CRANFIELD UNIVERSITY

AMINU ALHAJI HAMISU

PETROLEUM REFINERY SCHEDULING WITH CONSIDERATION FOR UNCERTAINTY

SCHOOL OF ENGINEERING
Offshore, Process and Energy Engineering

PhD Thesis
Academic Year: 2014 - 2015

Supervisor: Dr. Yi Cao
Co-supervisor: Prof. Antonis Kokossis
July 2015

CRANFIELD UNIVERSITY

SCHOOL OF ENGINEERING
Offshore, Process and Energy Engineering

PhD

Academic Year 2014 - 2015

AMINU ALHAJI HAMISU

Petroleum Refinery Scheduling with Consideration for Uncertainty

Supervisor: Dr. Yi Cao
Co-supervisor: Prof. Antonis Kokossis
July 2015

This thesis is submitted in fulfilment of the requirements for the degree of PhD in Process Systems Engineering

ABSTRACT

Scheduling refinery operation promises a big cut in logistics cost, maximizes efficiency, organizes allocation of material and resources, and ensures that production meets targets set by planning team. Obtaining accurate and reliable schedules for execution in refinery plants under different scenarios has been a serious challenge. This research was undertaken with the aim to develop robust methodologies and solution procedures to address refinery scheduling problems with uncertainties in process parameters.

The research goal was achieved by first developing a methodology for short-term crude oil unloading and transfer, as an extension to a scheduling model reported by Lee et al. (1996). The extended model considers real life technical issues not captured in the original model and has shown to be more reliable through case studies. Uncertainties due to disruptive events and low inventory at the end of scheduling horizon were addressed. With the extended model, crude oil scheduling problem was formulated under receding horizon control framework to address demand uncertainty. This work proposed a strategy called fixed end horizon whose efficiency in terms of performance was investigated and found out to be better in comparison with an existing approach.

In the main refinery production area, a novel scheduling model was developed. A large scale refinery problem was used as a case study to test the model with scheduling horizon discretized into a number of time periods of variable length. An equivalent formulation with equal interval lengths was also presented and compared with the variable length formulation. The results obtained clearly show the advantage of using variable timing. A methodology under self-optimizing control (SOC) framework was then developed to address uncertainty in problems involving mixed integer formulation. Through case study and scenarios, the approach has proven to be efficient in dealing with uncertainty in crude oil composition.

Keywords: Refinery optimization, mixed integer programming, modelling, receding horizon, self-optimizing control.

ACKNOWLEDGEMENTS

I would like to express my gratitude to Almighty Allah for giving me the strength, perseverance, persistence and good health to complete this chapter in my life.

To my sponsors: Petroleum Technology Development Fund (PTDF), your financial assistance has been the backbone in this journey. My sincere appreciation goes to my employer: Ahmadu Bello University Zaria, for giving me the opportunity to purse this research studies. This acknowledgement cannot be complete without appreciating the help rendered by Prof. Mohammed Dabo, Dr. S. M. Waziri and Mal. Adam Dauda.

I would like to thank my supervisor in the person of Dr. Yi Cao for his guidance, supervision, constructive criticisms and useful advices. To my first supervisor Dr. Meihong Wang, I benefitted immensely from your guidance. My co-supervisor in the person of Prof. Antonis Kokossis has also helped a lot. I remain grateful.

Special appreciation goes to my mum and other members of my family. Without your love, prayers and support, I wouldn't have gone this far. A big thank you!

To my wife Hadiza, you are such a rare gem for sacrificing your time, deferring your studies; just to ensure that my needs are well catered for. I assure you I will continue to be a good and caring husband.

To my lovely sons, Muhammad Hamisu (Mubarak) and Sadiq I do this for you and your siblings so that you will always be proud of having me as your father.

I sincerely wish to extend my special appreciation to my relatives, friends, office mates and members of community. I could not have completed this thesis without your words of encouragement and support.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

BB	Branch and Bound
bbl	Barrels
bpsd	Barrels per stream day
AGO	Automotive Gas Oil
ANN	Artificial Neural Network
API	American Petroleum Institute
ASTM	American Society for Testing Materials
CCR	Continuous Catalyst Regeneration Unit
CDU	Crude Distillation Unit
CDUs	Crude Distillation Units
CRU	Catalytic Reforming Unit
CT	Charging Tank
CV	Control Variable
DICOPT	Discrete and Continuous Optimizer
EBP	End Boiling Point
ETBE	Ethyl Tertiary Butyl Ether
FCC	Fluid Catalytic Cracking Unit
FI	Fractionation Index
GAMS	General Algebraic Modelling Systems
GB	Gasoline Blending
GBD	Generalized Benders Decomposition
GUI	Graphical User Interface
HDS	Hydro-desulphurisation
HVGO	Heavy Vacuum Gas Oil
IBP	Initial Boiling Point
KHU	Kero Hydrotreating Unit
KKT	Karush Kun Tucker
KRPC	Kaduna Refining and Petrochemical Company
LHS	Left Hand Side
LP	Linear Programming
LPG	Liquified Petroleum Gas
LVGO	Light Vacuum Gas Oil

MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
MPC	Model Predictive Control
MTBE	Methyl Tertiary Butyl Ether
NCO	Necessary Condition of Optimality
NHU	Naphtha Hydrotreating Unit
NLP	Nonlinear Programming
PC	Personal Computer
PID	Proportional Integral Derivative
PTDF	Petroleum Technology Development Fund
RHS	Right Hand Side
SOC	Self-Optimizing Control
SR	Straight Run
SSE	Sum of Square Error
ST	Storage Tank
STN	State Task Network
TAME	Tertiary Amyl Methyl Ether
TBP	True Boiling Point
TBR	Trickle bed Reactor
TGO	Total Gas Oil
ULSD	Ultra-low Sulphur Diesel
VDU	Vacuum Distillation Unit
VO	Vacuum Overhead
VR	Vacuum Residue
WRPC	Warri Refining and Petrochemical Company

1 INTRODUCTION

1.1 Background

In recent years the downstream sector of the petroleum industry faces great challenges to survive competition, improve profit margin, and to operate within the boundaries of the environmental legislations (Li et al., 2012b). Despite these issues, petroleum refiners operate while taking into consideration the uncertainty associated with rise and fall in product demands, unavoidable change in crude oil prices, fluctuation in quality and composition of feed material, lead time, and quality of gasoline and diesel produced. This necessitates exploring viable alternatives to compete successfully and remain in business (Li et al., 2012a).

The current practice in the industry is that refiners resort to devising reliable and the most cost effective and feasible operational procedures to address both economic and environmental issues that have significant impacts on the refining business through planning and scheduling. From Karuppiah et al. (2008), planning and scheduling of refining operations are necessary as benefits in terms of production cost savings and feed improvement are potentially realized. According to Fagundez and Faco (2007), planning and scheduling allow optimum utilization of resources; ensure availability of high quality products and guarantee a positive return on investment.

While planning is forecast driven, scheduling on the other hand, is order driven; making use of available resources and time to model and solve refinery operational problems. Planning always precedes scheduling and the planning decisions are generated for implementation during scheduling; implying that good scheduling is a direct consequence of good planning (Kelly and Mann, 2003a). Integrating the two will improve efficiency and reliability of the refinery decision making processes, though it is still a challenge. Moreover, consideration to uncertainty offers robustness and flexibility.

1.2 Configuration of an oil refinery

An oil refinery processed crude oil of varying compositions into useful petroleum products while utilizing various economic and environmental alternatives (Gary and Handwerk, 1984). Its configuration varies from one refinery to another depending on the products demand and quality requirements of available customers. For example, some refineries in Nigeria like Kaduna Refining and Petrochemical Company (KRPC), and Warri Refining and Petrochemical Company (WRPC) were designed to produce petrochemicals in addition to the conventional fuel products.

Petroleum refineries differ in the plant configurations. Despite the differences, however most process units are common. They are: crude distillation unit (CDU), vacuum distillation unit (VDU), fluid catalytic cracking unit (FCC), naphtha hydrotreating unit (NHU), catalytic reforming unit (CRU) and gas treating unit. Alkylation and Isomerization process units are also part of refinery production plant.

In general, most refineries, in addition to the processing units mentioned in the preceding paragraph, have one or more units and this varies depending on the design that suits the refiners plan. Figure 1-1 is a process flow diagram of a typical oil refinery plant showing most of the unit processes, with stream connections from crude oil feed to the final products. Other refinery configurations may have more or less of the units presented here. For example, utility section and blending units are not shown in Figure 1-1.

Also of importance in other refinery configurations are the use of butane or oxygenated compounds (oxygenates) as additive materials in blending units. The materials are added to improve octane rating of the final products. Oxygenates are ether compounds derived from their respective alcohols. They include: Methyl tertiary butyl ether (MTBE), Ethyl tertiary butyl ether (ETBE) and Tertiary amyl methyl ether (TAME). Of these three oxygenates, MTBE is the most acceptable in gasoline blending, meeting all the gasoline pool objectives. This compound has the blending quality of 109 octanes, a RVP blending of 8–10 psi and a boiling point of 131◦F (Jones and Pujado, 2006).

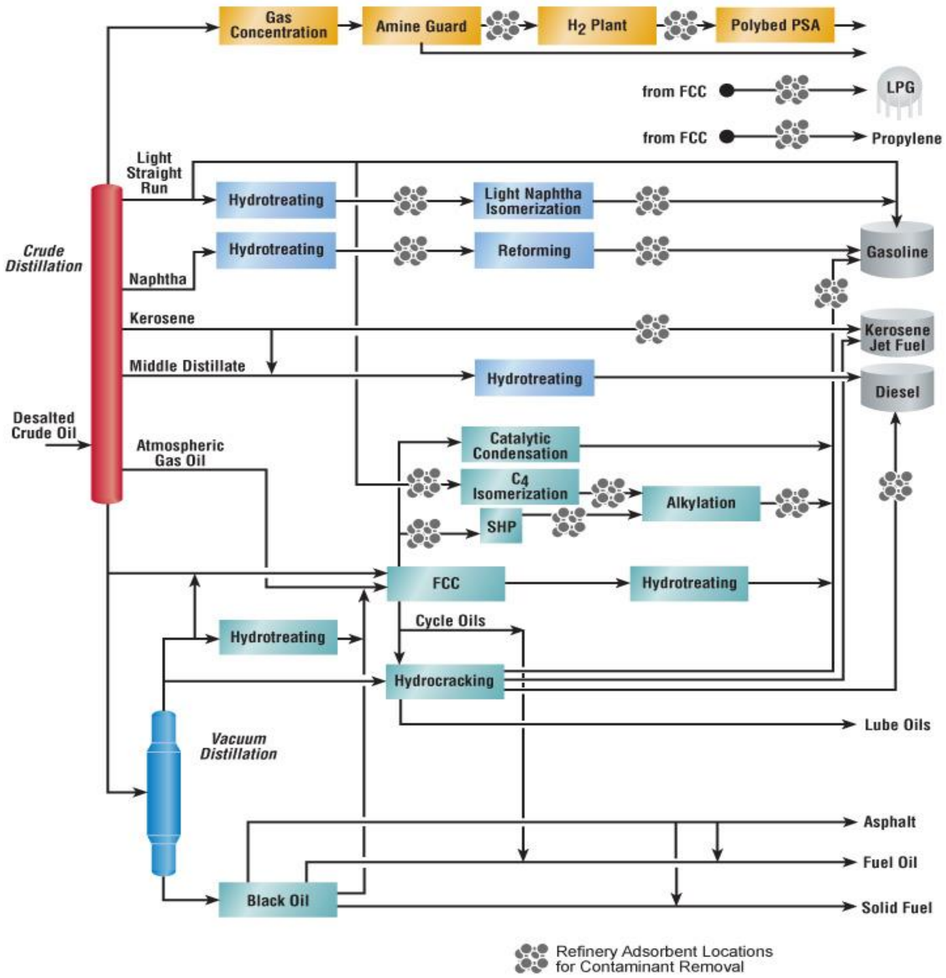


Figure 1-1: A process flow diagram of an oil refinery plant (Anon, 2011)

1.3 Motivation

Traditionally, petroleum refinery operations are based on heuristic rules. The recent advancements in modern computing provide opportunities for automation, hence systematic approaches are always devised to generate guidelines and operational procedures that guarantee smooth conduct of refining business at minimal cost. While mathematical techniques for refinery planning have a long established popularity in petroleum research studies, much less has been reported in scheduling of production area, and to some extent in crude oil scheduling. Models developed previously have shortcomings in one way or the other that practical implementation of decisions obtained from solving the models may fail to reflect realities. Some of these modelling issues have been addressed in this work.

Generally, crude oil refinery operates under economic and environmental conditions bounded with uncertainties. According to Mula et al. (2006), models which do not take into cognizance a number of uncertainties can be expected to generate unreliable decisions when compared to models that explicitly or implicitly incorporate those uncertainties. In most of the work reported in refinery planning and scheduling, uncertainties from design point of view predominate. However, there is also a need to consider operational uncertainties as they affect the accuracy and robustness of the overall schedule. This challenge has been taken care of in this study.

Developing methodologies and solution algorithms for scheduling of refinery systems with uncertainty considerations is therefore imperative. Obtaining accurate and reliable schedules for crude oil unloading, refining and blending of final products within the scheduling cycle is the motivation behind this work. A variety of modelling and solution options are developed to match peculiarities of problems in different refinery subsystems with decisions to be implemented in a real plant.

1.4 Novelty

In process design, uncertainties are considered in order to generate robust schedules in anticipation of unforeseen circumstances. However, operational uncertainties in the form of disturbances do manifest during schedule execution in the real plant and therefore more efficient techniques have to be developed and applied in the schedule generation. Therefore this study will propose novel approaches to model and deal with uncertainty as disturbance in refinery scheduling operation. To achieve the objectives of this research, a number of contributions have been made to scientific body of knowledge in this area of study.

Firstly, an existing mixed integer linear programming (MILP) model by Lee et al. (1996), which was formulated to minimise operational cost associated with crude oil unloading, processing and inventory control, has been extended to make the model reflects real industrial applications. In this work, the model was extended by including important technical details to adequately capture real industrial practices in crude oil scheduling (Hamisu et al., 2013a; Hamisu et al., 2013b).

Among other things, the extended model accounts for interval-interval charging rate fluctuations in CDU, demand violation against obtaining infeasible solution and adopt more realistic operational procedures (Hamisu et al., 2013a; Hamisu et al., 2013b). The extended model was assessed relative to the existing model to highlight the benefits derived in terms of performance. Also, some scenarios were created to make recommendations to the refinery operators in deciding the best schedule to use.

The model was then used to demonstrate the capability of fixed end horizon control strategy to accommodate CDU demand uncertainty within the scheduling horizon. The result was then compared with another control strategy of model predictive control (moving end horizon control) for scheduling crude oil unloading presented in Yüzgeç et al. (2010). The approach proposed in this work is more realistic considering that plant operators work with schedules for a specified period of time with fixed deadline and have more degrees of freedom in accommodating uncertainties since the solution search covers the whole scheduling horizon.

A mixed integer nonlinear programming formulation for simultaneous optimization of production scheduling with product blending was developed to include blending units in addition to other units commonly found in oil refinery. The model considers crude oil characteristics with pseudo-components generated from ASPEN plus for two different crude oil grades. In addition to flow rates, crude compositions are also considered. The CDU model is based on swing cut approach and the objective of the optimization model is to maximize profit while generating feasible schedules within time horizon.

A data driven self-optimizing control (SOC) strategy was developed to deal with multi-period scheduling problems under uncertain conditions. The goal was to achieve global optimum by maintaining the gradient of the cost function at zero via approximating necessary conditions of optimality (NCO) over the whole uncertain parameter space. A regression model for the plant expected revenue (profit) as a function of independent variables using optimal operation data was obtained and a feedback input (manipulated variable) was derived. Data for regression was generated from the mixed integer nonlinear programming model discussed in the preceding paragraph.

1.5 Aims and Objectives

The aim of this study is to develop robust methodologies and solution procedures to address refinery scheduling problems under uncertain conditions. The main objectives are:

- To develop a mixed integer linear programming formulation for short-term crude oil unloading, tank inventory management, and CDU charging schedule as an extension to a previous work reported by Lee et al. (1996).
- To investigate the performance of the extended model through case studies and create scenarios to generate schedules under disruptive event and low inventory at the end of scheduling horizon.
- To devise a solution alternative to deal with uncertainty in crude oil scheduling via model predictive control strategy.
- To develop a mixed integer nonlinear programming formulation for simultaneous optimization of production scheduling with product blending.
- To develop a data driven SOC strategy for multi-periods scheduling problems.
- To apply the SOC strategy to solve discrete time mixed integer nonlinear programming model for production scheduling with product blending. Disturbance scenarios (uncertainties in crude oil compositions) will be introduced to test the efficacy of the SOC method.

1.6 Outline of Thesis

Chapter 2 focuses on the literature review for refinery scheduling with discussion on the techniques available in literature to address uncertainties. Modelling of refinery subsystems and current and future direction in this research area will be discussed.

Chapter 3 discusses modelling crude oil unloading area where benefits of our formulation (extended MILP model) for crude oil unloading scheduling with tank inventory management were highlighted.

Chapter 4 presents receding horizon approaches to handle problems in crude oil scheduling, blending, and tanks inventory management under CDU demand uncertainties. Comparison between fixed-end and moving-end strategies in terms of performance was discussed.

In Chapter 5, a novel mixed integer nonlinear formulation for short-term scheduling of refinery production with product blending will be covered.

Chapter 6 covers multi-period data driven SOC strategy to address uncertainties in a large-scale refinery production scheduling problem.

Finally, conclusions and recommendations are presented in Chapter 7.

1.7 Publications and Conferences

Journal paper

Hamisu, A. A., Kabantiok, S., & Wang, M.; Refinery Scheduling of Crude oil Unloading with Tank Inventory Management; Computers and Chemical Engineering 55, (2013) 134-147.

Conferences

Hamisu, A. A., Kabantiok, S., & Wang, M.; “An improved MILP model for scheduling crude oil unloading, storage and processing” pp. 631-636. 23rd European Symposium on Computer Aided Process Engineering, ESCAPE23 held in Lappeenranta, Finland on 9-12/06/2013.

Hamisu, A. A., Cao, Y., & Kokossis, A.; “Scheduling crude oil blending and tanks inventory control under CDU demand uncertainty: A receding horizon approach” pp. 260-265. 20th International Conference on Automation and Computing, ICAC14 held at Cranfield University, Bedfordshire, UK on 12-13/09/2014.

Papers in preparation (Journal)

Hamisu, A. A., Cao, Y., & Kokossis, A.; Receding horizon approach for scheduling crude oil blending and tanks inventory management

Hamisu, A. A., Cao, Y., & Kokossis, A.; Refinery production scheduling under self-optimizing control framework

2 LITERATURE REVIEW

In a petroleum refinery, optimization is performed at three levels of decision, namely; planning, scheduling and control. The relationship between the three levels is such that planning set targets while scheduling executes the target to provide optimal values of decision variables as set points for controllers. Moreover, control actions through feedback mechanisms can be applied to address scheduling problems with uncertainty in process parameters. Integrating these levels in a complex plant like refinery is virtually impossible. However, at most a combination of two levels can be handled together when the refinery plant is decomposed into subsystems (crude oil unloading area, production area and product blending area) and treat the subsystems separately.

This chapter presents literature review on refinery scheduling with considerations on techniques and algorithmic procedures used to deal with problems under uncertain conditions. The review will discuss formulation of optimization problems as linear programming (LP), nonlinear programming (NLP), mixed integer linear programming (MILP), and mixed integer nonlinear programming (MINLP). Modelling and simulation tools used in this research work will then be discussed. Subsequent paragraphs in this chapter will be on the relationship between planning and scheduling, then broad areas of petroleum refinery including process units for scheduling, consideration for uncertainties and, the current and future trend in refinery scheduling.

2.1 Refinery Optimization Problems

Edgar et al. (2001) defined optimization as ‘’the use of specific methods to determine the most cost-effective and efficient solution to a problem or design for a process’’. It is concerned with selecting the best among many solution alternatives using efficient quantitative methods. Optimization aims at finding the values of decision variables in process that yield the best value of performance criterion. Optimization problem formulation consists of the following components:

- Objective function
- Constraints
- Decision variable(s) and
- Parameters

The objective function is usually a mathematical expression relating decision variables with coefficients called parameters. Constraints on the other hand relate decision variables with coefficients and right hand side (RHS) values. The constraints can be equality or inequality. When formulated mathematically, optimization problems potentially involve many of the components mentioned above. In relation to obtaining solution of optimization problem, three important concepts are defined:

Feasible region: is the region of feasible solutions.

Feasible solution: are set of variables that satisfy equality and inequality constraints. and

Optimal solution: a feasible solution that provides the optimal value of the objective function.

From these definitions, an optimal solution must not only achieve an extremum of the objective function, such as minimizing cost or maximizing profit but also must satisfy all of the constraints (Edgar et al., 2001).

Depending on the nature of the objective function and constraints, optimization problem can be LP, NLP, MILP or MINLP. In the past decades, optimization problems are solved using manual calculations at very high computational cost and with no guarantee to obtain accurate results. This was later improved slightly with the availability of spreadsheet packages, though less rigorous compared to the manual computational approach. The recent advancement in computing coupled with the availability of software programmes makes it easier to solve optimization problems within reasonable time frame. The algorithm embedded in the software programmes depends on the nature of the optimization problem required to solve.

2.1.1 LP

LP is a class of optimization problem in which both the objective function and constraints are linear. LP is the most widely encountered optimization problem in manufacturing and processing industries, which constitutes number of variable(s) and constraints (Edgar et al., 2001). As an example, LP problem can be formulated as,

$$\text{Minimize: } f = x_1 + 2x_2 - 5x_3 \tag{2-1}$$

$$\text{Subject to: } \quad -2x_2 + x_3 \leq 8$$

$$x_1 + x_3 = -4$$

$$x_1, x_2, x_3 \geq 0$$

In Equation 2-1, the objective function f is to be minimized. The objective function has no products of two variables (bilinear terms) or three variables (trilinear terms). Also in the objective function, there is no division of variables. Variables in basic functions like trigonometric, exponential, differential and integral are not included. Therefore the objective function is linear with respect to the variables. The second and third mathematical relations in Equation 2-1 are inequality and equality constraints respectively. Like objective function, the constraints are also linear based on the reasons already stated. The last expression is called bounds forcing all the variables to be positive. For example the bounds may be representing capacities of processing units in refinery which can never be negative.

LP problems can be solved using a two-phase procedure called simplex method. The first phase finds an initial basic feasible solution if a solution of the problem exist and reports detail information for a case where no solution is available. No solution to a problem may be due to inconsistency in constraints. In the second phase, the solution depends on the outcome of the first phase and the result can be positive (optimum found) or negative (unbounded minimum). Most commercial solvers work based on this algorithm.

LP is usually preferred due to the ease of formulation and can be used to approximate nonlinear model around its steady state; this reduces the complexity and of course makes it less hectic to solve. Though, its choice is usually a trade-off between simplicity and robustness (Floudas and Lin, 2005). Although employed in most process systems, LP does not receive a wider acceptance in refinery scheduling.

2.1.2 NLP

NLP is an optimization problem that seeks to minimize (or maximize) a nonlinear objective function subject to linear or nonlinear constraints. Problems formulated as NLP are more accurate compared to their LP counterparts since most chemical processes are nonlinear in nature. Refinery models that account for nonlinear relationship of process variables are more reliable and represent the refinery systems more closely. The general representation of NLP problems is as shown in Equation 2-2.

$$\text{Minimize: } f(\mathbf{x}) \qquad \mathbf{x}=[x_1\ x_2 \dots x_n]^T \tag{2-2}$$

$$\text{Subject to: } h_i(\mathbf{x}) = b_i \qquad i = 1, 2, \dots, m$$

$$g_j(\mathbf{x}) \leq c_j \qquad j = 1, \dots, r$$

In this formulation, bilinear and trilinear terms, and basic mathematical functions can be found. In Equation 2-2, at least the objective function $f(\mathbf{x})$, the equality constraint $h_i(\mathbf{x})$ or the inequality constraint $g_j(\mathbf{x})$ must be nonlinear.

The challenge in modelling using NLP formulation is that of achieving a reasonable convergence. This is largely due to the fact that many real-valued functions are non-convex. Convexity of feasible region can only be guaranteed if constraints are all linear. Moreover, it is a difficult task to tell if an objective function or inequality constraints are convex or not. However, convexity test can be carried out to satisfy first-order necessary conditions of optimality popularly known as Kuhn-Tucker conditions (also called KKT conditions). Most algorithms embedded in commercial solvers terminate when these conditions are satisfied within some tolerance. For problems with a few number of variables, KKT solutions can sometimes be found analytically and the one with the best objective function value is chosen. It is not within the scope of this work to discuss KKT conditions in more detail. The reader should refer to Edgar et al. (2001) or other related materials.

Unlike LP, NLP are reported in a significant number of publications in refinery problems involving blending relation and pooling. Moro et al. (1998) developed a non-linear optimization model for the entire refinery topology with all the process units considered and non-linearity due to blending included. Their work has been extended by Pinto et al. (2000); Neiro and Pinto (2005) for multi-period and multi-scenario cases involving non-linear models. In this work, nonlinearity is considered in the development of scheduling model for refinery production with product blending.

2.1.3 MILP

This optimization problem involves discrete and continuous decisions, with linear objective function(s) and linear constraint(s). MILP allows the discrete and continuous features of optimization problem to be adequately represented; thus enabling refiners to select the optimum allocation of task to processing units in the refinery plant. A decision to use or not to use particular equipment at a particular time period can be modelled using binary variables (0-1). The value ‘1’ means the equipment is in use and ‘0’ otherwise. Besides 0 and 1, integer variables can be real numbers 0, 1, 2, 3, and so on. Sometimes integer variables are treated as if they were continuous in problems where the variable range contains large number of integers. In such a case, the optimal solution is rounded to the nearest integer value. Generally, MILP problem is presented in the following form:

$$\text{Minimize: } \boldsymbol{c}_x^T\,\mathbf{x} + \boldsymbol{c}_y^T\,\mathbf{y} \tag{2-3}$$

$$\text{Subject to: } A\mathbf{x} + B\mathbf{y} \leq 0$$

$$\mathbf{x} \geq 0$$

$$\mathbf{y} \in \{0,1\}^q$$

The objective function here depends on two sets of variables, $\boldsymbol{x}$ and $\boldsymbol{y}$; $\boldsymbol{x}$ is a variable vector representing continuous decisions (volume, flowrates, temperature, concentration) and $\boldsymbol{y}$ variables represent discrete decisions. A, B and $\boldsymbol{c}$ are the coefficient matrices.

Like LP, MILP problems are linear in the objective function and constraints hence the problems are readily solved by many LP solvers. MILP problems are much harder to solve than their LP counterparts. As the number of integer variables are becoming larger, the computational time for even the best available MILP solvers increases rapidly. Using branch and bound (BB) algorithm embedded in commercial solvers such as CPLEX, GUROBI, MOSEK, SULUM, XA and XPRESS, optimal solution of MILP problems can be obtained.

BB works by generating LP relaxation of the original MILP problem, allowing the 0 or 1 constraint to be relaxed (taking value anywhere between 0 and 1). The algorithm starts by solving the LP relaxation such that if all the discrete variables have integer values, the solution solves the original problem otherwise one or more discrete variables has a fractional value and the solution search has to continue through branching. To continue with the solution search BB chooses one of the discrete variables and creates LP subproblems by fixing this variable at 0, then at 1. If either of the subproblem has an integer solution or infeasible, the subproblem will not be investigated further. If the objective value of the subproblem is better than the best value found so far, it replaces this best value. A bounding test is then applied to each subproblem and if the test is satisfied, the subproblem will not be investigated further otherwise branching continues (Edgar et al., 2001).

Most of the problems reported in refinery scheduling are MILPs especially in crude oil unloading area due to the need to consider both continuous and discrete decisions. The model presented in the next chapter of this work was formulated as MILP problem and solved using CPLEX solver in GAMS software programme.

2.1.4 MINLP

Many process systems are best described with nonlinear models. Therefore in addition to being mixed integer, this class of optimization problem include nonlinearity in the objective function, or constraints or both. The general representation of this optimization problem is:

$$\text{Minimize: } f(\mathbf{x}, \mathbf{y}) \tag{2-4}$$

$$\text{Subject to: } \boldsymbol{h}(\mathbf{x}, \mathbf{y}) = 0$$

$$\boldsymbol{g}(\mathbf{x}, \mathbf{y}) \leq 0$$

$$\boldsymbol{x} \in \mathbb{R}^n$$

$$\boldsymbol{y} \in \{0,1\}^q$$

MINLP are much harder to solve than LP, NLP or MILP due to the combinatorial nature of the problem which arises from the presence of binary variables, and, when the nonlinear functions are nonconvex; the solution converges to a local optimum. Like MILP, MINLP can also be solved using BB with the main difference being that the relaxation at each node is NLP rather than LP. Another algorithm to solve MINLP problem is the Generalized Benders Decomposition (GBD). The GBD algorithm works based on the principles of partitioning the variable set, followed by decomposition of the problem and finally refinement is done iteratively.

In the partitioning of the variable set, the $\mathbf{y}$ variables are referred to as complicating variables and handled differently from the $\boldsymbol{x}$ variables thus enabling the algorithm to be used to handle bilinear non-convexities in a rigorous manner. Decomposition involves solving the problem by considering two types of derived problems: a primal problem which provides an upper bound on the MINLP, and a master problem which provides a lower bound on the MINLP. Using the information obtained from any given primal and master problems, new sets of primal and master problems are created in such a way that the bounds become tighter and within a finite number of iterations convergence can be achieved. Integer cuts may be added in order to avoid generating any combination of the binary variables twice.

MINLP problem can also be solved using another algorithm called Outer approximation (Duran and Grossmann, 1986; Floudas, 1995). The algorithm which has an interface with General Algebraic Modelling Systems (GAMS) and is implemented in a software programme called Discrete and Continuous Optimizer (DICOPT). It works through a series of iterations in such a way that at each major iteration, two subproblems (a continuous variable nonlinear program and a linear mixed-integer program) are solved.

2.2 Modelling and Simulation Tools

GAMS, Aspen PLUS and Matlab are used in this study. GAMS was used for the modelling and optimization of all MILP and MINLP formulations developed in this work. Crude characterization to generate pseudo-components for distribution to corresponding cut fractions was achieved using Aspen PLUS. While the regression analysis for the data driven self-optimizing control (SOC) was carried out in Matlab. Brief introduction of the software tools will be given.

2.2.1 GAMS

GAMS is a modelling tool developed for setting up and solving large-scale optimization problems. It was developed to address optimization problems in the early 1970s with the following objectives:

- Providing the language base that will allow easy representation of compact data and complex models.
- Allowing changes to be made in models without difficulty.
- Permitting model description that is not dependent on algorithms used to achieve solution (Rosenthal, 2012).

The GAMS modelling language is algebraic with optional interfaces for LP, NLP, MILP and MINLP solvers. The modelling system is available in a wide variety of platforms ranging from personal computers (PCs) to workstations and mainframe computers. This software programme works by accepting model specifications as a system of algebraic equations, then parses the equations to transform them into a form that can easily be evaluated numerically by its interpreter. Before the processed model is made available to solver, some analysis are also carried out by the modelling system to determine the model structure (Edgar et al., 2001).

GAMS is a powerful tool used in most academic research activities as it allows users to specify the structure of the optimization model, specify data and calculate data fed into the model, solve the model based on the constraints imposed and aid the comparative statistical analysis of results. Models in Chapters 3, 4 and 5 in this work are solved using this software programme.

2.2.2 Aspen PLUS

Aspen PLUS is a simulation package providing an environment for modelling, design, optimization, and performance monitoring of chemical processes. It has a graphical user interface (GUI) that allows users to create and manipulate fluid packages or component lists in the simulation environment. Using Aspen PLUS for crude oil characterization, the user can:

- Define components
- Enter assay data for any number of crudes
- Blend the crudes to produce feed material for distillation units
- Generate pseudo-components for individual crudes and crude blends
- Carry out assay data analysis
- View and interprets results.

2.2.3 Matlab

Matlab is a high-performance language for technical computing. It integrates computation, visualization, and programming environment. Matlab was developed as an interactive program for doing matrix calculations and has now grown to a high level mathematical language that can solve integral and differential equations numerically and plot a wide variety of two and three dimensional graphs (O'Connor, 2012). It has sophisticated data structures, contains built-in editing and debugging tools, and supports object-oriented programming. These factors make Matlab an excellent tool for teaching and research.

The recent work of Ferris et al. (2011) provides a means by which GAMS and Matlab can interface. GDXMRW utilities in GAMS allow data to be imported/exported between GAMS and Matlab and to call GAMS models from Matlab and get results back in Matlab. The software gives Matlab users the ability to use all the optimization capabilities of GAMS, and allows visualization of GAMS models directly within Matlab.

2.3 Planning and Scheduling

In oil and gas industries, decisions have to be taken to operate plants at minimum cost in order to improve the overall profit margin. In refineries, such decisions include selection of suitable raw materials to process, identification of unit equipment to use, specification of the sequence of operations, and matching amounts to be produced with the product demand from customers. Considering the complexity of refinery operations, optimization tools are employed to generate the most effective, reliable and robust procedures in decision making processes.

Planning and scheduling procedure has been the subject many researchers find a great deal of opportunity to contribute towards addressing refinery myriad optimization problems. According to Grossmann et al. (2002), planning and scheduling refer to a systematic way of sequencing a task and allocating the task to equipment and personnel overtime in such a way that production targets are met while ensuring compliance with industry operational standards. Planning sets targets for implementation at scheduling level. In a crude oil refinery, planning and scheduling help improve profit margin and reduce losses arising from instability caused by wide variations of crude-charge qualities (Ishuzika et al., 2007).

At managerial level, managers are tasked with the responsibility to decide on the crude oil type to source for, the items to produce, the operating route to use, the selection of catalytic material to speed up chemical reactions and the best operating mode to adopt for each process. In process plant, operators decide on operating condition for every single piece of equipment, product distribution, detailed process flow and also monitor the plant performance (Zhang and Zhu, 2000). Proper planning and scheduling relates flow of materials from one unit to the other or connect decisions between two successive time periods, hence, guiding the personnel on order to follow towards realization of the production objectives.

In most research studies, dealing with planning and scheduling seems to be confusing (Al-Qahtani and Elkamel, 2010). However, in general, the difference is that " while planning focused on the high level decisions such as investment in new facilities and set targets on the amount and quality of end products to manufacture over longer time horizons, scheduling on the other hand is a short-term plan assigned to facilitate the accomplishment of the optimal production targets at due dates or at the end of a given time horizon" (Ierapetritou and Floudas, 1998). Kong (2002) is of the view that operational planning is synonymous to scheduling at the production stage.

While in planning maximization of profit is the ultimate goal, in scheduling the emphasis is rather on exploring the feasibility of accomplishing a task within a given time frame (Grossmann et al., 2002). The usual practice in the refining industry is to follow a hierarchical order; solving planning problem first to define production targets and then employing scheduling tool to provide the means of achieving those targets. The interdependence of these two optimization strategies diminished when a lengthy time horizon is considered, resulting in treating the two separately.

Despite being at different levels of decision-making, both planning and scheduling have economics as their optimization criterion and to some extent depends on decisions emanating from other levels in optimization hierarchy. Figure 2-1 presents flow information diagram illustrating different levels of decision making in the plant optimization hierarchy. The hierarchy of decision making is composed of three main levels. Planning and advanced control at the first and third levels respectively. Scheduling is at the second level and is mostly considered at lower corporate level (Zhang, 2006). The optimal values of decision variables in scheduling provide the set points for controllers.

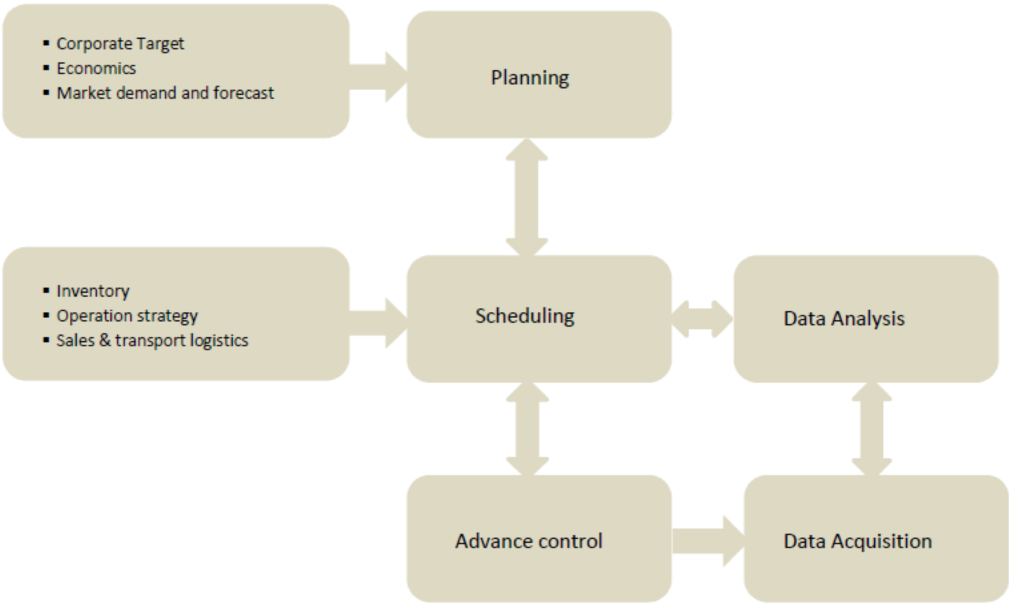


Figure 2-1: Hierarchy in decision making

2.4 Scheduling for Refinery Subsystems

The review here covers the crude oil unloading area, production area and product blending area. It is through crude unloading area refinery receives raw material (crude oil) for transfer to downstream units for processing. The production area transforms crude oil into intermediate products and the products are then sent to blending units for further processing. Review of different work for units of the refinery subsystems/areas will be discussed in the following sub-sections.

2.4.1 Crude Oil Unloading Area

Crude oil scheduling is a crucial part of the refinery supply chain (Saharidis et al., 2009). It is a process that involves specifying the timing and sequence of operations in this order of vessel arrival, crude oil unloading to storage tanks, transferring crude oil parcels from storage tanks to charging tanks and finally sending the mixed crude oil to Crude Distillation Units (CDUs) for component separations and downstream processing. A typical schedule sets daily targets for production with consideration on storage and charging tanks’ capacities, CDU capacity utilization and pumping capabilities. It also determines the quality and quantity of crude mixing materials in the charging tanks in order to produce blends that satisfy the requirements of planning team. Each of these activities is associated with cost. The objective of scheduling is to minimize the total cost while following the feasible operational procedures (Jia et al., 2003).

Crude oil unloading area provides the platform for supplying the raw material to be processed in the refinery plant. It has the facility for receiving crude oil material and transfer the bulk quantity to the refinery plant for processing via pipeline, large tankers and sometimes, by railroad (Guyonnet et al., 2009). In the refinery plant, care is always taken not to degrade more expensive crude with cheaper and low grade crude oil material by carrying out an unloading process such that different grades are transferred into different tanks. Segregating the different crude materials offers a greater degree of freedom to the refiners in preparing blend recipes.

It is an operational policy that while storage tank is receiving crude oil from vessel, it cannot feed charging tank at the same time. This will enable tank level differences to be checked (Kelly and Mann, 2003b). Removal of brine is normally done on receipt of crude parcel before transfer from storage to charging tanks. Blending of crude oil is carried out in charging tanks to prepare blends according to the CDUs demand and adequately supplied to meet downstream processing units’ specifications. Figure 2-2 is the schematic showing the components of the crude oil unloading area.

Research focus in crude oil unloading area has been primarily on modelling to generate reliable schedules that reflect the ever changing dynamic environment under which petroleum refineries operate. Since scheduling of crude oil operations usually involves continuous and discrete decisions, MILP or MINLP are used in formulating the scheduling problems. One of the most important methodology developed is the work of Lee et al. (1996) that addresses the problem of inventory management of a refinery that receives different crude parcels within fixed scheduling horizon. Bassett et al. (1996) considers a model based approach to address a scheduling problem while considering number of units/ equipment involved number of operations, available resources and length of scheduling horizon.

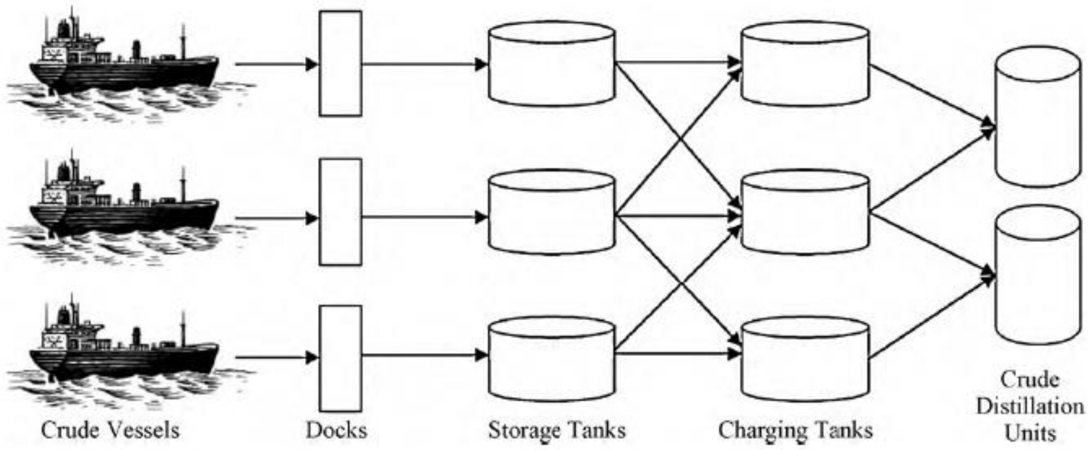


Figure 2-2: Crude oil unloading, storage, blending and CDU charging (Yüzgeç et al., 2010)

Two popular approaches based on time representation of scheduling horizon have been used in formulating scheduling problems: discrete-time formulation and continuous-time formulation. A third but less popular approach combines these two time formulations to develop mixed time formulation (Westerlund et al., 2007). Mouret et al. (2009) introduced a new approach for continuous-time formulation known as priority-slots based method. Pinto et al. (2000) used variable length time slots to create short-term scheduling of crude oil operations in a 200,000 bpd refinery that receives about ten different crude types in seven storage tanks. They used uniform time discretization of 15 minutes to generate an MILP problem that proved to be infeasible with the available optimization tools at that time.

Shah (1996) adopted mathematical programming technique to develop a model for a single refinery consisting of scheduled ship arrivals, port infrastructure, pipeline details, and production requirements and planned CDU runs, based on uniform time discretization with the objective of minimizing the tank heels. Yee and Shah (1998) used two methods to tighten the relaxation gap and narrow down the search space for integer solution of scheduling problem in a multipurpose plant. The use of time discretization presents some challenges making other researchers to seek for more possible options such as event-based formulations.

Saharidis et al. (2009) presented MILP formulation with uniform discrete-time intervals where the intervals are based on events instead of hours. Jia et al. (2003) developed a model for scheduling of oil refinery operations based on unit specific event point formulation using the state task network (STN) representation introduced by Kondili et al. (1993). Moro and Pinto (2004) developed a global event-based continuous-time model for crude oil inventory management of a refinery which processes several types of crude oil. Saharidis et al. (2009) used an event-based time formulation for scheduling of crude oil unloading, storage and charging of CDUs. The goal of their model was to optimize crude oil blending and cut down the number of tank setup during vessel unloading thereby reducing the number of tanks used.

Simplification of a complex case to problems of manageable size is an incentive in refinery scheduling. Several authors have adopted an approach that breaks down large scheduling problems into smaller problems. Harjunkoski and Grossmann (2001) used a spatial decomposition strategy to split large scheduling problem for steel production into smaller programmes. This method produced solution within 1-3% of the global optimum. Shah et al. (2009) presented a general novel decomposition scheme which breaks down the refinery scheduling problem spatially into subsystems. The subsystems were solved to optimality and the optimal results were integrated to obtain the optimal solution for the entire problem. This results in fewer continuous and binary variables compared to centralized systems.

2.4.2 Refinery Plant Production Area

This covers the mainstream operation of the refinery. In the production area, we find most of the process units accomplishing the unit operations that make up the crude oil processing. Review will be given on modelling of CDU, VDU, NHU and FCC units. Rigorous and simplified models are discussed in the units' modelling.

2.4.2.1 CDU Modelling

CDUs are the first major processing units in the refinery. They receive crude oil from charging tanks and separate the components of the hydrocarbon material on the basis of differences in boiling point through a separation technique called distillation. The processing units following CDU will have feed stocks that meet their particular specifications (Watkins, 1979). Figure 2-3 is the process schematic of a typical CDU with auxiliary facilities (Ronald and Colwell, 2010).

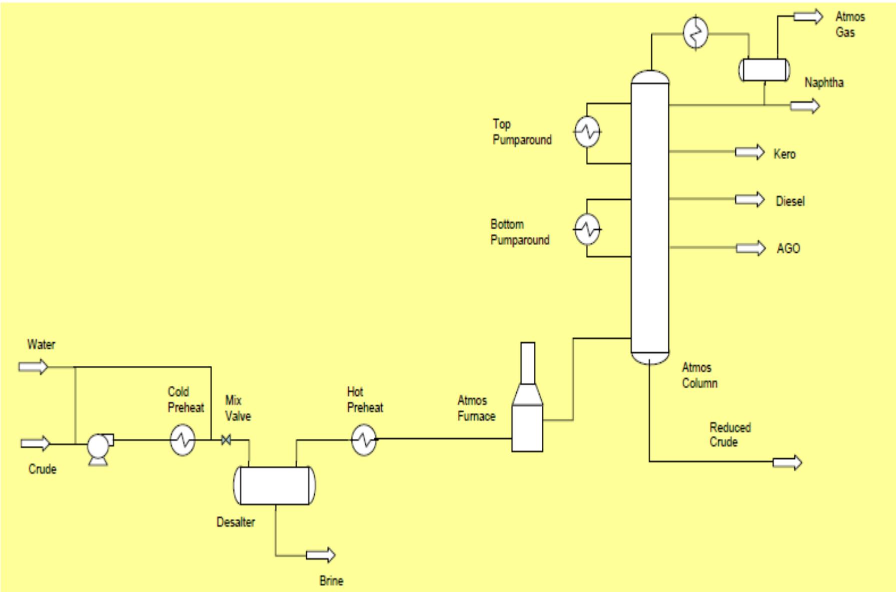


Figure 2-3: Process schematic of refinery CDU (Ronald, and Colwell 2010)

In CDU modelling, yield of cut fractions are obtained from simulation of rigorous or empirical models. Rigorous models simulate a CDU as a general distillation column, using thermodynamic properties, energy and material balances and equilibrium relations along the whole column to generate flow rates, composition of internal and external streams and process conditions as outputs. Empirical models, on the other hand, use empirical correlations to establish material and energy balances for CDU (Li et al., 2005).

The crude assay is characterized to facilitate the computation of the CDU yields; thus CDU is modelled in a way similar to any multicomponent, multistage distillation column (Kumar et al., 2001). This requires at least the following information.

- Whole crude True Boiling Point (TBP) curve
- Whole crude American Petroleum Institute (API) gravity and
- Whole crude light ends analysis (Watkins, 1979).

TBP curve is presented in Figure 2-4 as a plot of TBP temperature versus volume percent vaporized, which along with the specific gravity of crude oil characterize the feed material (Basak et al., 2002). With the TBP curve, the component distribution of material being tested can be analyzed in accordance with the laid down procedures developed by the American Society for Testing Materials (ASTM). TBP distillations are normally run only on crude oils and not on petroleum fractions (Watkins, 1979).

American Petroleum Institute (API) gravity is defined as a ‘‘specific gravity scale measuring the relative density of various petroleum liquids, expressed in degrees. It is an arbitrary scale expressing the gravity or density of liquid petroleum products devised jointly by the American Petroleum Institute and the National Bureau of Standards. The measuring scale is calibrated in terms of degrees API. Oil with the least specific gravity has the highest API gravity. The formula for determining API Gravity is: API gravity = (141.5/specific gravity at 60 degrees F) – 131.5’’ (Hopkins, 2012).

In the refinery, the term ‘light ends’ generally means any discrete component lighter than heptane which can be identified by a name. These include everything from hydrogen through the hexanes. A more narrow definition might consider C3 and C4 liquids as light ends since, in many refineries, ethane and lighter are used as fuel gas and pentanes and hexanes are blended directly into gasoline (Watkins, 1979). These components are incorporated in most of the commercial simulation packages like Aspen PLUS for rigorous modelling.

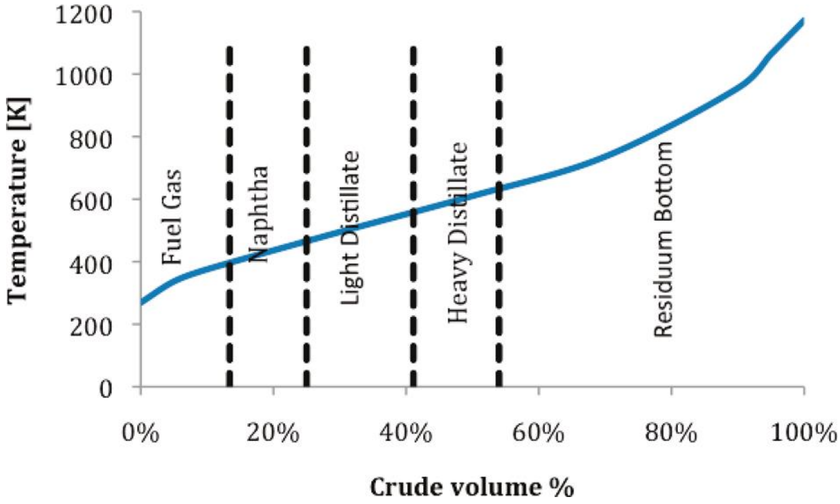


Figure 2-4: Crude oil TBP curve showing cut fractions (Alattas et al., 2011)

CDUs of a refinery can be modelled using different approaches. These include: fixed yield representation, swing cut model (Li et al., 2005; Zhang et al., 2001), and fractionation index (FI) (Alattas et al., 2011; Alattas et al., 2012). In fixed yield approach, distillation behaviour is pre-determined using the crude assay information run in a computer simulation program (simulator). The simulator determines cuts at designated temperature and pass the resulting yield and property information to LP planning model (Trierwiler and Tan, 2001; Li et al., 2005). Figure 2-5 is the schematic representation of this approach. The major drawback of this procedure is that it does not reflect real life refinery operation where there are different operating modes. Also, the yield prediction might not be optimal since the CDU is modelled using linear functions of the crude feed (Alattas et al., 2008).

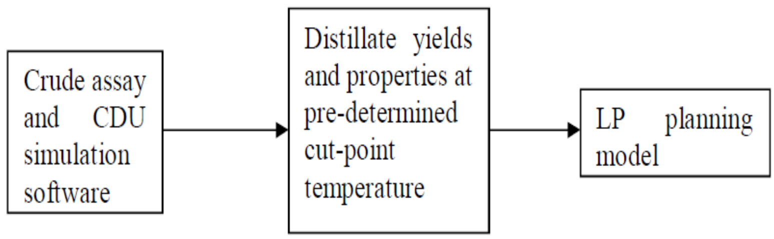


Figure 2-5: The flow diagram of fixed yield structure representations (Trierwiler and Tan, 2001)

An improvement to fixed yield representation is the swing cut approach where the cut fraction is optimized. After determining the desired product cuts of the crude, about 5% to 7% of the yield around adjacent fractions of the crude is allowed to change as in Figure 2-6, so as to improve the cost function (Zhang et al., 2001; Trierwiler and Tan, 2001). The minimum modifications required for the swing cuts approach allow more optimization opportunity and possible blending of different operating modes. Despite this improvement, their model does not reflect the nonlinearity of the process, but it provides an incentive to further improve the planning/scheduling model and calculate more accurate yields (Alattas et al., 2008). However, Menezes et al. (2013) improved the swing cut approach by considering light and heavy swing cuts qualities to be different from the bulk or whole swing cut properties. Their formulation introduced nonlinearity and hence provides more accurate predictions.

In FI approach, the CDU is modelled as a series of fractionation units based on previous works on equilibrium flash calculation of distillation column by Geddes (1958). The idea was extended by Alattas et al. (2011) providing a nonlinear method for determining product stream compositions and cut point temperatures in the CDU thus avoiding the rigour of complex and time-consuming energy, equilibrium, and momentum calculations. One major setback of this approach is that the yield purity is never guaranteed considering that the bottom product collected as yield at a particular temperature T1 in PB1 may not have been completely condensed. This results in the temperature of the vapour going to the next stage enters with entrained liquid of the bottom product, making the optimization problem nonconvex. Also, the solution instability resulting from the model being highly nonlinear, makes FI approach not suitable for control studies. Figure 2-7 illustrates the FI model representation. It is outside the scope of this thesis to discuss much on the CDU modelling; the reader should refer to papers and books already cited in this section for detail.

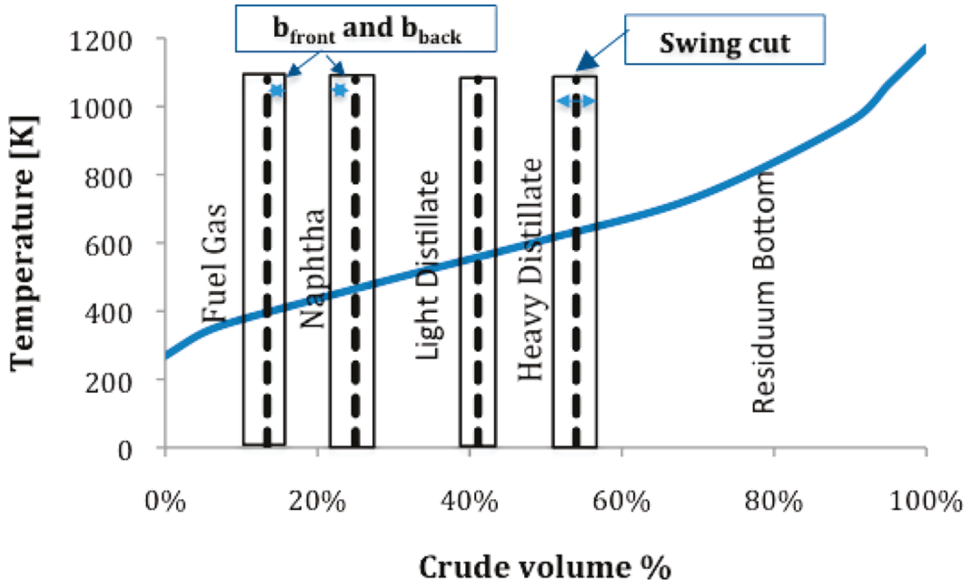


Figure 2-6: Crude oil TBP curve with swing cuts (Alattas et al., 2011)

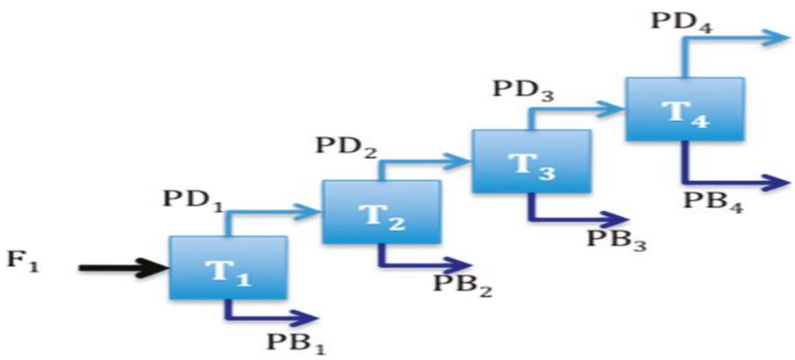


Figure 2-7: CDU representations for the FI model (Alattas et al., 2011)

2.4.2.2 VDU Modelling

This unit processes atmospheric residue from CDU by re-heating the heavy fractions and fed into the vacuum tower with vacuum steam to obtain the cut fractions based on TBP of the 'cuts' generated during crude oil characterization. The primary purpose of the vacuum steam is to reduce the hydrocarbon partial pressure in the flash zone of the vacuum tower. Lowering the hydrocarbon partial pressure in the flash zone enables vaporisation and hence distillate production. The specification for the vacuum gas oil is also in form of TBP (Ejikeme-Ugwu, 2012). VDU process schematic is shown in Figure 2-8

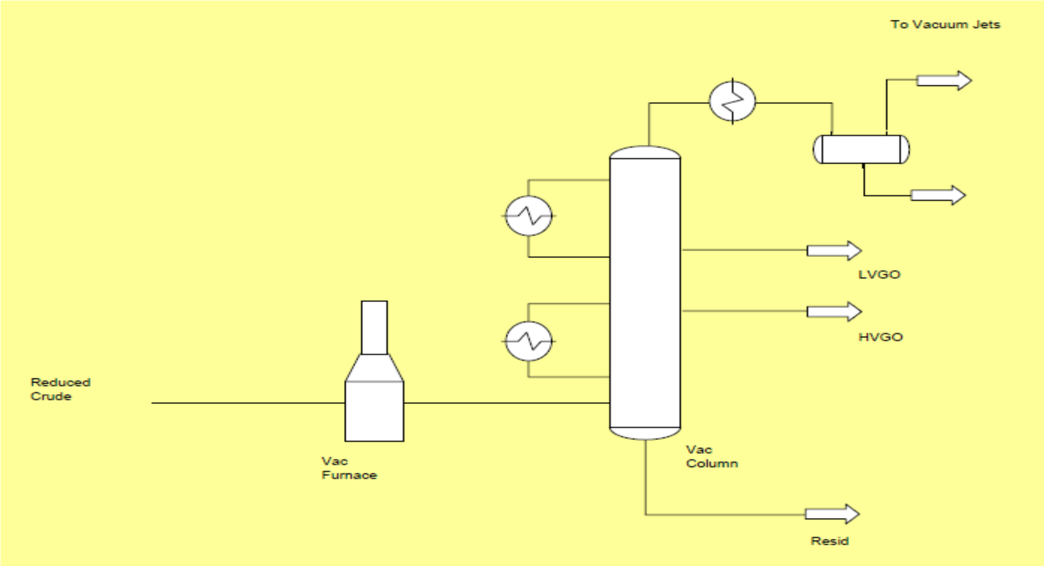


Figure 2-8: Process schematic of a typical refinery VDU (Ronald and Colwell, 2010)

Unlike CDU, VDU modelling does not record a large number of publications in process modelling research (Rodolfo et al., 2010). However, a number of researchers have used commercial software packages such as Aspen PLUS, Aspen HYSYS, Aspen PIMS; to generate yields for cut fractions. Ejikeme-Ugwu (2012) used Aspen HYSYS to obtain yields for vacuum overhead (VO), light vacuum gas oil (LVGO), heavy vacuum gas oil (HVGO) and vacuum residue (VR) for different volumetric ratio of crude mixture using rigorous simulation.

2.4.2.3 NHU Modelling

NHU is designed to reduce sulphur content and other impurities in gas oils from CDU and VDU to the specification of downstream processing units through hydrodesulphurization (HDS) process (see Figure 2-9 for process schematic). Product yield from NHU is placed within 95-98 % (Gary andHandwerk, 1984); this was reported by Ejikeme-Ugwu (2012) based on the fact that not much has been done in this area of study. However, some researchers worked towards developing a kinetic model that should be able to estimate the most accurate operating conditions necessary to achieve sulphur level that meets the desired specification.

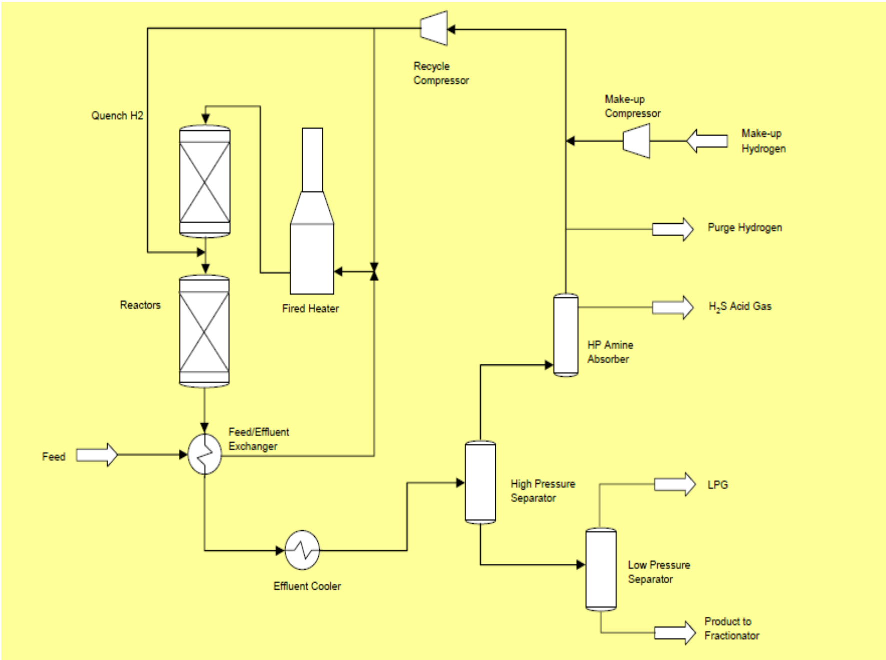


Figure 2-9: Process schematic of a typical refinery NHU (Ronald and Colwell, 2010)

López-García and Roy-Auberger (2003) have developed a kinetic model and conducted experiments adapted to ultra-low sulphur diesel (ULSD) production for industrial feedstocks. The model is based on a lumped reaction scheme distinguishing three refractory sulphur families based on Langmuir-Hinshelwood kinetics. The Langmuir-Hinshelwood representation takes into account the inhibiting effect of aromatics and nitrogen species on HDS. Their results indicate a good agreement between most experimental and predicted sulphur content.

Boesen (2010) investigates diesel hydrotreating reactions and developed a kinetic model. He used the model to study the kinetics of hydrogenation of naphthalene on a commercial CoMo catalyst. He further conducted an experiment at industrial temperatures and pressure, using naphthalene as a model compound, and found out that intra-particle diffusion resistance might have impact on the reaction rate.

Jarullah et al. (2011) used optimization techniques to obtain the best values of kinetic parameters in trickle-bed reactor (TBR) for HDS process based on pilot plant experiment. The technique adopted in their work minimized the sum of the square errors (SSE) between the experimental and predicted concentrations of sulphur compound in the products using linear and non-linear regressions methods. The authors went further to carry out an economic analysis of an industrial refining unit involving hydrotreatment (Jarullah et al., 2012).

2.4.2.4 FCC Modelling

FCC is employed to produce gasoline from crude oil. FCC typically consist of a riser where hydrocarbon materials react in the presence of a catalyst, a reactor to separate gasoline and catalyst, and a regenerator to burn off coke and other impurities from the used catalyst (Whitcombe et al., 2003; Whitcombe et al., 2006). The reactivated catalyst are sent back through the riser in a cyclic process (Kunii and Levenspiel, 1991). Figure 2-10 presents the FCC process schematic equipped with other facilities (Ronald and Colwell, 2010).

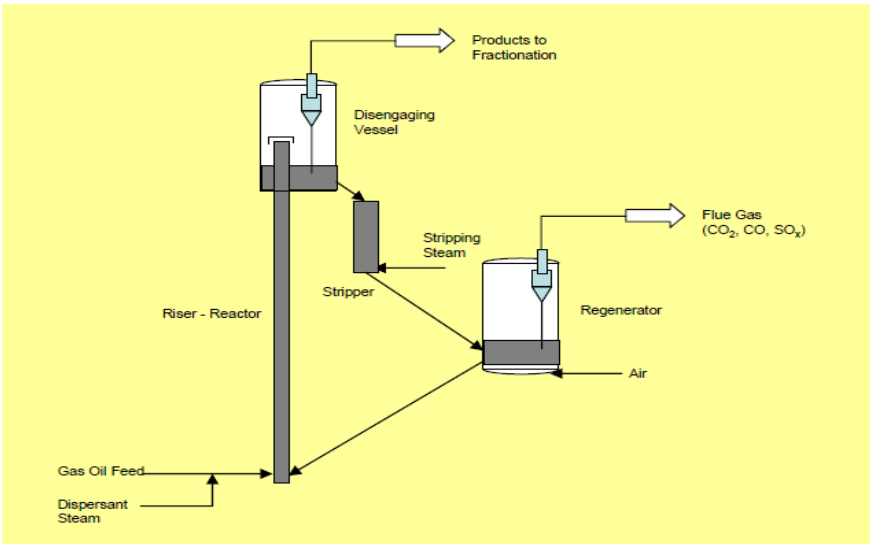


Figure 2-10: Process schematic of a typical refinery FCC (Ronald and Colwell, 2010)

To model FCC, (Gary and Handwerk, 1984) used hand-calculation procedure to obtain yield correlations to be used in the main planning/scheduling model. The procedure was reported in Li et al. (2005). Al-Enezi et al. (1999) developed regression models for predicting product yields and fluid properties for the FCC. Researchers like Al-Enezi and Elkamel (2000); Michalopoulos et al. (2001) and a host of others employed artificial neural network (ANN) model to study the steady state behaviour of an industrial FCC. This has pointed a way to effectively develop a surrogate/empirical/black box model capable of predicting the volume percent of conversion based on input variables.

The general view is that refinery processes like FCC operation are complex in nature. These processes are characterized by high dimensional representation and strong interaction among the process parameters, posing a serious challenge studying FCC. Modelling FCC usually requires the application of mass and heat transfer, fluid mechanics, thermodynamics, and kinetics, which results in the formulation of a system of nonlinear, coupled algebraic and/or differential equations. These are described by a large number of equations requiring many parameters to be estimated.

2.4.2.5 CRU Modelling

CRU or reformer is primarily for improving the octane rating of naphtha feedstock to the level that makes the reformate product suitable as a gasoline blend stock (Antos and Aitani, 2004), thus upgrades the gasoline quality in the final product (Majid and Sadat, 2012). Like NHU not much has been reported in CRU modelling but a few number of researchers have contributed in kinetic study of the process. Raouf et al. (2011) investigates the dehydrogenation, dehydrocyclization, and hydrocracking reaction to characterize the catalysts performance toward higher activity and selectivity to desired products. In their study, the performance of catalysts was studied under the operating condition of weight hour space velocity in the range of (1-2 hr^{-1}) and reaction temperature in the range of (480-510 °C). They found out that the conversion of heavy naphtha components (Paraffin's and Naphthenes) is directly proportional to the reaction temperature and inversely proportional to the weight hour space velocity.

The reader should refer to articles on catalytic reforming of naphtha for detail on how the process operates. Figure 2-11 illustrates the schematic of the process.

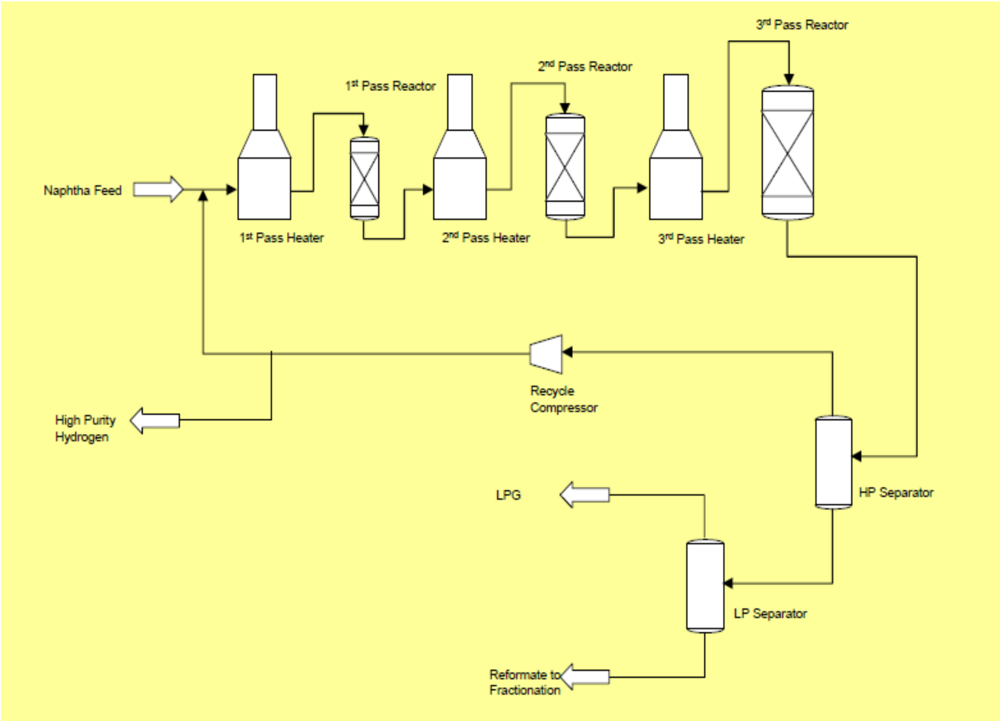


Figure 2-11: Process schematic of a typical refinery CRU (Ronald and Colwell, 2010)

2.4.3 Production with Product Blending

The production with product blending subsystems included gasoline and diesel blending units in addition to the other main refinery production units (CDU, VDU, NHU and FCC). The purpose of blending operation is to produce final products that satisfy quality requirements and demand of a customer and also meet the environmental regulations set by the government. The goal of integrating production with product blending is to allow more realistic exchange of information and flow of material between these subsystems. This generates more reliable schedules and offers comprehensive cost minimization options that allow production to follow correct operational sequence. Revenue along with production schedule, production profile, and inventory levels for component and product tanks are determined.

Despite the benefit inherent in simultaneous optimization of production with blending, it appears fewer publications have been reported in this area of research. Planning/scheduling models for production and products blending subsystems have been developed by Aronofsky et al. (1978); Kendrick et al. (1981); Moro et al. (1998); Pinto et al. (2000); Joly et al. (2002); Li et al. (2005); Alattas et al. (2012) and Tong et al. (2012). These methodologies depict the whole plant topology but the models differ in the way the optimization problem was formulated, size of the problem, complexity of the units involved and objectives aim to achieve. Some scheduling models of production with blending subsystems focused on specific product orders and developed based on a specific time formulation.

Scheduling model presented by Jia and Ierapetritou (2004) for refinery production subsystem considers fractionation and reaction processes using continuous time formulation. The major drawback of their approach is the non-inclusion of other vital units like FCC, NHU and CRU; making the model unreliable and hence inaccurate. A simultaneous slot based short-term scheduling and off-line blending of gasoline products has been reported in Méndez et al. (2006) in both discrete and continuous time domain in which an integrated MINLP problem is solved as iterative MILPs. Another MINLP slot based formulation that relies on iterative MILP solution procedure is the work of Li et al. (2010). Also, their model is based on gasoline product but incorporate many real life features like changeovers, non-identical blenders, minimum run length etc.

Cuiwen et al. (2013) developed mathematical formulations as MINLP and devises a solution algorithm that solves real world refinery scheduling problems for production with diesel blending. It is important to note that in real life refinery operation, other products like gasolines are also blended in addition to the diesel product grades. Hence, the major setback in their approach is that the model was developed based on refinery configuration that processes only diesel products. However, the MINLP model was able to capture both certain and uncertain events. The model uncertainties are solved using online data driven rolling horizon strategy.

2.5 Refinery Scheduling with Consideration to Uncertainty

Most of the work reported in refinery planning/scheduling are based on deterministic formulation with less consideration to uncertainties in the model parameters (Lin et al., 2004). Deterministic models assume that parameters are known with certainty (Liu and Sahinidis, 1996). Moreover, it has been observed by Petkov and Maranas (1997) that failure to account for uncertainty in raw material and product prices, demand and other market conditions could affect customer satisfaction, high inventory cost and may likely aid business misfortune. Uncertainty consideration in manufacturing systems could offer a huge success (Mula et al., 2006).

Different approaches have been proposed in literature to deal with refinery optimization under uncertainty. For example, stochastic optimization which could be two-stage or multistage with recourse (Al-Qahtani and Elkamel, 2010; Liu and Sahinidis, 1996; Sahinidis, 2004) can be employed to deal with problems in which some uncertain parameters are included in the cost function and constraints. In stochastic programming, these uncertain parameters are usually described by probability distributions or by possible scenarios (Clay and Grossmann, 1997; Liu and Sahinidis, 1996; Ierapetritou and Pistikopoulos, 1996).

The refinery scheduling problems under uncertainty are among the most challenging optimization problems. Despite their complexity, a number of research studies have been reported in the literature. A two-stage model to deal with uncertainties in ship arrival times and demand was proposed by Wang and Rong (2010). Their work integrates chance-constrained programming and fuzzy programming in the first stage to develop a model that can be transformed into a deterministic counterpart and employ a scenario-based framework in the second stage.

Lin et al. (2004) proposed a novel robust optimization framework to deal with bounded uncertainty, producing optimal solutions that are immune to changes in the coefficients of the objective function and changes in the left-hand-side and right-hand-side parameters of inequality constraints. They extended this idea to address uncertainty with known probability distribution (Janak et al., 2007). The optimization framework was further extended to a deterministic robust counterpart model to deal with demand uncertainty (Li et al., 2012b) and solved using branch and bound global optimization algorithm proposed in (Li et al., 2012a). Cao et al. (2009) presented chance-constrained stochastic MINLP and fuzzy programming models for crude oil scheduling under demand uncertainty.

2.6 Current and Future Directions

Traditionally, uncertainties are considered at the design stage as preventive measures to ensure schedules generated are reliable under uncertain operational conditions. Also, reactive measures have to be in place to keep track of changes in process conditions, constraints, or performance criteria. Until recently, less attention was given to the scheduling of refinery systems using control theory. From control point of view, uncertainty can be accommodated as a disturbance introduced into a system operating at steady state. Therefore refinery scheduling problems can be formulated and solved in a closed loop control fashion.

2.6.1 Control Optimization Strategies as Viable Alternatives

Various alternative formulations have been proposed in modelling supply chain problems under uncertainty. Control theories provide sufficient mathematical tools to address uncertainty in process systems (Sarimveis et al., 2008). In scheduling problems, system dynamics are defined using discrete time representations, material balance, and component balance while updating state of the system based on current value of the uncertain parameter. In reality, solution procedure under particular framework mimics close loop feedback control structure as actions to be taken at any time instant depend on the output value at previous times. Uncertainty (disturbance) affects the system states like flowrates, inventory levels, and schedule generated considering the entire uncertain parameter space is adjudged to be robust.

From process point of view, two types of uncertainties are to be expected: endogenous uncertainties that manifest when operators have little knowledge about the process itself, for example kinetic parameters of reaction system, mass transfer rate in CDU, etc. and exogenous uncertainties introduced externally but have impacts on the process. In refinery systems, exogenous uncertainties could be crude oil feed rate, composition, fuel products recycled into the system, composition of additives used in blending units etc. In this work, uncertainties due to crude oil feed rate and crude oil composition were addressed.

2.6.1.1 Receding horizon

Receding horizon under the framework of model predictive control has been reported for production scheduling as a powerful tool to address disruptive events. Kopanos and Pistikopoulos (2014) developed a solution procedure that works with multiparametric programming to address uncertainty for systems with bounded uncertain parameters. Their approach suffers a major setback as problems involving MINLP was out of their consideration. However, the concept proposed is still promising in that large scale optimization problems can be solved.

Receding horizon has been applied successfully in Goodwin et al. (2006) to address mining problems. Non-uniform time discretization was proposed to formulate the problem described using state-space representation. The dynamic model captures real time issues and uses mining action as control input. In Munawar and Gudi (2005), receding horizon was considered as a tool for handling disruptive effects on reactive scheduling. Problems were formulated at different levels to verify the robustness of the control theory approach in generating reliable schedules.

In Yüzgeç et al. (2010), a model predictive control strategy was presented to address uncertainty in demand of crude oil from blending tanks using moving horizon control strategy. The solution procedure adopted in the paper is similar to moving end control strategy employed in this work to compare with our fixed end horizon approach. Their approach is not a good option for customers with fixed deadline due to low degree of freedom as solution search does not cover the entire length of the scheduling horizon. In production area of refinery, Cuiwen et al. (2013) used similar approach successfully.

More detail about this methodology will be given in Chapter 4.

2.6.1.2 Self-optimizing control

Self-optimizing control strategy (SOC) has been a technique to deal with uncertainty in most chemical processes. Although it records a significant number of publications, the concept has never been applied in petroleum refinery scheduling. It has been shown in Kariwala (2007); Alstad and Skogestad (2007); Kariwala et al. (2008); Jäschke and Skogestad (2011); Ye et al. (2012a); and Ye et al. (2012b) that SOC is a reliable technique for solving problems with uncertainty in process parameters. Applying the solution strategy on refinery production problems should result in generating optimal schedules globally.

Using SOC, controlled variables (CV) can be selected so that when they are maintained at constant set points the overall plant operation is optimal or near optimal despite various uncertainties. In this study, the focus will be on maintaining the gradient of the cost function at zero via Taylor series approximation of CVs over the whole parameter space. The CV should approximate the gradient adequately (Ye et al., 2012b). The detail of the methodology and how it works will be discussed in Chapter 6.

2.6.2 An Integrated Approach

Several models for planning and scheduling of refinery systems are reported separately in literature. The two decision levels are interwoven with scheduling mainly executing orders set by planning. A model that integrates planning and scheduling will improve the efficiency and profitability of a refinery business. An integrated planning and scheduling with consideration to endogenous and exogenous uncertainties will aid more reliable decisions. This motivates some researchers to exploit different ways to model and solve the plant-wide problems. Few research studies reported include Mouret et al. (2011);

Verderame et al. (2010); Munawar and Gudi (2005); Pinto et al. (2000); Joly et al. (2002); and Luo and Rong (2009).

In most of the work reviewed in refinery planning and scheduling, exogenous uncertainties predominate. However, there is also a need to consider endogenous uncertainties as they affect the quality and economics of the overall production.

2.7 Summary of Knowledge Gap in Refinery Scheduling

Below are the highlights of the knowledge gap this research study finds worthy to fill.

- Models developed previously have shortcomings in one way or the other that practical implementation of decisions obtained from solving the models may fail to reflect realities. Therefore there is the need to develop a more reliable model for crude oil scheduling.
- While mathematical techniques for refinery planning have a long established presence in petroleum research studies, much less has been reported in scheduling of production area. Accurate model for simultaneous optimization of production with product blending is necessary in order to generate optimal schedules at minimum cost.
- Generally, crude oil refinery operates under economic and environmental conditions bounded with uncertainties. Models which take into cognizance a number of uncertainties can be expected to generate reliable decisions. In most of the work reported in refinery scheduling, uncertainties from design point of view predominate. However, there is also a need to consider operational uncertainties (uncertainty in the form of disturbance) as they affect the accuracy and robustness of the overall schedule.
- This study fills these gaps as discussed in Section 1.4 of the introductory chapter. Work done to address the issues raised will be reported in Chapters 3, 4, 5 and 6.

3 MODELLING CRUDE OIL UNLOADING AREA

Being an integral part of the refinery supply chain, optimization of crude oil refining processes promises a big cut in operational and logistic costs of the whole refinery plant. Better economic performance is achieved by developing robust procedures for short-term scheduling of material flow in crude oil unloading area. The work in this chapter is on the modelling, investigating the model performance through case studies, and schedule generation under uncertain conditions.

In research studies, crude oil scheduling problems are often formulated as optimization model with operating cost as the objective function. The challenge with building models for crude oil scheduling lies in knowing and including what is relevant for the specific decisions that are to be made using the model and neglecting the elements that are not relevant. Selection of units with arrangements on the sequence of operation with regards to modelling of crude oil scheduling problems requires a systematic approach.

Since scheduling of crude oil operations usually involves discrete and continuous decisions (e.g. vessel unloading, tank switching, flow of mixed crude, etc.), mixed integer linear programming (MILP) or mixed integer nonlinear programming (MINLP) are used in formulating the optimization problem. A significant number of techniques were developed for generating schedules in this area of study. However, there is still a gap of knowledge that needs to be bridged towards the development of more reliable procedures that are not only acceptable to the planning team but also have the capability for guaranteeing performance during execution in the real refinery plant. Model presented in Lee et al. (1996) has been a benchmark upon which other crude oil scheduling models were built. This research study also finds the model suitable for used in generating schedules under uncertainty.

In this chapter, a methodology for short-term crude oil unloading, tank inventory management, and crude distillation unit (CDU) charging is developed as an extension to Lee et al. (1996) model. The extended model considers real life issues not captured in the original model and was developed through reformulation in which the problem statement was modified to account for certain details. The performance of the extended model was assessed through case studies. The reformulation was based on established operating rules in petroleum refineries, material balances, resource allocations, sequencing order, product quality, and demand of mixed crude oil.

Scenarios were created to offer recommendations to plant operators on the best schedule to use. Uncertainties due to disruptive events (CDU shutdown), and low inventory at the scheduling horizon were also considered.

3.1 Model Formulation for Crude Oil Scheduling

3.1.1 Problem Definition

Same as in Lee et al. (1996), this study considers a coastal refinery with docking stations (where the crude vessels unload their content), storage tanks (for holding crude oil before transfer to charging tanks), and charging tanks where blending operation is carried out for subsequent transfer to CDUs in accordance with the CDUs mixed crude oil quality requirements. These transfer operations are achieved in different units/facilities interconnected by means of a pipe network. Throughout the scheduling horizon, industry operational practice is observed. The following technical details are available to adequately define the crude oil scheduling problem.

- Number of vessels, amount and crude oil parcel conveyed and the arrival and departure times of each vessel.
- Number of units/facilities for the crude oil transfer from vessel down to the CDU with their capacity limits, initial inventory levels and interconnections.
- Upper and lower bounds on the stream flows across the connecting units/facilities.
- Specification of key components with their permissible concentration ranges.

- Information on dedication of certain tanks for receiving specific crude oil types.
- Other information such as CDUs demand of mixed crude oil from charging tanks, unloading and sea waiting costs of vessels, inventory costs for charging and storage tanks, tank-tank set up cost, changeover cost, and shutdown cost for CDUs.

With the information above, the scheduling problem is to minimize the overall cost of operation by determining the following optimization variables:

- Waiting time for each vessel until the unloading process begins.
- Unloading duration for each vessel.
- Volume per unit time of crude oil unloaded for each vessel.
- Volumes per unit time of crude oil transferred from vessels to storage tanks then to charging tanks and finally to CDUs.
- Vessels, storage and charging tanks' inventory levels at each time interval within the scheduling horizon.
- CDU charging rates.
- Time and sequence of charging mixed crude oil into each CDU.
- Time and sequence of crude oil transfer from storage tanks to charging tanks.
- Concentration of key component (such as sulphur) in charging tanks.

3.1.2 Model Assumptions

Same as in Lee et al. (1996), Li et al. (2007), Yüzgeç et al. (2010), Reddy et al. (2003), and Pan et al. (2009); the following assumptions are considered in this section.

1. The unloading operation is carried out in only one docking station.
2. Volume of crude oil remaining in the pipeline is negligible compared to the total volume processed in the entire scheduling horizon.
3. The time for change-over is negligible compared to the entire scheduling horizon.
4. Perfect mixing occurs in the charging tank and mixing time is negligible.

5. Continuous demand order matches the limits of the CDU operations.

3.1.3 Objective Function

The objective function is the cost function to be minimized, which includes unloading and sea waiting costs for the crude oil vessels, the storage and charging tanks' inventory costs, changeover cost and the penalties for CDU shutdown and tank-tank transfer.

$$COPR = CUNL_v \sum_{v=1}^{NV} (TL_v - TF_v) + CSEA_v \sum_{v=1}^{NV} \left(TF_v - T_{ARR,v}\right) \tag{3-1}$$

$$+ CINST_i \sum_{i=1}^{NST} \sum_{t=1}^{NSCH} \left(\frac{VS_{i,t} + VS_{i,t-1}}{2}\right)$$

$$+ \quad CINBT_j \sum_{j=1}^{NBT} \sum_{t=1}^{NSCH} \left(\frac{VB_{j,t} + VB_{j,t-1}}{2}\right)$$

$$+ \sum_{j=1}^{NBT} \sum_{l=1}^{NCDU} \sum_{t=1}^{NSCH} \left(CC \times Z_{j,l,t}\right) + \sum_{l=1}^{NCDU} \sum_{t=1}^{NSCH} CD \times XD_{l,t}$$

$$+ \sum_{i=1}^{NST} \sum_{t=1}^{NSCH} CS \times XS_{i,t}$$

In Equation 3-1, the unloading cost of crude vessels ($v = 1$ to NV) is the product of unloading cost per unit time interval, $CUNL_v$ and unloading duration (vessel departure time TL_v minus vessel unloading initiation time TF_v). Similarly, the sea waiting cost of crude vessels ($v = 1$ to NV) is the product of sea waiting cost per unit time interval, $CSEA_v$ and waiting duration (vessel unloading initiation time TF_v minus vessel arrival time $T_{ARR,v}$).

The storage tanks inventory cost is computed by multiplying the cost per unit time per unit volume, $CINST_i$ of tanks ($i = 1$ to NST) over the interval length ($t = 1$ to $NSCH$) with the average tanks' volumes $VS_{i,t}$ at two successive time periods t and $t - 1$. Charging tanks ($j = 1$ to NBT) inventory cost is computed in a similar way with $VB_{j,t}$ as the tanks' volume at time period t. $CINBT_j$ is the cost per unit time per unit volume.

The changeover cost for CDUs ($l = 1$ to $NCDU$) is proportional to the number of blended crude oil switching given by the binary variable $Z_{j,l,t}$ with CC as the cost for each switch operation. When there is CDU shutdown as discussed in one of the scenarios in this chapter, a binary variable $XD_{l,t}$ is activated and is penalized with CD as the cost. A binary variable $XS_{i,t}$ is activated whenever there is a tank-tank transfer operation. CS represents the cost penalty for each transfer operation.

3.1.4 Constraints

3.1.4.1 Rules of operation

Vessel unloading sequence

The arrival and departure of crude oil vessel at the docking station, takes place only once throughout the scheduling horizon.

$$\sum_{t=1}^{NSCH} XF_{v,t} = 1 \qquad v = 1, \dots, NV \tag{3-2}$$

$$\sum_{t=1}^{NSCH} XL_{v,t} = 1 \qquad v = 1, \dots, NV \tag{3-3}$$

The unloading process of each crude oil vessel must be after it arrives at the docking station as determined at the planning level.

$$TF_v \geq T_{ARR,v} \qquad v = 1, \dots, NV \tag{3-4}$$

The following two equations defined vessel initiation and completion times.

$$TF_v = \sum_{t=1}^{NSCH} tXF_{v,t} \qquad v = 1, \dots, NV \tag{3-5}$$

$$TL_v = \sum_{t=1}^{NSCH} tXL_{v,t} \qquad v = 1, \dots, NV \tag{3-6}$$

Based on the assumption that there is only one docking station, two vessels cannot unload crude oil at the same time. Therefore a vessel must finish unloading one time interval before the next vessel begins to unload.

$$TF_{v+1} \geq TL_v + 1 \qquad v = 1, \dots, NV \tag{3-7}$$

A vessel unloading is accomplished between the time intervals TF_v and TL_v .

$$XW_{v,i,t} \leq \sum_{m=1}^{t} XF_{v,m} \ , \qquad XW_{v,i,t} \leq \sum_{m=t}^{NSCH} XL_{v,m} \tag{3-8}$$

$$v = 1, \dots, NV, \qquad t = 1, \dots, NSCH$$

The binary variable $XW_{v,i,t}$ takes on value of 1 when crude oil vessel v is unloading to storage tank at time t.

The unloading duration is bounded by the two time intervals TF_v and TL_v.

$$TL_v - TF_v \geq 1 \qquad v = 1, \dots, NV \tag{3-9}$$

Standing gauge operation: this forbids flow in and out of tanks simultaneously. When the binary variable $XWS_{i,j,t}$ is equal to 1, it means storage tank i is feeding charging tank j at time t and therefore that storage tank i cannot receive crude oil from vessel v at that period of time t. In such a situation the binary variable $XW_{v,i,t}$ for crude transfer to storage tank i must be 0.

$$XWS_{i,j,t} \leq 1 - XW_{v,i,t} \tag{3-10}$$

$$v = 1, \dots, NV, \quad i = 1, \dots, NST, \qquad j = 1, \dots, NBT, \qquad t = 1, \dots, NSCH$$

Similarly, charging tanks cannot feed CDU when its receiving crude oil from storage tank forcing the variable $D_{j,l,t}$ for CDU charging to be 0.

$$D_{j,l,t} \leq 1 - XWS_{i,j,t} \tag{3-11}$$

$$i = 1, \dots, NST, \qquad j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH$$

Semi-continuous constraints: these are applied for feedstock to CDU $FBC_{j,l,t}$ to ensure that operation of the CDU is within the design flow rate and assumes no flow when CDU shuts down.

For normal operation the constraint is:

$$FBCmin_{j,l} \leq FBC_{j,l,t} \leq FBCmax_{j,l} \tag{3-12}$$

$$j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH$$

When CDU shuts down,

$$FBC_{j,l,t} = 0 \tag{3-13}$$

$$j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH$$

Flow constraint from storage tank to charging tank: for multiple storage tanks feeding charging tank (s), a pipeline can only be lined up to just one charging tank at a time. The total quantity received by charging tank (s) must not exceed the maximum flow rate from storage tanks. For connecting pipeline between storage and charging tanks when storage tanks are feeding charging tanks at the rate $FSB_{i,j,t}$ the constraint is represented as:

$$\sum_{i}^{NST} FSB_{i,j,t} \leq FSBmax_{i,j} \tag{3-14}$$

$$i = 1, \dots, NST, \qquad j = 1, \dots, NBT, \qquad t = 1, \dots, NSCH$$

Demand violation constraints: unlike in Lee et al. (1996) a violation in demand order is introduced here to make the model more flexible. This is necessary because the model becomes infeasible where supply failed to meet the exact demand. For demand of crude oil mix q from charging tank j, Equation 3-15 represents supply to meet exact or below actual demand and Equation 3-16 to account for supply to meet the exact or above actual demand.

$$\sum_{l=1}^{NCDU} \sum_{t=1}^{NSCH} FBC_{j,l,t} \geq DM_q\left(1 - \varepsilon 1_q\right) \quad \textbf{(3-15)}$$

$$j = 1, \ldots, NBT, \qquad q = 1, \ldots, NBT$$

and,

$$\sum_{l=1}^{NCDU} \sum_{t=1}^{NSCH} FBC_{j,l,t} \leq DM_q\left(1 + \varepsilon 2_q\right) \quad \textbf{(3-16)}$$

$$j = 1, \ldots, NBT, \qquad q = 1, \ldots, NBT$$

$\varepsilon 1_q$ is a parameter that specifies the demand violation of crude mix q in the negative direction (below the actual demand) and $\varepsilon 2_q$ specifies the demand violation of crude mix q in the positive direction (above the actual demand). When each of these parameters is 0, a demand violation is not allowed and when it is 1, a 100% violation in demand order is allowed. With these parameters, it is possible to carry out a sensitivity analysis to determine the maximum value of demand violation of each crude mix that will maintain the optimal solution of the MILP scheduling model.

Continuous flow constraint: at any time, one charging tank should be charging the CDU.

$$\sum_{j}^{NBT} D_{j,l,t} = 1 \quad \textbf{(3-17)}$$

$$l = 1, \ldots, NCDU, \qquad t = 1, \ldots, NSCH$$

Flow fluctuation constraints: widely varying interval-interval CDUs charging rate should be avoided because it disrupts CDU operation and may generate off specification cuts. Two constraints are imposed to limit the interval-interval variation in quantity fed to the CDU. These are:

$$FBC_{j,l,t-1} \geq FBC_{j,l,t}(1 - \beta_l) \quad \textbf{(3-18)}$$

$$j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH - 1$$

and

$$FBC_{j,l,t-1} \leq FBC_{j,l,t}(1 + \beta_l) \quad \textbf{(3-19)}$$

$$j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH - 1$$

β_l is a user defined parameter with values ranging between zero and one. If β_l is set at zero, no variation in interval-interval quantity while setting it to 1 implies that 100% variation is permitted. For the cases in this thesis a conservative value of 0.1 is used.

Changeover penalty: this is to consider a cost associated with switching of charging tanks any time it occurs. Lee et al. (1996) represents changeover as a point when a charging tank j at time $t - 1$ charges the CDU followed by another charging tank g at a later time t.

$$Z_{j,g,l,t} \geq D_{g,l,t} + D_{j,l,t-1} - 1 \quad \textbf{(3-20)}$$

$$j, g(j \neq g) = 1, \dots, NBT, \quad l = 1, \dots, NCDU, \quad t = 1, \dots, NSCH - 1$$

Equation 3-20 results in a large number of integer variables and constraints, making it computationally expensive for problems involving multiple CDUs. An improvement over this by Li et al. (2002) overcomes the challenge by reducing the changeover penalty variable $Z_{j,g,l,t}$ from a tetra-indexed variable to a tri-index variable $Z_{j,l,t}$. A simple approach adopted in their paper suggests the use of Equations 3-21 and 3-22.

$$Z_{j,l,t} \geq D_{j,l,t} - D_{j,l,t-1} \quad \textbf{(3-21)}$$

$$j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH - 1$$

$$Z_{j,l,t} \geq D_{j,l,t-1} - D_{j,l,t} \quad \textbf{(3-22)}$$

$$j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH - 1$$

The term $CC \times Z_{j,l,t}$ is added to the objective function. CC is the cost penalty for changeover.

Shutdown constraints: these are included to permit generating flexible schedules involving both shutdown and continual operations. Thus,

$$FBC_{j,l,t} \geq (1 - XD_{l,t})FBClo_{j,l,t} \tag{3-23}$$

$$j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH - 1$$

$$FBC_{j,l,t} \leq (1 - XD_{l,t})FBCup_{j,l,t} \tag{3-24}$$

$$j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH - 1$$

The binary variable $XD_{l,t}$ is zero during normal operation and takes on the value of 1 when CDU shuts down. The minimum flow rate threshold before CDU deemed to have shutdown, $FBClo_{j,l,t}$ is the lower bound on the flow FBC with $FBCup_{j,l,t}$ being the upper bound. The term $CD \times XD_{l,t}$ is added to the objective function. CD is the cost penalty for shutdown. With this constraint and penalty, a schedule can also be generated with one or more CDU not in operation. The implication is that uncertainty due to disruption in CDU operation has been taken care of and therefore will have no effect on the execution of the schedule should the uncertain event occur at any time within the scheduling horizon. The scenario to support this is considered in Case 3.

Set-up constraint: in real life situation, tank-tank transfer involves some activities when a crude vessel is allowed to unload into multiple storage tanks for subsequent transfer of the crude oil into charging tanks. A set-up cost is incurred anytime switching occurs between storage tanks and charging tanks. Including a set-up cost for these activities in the objective function minimizes the number of these activities.

$$XS_{i,t} \geq XWS_{i,j,t} - XWS_{i,j,t-1} \quad \textbf{(3-25)}$$

$$i = 1, \ldots, NST, \qquad j = 1, \ldots, NBT, \qquad t = 1, \ldots, NSCH - 1$$

This set-up cost is considered in Case 3 with more storage and charging tanks translating into a quite number of switchover operations. The term $CS \times XS_{i,t}$ is added to the objective function for this case. CS is the cost penalty for switching from tank to tank during tank-tank transfers. The binary variable $XS_{i,t}$ is activated whenever there is a tank-tank transfer operation

3.1.4.2 Hydraulic capacities

Flow constraints: flow of crude oil is bounded by the capacity of the pumping system available. For the main units/facilities for crude oil transfer, the following holds:

For crude oil flow from vessel to storage tank $FVS_{v,i,t}$ the following relation holds

$$FVSmin_{v,i}XW_{v,i,t} \leq FVS_{v,i,t} \leq FVSmax_{v,i}XW_{v,i,t} \quad \textbf{(3-26)}$$

$$v = 1, \ldots, NV, \qquad i = 1, \ldots, NST, \qquad t = 1, \ldots, NSCH$$

Similarly, for crude oil transfer from storage tank to charging tank $FSB_{v,i,t}$,

$$FSBmin_{i,j}XWS_{i,j,t} \leq FSB_{i,j,t} \leq FSBmax_{i,j}XWS_{i,j,t} \quad \textbf{(3-27)}$$

$$i = 1, \ldots, NST, \qquad j = 1, \ldots, NBT, \qquad t = 1, \ldots, NSCH$$

Flow from charging tank to CDU,

$$FBCmin_{j,l}D_{j,l,t} \leq FBC_{j,l,t} \leq FBCmax_{j,l}D_{j,l,t} \quad \textbf{(3-28)}$$

$$j = 1, \ldots, NBT, \qquad l = 1, \ldots, NCDU, \qquad t = 1, \ldots, NSCH$$

Capacity constraints: the volume of crude oil in storage $VS_{i,t}$ and charging tanks $VB_{j,t}$ at any time must be within the upper and lower bounds of the containing medium.

The capacity limitation for storage tank is:

$$VSmin_i \leq VS_{i,t} \leq VSmax_i \tag{3-29}$$

$$i = 1, \dots, NST, \quad t = 1, \dots, NSCH$$

and for charging tank,

$$VBmin_j \leq VB_{j,t} \leq VBmax_j \tag{3-30}$$

$$j = 1, \dots, NBT, \quad t = 1, \dots, NSCH$$

Crude oil material balance

Crude oil vessel: volume $VV_{v,t}$ of crude oil in vessel v at time t equals the difference between the initial crude volume and the overall volume transferred from the vessel up to time t. $VV_{v,0}$ is the volume at time 0.

$$VV_{v,t} = VV_{v,0} - \sum_{i=1}^{NST} \sum_{m=1}^{t} FVS_{v,i,m} \tag{3-31}$$

$$v = 1, \dots, NV, \quad t = 1, \dots, NSCH$$

For the whole scheduling horizon, the equation becomes:

$$VV_{v,0} = \sum_{i=1}^{NST} \sum_{t=1}^{NSCH} FVS_{v,i,t} \tag{3-32}$$

$$v = 1, \dots, NV$$

At any time period within the scheduling horizon, the following equation holds for crude oil vessels.

$$FVS_{v,i,t} \leq VV_{v,t} \tag{3-33}$$

$$v = 1, \dots, NV, \qquad i = 1, \dots, NST, \qquad t = 1, \dots, NSCH$$

Storage tank: Volume $VS_{i,t}$ of crude oil in storage tank i at time t equals the sum of the initial volume stored in the storage tank with the volume transferred into the storage tank up to time t, less volume transferred from the storage tank up to time t. $VS_{i,0}$ is the volume at time 0.

$$VS_{i,t} = VS_{i,0} + \sum_{v=1}^{NV} \sum_{m=1}^{t} FVS_{v,i,m} - \sum_{j=1}^{NBT} \sum_{m=1}^{t} FSB_{i,j,m} \tag{3-34}$$

$$i = 1, \dots, NST, \qquad t = 1, \dots, NSCH$$

At any time period within the scheduling, the following equation holds for storage tanks.

$$FSB_{i,j,t} \leq VS_{i,t} \tag{3-35}$$

$$i = 1, \dots, NST, \quad j = 1, \dots, NBT, \qquad t = 1, \dots, NSCH$$

Charging tank: Volume $VB_{j,t}$ of crude mix in charging tank j at time t equals the sum of the initial volume of crude mix in the charging tank with the volume transferred into the charging tank up to time t, less volume transferred from the charging tank up to time t. $VB_{j,0}$ is the volume at time 0.

$$VB_{j,t} = VB_{j,0} + \sum_{i=1}^{NST} \sum_{m=1}^{t} FSB_{i,j,m} - \sum_{l=1}^{NCDU} \sum_{m=1}^{t} FBC_{j,l,m} \tag{3-36}$$

$$j = 1, \dots, NBT, \qquad t = 1, \dots, NSCH$$

At any time period within the scheduling, the following equation holds for charging tanks.

$$FBC_{j,l,t} \leq VB_{j,t} \tag{3-37}$$

$$j = 1, \dots, NBT, \qquad l = 1, \dots, NCDU, \qquad t = 1, \dots, NSCH$$

Component material balance: the component material balance in storage tanks should only be used when there is mixing in storage tank due to difficulty in segregating crudes of different compositions. The mixing here is not the same as blending operation as the latter is limited to charging tanks only.

Storage tank: volume $vs_{k,i,t}$ of component k in storage tank i at time t equals the sum of volume of component k in the storage tank with the volume of component k transferred into the storage tank up to time t, less volume of component k transferred from the storage tank up to time t. $vs_{k,i,0}$ is the volume at time 0.

$$vs_{k,i,t} = vs_{k,i,0} + \sum_{m=1}^{t}\sum_{v=1}^{NV} fvs_{k,v,i,m} - \sum_{m=1}^{t}\sum_{j=1}^{NBT} fsb_{k,i,j,m} \qquad \textbf{(3-38)}$$

$$k = 1,\dots,NCOMP, \qquad i = 1,\dots,NST, \qquad t = 1,\dots,NSCH$$

Component volumetric flow from vessel to storage tank

$$fvs_{k,v,i,t} = FVS_{v,i,t}\, wv_{k,v} \qquad \textbf{(3-39)}$$

$$k = 1,\dots,NCOMP, \qquad v = 1,\dots,NV, i = 1,\dots,NST, \qquad t = 1,\dots,NSCH$$

Charging tank: volume $vb_{k,j,t}$ of component k in charging tank j at time t equals the sum of volume of component k in the charging tank with the volume of component k transferred into the charging tank up to time t, less volume of component k transferred from the charging tank up to time t. $vb_{k,j,0}$ is the volume at time 0.

$$vb_{k,j,t} = vb_{k,j,0} + \sum_{m=1}^{t}\sum_{i=1}^{NST} fsb_{k,i,j,m} - \sum_{m=1}^{t}\sum_{l=1}^{NCDU} fbc_{k,j,l,m} \qquad \textbf{(3-40)}$$

$$k = 1,\dots,NCOMP, \qquad j = 1,\dots,NBT, \qquad t = 1,\dots,NSCH$$

Component volumetric flow from storage tank to charging tank

$$fsb_{k,i,j,t} = FSB_{i,j,t}\, ws_{k,i} \qquad \textbf{(3-41)}$$

$$k = 1,\dots,NCOMP, i = 1,\dots,NST, \qquad j = 1,\dots,NBT, \qquad t = 1,\dots,NSCH$$

3.1.4.3 Property specification

Component flow specification: the flow of key component from one tank to the other has a limit (Lee et al., 1996).

Component flow $fsb_{k,i,j,t}$ from storage to charging tank is bounded by an upper and a lower limit.

$$wsmin_{k,i}\, FSB_{i,j,t} \le fsb_{k,i,j,t} \le wsmax_{k,i}\, FSB_{i,j,t} \tag{3-42}$$

$k = 1, \dots, NCOMP, \quad i = 1, \dots, NST, \quad j = 1, \dots, NBT, \quad t = 1, \dots, NSCH$

Component flow $fbc_{k,j,l,t}$ specification for flow from charging tank to CDU is:

$$wbmin_{k,j}\, FBC_{j,l,t} \le fbc_{k,j,l,t} \le wbmax_{k,j}\, FBC_{j,l,t} \tag{3-43}$$

$k = 1, \dots, NCOMP, \quad j = 1, \dots, NBT, \quad l = 1, \dots, NCDU,$
$t = 1, \dots, NSCH$

Component volume limitation:

Storage tank: the limit for the volume $vs_{k,i,t}$ of component k in storage tank at any time is

$$wsmin_{k,i}\, VS_{i,t} \le vs_{k,i,t} \le wsmax_{k,i}\, VS_{i,t} \tag{3-44}$$

$k = 1, \dots, NCOMP, \quad i = 1, \dots, NST, \quad t = 1, \dots, NSCH$

Charging tank: the limit for the volume $vb_{k,j,t}$ of component k in charging tank at any time is

$$wbmin_{k,j}\, VB_{j,t} \le vb_{k,j,t} \le wsmax_{k,j}\, VB_{j,t} \tag{3-45}$$

$k = 1, \dots, NCOMP, \quad j = 1, \dots, NBT, \quad t = 1, \dots, NSCH$

3.2 Case studies

With the extended model, three case studies are considered in this section. Case 1 is the motivating example in Lee et al. (1996) paper with 24hr discrete time intervals spanning over 8 days. Case 2 is formulated from Case 1 but an 8hr interval was considered. Case 3 is modified from Example 4 of Lee et al. (1996). In this study, the following recommendations are adopted when implementing the extended model in GAMS and applicable to all cases.

- Karri et al. (2009) and Li et al. (2002) recommended a flow fluctuation constraint that puts upper and lower limits to the interval to interval fluctuations in crude oil processing rate. For all the cases considered in this study, a ceiling of 10% is fixed for flow variation while at the same time restricting the CDUs to run within the permissible minimum turndown ratio of 10:6.

- In consideration to the manner in which storage and charging tanks are configured as floating roof objects in a refinery and the volatile nature of crude oil, a minimum level of the fluid is always maintained in those tanks for safety reasons. This work suggests that a minimum level for all tanks be fixed at 100kbbl and a maximum value at 1100kbbl. The difference between these two values is in agreement with the volume difference used in Lee et al. (1996).

3.2.1 Case 1

The case study begins with the motivating example from the Lee et al. (1996) to illustrate how the ideas proposed in this work help in achieving better and realistic results. Like in Lee et al. (1996), this work considered a system with one docking station, two crude vessels (V1 and V2), two storage tanks (ST1 and ST2), two charging tanks (CT1 and CT2) and one CDU. The flow network is shown in Figure 3-1. As shown in Table 3-1, V1 and V2 arrive for unloading into the storage tanks on day 1 and day 5 respectively. In the table, other detailed information required for solving this problem is provided (Yüzgeç et al., 2010).

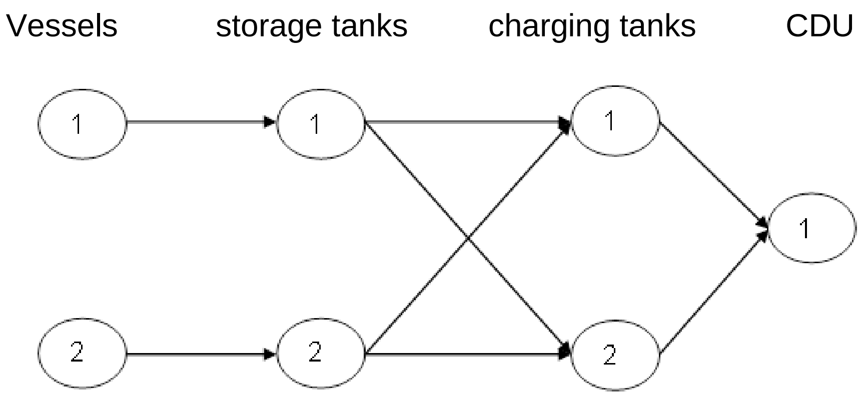


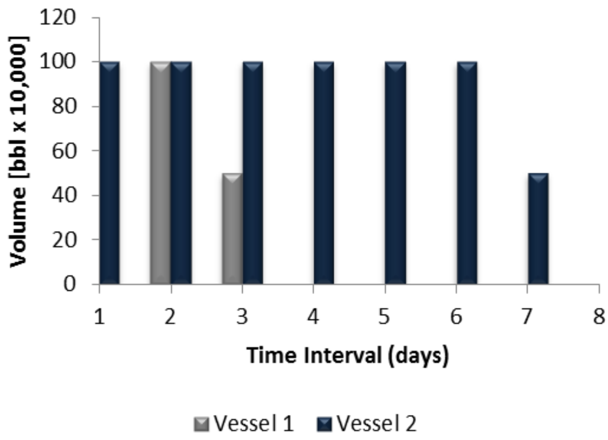
Figure 3-1: Flow network diagram for Case 1 (Lee et al., 1996)

The extended model was implemented in GAMS v 23.9.1 on a 4GB RAM dual core i5 processor computer, using the CPLEX solver. The optimal operating cost of processing 2.0Mbbl of crude in charging tanks was obtained in 0.765

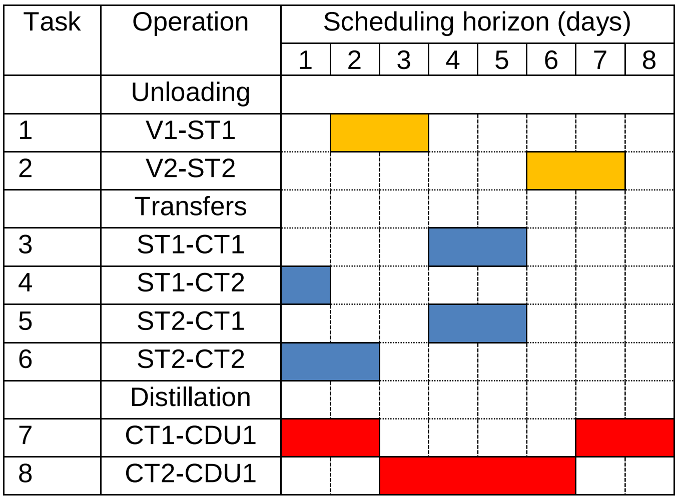
seconds as $216,425 after 1287 iterations in 35 nodes. It consists of $150,000 changeover cost, $58,000 unloading and sea waiting cost and $8,425 inventory cost. The optimal schedule generated for the problem is represented in Figure 3-2.

Table 3-1: System information for Case 1 (Yüzgeç et al., 2010)

Scheduling horizon(days)		8	
Time interval (hour)		24	
Number of vessels		2	
Number of storage tanks		2	
Number of charging tanks		2	
Number of CDU		1	
Crude vessels	Arrive/depart	Volume of crude	Key component
V1	1^{st} day/5^{th} day	1,000,000 bbl	0.01
V2	5^{th} day/8^{th} day	1,000,000 bbl	0.06
Storage Tanks	Capacities	Initial volume	Key component
ST1	1,100,000 bbl	250,000 bbl	0.01
ST2	1,100,000 bbl	750,000 bbl	0.06
Charging Tanks	Capacities	Initial volume	Initial(min., max)
CT1	1,100,000 bbl	500,000 bbl	0.02(0.015-0.025)
CT2	1,100,000 bbl	500,000 bbl	0.05(0.045-0.055)
Vessel unloading cost [$/day]		8,000	
Sea waiting cost [$/day]		5,000	
Storage tank inventory unit cost [$/(day x		0.005	
Charging tank inventory unit cost [$/(day x		0.008	
Unit changeover cost for charged oil switch in		50,000	
Demand of crude mix from charging tanks to CDU for the whole scheduling horizon		Blend 1	1,000,000 bbl
		Blend 2	1,000,000 bbl
Flow constraints		Minimum(bbl/day)	Maximum(bbl/day)
Flow from vessel to storage tank		0	500,000
Flow from storage tank to charging tank		0	500,000
Flow from charging tank to CDU		50,000	500,000



(a)



(b)

Figure 3-2: Optimal schedule for Case 1

From the schedule shown in Figures 3-2(a) and 3-2(b), V1 arrives on the first day as determined at the planning level but unloading was delayed until the second day because the standing gauge operation forbids the vessel from unloading (since ST1 was busy on that day, transferring crude to CT2). This V1 unloads only 500,000bbl of crude oil on the second day and the remaining 500,000bbl on the third day. Unloading on the first day will amount to a savings of $5,000 of sea waiting cost but will increase the inventory levels of the storage and charging tanks incurring an additional switchover cost of $50,000. This is due to the fact that increase in the inventory level of storage tank implies an increase in the charging tank inventory level which will ultimately increase the charging tank switch over frequency. For the same reason as V1, V2 equally arrives on the fifth day but does not begin unloading until the sixth day. V2 unloads 500,000bbl on the sixth day and the remaining 500,000bbl on the seventh day. Furthermore, V2 cannot unload earlier than the sixth day because ST2 was busy transferring crude oil to CT1 on the fourth and the fifth days and cannot transfer crude oil to ST1 as this tank is dedicated to receive crude oil only from the V1.

Transfers from storage to charging tanks also happen only when the charging tanks are not charging the CDU. ST1 transfers to CT1 only on days 4 and 5 and to CT2 only on the first day because these tanks do not charge the CDU on these days as shown in Figure 3-2(b). ST1 is actually transferring to CT2 on the first day from its initial inventory level of 250,000bbl (Table 3-1) since V1 starts unloading after day 1. Plots of volume variation in the storage and charging tanks are presented in Figures 3-3 and 3-4. From the figures, the inventory level in the storage tanks goes up at the end of the horizon, while that of the charging tanks is kept as minimal as possible because the charging tanks inventory cost is higher than storage tanks inventory cost.

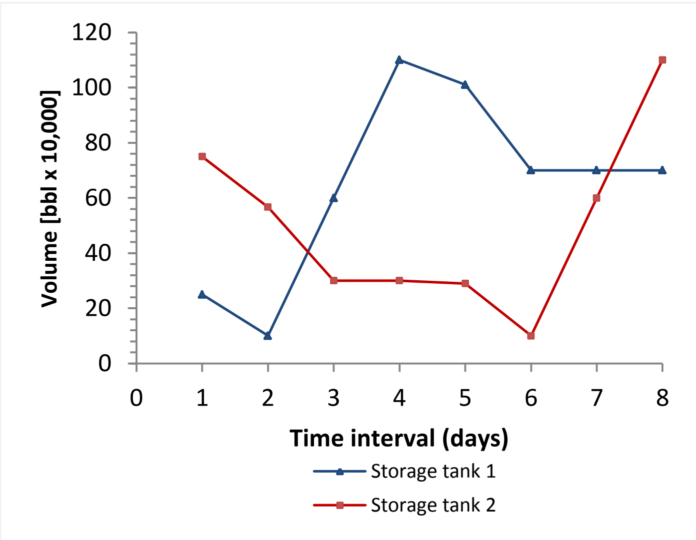


Figure 3-3: Optimal volume variations in storage tanks

Figure 3-3 shows that the required minimum tank level of 100,000bbl was maintained and flow from the vessel to the storage tank was actually accounted for by an equivalent rise in the storage tank level during and immediately after the period that the vessel unloaded to the storage tank. For example a 1,100,000 bbl rise in volume level in ST1 occurs on the fourth day, which is exactly one day after V1 finishes unloading into ST1. Armed with the information that the V2 will arrive on day 5, ST2 is scheduled to quickly unload its content down to the minimum volume from day 1 until day 6 so that it can receive from V2 rights from that day 6 to minimize sea waiting cost. ST2 took a longer period of more than 5 days to reach the minimum tank level because its initial inventory level is higher (Table 3-1).

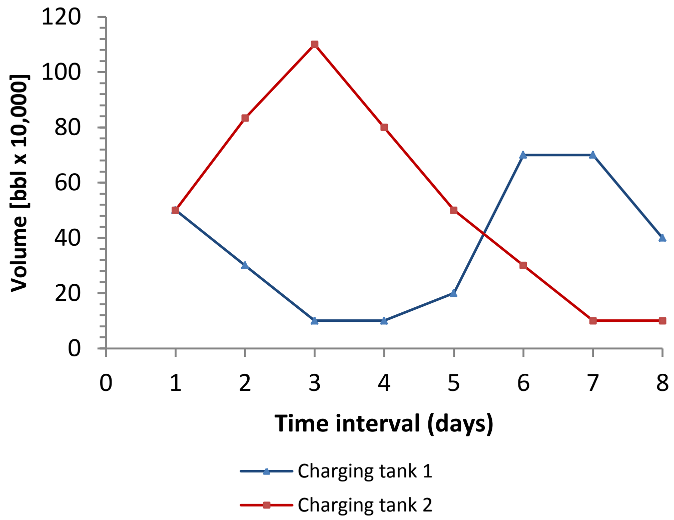


Figure 3-4: Optimal volume variations in charging tanks

In Figure 3-4, CT1 transfers 200,000bbl of blended crude oil 1 to the CDU from day 1 to day 2 then another 200,000bbl of the same blended crude oil until the tank reaches its minimum level at day 3 after which tank switchover occurs so that it can be loaded while CT2 charges the CDU. During the period that CT2 feeds the CDU, CT1 receives a total of 100,000bbl on day 4 from ST1 and ST2 and a total of 500,000bbl on day 5 from the same storage tanks to prepare a blend for days 7 and 8. A total of two changeovers are recorded in this case study.

Changeover is expensive because it poses a big disturbance to the CDU but cannot be altogether avoided. In an attempt to minimize the changeover frequency at all cost, an unrealistic and sudden drop in CDU charge rate are reported in some instances in Lee et al. (1996) paper. This sudden change can leads to the production of cut fractions with low quality in terms of component separation. In this study a flow fluctuation constraint is introduced, which determines the interval to interval fluctuation of the CDU charge rate. The changeover cost computed using the original model is $100,000 against $150,000 for the extended model. The benefit of including interval to interval constraint in the extended model is therefore assessed not in terms of cost but in its ability to ensure that CDU charging rate is within the acceptable limits.

In Figure 3-5, the CDU charging schedule for the extended model has shown that the CDU charging rate is in the range of 200,000bbl to 300,000bbl throughout the 8 day period, a huge difference from the original model where fluctuation in CDU charge rate exceeded 100% in one instance. The CDU charging is also within the permissible minimum turndown ratio of 10:6. At the end of the horizon, the total quantity of blended crude oil 1 and 2 actually matches demand for each.

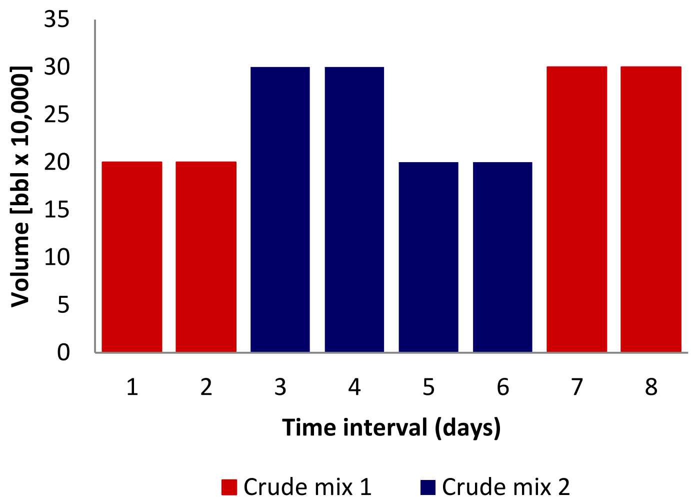


Figure 3-5: Optimal CDU charging schedule

Figure 3-6 represents the concentration of the key component (sulphur) in charging tanks. A plot of concentrations of sulphur in CT1 and CT2 in Figure 3-6 clearly indicates that in the course of the blending operations, the sulphur level for both tanks did not exceed their maximum levels specified. Ideally, the variation of sulphur concentration in tanks should be constant on days when there is no transfer of crude oil into the tanks. However, a minor discrepancy is noted here, for example, in CT1, the sulphur concentrations are 0.020 vol/vol and 0.017 vol/vol on days 1 and 2 respectively. This discrepancy is due to the linearized bilinear equation used to avoid non-linearity in the model. Despite this discrepancy, the maximum level of sulphur was not exceeded in the charging tanks.

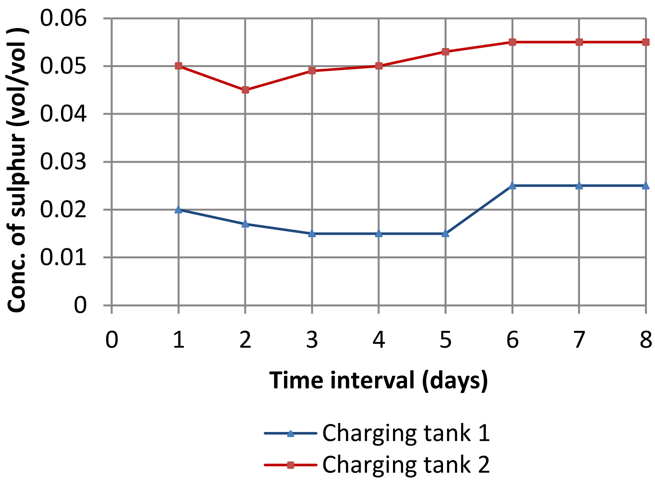


Figure 3-6: **Optimal variation in concentration of sulphur**

3.2.2 Case 2

This case is same as Case 1 except that the horizon further splits into 8-hour time interval. An 8-hour time period is chosen because a typical refinery operates based on 8-hr shift. The total operating cost of $199,460 was obtained after 17,630 iterations using 247 nodes in 2.380 seconds. The 8-hour schedule results in a difference of $16,965 compared to the 24-hr schedule (Case 1). The vessel unloading schedule for the two cases shows a slight difference as V1 and V2 starts unloading earlier in Case 2. Table 3-2 shows a comparison between the various costs incurred for Cases 1 and 2 and the optimal schedule for both cases is presented in Figure 3-7.

Table 3-2: Comparison between optimal cost for Cases 1 and 2

Cost	Case 1(24-hr period)	Case 2 (8-hr period)
Sea waiting cost ($)	10,000	0
Unloading cost ($)	48,000	40,050
Storage tank inventory cost	3,358	4,630
Charging tank inventory	5,067	4,780
Changeover cost ($)	150,000	150,000
Operating cost ($)	216,425	199,460

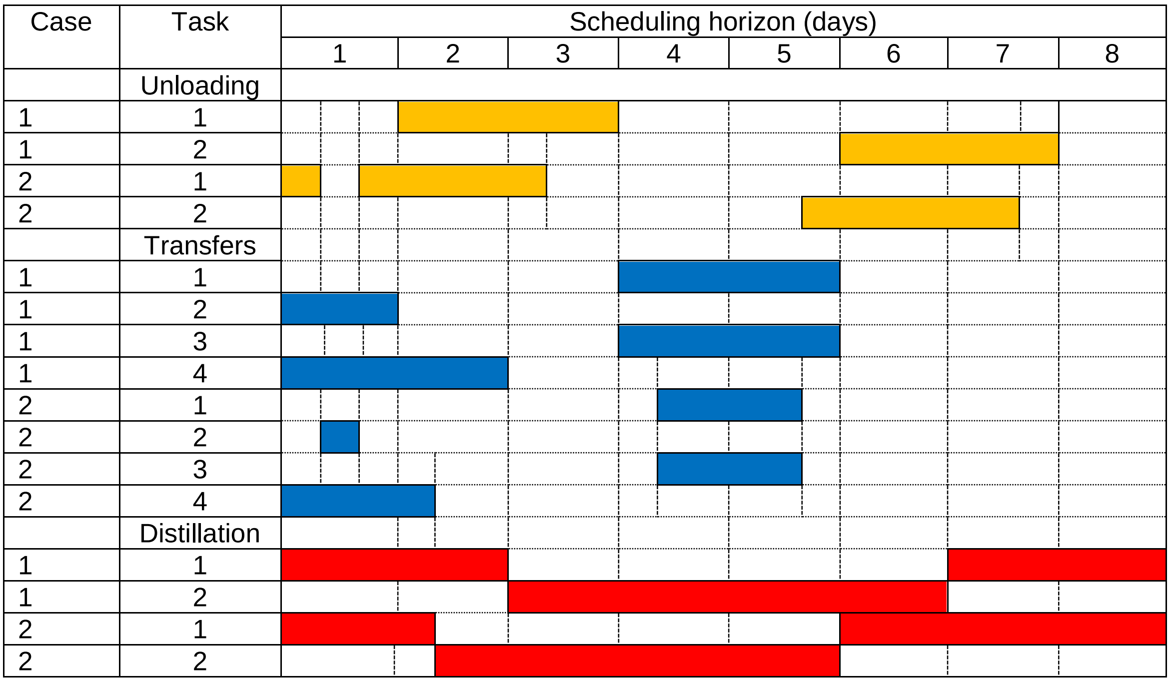


Figure 3-7: Comparison of optimal schedule for Cases 1 and 2

It is obvious from Figure 3-7 that the two vessels starts unloading on the actual days determined at the planning level incurring no sea waiting costs. V1 has to stop unloading after 8hr of the first day in order for ST1 to transfer crude to CT2. This decision would have been hidden if 24hr time period is adopted as it basically reveals information from day to day without exploring other events happening within the day. For discrete-time representation, using smaller time intervals creates more decision points, giving the model more flexibility in searching for optimal values for the decision variables. For example the first changeover operation in Case 1 could be assumed to have taken place at the end of the second day which is not true. The second changeover operation is equally delayed to the end of sixth day implying that the CDU may not have a sufficient amount of blended crude oil to sustain it on the seventh day. The two cases recorded the same number of changeover operations. The inventory levels are also compared and presented in Figure 3-8 and Figure 3-9.

Since storage inventory cost depends on both the quantity and time of storage, it is a direct function of the area bounded by the curve and the two axes. In Figure 3-8, volume variation for both the 24-hr and 8-hr curves have shown a shrinking of these areas to minimize the inventory cost. The 24-hr (Case 1) period however shows a better shrinking of this area by having steeper slopes than the 8-hr (Case 2) period. ST1 in both cases has almost the same quantity of crude oil on the sixth day and maintains this volume up to the end of the scheduling horizon. For ST2, Case 1 has the lower inventory level reaching the minimum amount on day 6 before raising again to a level same as Case 2 at the end of the horizon. This accounts for lower inventory cost of Case 1 compared to Case 2.

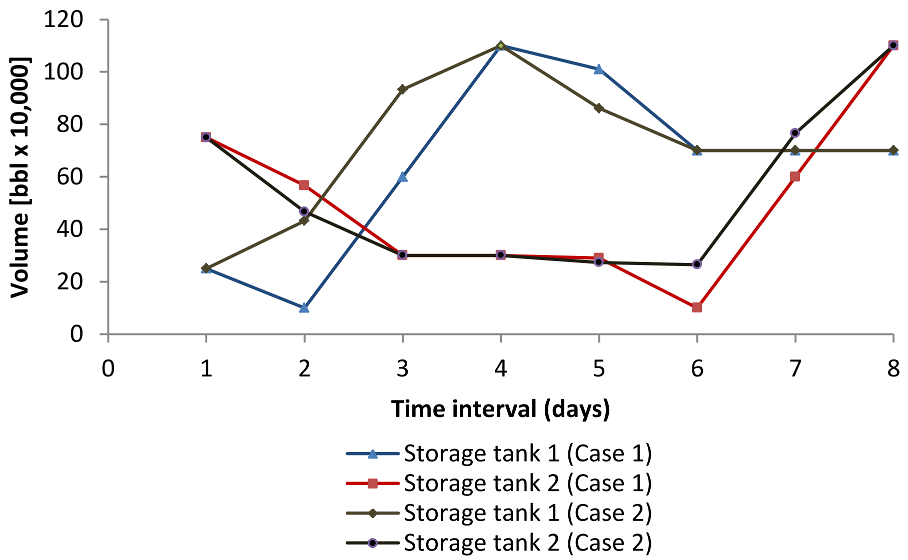


Figure 3-8: Optimal volume variations in storage tanks for Case 1 and Case 2

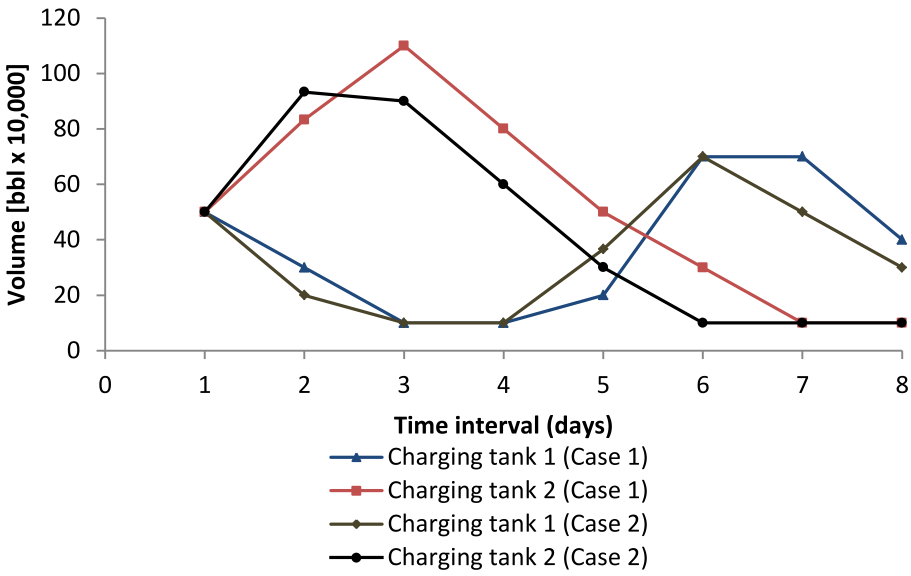


Figure 3-9: Optimal volume variations in charging tanks for Case 1 and Case 2

As can be seen in Figure 3-9, optimal volume variations for charging tanks do not follow the same trend as those for storage tanks. This is because charging tanks stand between semi continuous operations of loading/unloading of storage tanks and the continuous running of the CDUs (when there is no shutdown within the scheduling horizon). At the end of the horizon the inventory levels of charging tanks usually become low. Comparing the two cases above, inventory level of CT2 have the same minimum value on day 7 for both cases and maintain this volume up to day 8. For CT1, the inventory level is higher in Case 1, accounting for the higher inventory cost presented in Table 3-2.

On the basis of total operating costs incurred by the two cases, Case 2 has the smaller cost value. Case 1 is better in terms of storage inventory cost but is outperformed by Case 2 when charging inventory cost is considered. Comparing these two cases clearly shows the advantage of using smaller time interval. Nevertheless, there is a limit to which smaller time intervals can be used. This example is a simplification of real refinery scheduling problems.

3.2.3 Case 3

Case discussed in this section considers typical industrial issues faced in real life. Besides, the size of the problem has been extended to accommodate more resources. The features below were considered in the extended model.

- Closing stocks are fixed to avoid low inventory at the end of the scheduling horizon.
- A setup penalty for tank-tank is introduced and added to the objective function to deter unnecessary switching when storage tank transfer crude oil into charging tank.
- Shutdown constraint is made active to generate schedule that is immune to CDU disruption during execution in the real plant.

The system consists of a docking station, three vessels, six storage tanks, four charging tanks and three CDUs. System information is obtained from Lee et al. (1996) with slight modifications on the charging tanks' minimum and maximum capacities and is presented in Table 3-3.

In this study, the setup penalty included in the objective function is chosen based on the importance of the tanks transfer operations relative to two other critical operations namely shutdown operation and charging tanks switching operations. These two operations cannot be compromised while trying to avoid tank-tank transfers. Also the CDU cannot be shut down in an effort to prevent frequent changeover operations.

Based on this, a setup cost for tank-tank transfer much less than the changeover cost is used. A figure is selected so that the total setup cost at any time does not exceed the cost of a changeover operation. For this Case a conservative cost of $500 per setup operation is used. Figure 3-10(a) compares the tank-tank transfer operations with and without the set-up penalty and Figure 3-10(b) presents the flow network.

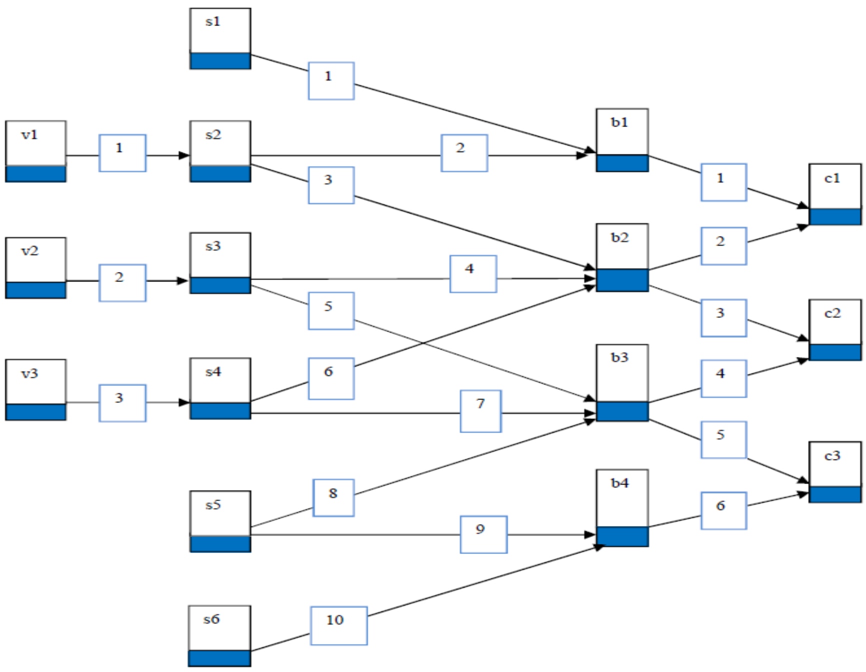
Table 3-3: System information for Case 3 (Lee et al., 1996)

Scheduling horizon(days)			15	
Vessels	Arrive/depart		Volume of crude	Key component
V1	1^{st} /6^{th}		600,000 bbl	0.03
V2	6^{th} /11^{th}		600,000 bbl	0.05
V3	11^{th} /15^{th}		600,000 bbl	0.065
Storage Tanks	Capacities		Initial volume(bbl)	Key component Initial(min, max)
	Min.	Max.		
ST1	100,000bbl	900,000bbl	600,000	0.031(0.025-0.038)
ST2	100,000bbl	1,100,000bbl	100,000	0.03(0.02-0.04)
ST3	100,000bbl	1,100,000bbl	500,000	0.05(0.04-0.06)
ST4	100,000bbl	1,100,000bbl	400,000	0.065(0.06-0.07)
ST5	100,000bbl	900,000bbl	300,000	0.075(0.07-0.078)
ST6	100,000bbl	900,000bbl	600,000	0.075(0.07-0.078)
Charging Tanks	Capacities		Initial volume(bbl)	Key component Initial(min, max)
	Min.	Max.		
CT1	100,000bbl	1,100,000bbl	50,000 bbl	0.0317(0.03-0.035)
CT2	100,000bbl	1,100,000bbl	300,000 bbl	0.0483(0.043-0.05)
CT3	100,000bbl	1,100,000bbl	300,000 bbl	0.0633(0.06-0.065)
CT4	50,000bbl	850,000bbl	300,000 bbl	0.075(0.071-0.08)
Vessel unloading cost [$/day]			7,000	
Sea waiting cost [$/day]			5,000	
Storage tank inventory unit cost [$/(day x			0.005	
Charging tank inventory unit cost [$/(day x			0.006	
Unit changeover cost for charged oil switch			30,000	
Tank-tank setup cost [$/setup]			500	
Demand of crude mix from charging tanks to CDU for the whole scheduling period			Blend 1	600,000 bbl
			Blend 2	600,000 bbl
			Blend 3	600,000 bbl
			Blend 4	600,000 bbl

In each situation a total of 1,500,000bbl of crude has been transferred from storage tanks to charging tanks in the scheduling horizon. When set-up penalty is included, the number of tanks transfer tasks decreased from 8 to 7 even though the same amount of crude oil has been transferred. This is because less critical activities were merged into a single activity to cut down setup cost. For every task represented by the blue strips in Figure 3-10(a), two sets of operations are performed at the boundaries of the intervals: one operation at the beginning and another one at the end. Without a tank-tank setup penalty, there are 8 tasks involving 16 operations. Adding such penalty reduces the number of operations from 16 to 14, which is over 12% slash in the number of operations required.

Task	Operation	Scheduling horizon (days)														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
		Tank-tank transfer with set-up penalty (bbl x 10,000)														
1	ST1-CT1	5, 25														
2	ST2-CT1			25												
4	ST3-CT2				25								5			
5	ST3-CT3											7				
7	ST4-CT3					25										
8	ST5-CT3											3				
10	ST6-CT4								5, 25							
		Tank-tank transfer without set-up penalty (bbl x 10,000)														
1	ST1-CT1	10, 25														
2	ST2-CT1			25												
3	ST2-CT2				14.714											
4	ST3-CT2													5		
5	ST3-CT3					6.667					6.667					
6	ST4-CT2				10.286											
7	ST4-CT3					3.333					13.333					
10	ST6-CT4							5, 25								

(a)



(b)

Figure 3-10: Optimal tank-tank schedule

This case involves a small amount as penalty for tank-tank switching and as the magnitude of this penalty is made to be larger, more operations that are not critical to the tank transfer will be cut down. The optimal schedule with set-up cost is presented in Figure 3-11.

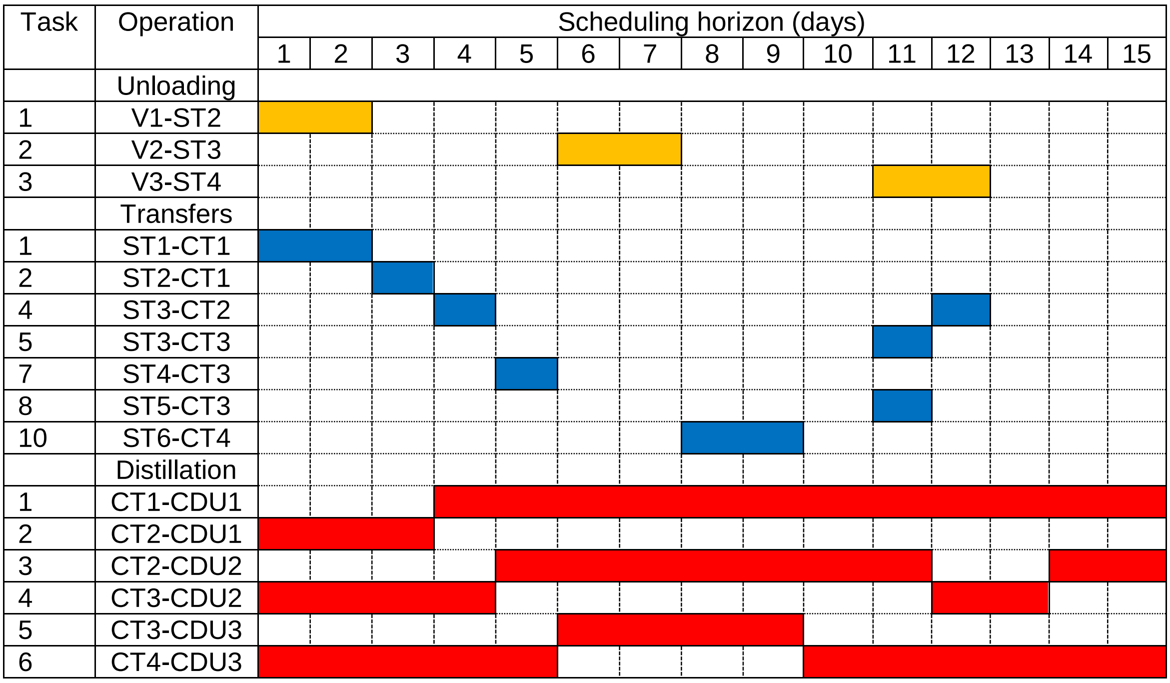


Figure 3-11: Optimal schedule (with set up cost) for Case 3

The proposed formulation is solved in 16.29 seconds using 1391 nodes. Total operating cost for this case is $ 360,867 lower than example 4 of Lee et al. (1996) optimal cost ($420,999). The cost reduction is due to the cost penalty for tank-tank transfer and sea waiting cost was not incurred as vessel unloading was not delayed. The effort here is not focussed on comparing with Lee et al. (1996) because their work does not include a set-up penalty for tank-tank transfer and uses different limits for storage and charging tanks safety stocks. Rather, the focus here is to draw attention to the need to include a setup penalty each time a tank-tank transfer operation occurs.

Figure 3-12 shows the optimal volume variation for the storage tanks. Understandably the inventory levels in the storage tanks are kept higher than charging tanks due to the fact that charging tanks are transferring mixed crude oil to CDU as soon as the blends are processed to satisfy the CDU demand while the storage tanks act as reservoir, receiving crude oil directly from vessels.

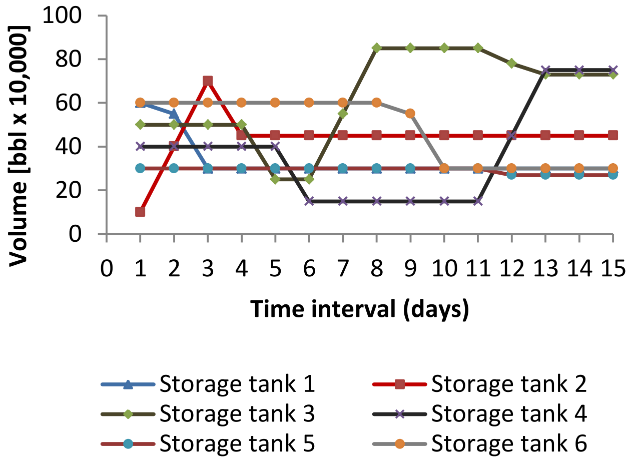


Figure 3-12: Optimal volume variations in storage tanks

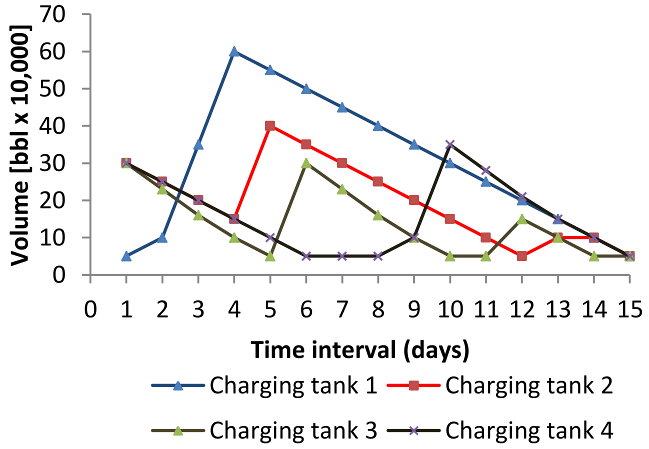


Figure 3-13: Optimal volume variations in charging tanks

In Figure 3-13, the volumes in charging tanks show the usual trend of running to a minimum level at the end of the horizon. Fixing of closing stocks that enables the schedule to be extended beyond its horizon is recommended in this study. This is a decision based on uncertainty of demand. Therefore, the demand constraint needs to be adjusted so that the volume processed at least exceeds demand. Mandating the model to extend beyond its horizon and still meet exact demand within its horizon is infeasible. On the other hand increase in demand for CDUs is associated with costs. The most cumbersome aspect is the decision to make on the range of violation in demand order that will maintain the feasibility and optimality of the cost function. The closing stock volume also affects the optimal result computed. All these scenarios open up certain information that can guide the scheduler in deciding what schedules to use, and what the implications are for using a particular schedule. Scenarios are created from this case as discussed below.

3.2.3.1 Scenario A

This scenario considers a situation where a minimal demand violation is imposed for an extended horizon of two additional days (to 17 days). A demand violation of 6% is allowed for blended crude 1 (decrease) while 9% is allowed for blended crudes 2, 3 and 4 (increase). Closing stock inventories for the charging tanks is fixed at 250,000 bbl for blended crudes 1 and 4 and 150,000bbl for blended crudes 2 and 3. These modifications are shown in Table 3-4.

Table 3-4: Scenario A data

Blended crude oil	Demand violation	Demand volume (bbl)	Processed volume(bbl)	15^{th} day closing stock(bbl)
1	6 %	600,000	600,000	250,000
2	9 %	600,000	654,000	150,000
3	9 %	600,000	654,000	150,000
4	9%	600,000	654,000	250,000

Overall operating cost of \$395,316 was incurred in 5.213 seconds using 400 nodes which is about 9.55 % higher than the base case. Assuming the cost is evenly spread per unit volume processed, then the cost per bbl for an extended horizon is \$0.1543 (\$395,316 divided by 2,562,000bbl) while the cost per bbl for the base case is \$0.1504 (\$360,867 divided by 2,400,000bbl). Again, based on cost per unit volume processed, the base case has the lower operating cost value. Better results for the base case may not be unconnected with the fact that this scenario took additional two days to process the blends incurring an additional cost.

Because of the demand violation, quantity of blended crude 1 meets exact demand, while blended crudes 2, 3 and 4 were above demand. The quantity of blended crude 1 processed meet exact demand even when violation of 6% is allowed; this is because the extended model is more sensitive to the increase in demand order. Demand violation of 6% up to 88% for blended crude 1 does not change the optimal operating cost. However, with violation above 88% the operating cost assumed a different value. Violation in demand of blended crude 2, 3 or 4 below 9% generates infeasible solution.

3.2.3.2 Scenario B

Here demand violation for all the crude mixes are allowed so that all the CDUs process above demand. When the same closing stock for scenario A was used the model was infeasible because of insufficient stock in the charging tanks. The 15th day closing stocks for these tanks were increased as in Table 3-5.

Table 3-5: Scenario B data

Blended crude oil	Demand volume (bbl)	Processed volume (bbl)	15^{th} day closing stock (bbl)
1	600,000	620,000	300,000
2	600,000	654,000	200,000
3	600,000	650,000	150,000
4	600,000	654,000	250,000

The operating cost is $394,500 generated in 28.892 seconds using 2640 nodes. It is obvious from the results that scenario B is more cost effective as compared with scenario A. This can be verified further by comparing total operating cost with the volume processed. In scenario A, a total of 2,562,000bbl was processed at a cost of $395,316 which is about $0.1543 per barrel. Scenario B handles 2,578,000bbl at a cost of $394,500 which is about $0.1530 per barrel. Comparing just the operating costs for the two scenarios, scenario B involves a smaller operating cost. Also, when the cost per barrel is compared, scenario B is still a better option to go by.

3.2.3.3 Scenario C

In the preceding scenarios and the base case, schedules are generated while all the three CDUs are in operation. In some circumstances one CDU may not be operated due to maintenance or breakdown and schedules can still be generated with the available CDUs at an extra cost. In this scenario a disruption is introduced such that one of the CDUs is shut down. This will enable generating a schedule that anticipates no operation of CDU 2. All the blended crudes have to be processed by CDUs 1 and 3. A demand violation of 5% is allowed for blended crudes 1 and 4 while 7% is allowed for blended crudes 2 and 3. Closing stock inventories for the charging tanks are fixed at 200,000 bbl for blended crudes 1 and 4 and 50,000bbl for blended crudes 2 and 3. This generates schedule at the cost of $474,747. There is no cost comparison with the preceding scenarios because shutdown results in an additional cost. The schedule is shown in Figure 3-14.

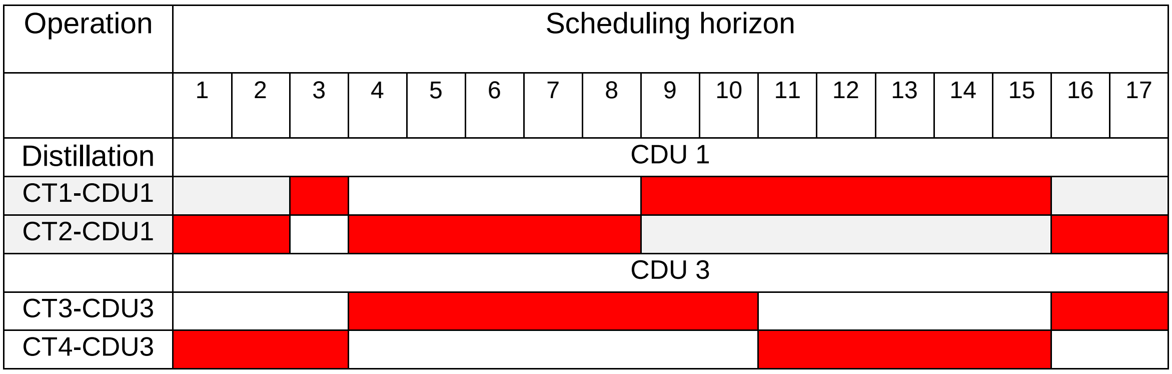


Figure 3-14: Optimal CDU schedules for Scenario C

3.3 Summary of contributions in this chapter

Below is the highlight of the contributions in this chapter. Here, the following constraints are included to come up with a more reliable MILP short-term scheduling model addressing real life refinery operational issues.

- Flow fluctuation constraints: These are added to prevent interval-interval variation of CDU charging rates. The constraints are enforced using Equations 3-18 and 3-19. These constraints were not included in Lee et al. (1996) and as a result schedules generated using their model produced unrealistic widely fluctuating CDU charging rate.
- CDU shutdown constraints with penalty: Because of the huge losses associated with shutdown, it is highly undesirable and plants are for most times run continuously. However, uncertainty due to disruption cannot be

avoided altogether. This study therefore considers constraints that allow generating schedules even when not all the CDUs are in operation. The constraints are represented by Equations 3-23 and 3-24. A shutdown penalty is included in the objective function to minimize any cost associated with the shutdown operation.

- Set-up constraint (Equation 3-25) with penalty: This is to optimize the number of activities prior to transfer from storage tanks to charging tanks for a case involving unloading into multiple storage tanks and subsequent transfer of crude oil into multiple charging tanks. The extended model schedules only important set-ups thereby minimizing the number of operations during tank-tank transfers when a set-up penalty is included in the objective function. This set-up constraint with penalty is considered in Case 3.
- Demand violation constraints: Unlike in Lee et al. (1996), violations in demand order are introduced here to make the model more flexible. These are necessary because the model becomes infeasible where supply failed to meet exact demand. These are represented by Equations 3-15 and 3-16 and incorporated in Case 3.
- Standing gauge constraints are applied not only when charging tank feeds CDU but also during transfer from storage tanks to charging tanks (Equations 3-10 and 3-11). This is an industry practice which was not included in Lee et al. (1996).

4 CRUDE OIL SCHEDULING UNDER CDU DEMAND UNCERTAINTY

4.1 Receding Horizon Approach

In the preceding chapter, uncertainties due to crude distillation unit (CDU) disruption and low inventory in charging tanks are dealt with using some constraints while fixing closing stocks. An improvement to this procedure is to generate more reliable schedules with periodic update to keep track for changes in process conditions, constraints, or performance criteria. A control technique usually refers to as model predictive control (MPC) is an alternative that keeps the decision variables at the required values (set points) while generating an optimal schedule. A key feature of this control strategy is that current implementation of decision variables within the scheduling horizon can be done more accurately since the process is periodically updated. One form of MPC is a rolling or receding horizon; a strategy that allows repeated calculations and predictions updated based on the current value of decision variable.

In this chapter, scheduling problem of crude oil transfer, blending and CDU charging has been formulated under the framework of receding horizon control strategy. The extended model developed in the previous chapter is adopted. The model considers a refinery receiving crude oil from vessels via pipeline; storing the crude oil in tanks and transferring the crude oil to charging tanks where blending operation is carried out. The blended crude oils are transferred to CDUs in accordance with the CDUs crude oil quality requirements.

4.1.1 Problem Definition

Given all the necessary information about the crude parcel, unit facilities, length of scheduling horizon, stream connections, CDU mixed crude oil requirements and the extended model, the task is to recommend to a refinery operator the feasible and smooth operational procedures that guarantee performance at minimum cost even in the presence of uncertainty (disturbance).

4.1.2 Methodology

Receding horizon is a strategy based on obtaining outputs or current state of a system and predicting subsequent future outputs or states using previous states of the system. The algorithm is made up of two elements: a prediction model of the system and the optimization tool (Yüzgeç et al., 2010).

The set of future decisions are computed by the optimization tool according to the constraints and cost function. The optimization problem is solved over a certain horizon length where a sequence of decision variables are determined for a number of time steps and then implementing only the first step in the series. This is achieved using the prediction model where a set of decisions are obtained and optimized for implementation in a real plant. The time then moves by one step with the information from the preceding time step used as input and the process is repeated until the last step. The difference between two time steps is given by the sampling time chosen (Goodwin et al., 2006).

Based on the prediction horizon length, receding horizon strategy can be fixed-end (where the prediction length is varying) or moving-end (in which the length is constant). In the fixed end receding horizon presented in this work, the length is decreasing when moving from one time step to the next as shown in Figure 4-1. Moving end receding horizon presented in Figure 4-2 here follows similar solution procedure in Yüzgeç et al. (2010).

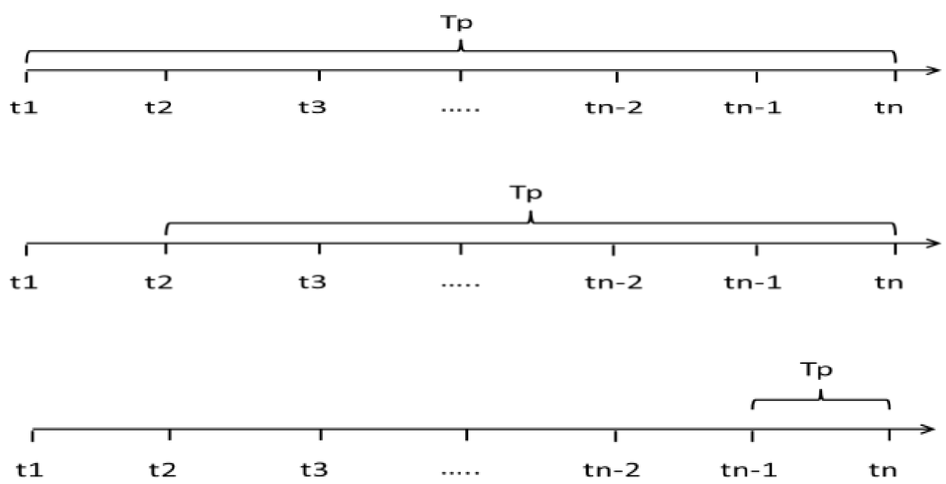


Figure 4-1: Fixed end receding horizon

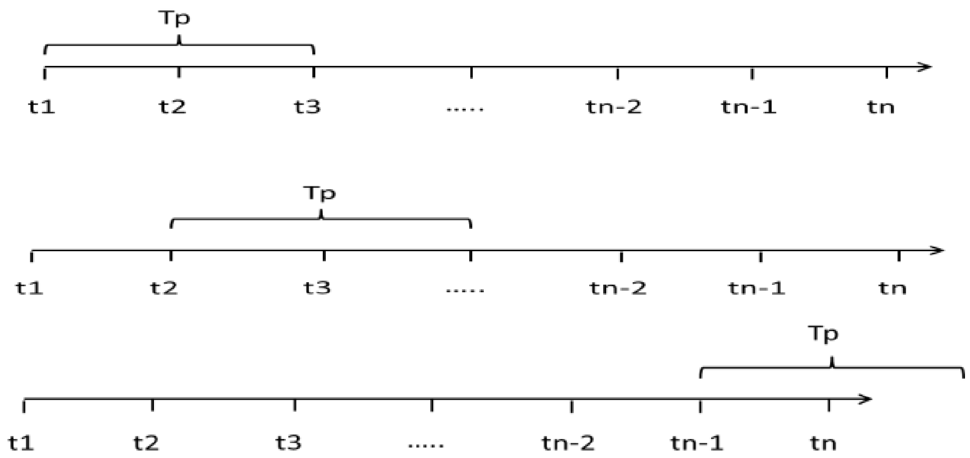


Figure 4-2: Moving end receding horizon

In this work, crude oil scheduling problem involving crude oil unloading, blending and CDU charging is solved over the fixed end and moving end receding horizon strategies. The key advantage of the strategies is that they accommodate new information or uncertain parameters (disturbance) such as change in demand of blended crude by CDU within the scheduling horizon.

Without disturbance, the states of the system using receding horizon strategies will be approximately close to those obtainable using the traditional approach. The strategy presented in this study (fixed end) was compared with the traditional approach and then with another strategy (moving end) using Case 1 and Case 2. Some disturbance scenarios were introduced to evaluate the performances of fixed end and moving end horizon strategies for recommendation to refiners and process operators.

4.2 Case Studies

The crude oil scheduling model discussed earlier was implemented in GAMS v 23.9.1 on a 4GB RAM dual core i5 processor computer, using the CPLEX solver. Case 1 and Case 2 are considered in this study to evaluate the performance of the receding horizon strategies. Some of the constraints in Chapter 3 are not applicable here and thus excluded from the optimization model. For example, shutdown is not allowed as all the CDUs should be in operation throughout the scheduling horizon so that flows from charging tanks to CDUs are modelled as semi-continuous variables.

A slight modification in the data should also be noted in the case studies. In this chapter, a minimum volume of 200 kbbl for all storage and charging tanks are used to ensure no infeasibility due to low inventory at the end of scheduling horizon.

4.2.1 Case 1

This simple case considered a system comprises of two crude parcels (V1 and V2), two storage tanks (ST1 and ST2), two charging tanks (CT1 and CT2) and one CDU. The data for this case is obtained from Case 1 in the preceding chapter with a slight modification and are presented in Table 4-1.

Table 4-1: System information for Case 1

Scheduling horizon(days)		8	
Time interval (hour)		24	
Number of vessels		2	
Number of storage tanks		2	
Number of charging tanks		2	
Number of CDU		1	
Crude vessels	Arrive/depart	Volume of crude	Key component
V1	1^{st} day/5^{th} day	1,000,000 bbl	0.01
V2	5^{th} day/8^{th} day	1,000,000 bbl	0.06
Storage Tanks	Capacities	Initial volume	Key component
ST1	1,100,000 bbl	250,000 bbl	0.01
ST2	1,100,000 bbl	750,000 bbl	0.06
Charging Tanks	Capacities	Initial volume	Initial(min., max)
CT1	1,100,000 bbl	500,000 bbl	0.02(0.015-0.025)
CT2	1,100,000 bbl	500,000 bbl	0.05(0.045-0.055)
Vessel unloading cost [$/day]		8,000	
Sea waiting cost [$/day]		5,000	
Storage tank inventory unit cost [$/(day x		0.005	
Charging tank inventory unit cost [$/(day x		0.008	
Unit changeover cost for charged oil switch in		50,000	
Demand of crude mix from charging tanks to CDU for the whole scheduling horizon		Blend 1	1,000,000 bbl
		Blend 2	1,000,000 bbl
Flow constraints		Minimum(bbl/day)	Maximum(bbl/day)
Flow from vessel to storage tank		0	500,000
Flow from storage tank to charging tank		0	500,000
Flow from charging tank to CDU		200,000	300,000

Unlike in Yüzgeç et al. (2010) where performance of model predictive control strategy was evaluated over different horizon lengths, the focus here is on the evaluation of the two receding horizon strategies in terms of efficiency to handle uncertainties towards the end of the scheduling horizon. Using the traditional approach the schedule for Case 1 is shown in Figure 4-3.

With Fixed-end receding horizon, the schedules generated at different time steps using 1 day as sampling time are presented in Figures 4-4 to 4-9. The nominal schedule is taken as time step 1 (starting point).

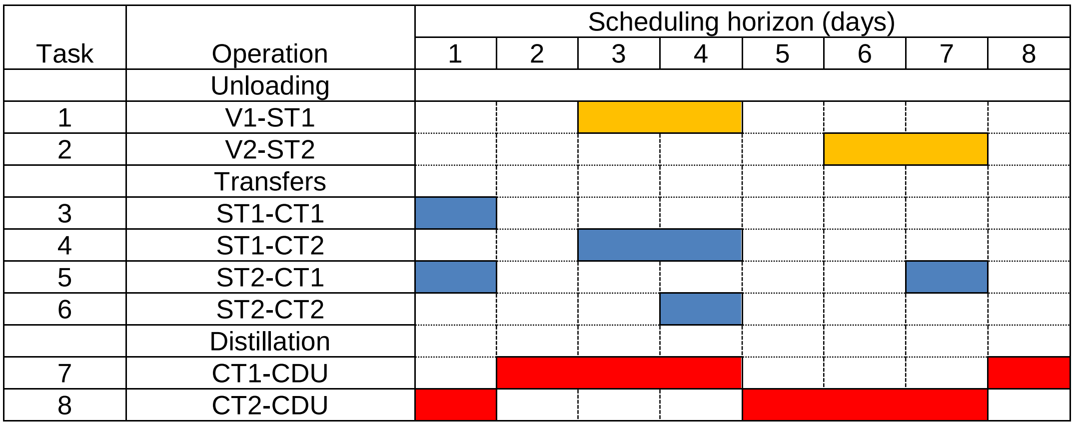


Figure 4-3: Optimal schedule for Case 1

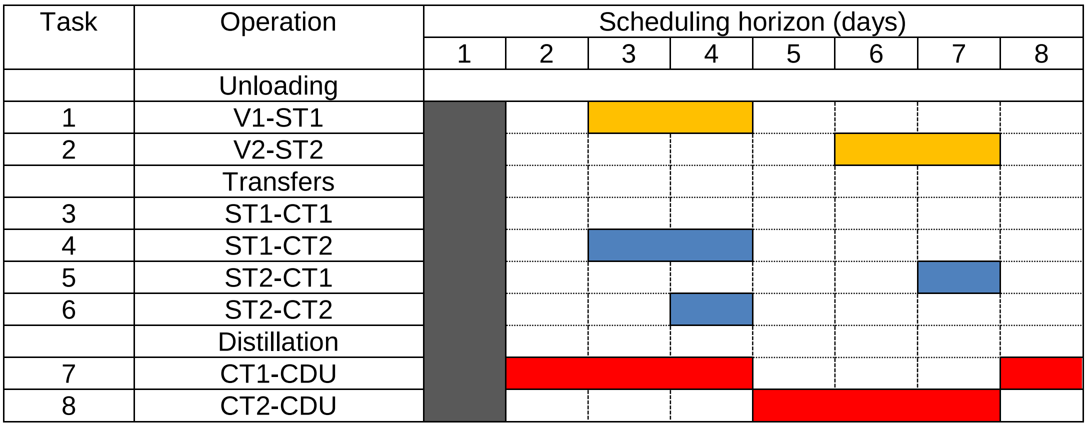


Figure 4-4: Optimal schedule for time step 2

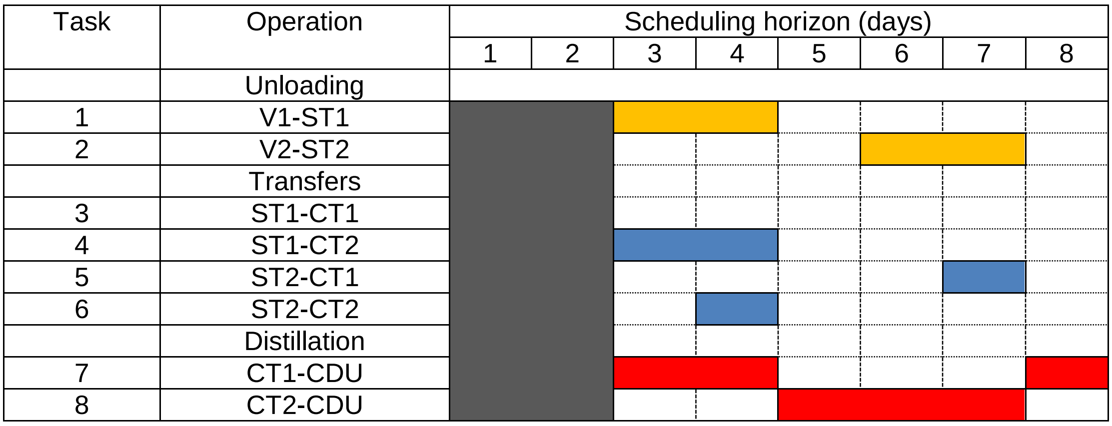


Figure 4-5: Optimal schedule for time step 3

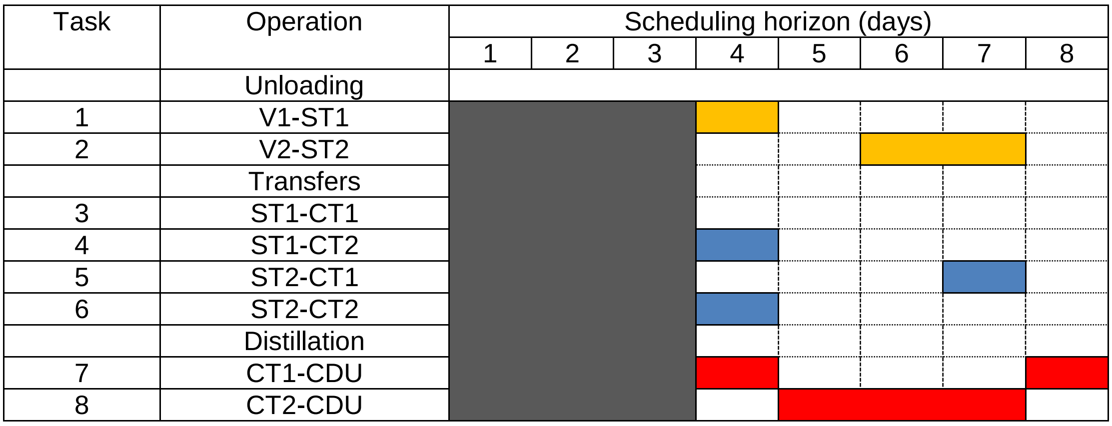


Figure 4-6: Optimal schedule for time step 4

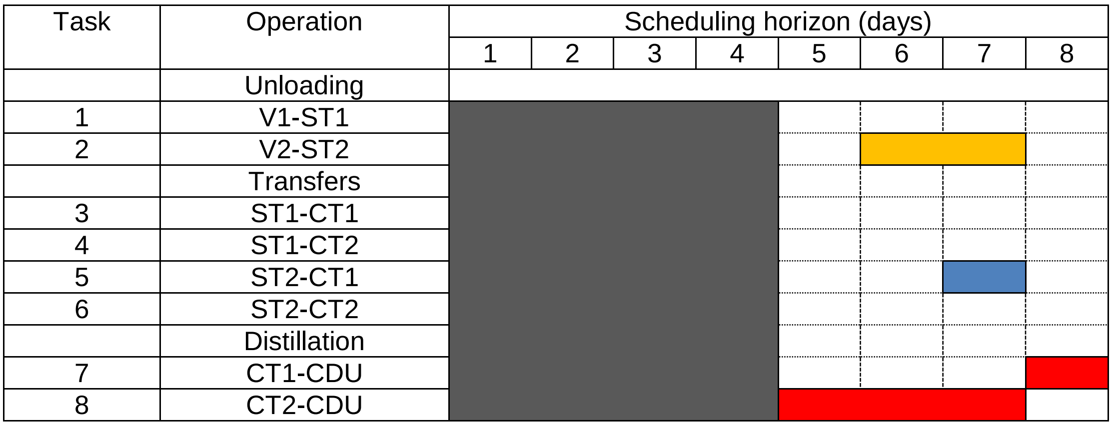


Figure 4-7: Optimal schedule for time step 5

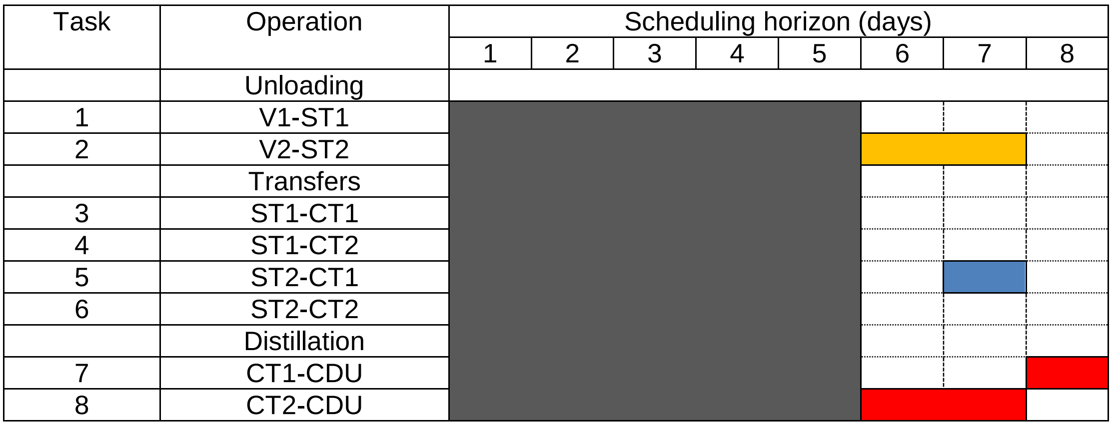


Figure 4-8: Optimal schedule for time step 6

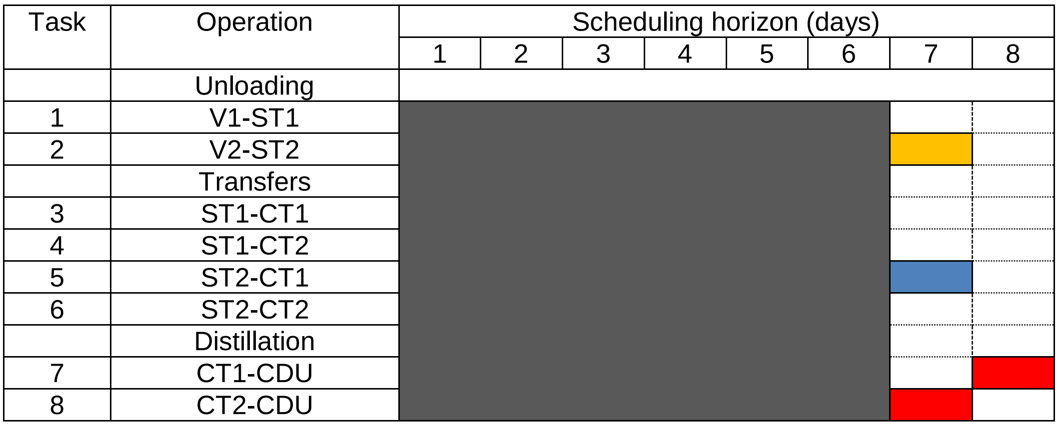


Figure 4-9: Optimal schedule for time step 7

In the figures, block shaded in black represent the schedules already implemented at the preceding time steps. Yellow shaded block represent crude parcel flowing into storage tank for current and future times. Blue horizontal bar represent flows from storage tank to charging tank for current and future times. Red horizontal bar is for CDU charging schedule for current and future times. It can be observed from the figures that for all the time steps, the schedules generated remain consistent with respect to the transfer operations and the CDU charging schedule throughout. This is exactly what to be expected without disturbance into the system.

The storage and charging tank inventory levels in Figures. 4-10 and 4-11 further clarified this.

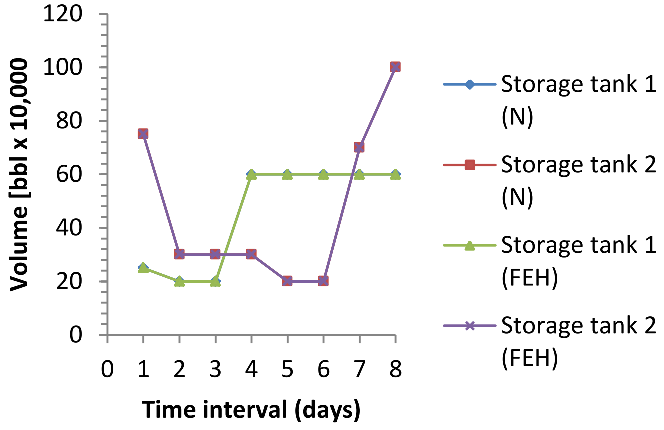


Figure 4-10: Storage tanks inventory levels for normal simulation and fixed end horizon strategy

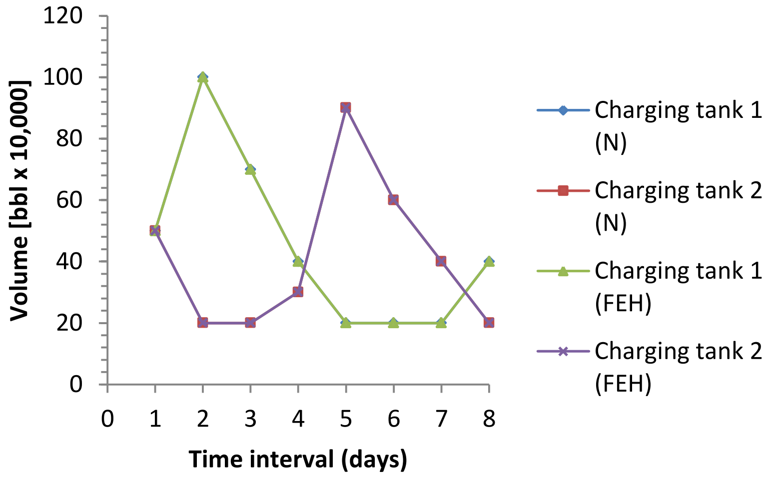


Figure 4-11: Charging tanks inventory levels for normal simulation and fixed end horizon strategy

4.2.2 Case 2

This case considers a more complex problem. It consists of three crude parcels (V1, V2 and V3), three storage tanks (ST1, ST2 and ST3), three charging tanks (CT1, CT2 and CT3) and two CDUs (CDU1 and CDU2). Here, mixing of different crude types in storage tanks is allowed since more often than not, the number of crude a refinery imports is more than the number of storage tanks available.

Using this case study, the two receding horizon strategies discussed earlier are compared. Data for this case study are obtained from the preceding chapter with slight modification and presented in Table 4-2.

The optimal CDU charging schedule from the charging tanks is presented in Figure 4-12. The inventory levels in storage and charging tanks presented in Figures 4-13 and 4-14 indicate that fixed end strategy approximates the nominal schedule more closely.

Table 4-2: System information for Case 2

<table>
<tr><td colspan="3">Scheduling horizon(days)</td><td colspan="2">12</td></tr>
<tr><td>Crude vessels</td><td colspan="2">Arrival time</td><td>Volume of crude</td><td>Key component</td></tr>
<tr><td>V1</td><td colspan="2">1st day</td><td>500,000 bbl</td><td>0.01</td></tr>
<tr><td>V2</td><td colspan="2">5th day</td><td>500,000 bbl</td><td>0.085</td></tr>
<tr><td>V3</td><td colspan="2">9th day</td><td>500,000 bbl</td><td>0.06</td></tr>
<tr><td rowspan="2">Storage tanks</td><td colspan="2">Capacities</td><td rowspan="2">Initial volume(bbl)</td><td rowspan="2">Key component Initial(min, max)</td></tr>
<tr><td>Min.</td><td>Max.</td></tr>
<tr><td>ST1</td><td>200,000bbl</td><td>1,000,000bbl</td><td>200,000</td><td>0.02(0.01-0.03)</td></tr>
<tr><td>ST2</td><td>200,000bbl</td><td>1,000,000bbl</td><td>200,000</td><td>0.05(0.04-0.06)</td></tr>
<tr><td>ST3</td><td>200,000bbl</td><td>1,000,000bbl</td><td>200,000</td><td>0.08(0.07-0.09)</td></tr>
<tr><td rowspan="2">Charging tanks</td><td colspan="2">Capacities</td><td rowspan="2">Initial volume(bbl)</td><td rowspan="2">Key component Initial(min, max)</td></tr>
<tr><td>Min.</td><td>Max.</td></tr>
<tr><td>CT1</td><td>200,000bbl</td><td>1,000,000bbl</td><td>300,000 bbl</td><td>0.02(0.025-0.035)</td></tr>
<tr><td>CT2</td><td>200,000bbl</td><td>1,000,000bbl</td><td>300,000 bbl</td><td>0.05(0.045-0.065)</td></tr>
<tr><td>CT3</td><td>200,000bbl</td><td>1,000,000bbl</td><td>300,000 bbl</td><td>0.08(0.075-0.085)</td></tr>
<tr><td colspan="3">Vessel unloading cost [$/day]</td><td colspan="2">10,000</td></tr>
<tr><td colspan="3">Sea waiting cost [$/day]</td><td colspan="2">5,000</td></tr>
<tr><td colspan="3">Storage tank inventory unit cost [$/(day x bbl)]</td><td colspan="2">0.004</td></tr>
<tr><td colspan="3">Charging tank inventory unit cost [$/(day x bbl)]</td><td colspan="2">0.008</td></tr>
<tr><td colspan="3">Unit changeover cost for charged oil switch in CDU[$]</td><td colspan="2">50,000</td></tr>
<tr><td colspan="3">Penalty for switching storage tanks when vessel is unloading</td><td colspan="2">8,000</td></tr>
<tr><td colspan="3" rowspan="3">Demand of crude mix from charging tanks to CDU</td><td>Blend 1</td><td>500,000 bbl</td></tr>
<tr><td>Blend 2</td><td>500,000 bbl</td></tr>
<tr><td>Blend 3</td><td>500,000 bbl</td></tr>
<tr><td colspan="3">Flow constraints</td><td>Minimum(bbl/day)</td><td>Maximum(bbl/day)</td></tr>
<tr><td colspan="3">Vessel to storage tank</td><td>0</td><td>250,000</td></tr>
<tr><td colspan="3">Storage tank to charging tank</td><td>0</td><td>250,000</td></tr>
<tr><td colspan="3">Charging tank to CDU</td><td>200,000</td><td>300,000</td></tr>
</table>

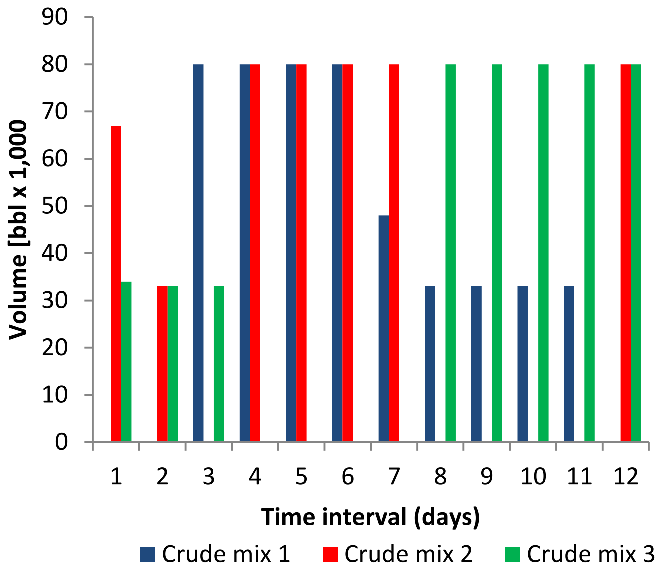


Figure 4-12: CDU charging schedule

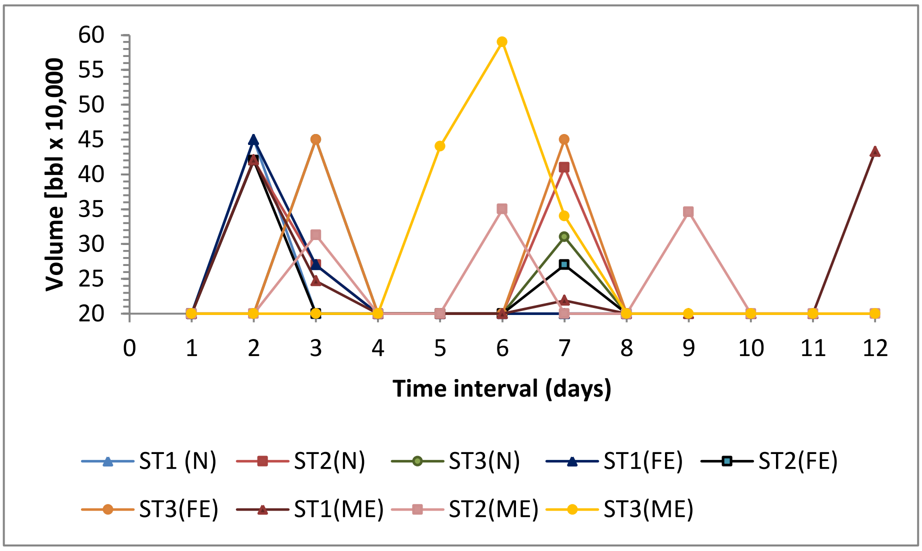


Figure 4-13: Storage tanks inventory levels for nominal simulation, fixed end and moving end horizon strategies

The volume profile of both storage and charging tanks are exactly the same using traditional approach and with fixed end horizon strategy, hence the two overlapped in the above figures.

From simulations carried out the fixed end strategy generate feasible and optimal schedules in all the time steps. But this is not the case for moving end as feasibility depends on the length of the prediction horizon. Shorter lengths generate infeasible schedules.

To compare the two in terms of cost, an equal length of prediction horizon are considered at time step 5 with fixed end being the better option, optimal operating cost of $116,749 against $ 216,388 for moving end horizon.

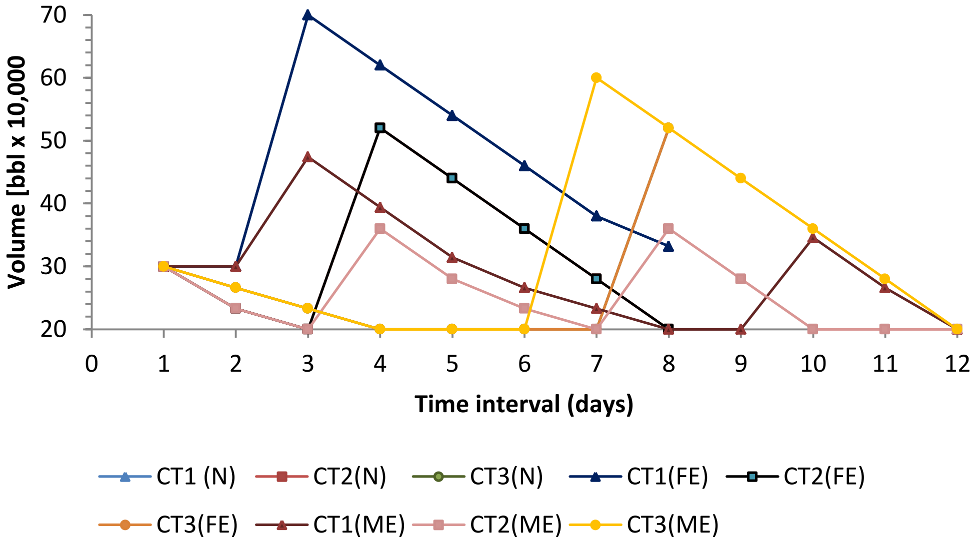


Figure 4-14: Charging tanks inventory levels for nominal simulation, fixed end and moving end horizon strategies

4.2.2.1 Disturbance scenarios

To further evaluate the performance of fixed end and moving end horizon strategies, two disturbance scenarios were introduced.

(A) Demand of blended crude 1 is increased from 500,000 bbl to 600,000 bbl and demand of blended crude 2 is increased to 580,000 bbl on the 5th day.

(B) With disturbance 1 and decrease in demand of blended crude 3 from 500,000bbl to 430,000bbl

In both scenarios, fixed end produces feasible schedule while moving end fails.

4.3 Summary of Findings in this Chapter

This chapter presents receding horizon control strategies to deal with uncertainty in crude oil scheduling problem.

- Two of such strategies (fixed-end and moving-end) are introduced as solution alternatives to handle demand uncertainty.
- Results obtained demonstrate that fixed end receding horizon strategy is a suitable alternative to solve refinery crude oil scheduling problem.
- Fixed end receding horizon strategy guarantees feasibility and optimality under disturbance scenarios.
- Fixed end receding horizon outperformed moving end horizon strategy in terms of performance as schedules are feasible in all the time steps.
- Fixed end horizon strategy approximates nominal schedule more closely and using equal prediction horizon length, it offers lower operational cost compared to moving end horizon ($116,749 against $ 216,388 at time step 5).
- It has also been shown in this study that crude oil scheduling problem can be formulated as an optimal control problem.

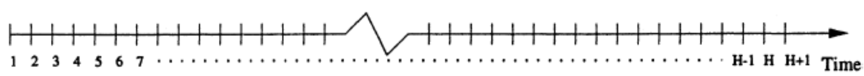
5 SCHEDULING REFINERY PRODUCTION WITH PRODUCT BLENDING

The downstream of the crude oil unloading and crude distillation unit (CDU) charging subsystem modelled in Chapter 3 is the refinery production area. This area formed the main refinery complex where cut fractions are produced from CDU as refinery intermediate products. Some of these intermediate products like fuel gas are readily available for sale to customers. The bulk of the intermediate products are sent to blending units for further processing to meet certain quality requirements set by customers and environmental laws. Scheduling of operational tasks is of paramount importance towards maximizing the overall refinery production income. In refinery production scheduling, certain features are considered in modelling CDU along with other processing units. These include the problem formulation as linear or nonlinear; time representation as discrete or continuous; and whether solution is obtained using simple, sequential or integrated approach.

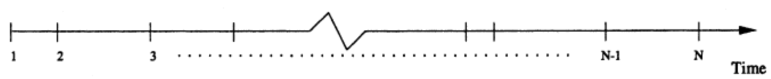
Even though mixed integer linear programming (MILP) formulations are used in refinery modelling such procedure is not sufficient due to the fact that most processes are nonlinear in nature. Failure to account for nonlinearity will result in generating unreliable schedules. Issues like this have been spotted in Chapter 3 where avoiding bilinear terms to maintain model linearity presents inconsistencies in sulphur concentration for blended crudes. In addition to being nonlinear, refinery scheduling problems involve discrete and continuous decisions, hence formulated as mixed integer nonlinear programming (MINLP). Models presented in Pinto et al. (2000; Méndez et al. (2006); Li et al. (2010); and Cuiwen et al. (2013) are all MINLPs. The main difference in these refinery production models lie in the time formulation adopted or developed (discrete or continuous), problem size and complexity (large-scale or small-scale), and the solution strategy devised to ensure feasibility and optimality.

Discrete time formulation requires that the length of the scheduling horizon be divided into a number of time intervals of equal or varying duration. In this formulation, the beginning and ending of all activities or events are forced to coincide with the boundaries of the time intervals. Binary variables are used to model the occurrence or non-occurrence of events at these time interval boundaries. In some way, discrete time formulation simplifies the model but introduces more binary variables making larger problems intractable or difficult to solve. The refinery scheduler has to decide on the length of the time interval to use based on the nature of the problem at hand. Larger time intervals oversimplify the problem giving inaccurate results. The use of smaller time intervals gives a more reasonable solution but requires higher computational efforts as seen in a small scale scheduling problem of crude oil unloading and CDU charging in Chapter 3.

Unlike the discrete time formulation, the continuous time representation allows events to occur at any time within the time interval boundaries. The idea is to split the time horizon into several variable time slots so that events are allowed to occur at the boundaries of the time intervals. Such formulations introduce flexibility and possibly eliminate unnecessary event time interval assignments, thus resulting in problem much smaller in size compared with its equivalent discrete time representation and hence require less computational efforts (Floudas and Lin, 2004). Despite these benefits however, variable event timing makes continuous time models difficult to handle as inventory and material balance have to be checked at each time slot to ensure solution feasibility (Méndez et al., 2006). Considering the advantages and limitations in the use of the aforementioned time representations, the choice between the two is still an open debate.



Discrete time representation



Continuous time representation

Figure 5-1: Discrete and Continuous time representations (Floudas and Lin, 2004)

Recognizing the fact that model development in refinery scheduling is mostly tied to the solution procedure adopted or developed, a number of concepts are usually employed; a simple approach that decompose a large problem into smaller size subproblems and treat the subproblems separately; a sequential approach that allows exchange of information between subproblems and integrate the two; and a more rigorous procedure that solves two subproblems simultaneously. To perform operations in the most efficient way, simultaneous optimization of production with intermediate product blending is necessary. The purpose is to effectively schedule the operation based on economic driving forces while satisfying physical constraints.

5.1 Model Formulation and Problem Definition

In this chapter, a novel MINLP scheduling model for production area with blending unit is developed to optimize the allocation of materials, distribution of resources, assignments of tasks and processing times of different crude slates in a petroleum refinery. The model considers crude oil characteristics with pseudo-components. In addition to flowrates, crude compositions are also considered. The CDU model is based on swing cut approach and the objective of the optimization model is to maximize profit while generating feasible schedules within time horizon. The scheduling horizon is discretized into a number of time periods of variable length.

5.1.1 Problem Definition

The following technical details are assumed to be available to the refinery scheduler:

1. A scheduling horizon [0, H].
2. Crude oil assays, compositions and limits on their flow rates.
3. Stream connections.
4. Costs of raw materials: crude oil feeds and butane additives.
5. Unit capacities of CDU and other downstream units along with their operating costs.

6. Yield coefficients of all streams generated from the main refinery production units with the exception of CDU in which yield is predicted using swing-cut model approach.
7. Bounds on the intermediate streams properties.
8. B blenders with specification on the component streams to be received at any given time period.
9. P products with specification on blender processing each of these products. Lower limits on the blend times and production rates have to be specified as well. Each blender is assigned to feed a specific product tank and receives input from specific components streams.
10. Specification limits on the products property indices and revenue realised from the products sales.
11. Q Product tanks with specification on blenders each storage tank should receive from. Limits on volume of product in each storage tank at any given time including time zero and demand for various products are specified.
12. Product tanks inventory costs.
13. S sales, their constituent products, amounts, and delivery time windows.

With these technical details, the problem here is to find feasible set of operations that maximize the overall refinery profit by determining the following decision variables:

1. The type and amount of crude oil processed over time.
2. I components flowrates and their quality indices.
3. Flow profiles of feeds into blending units.
4. Production volume of each blender over time, and the blending duration.
5. The inventory profiles of product tanks.
6. The amount of products available for sale during the scheduling horizon.

5.2 Mathematical Model Development

The motivation here is to come up with a refinery scheduling model that captures all the necessary interactions between production units and blending subsystem while solving the two simultaneously.

The aforementioned objectives cannot be achieved without some assumptions and consideration for certain operating rules. They are:

5.2.1 Operating Rules

1. CDU and other upstream units are in continuous operation during the scheduling horizon.
2. Blenders operate in a semi-continuous mode. When running, blender is connected to product storage tank and no sales of product at that period of time. When idle, blender is connected to a dummy storage tank and product stored in real tank will be available for sale.
3. A blender cannot process more than one product at any time.
4. A blender cannot feed more than one product tank at any time.
5. Products from different blenders can be processed at same time. Such decision is vital to avoid using tanks unnecessarily.
6. A blender cannot be fed while discharging products.
7. While feeding a blender, a product cannot be discharged at same time.

5.2.2 Model Assumptions

1. The flow of components streams is such that it meets minimum amount required for blending operation for the whole time periods.
2. Perfect mixing assumption for all blenders.
3. No changeover operations for blenders since specific component streams are assigned to each blender.
4. No changeover for product storage tanks since each tank is allocated to a specific product.
5. Each product is processed within the scheduling horizon.
6. All sales involve only one product at a time and multiple products sales can be decomposed into several single-product sales.

5.2.3 CDU Modelling with Crude Oil Characterization

Considering that crude oil is a complex mixture of components, a good understanding of its compositional information and thermo-physical properties is essential. It has been found from a significant number of research studies that obtaining detailed information about the all components is impractical. However, the crude oil feedstock can be decomposed into hypothetical components called pseudo-components that can be used in petroleum refinery studies. Unlike the existing methodologies that use fixed yield approach, refinery scheduling model developed in this chapter uses pseudo-components and light end hydrocarbon components to characterize the crude oil and then blended with any swing-cuts to form the CDU fractions. The pseudo-components were generated using Aspen plus simulator. The pseudo-components are distributed to the corresponding cut fractions based on the cuts initial boiling point (IBP) and end boiling point (EBP).

5.2.3.1 Mass balance for cut fractions

The model starts with mass balance of each cut fraction from a specific crude oil cr at time period t. The left hand side of Equation 5-1 represents the cut flow inside the CDU $FC_{cr,t,fc}$ which is the sum of the products of crude oil volumetric flowrate $FB_{cr,t}$ and volume fraction of the crude oil components from initial micro-cuts to final micro-cut $x_{FB,cr,t}$. The distribution of the initial micro-cuts mc to the corresponding final cut fc is based on the boiling range of the target cut fraction fr. Equation 5-1 does not include swing cut sw.

$$FC_{cr,t,fc} = \sum_{mc}^{fc} FB_{cr,t} x_{FB,cr,t} \qquad \forall\, cr, mc, t, fc \neq sw \tag{5-1}$$

When final micro-cut is a swing cut ($FC_{cr,t,fc=sw}$), it splits into light l and heavy h streams defined by $FS_{cr,t,fc=l}$ and $FS_{cr,t,fc=h}$ respectively. Thus introducing three non-negative variables as presented in Equations 5-2 and 5-3. Their values are optimized to match product quantity and quality specifications.

$$FC_{cr,t,fc=sw} = \sum_{mc}^{fc} FB_{cr,t} x_{FB,cr,t} \qquad \forall\, cr, mc, t, fc = sw \tag{5-2}$$

Equation 5-3 gives the size of the swing cut

$$FC_{cr,t,fc=sw} = FS_{cr,t,fc=l} + FS_{cr,t,fc=h} \qquad \forall\, cr, t, fc = sw \tag{5-3}$$

Flow $FR_{cr,t,fr}$ of each cut fraction fr can then be computed as the sum of final micro-cut and its corresponding light l and heavy swings h as follows:

$$FR_{cr,t,fr} \leq FC_{cr,t,fc} + FS_{cr,t,fc=l} + FS_{cr,t,fc=h} \qquad \forall\, cr, t, fr \tag{5-4}$$

Note that each cut fraction has different swing cut components and the first final micro-cut has no lighter swing component added to form the corresponding cut fraction. Similarly, the last final micro-cut has no heavy swing component in the corresponding cut fraction.

The product yields of CDU is related to the amount of crude oil processed at any given time instance. i.e.

$$FB_{cr,t} \geq \sum_{fr} FR_{cr,t,fr} \qquad \forall\, cr, t \tag{5-5}$$

5.2.3.2 Mass balance for crude oil

The amount of crude oil to be supplied must satisfy its minimum $FB_{cr,t,min}$ and maximum $FB_{cr,t,max}$ processing requirements. This however, depends also on the crude oil processing time $\varphi_{cr,t}$ and its composition $\omega_{cr,t}$. These are represented by the following constraints:

$$FB_{cr,t} \geq FB_{cr,t,min} \varphi_{cr,t}\, \omega_{cr,t} \qquad \forall\, cr, t \tag{5-6}$$

$$FB_{cr,t} \leq FB_{cr,t,max} \varphi_{cr,t}\, \omega_{cr,t} \qquad \forall\, cr, t \tag{5-7}$$

While $FB_{cr,t,min}$ and $FB_{cr,t,max}$ are in bbl per day, the crude oil processing time $\varphi_{cr,t}$ is a fraction of a day. Processing time of crude oil depends on the binary variable $XC_{cr,t}$ which decides whether crude cr is processed at time period t and the length of the production period LT_t.

$$\varphi_{cr,t} = LT_t\, XC_{cr,t} \qquad \forall\, cr, t \tag{5-8}$$

The sum of the production period lengths over all time periods gives the length of the scheduling horizon H.

$$H = \sum_t LT_t \tag{5-9}$$

5.2.4 Downstream Units

The yield, capacity, and quality constraints of other units in the refinery are formulated in accordance with the stream connections in refinery plants:

The yield of any intermediate product $F_{s',u,cr,t}$, which is the output stream s' from unit u is obtained by multiplying the yield coefficient $\eta_{s',u,cr,t}$ with input (feed) stream s to that particular unit ($F_{s,u,cr,t}$).

$$F_{s',u,cr,t} = \eta_{s',u,cr,t} F_{s,u,cr,t} \qquad \forall\, u, cr, t \tag{5-10}$$

A stream feeding a unit must satisfy the unit capacity cap_u requirement

$$\sum_{s'} F_{s',u,cr,t} \leq cap_u \qquad \forall\, u, cr, t \tag{5-11}$$

Streams are connected from one unit to another by means of splitters and mixers.

For splitters the following constraint holds:

$$F_{s,split,cr,t} = \sum_{s'} F_{s',split,cr,t} \qquad \forall\, split, cr, t \tag{5-12}$$

Similarly, for mixers the constraint is represented as

$$\sum_{s'} F_{s',mix,cr,t} = F_{s,mix,cr,t} \qquad \forall\, mix, cr, t \tag{5-13}$$

A special mixer is the blending unit (blender) that process component streams from splitters into blends of different quality attributes k as specified by customers. Output streams from blenders $F_{p,cr,t}$ are the refinery main products available for sale.

$$\sum_{s',u} F_{s',u,cr,t} = F_{p,cr,t} \qquad \forall\, p, cr, t \tag{5-14}$$

Product properties at time t, $\zeta_{k,p,t}$ must meet minimum or maximum specifications and are related to the component streams and additives properties $\xi_{k,s,u,cr,t}$.

Properties like vapour pressure, density, and sulphur in product streams should be less than or equal to a certain value. Octane rating on the other hand must be greater than or equal to some specific number.

$$\zeta_{k,p,t} F_{p,cr,t} \leq \sum_{s,u} \xi_{k,s,u,cr,t} F_{s,u,cr,t} \quad \forall\, p, cr, t \tag{5-15}$$

$$\zeta_{k,p,t} F_{p,cr,t} \geq \sum_{s,u} \xi_{k,s,u,cr,t} F_{s,u,cr,t} \quad \forall\, p, cr, t \tag{5-16}$$

5.2.5 Blending Operation

A blender operates in a semi-continuous mode and therefore at any time instant, the blender is either running or idle. When running, blender is connected to a product tank. Binary variables are defined to model blender when in operation and when in idle mode.

$$x_{b,p,t} = \begin{cases} 1 & \text{if blender } b \text{ is processing product } p \\ & \text{at time period t} \\ 0 & \text{otherwise} \end{cases} \qquad \forall\, b, p, t \tag{5-17}$$

$$y_{b,q,t} = \begin{cases} 1 & \text{if blender } b \text{ is feeding product tank } q \\ & \text{at time period t} \\ 0 & \text{otherwise} \end{cases} \qquad \forall\, b, q, t \tag{5-18}$$

$$z_{q,p,t} = \begin{cases} 1 & \text{if product tank } q \; is \text{ storing product } p \\ & \text{at time period t} \\ 0 & \text{otherwise} \end{cases} \qquad \forall\, q, p, t \tag{5-19}$$

The following relations hold true:

At any time period, if blender b feeds tank q and that tank stores product p then b processes p at that particular time period. i.e.

$$x_{b,p,t} \geq z_{q,p,t} + \ y_{b,q,t} - 1 \quad \forall\, b, p, q, t \tag{5-20}$$

If b processes p and feeds q at time period t, then q holds p at that particular time period.

$$z_{q,p,t} \geq x_{b,p,t} + \ y_{b,q,t} - 1 \quad \forall\, b, p, q, t \tag{5-21}$$

Each blender b cannot feed more than one product tank q at time period t. i.e.

$$\sum_{q} y_{b,q,t} \leq \ 1 \quad \forall\, b, t \tag{5-22}$$

Blender cannot simultaneously receive component streams for processing while feeding storage tank q. A binary variable $cs_{s,u,cr,t}$ is defined to denote that blender b is receiving component streams s of crude cr from refinery production unit u at time period t.

$$cs_{s,u,cr,t} = \begin{cases} 1 & \text{if blender } b \text{ is receiving from component} \\ & \text{streams at time period } t \\ 0 & \text{otherwise} \end{cases} \qquad \forall\, b, cr, t \tag{5-23}$$

The following constraint ensures that blender is either receiving component streams or feeding product tank.

$$cs_{s,u,cr,t} + y_{b,q,t} \leq \ 1 \quad \forall\, b, cr, q, t \tag{5-24}$$

Due to semi-continuous nature of its operation, not all the component streams are processed at the same time in the blender. Component streams that cannot be processed at a particular time period are temporarily stored to be used at a later time. Therefore each component stream splits into two non-negative variables. The amount processed by the blender at any time period is the fraction of the component streams received at that particular time. Equation 5-14 can then be transformed to:

$$\sum_{s',u} F_{s',u,cr,t} = F_{blend,cr,t} cs_{s,u,cr,t} + F_{stored,cr,t} \quad \forall\, b, cr, t \tag{5-25}$$

The actual amount produced during blending operation $FP_{p,t}$ should satisfy the following constraint

$$FP_{p,t} x_{b,p,t} \leq F_{blend,cr,t} \ \forall\, b, p, t \tag{5-26}$$

Therefore Equations 5-15 and 5-16 can be re-written as

$$\zeta_{k,p,t} FP_{p,t} \leq \sum_{s,u} \xi_{k,s,u,cr,t} F_{blend,cr,t} \quad \forall\, k, p, t \tag{5-27}$$

$$\zeta_{k,p,t} FP_{p,t} \geq \sum_{s,u} \xi_{k,s,u,cr,t} F_{blend,cr,t} \quad \forall\, k, p, t \tag{5-28}$$

During operation, a blender runs within its lower $RL_{p,t,min}$ and upper limits $RL_{p,t,max}$ and is related to the product processing time $\phi_{p,t}$.

$$\phi_{p,t} \geq RL_{p,t,min} \tag{5-29}$$

$$\phi_{p,t} \leq RL_{p,t,max} \tag{5-30}$$

The volume $VP_{p,t}$ produced from each blender depends on the amount processed by the blender (in bbl per day) and the product processing time (in hours). Thus,

$$VP_{p,t} = FP_{p,t} \phi_{p,t}\, x_{b,p,t} \tag{5-31}$$

The volume produced must be within its production limit and should not be more the capacity of the blender $cap_{blender}$.

$$VP_{p,t} \geq VP_{p,t,min} \tag{5-32}$$

$$VP_{p,t} \leq VP_{p,t,max} \quad \textbf{(5-33)}$$

$$VP_{p,t} \leq cap_{blender} \quad \textbf{(5-34)}$$

5.2.6 Product Storage and Inventory

From mass balance, a material inventory of each product in storage tank $INPT_{p,t}$ can be accounted for. This is calculated as the sum of the initial inventory in the tank at the beginning of each time period and the actual amount produced at that period less the actual amount ordered/sold to customers at the same period.

$$INPT_{p,t+1} = INPT_{p,t} + VP_{p,t} - VPS_{p,t} \quad \textbf{(5-35)}$$

$VPS_{p,t}$ is the actual amount of each product available for sale to customers at time period t. This amount must meet the demand $DM_{p,t}$ of customers throughout the scheduling horizon.

$$VPS_{p,t} \geq DM_{p,t} \quad \textbf{(5-36)}$$

The inventory must always be within products' lower and upper limits and must not exceed the tank capacity VPT_p.

$$INPT_{p,t} \geq INPT_{p,t,min} \quad \textbf{(5-37)}$$

$$INPT_{p,t} \leq INPT_{p,t,max} \quad \textbf{(5-38)}$$

$$INPT_{p,t} \leq VPT_p z_{q,p,t} \quad \textbf{(5-39)}$$

As noted in Chapter 3, it is an operational policy to keep minimum safety stock above tanks bottom levels in order to safeguard floating device. To prevent tanks from running out of stock at the end of the scheduling horizon, periodic constraint on the inventory is imposed. i.e.

$$INPT_{p,t+1} \leq INPT_{p,1} \tag{5-40}$$

This ensures that low inventory at the end of the scheduling horizon is avoided. Rebennack et al. (2011) recommends that only one of the storage tanks safety stock values is fixed while leaving the values for other tanks as variables to be determined by model solution. This is to avoid being trapped in the infeasibility region.

5.2.7 Objective Function

The objective function is computed as the overall refinery profit PR which is the revenue generated from selling the products minus all the costs associated with raw material, unit operation, inventory, purchased intermediate (additive), and penalties.

$$\begin{aligned} PR = \sum_t \sum_p pf_p * VPS_{p,t} - \sum_t \sum_{cr} ct_{cr} * FB_{cr,t} * \varphi_{cr,t} \\ - \sum_t \sum_u g_u * F_{s,u,cr,t} * \varphi_{cr,t} - \sum_t \sum_p pst_p * INPT_{p,t} \\ - \sum_t ui * BUT_t - \sum_t penalties \end{aligned} \tag{5-41}$$

The revenue is computed as product of price of product per bbl pf_p and the total amount sold to customers $VPS_{p,t}$. Raw material cost is obtained by multiplying the cost per bbl ct_{cr} with the amount of crude oil processed $FB_{cr,t}$ and the processing time $\varphi_{cr,t}$. Similarly, unit operation cost is the product of cost per bbl g_u processed in each unit, amount processed in each unit $F_{s,u,cr,t}$ and the processing time $\varphi_{cr,t}$. Inventory cost is computed by multiplying inventory cost per bbl stored pst_p with the amount stored $INPT_{p,t}$. Purchased intermediate (butane) cost is obtained in a similar way, multiplying butane cost per bbl ui and the amount used BUT_t. Penalty is incurred when quality requirements of the products are not met.

5.3 Case Study

A case study of a real refinery that processes two crude oil grades (light and heavy) is considered here. The refinery plant depicts production area with blending subsystem. Figure 5.2 is the process schematic of the material flow in the oil refinery plant. In the figure, crude oil is separated in CDU into straight-run (SR) fuel gas, SR naphtha, SR gasoline, SR distillate, SR gas oil and SR residuum. Pseudo-components were generated from ASPEN plus for the two crude oil grades and are distributed to their respective cut fractions based on IBP and EBP temperature ranges of the cuts.

The cut fractions' IBP and EBP are presented in Table 5-1 with the TBP curve, API, and specific gravity for the two crudes given in Table 5-2 (Alattas et al., 2011). Of the crude oil types, Crude 1 is more expensive with low sulphur content (sweet crude) than Crude 2 with high sulphur content (sour crude). The scheduling horizon is of 10 days. The limits on the crude oils availability are given in Table 5-3. Other technical details for use in the model are given in Tables (5-4) to (5-11).

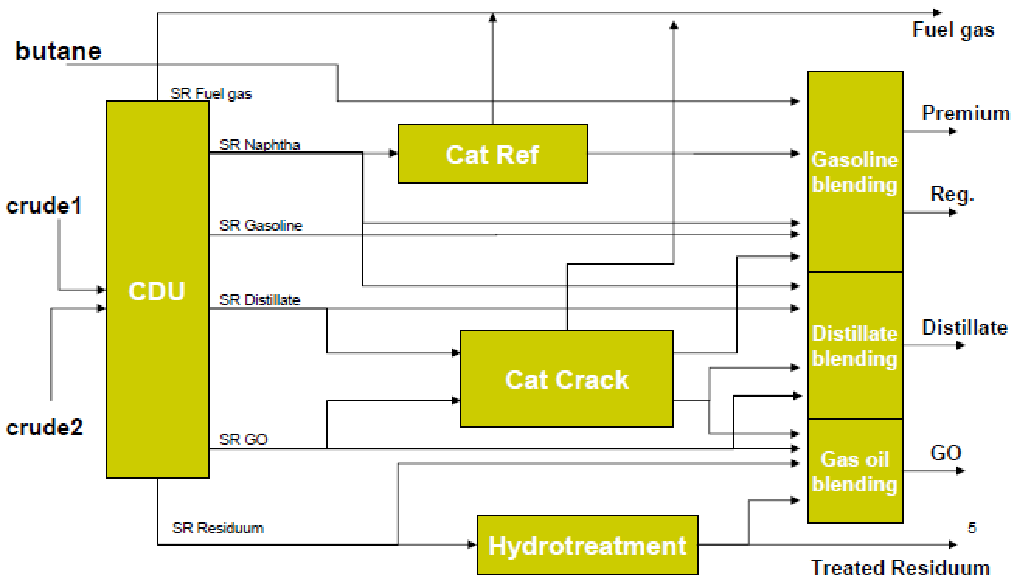


Figure 5-2: Refinery production with product blending(Alattas et al., 2011)

The lighter products such as SR gasoline and SR fuel gas are sent directly to the blending unit or markets. The medium products such as SR distillate and SR gas oil are catalytically cracked in FCC and then sent to the blending unit. SR naphtha is catalytically reformed in CRU, and then sent to the blending unit. Part of the SR residuum is sent to the hydro treatment unit for removal of sulphur in this intermediate product. The residuum is then passed onto the blending operations. The final products from these processes are fuel gas, premium gasoline, regular gasoline, distillate, and gas oil. With the exception of fuel gas, these final products are blends which meet quality specifications such as octane level, vapour pressure, density and sulphur content. Also in the figure, there is a butane stream, a material with high octane rating for used in gasoline blending.

Table 5-1: Crude cuts IBP and EBP

	IBP (^{0}F)	**EBP (^{0}F)**
SR-fuel gas	-126.67	82.13
SR-gasoline	82.13	283.73
SR-naphtha	235.13	379.13
SR-distillate	290.93	604.13
SR-gas oil	515.93	712.13
SR-residuum	620.33	1442.93

Table 5-2: Crude assay data

Crude oil	API	Specific gravity	LV% distilled	TBP (^{0}F)
Crude 1	37	0.84	0	5.5
			5	108.6
			10	162.6
			30	341.5
			50	527.1
			70	745.3
			90	1045.3
			95	1178.9
			100	1313.2

Crude 2	32.4	0.8631	0	73.7
			5	169.8
			10	218.9
			30	415.9
			50	614.2
			70	861.5
			90	1184.8
			95	1339.6
			100	1494.2

Table 5-3: Crude oil availability (1000s bbl/day)

Limit/days	1	2	3	4	5	6	7	8	9	10
Minimum	20	20	20	20	20	20	20	20	20	20
Maximum	200	200	200	200	200	200	200	200	200	200

Table 5-4: Refinery raw material/operating costs and product prices

Raw material costs ($/bbl)	
Crude 1	75
Crude 2	65
Butane	67.5
Operating costs ($/bbl processed)	
Crude distillation	5
Catalytic reformer	7.5
Catalytic cracker	40
Catalytic cracker - Gas oil feed	4
Hydrotreater - Distillate feed	5
Inventory cost	0.00306
Product prices ($/bbl)	
Premium gasoline	135
Regular gasoline	121
Distillate	87
Gas oil	76.5
Fuel gas	35

Table 5-5: Yield patterns for the downstream process units

Output yields	Crude 1		Crude 2	
Catalytic reformer				
Reformed fuel gas	0.129		0.099	
Reformate for gasoline blending	0.807		0.836	
Loss	0.064		0.065	
	1.000		**1.000**	
Catalytic cracker	**DS**	**GO**	**DS**	**GO**
Cracked fuel gas	0.30	0.31	0.36	0.38
Cracked gasoline	0.59	0.59	0.58	0.60
Gas oil (for distillate or gas oil blending)	0.21	0.22	0.15	0.15
	1.100	**1.12**	1.09	1.09
Hydrotreater	RS			
Desulphurized residuum	0.97			

Table 5-6: Capacities of process units (1000 bbl/day)

Crude distillation	100
Catalytic reformer	20
Catalytic cracker	30
Product tank	150

Table 5-7: Blending information from yields

Premium and Regular Gasoline	Clear Research Octane		Vapour Pressure (mmHg)	
SR gasoline (from crude unit)	78.5		18.4	
SR naphtha (from crude unit)	65.0		6.54	
Reformate (from reformer)	104.0		2.57	
Cracked gasoline(from cat cracker)	93.7		6.90	
Butane	91.8		199.2	
	Density (lb/bbl)		Sulphur (lb/bbl)	
	Crude 1	Crude 2	Crude 1	Crude 2
Distillate				
SR naphtha (from crude unit)	272.0	272.0	0.283	1.48
SR distillate (from crude unit)	292.0	297.6	0.526	2.83

SR gas oil (from crude unit)	295.0	303.3	0.980	5.05
Cracked gas oil	294.4	299.1	0.353	1.31
Gas oil blend				
Cracked gas oil	294.4	299.1	0.353	1.31
SR gas oil	295.0	303.3	0.980	5.05
SR residuum	343.0	365.0	4.700	11.00
Hydrotreated residuum		365.0		6.00

Table 5-8: Product quality specifications

	Clear Research Octane	Vapour Pressure (mmHg)	Density (lb/bbl)	Sulphur (lb/bbl)
Premium gasoline	(≥) 90	(≤) 12.7		
Regular gasoline	(≥) 86	(≤) 12.7		
Distillate			(≤) 306	(≤) 0.5
Gas oil			(≤) 352	(≤)3.5

Table 5-9: minimum run length for each blending operation (per day)

Products/days	1	2	3	4	5	6	7	8	9	10
Premium gasoline	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Regular gasoline	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Distillate	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Gas oil	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Fuel gas	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 5-10: Demand of final products (1000s bbl per day)

Products/days	1	2	3	4	5	6	7	8	9	10
Premium gasoline	42.3	42.3	42.3	42.3	42.3	42.3	42.3	42.3	42.3	42.3
Regular gasoline	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
Distillate	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
Gas oil	36.8	36.8	36.8	36.8	36.8	36.8	36.8	36.8	36.8	36.8
Fuel gas	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5

Table 5-11: Bounds on amount produced and tank inventory (1000s)

	Volume flow of products (bbl/day)		Inventory of products (bbl)	
	Minimum	Maximum	Lower	Upper
Premium gasoline	10	80	30	80
Regular gasoline	10	80	25	60
Distillate	10	80	10	60
Gas oil	10	80	10	60
Fuel gas	10	80	15	80

The results for crude oil characterization are in Appendices A and B.

The model was implemented in GAMS and solved using Couenne MINLP solver and the solution was obtained to be a profit of $38,533,250 for the whole scheduling horizon. This cannot be claimed to be a global solution as Couenne is not a global optimizer. In other words, there is no guarantee that the solution obtained is the global optimum.

The information on the optimal refinery plant economics, crude oil processing rates, processing times, product sales, and product inventories are summarized in Tables 5-12, 5-13, 5-14 and 5-15 respectively.

Table 5-12: Income and costs generated for the whole scheduling horizon ($1000)

Parameter	Value
Profit	38,533.250
Sales	175,951.321
Raw material cost	122,015.66
Unit operation cost	14,373.322
Inventory cost	6.313
Purchased intermediate	678.939
Other cost (penalties)	343.837

Table 5-13: Raw material processing information

period	length	Crude 1 processed			Crude 2 processed		
		Rate (1000s bbl/day)	Volume (1000s bbl)	Time (hr)	Rate (1000s bbl/day)	Volume (1000s bbl)	Time (hr)
1	1.336	96.144	128.4484	32.062	72.603	96.99761	32.062
2	0.520	103.984	54.07168	12.478	96.016	49.92832	12.478
3	0.512	102.429	52.44365	12.291	96.245	49.27744	12.291
4	0.504	99.172	49.98269	12.099	100.828	50.81731	12.099
5	0.526	105.149	55.30837	12.618	94.521	49.71805	12.618
6	0.516	103.139	53.21972	12.377	96.861	49.98028	12.377
7	0.875	102.291	89.50463	20.996	96.757	84.66238	20.996
8	1.016	100.041	101.6417	24.380	96.883	98.43313	24.380
9	0.896	179.162	160.5292	21.499	20.838	18.67085	21.499
10	3.300	65.999	217.7967	79.199	65.999	217.7967	79.199

Table 5-14: Product sales

period	Product sales (1000s bbl)				
	Premium gasoline	Regular gasoline	Distillate	Gas oil	Fuel gas
1	80.319	135	150	150.145	85
2	42.3	10	10	36.8	17.5
3	42.3	10	10.131	36.8	17.5
4	42.3	10	10	43.161	17.5
5	42.3	10	10	50.357	17.5
6	42.3	10	10	61.812	17.5
7	42.3	10	10	69.879	17.5
8	42.3	10	10	76.79	17.5
9	42.3	10	10	61.343	17.5
10	51.303	35	20	89.212	25

Table 5-15: Product inventory levels

period	Product inventories (1000s bbl)				
	Premium gasoline	Regular gasoline	Distillate	Gas oil	Fuel gas
1	150	150	150	150	150
2	80	25	10	26.137	75
3	73.307	25	10	15.632	67.5
4	66.625	25	10	10	60
5	59.807	25	10	10	52.5
6	53.002	25	10	10	45
7	46.509	25	10	10	37.5
8	39.723	25	10	10	30
9	32.609	25	10	10	22.5
10	30	25	10	10	15

5.4 Consideration for Discrete-time with Equal Interval Length

The result presentations and discussions in the preceding section were based on variable time formulation of the scheduling problem. Results for an equivalent formulation with equal interval length of time periods are presented here. An equal interval length of 1 day for the whole scheduling horizon is used. That is, the 10 day scheduling horizon is discretized into 10 time periods of equal length. The scheduling problem is then solved again to obtain an optimal profit of $29,621,550. This is less than the amount $38,533,250 obtained for the variable length time formulation. The interest here is not to compare the two solutions directly since the difference in the time formulation means the two problems are not exactly the same, but to show the benefit of using a better approach. Optimal refinery plant economics and crude oil processing details for this uniformly discretized problem are given in Tables 5-16 and 5-17.

Table 5-16: Income and costs generated for the whole scheduling horizon ($1000)

Parameter	Value
Profit	29,621.550
Sales	172,497.900
Raw material cost	128,489.800
Unit operation cost	13,659.440
Inventory cost	6.398
Purchased intermediate	720.696
Other cost (penalties)	0

Table 5-17: Raw material processing information

period	length	Crude 1 processed			Crude 2 processed		
		Rate (1000s bbl/day)	Volume (1000s bbl)	Time (hr)	Rate (1000s bbl/day)	Volume (1000s bbl)	Time (hr)
1	1	117.224	117.224	12.000	20.000	20.000	12.000
2	1	126.865	126.865	14.759	20.000	20.000	9.241
3	1	168.023	168.023	13.732	20.000	20.000	10.268
4	1	151.038	151.038	12.000	20.000	20.000	12.000
5	1	180.000	180.000	12.000	20.000	20.000	12.000
6	1	119.967	119.967	12.000	80.033	80.033	12.000
7	1	139.872	139.872	12.000	60.128	60.128	12.000
8	1	145.243	145.243	12.000	54.757	54.757	12.000
9	1	143.913	143.913	12.000	56.087	56.087	12.000
10	1	89.254	89.254	12.000	31.839	31.839	12.000

Comparing the two time formulations of the scheduling problem in terms of costs presented in Table 5-12 (variable timing) and Table 5-16 (uniform discretization), the later gives larger values in most of the cost components. The revenue generated with variable timing is higher than the amount obtained using uniform time discretization. This in turn generates higher profit in favour of the formulation with varying time periods.

From Table 5-13, it can be observed from the second column that variable time formulation records the actual duration of each task in a given time period and therefore reflects the actual processing times and hence the amount processed at each time period. This is not the case for uniform time discretization as events are forced to take place at the boundary of intervals. Despite the benefits of variable time formulation as demonstrated in this particular problem, the approach may be inappropriate in other problems based on the reasons stated in the introductory part of this chapter.

One interesting thing to observe from processing time columns in Tables 5-13 and 5-17 is that in variable timing the two crudes are processed simultaneously (in parallel) while in uniform time discretization the crudes are processed sequentially. This is strange considering that the difference in the two formulations lie only in the interval timing. This scenario may be an indication that the solutions obtained are not global.

5.5 Summary of Contributions in this Chapter

In refinery scheduling, model development is in most cases tied to the solution procedure adopted or developed to solve the model. Most of the existing methodologies are based on:

1. A simple approach that decompose a large problem into smaller size subproblems and treat the subproblems separately.
2. A sequential approach that allow exchange of information between subproblems and integrate the two and,
3. A more rigorous procedure that solves two subproblems simultaneously.

To perform operations in the most efficient way, simultaneous optimization of production with intermediate product blending is necessary. This is to ensure reliable schedules are generated while satisfying physical and economic constraints.

- In this chapter, a novel MINLP scheduling model for production area with blending unit was developed to optimize the allocation of materials, distribution of resources, assignments of tasks and processing times of different crude slates in a petroleum refinery.

- The model considers crude oil characteristics with pseudo-components. In addition to flowrates, crude oil compositions are also considered making the model suitable for control studies.
- The CDU model is based on swing cut approach and the objective of the optimization model was to maximize profit while generating feasible schedules within time horizon.
- The scheduling horizon is discretized into a number of time periods of variable length and then equal length of 1 day was considered thereafter.
- A large scale refinery problem was used as a case study to test the model.
- The results obtained from the case study shows that reliable decisions can be obtained for implementation in real plants.

6 REFINERY PRODUCTION WITH UNCERTAINTY IN CRUDE OIL COMPOSITION

One of the challenges in refinery scheduling is the generation of schedules with consideration to uncertainty in process parameters. Fluctuation in product demand, change in crude oil composition, and other uncertainties do manifest during execution of the schedules. In the presence of these uncertainties, the schedule generated under deterministic conditions may become infeasible, suboptimal or difficult to implement. To deal with these uncertainties, a number of preventive and reactive alternatives are developed in literature. While preventive scheduling seeks to incorporate uncertainty at the initial stage before its realization, the reactive scheduling on the other hand takes corrective action after a disturbance is introduced into the system.

With a robust control action through feedback, uncertainty due to fluctuation in crude oil composition, change in crude oil flow rate, and change in qualities and quantities of additives can be addressed. The failure or success in tackling these issues depends on the efficiency of the algorithm employed. Although the methodology presented in Chapter 4 can be used effectively to address uncertainty in the main refinery production area, a more efficient technique that is able to cancel the effect of disturbances is presented here. The burden associated with solving optimization problems repeatedly will be avoided. This viable alternative technique is called self-optimizing control (SOC). It involves selection of control variables (CVs) so that when the CVs are controlled at their set points, the overall plant operation is optimal or near optimal even in the presence of uncertainties. Therefore in this chapter, a data driven SOC strategy for multi-period scheduling problems will be developed. The performance of the method will be elucidated using case studies. The next section discussed general methodology for SOC and will then be followed by data driven SOC for the problem under consideration.

6.1 Self -Optimizing Control Strategy

Most processes in chemical plants including refinery are operated in such a way that operators set decision variables as set points and with the aid of proportional integral derivative (PID) controllers, these set points are kept at their desired values. To satisfy requirements set by environmental laws, operate within safety limits, survive market competition and to meet tighter quality specifications of products; plants must operate near optimal. Self-optimizing control as a strategy helps to achieve the aforementioned objectives by selecting appropriate control variables (CVs) so that when they are maintained at their set point values, the overall plant operation is optimal or near optimal even in the presence of uncertainties (Skogestad, 2000).

When an uncertainty in the form of disturbance is introduced into a chemical plant, measurements are taken and control actions are implemented to compensate for the effects of the uncertainty. In the past decades, several techniques for CV selections have been reported. Most of these techniques require process models to determine CVs offline and largely depend on the ability to linearize nonlinear models around their nominal operating points. This procedure is time-consuming which results in the plant operation being locally optimal and become impractical where no process model is available (Kariwala, 2007; Alstad and Skogestad, 2007).

Despite the benefits of applying SOC, there are challenges emanating from the CV selection. The selected CVs must be such that they give acceptable loss and therefore are able to avoid any need to re-optimize set points when uncertainties are introduced into the system. Difficulty arising from using model for SOC has been overcome by incorporating measurements in the optimization framework. Single measurements or combination of measurements may be used as CVs. Halvorsen et al. (2003) introduced methods for finding subset or combination of measurements as controlled variables. Controlling these subset or combination of measurement at constant set points implies operating the plant at desired economic condition. Overcoming challenges due to model linearization requires a global approach.

Necessary condition of optimality (NCO) is a viable complementary method that seeks to overcome the local shortcomings of the existing SOC methodologies (Jäschke and Skogestad, 2011). François et al. (2005) are of the view that measurements can be used to enforce NCO in the presence of uncertainty where the NCO are separated into active constraints and cost sensitivities (gradients). Owing to the fact that some NCO components are non-measurable online due to the presence of uncertain parameter in the objective function, Ye et al. (2012b) proposed that CVs can be selected in such a way that they approximate unmeasured NCO over the whole uncertain parameter space. The CVs can then be obtained through regression methods. The CV selection problem is therefore transformed into a regression problem and does not need a model to be a priori (Ye et al., 2012a). The difficulty using NCO lies in the inability to compute the gradient online.

Recently, a methodology was developed by Girei et al. (2014) that computes CVs as function of measurements from real plant or simulated data using finite difference approximation. Grema and Cao (2014) extended the methodology to dynamical systems where the gradient is approximated using Taylor series expansion. Their approach is not directly applicable for problems involving mixed integer programming with multiple time periods and therefore a new methodology has to be developed. This is the motivation behind this chapter.

Therefore in this study, a multi-period data driven approach involving mixed integer problems to determine CV as a function of measurements is presented. The methodology is then applied to refinery scheduling problem with uncertainties in crude oil composition.

6.1.1 Data Driven Self-optimizing Control for Scheduling

Although the methodology is developed to deal with mixed integer problems, the discussion here will be mainly on scheduling. Generally, scheduling is a static mixed integer optimization problem with uncertainties in model parameters represented as disturbances. This can be formulated as

$$\min_{\mathrm{u}} J(\mathbf{u}, \mathbf{d}) \tag{6-1}$$

subject to

$$\mathbf{g}(\mathbf{u},\mathbf{d}) \leq 0 \qquad \mathbf{u}_b\colon (\mathbf{0},\mathbf{1}) \tag{6-2}$$

Where J is an objective function to be minimized (cost or negative profit). As the problem is mixed integer, the control inputs are separated into continuous manipulated variables $\mathbf{u_c}$ and integer manipulated variables $\mathbf{u_b}$ with $\mathbf{u_c}, \mathbf{u_b} \in \mathbb{R}^{n_u}$. The integer manipulated variables range from 0 to 1 and $\mathbf{d} \in \mathbb{R}^{n_d}$ are the uncertain parameters or disturbances. $\mathbf{g}\colon \mathbb{R}^{n_u}\ X\ \mathbb{R}^{n_d} \rightarrow \mathbb{R}^{n_g}$ are the constraints to be satisfied, which are usually related to unit capacities, mass balance, inventory, and storage. The variables $\mathbf{u_b}$ here are typically chosen to control the continuous variables such as flowrates by either forcing one or more variables to be in between 0 and 1. For simplicity, a single manipulated variable that is varying with time periods is assumed. For t time periods and y measurements, Equation 6-1 can be transformed into

$$J = \sum_t J_t(u_t, \boldsymbol{y_t}, \boldsymbol{d_t}) \qquad \forall\, t \tag{6-3}$$

Where J_t is the contribution of J in each time period or event point t. $u_t, \boldsymbol{y_t}, \text{and } \boldsymbol{d_t}$ are manipulated variables, measurements, and disturbances at time period t respectively. The scheduling horizon H is discretized into time periods t_n $(n = 1, 2, 3, \dots, N)$ of variable lengths LT_n. Variable time discretization is based on the fact that events or activities do not always happened at the time boundaries. i.e. for scheduling horizon of 10 days discretized into 10 time periods, some task can take less or more than 1 day to complete. To obtain CVs, the following procedures are followed.

1. Manipulated variables u are identified along with flow streams y that disturbances will have an immediate impact upon. These flow streams are the measurements. The scheduling model is then solved to obtain solution vector $u_{0,t} = u_{0,1}, u_{0,2}, u_{0,3}, \dots, u_{0,N}$ for the manipulated variables, $\boldsymbol{y_{0,t}} = \boldsymbol{y_{0,1}}, \boldsymbol{y_{0,2}}, \boldsymbol{y_{0,3}}, \dots, \boldsymbol{y_{0,N}}$ for the measurements and J_0 as profit (or cost). The solution from the first simulation run represents the nominal schedule.

2. The manipulated variables are then slightly but randomly perturbed for the whole time periods or event points to have

$$u_{i,t} = u_{i,1}, u_{i,2}, u_{i,3}, \dots, u_{i,N} \;, \qquad i = 1, 2, 3, \dots, I \tag{6-4}$$

and the scheduling model is simulated for i trajectories to obtain measurements

$$\boldsymbol{y}_{i,t} = \boldsymbol{y}_{i,1}, \boldsymbol{y}_{i,2}, \boldsymbol{y}_{i,3}, \dots, \boldsymbol{y}_{i,N} \tag{6-5}$$

and (cost or negative profit) J_i.

y is a vector because at each time period, there may be more than one measurement $(m = 1, 2, 3, \dots, M)$. The manipulated variable is included as one of the measurements

3. The gradient (change in objective function with respect to manipulated variables) is the CV and approximated using Taylor series expansion. This can be derived as follows.

Considering that the objective function is changing with respects to multiple manipulated variables corresponding to different time periods, the following equation holds true:

$$\begin{aligned}
J_1 - J_0 &= CV_{1,1}\Delta u_{1,1} + CV_{1,2}\Delta u_{1,2} + CV_{1,3}\Delta u_{1,3} + \;\dots\; + CV_{1,N}\Delta u_{1,N} \\
J_2 - J_0 &= CV_{2,1}\Delta u_{2,1} + CV_{2,2}\Delta u_{2,2} + CV_{2,3}\Delta u_{2,3} + \;\dots\; + CV_{2,N}\Delta u_{2,N} \\
J_3 - J_0 &= CV_{3,1}\Delta u_{3,1} + CV_{3,2}\Delta u_{3,2} + CV_{3,3}\Delta u_{3,3} + \;\dots\; + CV_{3,N}\Delta u_{3,N} \\
\vdots \qquad & \qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \qquad \dots \qquad \vdots \\
J_I - J_0 &= CV_{I,1}\Delta u_{I,1} + CV_{I,2}\Delta u_{I,2} + CV_{I,3}\Delta u_{I,3} + \;\dots\; + CV_{I,N}\,\Delta u_{I,N}
\end{aligned} \tag{6-6}$$

Where,

$$\Delta u_{1,1} = (u_1 - u_0)_1\ ,\ \Delta u_{1,2} = (u_1 - u_0)_2\ , \quad \ldots,\ \Delta u_{1,N} = (u_1 - u_0)_N \qquad \textbf{(6-7)}$$

$$\Delta u_{2,1} = (u_2 - u_0)_1\ ,\ \Delta u_{2,2} = (u_2 - u_0)_2\ , \quad \ldots,\ \Delta u_{2,N} = (u_2 - u_0)_N$$

$$\Delta u_{3,1} = (u_3 - u_0)_1\ ,\ \Delta u_{3,2} = (u_3 - u_0)_2\ , \quad \ldots,\ \Delta u_{3,N} = (u_3 - u_0)_N$$

$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots \qquad \ldots \quad \vdots \qquad \vdots$$

$$\Delta u_{I,1} = (u_I - u_0)_1\ ,\ \Delta u_{I,2} = (u_I - u_0)_2\ , \quad \ldots,\ \Delta u_{I,N} = (u_I - u_0)_N$$

The control variables

$$\begin{bmatrix} CV_{1,1}, & CV_{1,2}, & CV_{1,3}, & \ldots & CV_{1,N} \\ CV_{2,1}, & CV_{2,2}, & CV_{2,3}, & \ldots & CV_{2,N} \\ CV_{3,1}, & CV_{3,2}, & CV_{3,3}, & \ldots & CV_{3,N} \\ & & \vdots & & \\ CV_{I,1}, & CV_{I,2}, & CV_{I,3}, & \ldots & CV_{I,N} \end{bmatrix}$$

are non-measurable online and therefore can be replaced with measurement functions. Thus,

$$CV_{1,1} = (\theta_0 + \theta_1 y_{1,1} + \theta_2 y_{1,2} + \theta_3 y_{1,3} + \ldots + \theta_M y_{1,M})_1 \qquad \textbf{(6-8)}$$

$$CV_{1,2} = (\theta_0 + \theta_1 y_{1,1} + \theta_2 y_{1,2} + \theta_3 y_{1,3} + \ldots + \theta_M y_{1,M})_2$$

$$CV_{2,1} = (\theta_0 + \theta_1 y_{2,1} + \theta_2 y_{2,2} + \theta_3 y_{2,3} + \ldots + \theta_M y_{2,M})_1$$

$$\vdots$$

$$CV_{I-1,N} = (\theta_0 + \theta_1 y_{I-1,1} + \theta_2 y_{I-1,2} + \theta_3 y_{I-1,3} + \ldots + \theta_M y_{I-1,M})_N$$

$$CV_{I,N-1} = (\theta_0 + \theta_1 y_{I,1} + \theta_2 y_{I,2} + \theta_3 y_{I,3} + \ldots + \theta_M y_{I,M})_{N-1}$$

$$CV_{I,N} = (\theta_0 + \theta_1 y_{I,1} + \theta_2 y_{I,2} + \theta_3 y_{I,3} + \ldots + \theta_M y_{I,M})_N$$

Substituting Equation 6-8 into Equation 6-6 gives

$$J_1 - J_0 = \theta_0(x_0)_1 + \theta_1(x_1)_1 + \theta_2(x_2)_1 + \ \ldots \quad +\theta_M(x_M)_1 \tag{6-9}$$

$$J_2 - J_0 = \theta_0(x_0)_2 + \theta_1(x_1)_2 + \theta_2(x_2)_2 + \ \ldots \quad +\theta_M(x_M)_2$$

$$J_3 - J_0 = \theta_0(x_0)_3 + \theta_1(x_1)_3 + \theta_2(x_2)_3 + \ \ldots \quad +\theta_M(x_M)_3$$

$$\vdots$$

$$J_I - J_0 = \theta_0(x_0)_I + \theta_1(x_1)_I + \theta_2(x_2)_I + \ \ldots \quad +\theta_M(x_M)_I$$

Where,

$$(x_0)_1 = (\Delta u_{1,1} + \Delta u_{1,2} + \Delta u_{1,3} + \ldots + \Delta u_{1,N})_1 \tag{6-10}$$

$$(x_1)_1 = (y_{1,1}\Delta u_{1,1} + y_{1,2}\Delta u_{1,2} + y_{1,3}\Delta u_{1,3} + \ldots + y_{1,N}\Delta u_{1,N})_1$$

$$(x_2)_3 = (y_{2,1}\Delta u_{2,1} + y_{2,2}\Delta u_{2,2} + y_{2,3}\Delta u_{2,3} + \ldots + y_{2,N}\Delta u_{2,N})_3$$

$$\vdots$$

$$(x_M)_I = (y_{M,1}\Delta u_{I,1} + y_{M,2}\Delta u_{I,2} + y_{M,3}\Delta u_{I,3} + \ldots + y_{M,N}\Delta u_{I,N})_I$$

Equation 6-9 can be re-arranged to

$$\Delta J_i = \boldsymbol{x}_i\boldsymbol{\theta} \tag{6-11}$$

Equation 6-11 can then be re-written as

$$\boldsymbol{Y} = \boldsymbol{X\theta} \tag{6-12}$$

Implying that ΔJ_i is represented by vector $\boldsymbol{Y}$ and $\boldsymbol{x}_i$ by vector $\boldsymbol{X}$.

Using regression $\boldsymbol{\theta}$ can be determined.

$$\widehat{\boldsymbol{\theta}} = (\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X})^{-\mathbf{1}}\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{Y} \tag{6-13}$$

Using the rule of thumb, the data points for regression should be at least ten times the number of coefficients to be estimated.

By analogy, Equation 6-8 can be represented in condensed form as

$$CV = \theta_0 + \theta_1 y_1 + \theta_2 y_2 + \theta_3 y_3 + \ldots + \theta_M y_M \tag{6-14}$$

Controlling gradient at zero implies the LHS of Equation 6-14 equal to zero. It is important to note that $y_{M,t}$ is the manipulated variable as mentioned in step 2 of the solution procedure.

Therefore at each time period, the optimal feedback control input is obtained as:

$$u_{fb,t} = -\frac{1}{\theta_M}[\theta_0 + \theta_1 y_1 + \theta_2 y_2 + \theta_3 y_3 + \ldots + \theta_{M-1} y_{M-1}] \tag{6-15}$$

Some values of the integer manipulated variables may be slightly below 0 or above 1. In such a case the variables are said to be ‘saturated’ and a constraint has to be imposed, forcing the saturated variables to be equal to their corresponding nearest value (0 or 1).

Implementing this feedback strategy in a close loop fashion will incur loss. The loss can be computed as

$$L = \frac{J_0 - J(\mathrm{u}_{fb}, \mathrm{d})}{J_0} \times 100 \tag{6-16}$$

Where J_0 is the true optimal J, while $J(\mathrm{u}_{fb}, \mathrm{d})$ is the objective function corresponding to implementing Equation 6-15 to maintain the CV at zero.

6.2 Case study

The real refinery problem in Chapter 5 is adopted here to show the applicability of the solution approach developed in this chapter. The same model and same operational data; the only difference being that the binary variable $XC_{cr,t}$ is allowed to take any value between 0 and 1. The optimal profit J_0 in this case was obtained as \$56,696,407. Allowing $XC_{cr,t}$ to include both discrete and continuous values makes the profit different from the amount \$38,533,250 obtained in Chapter 5. The optimal values of the variables $XC_{cr,t}$ are used as parameters in the SOC model. The optimal parameter values of crude 2 (manipulated variables) are then perturbed slightly but randomly around their nominal operating points to form sequence of solutions to be used for regression analysis. 20x9 (180) data points were generated in accordance with Equation 6-11 from which 8 regression coefficients are obtained. The regression coefficients determined are presented in Table 6-1.

Table 6-1: Parameter values from regression

Coefficient	Value (x 10^4)
θ_0	6.7996
θ_1	0.1396
θ_2	0.4154
θ_3	0.0430
θ_4	-0.2164
θ_5	-0.1722
θ_6	-0.1252
θ_7	-5.9679

This gives the optimal feedback control law:

$$u_{fb,t} = (1/5.9679)[6.7996 + 0.1396y_{1,t} + 0.4154y_{2,t} + 0.0430y_{3,t} - 0.2164y_{4,t} - 0.1722y_{5,t} - 0.1252y_{6,t}] \quad \textbf{(6-17)}$$

The measurements $y1 - y6$ are SR fuel gas, SR gasoline, SR naphtha, SR distillate, SR gas oil, and SR residuum streams of crude 1 respectively. Cases with and without uncertainties are considered to illustrate the capability of the approach presented in this work. Scenarios of different uncertainties were created and the approach proved to be promising in each situation.

6.2.1 Case 1

This first case assumed no uncertainty is introduced into the system. The optimal objective value of the base case model with nominal values of the manipulated variables is compared with the objective value obtained after feedback implementation with no disturbance. The optimal profit for the base case model was obtained as $56,696,407. Implementing Equation 6-17 in the base model results in a profit of $50,523,054. The loss was computed in accordance with Equation 6-16 to obtain a value of 10.888%. Scenarios in the next case will better illustrate the advantage of SOC.

6.2.2 Case 2

This case considers uncertainties in a number of scenarios to appreciate the performance of SOC methodology.

6.2.2.1 Scenario A

This scenario consider a change in composition of crude 1 by 5% for the whole scheduling horizon. The measurements representing cut fractions from crude 1 are taken and the optimal manipulated variable is computed and implemented in the SOC model to obtain optimal profit $J(\mathrm{u}_{fb}, \mathrm{d})$ of \$53,403,869. Compared with the optimal value of \$56,696,407, a loss of 5.807 % was obtained. The production levels of the cut fractions using SOC are compared with the actual amounts produced at the nominal operating conditions. These are shown in Figures 6-1 to 6-6.

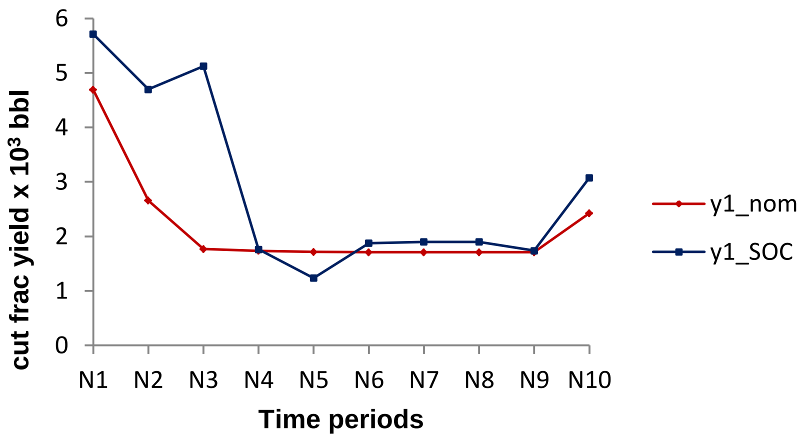


Figure 6-1: Production levels for SR fuel gas at different time periods

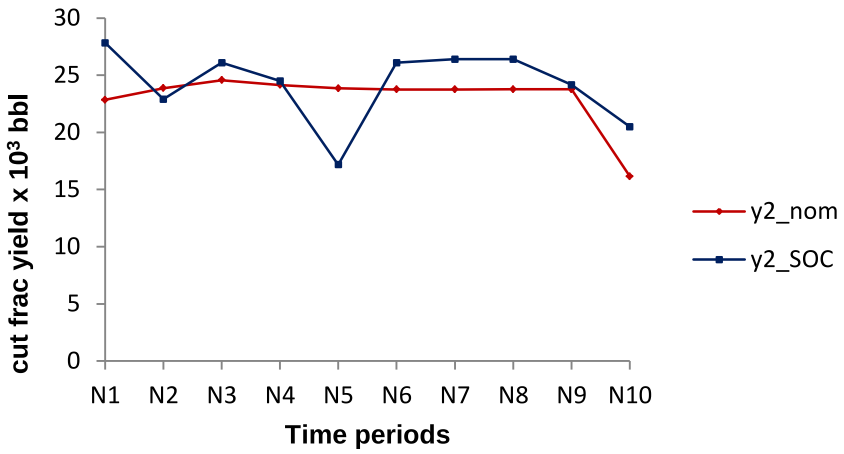


Figure 6-2: Production levels for SR gasoline at different time periods

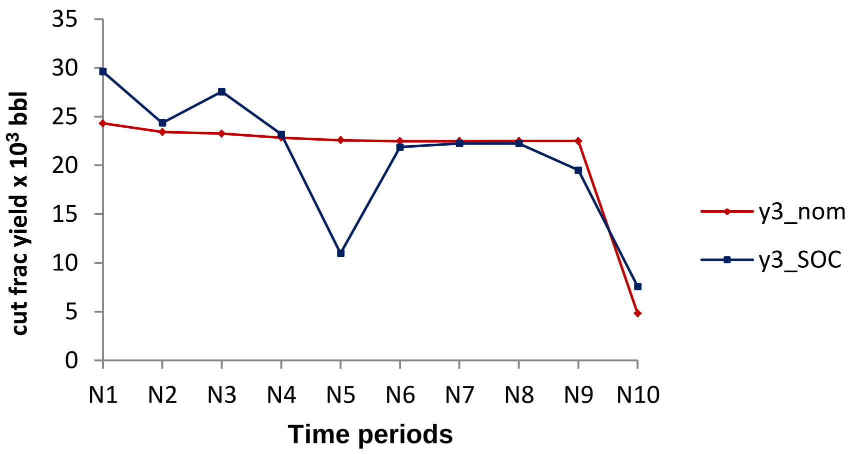


Figure 6-3: Production levels for SR naphtha at different time periods

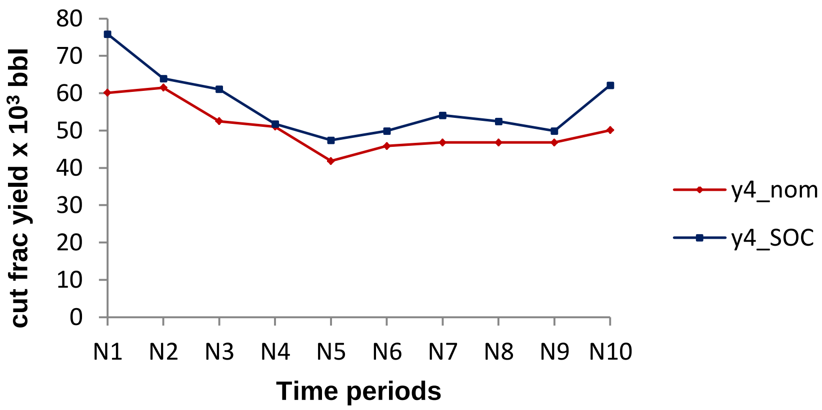


Figure 6-4: Production levels for SR distillate at different time periods

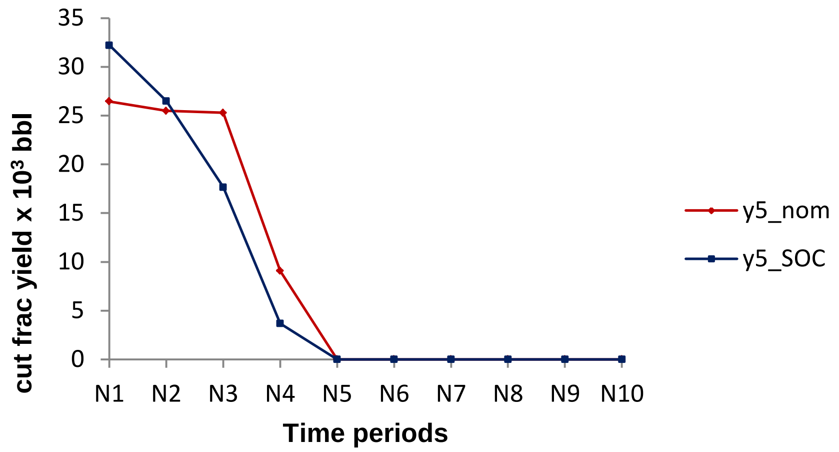


Figure 6-5: Production levels for SR gas oil at different time periods

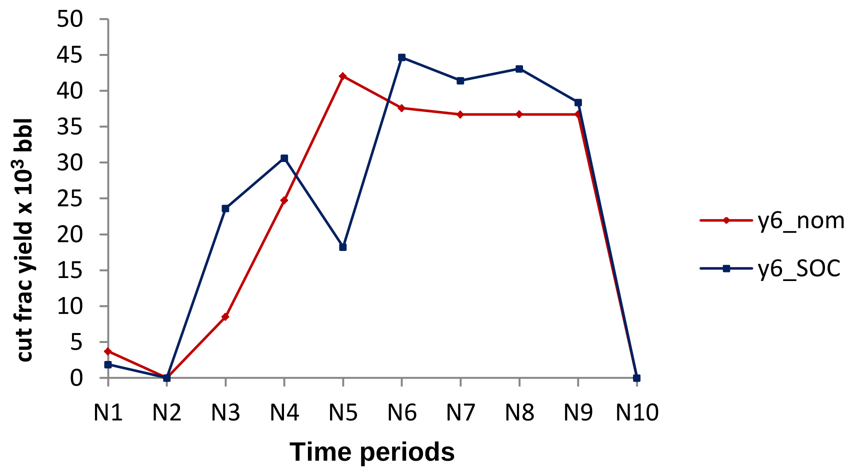


Figure 6-6: Production levels for SR residuum at different time periods

With the exception of SR fuel gas and SR distillate streams from the figures above, other cut fractions have their production levels approaching minimal values at the end of the scheduling horizon. Deviations from true optimal values due to feedback control for the cut fractions is not unconnected with the fact that refinery production has so many constraints to be satisfied. The amount produced depends on the CDU processing capabilities. Setting the upper limit for the crudes to be processed in CDU is an industrial practice that cannot be ignored. Mandating the plant to operate within this limit will therefore have an impact on the maximum permissible tuning that will allow the feedback implementation to restore the plant profit. Considering this limitation, the loss of 5.807% obtained is still a reasonable value.

6.2.2.2 Scenario B

In this scenario, a 3% change in composition is considered with the other information exactly same as in Scenario A. The profit due to feedback implementation strategy was found to be $54,196,473 against $56,696,407 for the true optimal value. This translates to 4.409% loss which is better compare to Scenario A. This improvement is due the magnitude of the disturbance being smaller in this scenario. Again, based on the reasons mentioned in the preceding scenario, this loss value of 4.409% is still within the acceptable range.

6.2.2.3 Scenario C

Here, there is an increase in composition by 9% on the first period then a drop of 4% is recorded on the fifth period. This scenario is more common in refineries where fluctuation do occur from one time period to another. The profit recorded due to SOC is $52,218,634. Comparing with the true optimal value gives a loss of 7.898%. For the first two time periods, the u_{fb} values are -0.0919 and -0.0444 respectively. These cannot be implemented because $\boldsymbol{u_b}$ must be between 0 and 1. Saturation is therefore applied here forcing the two values to be zero.

The loss value in this scenario is greater than those obtained in Scenarios A and B due to fact that fluctuation is more intense here with an abrupt change by 9% at the initial stage and a sudden drop by 4% on the fifth period.

In summary, the loss values are greater than 1% in all scenarios because the refinery plant is a complex with a multiple number of units interconnected and hence the units cannot be treated independently. Even though decisions from scheduling are implemented on a day-to-day basis, the schedule generation does not follow the same pattern. All schedules decisions no matter the length of the horizon have to be obtained at the same time instance for implementation at later dates.

6.3 Summary of Contributions in this Chapter

Dealing with process uncertainties is one of the main challenges hindering smooth operations in refinery plants. In such process plants, fluctuation in product demand, change in crude oil composition, and other parametric uncertainties in the form of disturbances are very common. In the presence of those disturbances, schedule generated under deterministic conditions may become infeasible, suboptimal or difficult to implement. This chapter develops a reliable methodology under self-optimizing control framework to deal with uncertainties in mixed integer problems such as those encountered in refinery scheduling. This contributes to knowledge and below is the highlights of these contributions.

- The methodology addressed problems posed as mixed integer programming and computes CVs as function of measurements from real plant or simulated data using Taylor series expansion
- The procedure went beyond addressing feasibility issues due to the influence of uncertain parameters but also ensure optimal or near optimal operation is maintained. This is first to be reported not only in refinery but also in the broad area of scheduling as a whole.
- The methodology was applied to refinery scheduling problem with uncertainties in crude oil compositions to come up with a feedback control law that compensates for the effect of the uncertainties.
- Through case studies, the idea presented was able to effectively deal with the situation at hand with percentage loss within a reasonable degree.

7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

The idea to carry out this research was conceived with the aim to develop robust methodologies and solution procedures to address refinery scheduling problems under disturbances. The goal was attained through:

1. Developing a mixed integer linear programming formulation for short-term crude oil unloading, tank inventory management, and crude distillation unit (CDU) charging schedule as an extension to a previous work reported by Lee et al. (1996).
2. Investigating the performance of the extended model with case studies.
3. Devising a solution alternative to deal with uncertainty in crude oil scheduling via model predictive control strategy.
4. Developing a discrete time mixed integer nonlinear programming (MINLP) formulation for simultaneous optimization of production scheduling with product blending.
5. Developing a data driven self-optimizing control (SOC) strategy for multi-period mixed integer problems.
6. Applying the SOC strategy to solve the MINLP model developed in item (4).
7. Introducing disturbance scenarios (uncertainties in crude oil compositions) to test the efficacy of the SOC method.

All these were reported in different sections of the thesis.

7.1.1 Modelling Crude Oil Unloading Area

A methodology for short-term crude oil unloading, tank inventory management, and CDU charging was developed as an extension to Lee et al. (1996) model. The extended model considers real life issues not captured in the original model and was built through reformulation in which the problem statement was modified to account for certain details, and then To investigate the performance of the model through case studies. The reformulation was based on established operating rules in petroleum refineries, material balances, resource allocations, sequencing order, product quality, and demand of mixed crude oil.

Scenarios were created to offer recommendations to plant operators on the best schedule to use. Uncertainties due to disruptive events (CDU shutdown), and low inventory at the end of scheduling horizon were also considered.

7.1.2 Crude Oil Scheduling under CDU Demand Uncertainty

This section has gone a step beyond forecast on the likelihood of occurrence of uncertainty by strategizing and devising alternative procedures that generate more reliable schedules with periodic update to keep track of changes in process conditions, constraints, or performance criteria. A control technique usually referred to as model predictive control (MPC) is an alternative that keeps the decision variables at the required values (set points) while driving the scheduling process to an economic optimum. A key feature of this control strategy is that the current implementation of decision variables within the scheduling horizon can be done more accurately since the process is periodically updated. One form of MPC is a rolling or receding horizon; a strategy that allows repeated calculations and predictions updated based on the current value of decision variable.

In this section of the thesis, scheduling problem of crude oil transfer, blending and CDU charging has been formulated under the framework of receding horizon control strategy. The extended model developed in chapter 3 was adopted. The strategy presented in this study (fixed end) was compared with the traditional approach and then with another strategy (moving end) using case studies. Some disturbance scenarios were introduced to evaluate the performances of fixed end and moving end horizon strategies for recommendation to refiners and process operators.

Results obtained have shown that fixed end receding horizon strategy can be relied upon to solve refinery crude oil scheduling problem and was able to guarantee feasibility and optimality under disturbance scenarios. It outperformed moving end horizon strategy in terms of performance as schedules are feasible in all time steps. It also approximates nominal schedule more closely and using equal prediction horizon length, it offers lower operational cost compared to moving end horizon ($116,749 against $ 216,388 at time step 5).

7.1.3 Scheduling Refinery Production with Product Blending

This section extends the research studies to the main refinery production area integrated with blending units. The motivation was to come up with a refinery scheduling model that captures all the necessary interactions between production units and blending subsystem while solving the two simultaneously. In refinery scheduling, model development is in most cases tied to the solution procedure adopted or developed to solve the model. Most of the existing methodologies are based on:

1. A simple approach that decompose a large problem into smaller size subproblems and treat the subproblems separately.
2. A sequential approach that allow exchange of information between subproblems and integrate the two and,
3. A more rigorous procedure that solves two subproblems simultaneously.

To perform operations in the most efficient way, simultaneous optimization of production with intermediate product blending is necessary. This is to ensure reliable schedules are generated while satisfying physical and economic constraints.

This section of the thesis reported a novel MINLP scheduling model for production area with blending unit to optimize the allocation of materials, distribution of resources, assignments of tasks and processing times of different crude slates in a petroleum refinery. The model considers crude oil characteristics with pseudo-components. In addition to flowrates, crude oil compositions were also considered making the model suitable for control studies. Modelling the first unit, CDU was based on swing cut approach and the objective of the whole refinery model was to maximize profit while generating feasible schedules within time horizon. A large scale refinery problem was used as a case study to test the model with scheduling horizon discretized into a number of time periods of variable length. The results obtained from the case study shows that reliable decisions can be obtained for implementation in real plants.

7.1.4 Refinery Production with Uncertainty in Crude Oil Composition

An approach under SOC framework was developed in this section for use in addressing mixed integer refinery scheduling problems under uncertainty in crude oil composition. The methodology computes CVs as a function of measurements from real plant or simulated data using Taylor series expansion to come up with a feedback control law that when implemented in the plant it compensates for the effect of the uncertainties. The approach has never been reported for mixed integer problems, not only in refinery but also in the broad area of scheduling as a whole. Through case studies, the idea presented was able to effectively deal with the situation at hand with percentage loss within a reasonable degree.

7.2 Recommendations

Various alternative formulations have been presented to deal with refinery problems under parametric uncertainties. These formulations have been shown to be efficient in a number of case studies involving small-scale to large-scale refinery scheduling problems. Despite these, there are opportunities to expand the work to another level and therefore the following are recommended.

1. Uncertainty consideration for refineries where unloading takes place in more than one docking station.
2. The problems reported in refinery production area involve processing two grades of crude oils. Problems involving more than two crude parcels should also be investigated.
3. Formulation of the refinery scheduling problem using multi-objective criteria: maximizing profit and minimizing emissions to meet both economic and environmental requirements.

4. Data used to compute CVs were generated via model simulation. A real refinery plant data should give more realistic results.
5. Other uncertain parameters like temperature, pressure and viscosity of crude feed material should also be considered; separately and then when all are introduced into the refinery at the same time.
6. Multiparametric programming approach for MINLP problems is still a challenge that needs to be overcome. This will solve refinery scheduling problems involving multiple uncertain parameters.
7. Several models for planning and scheduling of refinery systems are reported separately in literature. The two decision levels are interwoven with scheduling mainly executing orders set by planning. A model that integrates planning and scheduling will improve the efficiency and profitability of a refinery business.
8. An integrated planning and scheduling with consideration to endogenous and exogenous uncertainties will aid more reliable decisions.

REFERENCES

Alattas, A.M., Grossmann, I.E. & Palou-Rivera, I., 2011. Integration of Nonlinear Crude Distillation Unit Models in Refinery Planning Optimization. *Industrial & Engineering Chemistry Research*, 50(11), pp.6860–6870. Available at: http://pubs.acs.org/doi/abs/10.1021/ie200151e.

Alattas, A. M., Grossman, I. E. & Palou-Rivera, I., 2008. Optimal Model-based Production Planning for Refinery Operations. In *AIChE 100-2008 AIChE Annual Meeting, Conference Proceedings.*

Alattas, AM, Grossmann, IE & Palou-Rivera, I., 2012. Refinery Production Planning: Multiperiod MINLP with Nonlinear CDU Model. *Industrial & Engineering …*, 51, pp.12852–12861. Available at: http://pubs.acs.org/doi/abs/10.1021/ie3002638 [Accessed September 21, 2013].

Al-Enezi, G. & Elkamel, A., 2000. Predicting the effect of feedstock on product yields and properties of the FCC process. *Petroleum science and technology*, 18(2000), pp.407–428. Available at: http://www.tandfonline.com/doi/abs/10.1080/10916460008949853 [Accessed September 5, 2013].

Al-Enezi, G., Fawzi, N. & Elkamel, A., 1999. Development of regression models to control product yields and properties of the fluid catalytic cracking process. *Petroleum Science and Technology*, 17(5-6), pp.535–552. Available at: http://www.tandfonline.com/doi/abs/10.1080/10916469908949733 [Accessed September 5, 2013].

Al-Qahtani, K. & Elkamel, a., 2010. Robust planning of multisite refinery networks: Optimization under uncertainty. *Computers & Chemical Engineering*, 34(6), pp.985–995. Available at: http://linkinghub.elsevier.com/retrieve/pii/S009813541000075X [Accessed August 24, 2013].

Alstad, V. & Skogestad, S., 2007. Null space method for selecting optimal measurement combinations as controlled variables. *Industrial and Engineering Chemistry Research*, 46(3), pp.846–853.

Anon, 2011. Refining flow scheme [Homepage of Honey well company][online]. Available at: http://www.uop.com/refining-flowscheme-2/ [Accessed August 5, 2012].

Antos, G.J. and Aitani, A.M., 2004. *Catalytic naphtha reforming* 2nd ed., USA.

Aronofsky, J S, Dutton, J M, and Tayyabkhan, M.T., 1978. *Managerial Planning with Linear Programming*, New York: John Wiley and Sons.

Basak, K. et al., 2002. On-Line Optimization of a Crude Distillation Unit with Constraints on Product Properties. *Industrial & Engineering Chemistry Research*, 41(6), pp.1557–1568. Available at: http://pubs.acs.org/doi/abs/10.1021/ie010059u.

Bassett, M.H., Pekny, J.F. & Reklaitis, G. V., 1996. Decomposition techniques for the solution of large-scale scheduling problems. *AIChE Journal*, 42(12), pp.3373–3387. Available at: http://doi.wiley.com/10.1002/aic.690421209.

Boesen, R., 2010. *Investigation and Modelling of Diesel Hydrotreating Reactions*. Available at: http://www.w.seeit-alliance.eu/upload/institutter/ere/phd2011/rasmusrisumboesenphd.pdf [Accessed September 5, 2013].

Cao, C., Gu, X. & Xin, Z., 2009. Chance constrained programming models for refinery short-term crude oil scheduling problem. *Applied Mathematical Modelling*, 33(3), pp.1696–1707. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0307904X08000772 [Accessed August 25, 2013].

Clay, R.L. & Grossmann, I.E., 1997. A disaggregation algorithm for the optimization of stochastic planning models. *Computers & Chemical Engineering*, 21(7), pp.751–774. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135496002864.

Connor, A.J.O., Introduction to MATLAB. In pp. 1–39.

Cuiwen, C., Xingsheng, G. & Zhong, X., 2013. A Data-Driven Rolling-Horizon Online Scheduling Model for Diesel Production of a Real-World Refinery. *AIChE Journal*, 59, pp.1160–1174.

Duran, M. & Grossmann, I., 1986. An outer-approximation algorithm for a class of mixed-integer nonlinear programs. *Mathematical Programming*, 36(3), pp.307–339.

Edgar, T. F., Himmelblau, D. M. & Lasdon, L.S., 2001. *Optimization of chemical processes* 2nd ed. T. E. Casson, ed., Newyork: McGraw-Hill Chemical Engineering Series.

Ejikeme-Ugwu, E., 2012. *Planning for the integrated refinery subsystems*. Cranfield University.

Fagundez, F.D. & Faco, J.L.D., 2007. Applying Optimal Control to Jetty Scheduling Problems. *MISTA*, pp.167–174.

Ferris, M.C., Jain, R. & Dirkse, S., 2011. GDXMRW : Interfacing GAMS and MATLAB. , 53706(February).

Floudas, C., 1995. *Nonlinear and Mixed-Integer Optimization*, New York: Oxford University Press.

Floudas, C. a. & Lin, X., 2004. Continuous-time versus discrete-time approaches for scheduling of chemical processes: a review. *Computers & Chemical Engineering*, 28(11), pp.2109–2129. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135404001401 [Accessed August 10, 2013].

Floudas, C.A. & Lin, X., 2005. Mixed Integer Linear Programming in Process Scheduling: Modeling, Algorithms, and Applications. *Annals of Operations Research*, 139, pp.131–162.

François, G., Srinivasan, B. & Bonvin, D., 2005. Use of measurements for enforcing the necessary conditions of optimality in the presence of constraints and uncertainty. *Journal of Process Control*, 15(6), pp.701–712.

Gary, J.H. & Handwerk, G.., 1984. *Petroleum Refining Technology and Economics* 2nd Editio., Marcel Dekker, Inc.

Geddes, R.L., 1958. A General Index of Fractional Distillation Power for Hydrocarbon Mixtures. *AIChE J*, 4, pp.389–392.

Girei, A. et al., 2014. Data-driven self-optimizing control. In *24th European Symposium on Computer Aided Process Engineering*. pp. 649–654.

Goodwin, G.C. et al., 2006. Receding horizon control applied to optimal mine planning. *Automatica*, 42(8), pp.1337–1342. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0005109806000720 [Accessed August 19, 2013].

Grema, A.S. & Cao, Y., 2014. Optimal feedback control for reservoir waterflooding. In *20th International Conference on Automation and Computing*. pp. 20–25.

Grossmann, IE, Van den Heever, SA & Harjunkoski, I., 2002. Discrete optimization methods and their role in the integration of planning and scheduling. *AIChE Symposium …*. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.12.1826&rep=rep1&type=pdf [Accessed September 5, 2013].

Guyonnet, P., Grant, F.H. & Bagajewicz, M.J., 2009. Integrated Model for Refinery Planning, Oil Procuring, and Product Distribution. *Industrial & Engineering Chemistry Research*, 48(1), pp.463–482. Available at: http://pubs.acs.org/doi/abs/10.1021/ie701712z.

Halvorsen, I.J. et al., 2003. Optimal Selection of Controlled Variables. *Industrial & Engineering Chemistry Research*, 42(14), pp.3273–3284. Available at: http://pubs.acs.org/doi/abs/10.1021/ie020833t.

Hamisu, A. A., Kabantiok, S. & Wang, M., 2013. Refinery scheduling of crude oil unloading with tank inventory management. *Computers & Chemical Engineering*, 55, pp.134–147. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135413001105 [Accessed August 24, 2013].

Hamisu, A.A., Kabantiok, S. & Wang, M., 2013. An Improved MILP model for scheduling crude oil unloading, storage and processing. In *Computer Aided Chemical Engineering*. Elsevier Ltd, pp. 631–636. Available at: DOI: 10.1016/B978-0-444-63234-0.50106-8.

Harjunkoski, I. & Grossmann, I.E., 2001. A decomposition approach for the scheduling of a steel plant production. *Computers & Chemical Engineering*, 25(11-12), pp.1647–1660. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135401007293.

Hopkins, 2012. No Title. Available at: http://www.oilandgasiq.com/glossary/api-gravity/.

Ierapetritou, M.G. & Floudas, C.A., 1998. Effective Continuous-Time Formulation for Short-Term Scheduling. 2. Continuous and Semicontinuous Processes. *Industrial & Engineering Chemistry Research*, 37, pp.4360–4374.

Ierapetritou, M.G. & Pistikopoulos, E.N., 1996. Batch Plant Design and Operations under Uncertainty. *Industrial & Engineering Chemistry Research*, 35(3), pp.772–787. Available at: http://pubs.acs.org/doi/abs/10.1021/ie950263f.

Ishuzika, I. T., Ueki, O., Ukamo, U., 2007. *Improve refinery margins with integrated planning and scheduling systems*,

J. Michalopoulos, S. Papadokonstadakis, G. Arampatzis, A.L., 2001. Modelling of an industrial fluid catalytic cracking unit using neural networks. *Chemical Engineering Research and Design*, 79(2), pp.137–142. Available at: http://www.sciencedirect.com/science/article/pii/S026387620172028X [Accessed September 6, 2013].

Janak, S.L., Lin, X. & Floudas, C.A., 2007. A new robust optimization approach for scheduling under uncertainty: II. Uncertainty with known probability distribution. *Computers & Chemical Engineering*, 31, pp.171–195.

Jarullah, A.T., Mujtaba, I.M. & Wood, A.S., 2011. Kinetic parameter estimation and simulation of trickle-bed reactor for hydrodesulfurization of crude oil.

Chemical Engineering Science, 66(5), pp.859–871. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0009250910006780 [Accessed August 24, 2013].

Jarullah, A.T., Mujtaba, I.M., and Wood, A.S., 2012. Economic Analysis of an Industrial Refining Unit Involving Hydrotreatment of Whole Crude Oil in Trickle Bed Reactor using gPROMS. In *Computer Aided Chemical Engineering*. pp. 652–656.

Jäschke, J. & Skogestad, S., 2011. NCO tracking and self-optimizing control in the context of real-time optimization. *Journal of Process Control*, 21(10), pp.1407–1416.

Jia, Z. & Ierapetritou, M., 2004. Efficient short-term scheduling of refinery operations based on a continuous time formulation. *Computers & Chemical Engineering*, 28(6-7), pp.1001–1019. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135403002394 [Accessed August 21, 2013].

Jia, Z., Ierapetritou, M. & Kelly, J.D., 2003. Refinery Short-Term Scheduling Using Continuous Time Formulation: Crude-Oil Operations. *Industrial & Engineering Chemistry Research*, 42(13), pp.3085–3097. Available at: http://pubs.acs.org/doi/abs/10.1021/ie020124f.

Joly, M., Moro, L. & Pinto, J., 2002. Planning and scheduling for petroleum refineries using mathematical programming. *Brazilian Journal of Chemical …*, 19(02), pp.207–228. Available at: http://www.scielo.br/scielo.php?pid=S0104-66322002000200008&script=sci_arttext [Accessed September 6, 2013].

Jones, D.S. and Pujado, P.R., 2006. *Handbook of Petroleum Processing*, Netherland: Springer.

Kariwala, V., 2007. Optimal measurement combination for local self-optimizing control. *Industrial and Engineering Chemistry Research*, 46(11), pp.3629–3634.

Kariwala, V., Cao, Y. & Janardhanan, S., 2008. Local self-optimizing control with average loss minimization. *Industrial and Engineering Chemistry Research*, 47(4), pp.1150–1158.

Karri, B., Srinivasan, R. & Karimi, I. a., 2009. Robustness Measures for Operation Schedules Subject to Disruptions. *Industrial & Engineering Chemistry Research*, 48(20), pp.9204–9214. Available at: http://pubs.acs.org/doi/abs/10.1021/ie900505a.

Karuppiah, R., Furman, K. & Grossmann, I., 2008. Global optimization for scheduling refinery crude oil operations. *Computers & Chemical …*, 32, pp.2745–2766. Available at: http://www.sciencedirect.com/science/article/pii/S0098135407002803 [Accessed September 6, 2013].

Kelly, J. & Mann, J., 2003. Crude oil blend scheduling optimization: an application with multimillion dollar benefits. Part 2. *Hydrocarbon processing*. Available at: http://cat.inist.fr/?aModele=afficheN&cpsidt=14945876 [Accessed August 25, 2013].

Kendrick, D, Meeraus, A, and Suh, J.S., 1981. *Oil Refinery Modeling with the GAMS language*, Tech. rep., Center of Energy Studies, University of Texas.

Kondili, E., Pantelides, C. & Sargent, R., 1993. A general algorithm for short-term scheduling of batch operations—I. MILP formulation. *Computers & Chemical …*, 17(2), pp.211–227. Available at: http://www.sciencedirect.com/science/article/pii/009813549380015F [Accessed September 16, 2013].

Kong, M.-T., 2002. *Downstream oil products supply chain optimization*. Imperial College London.

Kopanos, G.M. & Pistikopoulos, E.N., 2014. Reactive scheduling by a multiparametric programming rolling horizon framework: A case of a network of combined heat and power units. *Industrial and Engineering Chemistry Research*, 53(11), pp.4366–4386.

Kumar, V. et al., 2001. A crude distillation unit model suitable for online applications. *Fuel Processing Technology*, 73(1), pp.1–21. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0378382001001953.

Kunii D, L.O., 1991. *Fluidisation Engineering* 2nd ed., USA: Butterworth–Heinemann.

Lee, H. et al., 1996. Mixed-Integer Linear Programming Model for Refinery Short-Term Scheduling of Crude Oil Unloading with Inventory Management. *Industrial & Engineering Chemistry Research*, 35(5), pp.1630–1641. Available at: http://pubs.acs.org/doi/abs/10.1021/ie950519h.

Li, J. et al., 2007. Improving the robustness and efficiency of crude scheduling algorithms. *AIChE Journal*, 53(10). Available at: http://onlinelibrary.wiley.com/doi/10.1002/aic.11280/full [Accessed August 25, 2013].

Li, J., Karimi, I. & Srinivasan, R., 2010. Recipe Determination and Scheduling of Gasoline Blending Operations. *AIChE Journal*, 56(2), pp.441–465.

Li, J., Misener, R. & Floudas, C., 2012a. Continuous-time modeling and global optimization approach for scheduling of crude oil operations. *AIChE Journal*, 58(1), pp.205–226. Available at: http://onlinelibrary.wiley.com/doi/10.1002/aic.12623/full [Accessed September 6, 2013].

Li, J., Misener, R. & Floudas, C., 2012b. Scheduling of crude oil operations under demand uncertainty: A robust optimization framework coupled with global optimization. *AIChE Journal*, 58(8), pp.2373–2396. Available at: http://onlinelibrary.wiley.com/doi/10.1002/aic.12772/full [Accessed September 6, 2013].

Li, W., Hui, C.-W. & Li, A., 2005. Integrating CDU, FCC and product blending models into refinery planning. *Computers & Chemical Engineering*, 29(9), pp.2010–2028. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135405001341 [Accessed August 6, 2013].

Lin, X., Janak, S. & Floudas, C., 2004. A new robust optimization approach for scheduling under uncertainty:: I. Bounded uncertainty. *Computers & chemical engineering*, 28, pp.1069–1085. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135406001591 [Accessed September 13, 2013].

Liu, M. & Sahinidis, N., 1996. Optimization in process planning under uncertainty. *Industrial & Engineering Chemistry …*, 35(96), pp.4154–4165. Available at: http://pubs.acs.org/doi/abs/10.1021/ie9504516 [Accessed September 6, 2013].

López-García, C. & Roy-Auberger, M., 2003. Analysis and Kinetic Modeling in ULSD Hydrotreating. *Prepr. Pap.-Am. Chem. …*, 48(2), pp.681–682. Available at: https://web.anl.gov/PCS/acsfuel/preprint archive/Files/48_2_New York_10-03_0666.pdf [Accessed September 5, 2013].

Luo, C. & Rong, G., 2009. A Strategy for the Integration of Production Planning and Scheduling in Refineries under Uncertainty. *Chinese Journal of Chemical Engineering*, 17(1), pp.113–127. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1004954109600422 [Accessed August 9, 2013].

Majid, M. and Sadat, M.H., 2012. Kinetic Investigation of Catalyst Deactivation in Catalytic Reforming of Naphtha, Chemical Product and Process Modeling. , 7(1).

Méndez, C. a. et al., 2006. A simultaneous optimization approach for off-line blending and scheduling of oil-refinery operations. *Computers and Chemical Engineering*, 30(4), pp.614–634.

Menezes, B.C., Kelly, J.D. & Grossmann, I.E., 2013. Improved swing-cut modeling for planning and scheduling of oil-refinery distillation units. *Industrial and Engineering Chemistry Research*, 52(51), pp.18324–18333.

Moro, L., Zanin, A. & Pinto, J., 1998. A planning model for refinery diesel production. *Computers & Chemical Engineering*, 22, pp.1039–1042. Available at: http://www.sciencedirect.com/science/article/pii/S0098135498002099 [Accessed September 6, 2013].

Moro, L.F.L. & Pinto, J.M., 2004. Mixed-Integer Programming Approach for Short-Term Crude Oil Scheduling. *Industrial & Engineering Chemistry Research*, 43(1), pp.85–94. Available at: http://pubs.acs.org/doi/abs/10.1021/ie030348d.

Mouret, S., Grossmann, I.E. & Pestiaux, P., 2011. A new Lagrangian decomposition approach applied to the integration of refinery planning and crude-oil scheduling. *Computers and Chemical Engineering*, 35(12), pp.2750–2766. Available at: http://dx.doi.org/10.1016/j.compchemeng.2011.03.026.

Mouret, S., Grossmann, I.E. & Pestiaux, P., 2009. A Novel Priority-Slot Based Continuous-Time Formulation for Crude-Oil Scheduling Problems. *Industrial & Engineering Chemistry Research*, 48(18), pp.8515–8528. Available at: http://pubs.acs.org/doi/abs/10.1021/ie8019592.

Mula, J. et al., 2006. Models for production planning under uncertainty: A review. *International Journal of Production Economics*, 103(1), pp.271–285. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0925527306000041 [Accessed August 7, 2013].

Munawar, S. a. & Gudi, R.D., 2005. A Multilevel, Control-Theoretic Framework for Integration of Planning, Scheduling, and Rescheduling. *Industrial & Engineering Chemistry Research*, 44(11), pp.4001–4021. Available at: http://pubs.acs.org/doi/abs/10.1021/ie040142s.

Neiro, S. & Pinto, J., 2005. Multiperiod optimization for production planning of petroleum refineries. *Chem. Eng. Comm.*, 192(1), pp.62–88. Available at: http://www.tandfonline.com/doi/abs/10.1080/00986440590473155 [Accessed September 6, 2013].

Pan, M., Li, X. & Qian, Y., 2009. New approach for scheduling crude oil operations. *Chemical Engineering Science*, 64(5), pp.965–983. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0009250908006003 [Accessed August 25, 2013].

Petkov, S.B. & Maranas, C.D., 1997. Multiperiod Planning and Scheduling of Multiproduct Batch Plants under Demand Uncertainty. *Industrial &*

Engineering Chemistry Research, 36(11), pp.4864–4881. Available at: http://pubs.acs.org/doi/abs/10.1021/ie970259z [Accessed September 16, 2013].

Pinto, J.M., Joly, M. & Moro, L.F.L., 2000. Planning and scheduling models for refinery operations. *Computers & Chemical Engineering*, 24(9-10), pp.2259–2276. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135400005718.

Pinto, J.M., Joly, M. & Moro, L.F.L., 2000. Planning and scheduling models for refinery operations. *Computers & Chemical Engineering*, 24, pp.2259–2276.

Raouf, S., Sukkar, K. & Hamied, R., 2011. Heavy Naphtha Reforming Reactions with Tri-metallic Catalysts, Experimental and Analytical Investigation. *Eng. & Tech.*, 29(10), pp.1917–1935. Available at: http://uotechnology.edu.iq/petrol_tech/papers/dr.khaled and ramzy/Text (5).pdf [Accessed September 6, 2013].

Reddy, P., Karimi, I. & Srinivasan, R., 2003. Short-term scheduling of refinery operations from unloading crudes to distillation. *Computer Aided …*, pp.304–309. Available at: http://www.sciencedirect.com/science/article/pii/S1570794603805618 [Accessed August 25, 2013].

Rodolfo B. Vadinal, M.R.W.M., 2010. New Method to Simulation of a Vacuum Distillation Unit in the Refining Process of Oil and the Reducing of the Vacuum Residue Generation.

Ronald (Ron) F. and Colwell, P.E., 2010. Oil refinery processes: A brief overview. *excellence in applied chemical engineering*.

Rosenthal, R.E., 2012. GAMS — A User ’ s Guide. , (January).

Saharidis, G., Minoux, M. & Dallery, Y., 2009. Scheduling of loading and unloading of crude oil in a refinery using event-based discrete time formulation. *Computers & Chemical Engineering*, 33, pp.1413–1426. Available at: http://www.sciencedirect.com/science/article/pii/S0098135409000659 [Accessed August 25, 2013].

Sahinidis, N. V., 2004. Optimization under uncertainty: state-of-the-art and opportunities. *Computers & Chemical Engineering*, 28(6-7), pp.971–983. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135403002369 [Accessed August 6, 2013].

Sarimveis, H. et al., 2008. Dynamic modeling and control of supply chain systems: A review. *Computers & Operations Research*, 35(11), pp.3530–

3561. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0305054807000366 [Accessed August 10, 2013].

Shah, N. et al., 2009. Centralized–decentralized optimization for refinery scheduling. *Computers & Chemical Engineering*, 33(12), pp.2091–2105. Available at: http://linkinghub.elsevier.com/retrieve/pii/S009813540900163X [Accessed September 16, 2013].

Shah, N., 1996. Mathematical programming techniques for crude oil scheduling. *Computers Chemical Engineering*, 20, pp.S1227–S1232.

Skogestad, S., 2000. Plantwide control: The search for the self-optimizing control structure. *Journal of Process Control*, 10(5), pp.487–507.

Tong, K., Feng, Y. & Rong, G., 2012. Planning under Demand and Yield Uncertainties in an Oil Supply Chain. *Industrial & Engineering Chemistry Research*, 51(2), pp.814–834. Available at: http://pubs.acs.org/doi/abs/10.1021/ie200194w.

Trierwiler, D., & Tan, R.L., 2001. Advances in crude oil LP modelling. In *Hydrocarbon Asia*. pp. 52–58.

Verderame, P.M. et al., 2010. Planning and Scheduling under Uncertainty: A Review Across Multiple Sectors. *Industrial & Engineering Chemistry Research*, 49(9), pp.3993–4017. Available at: http://pubs.acs.org/doi/abs/10.1021/ie902009k.

Wang, J. & Rong, G., 2010. Robust Optimization Model for Crude Oil Scheduling under Uncertainty. *Industrial & Engineering Chemistry Research*, 49(4), pp.1737–1748. Available at: http://pubs.acs.org/doi/abs/10.1021/ie900358z.

Watkins, R.N., 1979. *Petroleum Refinery Distillation* 2nd ed., Houston: Gulf Publishing Co.

Wenkai, L. et al., 2002. Scheduling Crude Oil Unloading, Storage, and Processing. *Industrial & Engineering Chemistry Research*, 41(26), pp.6723–6734. Available at: http://pubs.acs.org/doi/abs/10.1021/ie020130b.

Westerlund, J., Hastbacka, M., Forssell, S. and Westerlund, T., 2007. Mixed-time mixed-integer linear programming scheduling model. *Industrial & …*, 46, pp.2781–2796. Available at: http://pubs.acs.org/doi/abs/10.1021/ie060991a [Accessed September 16, 2013].

Whitcombe, J.M. et al., 2003. Application of sensitivity analysis to oil refinery emissions. *Reliability Engineering & System Safety*, 79(2), pp.219–224. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0951832002002326.

Whitcombe, J.M. et al., 2006. The use of sensitivity analysis and genetic algorithms for the management of catalyst emissions from oil refineries. *Mathematical and Computer Modelling*, 44(5-6), pp.430–438. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0895717706000045 [Accessed September 16, 2013].

Ye, L. et al., 2012a. A data-driven approach for selecting controlled variables. *Proceedings of 8th Intl. Symposium on …*, (2008), pp.904–909. Available at: http://www.nt.ntnu.no/users/skoge/prost/proceedings/adchem-2012/files/0062.pdf [Accessed August 25, 2013].

Ye, L. et al., 2012b. Approximating necessary conditions of optimality as controlled variables. *Industrial & Engineering Chemistry …*. Available at: http://pubs.acs.org/doi/full/10.1021/ie300654d [Accessed August 25, 2013].

Yee, K.L. & Shah, N., 1998. Improving the efficiency of discrete time scheduling formulation. *Computers & Chemical Engineering*, 22, pp.S403–S410. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135498000817.

Yüzgeç, U., Palazoglu, A. & Romagnoli, J. a., 2010. Refinery scheduling of crude oil unloading, storage and processing using a model predictive control strategy. *Computers & Chemical Engineering*, 34(10), pp.1671–1686. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0098135410000220 [Accessed August 25, 2013].

Zhang, J., Zhu, X.X. & Towler, G.P., 2001. A Simultaneous Optimization Strategy for Overall Integration in Refinery Planning. *Industrial & Engineering Chemistry Research*, 40(12), pp.2640–2653. Available at: http://pubs.acs.org/doi/abs/10.1021/ie000367c.

Zhang, N., 2006. Optimisation Is Key to High-performing Refineries. , 7(1983), pp.33–35.

Zhang, N. & Zhu, X., 2000. A novel modelling and decomposition strategy for overall refinery optimisation. *Computers & Chemical Engineering*, 24, pp.1543–1548. Available at: http://www.sciencedirect.com/science/article/pii/S0098135400005457 [Accessed September 6, 2013].

APPENDICES

Appendix A

Table A-1: Initial micro-cuts distribution into their respective cuts for Crude 1

Component	Volume fraction of assay	
H2O	0.001	
C1	0.002	SR-fuel gas
C2	0.005	
C3	0.005	
IC4	0.01	SW1
NC4	0.01	
IC5	0.005	SR-gasoline
NC5	0.025	
PC139F	0.0239693196	
PC162F	0.0251433162	
PC189F	0.025690828	
PC212F	0.0273153472	
PC238F	0.0286375053	
PC263F	0.0294267661	SW2
PC287F	0.0295128286	
PC312F	0.0288756885	SR-naphtha
PC337F	0.0277672152	
PC363F	0.0276849889	SW3
PC387F	0.027788517	
PC412F	0.0276623392	SR-distillate
PC438F	0.0273168272	
PC462F	0.0267776536	
PC487F	0.0260826898	

Component	Volume fraction of assay	
PC512F	0.0252686212	
PC537F	0.0248484816	
PC562F	0.0248378783	SW4
PC587F	0.0245594129	
PC612F	0.0240364511	SR-gas oil
PC637F	0.0233162189	
PC662F	0.0224594729	
PC687F	0.0215234731	SW5
PC712F	0.0205555674	
PC737F	0.0196598374	
PC763F	0.020217673	
PC787F	0.0211685451	
PC825F	0.0418487309	
PC875F	0.036875742	
PC925F	0.0306862509	
PC974F	0.0255985838	SR-residuum
PC1024F	0.0217873207	
PC1074F	0.0192086146	
PC1125F	0.0182555212	
PC1175F	0.0185063718	
PC1250F	0.0372011744	
PC1344F	0.00492822657	
	1	

Appendix B

Table B-1: Initial micro-cuts distribution into their respective cuts for Crude 2

Component	Volume fraction of assay	
H2O	0	
C1	0.001	
C2	0.0015	SR-fuel gas
C3	0.009	
IC4	0.004	SW1
NC4	0.016	
IC5	0.012	
NC5	0.017	
PC189F	0.017688523	SR-gasoline
PC212F	0.0280123511	
PC238F	0.0254032232	
PC263F	0.0254280205	SW2
PC287F	0.0254205875	
PC312F	0.0254077956	SR-naphtha
PC337F	0.0253895924	
PC363F	0.0253660942	SW3
PC387F	0.02533726	
PC412F	0.025354157	
PC438F	0.0258397715	
PC462F	0.0262087565	SR-distillate
PC487F	0.0262517514	
PC512F	0.025960761	
PC537F	0.0253743275	SW4
PC562F	0.0245530724	

Component	Volume fraction of assay	
PC587F	0.0235752844	
PC612F	0.0225884769	SR-gas oil
PC637F	0.022163461	
PC662F	0.0217942605	
PC687F	0.0213562878	SW5
PC712F	0.0208646828	
PC737F	0.0203341352	
PC763F	0.0197780962	
PC787F	0.0192082949	
PC825F	0.0366941323	
PC875F	0.0370493138	
PC925F	0.040925623	
PC974F	0.0381689435	SR-residuum
PC1024F	0.0316427922	
PC1074F	0.0257917206	
PC1125F	0.0214923226	
PC1175F	0.0183725942	
PC1250F	0.0321279838	
PC1344F	0.0320375374	
PC1447F	0.0305380121	
	1	