C5+ components) are drawn from the bottom. The top stream is totally condensed. There is only one feed tray for the de-butaniser and there are no side-draws.

The top product from the de-butanizers in all 3 LPG trains are combined using a mixer model to form the butane product stream. Similarly, the corresponding bottom products are combined to form the gasoline product stream.

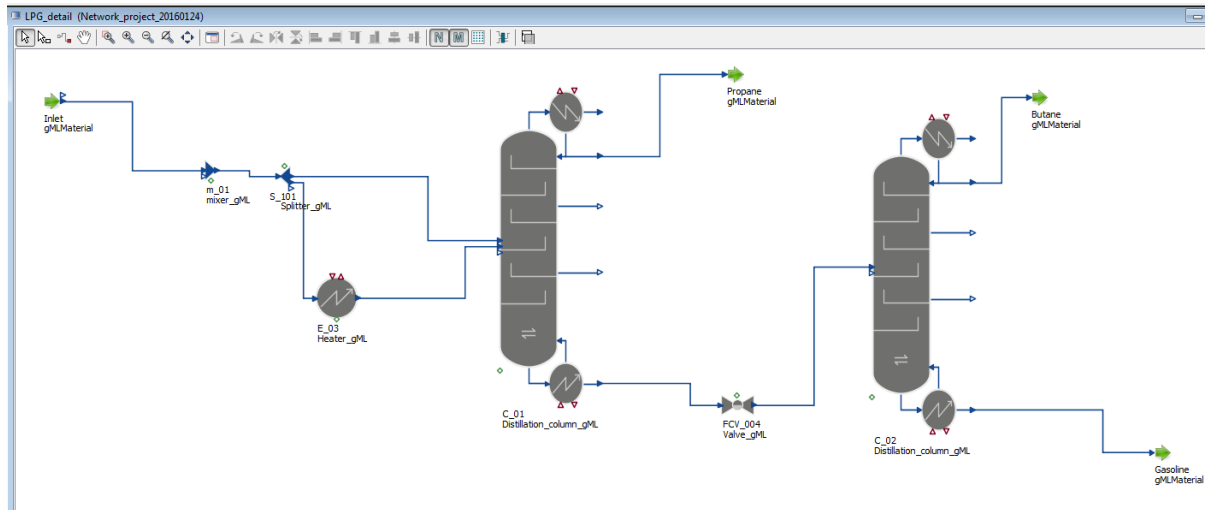


Figure 15: gPROMS topology of LPG plant model showing de-propanizer and de-butanizer

4.5 Model Initialization

The overall network model described in this chapter comprises approximately 278,000 nonlinear algebraic equations. The initialisation of such a large set of equations, i.e. obtaining a set of variable values that satisfy all equations and degree-of-freedom specifications, is a non-trivial task. A stage-wise approach was used for this purpose:

1. Develop separate (“standalone”) models for the individual sub-systems (e.g. compressor stations) described above.
2. Simulate the standalone sub-models. In the case of sub-models including complex units, such as distillation columns, the Model Initialization Procedures built into the gPROMS ProcessBuilder are essential for achieving this task in a robust and efficient manner.
3. Generate saved variables sets using the results of the simulated sub-models. In gPROMS, saved variable sets (SVS) store the values of all model variables at a particular simulation time and make them available for later re-use.

4. In the network model which is composed of the sub-models, use the SVS for the various sub-models to provide good initial guesses for the corresponding sub-systems.

4.6 Conclusion

The detailed modelling of the relevant unit operations that make up the network, have been described in this chapter. The approach for initialising such a large network model has also been presented. In the next chapter, the model validation is described.

Chapter 5. Model Validation

Before using the model described in Chapter 4 for network-wide optimisation, it is essential that it is validated against operational data from the BGC network to ensure that it can accurately represent current operating conditions in the network.

5.1 Thermodynamics & Property Models Validation

Multiflash physical property package is linked with the network model in gPROMS as a foreign object. Multiflash does PVT and EOS modeling and provides the property data dynamically to the gPROMS model. Peng-Robinson EOS was selected in Multiflash to describe the PVT properties of the system.

The thermodynamics in the Multiflash-linked gPROMS model is indirectly validated against plant and proxy-laboratory data. Where necessary, the SMIRK (Shell Modified and Improved Redlich-Kwong) equation of state is used to generate proxy laboratory data, taking advantage of the fact that SMIRK has already benefitted from decades of validation with Shell plant and laboratory data.

In the validation results presented below, VLE results from gPROMS are compared with results from the SMIRK-extension in Unisim^(R). The following validation cases were considered.

- Low Pressure
- High Pressure
- Sour Gas: H₂S is polar, which makes the effects of its presence in hydrocarbon mixtures difficult to predict.

The tables below show that there is no significant difference between VLE mole fractions from gPROMS-PR and SMIRK. The exception is for the trace components such as heptane and octane. However, at such low levels, the effect of even a relatively large increase or decrease in composition is quite negligible on the overall scale, and will not affect the results of the optimisation.

Table 14: Low Pressure Validation Case

	27.7 degC; 3.7 bar							
		Unisim_SMIRK		gPROMS_PR				
	Feed (w/w)	Vapour	Liquid	Vapour	Liquid	%ΔVapour	%ΔLiquid	
Methane	0.0839	0.0858	0.0009	0.0849	0.0008	1.1	5.3	
Ethane	0.2586	0.2643	0.0140	0.2616	0.0129	1.0	7.9	
Propane	0.2955	0.3010	0.0589	0.2986	0.0491	0.8	16.7	
iButane	0.0463	0.0469	0.0222	0.0466	0.0190	0.5	14.4	
nButane	0.1318	0.1328	0.0891	0.1325	0.0752	0.2	15.6	
iPentane	0.0424	0.0418	0.0693	0.0421	0.0666	0.9	3.9	
nPentane	0.0554	0.0539	0.1190	0.0547	0.1136	1.4	4.6	
Hexane	0.0482	0.0424	0.2985	0.0451	0.3030	6.5	1.5	
Heptane	0.0188	0.0127	0.2794	0.0153	0.2989	20.6	7.0	
Octane	0.0018	0.0007	0.0482	0.0011	0.0605	47.9	25.6	
CO2	0.0139	0.0142	0.0003	0.0140	0.0004	1.3	8.6	
N2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0	0.0	
H2S	0.0000	0.0000	0.0000	0.0000	0.0000	0.0	0.0	
H2O	0.0034	0.0035	0.0001	0.0034	0.0001	0.9	43.9	

Table 15: High Pressure, High Temperature Validation Case

	61 degC; 35.5 bar; 0 ppm H2S							
		Unisim_SMIRK		gPROMS_PR				
	Feed (w/w)	Vapour	Liquid	Vapour	Liquid	%ΔVapour	%ΔLiquid	
Methane	0.0839	0.1355	0.0199	0.134219	0.020269	0.9	2.0	
Ethane	0.2586	0.3489	0.1465	0.332708	0.136866	4.6	6.6	
Propane	0.2955	0.3075	0.2806	0.306692	0.270957	0.3	3.4	
iButane	0.0463	0.0363	0.0587	0.038267	0.058829	5.4	0.2	
nButane	0.1318	0.0915	0.1819	0.098508	0.18477	7.7	1.6	
iPentane	0.0424	0.0198	0.0704	0.023155	0.073467	16.7	4.3	
nPentane	0.0554	0.0229	0.0958	0.027145	0.100804	18.6	5.3	
Hexane	0.0482	0.0109	0.0945	0.01473	0.101451	35.0	7.4	
Heptane	0.0188	0.0022	0.0394	0.003382	0.042966	52.3	9.1	
Octane	0.0018	0.0001	0.0039	1.82E-04	0.004278	67.3	9.7	
CO2	0.0139	0.0210	0.0051	0.019804	0.00506	5.7	0.3	
N2	0.0000	0.0000	0.0000	-6.27E-18	-4.82E-19	0.0	0.0	
H2S	0.0000	0.0000	0.0000	2.30E-21	1.06E-21	0.0	0.0	
H2O	0.0034	0.0034	0.0034	0.001208	2.82E-04	64.6	91.7	

It is observed that, at low pressures as shown in Table 14, there is more deviation between gPROMS-PR and SMIRK for the liquid phase of the lighter components C1-C4. At higher pressures, this deviation in C1-C4 prediction is smaller. This is because at lower pressures, the composition of lighter hydrocarbons in the liquid phase is relatively small. At such low levels, a significant increase or decrease in composition is quite negligible on the overall scale.

Similarly, it is observed that at higher pressures as shown in Table 15 and Table 16, there is more deviation between gPROMS-PR and SMIRK for the vapour phase of the heavier components C4-C8. At lower pressures, this deviation in C4-C8 prediction is smaller. This is because at higher pressures, the composition of heavier hydrocarbons in the vapour phase is relatively small. At such low levels, a significant increase or decrease in composition is quite negligible on the overall scale.

Table 16: Sour Gas Validation Case

61 degC; 35.5 bar; 3000 ppm H2S								
	Feed (w/w)	Unisim_SMIRK		gPROMS_PR			%ΔVapour	%ΔLiquid
		Vapour	Liquid	Vapour	Liquid			
Methane	0.0844	0.1362	0.0202	0.133974	0.020314		1.6	0.8
Ethane	0.2600	0.3501	0.1485	0.332359	0.137604		5.1	7.3
Propane	0.2972	0.3075	0.2845	0.306582	0.273147		0.3	4.0
iButane	0.0466	0.0362	0.0594	0.03829	0.059347		5.8	0.1
nButane	0.1325	0.0910	0.1839	0.098579	0.18649		8.3	1.4
iPentane	0.0427	0.0197	0.0711	0.023177	0.074221		17.6	4.4
nPentane	0.0500	0.0204	0.0868	0.02443	0.091604		19.8	5.6
Hexane	0.0485	0.0108	0.0952	0.014742	0.102574		36.7	7.7
Heptane	0.0189	0.0022	0.0396	0.003378	0.043462		54.6	9.9
Octane	0.0018	0.0001	0.0039	1.81E-04	0.004328		71.4	11.4
CO2	0.0139	0.0211	0.0051	0.019772	0.00508		6.1	0.8
N2	0.0000	0.0000	0.0000	-2.27E-18	-1.75E-19		0.0	0.0
H2S	0.0027	0.0035	0.0016	0.00333	0.001546		6.0	3.4
H2O	0.0008	0.0012	0.0003	0.001205	2.84E-04		2.7	15.8

5.2 Network Model Validation

To establish a reliable basis for the optimisation studies, the network model has been validated by simulating actual operations of the BGC network. It should be noted that parameter estimation

methods have not been used in this work as the model predictions for each unit or equipment have been directly compared with the reference values from actual operating data. Validations were carried out for the different unit operations and results are presented in the sections below.

5.2.1 Compressors Model Validation

Compressor models have been validated by comparing simulated compressor duty with readings from the compressor motor control centre (MCC)³ panels in the compressor stations.

Table 17: Validation using Compressor Power Consumption Data

Compressor ID	MCC Reading (MW)	gPROMS Model (MW)	% Δ
CS2 Compressor K3	2.19	2.21	1
CS4 Compressor K4	2.68	2.75	3

As shown in Table 17, there is a no significant difference between model-predicted and measured power consumption for the compressor.

5.2.2 Pipeline Model Validation

The pipeline models have been validated by comparing simulated pressure drops ($\Delta P = P_{\text{upstream}} - P_{\text{downstream}}$) with measurements from pressure gauges upstream and downstream of a number of pipelines in the network.

Table 18: Validation of Pipeline models

³ Motor control centers are physical assembly of enclosures containing the motor starter, fuses or circuit breaker, electric instruments, meters and a device for disconnecting power.

Pipeline ID	Fluid (Phase)	Length (km)	Diameter (inch)	Measured ΔP (bar)	Predicted ΔP (bar)	Deviation (bar)
WQ Pipeline	Gas	50	40	0.42	0.38	0.04
Pipeline 4	Gas	8	12	1.9	0.8	1.1
Pipeline 6	Gas	10	18	2.9	2.06	0.84
Pipeline 41	Gas	35.2	48	2	0.2	1.8
Pipeline 43	Gas	34	24	3.1	0.55	2.55
Pipeline 28	Liquid	52	10	10	22	-12

It can be noted that, in most cases, the model under-predicts the pressure drop. Given the age of the pipeline infrastructure, it is strongly suspected that several pipelines contain sediments and asphaltene deposits. Asphaltenes and other debris will deposit over time as these lines have not been subjected to cleaning (“pigging”) in over a decade. Such deposits reduce the cross-sectional area, resulting in increased flow velocity and hence higher pressure drops.

Another possible reason for the deviations between measured and simulated pressure drops could be the existence of bends and elevation changes in the underground pipelines. As it was not feasible in the course of this work to excavate all the pipelines to get an adequate picture of their geometry, the frictional losses resulting from pipe bends and the head effects of elevation changes have not been modelled in detail.

Overall, in order to correct for pipeline bends, elevations and in-line deposits, the friction factor obtained from the Haaland correlation is multiplied by a pressure drop correction factor which is unique to each pipeline.

The WQ Pipeline is the newest pipeline in the systems and was only commissioned in 2015. Since this is a new line, it can be expected that sediments in the line would be negligible; hence this line is the most suitable for use in validating the pipeline model. As shown in Table 18, the model predicted pressure drop closely matches the measured pressure drop for the WQ pipeline.

5.2.3 NGL Plant Model Validation

The NGL plant model has been validated by comparing the gPROMS model prediction to plant performance data. The selected metric for validation is the NGL broadcut yield; this is a measure of mass flowrate of the de-ethanizer bottoms (C3+) known as ‘broadcut’ relative to the volumetric rate of the feed gas to the NGL plant. This metric was selected as it is a common KPI used in day-to-day plant monitoring.

Table 19: Validation of NGL Plant Model Using North Rumaila Operations Data

Metric	UoM	Plant Measurement	gPROMS Model	%Δ
Broadcut Yield (C3+ /Gas)	ton/mmscf	6.7	7.5	11

The yield deviation of 11% is probably due, at least partly, to the inherent degree of accuracy of the measuring instruments. In particular, field [non-fiscal] metering systems have an accuracy of around 10%.

5.2.4 LPG Plant Model Validation

The LPG plant model has been validated by comparing the gPROMS model prediction to plant performance data. The selected metrics for validation are the LPG plant product ratios for each product. This metric was selected as it is a common KPI used in day-to-day plant monitoring. The propane ratio is a measure of mass flowrate of the de-propanizer tops (C3 or propane) relative to the mass flowrate of ‘broadcut’ (C3+) feed to the LPG plant. The butane ratio is a measure of

mass flowrate of the de-butanizer tops (C4 or butane) relative to the mass flowrate of ‘broadcut’ (C3+) feed to the LPG plant. The gasoline ratio is a measure of mass flowrate of the de-butanizer bottoms (C5+) relative to the mass flowrate of ‘broadcut’ (C3+) feed to the LPG plant.

Table 20: Validation of LPG Plant Model Using KAZ Operations Data

Metric	UoM	Plant Measurement	gPROMS Model	%Δ
Propane Ratio (C3 /C3+)	ton/ton	0.47	0.51	4
Butane Ratio (C4/C3+)	ton/ton	0.32	0.26	-6
Gasoline Ratio (C5+/C3+)	ton/ton	0.21	0.23	2

The largest ratio difference observed between plant measurements and model is 6% for butane ratio. This difference is probably due to the inherent degree of accuracy of the measuring instruments. As mentioned in the previous section, field metering systems have an accuracy of around 10%. These validation results show that the LPG model provides an adequate representation of the actual LPG operational performance.

5.3 Conclusion

The above sections on thermodynamic model validation and unit operations model validations provides the basis for confidence in using these models for the optimisation of the case study gas network.

The chapters in Part III of this thesis focus on the gas network optimisation problems and solutions approaches.

PART III: NETWORK OPTIMISATIONS

Chapter 6. Optimisation Solution

Approach

The validated network model described in Chapter 4 and Chapter 5 forms the basis for the rest of the work described in this thesis. In particular, the optimisation of the BGC network will now be considered under various operational scenarios and the results will be analysed. The feasibility of different optimisation algorithms and methods will be tested on this large natural gas network.

The gPROMS ProcessBuilder platform was used for setting up and solving the optimisation problems. This takes advantage of the ability of the gPROMS platform to solve steady-state optimisation problems aiming to maximise or minimise any objective function subject to general sets of inequality and equality constraints. Both continuous and discrete optimisation decision variables can be handled.

The modeling and optimisations were carried out on a Microsoft Windows[®] 7 platform (64-bit operating system⁴) with a 2.90 GHz dual-core processor (AMD A6-5350M APU with Radeon™ HD Graphics) and 8GB RAM.

This chapter describes the optimisation solvers and the key optimisation parameters applied to the problem of optimizing the natural gas network.

⁴ It may be worth noting that a 32-bit operating system was used for the network modelling in the early stages of this work. However, this proved unable to cope with the increasing size of the underlying network model as the models of various key sub-systems were refined to be based on more detailed descriptions. The work was therefore continued on a 64-bit OS.

6.1 Optimisation Solvers

In-built NLP and MINLP solvers in gPROMS have been used for the nonlinear problems and mixed-integer-nonlinear problems respectively.

The gas flow split from some of the compressor stations introduces discrete variables to the natural gas network problem. This arises because, at any particular moment in time, it is more convenient for this flow to be routed in its entirety to either of the NGL processing plants, rather than to be split between the two.

The above problem can naturally be formulated as a MINLP. However, for most of the cases considered in this work, a relaxation of discreteness has been applied so that a NLP is solved instead of the potential MINLP problem arising from the network. For instance, instead of applying a discrete decision variable (e.g on/off) to the feed gas from different stations, a continuous flowrate factor is applied with a lower limit of 0 and an upper limit of 1. With this approach, a fraction of the gas flow can be routed to both NGL processing plants. In practice, such a split can be physically implemented in the field by introducing a flow ratio control to the gas output line from the various compressor stations.

Nevertheless, some of the cases considered have employed discrete variables, thereby solving the underlying MINLP problem; in such cases, a comparison is made to the corresponding relaxed cases.

6.1.1 NLP Solver

gPROMS uses the NLPSQP solver for NLP problems.

NLPSQP implements a sequential quadratic programming (SQP) method for the solution of a nonlinear programming (NLP) problem (Boggs & Tolle, 1995). In order to deal with large models, the NLP is formulated in the space of the optimisation decision variables only. All other variables

are eliminated by solving the model's nonlinear algebraic equations as and when required. This allows the optimisation objective function and constraints to be computed as functions of given values of the optimisation decision variables. The corresponding partial derivatives are also computed at the same time via the solution of the sensitivity equations of the nonlinear algebraic equation system.

NLPSQP employs a line search algorithm and uses a merit function to determine the size (i.e. step length) of the step to be taken. In this way, the algorithm drives progress towards the solution of the NLP, ensuring convergence to an optimum point. It should be noted that the latter is guaranteed only to be a locally optimal point, i.e. one that is better than all its neighbouring points within the feasible region determined by the optimisation constraints. In general, such local optima may depend on the initial guess of the optimisation decision variables. NLPSQP makes no attempt to identify a global optimum; thus, potentially better solutions might be obtained by a “multi-start” strategy, i.e. re-solving the problem multiple times starting from different initial guesses. However, due to time limitations, this was not attempted in the context of this work. The initial guesses used for this work are largely based on the plant's current operating points.

The NLPSQP solver uses four tolerances to decide whether or not a local optimal solution has been reached and all tolerances need to be satisfied. Each of the tolerances can be specified separately, which provides much flexibility to control the solution process and the outcome of the optimisation. The tolerances are closely related to the KKT conditions for the solution of the NLP (see Appendix A for more details).

Table 21 is an overview of the optimisation convergence criteria that have been applied in this work to assess optimisation progress and to terminate the optimisation. The table includes the description of each criterion and the tolerance values to be satisfied. It is worth noting that, if the criteria tolerances are not tight enough, a sub-optimal solution may be obtained.

Table 21: Optimisation Tolerances applied to the NLP Problem

Final Criteria	Convergence	Description	Target Value
Stationarity		Norm of the relative gradient of the Langrange function	0.05
Feasibility		Sum of constraint violations	0.1
Complementarity		Indicates no more ascent directions	0.1
Taylor (divided by objective value)		Rate of change (improvement) in the objective function	0.001

A more detailed description of the NLPSQP algorithm and definition of its algorithmic parameters can be found in the gPROMS ProcessBuilder documentation (Process Systems Enterprise Limited, 2015).

6.1.2 MINLP Solver

gPROMS uses the OAERAP (Outer Approximation Equality Relaxation Augmented Penalty) solver for MINLP problems. The OAERAP solver employs an outer approximation (OA) algorithm (Viswanathan & Grossmann, 1990) for the solution of the MINLP. An augmented penalty (AP) strategy is employed to increase the probability of a global solution being obtained. (Process Systems Enterprise Limited, 2015)

The OAERAP algorithm starts by solving the “fully relaxed” NLP problem, i.e. one in which discrete variables are treated as continuous ones within appropriate bounds. If, at the resulting solution, the relaxed discrete variables happen to take integer values, then this is deemed to constitute a solution of the original MINLP problem, and the algorithm therefore terminates.

Otherwise, the algorithm proceeds to solve a sequence of simpler optimisation problems, alternating between:

- “master” mixed integer linear programs (MILPs) that produce the next combination of discrete variables to be considered;
- “primal” nonlinear programs (NLPs) that determine an optimal solution for fixed values of the discrete variables.

The OAERAP algorithm employs two methods of obtaining initial guesses for the NLP Primal Problems. The first is to use the solution of the fully-relaxed problem as initial guesses for the solution of the primal problem at each iteration. An alternative approach is to use the solution of the MILP master problem, at the current iteration, to provide the initial guesses for the NLP primal problem. This is the default method.

As in the case of the NLPSQP algorithm described in section 6.1.1 above, the OAERAP algorithm provides no guarantee for the global optimality of the solution obtained.

An overview of the OAERAP algorithm can be found in the gPROMS Optimisation Guide (Process Systems Enterprise Limited, 2013).

6.2 Scaling of Variables

Decision variables often vary significantly in magnitude, which may adversely affect the performance of optimisation algorithms. Consequently, it is usually advantageous to implement appropriate scaling of the optimisation decision variables.

In gPROMS, the following transformation is applied to the vector of decision variables $\mathbf{x}$:

$$\hat{x} = ax + b \quad (34)$$

where $\hat{x}$ is the scaled value of x . The vectors a (factor) and b (offset) are calculated differently based on the chosen scaling strategy as described below:

- Scaling = 0 : no scaling;
- Scaling = 1 : scaling according to the range of the decision variables;
- Scaling = 2 : scaling according to the initial values of the decision variables;
- Scaling = 3 : scaling according to the initial value and gradient of the objective function.

The mathematical expression to determine a and b for the different scaling strategies can be found in the gPROMS ProcessBuilder documentation (Process Systems Enterprise Limited, 2015).

All four of the above scaling strategies have been applied to the profit optimisation problem to study the effect of scaling on optimal value and computational cost.

6.3 Initial Step Length

The step length is the fraction of the calculated step from the quadratic program that is actually taken in that iteration. The step length is computed using a merit function [Refer to section 2.2.2 for more background on this]. The step length applied to the solution of each quadratic subproblem influences the rate of convergence to the solution. In gPROMS, the initial step length for an optimisation problem can be set. The default initial step length is 1.

Different values (1, 0.75, 0.5 and 0.25) of the initial step length have been applied for the profit optimisation problem to study its effect on the optimal value and computational cost.

6.4 Conclusion

This chapter has provided an overview of the optimisation solvers and the key optimisation parameters applied to the problem of optimizing the natural gas network. The optimisation tolerances, variable scaling and initial step length are key algorithmic parameters, and their effect on the optimisation of gas network profitability will be discussed in the next chapter.

Chapter 7. Optimisation of Gas Network Profitability

Using the validated network model, optimisation of the natural gas network profitability has been carried out. Different optimisation methods and factors affecting the profitability optimum have been analysed.

The optimisation studies carried out were closely related to the business objectives listed in the introduction. The following profitability aspects were considered:

- maximise operating profit, taking account of
 - the values of the various products (dry sales gas, propane, butane and natural gasoline) based on market-driven contractual sales prices
 - variable production costs, including those of raw gas and utilities (electricity, and heating and cooling utilities)
- network bottlenecks limiting greater profitability
- significance of decision variables with respect to optimum profitability
- sensitivity of optimal profit improvement to market prices.

The complete network model described in the previous sections was used in all cases. The optimisation was carried out with respect to 77 decision variables, including feed gas rates from oil production, gas-to-NGL plant splits, distillation column reflux ratios and column boil-up ratios. The optimisation also took account of 47 inequality constraints including product specifications and equipment limits such as compressor duties (rated power), subsonic limit on velocities in pipelines and maximum flooding velocities in distillation columns.

The performance of the network under optimal operation was compared against a base point representing design operating conditions. The effects of variable scaling (cf. section 6.2) and step length (cf. section 6.3) on the optimal value and computational time have also been analysed.

For some of the optimisation cases, a MINLP formulation is compared against an NLP formulation for the same problem using the OAERAP and NLPSQP solvers respectively. A comparative analysis has been made of the different formulations and solutions.

7.1 Objective Function: Maximise Profit

A holistic single-period optimisation of the network model has been implemented in gPROMS. Mathematically, the objective function to be maximised is the rate of gross profit generation (\$/s):

$$\max_u \left(\sum_s \pi_s R_s(u) - K(u) \right) \quad (35)$$

where:

u = optimisation decision variables

π_s = unit price of product s (\$/kg)

R_s = production rate of product s (kg/s)

K = cost of operation per unit time (\$/s)

It is worth noting that, for this single-period profitability problem, no product inventory is considered. Therefore, production rate is equal to sales rate for each product.

The cost function, K in equation (35) is defined as:

$$K(u) = \left(\sum_i c_i^u u_i + \sum_j c_j^y y_j(u) \right) \quad (36)$$

where:

c_i^u = unit cost of independent variable u_i such a raw feed gas

c_j^y = unit cost of dependent variable y_j such as compressor energy consumption

Note that K does not include fixed costs (e.g. salary and benefits), facility, rentals etc.

The production rates R_s and the dependent variables y_j are functions of the optimisation decision variables u . They are a subset of the model's dependent variable x which can be determined by the solution of the network's process model equations:

$$F(u, x) = 0 \quad (37)$$

Appendix D shows the profitability problem as modeled in the gPROMS language.

The solution approach and results of a single-period profitability optimisation problem are presented in below sections.

7.2 Solution Approach

The following approaches were considered for holistically solving the large nonlinear network optimisation problem:

- NLP-based approach:

The discrete gas flow split variables are eliminated *ab initio* by modelling the gas split as continuous variables bounded between 0 and 1 [Refer to section 6.1 for more on eliminating

the discrete variable]. The profitability problem is then solved as a NLP optimisation using the NLPSQP solver.

- MINLP-based approach

Discrete gas flow split variables are applied and the profitability problem is solved as a MINLP optimisation using the OAERAP solver.

Both solution approaches are tested on the network, and the optimal solutions and computation times are compared.

7.2.1 Decision Variables, Constraints and Input Parameters

For the single-period profitability optimisation problem considered in this chapter, 77 degrees of freedom have been used in the solution of the optimisation problem. Table 22 outlines the types of decision variables used and the number of variables per type. The decision variables have been selected so that operators in the field can physically control the variables at the values produced by the solution of the optimisation problem. A listing of all the decision variables [including their initial values and bounds] used in the profitability problem is provided in Appendix B.

The feed gas intake from the upstream oil production is a key decision variable since, in actual operations, there is flexibility on how much gas can be received at the different compressor stations in the network. Considering all the feed streams and trains in the different compressor stations gives a total of 55 feed lines to the network.

Table 22: Optimisation decision variables

Decision Variable Type	Number
Feed Gas Rates from Oil production	55
Gas-to-NGL plants split ratios	4
Column Reflux Ratios	9
Column Boil-up Ratios	9
TOTAL	77

For the single-period profitability problem, 47 inequality constraints were imposed. These constraints relate to the physical limits of certain unit operations and also commercial limits on product specifications. These 47 inequality constraints are the explicit constraints imposed on the problem. There are several other implicit constraints which mostly correspond to conservation laws such as heat and mass balances; other implicit constraints are equipment performance equations e.g. compressor polytropic head equation. Table 23 outlines the types of explicit constraints applied and the number per type. A minimum compressor duty is not applied as anti-surge valves are usually in place to prevent the compressor from surging under conditions of low flowrate. Appendix C gives a listing of all the constrained variables and their bounds.

Table 23: Explicit Constraint types and numbers

Constrained Variable	Number
Compressor Duty	25
Pipeline Mach number	10
Column Max Flooding Velocity	9
Products Specification	3
TOTAL	47

Finally, the cost and price data used in the formulation of the profitability optimisation are outlined in Table 24.

Table 24: Cost and price data

	Unit Price	Price Unit
INPUT COSTS		
Gas Feed	0.035	\$/kg
Electricity Consumption (Compressors Duty)	0.1	\$/kWhr
Heating (Column Reboiler Duty)	0.019	\$/MJ
Cooling (Column Condenser Duty)	0.019	\$/MJ
SALES PRICES		
Dry Sales Gas	0.18	\$/kg
Propane	0.70	\$/kg
Butane	0.65	\$/kg
Gasoline	0.70	\$/kg

7.3 Comparison of Solution Algorithms

Profitability optimisations were carried out using the NLP (NLPSQP) and MINLP (OAERAP) approaches with no variable scaling i.e. scaling=0. The same cost and pricing data have been applied to both solution approaches. The same optimisation convergence tolerances have also been applied. The results for both approaches are outlined in Table 25.

Table 25: Comparison between optimisation approaches

	NLPSQP	OAERAP
OPTIMAL VALUE		
Gross Profit (\$/s)	106.6	106.3
COMPUTATIONAL STATISTICS		
Total CPU Time (s)	9,109	14,531
Optimiser CPU Time (s)	15.1	18.4
Number of NLP Iterations	38	66
Number of NLP Line Search Steps	65	105

There is only a slight difference in the optimal gross profit obtained from both solution approaches. This is mostly because the optimal values for all the gas flow splits to KAZ plant is 1.0 in both the NLP and MINLP cases.

The computational time for the solving the MINLP problem is significantly higher than for the equivalent NLP problem. As shown in the table, the actual computational time spent by the optimisation algorithm is a very small fraction of the total. The rest is spent in repeatedly solving the model equations for different combinations of optimisation decision variable values.

Considering the significantly higher computational cost for the OAERAP approach, this work shall proceed using the NLPSQP approach.

7.4 Effect of Variable Scaling

Using the NLPSQP solver, the effect of variable scaling on the NLP optimisation has been studied. [Refer to section 6.2 for some background on variable scaling]. Table 26 compares the profitability optimisation results derived by using the four different scaling strategies. The same decision

variables, constraints and price data [as presented in section 7.2.1] have been applied for all scaling strategies. The same optimisation convergence tolerances have also been applied.

Table 26: Comparison of Scaling Strategies

	Scaling=0 (No Scaling)	Scaling=1 (Variable Range)	Scaling=2 (Initial Values)	Scaling=3 (Initial Values & Gradient of Obj)
OPTIMAL VALUE				
Gross Profit (\$/sec)	106.6	92.4	106.6	106.6
COMPUTATIONAL STATISTICS				
Total CPU Time (seconds)	9,109	6,978	23,265	9,964
Optimiser CPU Time (seconds)	15.1	7.8	39.0	12.3
Number of NLP Iterations	38	31	101	42
Number of NLP Line Search Steps	65	44	248	74

The optimum profit value attained for scaling 1 strategy is significantly less than for the other strategies. For Scaling=1, the strategy is to transform all variables such that they belong to the interval $[-1,1]$. When optimising using strategy 1, it is observed that the final control variable values do not differ much from the corresponding initial guesses. The most probable explanation for this is that scaling in this case allows the optimisation convergence criteria to be satisfied at points that are actually far from the (local) optimum, thereby resulting in premature termination of the optimisation calculations.

The same optimal profits have been obtained from applying scaling strategies 0, 2 and 3. The computational cost of the different scaling strategies however differ. Profitability optimisation using scaling strategy = 0 (i.e. no scaling) results in the least computation time.

It can therefore be concluded that, for profitability optimisation of such natural gas networks, no benefit is derived from applying variable scaling. Therefore, the rest of this work shall proceed without applying variable scaling.

7.5 Effect of Initial Step Length

Using the NLPSQP solver, the effect of initial step-length on the NLP optimisation has also been studied. [Refer to sections 2.2.2 and 6.3 for some background on step length]. The profit optimisation run was done with scaling of 0.

Table 27 compares the profitability optimisation results derived from optimisation runs carried out with initial step lengths of 1, 0.75, 0.5 and 0.25. The same decision variables, constraints and price data [as presented in section 7.2.1] have been applied for all the cases. The same optimisation convergence tolerances have also been applied.

The case with initial step length of 1 resulted in the highest optimum profit. The computational time was also longest for the case with initial step length of 1.

The trend of the results indicate that the larger the initial step length, the more chance of reaching a true local optimum. When smaller fractions of step length are taken, it is likely the gas network profitability optimum will terminate prematurely before it reaches the local optimum.

Despite taking more computational time, the higher profit optimum attained for initial step length of 1 justifies setting initial steplength to 1 for the optimisation of the natural gas network.

Table 27: Varying Initial StepLength

Initial StepLength=	1	0.75	0.5	0.25
OPTIMAL VALUE				
Gross Profit (\$/sec)	106.6	106.5	106.2	105.0
COMPUTATIONAL STATISTICS				
Total CPU Time (seconds)	9,109	7,701	8,619	8,947
Optimiser CPU Time (sec)	15.1	10.1	12.8	11.6
Number of NLP Iterations	38	35	39	40
NLP Line Search Steps	65	54	67	68

7.6 Optimal Profit versus Base Operational Profit

The holistic single-period network profitability optimisation was carried out using the NLPSQP solver with no variable scaling i.e. scaling=0 and initial step length of 1. The decision variables, constraints and price data used are presented in section 7.2.1.

The gross profitability of the network under optimal operation was compared with the profit when operating at the design conditions. The reference design operational profit values have been computed by running a gPROMS simulation of the network under design operating conditions.

The results of this comparison are shown in Table 28. Profitability optimisation results in a potential 9 % profit increase compared to the base case. Assuming a 90% network availability (328.5 days of uptime in a year), there is a potential annual gross profit increase of about \$250 million in applying the optimised operating conditions compared to the un-optimised operating conditions.

This demonstrates the potential impact of applying model-based optimisation to the operation of a real-world natural gas network. Even in the scenario that only a small fraction of this value gap can be realised due to constraints or commercial factors not considered in this work, the potential financial benefit of applying such optimisation methods to a natural gas network is still very attractive.

Table 28: Optimum Profit versus Design Operational Profit

OBJECTIVE: Gross Profit	
Design Operational Value (\$/s)	97.8
Optimal Value (\$/s)	106.6
Annualised Δ (\$/yr)	250 million
Δ %	9%

It should be noted that the optimal solution and indeed the magnitude of profit improvement depends on the market prices of the products. The network optimisation model can therefore be used to find new optimal operating points when the market shifts.

More detailed analysis of the results [see section 7.8] indicates that this increase arises largely from the optimised routing of raw gas from the different compressor stations to the two NGL plants and, to a lesser but significant extent, from applying optimal reflux and boil-up ratios in the columns.

7.7 Network Bottlenecks

Active constraints and active bounds on decision variables at the optimum point can provide insights into the network bottlenecks that limit greater profitability. The values at the optimal point

and corresponding Lagrange multipliers of the decision variables and constraints are given in Appendix B and Appendix C respectively. Lagrange multipliers indicate the change in the optimal value of the objective function due to the relaxation of a given constraint. Those active constraints with large Lagrange multipliers are therefore a potential opportunity for debottlenecking of the Network. From the results at the optimal point, it is observed that the largest Lagrange multipliers correspond to flooding constraint for the de-ethanizer columns in both the KAZ and NR NGL plants. Since flooding is a function of the tray spacing and fluid velocities, an investment in de-ethanizers with modified tray spacing and dimensions could be an option for significantly increasing profitability.

7.8 Significance of Decision Variables to Optimum Profitability: The Gradient Ranking Method

Determining which decision variables have the largest effect on the objective function optimum can provide operational insights and support investment decision making. This is particularly helpful in actual operations where there are often limitations on manual or automated resources required to quickly adjust all the decision variables in the field. Knowing the most significant variables can guide in assigning resources to control those variables that have the highest leverage on approaching the objective function optimum.

A heuristic method for achieving this objective is presented in this section. The **gradient ranking method** determines significance of decision variables [in a constrained problem] by ranking the gradients of objective function with respect to each decision variable; i.e.:

$$\left| \frac{\partial(\text{ObjectiveFunction})}{\partial(\text{DecisionVariable})} \right| \quad (38)$$

This gradient indicates the magnitude of variation in the objective function with respect to a decision variable.

Below are the proposed steps in applying the gradient ranking method for determining significance of the decision variables:

1. From operational experience, select the decision variables that generally affect the performance of the network. This selection is empirical and does not need to be accurate. The selected variables should not be too many as this will increase computational cost. For this work, 77 decision variables were selected for the entire natural gas network.
2. Perform the network optimisation using the approach outlined in the previous sections.
3. In gPROMS, the gradient of objective function with respect to each decision variable is reported in the results of the optimisation.
4. Rank the absolute values of the gradients [see equation (38)] for all decision variables.
5. The top 30% of the largest non-zero gradients in the ranking are the most significant near the optimum.

For a given objective function, gradient rankings can be validated by assessing whether different optimisation methods arrive at similar rankings of the decision variables.

This method has been applied to the gross profit optimisation. Gradient rankings of profit optimisations for different scaling strategies have been compared (see Table 29). The ranking is from 1 to 77 where 1 is the largest gradient while 77 is the smallest gradient. [Appendix E gives the gradient values near the optimal point for Optimisation run with scaling =0]

For practical purposes, it is not the precise ranking of an individual variable that matter to the network optimisation. It is more important to know the set of decision variables that if controlled together will drive the network closer to the optimum value.

The following can be observed from Table 29 :

- Top Gradient Ranking Comparison [scaling 1 vs scaling 0]: The set of variables in the top 17 ranking of gradients are the same for both scaling 1 and scaling 0.
- Bottom Gradient Ranking Comparison [scaling 1 vs scaling 0]: Except for 6 variables, the set of variables in the bottom 30 ranking of gradient are the same for both scaling 1 and scaling 0. i.e. only 6 variables in the bottom 30 gradient ranking for scaling 1 are not in the bottom 30 variables for scaling 0.
- Top Gradient Ranking Comparison [scaling 3 vs scaling 0]: The set of variables in the top 6, the top 20, and the top 30 rankings are the same for both scaling 3 and scaling 0.
- Bottom Gradient Ranking Comparison [scaling 3 vs scaling 0]: The set of variables in the bottom 15 ranking are the same for both scaling 3 and scaling 0.

The strong intersection between variable sets in the top and bottom gradient rankings for Scaling 0 and 3 can be explained by the fact that both optimisation scaling strategies result in similar optimal values (see Table 26). It is however remarkable that even for the methods that produce different optimal values [i.e. Scaling 0 vs 1], the set of variables in the top 17 ranking are the same.

It can therefore be hypothesised that using the gradient ranking method, the set of variables in the top 30% of gradient rankings are mostly the same irrespective of optimisation scaling strategy applied.

It can also be hypothesised that using the gradient ranking method, the set of variables in the bottom 40% of gradient rankings are mostly the same irrespective of optimisation scaling strategy applied.

This hypothesis is tested in section 7.9.

Table 29: Gradient Ranking of Profit Optimisation for different Scaling Strategies

Decision Variable	Ranking Scaling=0	Ranking Scaling=1	Ranking Scaling=3
NR NGL De-ethanizer Reflux Ratio	1	1	1
KAZ 11.2 De-ethanizer Reflux Ratio	2	8	3
KAZ 11.1 De-ethanizer Reflux Ratio	3	7	2
NR NGL De-ethanizer Boilup Ratio	4	3	4
KAZ 11.1 De-ethanizer Boilup Ratio	5	9	6
KAZ 11.2 De-ethanizer Boilup Ratio	6	10	5
Markazia-to-KAZ Flow Ratio	7	2	7
Janubiya-to-KAZ Flow Ratio	8	4	8
Shamiya-to-KAZ Flow Ratio	9	6	9
Qurainat-to-KAZ Flow Ratio	10	5	10
Shamiya Stage2B Feed Gas Flowrate	11	16	11
Janubiya Stage2B Feed Gas Flowrate	12	12	12
Janubiya Stage2A Feed Gas Flowrate	13	15	13
Qurainat Stage2A Feed Gas Flowrate	14	11	17
Markazia Stage2A Feed Gas Flowrate	15	17	19
Qurainat Stage2B Feed Gas Flowrate	16	14	15
Shamiya Stage2A Feed Gas Flowrate	17	13	14
Markazia Stage2D Feed Gas Flowrate	18	19	16
Markazia Stage2C Feed Gas Flowrate	19	22	20
Markazia Stage2B Feed Gas Flowrate	20	18	18
CS5 Stage3A Feed Gas Flowrate	21	38	22
CS5 Stage3B Feed Gas Flowrate	22	36	21
CS3 Stage3B Feed Gas Flowrate	23	25	28
CS1 Stage3A Feed Gas Flowrate	24	20	23
CS1 Stage3B Feed Gas Flowrate	25	23	24
CS1 Stage3C Feed Gas Flowrate	26	21	25
CS4 Stage3A Feed Gas Flowrate	27	41	26
CS4 Stage3B Feed Gas Flowrate	28	40	27
Shamiya Stage3B Feed Gas Flowrate	29	68	30
CS3 Stage3A Feed Gas Flowrate	30	24	29
Janubiya Stage3B Feed Gas Flowrate	31	76	31
Rafidiyah 1 st Stage LP Feed Gas Flowrate	32	34	33
CS2 1 st Stage HP Feed Gas Flowrate	33	26	32
Zubair 1 st Stage LP Feed Gas Flowrate	34	32	34
HM 1 st Stage LP Feed Gas Flowrate	35	33	35
KAZ 12.2 De-butanizer Boilup Ratio	36	59	50
CS5 Stage2B Feed Gas Flowrate	37	28	41
CS4 Stage2A Feed Gas Flowrate	38	35	39
CS4 Stage2B Feed Gas Flowrate	39	37	40
CS2 Stage2 Feed Gas Flowrate	40	29	38
CS5 Stage2A Feed Gas Flowrate	41	27	37
CS3 Stage2B Feed Gas Flowrate	42	43	44
Janubiya Stage3A Feed Gas Flowrate	43	69	36
KAZ 12.1 De-propanizer Reflux Ratio	44	39	42

CS2 Stage3 Feed Gas Flowrate	45	30	43
Qurainat Stage3B Feed Gas Flowrate	46	70	52
Markazia Stage3D Feed Gas Flowrate	47	65	56
Markazia Stage3C Feed Gas Flowrate	48	72	49
Markazia Stage3B Feed Gas Flowrate	49	64	47
KAZ 12.3 De-propanizer Reflux Ratio	50	31	62
Shamiya Stage3A Feed Gas Flowrate	51	73	45
CS3 Stage2A Feed Gas Flowrate	52	44	51
Qurainat Stage3A Feed Gas Flowrate	53	75	46
CS1 Stage2A Feed Gas Flowrate	54	46	53
CS1 Stage2B Feed Gas Flowrate	55	45	54
CS1 Stage2C Feed Gas Flowrate	56	47	55
Markazia Stage3A Feed Gas Flowrate	57	66	48
HM 1 st Stage HP Feed Gas Flowrate	58	50	57
Zubair 1 st Stage HP Feed Gas Flowrate	59	51	58
Rafidiyah 1 st Stage HP Feed Gas Flowrate	60	49	59
Hammar Stage1 Feed Gas Flowrate	61	57	60
ZM Stage1 Feed Gas Flowrate	62	58	61
CS1 1 st Stage HP Feed Gas Flowrate	63	48	63
CS3 1 st Stage HP Feed Gas Flowrate	64	52	64
CS4 1 st Stage HP Feed Gas Flowrate	65	53	65
CS5 1 st Stage HP Feed Gas Flowrate	66	54	66
CS7 1 st Stage HP Feed Gas Flowrate	67	55	67
CS8 1 st Stage HP Feed Gas Flowrate	68	56	68
KAZ 12.2 De-propanizer Reflux Ratio	69	42	69
KAZ 12.1 De-butanizer Boilup Ratio	70	60	71
KAZ 12.3 De-butanizer Boilup Ratio	71	61	70
KAZ 12.2 De-butanizer Reflux Ratio	72	62	72
KAZ 12.1 De-butanizer Reflux Ratio	73	63	74
KAZ 12.3 De-butanizer Reflux Ratio	74	67	73
KAZ 12.2 De-propanizer Boilup Ratio	75	74	76
KAZ 12.1 De-propanizer Boilup Ratio	76	77	75
KAZ 12.3 De-propanizer Boilup Ratio	77	71	77

7.9 Test of Gradient Ranking Method for Variable Significance

Using the profitability optimisation with no scaling approach, a test of the gradient ranking method [presented in section 7.8] has been carried out. Assuming the negative-hypothesis that the top ranked variables are not very significant to attaining the optimal value, a test optimisation is carried out excluding the top ranked decision variables. Secondly, to demonstrate the relative lower significance of the bottom ranked variables, another test analyses the optimal values when an optimisation run is made excluding the least ranked decision variables. [For these tests, it should be ensured that assigned values of the non-controlled decision variables are feasible. Otherwise, the feasibility condition will not be satisfied during optimisation.]

Two optimisation runs were carried out for the variable significance test:

1. An optimisation run that excludes the set of decision variables in the top 20 ranking of gradients. i.e. only the variables in the bottom 57 of the rankings are used as degrees of freedom in the optimisation.
2. An optimisation run that excludes the set of decision variables in the bottom 41 ranking of gradients. i.e. only the variables in the top 36 of the rankings are used as degrees of freedom in the optimisation.

Table 30 compares the optimal values from the two optimisation test runs to optimal value of the optimisation using all 77 decision variables.

The result of the test shows that excluding the top 20 ranked variables does not yield any improvement in the optimal value, [the optimal value obtained is even lower than the design operational profit value of \$97.8/sec]. From this it can be concluded that the decision variables in the top 20 ranking by gradient, have a critical impact on the optimisation results. On the other hand, when the bottom 41 decision variables in the rankings are excluded from the decision variables, an optimal value of \$100.2/sec is attained. This optimum is closer to the optimum using

all variables, it can therefore be concluded that the set of decision variable in the top 20 ranking are indeed more significant than the set of variables in the bottom 41 ranking.

Table 30: Test of Significance of Decision Variables

	All Variables (77 Total)	Excluding Top 20 (57 Variables)	Excluding Bottom 41 (36 Variables)
OPTIMAL VALUES			
Gross Profit (\$/sec)	106.6	89.7	100.2
COMPUTATIONAL STATISTICS			
Total CPU Time (seconds)	9,109	8,553	5,766
Optimiser CPU Time (seconds)	15.1	4.5	0.9
Number of NLP Iterations	38	34	24
NLP Line Search Steps	65	87	56

When the set of decision variables in the bottom 41 ranking are excluded from the optimisation, the CPU time required for convergence is 1 ½ hours. This is an hour saving compared to the 2 ½ hours required for an optimisation run including all 77 decision variables. An additional benefit of determining the set of most significant decision variables [or eliminating the set of least significant decision variables] is the increased computational efficiency due to reduced problem complexity. This can be helpful during time-critical operational situations where a [near] optimal operating point needs to be quickly determined.

7.10 Sensitivity of Optimal Profit Improvement to Market Prices

In this section, the sensitivity of the profit optimum to varying market prices is analysed. When market prices of products change, it is critical to know how the network should be operated to reap the most benefit from the new product prices.

From the stated base prices, a 20% price increase and 20% price decrease has been applied to each product. The prices used in the profit optimisations are given in Table 31.

Table 31: Product Prices Varied for Profit Optimisation

	Price Unit	Base Price	20% Increase	20% Decrease
Dry Sales Gas	\$/kg	0.18	0.216	0.144
Propane	\$/kg	0.70	0.84	0.56
Butane	\$/kg	0.65	0.78	0.52
Gasoline	\$/kg	0.70	0.84	0.56

Optimisations have been run using different market prices for propane, butane, natural gasoline and dry sales gas. Each product price is varied one at a time while other product prices are kept at their base levels. For each price point, the gross profit using the design operating conditions is compared to the gross profit resulting from model-based optimisation. The results are presented in Table 32.

For dry sales gas and butane, it is observed that the higher the product pricing, the larger the percentage difference between the design operational profit and the optimal profit. On the other hand, for propane and natural gasoline, it is observed that the lower the product pricing, the larger the percentage difference between the design operational profit and the optimal profit. In general,

applying optimisation improves the gross profit of the network at both higher and lower prices for different products.

Table 32: Price Sensitivity of Profit Optimisation [Product Prices Varied Separately]

	Base	Dry Gas [+20%]	Dry Gas [-20%]	Propane [+20%]	Propane [-20%]	Butane [+20%]	Butane [-20%]	Gasoline [+20%]	Gasoline [-20%]
PROFIT									
Design (\$/s)	97.8	103.8	91.8	106.6	89.1	101.9	93.8	101.8	93.9
Optimal (\$/s)	106.6	114.5	98.9	114.8	99.2	112.4	102.7	111.7	103.5
%Δ	9.0	10.3	7.7	7.7	11.3	10.3	9.5	9.7	10.2
COMPUTATIONAL STATISTICS									
Total CPU Time (s)	9,109	8,552	12,366	11,533	6,649	7,502	11,025	6,978	8,357
Optimiser CPU Time (s)	15.1	10.3	16.4	15.6	17.5	10.9	13.7	8.6	10.9
NLP Iterations	38	36	50	46	24	34	47	29	35
NLP Line Search Steps	65	56	98	84	38	56	75	48	63

Table 33 shows the gradient ranking of the most significant decision variables for the higher propane price case. The ranking indicates that when propane prices rise, the current size of the de-ethanizer presents a bottleneck to even more profitability. It is remarkable that the columns/units with the most significant decision variables for the problem are precisely the same columns where the flooding constraint is stuck at the upper bound [The constrained values at the optimal point for the higher propane price optimisation are given in Appendix F]. As discussed in section 7.7, an analysis of the active constraints and Lagrange multipliers also reveals that de-ethanizer flooding

is a significant bottleneck for profitability of the gas network. It can be inferred that with a larger de-ethaniser column, there will be more flexibility to take advantage of increased propane prices.

This outcome is not obvious however. When trying to increase propane production, the default guess will be to focus on the de-propanizer variables. The optimisation approaches developed in this work however gives a clearer insight into the significant interactions.

Table 33: Top-5 Gradient Ranking of Variable Significance for Profit Optimisation at higher propane prices

Ranking	Decision Variable	Gradient
1	NR NGL De-ethanizer Reflux Ratio	23.1494
2	KAZ 11.1 De-ethanizer Boilup Ratio	4.7276
3	KAZ 11.2 De-ethanizer Boilup Ratio	4.7131
4	KAZ 11.1 De-ethanizer Reflux Ratio	4.5057
5	KAZ 11.2 De-ethanizer Reflux Ratio	4.0429

Optimisations have also been run in which the market prices for all the products have been varied together. For example, consider a scenario where all product prices double or a scenario where all product prices are halved. For each price scenario, the gross profit using the [unoptimised] design operating conditions is compared to the gross profit resulting from model-based optimisation. The results are presented in Table 34.

In general, the results at all price points indicate significant gains in profit when operating at the optimal point relative to the design point. It can be concluded that whether the market is up or down, it is valuable to apply profit optimisation methods to natural gas networks.

Table 34: Price Sensitivity of Profit Optimisation [All Product Prices Varied Together]

	Base	All Products [+100%]	All Products [+20%]	All Products [random decrease b/w 10-30%]	All Products [-50%]
PROFIT					
Design (\$/s)	97.8	211.7	120.6	82.1	40.9
Optimal (\$/s)	106.6	230.0	131.6	88.5	44.9
%Δ	9.0	8.6	9.1	7.8	9.8
COMPUTATIONAL STATISTICS					
Total CPU Time (s)	9,109	8,911	10,076	7,684	5,845
Optimiser CPU Time (s)	15.1	11.2	13.1	10.2	7.9
NLP Iterations	38	40	46	35	24
NLP Line Search Steps	65	61	75	60	45

7.11 Relative Economic Impact of Products with Varying Prices

With varying market prices, the relative economic impact of different products on optimum profit can be analysed. This is done by comparing the optimal production rates and product slate for each product in the different price cases. Two concepts are defined below for analysing the economic impact of products with varying prices.

1. **Product Capacity Margin:** Given a certain product price set, if the profit optimum requires more production of a particular product P_1 relative to the design (unoptimised) production, then product P_1 has a positive capacity margin at the given price point. If on the other hand, the profit optimum requires less production of a particular product P_2 relative to the design (unoptimised) production, then product P_2 has a negative capacity margin at the given price point. A positive capacity margin indicates that more production

of that particular product is required to optimise profitability of the entire network. A negative capacity margin on the other hand, indicates that production of a particular product can be reduced while optimising profitability of the entire network. The percentage optimum production of all products relative to their design (unoptimised) production levels can be ranked to determine the relative capacity margin of each product in the product slate. This analysis has been done for the different price scenarios mentioned in the previous section (see Table 32). The results of the capacity margin analysis are presented in Table 35.

2. **Product-Price Sensitivity:** At a given price set, this is expressed as the percentage change in optimum production of a product relative to the optimum production of that product at a defined base price set. Given a certain product price set, if the profit optimum requires more production of a particular product P_1 relative to the optimum at a defined base price case, then product P_1 has a positive price sensitivity at the given price point. If on the other hand, the profit optimum requires less production of a particular product P_2 relative to the optimum at a defined base price case, then product P_2 has a negative price sensitivity at the given price point. The product-price sensitivity is an indication of the economic impact of production rates with varying price scenarios. An analysis has been done for the different price scenarios mentioned in Table 31. The results are presented in Table 34.

7.11.1 Results

It can be seen in Table 35 that for the base price case, dry sales gas has the highest positive capacity margin (29%) followed by gasoline (22%) and then butane (4%). Propane actually has a negative capacity margin (-10%) at the base pricing. This indicates that, at the base propane price, the design operation results in too much propane production. The optimisation therefore reduces propane production in favour of other products in order to optimise the profit of the entire network.

Table 35: Economic Impact of Varying Product Prices on Optimal Production Rates

	Base Prices	Dry Gas [+20%]	Dry Gas [-20%]	Propane [+20%]	Propane [-20%]	Butane [+20%]	Butane [-20%]	Gasoline [+20%]	Gasoline [-20%]
OPTIMAL PRODUCTION RATES									
Dry Gas (kg/s)	215.5	218.6	205.4	205.5	228.8	218.8	211.1	217.6	215.6
Propane (kg/s)	56.7	55.0	60.8	62.9	49.9	54.8	61.2	54.9	58.2
Butane (kg/s)	32.5	33.1	29.7	27.8	35.5	48.9	27.4	32.8	47.3
Gasoline (kg/s)	34.1	34.7	34.3	33.3	34.9	19.1	34.5	35.4	17.6
Total Prod (kg/s)	338.8	341.4	330.2	329.5	349.1	341.6	334.2	340.7	338.7
OPTIMAL PRODUCT SLATE (as fraction of total production)									
Dry Gas (kg/kg)	0.636	0.640	0.622	0.624	0.655	0.641	0.632	0.639	0.637
Propane (kg/kg)	0.167	0.161	0.184	0.191	0.143	0.160	0.183	0.161	0.172
Butane (kg/kg)	0.096	0.097	0.090	0.084	0.102	0.143	0.082	0.096	0.140
Gasoline (kg/kg)	0.101	0.102	0.104	0.101	0.100	0.056	0.103	0.104	0.052
CAPACITY MARGIN (Δ OPTIMAL PRODUCTION RELATIVE TO DESIGN)									
Dry Gas	29%	31%	23%	23%	37%	31%	27%	31%	30%
Propane	-10%	-12%	-3%	0%	-20%	-13%	-2%	-13%	-7%
Butane	4%	6%	-5%	-11%	13%	56%	-12%	5%	51%
Gasoline	22%	24%	23%	19%	25%	-32%	23%	26%	-37%
SENSITIVITY (%Δ OPTIMAL PRODUCTION RELATIVE TO BASE PRICE CASE)									
Dry Gas	-	1.4	-4.7	-4.6	6.2	1.5	-2.0	1.0	0.0
Propane	-	-3.0	7.2	10.9	-12.0	-3.4	7.9	-3.2	2.6
Butane	-	1.8	-8.6	-14.5	9.2	50.5	-15.7	0.9	45.5
Gasoline	-	1.8	0.6	-2.3	2.3	-44.0	1.2	3.8	-48.4

In the case of 20% fall in dry gas price, the capacity margin of dry gas decreases and becomes equivalent to the capacity margin of gasoline (23%). The reduced economic impact of dry gas can be expected with a fall in its own price. What is less obvious, however, is that the capacity margin of butane becomes negative in this case while the capacity margin of propane rises significantly with a fall in gas price. The optimum profit in this case requires less production of butane and more production of propane compared with the base price case.

It can be seen from the sensitivity section of Table 35 that, if dry gas price drops by 20%, propane and gasoline production will be the most critical to profitability as they have the highest sensitivities (7.2% and 0.6% respectively) at that price point. The capacity margin for propane is however negative (-3%) which indicates that the design production rate of propane is still sufficient to deliver the potential optimum profit. If new investment is to be made on the basis of a forecasted 20% gas price decrease, the focus should be to increase the capacity for more gasoline by, for example, increasing the reflux drum size or condenser capacity in the de-butaniser.

In the case of a 20% rise in butane price, the capacity margin of gasoline becomes negative (-32%). This can be explained by the key decision variable of debutaniser boilup ratio which increases in all the LPG trains to drive more butane production. This increased boilup ratio leads to more gasoline component hydrocarbons ending up in the butane stream with the consequence that the butane specification constraint hits its lower bounds. See Appendix G for the constraint values at the optimum point for the case with butane price increase.

In the case of a 20% fall in gasoline price, the capacity margin of gasoline is lower as can be expected. Butane then becomes the product with the highest capacity margin with a potential 51% production increase at optimum compared to the unoptimised operation.

It is observed from the sensitivity section of Table 35 that, provided the pricing of gasoline is constant, the relative economic impacts [i.e. product-price sensitivity] of propane and butane move

in opposite directions i.e. if the sensitivity of propane rises, that of butane will decrease. An explanation for this is that the key decision variables that control propane and butane production (namely de-propaniser reflux and boil-up ratios) are constrained in common by flooding in the de-propaniser column. The corresponding flooding velocity is at its limit. See Appendix F for the constraint values at the optimum point for the case with propane price increase.

In general, this approach can support operational planning and investment strategy by applying below steps:

1. Based on the market outlook, a profit optimisation of the natural gas network is carried out at the forecasted prices.
2. The economic impact of the different products can then be determined using the methods described above i.e. capacity margin and product-price sensitivity.
3. The products with the highest positive capacity margin should be the focus for capacity increases. Relatively more investment should go into equipment that increase the production of the highest capacity margin products. A negative capacity margin for a certain product at a given price set [or price ranges] suggests that the gas network has excess-capacity for those products.

7.12 Conclusion

This chapter has presented the objective function and solution approach for the single period gas network profitability problem. The effect on the optimal solution of different solution algorithms, variable scaling and initial step length have also been analysed. The benefit of applying optimisation to network profitability have been demonstrated. The gradient ranking method has been presented to show the significance of decision variables to the optimal solution. In the next chapter, approaches and solutions to operational optimisation problems other than profitability are presented.

Chapter 8. Operational Optimisation

The validated network model has also been used to analyse a number of different operational optimisation cases beyond the profit maximisation case considered in Chapter 7. The full network model described in the previous sections was used in each case, and the optimisation was carried out with respect to 77 decision variables, including feed gas rates from oil production, gas-to-NGL plant splits, distillation column reflux ratios and column boil-up ratios. The optimisation also took account of 47 inequality constraints including product specifications and equipment limits such as compressor duties, subsonic limit on velocities in pipelines and distillation column maximum flooding velocities.

The optimisation studies carried out were closely related to the business objectives listed in the introduction. The following normal operational scenarios were considered:

- maximise total production, i.e. the total mass flowrate of all product streams irrespective of any economic factors
- maximise specific product yields, i.e. the ratio of that product's mass flowrate divided by the overall mass flowrate of gas entering the system
- minimise flaring, i.e. the difference between the total mass flowrate of gas entering the system and that of all product streams.

The following “abnormal” scenarios were also considered:

- maximise production under equipment failure resulting in unavailability of one of the two NGL trains at the Khor al Zubair plant

- maximise production under field decline, resulting in lower gas flowrates being received from the West Qurna field.

For each operational scenario, the performance of the network at the optimal operating point was compared against a base point representing design operating conditions.

8.1 Maximise Total Production

Here the objective function is total production maximisation i.e.

$$\max \sum_s \left(\sum_n R_{s,n} + \sum_m R_{s,m} \right) \quad (39)$$

where,

$R_{s,n}$ = Production rate of product s from NGL train n ($\forall n=1 \dots N$)

$R_{s,m}$ = Production rate of product s from LPG train m ($\forall m=1 \dots M$)

The total production maximisation problem applies the same 77 degrees of freedom and 47 inequality constraints as used in the profit maximisation problem [see section 7.2.1].

8.1.1 Results

The result of the total production objective function is presented in Table 36 . Operating at the optimal point results in a 24.5% increase in total production relative to the design operating point. On an annualized basis, this represents a potential production increase of about 2 million tonnes/yr compared to the un-optimised design operating conditions.

Unlike the profit function, the maximal production objective function does not take any account of the cost of gas intake or other operating costs. Thus the optimisation is limited only by gas

availability and the physical constraints in the system. On the other hand, the profit function reaches a point where taking in additional gas increases costs and limits the rise in profits.

Table 36: Optimum Total Production vs Design Operational Production

OBJECTIVE: TOTAL PRODUCTION	
Design Operational Value (kg/s)	288.5
Optimal Value (kg/s)	359.2
Annualised Δ (tonnes/yr)	+2,006,634
% Δ	+24.5%
Computational Statistics	
Total CPU Time (seconds)	13,184
Optimiser CPU Time (seconds)	17.4
Number of NLP Iterations	52
Number of NLP Line Search Steps	102

8.1.2 Significance of Decision Variables

Using the gradient ranking method described in section 7.8, the set of most significant variables for total production optimisation have been determined and shown in Table 37. It can be observed that compared to the set of decision variables in the top 20 ranking for profit optimisation, NGL de-ethanizer reflux and boil-up ratios do not feature in the top-20 ranking for production optimisation. This is because in the production optimisation, the profit motive is removed and hence there is no price-driven requirement for de-ethanizer control of the product slate.

Table 37: Top-20 Gradient Ranking of Variable Significance for Total Production Optimisation

Ranking	Decision Variable	Gradient
1	Markazia-to-KAZ Flow Ratio	3.974
2	Markazia Stage2A Feed Gas Flowrate	2.111
3	Qurainat-to-KAZ Flow Ratio	2.087
4	Shamiya-to-KAZ Flow Ratio	2.042
5	Janubiya-to-KAZ Flow Ratio	1.997
6	Qurainat Stage2B Feed Gas Flowrate	1.973
7	Shamiya Stage2B Feed Gas Flowrate	1.915
8	Janubiya Stage2A Feed Gas Flowrate	1.877
9	Qurainat Stage2A Feed Gas Flowrate	1.726
10	Shamiya Stage2A Feed Gas Flowrate	1.650
11	Janubiya Stage2B Feed Gas Flowrate	1.596
12	Markazia Stage2B Feed Gas Flowrate	1.594
13	Markazia Stage2C Feed Gas Flowrate	1.594
14	Markazia Stage2D Feed Gas Flowrate	1.594
15	HM 1 st Stage HP Feed Gas Flowrate	1.011
16	Zubair 1 st Stage HP Feed Gas Flowrate	1.011
17	Rafidiyah 1 st Stage HP Feed Gas Flowrate	1.010
18	Hammar Stage1 Feed Gas Flowrate	1
19	ZM Stage1 Feed Gas Flowrate	1
20	All CS1, CS3, CS 7 & CS8 Feed Gas Flowrates	1

8.2 Maximise Product Yields

When there is more demand in the market for one product relative to the other products from the natural gas network, it is desirable to selectively produce more of the higher demand product. Under normal market conditions, the higher demand for a given product would be reflected in a correspondingly higher price, which would make the problem amenable to the type of profitability optimisation considered in Chapter 7. However, there may be other considerations that could justify aiming at directly maximizing the production of a given product even if this is not fully reflected in the economics of the operation.

The objective function for this is yield maximisation i.e. the ratio of that product's mass flowrate divided by the overall mass flowrate of natural gas entering the system:

$$\max \left(\frac{\sum_n R_{s,n}}{\sum_c G_c} \right) \quad (40)$$

where,

$R_{s,n}$ = Production rate of product s from train n ($\forall n=1 \dots N$)

G_c = Feed gas rate to compressor station c ($\forall c=1 \dots C$)

The total production maximisation problem applies the same 77 degrees of freedom and 47 inequality constraints as used in the profit maximisation problem [see section 7.2.1].

Two additional constraints are applied to the yield maximisation problem:

- Total Yield [sum for all products] cannot exceed 1.0
- Minimum total production rate of 250 kg/s

Optimising yield for a particular component could result in an overall reduction of gas intake to the network. Hence a minimum total production rate constraint is also imposed to ensure the contractual market volumes are satisfied.

8.2.1 Results

Yield maximisation runs have been carried out for each product in the network. Table 38 shows the results. For all the product yield maximisation cases, the optimisation results in significant increases in the respective product yields relative to the base operating point.

For the maximum propane yield case, the gasoline and dry gas yields decrease in order to maximise propane yield. The butane yield however remains the same as in the base operating point. This case achieves an increased propane yield of 53%.

Table 38: Optimum Yield Cases for Various Products

	Base Operating Point	Optimal Propane Yield Case	Optimal Butane Yield Case	Optimal Gasoline Yield Case	Optimal Dry Gas Yield Case
Propane Yield (kg/kg)	0.197	0.302	0.172	0.213	0.083
Butane Yield (kg/kg)	0.098	0.098	0.204	0.092	0.07
Gasoline Yield (kg/kg)	0.088	0.073	0.036	0.133	0.075
Dry Gas Yield (kg/kg)	0.524	0.387	0.518	0.547	0.762
COMPUTATIONAL STATISTICS					
Total CPU Time (s)		10,309	27,925	9,786	3,146
Optimiser CPU Time (s)		15.6	66.6	16.3	4.1
NLP Iterations		50	123	46	14
NLP Line Search Steps		100	475	92	27

For the maximum butane yield case, the gasoline yield is strongly decreased in order to maximise the butane yield. The propane and dry gas yields are only slightly decreased relative to the base operating point. This case achieves an increased butane yield of 108%.

For the maximum gasoline yield case, only the butane yield is decreased in order to maximise gasoline yield. The yields of propane and dry gas are actually increased relative to the base operating point. This case achieves an increased gasoline yield of 51%.

For the maximum dry gas yield case, the yields of all the other components are decreased in order to maximise dry gas yield. The greatest decrease is observed in the propane yield which drops from 0.197 kg/kg in the base operating point to 0.083 kg/kg in the maximum dry gas yield case. This case achieves an increased dry gas yield of 45%.

8.2.2 Significance of Decision Variables to Maximum Yield

Using the gradient ranking method described in section 7.8, the set of the most significant variables for propane yield optimisation has been determined and shown in Table 39.

As can be expected, the depropanizer reflux strongly controls the selectivity. The flow rates of the 3rd stage feed gas in CS5 also rank high in significance. Referring to Table 4 for gas compositions, it is observed that CS5 3rd stage feed gas has the highest propane composition of all the gas streams in North Rumaila. This explains the high significance of this variable to the propane yield optimisation problem.

Maximising yield of a certain component drives the network to take more of the feed gas sources that are rich in the desired component at the expense of the feed sources that are less rich in the desired component. The optimisation algorithm prioritises stations with higher propane compositions in the feed gas. Specifically, feed gas intake from the lower pressure stages of the degassing station is increased while higher stage feed rates are decreased. This is because the lower

pressure stages are generally richer in propane compositions. [Refer to Table 3, Table 4, Table 5 and Table 6 for gas compositions from the various fields].

The optimal values of the decision variables for propane yield optimisation are given in Appendix H. The results show that the optimum yields require a higher flowrate from the low-pressure feed streams (3rd and LP stages) than for the high-pressure streams (1st and HP stages). This further corroborates the explanation given in the above paragraphs.

Table 39: Top-20 Gradient Ranking of Variable Significance for Maximum Propane Yield

Ranking	Decision Variable	Gradient
1	KAZ 12.1 De-propanizer Reflux Ratio	0.0309
2	KAZ 12.3 De-propanizer Reflux Ratio	0.0293
3	KAZ 12.2 De-propanizer Reflux Ratio	0.0252
4	KAZ 11.1 De-ethanizer Reflux Ratio	0.0189
5	KAZ 11.2 De-ethanizer Reflux Ratio	0.0188
6	NR NGL De-ethanizer Boilup Ratio	0.0179
7	KAZ 11.1 De-ethanizer Boilup Ratio	0.0175
8	KAZ 11.2 De-ethanizer Boilup Ratio	0.0175
9	NR NGL De-ethanizer Reflux Ratio	0.0166
10	KAZ 12.1 De-propanizer Boilup Ratio	0.0106
11	KAZ 12.3 De-propanizer Boilup Ratio	0.0103
12	KAZ 12.2 De-propanizer Boilup Ratio	0.0101
13	CS5 Stage3A Feed Gas Flowrate	0.0098
14	CS5 Stage3B Feed Gas Flowrate	0.0063
15	CS3 Stage3A Feed Gas Flowrate	0.0041
16	Markazia-to-KAZ Flow Ratio	0.0032
17	CS3 Stage3B Feed Gas Flowrate	0.0031
18	CS5 Stage2A Feed Gas Flowrate	0.0030
19	CS5 Stage2B Feed Gas Flowrate	0.0021
20	Markazia Stage2A Feed Gas Flowrate	0.0019

8.3 Mimimise Flaring

For this problem, the objective function is minimisation of total hydrocarbon loss i.e. fraction of natural gas fed to the network that does not end up in the hydrocarbon product streams. An example of hydrocarbon losses are liquid drop outs in the compressor stations. The function being minimised is essentially the hydrocarbon inefficiency of the network.

$$\min \left(\frac{\sum_c G_c - \sum_s (\sum_n R_{s,n} + \sum_m R_{s,m})}{\sum_c G_c} \right) \quad (41)$$

where,

$R_{s,n}$ = Production rate of product s from NGL train n ($\forall n=1 \dots N$)

$R_{s,m}$ = Production rate of product s from LPG train m ($\forall m=1 \dots M$)

G_c = Feed gas rate to compressor station c ($\forall c=1 \dots C$)

The flare minimisation problem applies the same 77 degrees of freedom and 47 inequality constraints as used in the profit maximisation problem [see section 7.2.1].

An additional constraint of minimum natural gas feed gas rate ($\sum_c G_c$) is added to the flare minimization problem. This brings the total number of constraints to 48.

If a lower bound inequality constraint is not applied to the total natural gas feed to the network, the optimisation solver tends to drive down the total natural gas feed intake in order to minimise the objective function. A minimum total gas feed rate constraint of 318 kg/s has been applied to the optimisation problem. This is the design operational natural gas feed rate to the network.

8.3.1 Results

The result of the flare minimization objective function is presented in Table 40. By applying rigorous optimisation, the hydrocarbon flaring from the network can be reduced by 90%

compared to the un-optimised operations. On an annualized basis, this represents a potential flare reduction of about 750 kt/yr when the network is operated at the optimal point. Appendix I gives the optimum operating conditions for the flare minimisation problem.

This potential flare reduction contributes significantly to decreasing CO₂ emissions and also enables cleaner air for the local population.

Table 40: Optimised Flaring vs Default Operational Flaring

OBJECTIVE: MINIMISE FLARING	
Default Operational Value (kg/kg)	0.093
Optimal Value (kg/kg)	0.009
%Δ	-90.3%
Annualised Δ (tons/yr)	-758,151
Computational Statistics	
Total CPU Time (seconds)	1,189
Optimiser CPU Time (seconds)	1.3
Number of NLP Iterations	4
Number of NLP Line Search Steps	5

8.3.2 Significance of Decision Variables

Using the gradient ranking method described in section 7.8, the set of the most significant variables [near the minima] for flare minimisation have been determined and shown in Table 41. The flow rates of the 3rd stage feed gas in the South Rumaila stations rank high in significance.

Analysis of the optimal values of the decision variables (see Appendix I) show a steep decrease in 3rd stage and LP stage feed gas rates in order to minimise flaring. The solution for flare

minimisation drives the network to take less of the lower pressure feed gas sources while taking more of the higher pressure feed gas streams. This can be explained by the fact that the lower pressure feed streams have more liquid hydrocarbon components which typically drop out in the flash vessel and are not always recovered out in the field. Indeed most of the flaring takes place in the burnpits that burn the liquid hydrocarbons that are expelled in the compressor stations.

One effect of the minimum flare result is that there are no spec give-aways for the propane, butane and gasoline products [Appendix J shows the values of the constrained variables at the optimum point]. The composition specifications of the propane, butane and gasoline product are tight on the lower bound of their respective constraints. This is because the intake of liquid rich feed streams is reduced in the flare optimisation solution to the point that the composition specifications of the liquid product streams are just met and no more i.e. the compositions are not higher than they are commercially required to be. Higher spec [or richer] LPG and gasoline products would mean more flaring. This is a useful insight and further demonstrates the benefit of holistic optimisation of natural gas networks.

Table 41: Top-15 Gradient Ranking of Variable Significance for Flare minimisation

Ranking	Decision Variable	Gradient
1	Markazia-to-KAZ Flow Ratio	0.13830
2	Janubiya-to-KAZ Flow Ratio	0.07254
3	Qurainat-to-KAZ Flow Ratio	0.06968
4	Shamiya-to-KAZ Flow Ratio	0.06926
5	Janubiya Stage3B Feed Gas Flowrate	0.00074
6	Janubiya Stage3A Feed Gas Flowrate	0.00073
7	Qurainat Stage3A Feed Gas Flowrate	0.00068
8	Shamiya Stage3A Feed Gas Flowrate	0.00065
9	Qurainat Stage3B Feed Gas Flowrate	0.00063
10	Shamiya Stage3B Feed Gas Flowrate	0.00062
11	Markazia Stage3A Feed Gas Flowrate	0.00061

12	Markazia Stage3B Feed Gas Flowrate	0.00061
13	Markazia Stage3D Feed Gas Flowrate	0.00061
14	Markazia Stage3C Feed Gas Flowrate	0.00051
15	CS2 Stage3 Feed Gas Flowrate	0.00041

8.4 Abnormal Operating Scenarios

The following “abnormal” scenarios were also considered:

- maximise production under equipment failure resulting in unavailability of one of the two NGL trains at the Khor al Zubair plant
- maximise production under field decline, resulting in lower gas flowrates being received from the West Qurna field.

8.4.1 Equipment Failure

In the event of equipment failure, it is desirable to re-optimize the network operation in order to minimise the adverse effects of the failure. Here we consider a case in which one of the two KAZ NGL trains can operate to only 20% of installed capacity. This scenario is modelled by introducing a new inequality constraint for the feed gas ratio to the turned-down KAZ 11.2 NGL train. With the feed ratio constraint in place, the entire network is then optimised to maximise total production as formulated in Equation (39).

The total production maximisation problem applies the same 77 degrees of freedom and 47 inequality constraints as used in the profit maximisation problem [see section 7.2.1].

There are however 2 additional constraints pertaining to the flow ratios of the liquid and vapour phases from the KAZ slug catcher to the KAZ NGL trains. This brings the total number of constraints to 49.

The total production in this scenario using current practices is obtained limiting the throughput of KAZ 11.2 Train to only 20% of installed capacity. This eliminates 70.2 kg/s of production.

Table 42 compares the optimal production rates with base values representing the rates that would result from the KAZ NGL train failure leading to deviation from normal design operation. Operating at the optimal point results in a total production increase of 35.3% relative to the un-optimised operating point during KAZ train failure. On an annualized basis, this represents a potential production increase of about 2.2 million tonnes/yr.

Table 42: Total Production Under Equipment (KAZ 11.2 Train) Failure: Optimum vs Default Operation

OBJECTIVE: TOTAL PRODUCTION	
Design Operational Value (kg/s)	218.3
Optimal Value (kg/s)	295.4
Annualised Δ (tons/yr)	+2,188,283
% Δ	+35.3%
Computational Statistics	
Total CPU Time (seconds)	16,490
Optimiser CPU Time (seconds)	34.7
Number of NLP Iterations	70
Number of NLP Line Search Steps	241

It appears that the potential benefits from a rigorous mathematical optimisation approach are even more pronounced for this abnormal operation than for those under normal scenarios (see Table

36). In such equipment failure cases, the optimisation methods outlined in this work can be used to significantly ameliorate the effects of abnormal situations on the network's operation.

8.4.2 Field Decline

The natural decline of a particular field supplying gas to the network may have adverse effects, and once again, an optimisation of the network operation taking account of these circumstances may be justified. Here we consider a scenario where the West Qurna field is in natural decline and seek to maximise total production from the network.

This scenario is modelled by constraining the feed gas rate to the West Qurna stations to a lower level compared to design or normal operation. Feed rates to CS 7 and CS 8 are constrained to 3 kg/s each, compared to the 8 kg/s that they can process under normal operation. With the feed rate constraint in place, the entire network is then optimised for total production as formulated in Equation (39).

The total production maximisation problem applies the same 77 degrees of freedom and 47 inequality constraints as used in the profit maximisation problem [see section 7.2.1].

By running a simulation using the network model in gPROMS, the total production in this scenario using current practices is obtained. These base values are compared in Table 43 with the optimal production rates. Operating at the optimal point results in a total production increase of 23.4% relative to the un-optimised operating point under field decline. On an annualized basis, this represents a potential production increase of about 1.8 million tonnes/yr.

Table 43: Total Production Under Field Decline: Optimum vs Default Operation

OBJECTIVE: TOTAL PRODUCTION	
Design Operational Value (kg/s)	278.5
Optimal Value (kg/s)	343.7
Annualised Δ (tons/yr)	+1,850,532
% Δ	+23.4%
Computational Statistics	
Total CPU Time (seconds)	6,771
Optimiser CPU Time (seconds)	13.0
Number of NLP Iterations	30
Number of NLP Line Search Steps	102

In the likely scenario of natural gas field declines, the optimisation methods outlined in this work can be used to significantly reduce the effects of abnormal situations on the network's operation.

8.5 Conclusion

This chapter has presented the objective function and solution approach for the production, product yields and flaring problems of a natural gas network. The benefits of applying optimisation to abnormal operating scenarios have also been demonstrated. While this chapter and the preceding chapter have considered single-period problems, the next chapter presents the solution approach and analysis of multi-period problem of natural gas networks.

Chapter 9. Multi-Period

Optimisation of Network

Profitability

The optimisation studies considered in Chapter 7 and Chapter 8 focused on a single operating period with given product prices and unit costs. The production rate for each product was assumed to be equal to its sales rate; thus, the potential of building up product inventories, or of using existing inventories to support sales, was not considered.

This chapter considers the simultaneous optimisation of production, sales and inventory over consecutive time periods with demands, prices and costs potentially varying across periods. The aim is to maximise the overall profit for the entire time horizon by varying, in each period, the process operating variables, sales rates (subject to contractually committed levels and maximum market demands) and the inventory levels (subject to storage capacities). Overall, this multi-period optimisation (MPO) problem, illustrated schematically in figure 16, aims to combine operational optimisation with commercial planning.

MPO forms an important part of supply chain planning. It is usually performed using very aggregate models of the individual nodes (e.g. production plants) in the chain. This may be justified, at least partly, given the uncertainty in various key inputs (e.g. product demands and prices) especially over the later periods of the time horizon under consideration. More pragmatically, such approximations are considered to be unavoidable given the very large-scale

nature of the underlying mathematical model required to describe the operation of large networks over multiple periods.

Nevertheless, in this chapter we aim to examine the feasibility and, more importantly, quantify the potential benefits that could arise from performing MPO calculation using detailed models of the individual network nodes, similar to those used for single-period optimisation in the previous two chapters.

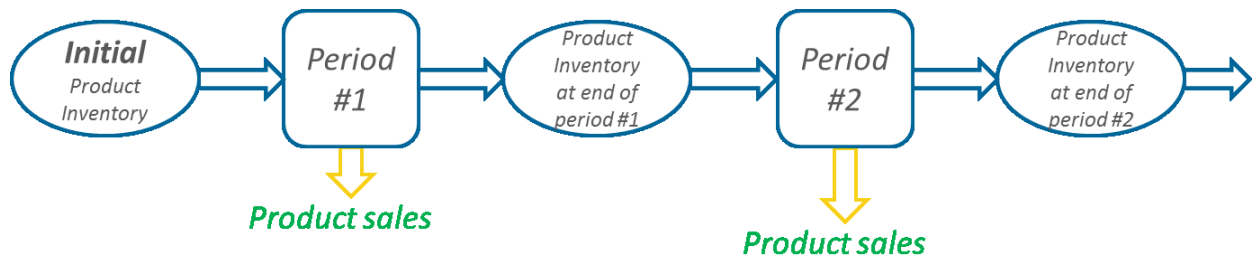


Figure 16: Multi-period optimisation

More specifically, we consider a two-period problem, with product prices in the second period being higher than in the first. Limitations on product storage tank capacities are also taken into account in addition to the constraints introduced in Chapter 7.

9.1 Mathematical formulation

We aim to maximise overall profitability by considering an objective function of Gross Profit (\$) = $\text{Revenue}_{\text{All_Periods}} - \text{Production Cost}_{\text{All_Periods}} - \text{Inventory Cost}_{\text{All_Periods}}$. Note that gross profit as defined in this work does not consider fixed costs (e.g. salary and benefits), facility, rentals etc.

Mathematically, this objective function can be expressed as:

$$\max \sum_{t=1}^{NP} \Delta T_t \cdot \left(\sum_s \pi_{s,t} D_{s,t} - K_t - \sum_s w_{s,t} \frac{I_{s,t} + I_{s,t-1}}{2} \right) \quad (42)$$

where:

NP = Number of periods under consideration

ΔT_t = Duration of period t

$\pi_{s,t}$ = Unit price of product s , in period t

$I_{s,t}$ = Inventory of s at the end of period t

$I_{s,t-1}$ = Inventory of s at the start of period t

$w_{s,t}$ = Unit cost of inventory per unit time, over period t (\$/kg/s)

$D_{s,t}$ = Sales rate of s , in period t (kg/sec)

K_t = Cost of operation per unit time (\$/sec)

The variation of product inventories from the start to the end of each period is described by the simple balance equation:

$$I_{s,t} = I_{s,t-1} + R_{s,t} \Delta T_t - D_{s,t} \Delta T_t, \quad t = 1, \dots, NP \quad (43)$$

where $R_{s,t}$ is the production rate of product s , in period t . The production and sales rates $R_{s,t}$ and $D_{s,t}$ are assumed to be constant over each period t , which results in linear inventory profiles over the period. The initial product inventories $I_{s,0}$ at the start of the time horizon are assumed to be known.

The inventories and product sales rates are subject to bounds constraints of the form:

$$0 \leq I_{s,t} \leq S_s \quad (44)$$

$$D_{st}^{min} \leq D_{st} \leq D_{st}^{max} \quad (45)$$

where:

S_s = Maximum storage capacity for product s

D_{st}^{min} = Minimum contractual sales rate of s in period t (kg/sec)

D_{st}^{max} = Market-limited maximum sales rate of s in period t (kg/sec)

The network operation over each period t is described by the process models:

$$F_{j,t}(u_{i,t}, x_{j,t}) = 0 \quad (46)$$

which, given the independent operational decision variables $u_{i,t}$ ($\forall i=1\dots I$) can be solved to determine the dependent variables $x_{j,t}$ ($\forall j=1\dots J$).

The production rates $R_{s,t}$ are a subset of (usually) the dependent variables $x_{j,t}$. Moreover, the operational cost function, K_t in equation (42) is generally defined as:

$$K_t = \left(\sum_i u_{i,t} c_{i,t}^u + \sum_j x_{j,t} c_{j,t}^x \right) \quad (47)$$

where:

$c_{i,t}^u$ = unit cost of independent variables (e.g. raw feed gas) in period t

$c_{j,t}^x$ = unit cost of dependent variables (e.g. compressor energy consumption) in period t

Overall, equations (42)-(47) describe a large-scale nonlinear programming problem that aims to maximise the overall profitability of the network over the entire time horizon, by determining optimal values for:

- the operational decision variables, $u_{i,t}$
- the product sales rates, $R_{s,t}$

over each period $t = 1, \dots, NP$.

9.2 Implementation of MPO in gPROMS

A multi-period framework has been set-up to optimise profit while controlling the inventory of the network. The configurations of process units and plants in the network are identical in all the periods, but the operating conditions, such as decision variables, input prices and period durations, can be varied.

Multi-period optimisation has been implemented in gPROMS as shown schematically in Figure 17. The operation of the network over multiple periods is described by a higher-level composite model comprising the following elements:

1. multiple instances of the network model, each instance corresponding to a different period; the single-period models are mathematically identical, each comprising equations (46) and the operational cost equation (47)
2. an equation defining the objective function (42), with the operational costs K_t being obtained by reference to the single-period sub-models
3. the inventory balance equations (43), with the production rates R_{st} being obtained from the single-period sub-models.

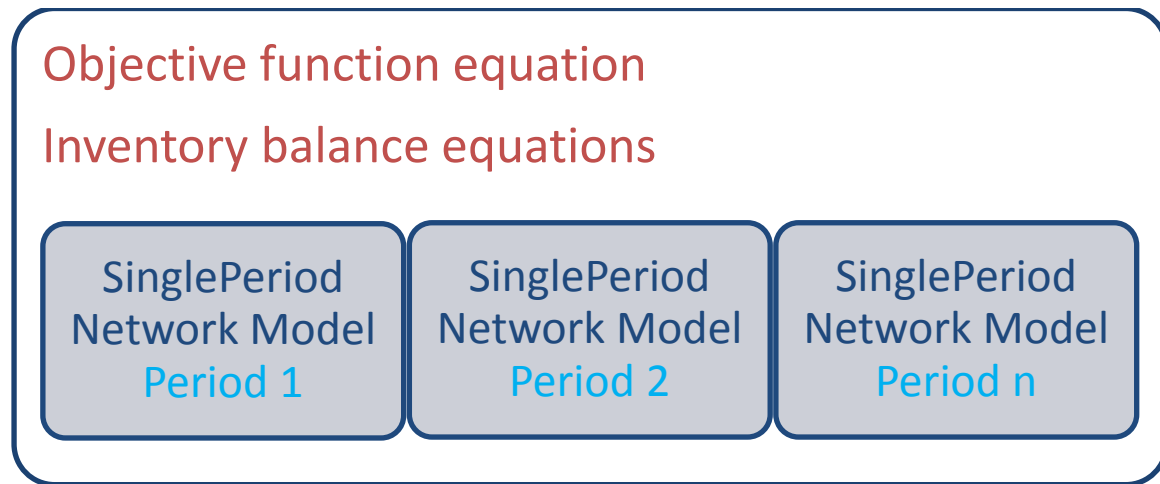


Figure 17: Composite Model of Multi-Period Operation

Appendix L shows the gPROMS language description of the above model.

The total number of equations in an NP -period multi-period problem is approximately NP times of the number of equations in the single-period network. For instance, while a single-period network problem involves about 280,000 equations, a 2-period multi-period problem involves about 560,000 equations.

9.3 A Two-Period Optimisation Case study

For simplicity, we consider a case study comprising only two periods, as this allows the underlying nonlinear programming problem to be solved using the standard Successive Quadratic Programming algorithm (NLPSQP solver) in gPROMS, while demonstrating the key features and benefits of the multi-period approach. The multi-period problem is initialized by using a text editor to create a Saved Variable Set (SVS) comprising a copy of an SVS for each period obtained by performing a simulation of a single-period problem at some nominal values of the operational decision variables u .

Initial guesses for the product sales rates D_{st} for both periods are set to equal values in order to avoid negative inventory during model initialisation.

9.3.1 Optimisation Decision Variables

Each period of the MPO problem applies the same degrees of freedom as used in the single-period profit optimisation problem [see section 7.2.1] excluding the gas-to-NGL split ratios for simplification. The gas split ratios from South Rumaila to KAZ NGL was set to a default value of 1 because all the single period optimisation runs resulted in optimum value 1 for these variables.

The sales rates for the liquid products (propane, butane and gasoline) act as additional degrees of freedom. Dry gas sales rate is not a decision variable: as there is no storage tank for this product, its sales rate must equal its production rate over each period. Overall, as summarised in Table 44, this results in a total of 152 decision variables.

Table 44: Decision Variable types and number of degrees of freedom per Period

Type of Decision Variable	Period 1	Period 2	Total
Feed Gas Rate from Oil production	55	55	110
Column Reflux Ratios	9	9	18
Column Boil-up Ratios	9	9	18
Sales Rates of propane, butane and gasoline	3	3	6
TOTAL	76	76	152

9.3.2 Constraints

While the single-period profit optimisation applies 47 inequality constraints, each period of the multi-period problem applies 40 inequality constraints. Limits on inventory (i.e. capacity of storage vessels) for the liquid products (propane, butane and gasoline) have been included as additional

inequality constraints for the multi-period profit optimisation. Furthermore, pipeline Mach number constraints have been omitted as it was observed from the single-period optimisations that, in all cases, the Mach numbers are much lower than the limit Mach number of 1.

This brings the number of inequality constraints to a total of 80 for the 2-period profit optimisation problem. Table 45 outlines the types of constraints applied and the number per type.

The values of the inventory constraint for each product are the tank storage capacities which are given in table 13.

Table 45: Multi-Period Constraint Type and Number

Type of Constrained Variable	Period 1	Period 2	Total
Product Inventory (Storage Capacity)	3	3	6
Compressor Duty	25	25	50
Column Max Flooding Velocity	9	9	18
Products Specification	3	3	6
TOTAL	40	40	80

9.3.3 Prices and Costs

The two periods are assumed to be of equal duration, with the corresponding ΔT_t being set to a notional value of 1 time unit. The cost and price data used in the optimisation are outlined in Table 46. It should be noted that all sales prices shown here are hypothetical. Feed gas costs and energy consumption are the only production costs taken into account. Fixed costs such as wages, rents etc. have not been considered.

Table 46: Cost and Price Data

	Period 1	Period 2	Units
INPUT COSTS			
Gas Feed	0.035	0.035	\$/kg
Electricity Consumption (Compressor Duty)	0.1	0.1	\$/kWhr
Heating (Column Reboiler Duty)	0.019	0.019	\$/MJ
Cooling (Column Condenser Duty)	0.019	0.019	\$/MJ
SALES PRICES			
Dry Gas	0.14	0.18	\$/kg
Propane	0.65	0.70	\$/kg
Butane	0.55	0.65	\$/kg
Gasoline	0.6	0.7	\$/kg

9.4 Case Study Results

The multi-period profit (gross) of the network under optimal operation and sales planning was compared with the corresponding profit when operating at the design conditions. The reference design operational profit values have been computed by running gPROMS simulations of the network for each period with actual design operating conditions and using the given product prices per period.

As shown in Table 47, multi-period profitability optimisation results in a potential 11.8 % profit increase compared to the design operating case. On an annualized basis⁵ [i.e. a duration of 6 months for each period], there is a potential gross profit increase of about \$300 million in applying

⁵ To calculate the annualized profit increase, the value of change in multi-period profit (i.e Optimum-Base) is multiplied by the number of seconds in the 6-month duration of each period.

the optimised operating conditions and sales rate compared to the un-optimised operating conditions and sales rate. This demonstrates the impact of applying model based optimisation to the operation of a real-world natural gas network. Even if only a small fraction of this value gap can be realised due to constraints or commercial factors not considered in this work, the potential financial benefit of applying such multi-period optimisation methods to a natural gas network is still considerable.

Table 47: Optimum Multi-Period Profit

OBJECTIVE: MULTI-PERIOD PROFIT	
Design Operational Value (\$/s)	179.9
Optimal Value (\$/s)	201.1
Annualised Δ (\$/yr)	301 million
% Δ	11.8%

It should be noted that the magnitude of profit improvement depends on the market prices of the products. The network multi-period optimisation model can therefore be used to find new optimal operating points when market conditions change. In particular, the product price difference between periods is an important factor in deciding whether keeping inventory is profitable or not. It is usually worth building up inventory when the material price is forecasted to be higher in the future. As illustrated by the results presented in Table 48, in period 1 with lower product sales prices, the optimisation reduces the product sales in order to build-up inventory. In period 2 where the product prices are higher, sales rate is pushed higher than for period 1 while inventory in period 2 gets depleted. Total sales rate in period 1 is 204.78 kg/s while total sales rate is 432.57 kg/s in period 2.

In general, to maximise the cumulative multi-period profit, optimisation can be used to quantify product sale decrease in the period with lower prices, plan sales increase for the period with higher prices, and manage inventory. Thus, MPO provides a rigorous quantitative basis for supply chain planning.

This MPO approach has possible applications in the commodity futures market where contracts can be made to trade products (e.g. propane) at a future date, but at a price and quantity agreed today. Since prices are determined by the market and quoted on commodity exchanges, this MPO method can be used to determine sales quantities that optimize profit over the time-frame including the current period and the future period.

Table 48: Initial and Optimal values of Variables for Commercial Planning

	Initial Guess (Both Periods)	Period 1, Optimum	Period 2, Optimum
SALES RATE			
Dry Gas (kg/s)	-	189.73	196.18
Propane (kg/s)	50	5.03	110.31
Butane (kg/s)	25	5.01	62.07
Gasoline (kg/s)	25	5.01	64.01
INVENTORY BUILD-UP RATE: $(I_{st} - I_{s,t-1})/\Delta T_t$			
Propane (kg/s)		53.9	-53.9
Butane (kg/s)		28.0	-28.0
Gasoline (kg/s)		29.2	-29.2

In addition to changing sales rates for the different periods, some other decision variables such as feed gas rate are also varied in the different periods albeit moderately. Appendix K shows the optimum decision variables values for the multi-period optimisation run.

9.5 Comparison of MPO with multiple Single-Period Optimisations

A simpler alternative to the MPO approach described above is to solve a sequence of single-period optimisation problems. For example, if the product prices are known to be different for two time periods, a single-period optimisation can be run for each time period to find the optimal operating conditions without holding any product inventory from one period to the next. Overall profitability can then be considered as the sum of the optimum from each single-period run. This simplified approach is likely to be less costly computationally than solving the integrated MPO problem. It is, therefore, worth comparing the quality of the solutions in terms of overall profitability obtained by the two approaches.

Using the decision variables and constraints presented in section 7.2.1, two successive single-period optimisations have been run using the cost and price data in Table 46. The results are summarized in Table 49 which compares network profitabilities achieved via (a) a base case operation under design conditions (b) optimisation applied to each of the two periods in sequence (“sequential optimisation”), and (c) the MPO approach.

It is evident from table 49 that MPO results in significantly improved profitability (11.8% over the base case) compared with that achieved via the sequential application of even a sophisticated single-period optimisation approach (8.4% over the base case). In particular, when product prices are expected to be higher in future periods, the MPO approach deliberately reduces product sales rates, preferring instead to build up inventories that can be sold more profitably in subsequent periods. In contrast, the sequential optimisation approach myopically optimises the network operation based only on the current period’s product demands and prices.

This result shows that significant benefit can be derived from including sales planning and inventory considerations in the multi-period profit optimisation of the natural gas network.

Table 49: Profitability over 2-period operation

Integrated network profitability (\$/unit time)				% profitability improvement over base case
	Period #1	Period #2	Total	
Base operational case	82.1	97.8	179.9	
Sequential optimisation	88.5	106.6	195.1	8.4%
Multi-period optimisation	19.6	181.5	201.1	11.8%

On the other hand, as shown in Table 50, the computational cost of solving a two-period MPO problem in gPROMS is significantly higher than that incurred for two successive single-period problems.

Table 50: Computational Statistics (Sequential Single-Periods vs Simultaneous MPO)

	Single-Period, Period 1	Single-Period, Period 2	Multi-Period (MPO)
Total CPU Time (seconds)	7,684	9,109	75,378
Optimiser CPU Time (seconds)	10.2	15.1	34,527.7
Number of NLP Iterations	35	38	88
NLP Line Search Steps	60	65	185
Number of unknown variables	277,280	277,280	555,409

The multi-period optimisation took CPU time of about 21 hours while the successive single-period optimisations took only a combined 4½ hours. The proportion of the CPU time spent by the NLP solver for MPO (46% of the total solution time) was also much greater than for the single-period

problems (0.13% and 0.16% respectively). This is largely due to the size and structure of the MPO problem which includes many dense matrix operations.

Overall, however, in view of the very large money flows in such a network, the greater computing cost of the MPO approach vis-à-vis the sequential single-period approach is outweighed by the significantly improved profitability achieved by the former.

9.6 Conclusions

In this chapter, an MPO problem has been formulated and implemented using standard optimisation facilities within gPROMS.

2-period MPO case study has been solved. The solutions demonstrate significant benefits that may arise by the application of MPO - not just compared to the base case operations but even when compared with sequential applications of sophisticated single-period optimisation.

The resulting model size and computational cost of the MPO approach implies that a tailored solver that takes the specific structure of MPO problems into account, would be necessary in solving problems involving more realistic number of periods.

Chapter 10. Conclusions

This work was aimed at developing an accurate model of natural gas/NGL networks and using rigorous mathematical optimisation to study and enhance the operational profitability, flexibility, and environmental performance of such large networks and underlying facilities. Several major tasks were involved in achieving this objective:

- Using real world data, develop and validate a detailed, physics-based model for a region-wide natural gas/NGL network involving gathering, transport, processing and sales of natural gas and associated liquids.
- Develop objective functions and determine parameters for optimisation and analysis of natural gas network problems of profitability, operational flexibility and environmental performance.
- Examine holistic single- and multi-period optimisation approaches to solve the large nonlinear problem of region-wide natural gas/NGL supply chain model.
- Study the impact of applying model based optimisation to the operations and profitability of natural gas networks.

Given the challenges outlined above, the key conclusions and contributions of this work are highlighted below followed by recommendations for further research.

10.1 Key Conclusions from this Work

1. Significant economic benefits can be achieved via the holistic optimisation of natural gas production and processing networks. The use of detailed physics-based models of processing plants in this context significantly increases the probability of the solutions

obtained being both optimal and practically implementable. A key contribution of this thesis has been to demonstrate that, notwithstanding the underlying mathematical complexity, such optimisations are now feasible using current process modelling technology.

2. Real-world operational and facilities data was collected from the large natural gas network of Basrah Gas Co. (BGC) in Iraq.
3. A detailed high-fidelity model of a natural gas network was developed and validated with data from the Basrah Gas Co. (BGC) network. Thus, while previous works only studied subsystems of the natural gas chain, this work has modelled an integrated natural gas network from production to pipelines to processing to market, using detailed models of each individual component in the network.
4. The natural gas network model was developed using a commercially-available equation-based process modeling and optimisation tool. The model was constructed in a hierarchical manner, with models of the individual unit operations, production and processing facilities being embedded within a top-level model. The unit operation models were taken from standard libraries supplied with the modelling environment. The overall model comprises about 277,000 model equations.
5. Using the large natural gas network of BGC as a case study, optimisation approaches to find optima to profitability, production, flexibility problems of natural gas networks have been developed. To our knowledge, a successful undertaking of this scale and complexity has not been reported in the open literature to date.
6. The magnitudes of the resulting improvements in optimised operations are significant. Profitability optimisation results in a potential 9% profit increase compared to the base case representing un-optimised operating conditions. More detailed analysis of the results indicates that this increase arises largely from the optimised routing of raw gas from the different compressor stations to the two NGL plants and, to a lesser but significant extent,

from applying optimal reflux and boil-up ratios in the columns. Furthermore, the active constraints and active bounds on decision variables at the optimum point and corresponding Lagrange multipliers were used to gain insights into the network bottlenecks limiting greater profitability.

7. A heuristic Gradient Ranking method has been developed for determining the relative impact of the decision variables on the objective function. The method has been found to give important insight into the most significant variables that can be operationally controlled to give the greatest improvement on the objective function optimum. Another benefit of applying this method is to reduce problem complexity and improve computational efficiency.
8. When market prices of products change, it is critical to know how the network should be operated to reap the most benefit from the new product prices. Product-price sensitivity and product capacity margin methods have been developed to assess the relative economic impact of the different products (dry gas, propane, butane and natural gasoline) in relation to optimal profitability with varying market prices. This method also gives insight to the equipment interactions and bottlenecks that are critical to optimum profitability.
9. A multi-period optimisation (MPO) approach has been developed to maximise the overall profit for multiple periods by varying, in each period, the process operating variables, sales rates and the inventory levels. The results show that the MPO approach results in significantly improved profitability (11.8% over the base case) compared with that achieved via the sequential single-period optimisation approach (8.4% over the base case). This demonstrates the benefit of the presented approach to supply chain optimisation over multiple periods, which bridges commercial planning with operational decisions. The greater computing time required for the multi-period problem (MPO) vis-à-vis the sequential single period approach is outweighed by the significantly improved profitability achieved with the MPO approach.

10. Significant improvements are also obtained for production under different operating scenarios. In particular, there is scope to increase total production from the network by 24%. In addition, the results show that it is possible to increase the yield of one individual product (dry gas, propane, butane or gasoline) by significant amounts (up to 45%, 53%, 108% and 51% respectively) if this is deemed to be desirable.
11. By applying rigorous optimisation, it has been shown that hydrocarbon flaring from the network can be reduced by 90% compared to the un-optimised operations. This potential flare reduction contributes significantly to decreasing CO₂ emissions and also enables cleaner air for the local population.
12. Abnormal operating scenarios of field decline and equipment failure were also considered. The results show that there is scope to increase total production by 35% relative to the rates that would result from equipment failure scenarios leading to deviation from normal design operation. From the optimisation results, there is also a potential to increase total production by 23% relative to the unoptimised rate per current operating practices in a scenario of gas field decline.
13. For some abnormal operating scenarios, the potential benefits from a rigorous mathematical optimisation approach are even more pronounced than those under normal scenarios. In such cases, the optimiser provides a tool that can be used to significantly mitigate the undesirable effects of abnormal situations on the operation of natural gas networks.

10.2 Recommendations for Further Research

The optimisation methods and approaches presented in this work provide a sound basis for further work in the area of natural gas network optimisation and analysis. Some recommendations for future research efforts are highlighted below.

More efficient multi-period optimisation

As demonstrated in Chapter 9, it is computationally very expensive to run the holistic multi-period problem simultaneously in gPROMS. The consecutive solution is also limited to fewer degrees of freedom. For more robust and efficient optimisation of the multi-period problem, a dedicated MPO solver should be used with the following considerations:

- When holistically solving multi-period optimisation, gPROMS does not take into account that certain variables only apply to certain periods. During simultaneous implementation in gPROMS, variables from all periods are used to control the output for any given period. This results in several dense matrix operations and is computationally costly.
- A more efficient implementation is one where only variables in a particular period are varied in that particular period. The objective function of the model is the sum of the individual period profits. The input variables in a period do not affect the output variables and the profits in other periods. It means that the output variables, profit and variable gradients of the individual periods can be calculated independently.
- A distributed computing approach may be used to reduce computation time.

Comparative analysis using different Solvers

Comparative analysis of different optimisation algorithms for solving single- and multi-period problems of large natural gas/NGL networks. Using the foreign object interface in gPROMS, it could be possible to optimise and analyse the gas network using different CAPE-OPEN compliant

NLP solvers. The optimal values and computational times obtained in this work can be compared with results using other optimisation solvers such as:

- Advanced primal-dual interior-point algorithm (Optimiser IPOPT) developed by (Wachter & Biegler, 2006)
- Generalised reduced-gradient algorithm (Optimiser CONOPT) developed by (Drud, 1994)

Application of Metaheuristic methods

Useful insights may be gained by applying metaheuristic methods to natural gas network optimisation problems. Metaheuristic methods such as simulated annealing, genetic algorithms and particle swarm optimisation implement some form of stochastic optimization. By searching over a large set of feasible solutions, metaheuristics may find good solutions. The optimal values and computational times obtained in this work could be compared with results of using metaheuristic methods.

Application of global optimisation methods

It would be instructive to apply global optimisation methods such as BARON and ANTIGONE to the single- and multi-period problems of large natural gas/NGL networks. The optimal values and computational times obtained in this work could be compared with results of using global optimisation methods.

However, the use of above mentioned codes is probably infeasible in the foreseeable future given the problem size. A more pragmatic approach could be the use of multi-start approach (Kucherenko & Sytsko, 2005), i.e. solving the optimisation problem as presented here, but trying a number different initial guesses for the decision variables.

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Glossary of Acronyms

\$- United States Dollars

AGRU- Acid Gas Removal Unit

BGC- Basrah Gas Company

C3- Propane

C4- Butane

C3+ - Hydrocarbons with 3 or more carbon atoms

C5+ - Hydrocarbons with 5 or more carbon atoms

CAPE- Computer-Aided Process Engineering

CPU- Computer Processing Unit

CS- Compressor Station

DOF- Degree of Freedom

DS- Degassing Station

EIA- Energy Information Administration

EOS- Equation of State

EW0- Enterprise Wide Optimisation

GTU- Gas Transmission Unit

HM- Hammar Mishrif

HP- High Pressure

KAZ- Khor Al Zubair

KKT- Karush-Kuhn-Tucker

KPI- Key Performance Indicator

LP- Low Pressure

LPG- Liquified Petroleum Gas

LTS- Low Temperature Separator

MCC- Motor Control Centre

MILP- Mixed Integer Linear Programming

MINLP- Mixed Integer Nonliner Programming

MMSCFD- Million standard cubic feet per day

MPO- Multi-Period Optimisation

NAG- Numerical Algorithm Group

NGBD- Nonconvex Generalized Benders decomposition

NGL- Natural Gas Liquids

NO_x- Nitrogen Oxides

NLP- Nonlinear Programming

NR- North Rumaila

OAERAP- Outer Approximation Equality Relaxation Augmented Penalty

PVT- Pressure, Volume, Temperature

SOC- South Oil Company

SO_x- Sulphur Oxides

SVS- Saved Variable Set

UoM- Unit of Measurement

WQ- West Qurna

ZM- Zubair Mishrif

Publications from this Thesis

Industry Journal

Gas Processing, September/October 2016: *Optimise an integrated natural gas production and distribution network*. pp 35-39

<http://www.gasprocessingnews.com/features/201610/optimize-an-integrated-natural-gas-production-and-distribution-network.aspx>

Conference Papers

- Gas Processors Association (GPA) Midstream Convention, San Antonio, Texas, April 2017: *Model-based Optimisation of the Operation of Integrated Natural Gas Production & Processing Networks*.
- Gas Processors Association (GPA) Annual Conference, Athens, September 2016: *Model-based Optimisation of the Operation of Integrated Natural Gas Production & Processing Networks*.
[Awarded 2nd Best Paper out of 20 papers presented]
- Advanced Processing Modelling Forum, London, April 2016: *Optimisation of Regional Gas Production & Processing Network*
- Advanced Processing Modelling Forum, London, April 2014: *Enhancing Multi-field Gas Production via Network Optimisation*

Appendix A: NLPSQP Algorithm in gPROMS

According to the gPROMS manual (Process Systems Enterprise Limited, 2013):

The NLPSQP solver uses four tolerances to decide whether or not a local optimal solution has been reached and all tolerances need to be satisfied.

Each of the tolerances can be specified separately which provides much flexibility to control the solution process and the outcome of the optimisation. The default value for the first three is zero, only OptimisationTolerance is specified by default to 10^{-3} . The value of zero takes on a special role for the tolerances 1-3: if they are set to zero, the value of OptimisationTolerance is applied instead (and properly reported).

1. FeasibilityTolerance - A real number in the range $[10^{-20}, 1.0]$; default 0.

$$\sum_{i=1}^{m_{\varepsilon q}} |h_i(x^k)| + \sum_{i=1}^{m-m_{\varepsilon q}} \max\{0, -c_i(x^k)\} + \sum_{i=1}^n \max\{0, x_i^L - x_i^k, x_i^k - x_i^U\} \leq \varepsilon_1$$

This denotes the magnitude of the sum over all constraint and bound violations.

2. ComplementarityTolerance - A real number in the range $[10^{-20}, 1.0]$; default 0.

$$\sum_{i=1}^{m_{\varepsilon q}} |\lambda_i h_i(x^k)| + \sum_{i=1}^{m-m_{\varepsilon q}} |\mu_i c_i(x^k)| + \sum_{i=1}^n |v_i| \max\{0, x_i^L - x_i^k, x_i^k - x_i^U\} \leq \varepsilon_2$$

The complementarity tolerance represents the sum over all violation of constraints and bounds, weighted by their influence on the gradient of the objective function.

3. TaylorTolerance - A real number in the range $[10^{-20}, 1.0]$; default 0.

$$\frac{\left| \nabla_x f(x^k)^T d^k \right|}{\left| f(x^k) \right| + 1} \leq \varepsilon_3$$

This tolerance is based on Taylor's theorem and represents the rate of change in the objective function between two iterations.

$$f(x^k + \alpha d^k) = f(x^k) + \alpha \nabla f(x^k)^T d^k + \frac{1}{2} \alpha^2 d^{kT} \nabla^2 f(x^k + t d^k) d^k, \text{ for some } t \in (0, \alpha)$$

where α is the step length.

4. OptimisationTolerance - A real number in the range $[10^{-20}, 1.0]$; default 0.001.

$$\max_{1 \leq i \leq n} \left| \frac{\nabla_x L(x^k, \lambda^k, \mu^k, v_l^k, v_u^k)_i w_i^k}{\left| L(x^k, \lambda^k, \mu^k, v_l^k, v_u^k) \right| + 1} \right| \leq \varepsilon_4$$

where

$$w_i^k = \begin{cases} x_i^k & \text{if } x_i^k \neq 0 \\ 1 & \text{if } x_i^k = 0 \end{cases}$$

The stationarity condition is a measure for the proximity to a local optimum. It is an approximation of

$$\nabla_x L \simeq 0.$$

f is the objective function;

c is the constraint vector (right-hand side);

m_{eq} is the number of equality constraints;

m is the total number of constraints;

n is the size of the variable vector x (i.e. the number of variables);

x^L and x^U are the vectors of the lower and upper bounds of variable x ;

d is the vector of corrections to x (i.e. the change in x during the current step);

λ is the Lagrange multiplier vector that corresponds to the equality constraint imposed on variable x ;

μ is the Lagrange multiplier vector that corresponds to the inequality constraints imposed on variable x ;

v is the Lagrange multiplier vector that corresponds to the bound constraints imposed on variable x ;

L is the Lagrange function

$$L(x, \lambda, \mu, v_l, v_u) = f(x) - \lambda^T h(x) - \mu^T c(x) - v_l^T (x - x^L) - v_u^T (x^U - x)$$

Successful termination:

- a. If the tolerances 1-4 are satisfied the algorithm terminates due to optimality.
- b. Otherwise, it is checked if there is no progress in the values of the objective function and the decision variables, as well as no constraint violation. In order to check this, the NoImprovementTolerance (ε_5) is used in the following tests:

$$\begin{aligned} |f(x^k) - f(x^{k-1})| &\leq \varepsilon_5, \\ \max_j (dx_j) &\leq \varepsilon_5, \\ \text{Feasibility Tolerance} &\leq \varepsilon_1 \end{aligned}$$

where dx_j is the step calculated for x_j in the latest line-search step.

If this test is successful, the optimisation terminates and reports the respective reason for the termination.

- c. After each line-search step, tests a. and b. are performed as well and can terminate the algorithm.

An optimisation is terminated unsuccessfully if

1. a function evaluation failure in a line search step occurs
2. after 10 steps without progress the final step is infeasible
3. the number of line search steps in a major iteration exceeds `MaximumLineSearchSteps`
4. the total number of function evaluations exceeds `MaxFun`

Appendix B: Decision Variables for Single-Period Profitability Optimisation (Scaling =0)

	Final Value	Initial Guess	LowerBound		UpperBound	
			Value	Lagrange Multiplier	Value	Lagrange Multiplier
CS1.Stage2A.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.06
CS1.Stage2B.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.06
CS1.Stage2C.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.06
CS1.Stage3A.SP_F_w.mass_flowrate	0.00	4.00	0.00	0.00	10.00	0.00
CS1.Stage3B.SP_F_w.mass_flowrate	0.00	4.00	0.00	0.00	10.00	0.00
CS1.Stage3C.SP_F_w.mass_flowrate	0.00	4.00	0.00	0.00	10.00	0.00
CS1_HP.Stage1.SP_F_w.mass_flowrate	8.00	5.00	0.00	0.00	8.00	0.10
CS2.Stage2.SP_F_w.mass_flowrate	5.46	6.00	0.00	0.00	10.00	0.00
CS2.Stage3.SP_F_w.mass_flowrate	0.00	3.00	0.00	0.00	10.00	0.00
CS2_HP.Stage1.SP_F_w.mass_flowrate	2.94	5.00	0.00	0.00	8.00	0.00
CS3.Stage2A.SP_F_w.mass_flowrate	7.07	5.00	0.00	0.00	10.00	0.00
CS3.Stage2B.SP_F_w.mass_flowrate	9.33	5.00	0.00	0.00	10.00	0.00
CS3.Stage3A.SP_F_w.mass_flowrate	0.00	4.00	0.00	0.00	10.00	0.00
CS3.Stage3B.SP_F_w.mass_flowrate	0.00	4.00	0.00	0.00	10.00	0.00
CS3_HP.Stage1.SP_F_w.mass_flowrate	8.00	5.00	0.00	0.00	8.00	0.11
CS4.Stage2A.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.04
CS4.Stage2B.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.04
CS4.Stage3A.SP_F_w.mass_flowrate	0.00	4.00	0.00	0.00	10.00	0.00
CS4.Stage3B.SP_F_w.mass_flowrate	0.00	4.00	0.00	0.00	10.00	0.00
CS4_HP.Stage1.SP_F_w.mass_flowrate	8.00	5.00	0.00	0.00	8.00	0.11
CS5.Stage2A.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.02
CS5.Stage2B.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.03
CS5.Stage3A.SP_F_w.mass_flowrate	0.00	4.00	0.00	0.01	10.00	0.00
CS5.Stage3B.SP_F_w.mass_flowrate	0.00	4.00	0.00	0.00	10.00	0.00
CS5_HP.Stage1.SP_F_w.mass_flowrate	8.00	5.00	0.00	0.00	8.00	0.11
CS7.Stage1.SP_F_w.mass_flowrate	15.00	5.00	0.00	0.00	15.00	0.11
CS8.Stage1.SP_F_w.mass_flowrate	15.00	5.00	0.00	0.00	15.00	0.11
Hammar.Stage1.SP_F_w.mass_flowrate	3.50	3.00	0.00	0.00	3.50	0.14
HammarMishrif.First_HP.SP_F_w.mass_flowrate	2.00	1.00	0.00	0.00	2.00	0.15
HammarMishrif.First_LP.SP_F_w.mass_flowrate	14.00	4.00	0.00	0.00	14.00	0.08
Janubiya.Stage2A.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.24
Janubiya.Stage2B.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.00
Janubiya.Stage3A.SP_F_w.mass_flowrate	6.13	4.00	0.00	0.00	10.00	0.00
Janubiya.Stage3B.SP_F_w.mass_flowrate	7.81	4.00	0.00	0.00	10.00	0.00
KAZ_11_1_DeEthanizer_Boilupratio	0.60	0.90	0.01	0.00	7.00	0.00
KAZ_11_1_DeEthanizer_Refluxratio	0.32	0.90	0.01	0.00	7.00	0.00

Appendix B: Decision Variables for Single-Period Profitability Optimisation (Scaling =0)

KAZ_11_2_DeEthanizer_Boilupratio	0.60	1.00	0.01	0.00	7.00	0.00
KAZ_11_2_DeEthanizer_Refluxratio	0.32	1.00	0.01	0.00	7.00	0.00
KAZ_12_1_DeButanizer_Boilupratio	1.90	0.50	0.01	0.00	7.00	0.00
KAZ_12_1_DeButanizer_Refluxratio	1.30	0.50	0.01	0.00	7.00	0.00
KAZ_12_1_DePropanizer_Boilupratio	1.63	0.50	0.01	0.00	7.00	0.00
KAZ_12_1_DePropanizer_Refluxratio	1.35	0.50	0.01	0.00	7.00	0.00
KAZ_12_2_DeButanizer_Boilupratio	0.69	0.50	0.01	0.00	7.00	0.00
KAZ_12_2_DeButanizer_Refluxratio	1.24	0.50	0.01	0.00	7.00	0.00
KAZ_12_2_DePropanizer_Boilupratio	1.81	1.00	0.01	0.00	7.00	0.00
KAZ_12_2_DePropanizer_Refluxratio	1.39	1.00	0.01	0.00	7.00	0.00
KAZ_12_3_DeButanizer_Boilupratio	1.93	0.50	0.01	0.00	7.00	0.00
KAZ_12_3_DeButanizer_Refluxratio	1.30	0.50	0.01	0.00	7.00	0.00
KAZ_12_3_DePropanizer_Boilupratio	1.79	0.50	0.01	0.00	7.00	0.00
KAZ_12_3_DePropanizer_Refluxratio	1.41	0.50	0.01	0.00	7.00	0.00
Markazia.Stage2A.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.25
Markazia.Stage2B.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.15
Markazia.Stage2C.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.14
Markazia.Stage2D.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.19
Markazia.Stage3A.SP_F_w.mass_flowrate	4.26	4.00	0.00	0.00	10.00	0.00
Markazia.Stage3B.SP_F_w.mass_flowrate	4.30	4.00	0.00	0.00	10.00	0.00
Markazia.Stage3C.SP_F_w.mass_flowrate	4.38	4.00	0.00	0.00	10.00	0.00
Markazia.Stage3D.SP_F_w.mass_flowrate	4.45	4.00	0.00	0.00	10.00	0.00
NGL_DeEthanizer_Boilupratio	0.45	0.10	0.01	0.00	7.00	0.00
NGL_DeEthanizer_Refluxratio	0.01	0.10	0.01	0.00	7.00	0.00
Qurainat.Stage2A.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.24
Qurainat.Stage2B.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.23
Qurainat.Stage3A.SP_F_w.mass_flowrate	4.67	4.00	0.00	0.00	10.00	0.00
Qurainat.Stage3B.SP_F_w.mass_flowrate	5.20	4.00	0.00	0.00	10.00	0.00
Rafidiyah.First_HP.SP_F_w.mass_flowrate	3.00	2.00	0.00	0.00	3.00	0.15
Rafidiyah.First_LP.SP_F_w.mass_flowrate	3.50	3.00	0.00	0.00	3.50	0.06
S_Ja.ms.SP_split(1).S_spec(1)	1.00	0.50	0.00	0.00	1.00	2.36
S_Mk.ms.SP_split(1).S_spec(1)	1.00	0.90	0.00	0.00	1.00	4.23
S_QU.ms.SP_split(1).S_spec(1)	1.00	0.50	0.00	0.00	1.00	2.25
S_SH.ms.SP_split(1).S_spec(1)	1.00	0.90	0.00	0.00	1.00	2.35
Shamiya.Stage2A.SP_F_w.mass_flowrate	10.00	5.00	0.00	0.00	10.00	0.18
Shamiya.Stage2B.SP_F_w.mass_flowrate	9.97	5.00	0.00	0.00	10.00	0.00
Shamiya.Stage3A.SP_F_w.mass_flowrate	4.56	4.00	0.00	0.00	10.00	0.00
Shamiya.Stage3B.SP_F_w.mass_flowrate	8.53	4.00	0.00	0.00	10.00	0.00
Zubair.First_HP.SP_F_w.mass_flowrate	1.50	1.00	0.00	0.00	1.50	0.14
Zubair.First_LP.SP_F_w.mass_flowrate	8.00	4.00	0.00	0.00	8.00	0.08
ZubairMishrif.Stage1.SP_F_w.mass_flowrate	7.00	5.00	0.00	0.00	7.00	0.14

*shaded cells indicate an active bound

Appendix C: Constrained Variables for Single-Period Profitability Optimisation

Constrained Variable	Value	Lower Bound		Upper Bound	
		Value	Lagrange Multiplier	Value	Lagrange Multiplier
Butane_spec	0.82	0.72	0.00	1.00	0.00
CS1_A_DriverPower	2110.40	0.00	0.00	4930.00	0.00
CS1_B_DriverPower	2110.40	0.00	0.00	4930.00	0.00
CS1_C_DriverPower	2110.40	0.00	0.00	4930.00	0.00
CS2_DriverPower	1200.80	0.00	0.00	3300.00	0.00
CS3_A_DriverPower	1419.80	0.00	0.00	2900.00	0.00
CS3_B_DriverPower	1595.10	0.00	0.00	2900.00	0.00
CS4_A_DriverPower	2398.50	0.00	0.00	4930.00	0.00
CS4_B_DriverPower	2398.50	0.00	0.00	4930.00	0.00
CS5_A_DriverPower	1797.90	0.00	0.00	3300.00	0.00
CS5_B_DriverPower	1797.90	0.00	0.00	3300.00	0.00
Gasoline_spec	0.70	0.70	3.50	1.00	0.00
HammarMishrif_DriverPower	2512.50	0.00	0.00	4400.00	0.00
Janubiya_A_DriverPower	5331.50	0.00	0.00	5900.00	0.00
Janubiya_B_DriverPower	5900.00	0.00	0.00	5900.00	0.00
KAZ_11_1.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.00	0.00	0.00	1.00	16.46
KAZ_11_2.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.00	0.00	0.00	1.00	16.48
KAZ_12_1.C_01.column.SIZE_trayed(1).max_flooding_percentage	1.00	0.00	0.00	1.00	7.44
KAZ_12_1.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.44	0.00	0.00	1.00	0.00
KAZ_12_2.C_01.column.SIZE_trayed(1).max_flooding_percentage	1.00	0.00	0.00	1.00	8.44
KAZ_12_2.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.31	0.00	0.00	1.00	0.00
KAZ_12_3.C_01.column.SIZE_trayed(1).max_flooding_percentage	1.00	0.00	0.00	1.00	7.43
KAZ_12_3.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.42	0.00	0.00	1.00	0.00
Markazia_A_DriverPower	4728.10	0.00	0.00	5900.00	0.00
Markazia_B_DriverPower	4814.90	0.00	0.00	5900.00	0.00
Markazia_C_DriverPower	4844.10	0.00	0.00	5900.00	0.00
Markazia_D_DriverPower	4869.10	0.00	0.00	5900.00	0.00
NR_NGL.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.00	0.00	0.00	1.00	23.51
Pipeline1_Mach	0.03	0.00	0.00	0.80	0.00
Pipeline28_Mach	0.00	0.00	0.00	0.80	0.00
Pipeline29A_Mach	0.01	0.00	0.00	0.80	0.00
Pipeline29B_Mach	0.01	0.00	0.00	0.80	0.00
Pipeline2_Mach	0.03	0.00	0.00	0.80	0.00

Appendix C: Constrained Variables for Single-Period Profitability Optimisation

Pipeline41_Mach	0.01	0.00	0.00	0.80	0.00
Pipeline42A_Mach	0.00	0.00	0.00	0.80	0.00
Pipeline7_Mach	0.01	0.00	0.00	0.80	0.00
Pipeline8_Mach	0.01	0.00	0.00	0.80	0.00
Propane_spec	0.70	0.70	87.05	1.00	0.00
Qurainat_A_1_DriverPower	2104.70	0.00	0.00	4350.00	0.00
Qurainat_A_2_DriverPower	2756.70	0.00	0.00	6100.00	0.00
Qurainat_B_1_DriverPower	2266.20	0.00	0.00	4350.00	0.00
Qurainat_B_2_DriverPower	2849.40	0.00	0.00	6100.00	0.00
Rafidiyah_DriverPower	628.13	0.00	0.00	2200.00	0.00
Shamiya_A_DriverPower	4825.40	0.00	0.00	6100.00	0.00
Shamiya_B_DriverPower	6075.40	0.00	0.00	6100.00	0.00
WQpipeline_Mach	0.01	0.00	0.00	0.80	0.00
Zubair_DriverPower	1435.70	0.00	0.00	4400.00	0.00

***shaded cells indicate an active bound**

Appendix D: gPROMS Equation Based Language for Gas Network

Model

Model Entity

PARAMETER

NoProduct AS INTEGER

Prices AS ARRAY (NoProduct) OF REAL

#Unit_cost AS FOREIGN_OBJECT "ExcelFO"

NoInputVar AS INTEGER

NoOutputVar AS INTEGER

Unit_cost_input AS ARRAY (NoInputVar) OF REAL

Unit_cost_output AS ARRAY (NoOutputVar) OF REAL

Period AS REAL

VARIABLE

Total_product as mass_flowrate

Yield_propane as fraction

Yield_butane as fraction

Yield_gasoline as fraction

Yield_dry_gas as fraction

Total_yield as fraction

Propane_spec as fraction

Butane_spec as fraction

Gasoline_spec as fraction

Total_Feed as mass_flowrate

Flare_total as mass_flowrate

Profit as dollars

Revenue as dollars

Total_cost as dollars

cost_InputVar as dollars

cost_OutputVar as dollars

InputVar AS ARRAY (NoInputVar) OF mass_flowrate

OutputVar AS ARRAY (NoOutputVar) OF duty

ProductRate AS ARRAY (NoProduct) OF mass_flowrate

Appendix D: gPROMS Equation Based Language for Gas Network Model

CS1_A_DriverPower as duty

CS1_B_DriverPower as duty

CS1_C_DriverPower as duty

CS2_DriverPower as duty

CS3_A_DriverPower as duty

CS3_B_DriverPower as duty

CS4_A_DriverPower as duty

CS4_B_DriverPower as duty

CS5_A_DriverPower as duty

CS5_B_DriverPower as duty

Shamiya_A_DriverPower as duty

Shamiya_B_DriverPower as duty

#For Qurainat first and second stages are on the same shaft while, third stage is on different shaft.

Qurainat_A_1_DriverPower as duty

Qurainat_A_2_DriverPower as duty

Qurainat_B_1_DriverPower as duty

Qurainat_B_2_DriverPower as duty

Markazia_A_DriverPower as duty

Markazia_B_DriverPower as duty

Markazia_C_DriverPower as duty

Markazia_D_DriverPower as duty

Janubiya_A_DriverPower as duty

Janubiya_B_DriverPower as duty

Zubair_DriverPower as duty

Rafidiyah_DriverPower as duty

HammarMishrif_DriverPower as duty

NGL_DeEthanizer_Refluxratio as molar_ratio

NGL_DeEthanizer_Boilupratio as molar_ratio

KAZ_11_1_DeEthanizer_Refluxratio as molar_ratio

KAZ_11_1_DeEthanizer_Boilupratio as molar_ratio

KAZ_11_2_DeEthanizer_Refluxratio as molar_ratio

KAZ_11_2_DeEthanizer_Boilupratio as molar_ratio

KAZ_12_1_DePropanizer_Refluxratio as molar_ratio

KAZ_12_1_DePropanizer_Boilupratio as molar_ratio

KAZ_12_1_DeButanizer_Refluxratio as molar_ratio

KAZ_12_1_DeButanizer_Boilupratio as molar_ratio

KAZ_12_2_DePropanizer_Refluxratio as molar_ratio

Appendix D: gPROMS Equation Based Language for Gas Network Model

KAZ_12_2_DePropanizer_Boilupratio as molar_ratio

KAZ_12_2_DeButanizer_Refluxratio as molar_ratio

KAZ_12_2_DeButanizer_Boilupratio as molar_ratio

KAZ_12_3_DePropanizer_Refluxratio as molar_ratio

KAZ_12_3_DePropanizer_Boilupratio as molar_ratio

KAZ_12_3_DeButanizer_Refluxratio as molar_ratio

KAZ_12_3_DeButanizer_Boilupratio as molar_ratio

Pipeline1_Mach as fraction

Pipeline2_Mach as fraction

Pipeline7_Mach as fraction

Pipeline8_Mach as fraction

Pipeline28_Mach as fraction

Pipeline29A_Mach as fraction

Pipeline29B_Mach as fraction

Pipeline41_Mach as fraction

Pipeline42A_Mach as fraction

WQpipeline_Mach as fraction

UNIT

CS2 AS CS_1T

CS5 AS CS_2T

NR_NGL AS NGL_detail

GTU_NR AS sink_material_gML

CS2_HP AS HP_Freeflow

pipeline10 AS Pipe_distributed_gML

pipeline4 AS Pipe_distributed_gML

pipeline3 AS Pipe_distributed_gML

CS5_HP AS HP_Freeflow

pipeline9 AS Pipe_distributed_gML

CS4 AS CS_2T

CS4_HP AS HP_Freeflow

Shamiya AS CS_2T_SR

pipeline29A AS Pipe_distributed_gML

GTU_11_1 AS sink_material_gML

Gasoline AS sink_material_gML

KAZ_12_1 AS LPG_detail

Appendix D: gPROMS Equation Based Language for Gas Network Model

Propane AS sink_material_gML
Butane AS sink_material_gML
CS1 AS CS_3T
pipeline2 AS pipe_gML
Janubiya AS CS_2T_SR
pipeline41 AS Pipe_distributed_gML
pipeline1 AS pipe_gML
CS1_HP AS HP_Freeflow
Qurainat AS CS_2T_SR
pipeline29B AS Pipe_distributed_gML
pipeline6 AS Pipe_distributed_gML
pipeline5 AS Pipe_distributed_gML
CS3_HP AS HP_Freeflow
CS3 AS CS_2T
KAZ_11_1 AS NGL_detail
FirstStage_SC AS Slugcatcher
OtherStage_SC AS Slugcatcher
K1 AS Booster
K2 AS Booster
S_1 AS Mixer_gML
KAZ_SC AS Slugcatcher
K_02 AS Booster
S_2 AS Mixer_gML
SA1 AS Stream_analyzer_gML
SA2 AS Stream_analyzer_gML
NR_Liq_Stripper AS Liquid_Stripper
Liq_Stripper_11_1 AS Liquid_Stripper
pipeline28 AS Pipe_distributed_gML
S_001 AS Mixer_gML
S_002 AS Mixer_gML
S_QU AS Splitter_gML
pipeline42A AS Pipe_distributed_gML
pipeline42B AS Pipe_distributed_gML
S_003 AS Mixer_gML
S_Ja AS Splitter_gML
S_SH AS Splitter_gML
Zubair AS CS_Recip

Appendix D: gPROMS Equation Based Language for Gas Network Model

```
pipeline43 AS Pipe_distributed_gML
HammarMishrif AS CS_Recip
S_006 AS Mixer_gML
S_007 AS Mixer_gML
S_008 AS Splitter_gML
KAZ_12_2 AS LPG_detail
KAZ_12_3 AS LPG_detail
S_009 AS Mixer_gML
S_010 AS Mixer_gML
S_011 AS Mixer_gML
S_012 AS Splitter_gML
K_001 AS Booster
KAZ_11_2 AS NGL_detail
Liq_Stripper_11_2 AS Liquid_Stripper
GTU_11_2 AS sink_material_gML
S_013 AS Splitter_gML
Rafidiyah AS CS_Recip
pipeline7 AS Pipe_distributed_gML
pipeline8 AS Pipe_distributed_gML
S_014 AS Mixer_gML
S_015 AS Mixer_gML
Markazia AS CS_4T_SR
S_Mk AS Splitter_gML
Hammar AS HP_Freeflow
ZubairMishrif AS HP_Freeflow
IBC AS Booster
CS8 AS HP_Freeflow
S_017 AS Mixer_gML
WQpipeline AS Pipe_distributed_gML
CS7 AS HP_Freeflow
SA_propane AS Stream_analyzer_gML
SA002 AS Stream_analyzer_gML
SA003 AS Stream_analyzer_gML

SET

# Start Dynamic Connections
Butane.nset := 0;
```

```
FirstStage_SC.number_inlets := 4;

Gasoline.nset := 0;

GTU_11_1.nset := 0;

GTU_11_2.nset := 0;

GTU_NR.nset := 0;

KAZ_11_1.number_inlet := 2;

KAZ_11_2.number_inlet := 2;

KAZ_12_1.number_inlets := 1;

KAZ_12_2.number_inlets := 1;

KAZ_12_3.number_inlets := 1;

KAZ_SC.number_inlets := 3;

Liq_Stripper_11_1.number_inlets := 2;

Liq_Stripper_11_2.number_inlets := 2;

NR_Liq_Stripper.number_inlets := 5;

NR_NGL.number_inlet := 4;

OtherStage_SC.number_inlets := 5;

pipeline1.nset := 0;

pipeline2.nset := 0;

pipeline3.nset := 0;

pipeline4.nset := 0;

pipeline5.nset := 0;

pipeline6.nset := 0;

pipeline7.nset := 0;

pipeline8.nset := 0;

pipeline9.nset := 0;

pipeline10.nset := 0;

pipeline28.nset := 0;

pipeline29A.nset := 0;

pipeline29B.nset := 0;

pipeline41.nset := 0;

pipeline42A.nset := 0;

pipeline42B.nset := 0;

pipeline43.nset := 0;

Propane.nset := 0;

SA1.nset := 0;

SA2.nset := 0;

SA002.nset := 0;
```

```
SA003.nset := 0;

SA_propane.nset := 0;

S_1.no_inlets := 2;

S_1.nset := 0;

S_001.no_inlets := 2;

S_001.nset := 0;

S_2.no_inlets := 4;

S_2.nset := 0;

S_002.no_inlets := 4;

S_002.nset := 0;

S_003.no_inlets := 3;

S_003.nset := 0;

S_006.no_inlets := 4;

S_006.nset := 0;

S_007.no_inlets := 2;

S_007.nset := 0;

S_008.no_splits := 3;

S_008.nset := 0;

S_009.no_inlets := 3;

S_009.nset := 0;

S_010.no_inlets := 3;

S_010.nset := 0;

S_011.no_inlets := 3;

S_011.nset := 0;

S_012.no_splits := 2;

S_012.nset := 0;

S_013.no_splits := 2;

S_013.nset := 0;

S_014.no_inlets := 2;

S_014.nset := 0;

S_015.no_inlets := 2;

S_015.nset := 0;

S_017.no_inlets := 2;

S_017.nset := 0;

S_Ja.no_splits := 2;

S_Ja.nset := 0;

S_Mk.no_splits := 2;
```

Appendix D: gPROMS Equation Based Language for Gas Network Model

```
S_Mk.nset := 0;

S_QU.no_splits := 2;

S_QU.nset := 0;

S_SH.no_splits := 2;

S_SH.nset := 0;

WQpipeline.nset := 0;

# End Dynamic Connections


Period:= 1; #Period duration in seconds

NoProduct:=4;

Prices:= [0.18, 0.70, 0.65, 0.7];

#Unit_cost:="Optimisation_input.xlsx";

NoInputVar:=55;

NoOutputVar:=68;

For i:=1 TO NoInputVar DO

Unit_cost_input(i):=0.035; #$/kg

END


#Electricity input cost

For i:=1 TO 50 DO

Unit_cost_output(i):=0.1/3600; #$/kW-sec

END


#Heating input cost

For i:=51 TO NoOutputVar DO

Unit_cost_output(i):=0.019/1000; #$/kJ

END


#For i:=(NoOutputVar-1) TO NoOutputVar DO

#Unit_cost_output(i):=0.07;

#END


TOPOLOGY

CS5.Outlet = pipeline10.inlet;

CS2_HP.Outlet = pipeline3.inlet;

CS2.Outlet = pipeline4.inlet;
```

```
CS5_HP.Outlet = pipeline9.inlet;

CS1.Outlet = pipeline2.inlet;

CS1_HP.Outlet = pipeline1.inlet;

CS3_HP.Outlet = pipeline5.inlet;

CS3.Outlet = pipeline6.inlet;

NR_NGL.GTU = GTU_NR.inlet;

pipeline5.outlet = FirstStage_SC.Inlet(2);

pipeline3.outlet = FirstStage_SC.Inlet(3);

pipeline1.outlet = FirstStage_SC.Inlet(4);

pipeline6.outlet = OtherStage_SC.Inlet(2);

pipeline4.outlet = OtherStage_SC.Inlet(3);

pipeline2.outlet = OtherStage_SC.Inlet(4);

FirstStage_SC.Gas = K1.Inlet;

OtherStage_SC.Gas = K2.Inlet;

K1.Outlet = NR_NGL.Feed(1);

K2.Outlet = NR_NGL.Feed(2);

pipeline41.outlet = KAZ_SC.Inlet(1);

K_02.Outlet = KAZ_11_1.Feed(1);

KAZ_11_1.GTU = GTU_11_1.inlet;

KAZ_11_1.Liquids = S_2.inlet(1);

S_1.outlet = SA1.inlet;

S_2.outlet = SA2.inlet;

FirstStage_SC.Liquids = NR_Liq_Stripper.Inlet(1);

OtherStage_SC.Liquids = NR_Liq_Stripper.Inlet(2);

K1.Liquid = NR_Liq_Stripper.Inlet(3);

K2.Liquid = NR_Liq_Stripper.Inlet(4);

NR_Liq_Stripper.Gas = NR_NGL.Feed(3);

NR_Liq_Stripper.Liquids = S_1.inlet(1);

NR_NGL.Liquids = S_1.inlet(2);

K_02.Liquid = Liq_Stripper_11_1.Inlet(1);

Liq_Stripper_11_1.Gas = KAZ_11_1.Feed(2);

Liq_Stripper_11_1.Liquids = S_2.inlet(2);

SA1.outlet = pipeline28.inlet;

Qurainat.Outlet = S_QU.Inlet;

pipeline29A.outlet = S_003.inlet(1);

pipeline29B.outlet = S_003.inlet(2);

S_003.outlet = pipeline41.inlet;
```

```
Janubiya.Outlet = S_Ja.Inlet;

S_Ja.Outlet(1) = pipeline29A.inlet;

Shamiya.Outlet = S_SH.Inlet;

S_SH.Outlet(1) = S_001.inlet(1);

S_QU.Outlet(1) = S_001.inlet(2);

S_001.outlet = pipeline29B.inlet;

S_Ja.Outlet(2) = S_002.inlet(1);

S_SH.Outlet(2) = S_002.inlet(2);

S_QU.Outlet(2) = S_002.inlet(3);

S_002.outlet = pipeline42A.inlet;

pipeline42A.outlet = pipeline42B.inlet;

pipeline42B.outlet = OtherStage_SC.Inlet(5);

pipeline43.outlet = KAZ_SC.Inlet(2);

Zubair.Outlet = S_006.inlet(1);

HammarMishrif.Outlet = S_006.inlet(2);

S_006.outlet = pipeline43.inlet;

SA2.outlet = S_007.inlet(1);

pipeline28.outlet = S_007.inlet(2);

S_007.outlet = S_008.Inlet;

S_008.Outlet(1) = KAZ_12_3.Inlet(1);

S_008.Outlet(2) = KAZ_12_2.Inlet(1);

S_008.Outlet(3) = KAZ_12_1.Inlet(1);

KAZ_12_3.Propane = S_009.inlet(1);

KAZ_12_3.Butane = S_010.inlet(1);

KAZ_12_3.Gasoline = S_011.inlet(1);

KAZ_12_2.Propane = S_009.inlet(2);

KAZ_12_2.Butane = S_010.inlet(2);

KAZ_12_2.Gasoline = S_011.inlet(2);

KAZ_12_1.Propane = S_009.inlet(3);

KAZ_12_1.Butane = S_010.inlet(3);

KAZ_12_1.Gasoline = S_011.inlet(3);

K_001.Outlet = KAZ_11_2.Feed(1);

KAZ_11_2.GTU = GTU_11_2.inlet;

K_001.Liquid = Liq_Stripper_11_2.Inlet(1);

Liq_Stripper_11_2.Gas = KAZ_11_2.Feed(2);

KAZ_SC.Gas = S_012.Inlet;

S_012.Outlet(1) = K_02.Inlet;
```

Appendix D: gPROMS Equation Based Language for Gas Network Model

```
S_012.Outlet(2) = K_001.Inlet;

KAZ_SC.Liquids = S_013.Inlet;

S_013.Outlet(1) = Liq_Stripper_11_1.Inlet(2);
S_013.Outlet(2) = Liq_Stripper_11_2.Inlet(2);

KAZ_11_2.Liquids = S_2.inlet(3);

Liq_Stripper_11_2.Liquids = S_2.inlet(4);

Rafidiyah.Outlet = KAZ_SC.Inlet(3);

pipeline7.outlet = FirstStage_SC.Inlet(1);

pipeline9.outlet = S_014.inlet(2);

S_014.outlet = pipeline7.inlet;

S_015.outlet = pipeline8.inlet;

pipeline8.outlet = OtherStage_SC.Inlet(1);

pipeline10.outlet = S_015.inlet(2);

CS4_HP.Outlet = S_014.inlet(1);

CS4.Outlet = S_015.inlet(1);

Markazia.Outlet = S_Mk.Inlet;

S_Mk.Outlet(1) = S_003.inlet(3);

S_Mk.Outlet(2) = S_002.inlet(4);

Hammar.Outlet = S_006.inlet(3);

ZubairMishrif.Outlet = S_006.inlet(4);

S_017.outlet = WQpipeline.inlet;

CS7.Outlet = S_017.inlet(1);

CS8.Outlet = S_017.inlet(2);

WQpipeline.outlet = IBC.Inlet;

IBC.Outlet = NR_NGL.Feed(4);

IBC.Liquid = NR_Liq_Stripper.Inlet(5);

S_009.outlet = SA_propane.inlet;

SA_propane.outlet = Propane.inlet;

S_010.outlet = SA003.inlet;

SA003.outlet = Butane.inlet;

S_011.outlet = SA002.inlet;

SA002.outlet = Gasoline.inlet;
```

EQUATION

Model equations

Total_product=Propane.inlet.F + Butane.inlet.F + Gasoline.inlet.F + GTU_NR.inlet.F + GTU_11_1.inlet.F + GTU_11_2.inlet.F;

Appendix D: gPROMS Equation Based Language for Gas Network Model

#Spec checks

Propane_spec= Propane.REP().Molar_fraction("PROPANE");

Butane_spec= Butane.REP().Molar_fraction("IBUTANE")+ Butane.REP().Molar_fraction("NBUTANE");

Gasoline_spec=
Gasoline.REP().Molar_fraction("IPENTANE")+Gasoline.REP().Molar_fraction("NPENTANE")+Gasoline.REP().Molar_fraction("HEXANE")
);

Compressor Duty constraints definition

CS1_A_DriverPower = CS1.K3A.P_t + CS1.K4A.P_t;

CS1_B_DriverPower = CS1.K3B.P_t + CS1.K4B.P_t;

CS1_C_DriverPower = CS1.K3C.P_t + CS1.K4C.P_t;

CS2_DriverPower = CS2.K3.P_t + CS2.K4.P_t;

CS3_A_DriverPower = CS3.K3A.P_t + CS3.K4A.P_t;

CS3_B_DriverPower = CS3.K3B.P_t + CS3.K4B.P_t;

CS4_A_DriverPower = CS4.K3A.P_t + CS4.K4A.P_t;

CS4_B_DriverPower = CS4.K3B.P_t + CS4.K4B.P_t;

CS5_A_DriverPower = CS5.K3A.P_t + CS5.K4A.P_t;

CS5_B_DriverPower = CS5.K3B.P_t + CS5.K4B.P_t;

Shamiya_A_DriverPower = Shamiya.K3_1A.P_t + Shamiya.K3_2A.P_t + Shamiya.K4A.P_t;

Shamiya_B_DriverPower = Shamiya.K3_1B.P_t + Shamiya.K3_2B.P_t + Shamiya.K4B.P_t;

#For Qurainat first and second stages are on the same shaft while, third stage is on different shaft.

Qurainat_A_1_DriverPower = Qurainat.K3_1A.P_t + Qurainat.K3_2A.P_t;

Qurainat_A_2_DriverPower = Qurainat.K4A.P_t;

Qurainat_B_1_DriverPower = Qurainat.K3_1B.P_t + Qurainat.K3_2B.P_t;

Qurainat_B_2_DriverPower = Qurainat.K4B.P_t;

Markazia_A_DriverPower = Markazia.K3_1A.P_t + Markazia.K3_2A.P_t + Markazia.K4A.P_t;

Markazia_B_DriverPower = Markazia.K3_1B.P_t + Markazia.K3_2B.P_t + Markazia.K4B.P_t;

Markazia_C_DriverPower = Markazia.K3_1C.P_t + Markazia.K3_2C.P_t + Markazia.K4C.P_t;

Markazia_D_DriverPower = Markazia.K3_1D.P_t + Markazia.K3_2D.P_t + Markazia.K4D.P_t;

Janubiya_A_DriverPower = Janubiya.K3_1A.P_t + Janubiya.K3_2A.P_t + Janubiya.K4A.P_t;

Janubiya_B_DriverPower = Janubiya.K3_1B.P_t + Janubiya.K3_2B.P_t + Janubiya.K4B.P_t;

Zubair_DriverPower = Zubair.K101.P + Zubair.K102.P;

Rafidiyah_DriverPower = Rafidiyah.K101.P + Rafidiyah.K102.P;

HammarMishrif_DriverPower = HammarMishrif.K101.P + HammarMishrif.K102.P;

#Input variables for profit optimisation

InputVar(1)= CS1.Stage2A.SP_F_w.mass_flowrate;

InputVar(2)= CS1.Stage3A.SP_F_w.mass_flowrate;
InputVar(3)= CS1.Stage2B.SP_F_w.mass_flowrate;
InputVar(4)= CS1.Stage3B.SP_F_w.mass_flowrate;
InputVar(5)= CS1.Stage2C.SP_F_w.mass_flowrate;
InputVar(6)= CS1.Stage3C.SP_F_w.mass_flowrate;
InputVar(7)= CS2.Stage2.SP_F_w.mass_flowrate;
InputVar(8)= CS2.Stage3.SP_F_w.mass_flowrate;
InputVar(9)= CS3.Stage2A.SP_F_w.mass_flowrate;
InputVar(10)= CS3.Stage3A.SP_F_w.mass_flowrate;
InputVar(11)= CS3.Stage2B.SP_F_w.mass_flowrate;
InputVar(12)= CS3.Stage3B.SP_F_w.mass_flowrate;
InputVar(13)= CS4.Stage2A.SP_F_w.mass_flowrate;
InputVar(14)= CS4.Stage3A.SP_F_w.mass_flowrate;
InputVar(15)= CS4.Stage2B.SP_F_w.mass_flowrate;
InputVar(16)= CS4.Stage3B.SP_F_w.mass_flowrate;
InputVar(17)= CS5.Stage2A.SP_F_w.mass_flowrate;
InputVar(18)= CS5.Stage3A.SP_F_w.mass_flowrate;
InputVar(19)= CS5.Stage2B.SP_F_w.mass_flowrate;
InputVar(20)= CS5.Stage3B.SP_F_w.mass_flowrate;
InputVar(21)= CS1_HP.Stage1.SP_F_w.mass_flowrate;
InputVar(22)= CS2_HP.Stage1.SP_F_w.mass_flowrate;
InputVar(23)= CS3_HP.Stage1.SP_F_w.mass_flowrate;
InputVar(24)= CS4_HP.Stage1.SP_F_w.mass_flowrate;
InputVar(25)= CS5_HP.Stage1.SP_F_w.mass_flowrate;
InputVar(26)= CS7.Stage1.SP_F_w.mass_flowrate;
InputVar(27)= CS8.Stage1.SP_F_w.mass_flowrate;
InputVar(28)= Qurainat.Stage2A.SP_F_w.mass_flowrate;
InputVar(29)= Qurainat.Stage3A.SP_F_w.mass_flowrate;
InputVar(30)= Qurainat.Stage2B.SP_F_w.mass_flowrate;
InputVar(31)= Qurainat.Stage3B.SP_F_w.mass_flowrate;
InputVar(32)= Shamiya.Stage2A.SP_F_w.mass_flowrate;
InputVar(33)= Shamiya.Stage3A.SP_F_w.mass_flowrate;
InputVar(34)= Shamiya.Stage2B.SP_F_w.mass_flowrate;
InputVar(35)= Shamiya.Stage3B.SP_F_w.mass_flowrate;
InputVar(36)= Janubiya.Stage2A.SP_F_w.mass_flowrate;
InputVar(37)= Janubiya.Stage3A.SP_F_w.mass_flowrate;
InputVar(38)= Janubiya.Stage2B.SP_F_w.mass_flowrate;

Appendix D: gPROMS Equation Based Language for Gas Network Model

```
InputVar(39)= Janubiya.Stage3B.SP_F_w.mass_flowrate;

InputVar(40)= Markazia.Stage2A.SP_F_w.mass_flowrate;

InputVar(41)= Markazia.Stage2B.SP_F_w.mass_flowrate;

InputVar(42)= Markazia.Stage2C.SP_F_w.mass_flowrate;

InputVar(43)= Markazia.Stage2D.SP_F_w.mass_flowrate;

InputVar(44)= Markazia.Stage3A.SP_F_w.mass_flowrate;

InputVar(45)= Markazia.Stage3B.SP_F_w.mass_flowrate;

InputVar(46)= Markazia.Stage3C.SP_F_w.mass_flowrate;

InputVar(47)= Markazia.Stage3D.SP_F_w.mass_flowrate;

InputVar(48)= Zubair.First_HP.SP_F_w.mass_flowrate;

InputVar(49)= Zubair.First_LP.SP_F_w.mass_flowrate;

InputVar(50)= ZubairMishrif.Stage1.SP_F_w.mass_flowrate;

InputVar(51)= Hammar.Stage1.SP_F_w.mass_flowrate;

InputVar(52)= HammarMishrif.First_HP.SP_F_w.mass_flowrate;

InputVar(53)= HammarMishrif.First_LP.SP_F_w.mass_flowrate;

InputVar(54)= Rafidiyah.First_HP.SP_F_w.mass_flowrate;

InputVar(55)= Rafidiyah.First_LP.SP_F_w.mass_flowrate;


Total_Feed= SIGMA(InputVar);

#Yield Equations


Yield_propane=Propane.inlet.F/Total_Feed;

Yield_butane=Butane.inlet.F/Total_Feed;

Yield_gasoline=Gasoline.inlet.F/ Total_Feed;

Yield_dry_gas= (GTU_NR.inlet.F+GTU_11_1.inlet.F+GTU_11_2.inlet.F)/Total_Feed;

Total_yield=Yield_dry_gas+Yield_propane+Yield_butane+Yield_gasoline;


Flare_total=Total_Feed-Total_product;


#Column variables for optimisation

NGL_DeEthanizer_Refluxratio=NR_NGL.C_2.REP().Reflux_ratio_molar;

NGL_DeEthanizer_Boilupratio=NR_NGL.C_2.REP().Boilup_ratio_molar;


KAZ_11_1_DeEthanizer_Refluxratio=KAZ_11_1.C_2.REP().Reflux_ratio_molar;

KAZ_11_1_DeEthanizer_Boilupratio=KAZ_11_1.C_2.REP().Boilup_ratio_molar;
```

Appendix D: gPROMS Equation Based Language for Gas Network Model

```
KAZ_11_2_DeEthanizer_Refluxratio=KAZ_11_2.C_2.REP().Reflux_ratio_molar;
KAZ_11_2_DeEthanizer_Boilupratio=KAZ_11_2.C_2.REP().Boilup_ratio_molar;

KAZ_12_1_DePropanizer_Refluxratio=KAZ_12_1.C_01.REP().Reflux_ratio_molar;
KAZ_12_1_DePropanizer_Boilupratio=KAZ_12_1.C_01.REP().Boilup_ratio_molar;
KAZ_12_1_DeButanizer_Refluxratio=KAZ_12_1.C_02.REP().Reflux_ratio_molar;
KAZ_12_1_DeButanizer_Boilupratio=KAZ_12_1.C_02.REP().Boilup_ratio_molar;

KAZ_12_2_DePropanizer_Refluxratio=KAZ_12_2.C_01.REP().Reflux_ratio_molar;
KAZ_12_2_DePropanizer_Boilupratio=KAZ_12_2.C_01.REP().Boilup_ratio_molar;
KAZ_12_2_DeButanizer_Refluxratio=KAZ_12_2.C_02.REP().Reflux_ratio_molar;
KAZ_12_2_DeButanizer_Boilupratio=KAZ_12_2.C_02.REP().Boilup_ratio_molar;

KAZ_12_3_DePropanizer_Refluxratio=KAZ_12_3.C_01.REP().Reflux_ratio_molar;
KAZ_12_3_DePropanizer_Boilupratio=KAZ_12_3.C_01.REP().Boilup_ratio_molar;
KAZ_12_3_DeButanizer_Refluxratio=KAZ_12_3.C_02.REP().Reflux_ratio_molar;
KAZ_12_3_DeButanizer_Boilupratio=KAZ_12_3.C_02.REP().Boilup_ratio_molar;

#Mach numbers for pipelines
Pipeline1_Mach=pipeline1.REP().Velocity/331; #Using speed of sound in air, m/s
Pipeline2_Mach=pipeline2.REP().Velocity/331;
Pipeline7_Mach=pipeline7.REP().Pipe_velocity(1)/331;
Pipeline8_Mach=pipeline8.REP().Pipe_velocity(1)/331;
Pipeline28_Mach=pipeline28.REP().Pipe_velocity(1)/331;
Pipeline29A_Mach =pipeline29A.REP().Pipe_velocity(1)/331;
Pipeline29B_Mach =pipeline29B.REP().Pipe_velocity(1)/331;
Pipeline41_Mach=pipeline41.REP().Pipe_velocity(1)/331; #Using speed of sound in air, m/s
Pipeline42A_Mach =pipeline42A.REP().Pipe_velocity(1)/331;
WQpipeline_Mach =WQpipeline.REP().Pipe_velocity(1)/331;

#Output Variables for profit optimisation
OutputVar(1)= CS1.K4A.energy.Energy;
OutputVar(2)= CS1.K3A.energy.Energy;
OutputVar(3)= CS1.K4B.energy.Energy;
OutputVar(4)= CS1.K3B.energy.Energy;
OutputVar(5)= CS1.K4C.energy.Energy;
OutputVar(6)= CS1.K3C.energy.Energy;
```

OutputVar(7)= CS2.K4.energy.Energy;
OutputVar(8)= CS2.K3.energy.Energy;
OutputVar(9)= CS3.K4A.energy.Energy;
OutputVar(10)= CS3.K3A.energy.Energy;
OutputVar(11)= CS3.K4B.energy.Energy;
OutputVar(12)= CS3.K3B.energy.Energy;
OutputVar(13)= CS4.K4A.energy.Energy;
OutputVar(14)= CS4.K3A.energy.Energy;
OutputVar(15)= CS4.K4B.energy.Energy;
OutputVar(16)= CS4.K3B.energy.Energy;
OutputVar(17)= CS5.K4A.energy.Energy;
OutputVar(18)= CS5.K3A.energy.Energy;
OutputVar(19)= CS5.K4B.energy.Energy;
OutputVar(20)= CS5.K3B.energy.Energy;
OutputVar(21)= Shamiya.K3_1A.energy.Energy;
OutputVar(22)= Shamiya.K3_1B.energy.Energy;
OutputVar(23)= Shamiya.K3_2A.energy.Energy;
OutputVar(24)= Shamiya.K3_2B.energy.Energy;
OutputVar(25)= Shamiya.K4A.energy.Energy;
OutputVar(26)= Shamiya.K4B.energy.Energy;
OutputVar(27)= Janubiya.K3_1A.energy.Energy;
OutputVar(28)= Janubiya.K3_1B.energy.Energy;
OutputVar(29)= Janubiya.K3_2A.energy.Energy;
OutputVar(30)= Janubiya.K3_2B.energy.Energy;
OutputVar(31)= Janubiya.K4A.energy.Energy;
OutputVar(32)= Janubiya.K4B.energy.Energy;
OutputVar(33)= Qurainat.K3_1A.energy.Energy;
OutputVar(34)= Qurainat.K3_1B.energy.Energy;
OutputVar(35)= Qurainat.K3_2A.energy.Energy;
OutputVar(36)= Qurainat.K3_2B.energy.Energy;
OutputVar(37)= Qurainat.K4A.energy.Energy;
OutputVar(38)= Qurainat.K4B.energy.Energy;
OutputVar(39)= Markazia.K3_1A.energy.Energy;
OutputVar(40)= Markazia.K3_1B.energy.Energy;
OutputVar(41)= Markazia.K3_1C.energy.Energy;
OutputVar(42)= Markazia.K3_1D.energy.Energy;
OutputVar(43)= Markazia.K3_2A.energy.Energy;

Appendix D: gPROMS Equation Based Language for Gas Network Model

```
OutputVar(44)= Markazia.K3_2B.energy.Energy;

OutputVar(45)= Markazia.K3_2C.energy.Energy;

OutputVar(46)= Markazia.K3_2D.energy.Energy;

OutputVar(47)= Markazia.K4A.energy.Energy;

OutputVar(48)= Markazia.K4B.energy.Energy;

OutputVar(49)= Markazia.K4C.energy.Energy;

OutputVar(50)= Markazia.K4D.energy.Energy;


OutputVar(51)=-NR_NGL.C_2.REP().Condenser_heat_duty; #in KJ/sec

OutputVar(52)=NR_NGL.C_2.REP().Reboiler_heat_duty; #in KJ/sec

OutputVar(53)=-KAZ_11_1.C_2.REP().Condenser_heat_duty; #in KJ/sec

OutputVar(54)=KAZ_11_1.C_2.REP().Reboiler_heat_duty; #in KJ/sec

OutputVar(55)=-KAZ_11_2.C_2.REP().Condenser_heat_duty; #in KJ/sec

OutputVar(56)=KAZ_11_2.C_2.REP().Reboiler_heat_duty; #in KJ/sec

OutputVar(57)=-KAZ_12_1.C_01.REP().Condenser_heat_duty; #in KJ/sec

OutputVar(58)=KAZ_12_1.C_01.REP().Reboiler_heat_duty; #in KJ/sec

OutputVar(59)=-KAZ_12_1.C_02.REP().Condenser_heat_duty; #in KJ/sec

OutputVar(60)=KAZ_12_1.C_02.REP().Reboiler_heat_duty; #in KJ/sec

OutputVar(61)=-KAZ_12_2.C_01.REP().Condenser_heat_duty; #in KJ/sec

OutputVar(62)=KAZ_12_2.C_01.REP().Reboiler_heat_duty; #in KJ/sec

OutputVar(63)=-KAZ_12_2.C_02.REP().Condenser_heat_duty; #in KJ/sec

OutputVar(64)=KAZ_12_2.C_02.REP().Reboiler_heat_duty; #in KJ/sec

OutputVar(65)=-KAZ_12_3.C_01.REP().Condenser_heat_duty; #in KJ/sec

OutputVar(66)=KAZ_12_3.C_01.REP().Reboiler_heat_duty; #in KJ/sec

OutputVar(67)=-KAZ_12_3.C_02.REP().Condenser_heat_duty; #in KJ/sec

OutputVar(68)=KAZ_12_3.C_02.REP().Reboiler_heat_duty; #in KJ/sec


#Product rate variables for profit optimisation

ProductRate(1)=GTU_NR.inlet.F + GTU_11_1.inlet.F + GTU_11_2.inlet.F;

ProductRate(2)=Propane.inlet.F;

ProductRate(3)=Butane.inlet.F;

ProductRate(4)= Gasoline.inlet.F;


#Cost Calculation

cost_InputVar = SIGMA(InputVar*Unit_cost_input);

cost_OutputVar = SIGMA(OutputVar*Unit_cost_output);

Total_cost= cost_InputVar+cost_OutputVar; # $/sec
```

```
#Profit Calculations

Revenue=SIGMA(ProductRate*Prices); #$/sec

Profit=Period*(Revenue-Total_cost);


INITIALISATION_PROCEDURE default_initialisation_procedure DEFAULT

# Start Initialisation Procedure Specifications

USE

  Liq_Stripper_11_1 : DEFAULT;

  Liq_Stripper_11_2 : DEFAULT;

  NR_Liq_Stripper : DEFAULT;

  pipeline1 : Init;

  pipeline10 : Init;

  pipeline2 : Init;

  pipeline28 : Init;

  pipeline29A : Init;

  pipeline29B : Init;

  pipeline3 : Init;

  pipeline4 : Init;

  pipeline41 : Init;

  pipeline42A : Init;

  pipeline42B : Init;

  pipeline43 : Init;

  pipeline5 : Init;

  pipeline6 : Init;

  pipeline7 : Init;

  pipeline8 : Init;

  pipeline9 : Init;

  WQpipeline : Init;

END

# End Initialisation Procedure Specifications
```

Process Entity

The process entity consists of 18,553 lines of gPROMS language code and is not included here.

It defines the physical property calculations and conservation equations in each of the unit models in the network.

Appendix E: Gradient of Decision Variables near Optimal Profit point

Decision Variable	Gradient Value
Flowsheet.NR_NGL.C_2.REP(1).Reflux_ratio_molar(1)	20.4066
Flowsheet.KAZ_11_2.C_2.REP(1).Reflux_ratio_molar(1)	9.98317
Flowsheet.KAZ_11_1.C_2.REP(1).Reflux_ratio_molar(1)	9.91773
Flowsheet.NR_NGL.C_2.REP(1).Boilup_ratio_molar(1)	5.80563
Flowsheet.KAZ_11_1.C_2.REP(1).Boilup_ratio_molar(1)	4.96692
Flowsheet.KAZ_11_2.C_2.REP(1).Boilup_ratio_molar(1)	4.95645
Flowsheet.S_Mk.ms.SP_split(1).S_spec(1)	2.09074
Flowsheet.S_Ja.ms.SP_split(1).S_spec(1)	1.45508
Flowsheet.S_SH.ms.SP_split(1).S_spec(1)	1.41045
Flowsheet.S_QU.ms.SP_split(1).S_spec(1)	1.13233
Flowsheet.Shamiya.Stage2B.SP_F_w.mass_flowrate	0.877549
Flowsheet.Janubiya.Stage2B.SP_F_w.mass_flowrate	0.862922
Flowsheet.Janubiya.Stage2A.SP_F_w.mass_flowrate	0.604691
Flowsheet.Qurainat.Stage2A.SP_F_w.mass_flowrate	0.538405
Flowsheet.Markazia.Stage2A.SP_F_w.mass_flowrate	0.531921
Flowsheet.Qurainat.Stage2B.SP_F_w.mass_flowrate	0.526754
Flowsheet.Shamiya.Stage2A.SP_F_w.mass_flowrate	0.500286
Flowsheet.Markazia.Stage2D.SP_F_w.mass_flowrate	0.478339
Flowsheet.Markazia.Stage2C.SP_F_w.mass_flowrate	0.474961
Flowsheet.Markazia.Stage2B.SP_F_w.mass_flowrate	0.471139
Flowsheet.CS5.Stage3A.SP_F_w.mass_flowrate	0.405814
Flowsheet.CS5.Stage3B.SP_F_w.mass_flowrate	0.40141
Flowsheet.CS3.Stage3B.SP_F_w.mass_flowrate	0.399469
Flowsheet.CS1.Stage3A.SP_F_w.mass_flowrate	0.393284
Flowsheet.CS1.Stage3B.SP_F_w.mass_flowrate	0.393284
Flowsheet.CS1.Stage3C.SP_F_w.mass_flowrate	0.393284
Flowsheet.CS4.Stage3A.SP_F_w.mass_flowrate	0.393042
Flowsheet.CS4.Stage3B.SP_F_w.mass_flowrate	0.393042
Flowsheet.Shamiya.Stage3B.SP_F_w.mass_flowrate	0.381649

Flowsheet.CS3.Stage3A.SP_F_w.mass_flowrate	0.380947
Flowsheet.Janubiya.Stage3B.SP_F_w.mass_flowrate	0.362603
Flowsheet.Rafidiyah.First_LP.SP_F_w.mass_flowrate	0.340537
Flowsheet.CS2_HP.Stage1.SP_F_w.mass_flowrate	0.339944
Flowsheet.Zubair.First_LP.SP_F_w.mass_flowrate	0.338758
Flowsheet.HammarMishrif.First_LP.SP_F_w.mass_flowrate	0.338753
Flowsheet.KAZ_12_2.C_02.REP(1).Boilup_ratio_molar(1)	0.32816
Flowsheet.CS5.Stage2B.SP_F_w.mass_flowrate	0.314102
Flowsheet.CS4.Stage2A.SP_F_w.mass_flowrate	0.307785
Flowsheet.CS4.Stage2B.SP_F_w.mass_flowrate	0.307785
Flowsheet.CS2.Stage2.SP_F_w.mass_flowrate	0.307531
Flowsheet.CS5.Stage2A.SP_F_w.mass_flowrate	0.306021
Flowsheet.CS3.Stage2B.SP_F_w.mass_flowrate	0.304891
Flowsheet.Janubiya.Stage3A.SP_F_w.mass_flowrate	0.296589
Flowsheet.KAZ_12_1.C_01.REP(1).Reflux_ratio_molar(1)	0.290352
Flowsheet.CS2.Stage3.SP_F_w.mass_flowrate	0.289629
Flowsheet.Qurainat.Stage3B.SP_F_w.mass_flowrate	0.28808
Flowsheet.Markazia.Stage3D.SP_F_w.mass_flowrate	0.281323
Flowsheet.Markazia.Stage3C.SP_F_w.mass_flowrate	0.280927
Flowsheet.Markazia.Stage3B.SP_F_w.mass_flowrate	0.280517
Flowsheet.KAZ_12_3.C_01.REP(1).Reflux_ratio_molar(1)	0.277481
Flowsheet.Shamiya.Stage3A.SP_F_w.mass_flowrate	0.273714
Flowsheet.CS3.Stage2A.SP_F_w.mass_flowrate	0.272602
Flowsheet.Qurainat.Stage3A.SP_F_w.mass_flowrate	0.271038
Flowsheet.CS1.Stage2A.SP_F_w.mass_flowrate	0.270824
Flowsheet.CS1.Stage2B.SP_F_w.mass_flowrate	0.270824
Flowsheet.CS1.Stage2C.SP_F_w.mass_flowrate	0.270824
Flowsheet.Markazia.Stage3A.SP_F_w.mass_flowrate	0.255621
Flowsheet.HammarMishrif.First_HP.SP_F_w.mass_flowrate	0.249785
Flowsheet.Zubair.First_HP.SP_F_w.mass_flowrate	0.249753
Flowsheet.Rafidiyah.First_HP.SP_F_w.mass_flowrate	0.249086
Flowsheet.Hammar.Stage1.SP_F_w.mass_flowrate	0.242869
Flowsheet.ZubairMishrif.Stage1.SP_F_w.mass_flowrate	0.242869

Flowsheet.CS1_HP.Stage1.SP_F_w.mass_flowrate	0.23936
Flowsheet.CS3_HP.Stage1.SP_F_w.mass_flowrate	0.228957
Flowsheet.CS4_HP.Stage1.SP_F_w.mass_flowrate	0.228957
Flowsheet.CS5_HP.Stage1.SP_F_w.mass_flowrate	0.228048
Flowsheet.CS7.Stage1.SP_F_w.mass_flowrate	0.228048
Flowsheet.CS8.Stage1.SP_F_w.mass_flowrate	0.228048
Flowsheet.KAZ_12_2.C_01.REP(1).Reflux_ratio_molar(1)	0.19326
Flowsheet.KAZ_12_1.C_02.REP(1).Boilup_ratio_molar(1)	0.163967
Flowsheet.KAZ_12_3.C_02.REP(1).Boilup_ratio_molar(1)	0.150178
Flowsheet.KAZ_12_2.C_02.REP(1).Reflux_ratio_molar(1)	0.123414
Flowsheet.KAZ_12_1.C_02.REP(1).Reflux_ratio_molar(1)	0.0760561
Flowsheet.KAZ_12_3.C_02.REP(1).Reflux_ratio_molar(1)	0.0730169
Flowsheet.KAZ_12_2.C_01.REP(1).Boilup_ratio_molar(1)	0.0528862
Flowsheet.KAZ_12_1.C_01.REP(1).Boilup_ratio_molar(1)	0.0305551
Flowsheet.KAZ_12_3.C_01.REP(1).Boilup_ratio_molar(1)	0.0241362

Appendix F: Constrained Variables for Profit Optimisation with Increased Propane Prices

Constrained Variable	Value	Lower Bound	Upper Bound
Flowsheet.Butane_spec	0.885225	0.72	1
Flowsheet.CS1_A_DriverPower	2110.41	0	4930
Flowsheet.CS1_B_DriverPower	2110.41	0	4930
Flowsheet.CS1_C_DriverPower	2110.41	0	4930
Flowsheet.CS2_DriverPower	1157.24	0	3300
Flowsheet.CS3_A_DriverPower	1589.23	0	2900
Flowsheet.CS3_B_DriverPower	1636.46	0	2900
Flowsheet.CS4_A_DriverPower	2398.54	0	4930
Flowsheet.CS4_B_DriverPower	2398.54	0	4930
Flowsheet.CS5_A_DriverPower	1784.07	0	3300
Flowsheet.CS5_B_DriverPower	1797.92	0	3300
Flowsheet.Gasoline_spec	0.6997	0.7[*]	1
Flowsheet.HammarMishrif_DriverPower	2512.51	0	4400
Flowsheet.Janubiya_A_DriverPower	4552.81	0	5900
Flowsheet.Janubiya_B_DriverPower	5900	0	5900
flowsheet.KAZ_11_1.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.00158	0	1[*]
flowsheet.KAZ_11_2.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.00159	0	1[*]
flowsheet.KAZ_12_1.C_01.column.SIZE_trayed(1).max_flooding_percentage	0.999686	0	1
flowsheet.KAZ_12_1.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.328192	0	1
flowsheet.KAZ_12_2.C_01.column.SIZE_trayed(1).max_flooding_percentage	0.999725	0	1
flowsheet.KAZ_12_2.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.411215	0	1
flowsheet.KAZ_12_3.C_01.column.SIZE_trayed(1).max_flooding_percentage	0.999714	0	1
flowsheet.KAZ_12_3.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.316066	0	1
Flowsheet.Markazia_A_DriverPower	4426.66	0	5900
Flowsheet.Markazia_B_DriverPower	4488.1	0	5900
Flowsheet.Markazia_C_DriverPower	4695.63	0	5900
Flowsheet.Markazia_D_DriverPower	4432.23	0	5900
flowsheet.NR_NGL.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.00041	0	1[*]
Flowsheet.Pipeline1_Mach	0.027366	0	0.8
Flowsheet.Pipeline28_Mach	0.004509	0	0.8
Flowsheet.Pipeline29A_Mach	0.007229	0	0.8
Flowsheet.Pipeline29B_Mach	0.00508	0	0.8
Flowsheet.Pipeline2_Mach	0.032322	0	0.8
Flowsheet.Pipeline41_Mach	0.008813	0	0.8
Flowsheet.Pipeline42A_Mach	8.12E-11	0	0.8
Flowsheet.Pipeline7_Mach	0.007243	0	0.8
Flowsheet.Pipeline8_Mach	0.01257	0	0.8
Flowsheet.Propane_spec	0.700018	0.7	1
Flowsheet.Qurainat_A_1_DriverPower	1891.97	0	4350
Flowsheet.Qurainat_A_2_DriverPower	2558.77	0	6100
Flowsheet.Qurainat_B_1_DriverPower	1981.74	0	4350
Flowsheet.Qurainat_B_2_DriverPower	2574.41	0	6100
Flowsheet.Rafidiyah_DriverPower	215.603	0	2200
Flowsheet.Shamiya_A_DriverPower	6094.51	0	6100
Flowsheet.Shamiya_B_DriverPower	4506.72	0	6100
Flowsheet.WQpipeline_Mach	0.010467	0	0.8
Flowsheet.Zubair_DriverPower	1175.44	0	4400

Appendix G: Constrained Variables for Profit Optimisation with Increased Butane Prices

Constrained Variable	Value	Lower Bound	Upper Bound
Flowsheet.Butane_spec	0.718673	0.72[*]	1
Flowsheet.CS1_A_DriverPower	2110.41	0	4930
Flowsheet.CS1_B_DriverPower	2110.41	0	4930
Flowsheet.CS1_C_DriverPower	2110.41	0	4930
Flowsheet.CS2_DriverPower	954.84	0	3300
Flowsheet.CS3_A_DriverPower	1582.43	0	2900
Flowsheet.CS3_B_DriverPower	1648.15	0	2900
Flowsheet.CS4_A_DriverPower	2639.09	0	4930
Flowsheet.CS4_B_DriverPower	2398.54	0	4930
Flowsheet.CS5_A_DriverPower	1814.55	0	3300
Flowsheet.CS5_B_DriverPower	1797.92	0	3300
Flowsheet.Gasoline_spec	0.864914	0.7	1
Flowsheet.HammarMishrif_DriverPower	2512.51	0	4400
Flowsheet.Janubiya_A_DriverPower	4979.65	0	5900
Flowsheet.Janubiya_B_DriverPower	5899.42	0	5900
flowsheet.KAZ_11_1.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.00029	0	1[*]
flowsheet.KAZ_11_2.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.00044	0	1[*]
flowsheet.KAZ_12_1.C_01.column.SIZE_trayed(1).max_flooding_percentage	1.00025	0	1[*]
flowsheet.KAZ_12_1.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.276844	0	1
flowsheet.KAZ_12_2.C_01.column.SIZE_trayed(1).max_flooding_percentage	1.00025	0	1[*]
flowsheet.KAZ_12_2.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.323566	0	1
flowsheet.KAZ_12_3.C_01.column.SIZE_trayed(1).max_flooding_percentage	1.0002	0	1[*]
flowsheet.KAZ_12_3.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.37934	0	1
Flowsheet.Markazia_A_DriverPower	4622.72	0	5900
Flowsheet.Markazia_B_DriverPower	4894.54	0	5900
Flowsheet.Markazia_C_DriverPower	4446.34	0	5900
Flowsheet.Markazia_D_DriverPower	5900	0	5900[*]
flowsheet.NR_NGL.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.00075	0	1[*]
Flowsheet.Pipeline1_Mach	0.027366	0	0.8
Flowsheet.Pipeline28_Mach	0.004473	0	0.8
Flowsheet.Pipeline29A_Mach	0.00707	0	0.8
Flowsheet.Pipeline29B_Mach	0.00521	0	0.8
Flowsheet.Pipeline2_Mach	0.032322	0	0.8
Flowsheet.Pipeline41_Mach	0.008919	0	0.8
Flowsheet.Pipeline42A_Mach	7.85E-11	0	0.8
Flowsheet.Pipeline7_Mach	0.007243	0	0.8
Flowsheet.Pipeline8_Mach	0.012725	0	0.8
Flowsheet.Propane_spec	0.699866	0.7[*]	1
Flowsheet.Qurainat_A_1_DriverPower	2013.33	0	4350
Flowsheet.Qurainat_A_2_DriverPower	2664.77	0	6100
Flowsheet.Qurainat_B_1_DriverPower	2625.36	0	4350
Flowsheet.Qurainat_B_2_DriverPower	3314.93	0	6100
Flowsheet.Rafidiyah_DriverPower	628.128	0	2200
Flowsheet.Shamiya_A_DriverPower	4970.58	0	6100
Flowsheet.Shamiya_B_DriverPower	6082.45	0	6100
Flowsheet.WQpipeline_Mach	0.010467	0	0.8
Flowsheet.Zubair_DriverPower	1435.72	0	4400

Appendix H: Optimum Variables for Propane Yield Optimisation

Decision Variable	Value	Lower Bound	Upper Bound
Flowsheet.CS1.Stage2A.SP_F_w.mass_flowrate	3.58438	0.001	10
Flowsheet.CS1.Stage2B.SP_F_w.mass_flowrate	2.59477	0.001	10
Flowsheet.CS1.Stage2C.SP_F_w.mass_flowrate	2.69719	0.001	10
Flowsheet.CS1.Stage3A.SP_F_w.mass_flowrate	8.00564	0.001	10
Flowsheet.CS1.Stage3B.SP_F_w.mass_flowrate	8.4969	0.001	10
Flowsheet.CS1.Stage3C.SP_F_w.mass_flowrate	8.90214	0.001	10
flowsheet.CS1_HP.Stage1.SP_F_w.mass_flowrate	0.036017	0	8
Flowsheet.CS2.Stage2.SP_F_w.mass_flowrate	0.993886	0.001	10
Flowsheet.CS2.Stage3.SP_F_w.mass_flowrate	0.754322	0.001	10
flowsheet.CS2_HP.Stage1.SP_F_w.mass_flowrate	0.052553	0	8
Flowsheet.CS3.Stage2A.SP_F_w.mass_flowrate	0.331355	0.001	10
Flowsheet.CS3.Stage2B.SP_F_w.mass_flowrate	0.085901	0.001	10
Flowsheet.CS3.Stage3A.SP_F_w.mass_flowrate	6.64602	0.001	10
Flowsheet.CS3.Stage3B.SP_F_w.mass_flowrate	6.64394	0.001	10
flowsheet.CS3_HP.Stage1.SP_F_w.mass_flowrate	0.046029	0	8
Flowsheet.CS4.Stage2A.SP_F_w.mass_flowrate	0.586895	0.001	10
Flowsheet.CS4.Stage2B.SP_F_w.mass_flowrate	0.602045	0.001	10
Flowsheet.CS4.Stage3A.SP_F_w.mass_flowrate	0.610667	0.001	10
Flowsheet.CS4.Stage3B.SP_F_w.mass_flowrate	0.614985	0.001	10
flowsheet.CS4_HP.Stage1.SP_F_w.mass_flowrate	0.046246	0	8
Flowsheet.CS5.Stage2A.SP_F_w.mass_flowrate	0.988307	0.001	10
Flowsheet.CS5.Stage2B.SP_F_w.mass_flowrate	0.582363	0.001	10
Flowsheet.CS5.Stage3A.SP_F_w.mass_flowrate	8.23227	0.001	10
Flowsheet.CS5.Stage3B.SP_F_w.mass_flowrate	8.34852	0.001	10
flowsheet.CS5_HP.Stage1.SP_F_w.mass_flowrate	0.040641	0	8
flowsheet.CS7.Stage1.SP_F_w.mass_flowrate	0.040768	0	15
flowsheet.CS8.Stage1.SP_F_w.mass_flowrate	0.040768	0	15
flowsheet.Hammar.Stage1.SP_F_w.mass_flowrate	0.023932	0	3.5
Flowsheet.HammarMishrif.First_HP.SP_F_w.mass_flowrate	0.00911	0	2
Flowsheet.HammarMishrif.First_LP.SP_F_w.mass_flowrate	10.1834	0	14
Flowsheet.Janubiya.Stage2A.SP_F_w.mass_flowrate	8.67028	0.001	10
Flowsheet.Janubiya.Stage2B.SP_F_w.mass_flowrate	8.74828	0.001	10
Flowsheet.Janubiya.Stage3A.SP_F_w.mass_flowrate	8.46327	0.001	10
Flowsheet.Janubiya.Stage3B.SP_F_w.mass_flowrate	6.77222	0.001	10
flowsheet.KAZ_11_1_DeEthanizer_Boilupratio	0.780024	0.01	7
flowsheet.KAZ_11_1_DeEthanizer_Refluxratio	0.685105	0.01	7
flowsheet.KAZ_11_2_DeEthanizer_Boilupratio	0.780793	0.01	7
flowsheet.KAZ_11_2_DeEthanizer_Refluxratio	0.684455	0.01	7
flowsheet.KAZ_12_1_DeButanizer_Boilupratio	1.35433	0.01	7
flowsheet.KAZ_12_1_DeButanizer_Refluxratio	0.442999	0.01	7
flowsheet.KAZ_12_1_DePropanizer_Boilupratio	2.68639	0.01	7
flowsheet.KAZ_12_1_DePropanizer_Refluxratio	0.743218	0.01	7
flowsheet.KAZ_12_2_DeButanizer_Boilupratio	2.72444	0.01	7
flowsheet.KAZ_12_2_DeButanizer_Refluxratio	4.46094	0.01	7
flowsheet.KAZ_12_2_DePropanizer_Boilupratio	2.83597	0.01	7
flowsheet.KAZ_12_2_DePropanizer_Refluxratio	1.00038	0.01	7
flowsheet.KAZ_12_3_DeButanizer_Boilupratio	1.96991	0.01	7
flowsheet.KAZ_12_3_DeButanizer_Refluxratio	0.495141	0.01	7
flowsheet.KAZ_12_3_DePropanizer_Boilupratio	2.72894	0.01	7
flowsheet.KAZ_12_3_DePropanizer_Refluxratio	0.776172	0.01	7
Flowsheet.Markazia.Stage2A.SP_F_w.mass_flowrate	9.10193	0.001	10
Flowsheet.Markazia.Stage2B.SP_F_w.mass_flowrate	8.72956	0.001	10
Flowsheet.Markazia.Stage2C.SP_F_w.mass_flowrate	8.9334	0.001	10
Flowsheet.Markazia.Stage2D.SP_F_w.mass_flowrate	8.17991	0.001	10
Flowsheet.Markazia.Stage3A.SP_F_w.mass_flowrate	8.25921	0.001	10
Flowsheet.Markazia.Stage3B.SP_F_w.mass_flowrate	8.28762	0.001	10
Flowsheet.Markazia.Stage3C.SP_F_w.mass_flowrate	7.41085	0.001	10
Flowsheet.Markazia.Stage3D.SP_F_w.mass_flowrate	5.58866	0.001	10
flowsheet.NGL_DeEthanizer_Boilupratio	0.771076	0.01	7
flowsheet.NGL_DeEthanizer_Refluxratio	0.688294	0.01	7
Flowsheet.Qurainat.Stage2A.SP_F_w.mass_flowrate	8.79616	0.001	10
Flowsheet.Qurainat.Stage2B.SP_F_w.mass_flowrate	8.95361	0.001	10
Flowsheet.Qurainat.Stage3A.SP_F_w.mass_flowrate	6.71236	0.001	10
Flowsheet.Qurainat.Stage3B.SP_F_w.mass_flowrate	7.77765	0.001	10
Flowsheet.Rafidiyah.First_HP.SP_F_w.mass_flowrate	0.020348	0	3
Flowsheet.Rafidiyah.First_LP.SP_F_w.mass_flowrate	0.042928	0	3.5
Flowsheet.S_Ja.ms.SP_split(1).S_spec(1)	0.994589	0	1
Flowsheet.S_Mk.ms.SP_split(1).S_spec(1)	0.994453	0	1
Flowsheet.S_QU.ms.SP_split(1).S_spec(1)	0.995845	0	1
Flowsheet.S_SH.ms.SP_split(1).S_spec(1)	0.998774	0	1
Flowsheet.Shamiya.Stage2A.SP_F_w.mass_flowrate	8.91721	0.001	10
Flowsheet.Shamiya.Stage2B.SP_F_w.mass_flowrate	8.91097	0.001	10
Flowsheet.Shamiya.Stage3A.SP_F_w.mass_flowrate	7.99984	0.001	10
Flowsheet.Shamiya.Stage3B.SP_F_w.mass_flowrate	9.04648	0.001	10
Flowsheet.Zubair.First_HP.SP_F_w.mass_flowrate	0.009109	0	1.5
Flowsheet.Zubair.First_LP.SP_F_w.mass_flowrate	4.7414	0	8
flowsheet.ZubairMishrif.Stage1.SP_F_w.mass_flowrate	0.042944	0	7

Appendix I: Optimum Decision Variables for Flare Minimisation

Decision Variable	Value	Lower Bound	Upper Bound
Flowsheet.CS1.Stage2A.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.CS1.Stage2B.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.CS1.Stage2C.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.CS1.Stage3A.SP_F_w.mass_flowrate	0.001	0.001	10
Flowsheet.CS1.Stage3B.SP_F_w.mass_flowrate	0.001	0.001	10
Flowsheet.CS1.Stage3C.SP_F_w.mass_flowrate	0.001	0.001	10
flowsheet.CS1_HP.Stage1.SP_F_w.mass_flowrate	8	0	8[*]
Flowsheet.CS2.Stage2.SP_F_w.mass_flowrate	8.55937	0.001	10
Flowsheet.CS2.Stage3.SP_F_w.mass_flowrate	0.001	0.001[*]	10
flowsheet.CS2_HP.Stage1.SP_F_w.mass_flowrate	6.30688	0	8
Flowsheet.CS3.Stage2A.SP_F_w.mass_flowrate	8.86459	0.001	10
Flowsheet.CS3.Stage2B.SP_F_w.mass_flowrate	6.08614	0.001	10
Flowsheet.CS3.Stage3A.SP_F_w.mass_flowrate	0.001	0.001[*]	10
Flowsheet.CS3.Stage3B.SP_F_w.mass_flowrate	1.6284	0.001	10
flowsheet.CS3_HP.Stage1.SP_F_w.mass_flowrate	8	0	8[*]
Flowsheet.CS4.Stage2A.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.CS4.Stage2B.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.CS4.Stage3A.SP_F_w.mass_flowrate	1.16164	0.001	10
Flowsheet.CS4.Stage3B.SP_F_w.mass_flowrate	1.29427	0.001	10
flowsheet.CS4_HP.Stage1.SP_F_w.mass_flowrate	8	0	8[*]
Flowsheet.CS5.Stage2A.SP_F_w.mass_flowrate	6.16016	0.001	10
Flowsheet.CS5.Stage2B.SP_F_w.mass_flowrate	9.77874	0.001	10
Flowsheet.CS5.Stage3A.SP_F_w.mass_flowrate	1.11001	0.001	10
Flowsheet.CS5.Stage3B.SP_F_w.mass_flowrate	0.001	0.001	10
flowsheet.CS5_HP.Stage1.SP_F_w.mass_flowrate	8	0	8[*]
flowsheet.CS7.Stage1.SP_F_w.mass_flowrate	15	0	15[*]
flowsheet.CS8.Stage1.SP_F_w.mass_flowrate	15	0	15[*]
flowsheet.Hammar.Stage1.SP_F_w.mass_flowrate	3.5	0	3.5[*]
Flowsheet.HammarMishrif.First_HP.SP_F_w.mass_flowrate	2	0	2[*]
Flowsheet.HammarMishrif.First_LP.SP_F_w.mass_flowrate	14	0	14[*]
Flowsheet.Janubiya.Stage2A.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Janubiya.Stage2B.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Janubiya.Stage3A.SP_F_w.mass_flowrate	0.846201	0.001	10
Flowsheet.Janubiya.Stage3B.SP_F_w.mass_flowrate	2.72116	0.001	10
flowsheet.KAZ_11_1_DeEthanizer_Boilupratio	1.4121	0.01	7
flowsheet.KAZ_11_1_DeEthanizer_Refluxratio	0.60386	0.01	7
flowsheet.KAZ_11_2_DeEthanizer_Boilupratio	1.44817	0.01	7
flowsheet.KAZ_11_2_DeEthanizer_Refluxratio	0.606327	0.01	7
flowsheet.KAZ_12_1_DeButanizer_Boilupratio	0.90485	0.01	7
flowsheet.KAZ_12_1_DeButanizer_Refluxratio	0.859421	0.01	7
flowsheet.KAZ_12_1_DePropanizer_Boilupratio	1.62738	0.01	7
flowsheet.KAZ_12_1_DePropanizer_Refluxratio	0.688789	0.01	7
flowsheet.KAZ_12_2_DeButanizer_Boilupratio	1.06947	0.01	7
flowsheet.KAZ_12_2_DeButanizer_Refluxratio	0.852987	0.01	7
flowsheet.KAZ_12_2_DePropanizer_Boilupratio	1.7402	0.01	7
flowsheet.KAZ_12_2_DePropanizer_Refluxratio	1.2445	0.01	7
flowsheet.KAZ_12_3_DeButanizer_Boilupratio	0.868125	0.01	7
flowsheet.KAZ_12_3_DeButanizer_Refluxratio	0.832073	0.01	7
flowsheet.KAZ_12_3_DePropanizer_Boilupratio	0.910736	0.01	7
flowsheet.KAZ_12_3_DePropanizer_Refluxratio	0.510921	0.01	7
Flowsheet.Markazia.Stage2A.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Markazia.Stage2B.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Markazia.Stage2C.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Markazia.Stage2D.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Markazia.Stage3A.SP_F_w.mass_flowrate	1.35414	0.001	10
Flowsheet.Markazia.Stage3B.SP_F_w.mass_flowrate	1.35414	0.001	10
Flowsheet.Markazia.Stage3C.SP_F_w.mass_flowrate	0.304755	0.001	10
Flowsheet.Markazia.Stage3D.SP_F_w.mass_flowrate	1.35414	0.001	10
flowsheet.NGL_DeEthanizer_Boilupratio	0.01	0.01[*]	7
flowsheet.NGL_DeEthanizer_Refluxratio	0.01	0.01[*]	7
Flowsheet.Qurainat.Stage2A.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Qurainat.Stage2B.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Qurainat.Stage3A.SP_F_w.mass_flowrate	1.02857	0.001	10
Flowsheet.Qurainat.Stage3B.SP_F_w.mass_flowrate	1.36125	0.001	10
Flowsheet.Rafidiyah.First_HP.SP_F_w.mass_flowrate	3	0	3[*]
Flowsheet.Rafidiyah.First_LP.SP_F_w.mass_flowrate	3.5	0	3.5[*]
Flowsheet.S_Ja.ms.SP_split(1).S_spec(1)	1	0	1[*]
Flowsheet.S_Mk.ms.SP_split(1).S_spec(1)	1	0	1[*]
Flowsheet.S_QU.ms.SP_split(1).S_spec(1)	1	0	1[*]
Flowsheet.S_SH.ms.SP_split(1).S_spec(1)	1	0	1[*]
Flowsheet.Shamiya.Stage2A.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Shamiya.Stage2B.SP_F_w.mass_flowrate	10	0.001	10[*]
Flowsheet.Shamiya.Stage3A.SP_F_w.mass_flowrate	0.86784	0.001	10
Flowsheet.Shamiya.Stage3B.SP_F_w.mass_flowrate	1.3516	0.001	10
Flowsheet.Zubair.First_HP.SP_F_w.mass_flowrate	1.5	0	1.5[*]
Flowsheet.Zubair.First_LP.SP_F_w.mass_flowrate	8	0	8[*]
flowsheet.ZubairMishrif.Stage1.SP_F_w.mass_flowrate	7	0	7[*]

Appendix J: Constrained Variables for Flare Minimisation

Constrained Variable	Value	Lower Bound	Upper Bound
Flowsheet.Butane_spec	0.70862	0.72[*]	1
Flowsheet.CS1_A_DriverPower	2110.41	0	4930
Flowsheet.CS1_B_DriverPower	2110.41	0	4930
Flowsheet.CS1_C_DriverPower	2110.41	0	4930
Flowsheet.CS2_DriverPower	1685.6	0	3300
Flowsheet.CS3_A_DriverPower	1670.28	0	2900
Flowsheet.CS3_B_DriverPower	1959.26	0	2900
Flowsheet.CS4_A_DriverPower	3069.91	0	4930
Flowsheet.CS4_B_DriverPower	3133.22	0	4930
Flowsheet.CS5_A_DriverPower	1846.81	0	3300
Flowsheet.CS5_B_DriverPower	1781.85	0	3300
Flowsheet.Gasoline_spec	0.696873	0.7[*]	1
Flowsheet.HammarMishrif_DriverPower	2512.51	0	4400
Flowsheet.Janubiya_A_DriverPower	3206.14	0	5900
Flowsheet.Janubiya_B_DriverPower	4210.47	0	5900
flowsheet.KAZ_11_1.C_2.column.SIZE_trayed(1).max_flooding_percentage	0.988567	0	1
flowsheet.KAZ_11_2.C_2.column.SIZE_trayed(1).max_flooding_percentage	0.994925	0	1
flowsheet.KAZ_12_1.C_01.column.SIZE_trayed(1).max_flooding_percentage	0.865081	0	1
flowsheet.KAZ_12_1.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.261155	0	1
flowsheet.KAZ_12_2.C_01.column.SIZE_trayed(1).max_flooding_percentage	0.937419	0	1
flowsheet.KAZ_12_2.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.294477	0	1
flowsheet.KAZ_12_3.C_01.column.SIZE_trayed(1).max_flooding_percentage	0.721269	0	1
flowsheet.KAZ_12_3.C_02.column.SIZE_trayed(1).max_flooding_percentage	0.25464	0	1
Flowsheet.Markazia_A_DriverPower	3512.69	0	5900
Flowsheet.Markazia_B_DriverPower	3550.56	0	5900
Flowsheet.Markazia_C_DriverPower	2841.16	0	5900
Flowsheet.Markazia_D_DriverPower	3550.56	0	5900
flowsheet.NR_NGL.C_2.column.SIZE_trayed(1).max_flooding_percentage	1.009	0	1[*]
Flowsheet.Pipeline1_Mach	0.027366	0	0.8
Flowsheet.Pipeline28_Mach	0.005621	0	0.8
Flowsheet.Pipeline29A_Mach	0.007586	0	0.8
Flowsheet.Pipeline29B_Mach	0.005247	0	0.8
Flowsheet.Pipeline2_Mach	0.032322	0	0.8
Flowsheet.Pipeline41_Mach	0.009755	0	0.8
Flowsheet.Pipeline42A_Mach	0	0	0.8
Flowsheet.Pipeline7_Mach	0.007243	0	0.8
Flowsheet.Pipeline8_Mach	0.011837	0	0.8
Flowsheet.Propane_spec	0.695238	0.7[*]	1
Flowsheet.Qurainat_A_1_DriverPower	1171.61	0	4350
Flowsheet.Qurainat_A_2_DriverPower	2147.93	0	6100
Flowsheet.Qurainat_B_1_DriverPower	1343.98	0	4350
Flowsheet.Qurainat_B_2_DriverPower	2205.27	0	6100
Flowsheet.Rafidiyah_DriverPower	628.128	0	2200
Flowsheet.Shamiya_A_DriverPower	3219.93	0	6100
Flowsheet.Shamiya_B_DriverPower	3543.75	0	6100
Flowsheet.Total_Feed	318	318	400
Flowsheet.WQpipeline_Mach	0.010467	0	0.8
Flowsheet.Zubair_DriverPower	1435.72	0	4400

Appendix K: Optimum Decision Variable Values for MPO

	Period 1		Period 2	
	Initial Guess	Final Value	Initial Guess	Final Value
CS1.Stage2A.SP_F w.mass flowrate	0.04	1.25	0.07	1.59
CS1.Stage2B.SP_F w.mass flowrate	0.10	3.38	0.01	0.55
CS1.Stage2C.SP_F w.mass flowrate	0.03	0.99	0.03	1.32
CS1.Stage3A.SP_F w.mass flowrate	0.02	0.67	0.01	0.36
CS1.Stage3B.SP_F w.mass flowrate	0.06	1.89	0.02	0.16
CS1.Stage3C.SP_F w.mass flowrate	0.03	0.67	0.03	1.19
CS1_HP.Stage1.SP_F w.mass flowrate	8.00	8.00	8.00	8.00
CS2.Stage2.SP_F w.mass flowrate	1.90	3.19	0.80	7.80
CS2.Stage3.SP_F w.mass flowrate	1.20	0.00	0.20	0.00
CS2_HP.Stage1.SP_F w.mass flowrate	0.00	4.58	0.00	3.96
CS3.Stage2A.SP_F w.mass flowrate	3.30	3.43	3.30	3.57
CS3.Stage2B.SP_F w.mass flowrate	3.40	3.40	3.30	3.56
CS3.Stage3A.SP_F w.mass flowrate	5.80	4.89	5.50	5.95
CS3.Stage3B.SP_F w.mass flowrate	5.70	5.91	5.60	5.94
CS3_HP.Stage1.SP_F w.mass flowrate	2.00	8.00	8.00	8.00
CS4.Stage2A.SP_F w.mass flowrate	0.80	10.00	9.90	10.00
CS4.Stage2B.SP_F w.mass flowrate	9.00	10.00	5.70	10.00
CS4.Stage3A.SP_F w.mass flowrate	0.02	0.12	1.60	2.04
CS4.Stage3B.SP_F w.mass flowrate	5.00	1.97	0.40	0.03
CS4_HP.Stage1.SP_F w.mass flowrate	8.00	8.00	8.00	8.00
CS5.Stage2A.SP_F w.mass flowrate	5.50	8.96	6.90	8.88
CS5.Stage2B.SP_F w.mass flowrate	5.40	8.95	6.90	8.92
CS5.Stage3A.SP_F w.mass flowrate	6.20	2.04	4.50	1.84
CS5.Stage3B.SP_F w.mass flowrate	6.60	2.03	4.60	2.11
CS5_HP.Stage1.SP_F w.mass flowrate	8.00	8.00	8.00	8.00
CS7.Stage1.SP_F w.mass flowrate	15.00	15.00	15.00	15.00
CS8.Stage1.SP_F w.mass flowrate	15.00	15.00	15.00	15.00
Hammar.Stage1.SP_F w.mass flowrate	3.50	3.50	3.50	3.50
HammarMishrif.First_HP.SP_F w.mass flowrate	2.00	2.00	2.00	2.00
HammarMishrif.First_LP.SP_F w.mass flowrate	5.50	14.00	13.50	14.00
Janubiya.Stage2A.SP_F w.mass flowrate	9.90	10.00	10.00	9.99
Janubiya.Stage2B.SP_F w.mass flowrate	9.90	10.00	10.00	10.00
Janubiya.Stage3A.SP_F w.mass flowrate	3.20	4.34	2.30	4.40
Janubiya.Stage3B.SP_F w.mass flowrate	3.30	4.39	2.30	4.65
KAZ_11_1_DeEthanizer_Boilupratio	0.50	0.66	0.90	0.65
KAZ_11_1_DeEthanizer_Refluxratio	0.40	0.43	0.50	0.34
KAZ_11_2_DeEthanizer_Boilupratio	0.50	0.66	0.70	0.65
KAZ_11_2_DeEthanizer_Refluxratio	0.40	0.43	0.50	0.34
KAZ_12_1_DeButanizer_Boilupratio	3.00	1.39	1.50	1.51
KAZ_12_1_DeButanizer_Refluxratio	1.50	1.19	3.50	1.20
KAZ_12_1_DePropanizer_Boilupratio	1.50	1.54	1.20	1.49
KAZ_12_1_DePropanizer_Refluxratio	1.20	1.24	1.20	1.30
KAZ_12_2_DeButanizer_Boilupratio	0.40	1.40	2.00	1.54
KAZ_12_2_DeButanizer_Refluxratio	0.50	1.24	1.50	1.26
KAZ_12_2_DePropanizer_Boilupratio	0.10	1.71	1.50	1.65
KAZ_12_2_DePropanizer_Refluxratio	0.50	1.30	1.00	1.35
KAZ_12_3_DeButanizer_Boilupratio	2.80	1.43	3.00	1.25
KAZ_12_3_DeButanizer_Refluxratio	1.50	1.26	2.00	1.23
KAZ_12_3_DePropanizer_Boilupratio	2.00	1.69	1.50	1.65
KAZ_12_3_DePropanizer_Refluxratio	1.30	1.31	1.00	1.35
Markazia.Stage2A.SP_F w.mass flowrate	9.90	10.00	10.00	10.00
Markazia.Stage2B.SP_F w.mass flowrate	9.90	10.00	9.90	10.00
Markazia.Stage2C.SP_F w.mass flowrate	9.90	10.00	9.90	10.00
Markazia.Stage2D.SP_F w.mass flowrate	10.00	10.00	10.00	10.00
Markazia.Stage3A.SP_F w.mass flowrate	2.90	3.81	2.00	3.91
Markazia.Stage3B.SP_F w.mass flowrate	7.00	7.77	2.00	3.91
Markazia.Stage3C.SP_F w.mass flowrate	2.90	3.82	2.10	3.93
Markazia.Stage3D.SP_F w.mass flowrate	2.90	3.82	2.00	3.93
NGL_DeEthanizer_Boilupratio	0.90	0.44	0.50	0.44
NGL_DeEthanizer_Refluxratio	0.30	0.10	0.50	0.06
Qurainat.Stage2A.SP_F w.mass flowrate	10.00	10.00	10.00	10.00
Qurainat.Stage2B.SP_F w.mass flowrate	9.90	10.00	9.90	9.91
Qurainat.Stage3A.SP_F w.mass flowrate	3.10	4.05	2.10	4.18
Qurainat.Stage3B.SP_F w.mass flowrate	3.10	4.18	2.10	9.13
Rafidiyah.First_HP.SP_F w.mass flowrate	3.00	3.00	3.00	3.00
Rafidiyah.First_LP.SP_F w.mass flowrate	0.00	3.50	0.00	3.50
SalesRate(2)	50.00	5.03	50.00	110.31
SalesRate(3)	25.00	5.01	25.00	62.07
SalesRate(4)	25.00	5.01	25.00	64.01
Shamiya.Stage2A.SP_F w.mass flowrate	9.60	10.00	10.00	10.00
Shamiya.Stage2B.SP_F w.mass flowrate	9.90	10.00	10.00	10.00
Shamiya.Stage3A.SP_F w.mass flowrate	2.80	4.72	2.10	4.18
Shamiya.Stage3B.SP_F w.mass flowrate	3.10	4.06	2.10	8.56
Zubair.First_HP.SP_F w.mass flowrate	1.50	1.50	1.50	1.50
Zubair.First_LP.SP_F w.mass flowrate	7.70	8.00	7.50	8.00
ZubairMishrif.Stage1.SP_F w.mass flowrate	7.00	7.00	7.00	7.00

Appendix L: gPROMS Language for Multiperiod Hierarchical Model for Profit Optimisation

Process Entity

UNIT

Period1 AS Network_detail_multiperiod

Period2 AS Network_detail_multiperiod

PARAMETER

Inventory_init AS ARRAY (4) OF REAL

#where array size is NoProduct

VARIABLE

Cum_Profit as dollars

SET

Period1.Period:= 1; #Period duration in seconds (i.e 3600*24*30 is 1 month expressed in sec)

Period2.Period:= 1; #Period duration in seconds

Period1.Prices:= [0.14, 0.65, 0.55, 0.6];

Period2.Prices:= [0.18, 0.70, 0.65, 0.7];

Inventory_init:= [0, 5E5, 4E5, 4E5];

{19, 020 lines of code that DEFINE UNIT PARAMETERS for both periods}

EQUATION

#No inventory for Natural gas hence production equals sales

Period1.SalesRate(1)=Period1.ProductRate(1);

Period2.SalesRate(1)=Period2.ProductRate(1);

#Inventory Equation

WITHIN Period1 DO

For i:=1 TO NoProduct DO

Inventory(i)=Inventory_init(i)+ProductRate(i)*Period-SalesRate(i)*Period; #kg

END

END

```

WITHIN Period2 DO

For i:=1 TO NoProduct DO

Inventory(i)=Period1.Inventory(i)+ProductRate(i)*Period-SalesRate(i)*Period; #kg

END

END

#subsequents periods would have the same syntax as Period2

#Cost and Revenue Calculation

WITHIN Period1 DO

Revenue=SIGMA(SalesRate*Prices); #\$

Inventory_cost= SIGMA(Unit_cost_inventory*(Inventory+Inventory_init)/2); #\$

Profit=(Revenue-Production_cost-Inventory_cost)*Period;

END

WITHIN Period2 DO

Revenue=SIGMA(SalesRate*Prices); #\$

Inventory_cost= SIGMA(Unit_cost_inventory*(Inventory+Period1.Inventory)/2); #\$

Profit=(Revenue-Production_cost-Inventory_cost)*Period;

END

#subsequents periods would have the same syntax as Period2

#Profit Calculations

Cum_Profit=Period1.Profit+Period2.Profit;

{610 lines of code for UNIT OPERATIONS CONSERVATION AND FLOW EQUATIONS for sub-models of both periods}

ASSIGN

#Period1.SalesRate(1):=25; #e.g in ton/d or kg/s

Period1.SalesRate(2):=25;

Period1.SalesRate(3):=15;

Period1.SalesRate(4):=15;

#Period2.SalesRate(1):=25; #e.g in ton/d or kg/s

Period2.SalesRate(2):=20;

Period2.SalesRate(3):=10;

Period2.SalesRate(4):=10;

{9,686 lines of code for ASSIGNING VALUES TO KNOWN VARIABLES in all sub-models of both periods}

INITIALISATION_PROCEDURE

# Start Default Initialisation Procedure

USE

: DEFAULT;

```

```
END

SAVE "Network_detail_multiperiod_InitialGuess";

# End Default Initialisation Procedure

SOLUTIONPARAMETERS

DASolver := "DASOLV" [
  "InitialisationNLSolver" := "BDNLSOL" [
    "BlockSolver" := "SPARSE" [
      "MaxIterations" := 2000
    ]
  ],
  "ReinitialisationNLSolver" := "BDNLSOL" [
    "BlockSolver" := "SPARSE" [
      "MaxIterations" := 2000
    ]
  ],
  "IgnoreDAEIndexAnalysis" := TRUE
]

DOSolver := "CVP_SS" [
  "MINLPSolver" := "NLPSQP" [
    "ComplementarityTolerance" := 0.1,
    "FeasibilityTolerance" := 0.1,
    "NoImprovementTolerance" := 1E-5,
    "OptimisationTolerance" := 0.1,
    "Scaling" := 0,
    "TaylorTolerance" := 0.005
  ]
]

IgnoreDAEIndexAnalysis := ON

FPI := "eventFPI"

InitialisationProcedure := OFF

SequentialInitialisationProcedure := ON

SEQUENCE

SAVE "Network_detail_multiperiod_InitialGuess"

END
```