University of Alberta

Oil sands mine planning and waste management using goal programming

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A thesis submitted to the Faculty of Graduate Studies and Research in partial fulfillment of the requirements for the degree of Doctor of Philosophy

in

Mining Engineering

Department of Civil & Environmental Engineering

Spring 2013
Edmonton, Alberta

ABSTRACT

Strategic mine planning and waste management are important aspects of surface mining operations. Due to the limitations in lease area for oil sands mining, the pit phase advancement is carried out simultaneously with the construction of in-pit and ex-pit tailings impoundment dykes. Most of the materials used in constructing these dykes come from the oil sands mining operation including overburden, interburden and tailings coarse sand.

The primary research objectives are to develop, implement and verify a theoretical optimization framework based on Mixed Integer Linear Goal Programming (MILGP) model to: 1) determine the time and order of extraction of ore, dyke material and waste that maximizes the net present value of the operation – a strategic schedule; 2) determine the destination of the dyke material that minimizes construction cost – a dyke material schedule. Matlab programming platform was chosen for the MILGP model framework implementation. A large scale optimization solver, Tomlab/CPLEX, is used for this research.

To verify the research models, four oil sands case studies were carried out. The first three case studies highlight the techniques and strategies used in the MILGP model to integrate waste disposal planning with production scheduling in oil sands mining. The fourth case study, which involves the scheduling of 16,985 blocks, was compared with industry standard software, Whittle. No waste disposal planning was considered since Whittle does not provide such tools. The MILGP model generated an optimal production schedule with a 13% higher NPV than Whittle Milawa NPV and a 15% higher NPV than Whittle Milawa Balanced case. In comparison, while Whittle deferred ore mining to latter years, the MILGP model scheduled for more ore in the early years contributing to the increased NPV. The experiments also compared the annual stripping ratio, average grade and annual production. These results proved that the MILGP model framework provides a powerful tool for optimizing oil sands long term production schedules whilst giving us a robust platform for integrating waste disposal planning.

AKNOWLEDGMENT

I am most grateful to the almighty God for all that I have experienced in life and for the gifts I have been given especially as I travelled down this road of knowledge. “TO GOD BE THE GLORY”.

I also express my sincere gratitude towards my advisor, Dr Hooman Askari-Nasab. His leadership, support, attention to detail and hard work have set an example I hope to match some day. My sincere thanks and appreciation goes to my advisory committee members – Dr. Jozef Szymanski, Dr. David Sego, Dr. John Doucette, Dr. Clayton Deutsch and Dr. Erkan Topal. Your comments and corrections are appreciated.

I am grateful for the insight and encouragement from my colleagues Messrs Yashar Pourrahimian, Mohammad Tabesh, Mohammad Mahdi Badiozamani Tari, Hesameddin Eivazy, Shiv Prakash Upadhyay, Marclus Mwai, and Ms Samira Kalantari and Ms Elmira Torkamani. My gratitude also goes to all my friends in Edmonton for the support they offered me whilst pursuing this programme.

I thank my parents Isaac Ben-Awuah and Mercy Kyeiwaa for the encouragement I received from them and all that they lost in helping me acquire this knowledge. Finally and most importantly, I reserve the rest of my acknowledgements for my patient and loving family, Felicia, Nana, Barima, Paa and Nhyi, whose support have been a real blessing. To them I dedicate this thesis.

To the people enduring when no sign of reward is in sight. To the people pushing themselves and others beyond mediocrity. To the people who force luck to happen. To the people who go against the grain. To the people who think about others before thinking of themselves. To the people who constantly disprove that “you can’t do everything”. To the people who are not going quietly into their graves. To the people who dream of a world they want to know; to the people who dream out loud. For you are the people who inspire me.

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LIST OF ABBREVIATIONS

Parameters

DykeM	Dyke Material
ERCB	Energy Resources Conservation Board
ETF	External Tailings Facility
GP	Goal Programming
IB	Interburden
LP	Linear Programming
LTPP	Long Term Production Planning
MILGP	Mixed Integer Linear Goal Programming
MILP	Mixed Integer Linear Programming
MPMs	Mathematical Programming Models
NPV	Net Present Value
OB	Overburden
OI	Overburden and Interburden
OSLTPP	Oil Sands Long Term Production Planning
PP	Penalty and Priority
TCS	Tailings Coarse Sand

LIST OF NOMENCLATURE

Sets

$\boldsymbol{A} = \{1, \ldots\ldots, A\}$ set of all the possible mining locations (pits) in the model.

$\boldsymbol{J} = \{1, \ldots\ldots, J\}$ set of all the phases (pushbacks) in the model.

$\boldsymbol{K} = \{1, \ldots\ldots, K\}$ set of all the mining-cuts in the model.

$\boldsymbol{P} = \{1, \ldots\ldots, P\}$ set of all the mining-panels in the model.

$\boldsymbol{U} = \{1, \ldots\ldots, U\}$ set of all the possible destinations for materials in the model.

$B_p(V)$ for each mining-panel p, there is a set $B_p(V) \subset K$ defining the mining-cuts that belongs to the mining-panel p, where V is the total number of mining-cuts in the set $B_p(V)$.

$B_j(H)$ for each phase j, there is a set $B_j(H) \subset P$ defining the mining-panels within the immediate predecessor pit phases (pushbacks) that must be extracted prior to extracting phase j, where H is an integer number representing the total number of mining-panels in the set $B_j(H)$.

$C_p(L)$ for each mining-panel p, there is a set $C_p(L) \subset P$ defining the immediate predecessor mining-panels above mining-panel p that must be extracted prior to extraction of mining-panel p, where L is the total number of mining-panels in the set $C_p(L)$.

$M_p(Z)$ for each mining-panel p, there is a set $M_p(Z) \subset P$ defining the immediate predecessor mining-panels in a specified horizontal mining direction that must be extracted prior to extraction of mining-panel p at the specified level, where Z is the total number of mining-panels in the set $M_p(Z)$.

Indices

$a \in \{1,.....,A\}$ index for possible mining locations (pits).

$e \in \{1,.....,E\}$ index for element of interest in each mining-cut.

$j \in \{1,.....,J\}$ index for phases (pushback).

$k \in \{1,.....,K\}$ index for mining-cuts.

$p \in \{1,.....,P\}$ index for mining-panels.

$t \in \{1,......,T\}$ index for scheduling periods.

$u \in \{1,.....,U\}$ index for possible destinations for materials.

Decision variables

$b_p^t \in [0,1]$ a binary integer variable controlling the precedence of extraction of mining-panels. b_p^t is equal to one if the extraction of mining-panel *p* has started by or in period *t*, otherwise it is zero.

$c_k^{u,t} \in [0,1]$ a continuous variable representing the interburden dyke material portion of mining-cut *k* to be extracted and used for dyke construction at destination *u* in period *t*.

$s_k^{u,t} \in [0,1]$ a continuous variable representing the tailings coarse sand dyke material portion of mining-cut *k* to be extracted and used for dyke construction at destination *u* in period *t*.

$x_k^{u,t} \in [0,1]$ a continuous variable representing the ore portion of mining-cut *k* to be extracted and processed at destination *u* in period *t*.

$y_p^{a,t} \in [0,1]$ a continuous variable representing the portion of mining-panel *p* to be mined in period *t* from location *a*, which includes both ore, overburden and interburden dyke material and waste from the associated mining-cuts.

$z_k^{u,t} \in [0,1]$ a continuous variable representing the overburden dyke material portion of mining-cut k to be extracted and used for dyke construction at destination u in period t.

$d_1^{-,a,t}$ the negative deviation from the mining goal (tonnes) in period t at location a.

$d_2^{-,u,t}$ the negative deviation from the processing goal in period t at destination u (tonnes).

$d_3^{-,u,t}$ the negative deviation from the overburden dyke material goal in period t at destination u (tonnes).

$d_4^{-,u,t}$ the negative deviation from the interburden dyke material goal in period t at destination u (tonnes).

$d_5^{-,u,t}$ the negative deviation from the tailings coarse sand dyke material goal in period t at destination u (tonnes).

Parameters

a_1 the penalty paid per tonne in deviating from the mining goal.

a_2 the penalty paid per tonne in deviating from the processing goal.

a_3 the penalty paid per tonne in deviating from the overburden dyke material goal.

a_4 the penalty paid per tonne in deviating from the interburden dyke material goal.

a_5 the penalty paid per tonne in deviating from the tailings coarse sand dyke material goal.

$cb^{u,t}$ the cost in present value terms per tonne of interburden dyke material for dyke construction at destination u.

$ck^{u,t}$ — the cost in present value terms per tonne of overburden dyke material for dyke construction at destination u.

$cm^{a,t}$ — the cost in present value terms of mining a tonne of waste in period t from location a.

$cp^{u,e,t}$ — the extra cost in present value terms per tonne of ore for mining and processing at destination u.

$cs^{e,t}$ — the selling cost of element e in present value terms per unit of product.

$ct^{u,t}$ — the cost in present value terms per tonne of tailings coarse sand dyke material for dyke construction at destination u.

$d_k^{u,t}$ — the discounted economic mining-cut value obtained by extracting mining-cut k and sending it to destination u in period t.

d_k — the overburden dyke material tonnage in mining-cut k.

d_p — the overburden dyke material tonnage in mining-panel p.

f_k^e — the average percent of fines in ore portion of mining-cut k.

$\underline{f}^{u,t,e}$ — the lower bound on the required average fines percent of ore in period t at processing destination u.

$\overline{f}^{u,t,e}$ — the upper bound on the required average fines percent of ore in period t at processing destination u.

f_k^d — the average percent of fines in interburden dyke material portion of mining-cut k.

$\underline{f}^{u,t,d}$ — the lower bound on the required average fines percent of interburden dyke material in period t at dyke construction destination u.

$\overline{f}^{u,t,d}$ the upper bound on the required average fines percent of interburden dyke material in period t at dyke construction destination u.

g_k^e the average grade of element e in ore portion of mining-cut k.

$\underline{g}^{u,t,e}$ the lower bound on the required average head grade of element e in period t at processing destination u.

$\overline{g}^{u,t,e}$ the upper bound on the required average head grade of element e in period t at processing destination u.

$h_k^{u,t}$ the extra discounted cost of mining all the material in mining-cut k in period t as tailings coarse sand dyke material for construction at destination u.

l_k the tailings coarse sand dyke material tonnage in mining-cut k.

$m_k^{u,t}$ the extra discounted cost of mining all the material in mining-cut k in period t as interburden dyke material for construction at destination u.

n_k the interburden dyke material tonnage in mining-cut k.

n_p the interburden dyke material tonnage in mining-panel p.

o_k the ore tonnage in mining-cut k.

o_p the ore tonnage in mining-panel p.

$p_k^{u,t}$ the extra discounted cost of mining all the material in mining-cut k in period t as overburden dyke material for construction at destination u.

$p^{e,t}$ the price of element e in present value terms per unit of product.

P_1 the priority level associated with minimizing the deviations from the mining goal.

P_2 the priority level associated with minimizing the deviations from the processing goal.

P_3 the priority level associated with minimizing the deviations from the overburden dyke material goal.

P_4 the priority level associated with minimizing the deviations from the interburden dyke material goal.

P_5 the priority level associated with minimizing the deviations from the tailings coarse sand dyke material goal.

$q_k^{a,t}$ the discounted cost of mining all the material in mining-cut k in period t as waste from location a.

$q_p^{a,t}$ the discounted cost of mining all the material in mining-panel p in period t as waste from location a. Each mining-panel p contains its corresponding set of mining-cuts.

$r^{u,e}$ the proportion of element e recovered (processing recovery) if it is processed at destination u.

$T_m^{a,t}$ the mining goal (tonnes) in period t at location a.

$T_{pr}^{u,t}$ the processing goal in period t at destination u (tonnes).

$T_d^{u,t}$ the overburden dyke material goal in period t at destination u (tonnes).

$T_n^{u,t}$ the interburden dyke material goal in period t at destination u (tonnes).

$T_l^{u,t}$ the tailings coarse sand dyke material goal in period t at destination u (tonnes).

$v_k^{u,t}$ the discounted revenue obtained by selling the final products within mining-cut k in period t if it is sent to destination u, minus the extra discounted cost of mining all the material in mining-cut k as ore from location a and processing at destination u.

w_k the waste tonnage in mining-cut k.

w_p the waste tonnage in mining-panel p.

CHAPTER 1

INTRODUCTION

1.1 Background

Open-pit mining involves extracting blocks of material from the earth's surface to retrieve the ore contained in them or to access blocks of ore. This mining process causes the surface of the land to be continuously excavated causing an increasingly deeper pit to be formed until the end of the mine life (Hochbaum and Chen, 2000; Newman et al., 2010). Prior to the mining operation, the complex strategy of displacement of ore, waste, overburden, interburden and tailings over the mine life need to be decided and this is known as mine planning. Open-pit mine planning can be defined as the process of finding a feasible block extraction sequence that generates the highest net present value (NPV) subject to operational and technical constraints (Whittle, 1989). Mine planning is completed over different time horizons and these include short-term, medium-term, and long-term production scheduling. This research focuses on the long-term production scheduling optimization process which is the backbone of the entire mining operation. In mining projects, deviations from optimal mine plans may result in significant financial losses, future financial liabilities, delayed reclamation, and resource sterilization.

Oil sands waste disposal planning is currently handled as a post-production scheduling optimization activity (Fauquier et al., 2009). These are due to challenges that arise during the integration of such important major systems. These challenges include the size of the optimization problem resulting from scheduling different material types with multiple elements for multiple destinations. There is also the need to incorporate the availability of in-pit disposal areas with dyke construction planning on a continual basis throughout the mine life to support the tailings storage plan. Due to limited lease areas for oil sands operators, this is required to ensure the maximum use of in-pit and ex-pit tailings facilities for sustainable mining. Another challenge arises from competing objectives from such systems. Whilst production scheduling is driving NPV, waste disposal planning is driving sustainable mining and it becomes difficult to decide which targets must be traded off and at what cost.

The application of Mixed Integer Linear Goal Programming (MILGP) to the oil sands production scheduling and waste disposal planning problem as outlined in this thesis has been setup in an optimization framework that integrates multiple material types, elements, and destinations. It includes large-scale optimization, directional mining, and integration of mine production planning and waste management. The practical implementation of the MILGP model and the generated production schedules are also highlighted.

1.2 Statement of the Problem

Oil sands mining is increasingly becoming challenging as the public and law makers continue to put pressure on their waste management practices. Together with the limitations in lease areas, it has become necessary to look into effective and efficient waste disposal planning system. These systems should be well integrated into the long term mine plan in an optimization framework that creates value and a sustainable operation. In oil sands operations, the pit phase mining occurs simultaneously with the construction of in-pit dykes in the mined out areas of the pit and ex-pit dykes in designated areas outside the pit. These dykes are constructed to hold tailings that are produced during processing of the oil sands ore. The materials used in constructing these dykes come from the oil sands mining operation. The dyke materials are made up of overburden (OB), interburden (IB) and tailings coarse sand (TCS). Dykes with different configurations are required during the construction. The material sent to the processing plant (ore) must have a specified minimum amount of bitumen and percentage fines, while material sent for dyke construction (dyke material) must meet the fines requirement for the dyke construction location. Any material that does not qualify as ore or dyke material is sent to the waste dump.

In implementing an efficient MILGP model to incorporate waste management into Oil Sands Long Term Production Planning (OSLTPP), our objectives are to:

- Determine the order and time of extraction of ore, dyke material and waste to be removed from a predefined final pit limit over the mine life that maximizes the Net Present Value (NPV) of the operation.
- Determine the destination of dyke material that minimizes construction cost based on the construction requirements of the various dykes.

Prior to OSLTPP, we assume that the material in the final pit limit is discretized into a three-dimensional array of rectangular or cubical blocks called a block model. Attributes of the material in the block model such as rock types, densities, grades, or economic data are represented numerically (Askari-Nasab et al., 2011; Ben-Awuah and Askari-Nasab, 2011). Figure 1.1 shows the scheduling of oil sands multi-mine final pits block models containing K mining-cuts. Mining-cuts are clusters of blocks within the same level or mining bench that are grouped based on a similarity index defined using the attributes; location, grade, rock type and the shape of mining-cuts that are created on the lower bench. In this research, an agglomerative hierarchical clustering algorithm which seeks to generate clusters with reduced mining-cut extraction precedences compared with other automated methods is used (Tabesh and Askari-Nasab, 2011). Each mining-cut k, is made up of ore o_k, OB dyke material d_k, IB dyke material n_k, and waste w_k. The material in each mining-cut is to be scheduled over T periods depending on the goals and constraints associated with the mining operation. OB dyke material scheduled d_k^T, IB dyke material scheduled n_k^T, and TCS dyke material from the processed ore scheduled, l_k^T, must further be assigned to the dyke construction sites based on construction requirements. For period t_I, the dyke construction material required by site i is $dyke_i$. In addition, the final pit limit block model is divided into pushbacks. The material intersecting a pushback and a bench is known as a mining-panel. Each mining-panel contains a set of mining-cuts and is used to control the mine production operation sequencing.

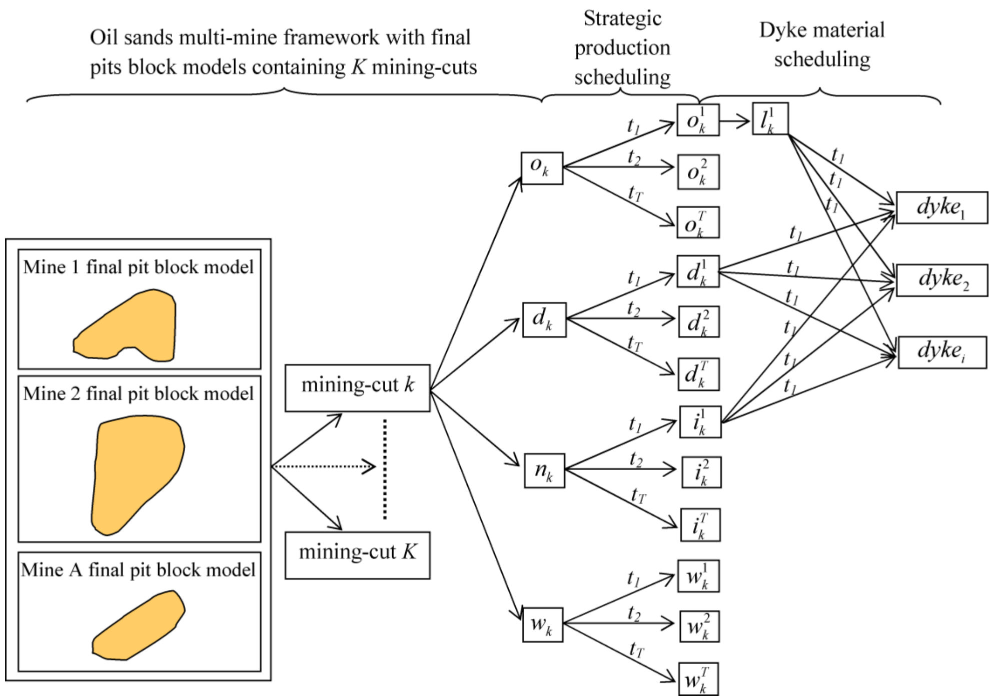

Figure 1.1: Schematic representation of the problem definition showing strategic production and dyke material scheduling modified after Ben-Awuah and Askari-Nasab (2011)

The strategic and dyke material production schedules to be developed are subject to a variety of economic, technical, and physical constraints. The constraints control the mining extraction sequence, ore and dyke material blending requirements and mining, processing, and dyke material goals. The mining, processing, and dyke material goals specify the quantities of material allowed for the mining operation, processing plant and dyke construction, respectively.

The schedules generated for OSLTPP drives the profitability and sustainability of an oil sands mining operation. The strategic production and dyke material schedules control the NPV of the operation and provide the platform for a robust waste management planning strategy. Lack of proper waste management planning can lead to environmental and sustainability challenges resulting in major financial liabilities or immediate mine closure by regulatory agencies.

1.3 Summary of Literature Review

Using mathematical programming optimization with exact solution methods to solve the Long Term Production Planning (LTPP) problem has proved to be robust. Mathematical programming models including Linear Programming (LP), Mixed Integer Linear Programming (MILP) and Goal Programming (GP) have the capability of considering multiple material types, elements, and destinations. Solving them with exact solution methods result in answers within known limits of optimality. As the solution gets closer to optimality, it leads to production schedules that generate higher NPV than those obtained from heuristic optimization methods. This has lead to extensive research on the application of mathematical programming models to the LTPP problem. Most of these models have been developed using LP and MILP. When these models are applied to the LTPP problem, they result in large scale optimization problems with numerous binary and continuous variables which become difficult to solve with the current state of hardware and software and may have lengthy solution times (Johnson, 1969; Gershon, 1983; Dagdelen, 1985; Dagdelen and Johnson, 1986; Akaike and Dagdelen, 1999; Caccetta and Hill, 2003). What makes these optimization problems more challenging are the large number of binary variables used to control the mining sequence, thus making the practical implementation of these models difficult.

Another mathematical programming modeling platform that has been exploited in solving the LTPP problem is GP. It can be said that in mining operations, one is faced with multiple objectives and in most cases it becomes necessary to trade off some targets for others. This is where GP becomes the appropriate modeling platform. GP allows for flexible formulation, specification of priorities among goals, and some level of interaction between the decision maker and the optimization process (Zeleny, 1980; Hannan, 1985). Against this background Zhang et al. (1993), Chanda and Dagdelen (1995) and Esfandiri et al. (2004) looked into the application of GP to the LTPP problem. They were however faced with the practical implementation of their models due to numerous constraints and size of the optimization problem.

Further research has been conducted using MILP with block clustering techniques to reduce the size of the LTPP problem prior to optimization (Askari-Nasab et al., 2010; Askari-Nasab et al., 2011). These have been successfully implemented for some basic large scale production scheduling problems. These production scheduling models have been developed in isolation from other mine production systems. One such system is waste disposal planning. Waste disposal is an important part of the mining operation and when not well managed can result in mine closure or unbearable financial liabilities. In oil sands mining, waste disposal planning is even more closely connected to the mine planning system due to the mining strategy used and the regulatory requirements from the Energy Resources Conservation Board (Directive 074) (McFadyen, 2008; Askari-Nasab and Ben-Awuah, 2011; Ben-Awuah and Askari-Nasab, 2011). Consequently, the lack of an integrated oil sands mine production scheduling and waste disposal planning system in an optimization framework is worrisome.

The GP, LP and MILP applications discussed lack the framework that can be used in solving the oil sands mine production scheduling and waste disposal planning problem. Some efforts have been made to combine GP and MILP models to solve some industrial problems because of the advantages of such hybrids. This hybridized model is referred to as MILGP. Using MILGP for oil sands production scheduling and waste disposal planning is appropriate because the structure enables the optimization solution to try achieving a set of goals where some goals can be traded off against one another depending on their priority. Hard constraints can also be converted to soft constraints which otherwise could lead to infeasible solutions. In simple terms, the advantage of using MILGP and deviational variables over other optimization formulations like LP or MILP is the fact that the deviational variables take values when an infeasible solution will otherwise have been returned. This allows an analyst to quickly pinpoint which goals are being relaxed. The analyst can then keep the results and change the input to obtain different results. In the case of an LP or MILP formulation, the optimizer will report infeasible solution and it may be difficult to understand which constraint is being violated and whether you can relax them or not.

The research question here is; “how can a production schedule be simultaneously generated for ore and dyke material to create maximum value and to support the sustainable development of an oil sands deposit”.

1.4 Objectives of the Study

Though operation research methods have been applied in mine production scheduling, little work has been done in terms of oil sands mine planning, which has a unique scenario when it comes to waste management. Oil sands mining profitability depends on a carefully planned and integrated mine planning and waste management strategy that generates value and sustainability by maximizing NPV and creating timely tailings storage areas with less environmental footprints. Recent mining regulations by the Energy Resources Conservation Board (Directive 074) (McFadyen, 2008) requires that oil sands mining companies develop an integrated mine planning and waste management strategy for their in-pit and external tailings facilities. This requires a new and more systematic approach in looking at the planning of oil sands mining operations.

The objective of this study is to develop a theoretical framework that i) maximizes the NPV of an oil sands mining operation, ii) minimizes dyke construction cost for tailings containment and iii) minimizes deviations from the production goals using a mixed integer linear goal programming (MILGP) model. The MILGP model incorporates multiple material types with multiple elements for multiple destinations in long-term production scheduling. The models are implemented and verified with Matlab programming platform and a branch and cut optimization algorithm using Tomlab/CPLEX solver (Holmström, 2009).

To achieve the objectives, this work includes the development of theoretical and conceptual framework that focuses on:

- Maximizing the NPV of the mining operation while generating a strategic production schedule for ore and dyke material.
- Minimizing the cost of constructing the dykes with different material types and locations while generating a dyke material schedule.
- Developing techniques and methodologies that can generate strategic production and dyke material schedules for large mine planning projects.
- Developing computer code/tools that implement the formulated models for large-scale oil sands mining projects.

1.5 Context and Scope of Work

This research deals with the development of mixed integer linear goal programming (MILGP) model for long-term open pit production scheduling optimization and waste management in oil sands mining. This involves using MILGP models to generate optimal long-term open pit production schedules for multiple material types and destinations in oil sands mining. The mining process is developed in a way that supports the in-pit and ex-pit waste management strategy in oil sands mining. Mining-cuts and mining-panels are used to provide practical mining environment during extraction. Mining-cuts are clusters of blocks within the same level or mining bench that are grouped based on a similarity index defined by the attributes; location, rock type, grade and shape of mining-cuts on the lower bench. The material intersecting a pushback and a mining bench is referred to as a mining-panel. Each mining-panel contains a set of mining-cuts. The main focus of this study is:

1. Developing geologic block models using Inverse Distance Weighting to estimate bitumen and fines in the oil sands deposit (ArcGIS, 2010).
2. Building economic block models for the oil sands deposit and using the LG algorithm (Lerchs and Grossmann, 1965) to generate the ultimate pit limit.
3. Generating a strategic production schedule for ore, dyke material and waste using the MILGP model.
4. Generating a dyke material schedule for multiple dyke construction destinations using the MILGP model.
5. Evaluating the impact of using the MILGP formulation for integrated production scheduling and waste disposal planning optimization.

It is assumed that data from the geologic block models are deterministic values and no attribute uncertainties will be considered. It is also assumed that the future cost and price data used for the economic block models are constant. This assumption means that as cost and price changes in the future, there is a need for re-optimization of the production schedules, which aligns with current industry practice.

Activities involved in collecting drilling and sampling data for developing the geologic block model will not be considered. Other geotechnical properties of the dyke construction material will not be modeled or considered during optimization as well as the technical details of the dyke design.

1.6 Research Methodology

The main motivation for conducting this research is to improve oil sands mine planning and waste management by providing an integrated production scheduling and waste disposal planning scheme based on a mixed integer linear goal programming (MILGP) mine planning framework. The first part of this study involved a literature survey on oil sands mining and waste management, open pit optimization and production scheduling algorithms, and clustering algorithms. Subsequently, two sets of oil sands drillhole data from mines in Alberta, Canada were analyzed for future experimental studies. Appropriate mining concepts, mathematical and numerical models were formulated to define the inputs and outputs of the MILGP mine planning framework. The research focuses on the development, analysis and implementation of two main components of the MILGP model: (i) maximize the net present value of the mining operation and (ii) minimize the waste management cost. Appropriate numerical modeling and solution techniques were deployed to convert the formulations into accomplishing our research objectives. Figure 1.2 illustrates a summary of the research methodology.

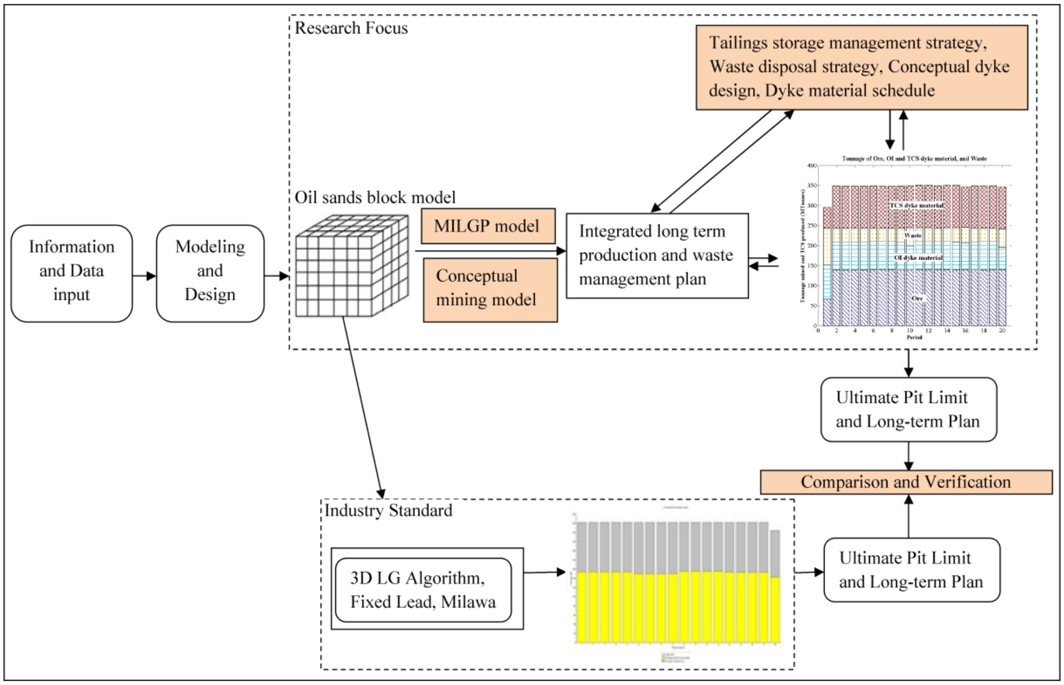

Figure 1.2: Summary of research methodology

Inverse distance weighting block models were developed using Gemcom GEMS (Gemcom Software International, 2012). The resulting geologic block models were used in setting up economic block models in Whittle (Gemcom Software International, 2012). The ultimate pit limit for these block models were generated using LG algorithm (Lerchs and Grossmann, 1965) in Whittle and used as the input data for the MILGP optimization model. The MILGP model framework has a user input interface capable of defining the block model data, production and dyke material scheduling requirements, and parameters for the waste management strategy. Matlab (2011) application was used as the programming platform to define the MILGP model and Tomlab/CPLEX (Holmström, 2009) solver which uses a branch and cut optimization algorithm was employed to solve the MILGP problem. This algorithm is a hybrid of branch-and-bound and cutting plane methods (Horst and Hoang, 1996; Wolsey, 1998). The user sets an optimization termination criterion in CPLEX known as the gap tolerance (EPGAP). The EPGAP, which is a measure of optimality, sets an absolute tolerance on the gap between the best integer objective and the objective of the best node remaining in the branch and cut algorithm. It instructs CPLEX to terminate once a feasible integer solution within the set EPGAP has been found. As the solution gets closer to optimality, it leads to production schedules that generate higher NPV than those obtained from heuristic optimization methods.

The models were implemented and verified with four experimental studies on two oil sands datasets. The MILGP model framework was used in generating an integrated practical annual long-term production and waste disposal schedules for three case studies. Subsequently, in the fourth case study comparisons were made of the worst, best, Milawa NPV and Milawa Balanced case scenarios in Whittle and the production schedule generated by the MILGP model. The experiments compared the annual stripping ratio, ore and waste production, average grade, and the respective NPVs of the project. The results were analyzed to draw the relevant conclusions with appropriate recommendations.

Summary of the research tasks that have been completed to achieve the objectives of this study are as follows:

- Develop a mathematical model to classify the oil sands block model into different material types based on the regulatory and technical requirements governing oil sands mining operations.
- Propose and develop a theoretical framework for a MILGP model to be used in integrating an oil sands long-term production plan and a waste disposal plan. This includes scheduling for both ore and dyke material simultaneously.
- Test, calibrate and verify the formulations with synthetic datasets and analyze the results in relation to the expected and inherent behavior of the theoretical and practical aspects of the formulations.
- Implement these formulations for oil sands mine case studies to generate life of mine ore and dyke material production schedules as well as dyke material schedules for multiple dyke construction destinations. For large block models, clustering algorithms will be used to combine blocks of similar material types to decrease the number of variables in the model and decrease the solution time of the solver.

- Quantify the impact of using the MILGP formulation and workflow for integrated oil sands mine planning with respect to NPV and practicality of the generated production schedules.
- Provide documentation on the work flow and parameter calibration.

In general, the development and implementation of the MILGP optimization model framework was undertaken in three major stages. The first stage involved the introduction of the MILGP model and how it can be applied for scheduling oil sands ore, overburden and interburden dyke material in an optimization framework (Ben-Awuah and Askari-Nasab, 2010; Ben-Awuah and Askari-Nasab, 2011). The second stage included extending the MILGP model for an integrated production scheduling and waste disposal planning scheme that schedules for ore, overburden, interburden and tailings coarse sand dyke material (Askari-Nasab and Ben-Awuah, 2011; Ben-Awuah et al., 2011; Ben-Awuah et al., 2012). Finally, an efficient form of the MILGP model was deployed. This uses an initial schedule, fewer pushback mining constraints and paneling of mining-cuts in addition to the block clustering and pushback mining techniques that have been previously implemented to generate fast practical solution to the integrated production scheduling and waste disposal planning problem (Ben-Awuah and Askari-Nasab, 2012a; Ben-Awuah and Askari-Nasab, 2012b). This approach was used to facilitate continuous feedback from the research community and the oil sands mining industry experts to improve the model.

1.7 Scientific Contributions and Industrial Significance of the Research

The main contribution of this research is the integration of production scheduling and waste disposal planning for oil sands mining in an optimization framework. This includes the development of multiple material types and multiple destination optimization techniques using MILGP in the context of mine planning. Also, the research uses penalty and priority parameters in optimization to enforce improved goal attainment in mine planning. Another aspect of this study is the integration of mixed integer linear programming and goal programming in solving large scale mine planning optimization problems using clustering and paneling techniques.

The implementation of an efficient MILGP model which uses techniques with fewer non-zero decision variables and constraints is highlighted as well. The NPV of the mine operation is maximized after optimization and the generated multiple material types schedule satisfies all set goals and constraints. In addition, the dyke construction cost is minimized for multiple dyke construction destinations.

The industrial significance of this research is the introduction of a MILGP model framework and workflow that seeks to enable the oil sands mining industry generate a strategic production and dyke material schedule for ore, dyke material and waste. This is in accordance with the requirements of sections 4.0, 4.2 and 4.5 of Directive 074 issued by the Energy Resources Conservation Board (McFadyen, 2008) on tailings performance and criteria for oil sands mining schemes. The formulation and workflow seeks to optimize the oil sands mining operation by maximizing NPV of the operation and minimizing dyke construction cost. The MILGP formulation can be applied to real case data using block clustering and paneling techniques, and large scale optimization solvers.

1.8 Organization of Thesis

Chapter 1 of this thesis is a general overview of the research. It discusses the background to the study, followed by the problem statement, the objectives of the study, the context and scope of the study, the proposed methodology and the contributions of this research.

Chapter 2, the literature review, provides an overview of mining and waste management in oil sands. It also provides a literature review of open pit mine planning and design; including a historical and recent perspective on final pit limit optimization and production scheduling algorithms. Clustering algorithms and its application in mine planning is also highlighted. The chapter concludes with the rationale for this PhD research.

Chapter 3 contains the theoretical framework for the Mixed Integer Linear Goal Programming (MILGP) mine planning model in two parts. The first part of the chapter discusses a conceptual oil sands mining and dyke design model. It describes how oil sands production scheduling and waste management can be integrated. The second part of the chapter focuses on formulating, modeling and developing the components of the MILGP model and their interrelationship. The application of block clustering and paneling techniques and their use in the MILGP model are elucidated.

Chapter 4 discusses the MILGP model implementation. The chapter describes the numerical modeling of the different components of the MILGP model and how they can be set in Matlab programming environment (MathworksInc., 2011) for Tomlab/CPLEX optimization solver (Holmström, 2009). This includes the numerical modeling of the objective function, goal functions and constraints. The chapter concludes with an elaboration on techniques for implementing an efficient MILGP model framework.

Chapter 5 presents the experimental design and experimentation with the MILGP model framework. This includes the implementation and verification of the model. Three oil sands mining case studies are discussed to elucidate the robustness and flexibility of the MILGP model framework in integrating production scheduling and waste disposal planning. A fourth oil sands mining case study was carried out to verify the model. Subsequently, the production schedules generated by the MILGP model and Whittle Milawa Balanced algorithm were compared. No dyke material was scheduled since Whittle do not have tools for this purpose. Relevant conclusions and recommendations were made by comparing the periodic stripping ratio, average grade, waste and ore production and the respective NPV.

Chapter 6, the last chapter, contains the thesis summary and concluding statements. The benefits and contributions of this research are highlighted as well as recommendations for future work in integrated mine planning and production scheduling.

CHAPTER 2

LITERATURE REVIEW

2.1 Background

This chapter is concerned with a literature review on oil sands mining and optimization and scheduling algorithms in open pit mining. This includes literature on oil sands waste management and dyke construction. Evaluation of past and recent developments in the optimization and scheduling algorithms used for open pit mining operations are also discussed. Algorithms used for open pit mine design and optimization are mainly open pit optimization algorithms and open pit production scheduling algorithms. Clustering algorithms for production scheduling are reviewed as well.

2.2 Oil Sands Formation

The mineral deposit under consideration is oil sands in the McMurray formation. There are five main soils or rock types associated with this deposit namely: 1) Muskeg/Peat 2) Pleistocene Unit 3) Clearwater Formation 4) McMurray Formation and 5) Devonian carbonates. The oil bearing rock type is the McMurray formation (MMF) which is also made up of three rock types. These are the Upper McMurray (UKM), the Middle McMurray (MKM) and the Lower McMurray (LKM). The McMurray formation is made up of coarse sand, fine sand, water and bitumen. The main element of interest is bitumen which exists in various grades across the formation. Details of the five rock types associated with the oil sands deposit are (Masliyah, 2010):

1. Muskeg/Peat – this is the topmost overburden material that contains the seeds and roots of native plants and is used for the topmost layer of the reclaimed land. Before mining, this layer is removed and stockpiled and later used for reclamation works.

2. Pleistocene Unit (PLU) and Clearwater Formation (CWF) – the next rock profiles are the PLU followed by the CWF. These are considered as waste rocks lying above the bitumen bearing McMurray formation. Materials from these

profiles are used for road and dyke construction in the mine depending on the soil properties and its mineral content.

3. McMurray Formation (UKM, MKM, LKM) – the bulk of the bitumen and gas reserves are contained within the McMurray interval in the oil sands area. The McMurray formation rests with profound unconformity on the Devonian carbonates and is unconformably overlain by the Clearwater formation. The McMurray formation ranges between 0 – 130m thick from Devonian highs to bitumount basins. The LKM is comprised of gravel, coarse sand, silt and clay with siderite as cement. The UKM and MKM comprises of micaceous, fine-to-medium-grained sand, silt and clay, with rare siderite as cement and intraclasts and pyrite nodules up to 10cm in diameter (Hein et al., 2000).

4. Devonian Carbonates (DVN) – this is the rock type which lies beneath the McMurray formation and is made up of numerous limestone outcrops. It marks the end of the oil sands deposit on a vertical profile.

To obtain details of the oil sands deposit, it is required that a detailed exploration program is undertaken where drilling is carried out and the resulting data logged for further analysis and modeling. Figure 2.1 shows a sketch of the vertical soil profile of an oil sands formation.

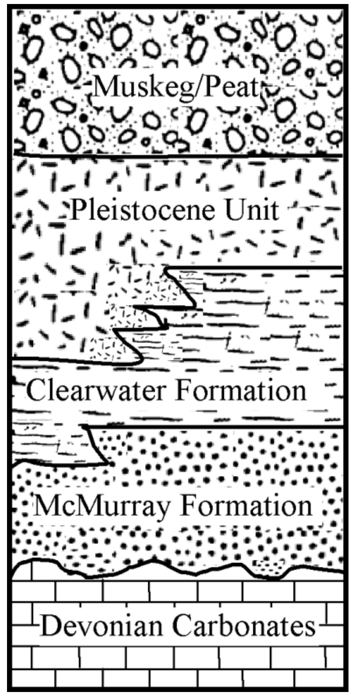

Figure 2.1: Sketch of the vertical soil profile of an oil sands formation modified after Dusseault (1977)

2.3 Oil Sands Mining and Waste Management

Oil sands also known as bituminous sands are sedimentary deposits that contain high molar mass viscous petroleum. The largest sources of crude bitumen in the world are Canada and Venezuela (Masliyah, 2010). The origin of the oil that is trapped in the sands to form the oil sands are; marine animals die and sink to the ocean bottom and become embedded by sedimentary minerals. Major alterations caused by aerobic and anaerobic processes, high temperatures and pressures and decomposition produce liquid petroleum. The liquid petroleum flows through the pores of the rock in which it was formed and migrates until it becomes trapped and cannot flow any further, thus forming an oil reservoir (Masliyah, 2010). In the case of the Alberta oil sands, the oil was trapped in the McMurray formation. Oil sands mining started in the 1960s with a surface mining operation that used hot water extraction to recover bitumen from the oil sands and an upgrading complex to upgrade the extracted bitumen to a light synthetic crude (Morgan, 2001). This mining operation involves the movement of huge amount of bituminous sands to the processing plant with over 80% being sent to the tailings dam after processing. The remaining waste material mined from the pits are sent to waste dumps or used for dyke construction. This makes waste management an important integral part of the oil sands mining process.

An issue that can bring a mine to its knees within the shortest possible time is the management of its waste. Waste management issues can also result in future unbearable financial liabilities. Strategies for managing oil sands mine waste in an environmentally acceptable manner, in the short and long-term, are a responsibility that cut across a wide range of disciplines. This includes geologists, geotechnical and mine planning engineers, tailings planners, operations and project teams (Fauquier et al., 2009). The team works towards the goal of building tailings dam dykes on time, within budget and design specifications. This involves managing tailings and the general mine waste. Tailings dams that are constructed to store tailings are usually constructed in-pit and dedicated disposal areas outside the pit due to the lack of lease area and the large amount of storage space required. The tailings are stored behind dykes that are constructed in the pit one section at a time as the mining advances. The tailings storage plan requires the in-pit and ex-pit dykes to be designed, constructed and operated on a continual basis throughout the mine life. The in-pit and ex-pit dyke construction materials are derived from the overburden and interburden seams of the deposit as well as tailings coarse sand from the processing plant (Fauquier et al., 2009). The dyke construction materials are predicted using the geologic block model. This makes it necessary that during the long-term production planning process, schedules for ore and dyke material are generated simultaneously to enable the consistent material supply to the plant and for dyke construction. The nature of dyke material required at any time depends on the dyke configuration and the location of the material within the dyke. A robust oil sands long-term plan should be able to supply ore for the plant and appropriate dyke material throughout the mine life.

2.4 Oil Sands Tailings Management and Dyke Construction

In oil sands tailings management, containment of large volumes of fluid fine tailings and long-term storage of matured fine tailings require special geotechnical considerations and tailings management techniques (Azam and Scott, 2005). The two main challenges in managing oil sands tailings are: environmental challenges and space limitations defined in the lease agreements. The environmental challenges include the toxicity of the tailings pore water and land reclamation. In dealing with this, dewatering techniques have been developed to decrease the volume of water in the tailings and to recycle the water to the processing plant. The regulatory requirement from Energy Resources Conservation Board referred to as Directive 074, requires oil sands companies to reduce the volume of fluid tailings and convert them to trafficable landscapes (Boratynec, 2003; Azam and Scott, 2005; McFadyen, 2008; Kalantari, 2011). Some of the tailings management techniques include using selective mining to reduce the volume of the processed fines, modifying the oil sands extraction process to reduce the volume of dispersed fines and developing non-segregating tailings. The lease area limitation causes the need for in-pit tailings containment in addition to dedicated disposal areas. In-pit tailings containment reduces the volume of disturbed landscape and can be reclaimed much easier due to its topographical layout. In-pit tailings containment requires an integrated mine planning scheme where, as the mining proceeds tailings containment areas are made available; as well as providing ore to the process plant and dyke material for in-pit or ex-pit dyke construction.

Depending on the dykes' designs, they have different configurations at different locations within the dyke and hence require different material types. Some of the dyke construction methods shown in Figure 2.2 are: 1) upstream construction, 2) downstream construction, and 3) centerline construction. In general, tailings impoundment usually starts with the construction of a starter dyke using overburden and interburden dyke material. The starter dyke is designed to retain water for start-up of the mineral processing plant and to contain tailings during the first year of operation. As production of tailings continues, some of the tailings coarse sand produced from hydrocyclones are used to increase the size of the dyke to hold more tailings and recycle water. The dam capacity must continually be increased as more tailings storage volume is required. It is important to keep accurate records of the supernatant pond and the crest elevations of the tailings dam embankments. These records are reviewed continuously with the design as the construction proceeds. Each tailings facility has some special characteristics mainly because of the nature of the site and the available construction material as well as the construction sequence usually controlled by mine operations (Ben-Awuah and Akayuli, 2008; Sego, 2010).

In upstream construction, from the starter dyke the crest of the dam moves towards the supernatant pond. This involves placing dyke material on top of previously placed tailings beach. The properties of the deposited tailings in the pond therefore become important since the embankment is continuously being constructed on a soft foundation of previously placed tailings. In downstream construction, from the starter dyke the crest of the dam continuously moves away from the pond. The newly placed dyke material is constructed over a natural foundation. This requires large volumes of tailings coarse sand on a more competent foundation. The large material requirements usually make it a less desirable construction technique. With the centerline construction, this is a compromise between the two discussed methods. During construction, the upstream portion is usually beached whilst the downstream portion is compacted. In addition to tailings coarse sand used to construct the downstream portion, waste rock can be used as well. This allows for a steeper slope angle and hence less material handling requirements. More literature that provides details on dyke construction methods for tailings facilities are provided by Vick (1983) and Sego (2010). These dykes are constructed simultaneously as the mine phase advances and the dyke footprints are released.

Currently, scheduling of dyke material is carried out as a post production scheduling optimization activity done after mining has started and this may result in inconsistent production of dyke material at different periods during the mine life. It is also a regulatory requirement that life of mine schedules and tailings management strategies are documented and reported annually resulting in the need for a more systematic approach towards oil sands waste management (McFadyen, 2008).

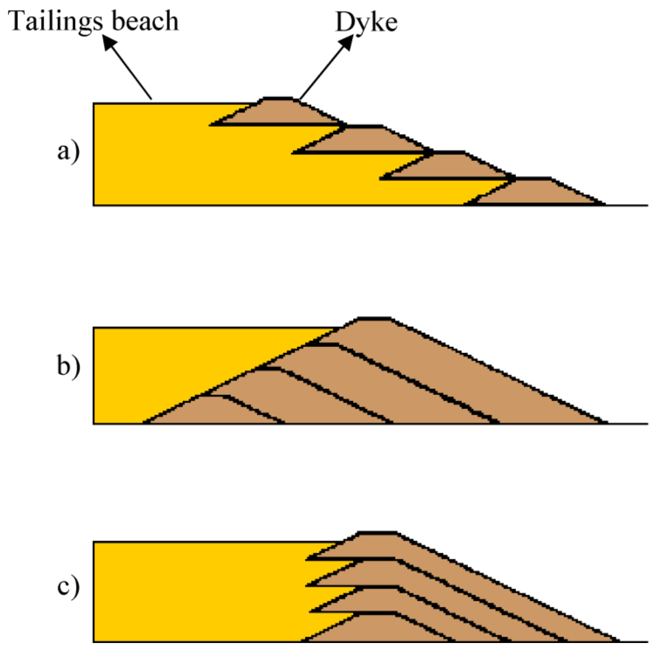

Figure 2.2: a) Upstream construction, b) downstream construction, and c) centerline construction (after Vick, 1983)

2.5 Open Pit Optimization Algorithms

Mining is the process of extracting a beneficial naturally occurring resource from the earth and historical assessment of mineral resource evaluations has demonstrated the sensitivity of project profitability to decisions based on mine planning (Askari-Nasab and Awuah-Offei, 2009; Newman et al., 2010). Open pit mining can be referred to as the continuous development and superimposition of a geometric surface onto a mineral reserve. This geometric surface is termed the pit and the material within this pit boundary is known as the mineable reserve. The size and shape of the pit is determined by economic and technical factors, and production constraints. The pit that exists at the end of the mining operation is called the ultimate or final pit. Before the final pit, there are a series of intermediate pits sometimes referred to as pushbacks. Determining the size and shape of the final pit involves the use of open pit optimization algorithms (Lerchs and Grossmann, 1965; Askari-Nasab, 2006; Hustrulid and Kuchta, 2006). The final pit limit defines the size and shape of the open pit at the end of the mine life subject to economic, technical and operational constraints. The pit limits is used in determining the boundary layouts and location of mine infrastructure such as processing plants, tailings facilities, waste dumps and mine offices. Beyond the final or ultimate pit limit, the open pit mining of a given deposit will be uneconomic. The optimum final pit limit therefore defines the pit outline containing the material extracted to give the total maximum profit whilst satisfying all field constraints (Caccetta and Giannini, 1990; Asa, 2002).

Starting from the late 1950's when the application of computer models to mining started, many research works have been done in finding a good practical solution to the ultimate pit limit problem. Two modeling approaches known as the graph theory and dynamic programming algorithm were introduced by Lerchs and Grossmann (1965). The models use the economic block model to generate an ultimate pit limit where the time value of money is not considered as well as the extraction time of the blocks. Under this assumption, there is no importance attached to the extraction time of a more valuable block to that of a less valuable block. Over the years, the graph theory has proven to be reliable in determining the final pit limit. Subsequently, many researchers have implemented this theory or in their modified forms in solving pit optimization problems (Picard, 1976; Whittle, 1988; Zhao and Kim, 1992; Underwood and Tolwinski, 1998; Khalokakaie et al., 2000a; Khalokakaie et al., 2000b; Khalokakaie et al., 2000c). Pana and Davey (1965) proposed a moving cone algorithm that works with similar assumptions as the graph theory and the dynamic programming model. Their algorithm was generating overlapping cones and could not examine all combinations of adjacent blocks thus failing to give consistent and realistic results. Currently, the most widely used open pit limit optimization methods are the Floating Cone and Lerchs and Grossman algorithm.

2.5.1 The Floating Cone and Lerchs and Grossman Algorithm

The main classical methods that continue to feature prominently in the literature for pit limit optimization are the floating/moving cone method (Laurich, 1990) and the LG 3D algorithm (Lerchs and Grossmann, 1965). The floating cone method initializes with a reference block as the starting point for expanding the pit upwards constrained to the pit slope rules. The upward expansion will include all blocks which must be removed before the reference block, forming a cone whose economic value can be calculated. A second reference block can be added to the cone and the incremental economic value generated by mining this block added to the value of the cone. This process continues until the maximum economic value of the cone is obtained. The limitations of this approach include: (i) the order in which the reference blocks are selected determines the final pit outline; (ii) the economic value of the cone for many reference blocks must be calculated before generating an acceptable pit outline which may not be optimal. This method is still widely used in practice (Newman et al., 2010).

The LG algorithm continues to feature prominently in recent applications because it provides a computationally tractable method for pit limit design. The final pit limit problem can be cast as an integer programming problem which has a unimodular structure. Generating the solution for the relaxed LP problem is therefore sufficient (Hochbaum and Chen, 2000). With this problem structure, Lerchs and Grossman (1965) proposed a maximum-weight closure algorithm that takes advantage of network structure to generate an optimal solution. This algorithm has become popular in practice due to its fast solution times and accuracy. It has currently been incorporated in many commercial pit limit design software packages such as Whittle, Vulcan Chronos and NPV Schedular (Datamine Corporate Limited, 2008; Gemcom Software International Inc., 2012; Maptek Software Pty Ltd, 2012).

2.6 Open Pit Production Scheduling Algorithms

The problem of long-term production planning (LTPP) has been a major research area for quite some time now and though tremendous improvements have been made, the current challenging mining environment poses new sophisticated problems. Effective LTPP is critical in the profitability of surface mining ventures and can increase the life of mine considerably. Recent production scheduling algorithms and formulations in literature have been developed along two main research areas: 1) heuristic methods and 2) exact solution methods for optimization (Askari-Nasab and Awuah-Offei, 2009).

Commercial mine scheduling software such as XPAC Auto Scheduler (Runge Limited, 2009), Whittle (Gemcom Software International Inc., 2012), and NPV

Scheduler (Datamine Corporate Limited, 2008) use heuristic methods to generate long-term production schedules. Heuristic methods iterate over different alternatives leading to the generation of the ultimate pit limit with each alternative having a different discounted cash flow and hence NPV of the operation. Due to this, the solution generated may be sub-optimal in terms of NPV.

Authors like Denby and Schofield (1995) and Askari-Nasab (2006) have done extensive research using artificial intelligence techniques to solve the problem of LTPP. Denby and Schofield (1995) used multi-objective optimization to deal with ore grade variance. Using genetic algorithm, Denby and Schofield (1995) tried to maximize value and minimize risk in open pit production planning. Askari-Nasab (2006) also developed and implemented an intelligent-based theoretical framework for open pit production planning. The drawback in the application of these techniques is the non reproducibility of the solution and a measure of the extent of optimality of the solution.

Exact solution methods for optimization with mathematical programming models (MPMs) have proved to be robust in solving the LTPP problem. They have the capability of considering multiple material types and multiple elements during optimization. Solving MPMs with exact solution methods result in solutions within known limits of optimality. As the solution gets closer to optimality, it leads to production schedules that generate higher NPV than those obtained from heuristic optimization methods. Goal programming (GP) is a MPM that uses exact solution methods for production scheduling optimization. The advantage of this model is that it allows for flexible formulation and the specification of priorities among goals or targets. This formulation also allows some form of interaction between the decision maker and the optimization process (Zeleny, 1980; Hannan, 1985). Depending on its use, some alterations are made to the formulation structure. Goal programming was applied to the mine scheduling problem using multiple criteria decision making formulation by Zhang et al. (1993). Multiple goals were considered based on their priorities. The model was tested for a surface coal mine production scheduling and implemented using a branch-and-bound method in ‘C’ programming language environment. This model was developed for a single ore type process. Chanda and Dagdelen (1995) used goal programming and an interactive graphics system for optimal blending in mine production. Their model sets up the blending problem with multiple goals and attempts to minimize the deviation from the goals using a Fortran 77 computer program based on simplex method of linear programming. The model was tested for a coal mine deposit, but due to some interactions involved in solving the problem, optimal solution cannot always be guaranteed. A mineral dressing criteria was defined by Esfandiri et al. (2004) and used in the optimization of an iron ore mine. A 0-1 non-linear goal programming model was defined based on multiple criteria decision making and the deviations for economics, mining and mineral dressing functions were minimized. This formulation was solved using LINGO software. The model was found to have limitations and constraints that are numerous for practical application.

Other mine and production related problems have been solved using goal programming with some modifications. Oraee and Asi (2004) used a fuzzy goal programming model for optimizing haulage system in an open pit mine. Due to the variations in operating conditions caused by technical, operational, and environmental factors for a mechanical shovel, their model use fuzzy numbers to represent parameters for these operating conditions in optimization. They argue that, their model generates a more realistic results than those based on random numbers derived from probability distributions. A 0-1 goal programming model was developed by Chen (1994) for scheduling multiple maintenance projects for a mineral processing equipment at a copper mine. Using 0-1 decision variables and multiple scheduling periods, the model scheduled for four projects, 40 jobs and nine types of resources. In comparison to a heuristic method that was already used by the mine, the goal programming model reduced the project duration, total project cost and overall workload. Many industrial production planning and project selection decision making problems have been solved making use of the advantages of goal programming formulations (Jääskeläinen, 1969; Mukherjee and Bera, 1995; Leung et al., 2003; Lee et al., 2010).

Other MPMs that uses exact solution methods for optimization of mine production schedules are mixed integer linear programming (MILP) and linear programming (LP). Initial works that was carried out by Johnson (1969), Gershon (1983) and Dagdelen (1985) developed linear programming (LP) and mixed integer linear programming (MILP) formulations that uses integer variables for optimizing mine schedules. Their formulations could not ensure feasible solutions for all cases and could not overcome the issue of solving large integer programming problems. An integer programming formulation that was developed by Dagdelen and Johnson (1986) uses Lagrangian relaxation and subgradient optimization algorithm to solve the LTPP problem. Subsequent integer programming models developed by Akaike and Dagdelen (1999), and Caccetta and Hill (2003) use 4D-network relaxation and subgradient optimization algorithm, and branch and cut algorithm respectively to solve the LTPP optimization problem. These authors note that implementation on large scale problems or with dynamic cut off grades was a challenge.

MILP formulations that was developed by Ramazan and Dimitrakopoulos (2004a) attempt to reduce the number of binary variables and solution times by setting certain variables as binary and others as continuous. This resulted in partial mining of blocks that have the same ore value affecting the NPV generated. Ramazan et al. (2005) and Ramazan (2007) developed an MILP model that uses an aggregation method to reduce the number of integer variables in scheduling. This formulation was solved based on fundamental tree algorithm and was used in scheduling a case with 38,457 blocks within the final pit limit. The problem was broken down into four push-backs based on the nested pit approach using Whittle (Gemcom Software International Inc., 2012) and formulated as separate MILP models. This may not guarantee a global optimum solution of the problem. Caccetta and Hill (2003) presented an MILP model and Boland et al. (2009) presented an LP approach to generate mine production schedules with block processing selectivity. They however did not present enough information on the generated schedules to enable an assessment of the practicality of the solutions from mining operation point of view.

Recent research work by Askari-Nasab et al. (2011) on the application of exact solution methods of optimization to the LTPP problem has lead to the development of mixed integer linear programming (MILP) models that use block clustering techniques to deal with the problem of having large number of decision variables. With a combination of their MILP models and a block clustering algorithm, Askari-Nasab et al. (2011) applied their models to a large scale problem. The formulations use a combination of continuous and binary integer variables. The continuous variables control the portion of a block to be extracted in each period and binary integer variables control the order of block extraction or precedence of mining-cuts through a dependency directed graph using depth-first-search algorithm. The concept of mining-cuts using clustering techniques is reinforced as an option for solving MILP problems for large scale deposits. The formulation was implemented on an iron ore mine intermediate scheduling case study over twelve periods in Tomlab/CPLEX (Holmström, 2009) environment. This model does not consider multiple material types or waste disposal planning.

Due to the advantages that are presented by GP and MILP, some efforts have been made to combine these two techniques and used together for solving industrial problems. This hybrid termed as mixed integer linear goal programming (MILGP) has been used for scheduling and budgeting problems in nursing, business administration and manufacturing industries (Selen and Hott, 1986; Ferland et al., 2001; Liang and Lawrence, 2007; Nja and Udofia, 2009). MILGP formulation is the proposed model in this thesis for application to the oil sands mine LTPP problem.

2.6.1 The Goal Programming Model

The oil sands long-term mine production scheduling and waste disposal planning problem will be formulated using a combination of mixed integer and goal programming formulations. Using goal programming is appropriate in this context because the structure enables the optimization solution to try achieving a set of goals where some goals can be traded off against one another depending on their priority. Hard constraints can also be converted to soft constraints which otherwise could lead to infeasible solutions. In simple terms, goal programming allows for flexible formulation and the specification of priorities among goals (Liang and Lawrence, 2007).

The formulated model for the strategic production and dyke material scheduling problem has an objective function, goal functions and constraints. The goal functions are mining, processing and dyke construction. These goals will be prioritized according to the impact of a deviation from their targets on the entire mining operation. The general form of goal programming as applied in multiple criteria decision making optimization can be mathematically expressed as in Equations (2.1) to (2.6) (Hannan, 1985; Ferland et al., 2001; Esfandiri et al., 2004; Liang and Lawrence, 2007):

Objective function:

$$Z = \sum \left(P_i \left(d_i^+ + d_i^- \right) \right) \tag{2.1}$$

Goal functions:

$$\sum C_{ij} X_j + d_i^- + d_i^+ = G_i \tag{2.2}$$

Constraints:

$$\sum D_{ij} X_j = T_i \tag{2.3}$$

$$\sum E_{ij} X_j \le M_i \tag{2.4}$$

Limitations:

$$\forall X_j,\ d_i^+,\ d_i^- \ge 0 \tag{2.5}$$

$$P_1 \ge P_2 \ge \ldots\ldots\ldots\ldots P_i \tag{2.6}$$

Where:

- $\mathrm{P}_i = i$-th priority
- $\mathrm{X}_j =$ decision variable
- $\mathrm{G}_i =$ target level of i-th goal
- $T_i,\ M_i =$ right-hand side limits

- C_{ij} = unit contribution of activity j-th to goal
- D_{ij}, E_{ij} = unit contribution of activity j-th to system constraints
- d_i^+ = positive deviation
- d_i^- = negative deviation

2.7 Clustering and Paneling

Clustering can be referred to as the task of grouping similar entities together so that maximum intracluster similarity and intercluster dissimilarity are achieved. This can be modeled and solved as a mathematical programming problem but will require more resources and time. Therefore non-exact algorithms have been developed in the literature in dealing with these problems. These algorithms are usually implemented by defining a measure of similarity or dissimilarity among the objects. There are two main categories: partitional and hierarchical clustering. Partitional clustering is done by partitioning data objects into a number of groups. Hierachical clustering on the other hand is performed by creating a hierarchy of clusters. In comparison, hierarchical clustering creates better clusters though more CPU time is required (Johnson, 1967; Feng et al., 2010; Tabesh and Askari-Nasab, 2011). The clustering algorithms used for this research have been customized purposely for solving mine production scheduling problems. These are fuzzy logic clustering algorithm and hierarchical clustering algorithm (Kaufman and Rousseeuw, 1990; Mathworks Inc., 2011; Tabesh and Askari-Nasab, 2011). The hierarchical clustering algorithm and computer code used for this study were developed by Tabesh and Askari-Nasab (2011). Figure 2.3 shows 8 mining-cuts created with hierarchical clustering algorithm. In addition, the final pit limit block model is divided into pushbacks. The material intersecting a pushback and a bench is known as a mining-panel. Each mining-panel contains a set of mining-cuts and is used to control the mine production operation sequencing. Figure 2.3 also shows three mining-panels. Mining-panel 'A' contains the set of mining-cuts 1, 2, 3 and 6; mining-panel 'B' contains the set of mining-cuts 4 and 5; mining-panel 'C' contains the set of mining-cuts 7 and 8.

One of the main problems associated with finding the optimal long-term production schedule is that, the size of the problem grows exponentially as the number of blocks increases (Askari-Nasab and Awuah-Offei, 2009) resulting in insufficient computer memory during optimization. This is caused by an increase in the number of decision variables and constraints resulting mainly from the block mining precedence. An efficient way of dealing with this problem is by applying clustering and paneling techniques. Clustering is a technique used for aggregating blocks in a block model. Paneling is the process of creating a set of mining-cuts on a mining bench contained within a pushback. In the clustering algorithm used in this research, blocks within the same level or mining bench are grouped into clusters based on the attributes: location, rock-type, and grade distribution. These clusters of blocks are referred to as mining-cuts and they have similar attribute definitions to that of the blocks such as coordinates representing the spatial location of the mining-cut.

This block aggregation approach will summarize ore data as well as maintain an important separation of lithology. The total quantity of contained elements in the blocks will be modeled for the mining-cuts to ensure the accuracy of the estimated values. This approach also ensures the planning of a practical equipment movement strategy based on the contained elements and tonnages in the mining-cuts. It is important to note that, clustering of blocks in a block model to mining-cuts reduces the degree of freedom of variables or resolution of the problem when finding the mining sequence that maximizes the NPV of the operation. This may lead to reduced NPV values as compared to a high resolution block level optimization (Askari-Nasab and Awuah-Offei, 2009). Also, each mining-panel contains a set of mining-cuts and is used to control the mine production operation sequencing.

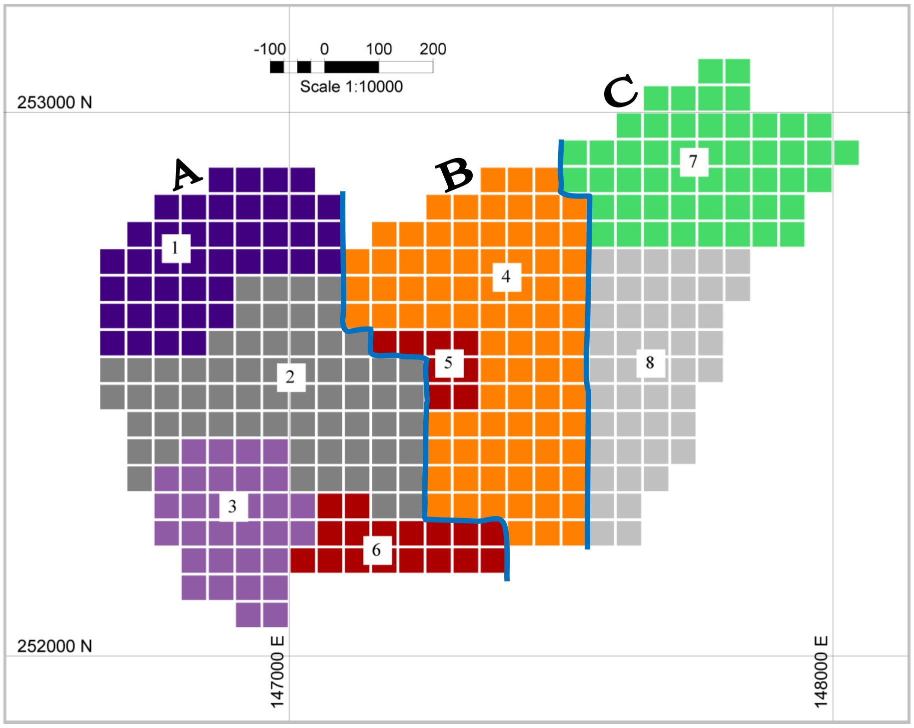

Figure 2.3: 8 Mining-cuts of blocks from hierarchical clustering, and 3 mining-panels

2.8 Rationale for PhD Research

Applying Mathematical Programming Models (MPMs) like Linear Programming (LP), Mixed Integer Linear Programming (MILP) and Goal Programming (GP) with exact solution methods for optimization have proved to be robust. Solving MPMs with exact solution methods result in solutions within known limits of optimality. As the solution gets closer to optimality, it results in production schedules that generate higher NPV than those obtained from heuristic optimization methods. This has resulted in extensive research on the application of MPMs like LP and MILP to the LTPP problem. The inherent difficulty in applying these models to the LTPP problem is that, they result in large scale optimization problems containing many binary and continuous variables. These are difficult to solve with the current computing software and hardware available and may have lengthy solution times. Though some researchers have made efforts in reducing the solution time associated with solving MPMs, their models were not capable of dealing with large block model sizes or could not generate feasible practical mining strategies (Johnson, 1969; Gershon, 1983; Dagdelen, 1985; Akaike and Dagdelen, 1999; Ramazan, 2001; Caccetta and Hill, 2003; Ramazan and Dimitrakopoulos, 2004a). These publications note that the size of the resulting LP and MILP models is a major problem because it contains too many binary and continuous variables.

GP is another mathematical programming modeling platform that have been used in solving the LTPP problem. It permits flexible formulation, specification of priorities among goals, and some level of interactions between the decision maker and the optimization process (Zeleny, 1980; Hannan, 1985). This lead to its application to the LTPP problem by Zhang et al. (1993), Chanda and Dagdelen (1995) and Esfandiri et al. (2004). They were however unable to practically implement their models due to the numerous mining production constraints and size of the optimization problem. Recent implementation of MILP models with block clustering techniques were undertaken for an Iron ore deposit (Askari-Nasab et al., 2010; Askari-Nasab et al., 2011). It however lacks the framework for the implementation of an integrated mine planning and waste management system as is the case required for sustainable oil sands mining. Due to the strategy required for sustainable oil sands mining and the regulatory requirements from Directive 074, waste disposal planning is closely related to the mine planning system (McFadyen, 2008; Askari-Nasab and Ben-Awuah, 2011; Ben-Awuah and Askari-Nasab, 2011). Currently, oil sands waste disposal planning is handled as a post production scheduling optimization activity. Consequently, the lack of an integrated sustainable oil sands mine production scheduling and waste disposal planning system in an optimization framework is worrisome. Modeling such an integrated mine planning system even adds more complexity to the LTPP problem. The first part of this thesis includes the implementation of a MILGP model for an integrated oil sands production scheduling and waste disposal planning system. The model takes into account multiple material types, elements and destinations, directional mining, waste management and sustainable practical mining strategies. The implementation of the MILGP model resulted in a large-scale optimization problem with lengthy solution times.

The second part of the thesis presents scheduling models and tests on how to generate MILGP formulations using fewer non-zero variables. It also discusses alternative techniques to MILGP pushback mining modeling for efficiency in solving the formulations. The tests show that there are significant differences in the time taken by the various MILGP models generated for the same deposit to maximize NPV and minimize dyke construction cost. Two oil sands data sets are used for four case studies in this research.

2.9 Summary and Conclusions

A review of the relevant literature for this research has been done. In mining projects, deviations from the optimal mine plan can have great impact on the mine economics. Over the last 50 years, continuous attempts have been made to address the pit limit and production scheduling optimization problems. This has resulted in numerous research works some of which have been outlined in this thesis. The research works can be classified in these thematic areas: (i) deterministic; (ii) stochastic; (iii) heuristic; and (iv) artificial intelligence methods. The LG 3D algorithm developed based on the graph theory by Lerchs and Grossmann (1965) for pit limit optimization is still the most dominating model currently in use.

Research works in production scheduling optimization has mainly focused on optimizing processing plant feed or maximizing profits. Plant feed optimization methods involve using the grade of the blocks to control material sent to the plant. The resulting production schedule should provide a uniform adequate quality feed to the plant. Profit maximization on the other hand, attempts to generate a production schedule that maximizes the net present value of the mining project.

The limitations in pit limit and production scheduling optimization methods include: (i) inability to solve large industrial problems. These come about as a result of the large computer overheads, in terms of memory and speed, required in solving these problems; (ii) inability to deal with stochastic parameters such as ore grade, commodity price and production cost. Treating these parameters as deterministic variables can generate suboptimal results; (iii) inability to factor the extraction time in pit limits optimization. The final pit limit optimization algorithms assume an instantaneous extraction of the mineral resource to generate the pit outline; (iv) shortcoming in defining the economics of ore in relation to the overall mine economics; and (v) shortcoming in integrating other major activities like waste management and reclamation into the production scheduling optimization process. Waste management and reclamation are handled as post-production scheduling optimization processes.

These limitations can affect the viability or otherwise of mining projects emphasizing the need for optimization tools that takes into consideration these deficiencies. Consequently, it is important that robust models are developed to address these challenges. This research will introduce a MILGP mine planning framework which will improve how mining operations are engineered and managed.

CHAPTER 3

MILGP THEORETICAL FRAMEWORK

3.1 Background

This chapter focuses on the theoretical framework for a mixed integer linear goal programming model as applied to an integrated oil sands mine planning and waste management problem in this thesis. In general, the conceptual theoretical framework, the mathematical models and how they relate to each other in an optimization environment are developed for achieving the research objectives. The objective of this research is to develop a theoretical framework that maximizes the net present value of an oil sands mining operation and minimizes the waste management cost using a mixed integer linear goal programming model (MILGP). Though exact solution methods for optimization have been applied in mine planning, little work has been done in terms of planning of oil sands resources which has a unique scenario when it comes to waste management. Recent regulatory requirements by the Energy Resources Conservation Board (Directive 074) requires that oil sands mining companies develop life of mine plans which ties into their in-pit tailings disposal strategy (McFadyen, 2008). This requires a new approach for the planning of oil sands resources.

Figure 1.1 in Chapter 1 illustrates the main components of an oil sands mine planning and waste management problem. This includes generating a strategic production and dyke material schedule for an oil sands mining operation. These long term production schedules guide the development of medium and short term production schedules. Subsequently, based on short term requirements, the medium term and long term production schedules may need to be readjusted appropriately. The interaction is usually both a feed forward and a feed backward one as shown in Figure 3.1.

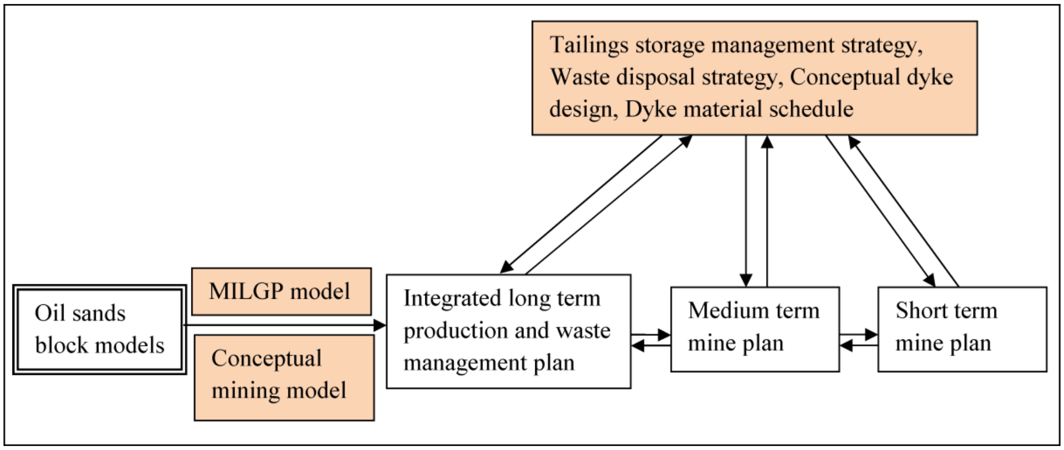

Figure 3.1: The MILGP model framework environment and interactions

This chapter focuses on formulating, modeling and developing the various aspects of the MILGP conceptual framework. This includes: (i) maximizing the net present value of the oil sands mining operation and (ii) minimizing waste management cost. The MILGP model comprises interactive and interrelated subsystems with processes and procedures in an optimization framework. The main integral parts of the MILGP framework are: (i) maximizing the net present value: consists of geological and economic block models and conceptual oil sands mine planning model (ii) minimizing waste management cost: consists of tailings storage management strategy, waste disposal strategy and conceptual dyke design. Section 3.2 discusses oil sands mining in general and section 3.3 highlights a conceptual oil sands mining model. Sections 3.4 and 3.5 describe the architecture of the MILGP model framework. This chapter concludes in section 3.6.

3.2 Oil Sands Mining and Material Classification System

Oil sands mining comprise the mining of overburden material and the McMurray formation. The overburden material is barren and the McMurray formation contains bitumen which is the desirable mineral. Most of the mined oil sands ore after processing finds its way to the tailings dam, making the tailings facility and waste management important aspects of this operation. Due to limited lease area, these tailings facilities are sited mostly in-pit and embankments or dykes are constructed to contain the tailings. Most of the materials used in constructing these dykes come from the mining operation which makes it necessary to have a plan for supplying the dyke material.

Depending on the dykes' designs, they have different configurations at different locations within the dyke and hence require different material types. Some of the main dyke construction methods used are: 1) upstream construction, 2) downstream construction, and 3) centerline construction. More literature that provides details on dyke construction methods for tailings facilities are provided by Vick (1983) and Sego (2010). These dykes are constructed simultaneously as the mine phase advances and the dyke footprints are released.

Currently, scheduling of dyke material is handled as a post resource optimization problem which may result in inconsistent production of dyke material at different periods during the mine life. It is also a regulatory requirement that life of mine schedules for tailings management strategies are documented and reported annually resulting in the need for a more systematic approach towards oil sands waste management (McFadyen, 2008).

The mineral deposit under consideration is oil sands in the McMurray formation. There are five main soil types associated with this deposit namely: 1) Muskeg/Peat 2) Pleistocene Unit 3) Clearwater Formation 4) McMurray Formation and 5) Devonian carbonates. A sketch of the soil profile of an oil sands formation can be seen in Figure 2.1. The oil sands mining system comprises of the removal of the overburden material and the mining of the McMurray formation. The overburden material comprises of muskeg/peat, the Pleistocene unit and the Clearwater formation. The muskeg/peat, which is barren is very wet in nature and therefore once the vegetation cover is removed, it is left for about 2 to 3 years to dry, making it easier to handle during stripping. This material is stockpiled for future reclamation works which is required for all disturbed landscapes. The mining of the Pleistocene and Clearwater formations, which is classified as waste, is to enable the exposure of the ore bearing McMurray formation. Some of this material is also used in the construction of dykes and roads required for the operation. The dyke construction is for the development of the tailings dam constructed either in the pit or elsewhere.

The classification of the oil sands material is basically driven by economic, technical and regulatory requirements (Dilay, 2001). The geotechnical requirement for dyke construction material varies depending on the dyke design configuration and location of the material within the dyke. The dyke construction material required from the oil sands mining operation (overburden and interburden) must have fines content less than approximately 50%. This type of material contains some amount of clays such as kaolinite, illite, chlorite and smectite (Wik et al., 2008) required as a binding material for improving the stability of the dykes. The waste from the Pleistocene and Clearwater formation is therefore classified based on the fines content. Material with percentage fines less than 50% is classified as dyke material which is required for dyke construction and that with fines more than 50% is classified as waste.

The mining of the oil bearing McMurray formation follows after the mining of the overburden material. By the regulatory and technical requirements, the mineable oil sand grade should be about 7% bitumen content (Dilay, 2001; Masliyah, 2010). All material satisfying this requirement is classified as ore and otherwise as waste. The ore is sent directly to the processing plant for bitumen extraction. This class of waste also known as interburden is reclassified based on the fines content. The material with fines content less than 50% is classified as dyke material and that with fines more than 50% is classified as waste. It is important to note that this material classification system is dynamic and can vary from one mine to another. The criteria may change depending on the grade distribution of the orebody under consideration. Cash flow analysis can also be used to classify the different material types.

3.3 Conceptual Mining Model

The key drivers for oil sands mine planning are the provision of a processable blend of ore at the required grade and the provision of tailings containment at the right time. Figure 3.2 shows a conceptual mining model, consistent with practical oil sands mining and waste management, used to illustrate how the MILGP production scheduling model works. The mining model is made up of an oil sands deposit area which is to be mined and simultaneously used as an in-pit tailings storage area as mining progresses in a specified direction and the in-pit tailings dyke footprints are released. Each oil sands mining-cut is made up of ore, OI dyke material and waste. After processing the ore to extract bitumen, two main types of tailings are produced; fine and coarse tailings. The coarse tailings, also referred to as TCS dyke material, and OI dyke material are used in the construction of dykes for tailings facilities. The fine tailings form the slurry which needs to be contained in the tailings facilities.

These tailings slurry have a wide range of environmental impacts causing public concerns and its management will continue to determine the sustainable mining of oil sands resources. Some of the public concerns (environmental impacts) include (Devenny, 2009):

- Large scarred areas
- Seepage and potential water contamination
- Trapping of birds and destruction of aquatic life
- Fugitive emissions
- Risk of a tailings dam failure
- Return of the land to traditional use
- Lack of progressive reclamation
- Intergenerational transfer of liability

Having an effective waste disposal planning system ensures that appropriate dyke materials and tailings storage areas are made available at the right time. This enables the maximum use of in-pit tailings facilities resulting in low-footprint tailings containment. Dyke materials needed to support engineered dyke designs can be effectively planned for and this will help in reducing the public concerns.

3.3.1 Tailings Storage Management Strategy

Each tonne of ore is made up of bitumen, fines, sand, and water. Using the oil sands extraction process ore volume changes on the path from ore to tailings (Devenny, 2009), the volume of tailings to be produced can be calculated to plan an appropriate storage management strategy. In the conceptual mining model, the tailings storage volume required and the total in-pit tailings facilities volume available is used to calculate the external tailings facility (ETF) volume needed to support the mining operation.

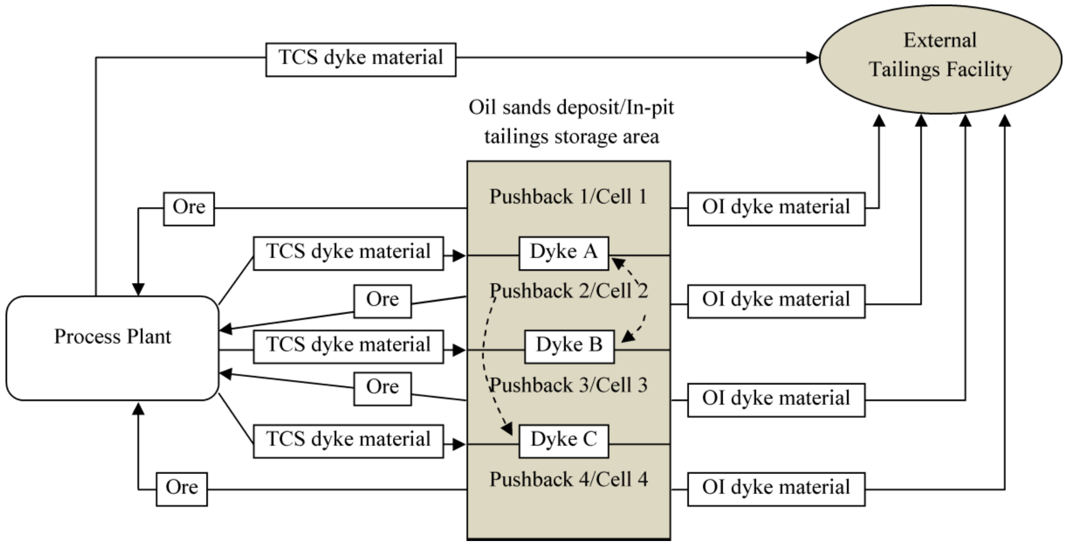

Figure 3.2: Conceptual mining model showing mining and waste management strategy modified after Askari-Nasab and Ben-Awuah (2011)

The oil sands deposit area was divided into pushbacks, which coincide with the areas required by tailings dam engineers to set up in-pit tailings facility cells. In the case of our illustrative example in Figure 3.2, the deposit covers an area of 8 km x 4 km with an average height of 75 m. Based on literature on oil sands mining operations with regards to standard sizes of ex-pit and in-pit tailings facility cells (Fort Hills Energy Corporation, 2009; Jackpine Mine, 2009; Kearl Oil Sands Project, 2009; Muskeg River Mine, 2009; Suncor Energy Incorporated Oil Sands, 2009; Syncrude Aurora North, 2009; Syncrude Aurora South, 2009; Syncrude Mildred Lake, 2009), it was decided to divide the mining area into four pushbacks which will result in four in-pit cells as shown in Figure 3.2. Each cell will have approximate dimensions of 2 km x 4 km x 75 m except cells 1 and 4. The mining operation will stay ahead of dyke construction by about 100 m resulting in cell 1 having a size of 1.9 km x 4 km x 75 m and cell 4 having a size of 2.1 km x 4 km x 75 m. It is assumed that mining will start in pushback 1 and progress south. During the mining of pushback 1, all IO and TCS dyke material will be sent to the ETF for the construction of the ETF dyke. Fluid fine tailings produced from pushback 1 will be sent to the ETF after the key trench and starter dyke construction is completed. Once mining of pushback 1 is completed, the dyke ‘A’ footprint required to construct cell 1 becomes available. OI and TCS dyke material from pushback 2 will be used for the construction of dyke ‘A’ to enable in-pit tailings storage to start in cell 1.

As mining progresses to pushbacks 3 and 4, the OI and TCS dyke material produced can be used to construct dykes ‘B’ and ‘C’ to make available cells 2 and 3, respectively, for tailings storage. Any excess OI and TCS dyke material can be used for other purposes like road construction, sand capping, and fines trapping as in non-segregating tailings. It is assumed that cell 4 will not be available for tailings storage until the end of the mine life; therefore it was not used for the volume balance calculations in the tailings storage management strategy. Table 3.1 shows estimates from the balancing of tailings storage requirements for the conceptual mining model. From the in-pit cell volumes generated for cells 1, 2, and 3, the required capacity of the ETF can be calculated and designed. The ETF was designed to cover an area of 1,600 ha with a height of 60 m resulting in a 13% excess containment capacity. The freeboard used for the designs is 5 m.

Table 3.1: Estimates for tailings storage requirements for the conceptual mining model

Material type	Oil sands deposit (Mtonnes)	Available dyke material (Mm^3)	Tailings/Waste produced (Mm^3)	Cells/ETF designed capacity (Mm^3)
Ore	2792.5	-	2251.1	Cell 1: 532
OI dyke	1697.8	797.6	-	Cell 2: 560
TCS dyke	2110.0	975.0	-	Cell 3: 560
Waste	375.9	-	179.0	ETF: 880

This tailings storage management strategy is based on the assumption that, all the available ore will be mined and processed. After the optimization of the production schedule, the actual mined ore tonnes can be used to reassess the tailings storage management strategy and appropriate modifications made. Further analysis of the conceptual mining model was done by starting the mining operation in pushback 4 and progressing north.

3.3.2 Conceptual Dykes’ Designs

Simplified conceptual dyke designs were made for all the dykes and used as the basis for OI and TCS dyke material scheduling in all pushbacks. It was assumed that each dyke is made up of a key trench, a starter dyke and the main dyke as shown in Figure 3.3. The key trench and starter dyke will be constructed using OI dyke material and the main dyke will be constructed using TCS dyke material. Once construction of the key trench and starter dyke is complete, the tailings facility can be used whiles construction of the main dyke progresses. In line with the geology of the McMurray formation, it was assumed that the ETF dyke will be constructed, possibly, on a weak foundation and the in-pit cell dykes will be constructed on good foundation, thus requiring different side slopes. The side slope for the in-pit dykes is 4:1 while that of the ETF dykes is 9:1. Table 3.2 shows the designed material requirements for the main dyke, starter dyke, and key trench at various destinations. The estimates are the minimum material required at the various destinations for dyke construction and any excess material can be used for other purposes.

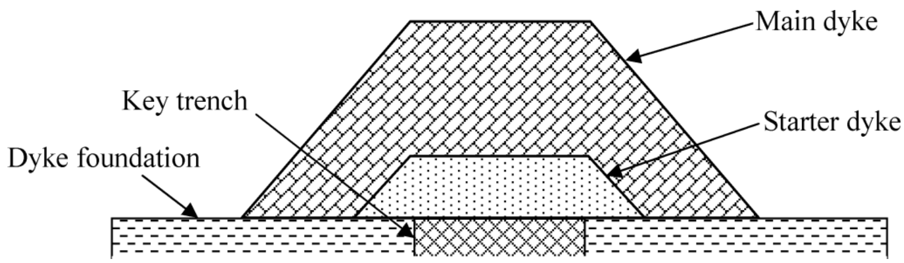

Figure 3.3: Schematic diagram showing cross section of a dyke (Askari-Nasab and Ben-Awuah, 2011)

Table 3.2: Material requirements for dykes at different locations

Dyke location	OI and TCS dyke material required (Mm^3)		
	Key trench	Starter dyke	Main dyke
ETF dyke	1.96	20.58	507.63
Dykes A+B+C	1.38	10.80	304.95

3.4 Orebody Block Modeling, some Assumptions, and Block Clustering

In long-term mine planning, one of the significant steps in the planning process is orebody block modeling. This is made up of the geologic and economic block models which serve as the backbone that drives the activities of the mine throughout its life (Hustrulid and Kuchta, 2006). It is assumed that the blocks within the block model are made of smaller regions known as parcels. A parcel is part of a block for which the rock-type, tonnage and element content are known.

A block can be made up of zero or more parcels and the total tonnage of the parcels may sum up to the block tonnage or it may be less. The difference, which is waste of unknown rock-type, is known as undefined waste. Neither the location nor the shape of a parcel within a block is defined but the spatial location of each block is defined by the coordinates of its center. Based on the ore tonnage and the grade in each block, the quantity of contained mineral are calculated (Askari-Nasab and Awuah-Offei, 2009; Gemcom Software International Inc., 2012). It is assumed that the orebody will be extracted using open pit mining techniques and a classical ultimate pit limit design will be generated based on the graph algorithm (Lerchs and Grossmann, 1965; Hustrulid and Kuchta, 2006). This pit outline contains reserves that maximize the profit. As demonstrated by Askari-Nasab and Awuah-Offei (2009), the ultimate pit limit generated directly when an optimal long-term scheduling algorithm is used will become a subset of the conventional ultimate pit limit that is generated using the Lerchs and Grossman's algorithm (Lerchs and Grossmann, 1965). With this basis, the process of finding the optimal long-term strategic production schedule will be divided into two steps: 1) determine the ultimate pit limit, and 2) generate a production schedule within the ultimate pit limit.

One of the main problems associated with finding the optimal long-term production schedule is that, the size of the problem grows exponentially as the number of blocks increases (Askari-Nasab and Awuah-Offei, 2009) resulting in insufficient computer memory during optimization. This is caused by an increase in the number of decision variables and constraints resulting mainly from the block mining precedence. An efficient way of dealing with this problem is by applying a clustering technique. Clustering is a technique used for aggregating blocks in a block model. In the clustering algorithm used in this research, blocks within the same level or mining bench are grouped into clusters based on the attributes: location, rock-type, and grade distribution. These clusters of blocks are referred to as mining-cuts and they have similar attribute definitions to that of the blocks such as coordinates representing the spatial location of the mining-cut. The clustering algorithm used for this research is a fuzzy logic clustering algorithm and hierarchical clustering algorithm (Kaufman and Rousseeuw, 1990; Askari-Nasab and Awuah-Offei, 2009; Tabesh and Askari-Nasab, 2011).

3.5 MILGP Model for OSLTPP and Waste Management

The OSLTPP and waste management problem is to find the time and sequence of extraction of ore, dyke material and waste mining-cuts to be removed from pre-defined open pit outlines and their respective destinations over the mine life, so that the NPV of the operation is maximized and dyke construction cost is minimized. In general, the MILGP formulation is for multiple material types and destinations as well as pushbacks which ties into the waste management strategy for oil sands operations. The production schedule is subject to a variety of technical, physical and economic goals and constraints which enforce mining extraction sequence, mining and dyke construction capacities and blending requirements. The notations used in the formulation of the OSLTPP and waste management problem have been classified as sets, indices, subscripts, superscripts, parameters and decision variables as outlined in the list of nomenclature.

3.5.1 Modeling of Economic Mining-Cut Value

The summary of economic data for each mining-cut known as economic mining-cut value is based on ore parcels within mining-cuts which could be mined selectively. The economic mining-cut value is a function of the value of the mining-cut based on the processing destination and the costs incurred in mining from a designated location and processing, and dyke construction at a specified destination. The cost of dyke construction is also a function of the location of the tailings facility being constructed and the type and quantity of dyke material used. The discounted economic mining-cut value for mining-cut k is equal to the discounted revenue obtained by selling the final product contained in mining-cut k minus the discounted cost involved in mining mining-cut k as waste minus the extra discounted cost of mining OB and IB dyke material, and generating TCS dyke material from mining-cut k for a designated dyke construction destination. This can be summarized by Equations (3.1) to (3.6). The discounted economic mining-panel value is the sum of the discounted economic mining-cut values of the mining-cuts belonging to that mining-panel.

Discounted economic mining-cut value = discounted revenue - discounted costs

$$d_k^{u,t} = v_k^{u,t} - q_k^{a,t} - p_k^{u,t} - m_k^{u,t} - h_k^{u,t} \tag{3.1}$$

The parameters in Equation (3.1) can be defined by Equations (3.2) to (3.6).

$$v_k^{u,t} = \sum_{e=1}^{E} o_k \times g_k^e \times r^{u,e} \times \left(p^{e,t} - cs^{e,t} \right) - \sum_{e=1}^{E} o_k \times cp^{u,e,t} \tag{3.2}$$

$$q_k^{a,t} = \left(o_k + d_k + n_k + w_k \right) \times cm^{a,t} \tag{3.3}$$

$$p_k^{u,t} = d_k \times ck^{u,t} \tag{3.4}$$

$$m_k^{u,t} = n_k \times cb^{u,t} \tag{3.5}$$

$$h_k^{u,t} = l_k \times ct^{u,t} \tag{3.6}$$

3.5.2 The MILGP Model Objective Functions

The objective functions of the MILGP model for OSLTPP and waste management can be formulated as: 1) maximizing the NPV of the mining operation, 2) minimizing the dyke construction cost for the waste management plan, and 3) minimizing the deviations from the set goals. The concepts presented in Askari-Nasab and Ben-Awuah (2011) was used as the starting point of this development. In implementing the MILGP model, the size of the mining-cuts used for production scheduling must be carefully selected to ensure that it is comparable to the selective mining units of the operation in practice. The formulation uses continuous decision variables, $y_p^{a,t}$, $x_k^{u,t}$, $z_k^{u,t}$, $c_k^{u,t}$, and $s_k^{u,t}$ to model mining and processing requirements, and OB, IB and TCS dyke material requirements respectively, for all mining locations and processing and dyke construction destinations. Using continuous decision variables allows for fractional extraction of mining-panels and mining-cuts in different periods for different locations and destinations. Continuous negative deviational variables, $d_1^{-,a,t}$, $d_2^{-,u,t}$, $d_3^{-,u,t}$, $d_4^{-,u,t}$

and $d_5^{-,u,t}$ have been defined to support the goal functions that control mining, processing, OB, IB and TCS dyke material, for all mining locations and processing and dyke construction destinations. The deviational variables provide a continuous range of units (tonnes) that the optimizer can choose from to satisfy the set goals. In the objective function, these deviational variables are minimized. No positive deviational variables were defined for the goal functions because any material required to be mined in excess of the goals will be sent to the waste dump which is comparatively less costly. The objective function also contains deviational penalty cost and priority (PP) parameters. The deviational penalty cost parameters, a_1, a_2, a_3, a_4, and a_5, penalizes the NPV for any deviation from the set goals. The priority parameters P_1, P_2, P_3, P_4 and P_5 are used to place emphasis on the goals that are more important. The PP parameters are set up to penalize the NPV if the set goals are not met as well as the most important goal. The model assumes that there exists a pre-emptive priority structure among the goals and this can be changed depending on the requirements of the mine management and aim of optimization.

When setting up these parameters, the planner needs to monitor how continuous mining proceeds period by period and the uniformity of tonnages mined per period; as well as the corresponding NPV generated, to keep track of how parameter changes affect these key performance indicators. In some scenarios, the limit for setting the PP parameters depends on the extent to which the planner wants to trade off NPV to meet the set goals. A higher PP parameter may enforce a goal to be met whilst reducing the NPV of the operation. A case showing this trend has been analyzed in Chapter 5. In general, the magnitude of the PP parameters should be calibrated based on the objectives of management. More weight should be assigned to a goal that has a higher priority for the management.

The three objective functions of the MILGP model for OSLTPP and waste management are represented by Equations (3.7) to (3.9) respectively.

$$Max\sum_{a=1}^{A}\sum_{j=1}^{J}\sum_{u=1}^{U}\sum_{t=1}^{T}\left(\sum_{\substack{k\in B_p\\ p\in B_j}}\left(v_k^{u,t}\times x_k^{u,t}-q_p^{a,t}\times y_p^{a,t}\right)\right) \tag{3.7}$$

$$Min\sum_{a=1}^{A}\sum_{j=1}^{J}\sum_{u=1}^{U}\sum_{t=1}^{T}\left(\sum_{\substack{k\in B_p\\ p\in B_j}}\left(p_k^{u,t}\times z_k^{u,t}+m_k^{u,t}\times c_k^{u,t}+h_k^{u,t}\times s_k^{u,t}\right)\right) \tag{3.8}$$

$$Min\sum_{a=1}^{A}\sum_{j=1}^{J}\sum_{u=1}^{U}\sum_{t=1}^{T}\left(\sum_{\substack{k\in B_p\\ p\in B_j}}\begin{bmatrix}P_1\left(a_1d_1^{-,a,t}\right)+P_2\left(a_2d_2^{-,u,t}\right)+P_3\left(a_3d_3^{-,u,t}\right)+\\ P_4\left(a_4d_4^{-,u,t}\right)+P_5\left(a_5d_5^{-,u,t}\right)\end{bmatrix}\right) \tag{3.9}$$

Equations (3.7) to (3.9) can be combined as a single objective function formulated as in Equation (3.10);

$$Max\sum_{a=1}^{A}\sum_{j=1}^{J}\sum_{u=1}^{U}\sum_{t=1}^{T}\left(\sum_{\substack{k\in B_p\\ p\in B_j}}\begin{bmatrix}\left(v_k^{u,t}\times x_k^{u,t}-q_p^{a,t}\times y_p^{a,t}\right)-\\ \left(p_k^{u,t}\times z_k^{u,t}+m_k^{u,t}\times c_k^{u,t}+h_k^{u,t}\times s_k^{u,t}\right)-\\ \left(\begin{matrix}P_1\left(a_1d_1^{-,a,t}\right)+P_2\left(a_2d_2^{-,u,t}\right)+P_3\left(a_3d_3^{-,u,t}\right)+\\ P_4\left(a_4d_4^{-,u,t}\right)+P_5\left(a_5d_5^{-,u,t}\right)\end{matrix}\right)\end{bmatrix}\right) \tag{3.10}$$

subject to the goal functions and constraints in sections 3.5.3 to 3.5.7.

3.5.3 The MILGP Model Goal Functions

In the proposed model, the goals to be achieved are the mining and processing targets, and OB, IB and TCS dyke materials targets in tonnes for all mining locations, and processing and dyke construction destinations. These goal functions are represented by Equations (3.11) to (3.15) respectively.

$$\sum_{j=1}^{J}\left(\sum_{p\in B_j}\left(o_p+d_p+n_p+w_p\right)\times y_p^{a,t}\right)+d_1^{-,a,t}=T_m^{a,t} \tag{3.11}$$

$$\sum_{p=1}^{P}\left(\sum_{k\in B_p}\left(o_k\times x_k^{u,t}\right)\right)+d_2^{-,u,t}=T_{pr}^{u,t} \tag{3.12}$$

$$\sum_{p=1}^{P}\left(\sum_{k\in B_p}\left(d_k \times z_k^{u,t}\right)\right)+d_3^{-,u,t}=T_d^{u,t} \tag{3.13}$$

$$\sum_{p=1}^{P}\left(\sum_{k\in B_p}\left(n_k \times c_k^{u,t}\right)\right)+d_4^{-,u,t}=T_n^{u,t} \tag{3.14}$$

$$\sum_{p=1}^{P}\left(\sum_{k\in B_p}\left(l_k \times s_k^{u,t}\right)\right)+d_5^{-,u,t}=T_l^{u,t} \tag{3.15}$$

Equation (3.11) represents the mining goal function which ensures the total amount of ore, dyke material and waste mined in each period from all mining locations equals the total available equipment capacity with a defined acceptable deviation. This goal is controlled by the continuous variable $y_p^{a,t}$. Equation (3.11) together with Equations (3.12) to (3.15) may be used in achieving a uniform stripping ratio over the mine life. A production schedule with a constant stripping ratio ensures that the mining equipment fleet size required is matched to material movement targets. To establish a proper production rate, among other things, multiple scenarios of yearly ore production rates must be investigated and the one with a uniform mill feed and the highest NPV considered. A variable mining goal that allows the mine planner to use different mining capacities throughout the mine life can be implemented with this model. This allows for consideration of future expansion projects either by owner or contract mining which in most cases increases profitability considerably. The set mining goal is a function of the ore reserve, targeted mine-life, designed processing capacity, overall stripping ratio, and the available capital for mining fleet acquisition.

Equation (3.12) represents the processing goal function which controls the mill feed. This goal helps the mine planner to provide a uniform feed throughout the mine life resulting in an effectively integrated mine-to-mill operation. In practice, the processing goal must be set with minimal periodic deviations to ensure maximum utilization of the mill. Depending on the ore grade distribution of the orebody, the processing goal may not be achieved in some periods. In such cases, pre-stripping could be explored to provide a uniform mill feed. This amounts to forcing the optimizer to mine waste in the early periods so that when ore production starts, the plant feed supply will be uniform and consistent.

Equations (3.13), (3.14) and (3.15) represent the dyke material goal functions which control dyke construction scheduling. These goals enable the mine planner to schedule the required dyke materials for all dyke construction destinations. The TCS dyke material generated from the processing plant is directly dependent on the mill feed. The schedules generated from the MILGP model give the planner good control over dyke material and provide a robust platform for effective dyke construction planning and tailings storage management. Movement of dyke material and dyke construction scheduling can be well integrated with the mining fleet management plan. Thus, timely tailings containment areas can be created for the storage of fluid fine tailings. In oil sands mining, being able to efficiently plan the waste management strategy results in a more profitable and sustainable operation.

3.5.4 The MILGP Model Grade Blending Constraints

The MILGP model grade blending constraints control the grade of ore bitumen, ore fines and interburden fines in the mined material for all processing and dyke construction destinations. These constraints are formulated by Equations (3.16) to (3.21).

$$\sum_{p=1}^{P}\sum_{k\in B_p} g_k^e \times o_k \times x_k^{u,t} - \overline{g}^{u,t,e}\sum_{p=1}^{P}\sum_{k\in B_p} o_k \times x_k^{u,t} \le 0 \tag{3.16}$$

$$\sum_{p=1}^{P}\sum_{k\in B_p} g_k^e \times o_k \times x_k^{u,t} - \underline{g}^{u,t,e}\sum_{p=1}^{P}\sum_{k\in B_p} o_k \times x_k^{u,t} \ge 0 \tag{3.17}$$

$$\sum_{p=1}^{P}\sum_{k\in B_p} f_k^e \times o_k \times x_k^{u,t} - \overline{f}^{u,t,e}\sum_{p=1}^{P}\sum_{k\in B_p} o_k \times x_k^{u,t} \le 0 \tag{3.18}$$

$$\sum_{p=1}^{P}\sum_{k\in B_p} f_k^e \times o_k \times x_k^{u,t} - \underline{f}^{u,t,e}\sum_{p=1}^{P}\sum_{k\in B_p} o_k \times x_k^{u,t} \ge 0 \tag{3.19}$$

$$\sum_{p=1}^{P}\sum_{k\in B_p} f_k^d \times n_k \times c_k^{u,t} - \overline{f}^{u,t,d}\sum_{p=1}^{P}\sum_{k\in B_p} n_k \times c_k^{u,t} \le 0 \tag{3.20}$$

$$\sum_{p=1}^{P}\sum_{k\in B_p} f_k^d \times n_k \times c_k^{u,t} - \underline{f}^{u,t,d}\sum_{p=1}^{P}\sum_{k\in B_p} n_k \times c_k^{u,t} \geq 0 \tag{3.21}$$

Equations (3.16) to (3.19) represent inequality constraints which monitor the mill feed quality. They specify the limiting grade requirements for ore bitumen and ore fines for processing. The objective of blending in production scheduling is to mine in a way that the run-of-mine materials meet the quality and quantity specification of the processing plant and dyke construction destinations. As more detailed planning is done in the short term, the planner is more concerned with reducing the mill head grade variability and hence blending of mill feed material becomes critical. The mill head grade is a function of the ore grade distribution, processing plant design and mine cash flow requirements.

Equations (3.20) and (3.21) represent inequality constraints that control the IB dyke material quality. They specify the limiting grade requirements for IB dyke material fines for dyke construction. The designs for dykes at different destinations come with specific dyke material requirements. Among other things, the dyke material quality defines the integrity of the tailings containment facilities constructed. Since in oil sands mining it is required by law to store large volumes of tailings with less environmental footprints, waste management directly impacts profitability and sustainability (McFadyen, 2008).

3.5.5 The MILGP Model Variables Control Constraints

In the proposed model, the variables control constraints monitor the logics of the variables that define mining, processing, dyke materials and goal deviations to ensure they are within acceptable ranges. These variables control constraints are represented by Equations (3.22) to (3.28).

$$\sum_{u=1}^{U}\sum_{k\in B_p}\left(o_k x_k^{u,t} + d_k z_k^{u,t} + n_k c_k^{u,t}\right) \leq \sum_{a=1}^{A}\sum_{p\in B_j}\left(y_p^{a,t}\left(o_p + d_p + n_p + w_p\right)\right) \tag{3.22}$$

$$\sum_{u=1}^{U} s_k^{u,t} \leq \sum_{u=1}^{U} x_k^{u,t} \tag{3.23}$$

$$\sum_{u=1}^{U}\sum_{t=1}^{T} x_k^{u,t} \leq 1 \tag{3.24}$$

$$\sum_{u=1}^{U}\sum_{t=1}^{T} y_p^{u,t} \leq 1 \tag{3.25}$$

$$\sum_{u=1}^{U}\sum_{t=1}^{T} z_k^{u,t} \leq 1 \tag{3.26}$$

$$\sum_{u=1}^{U}\sum_{t=1}^{T} c_k^{u,t} \leq 1 \tag{3.27}$$

$$\sum_{u=1}^{U}\sum_{t=1}^{T} s_k^{u,t} \leq 1 \tag{3.28}$$

Equation (3.22) outlines inequalities that ensure that the total material mined from mining-panel p in any given scheduling period from any mining location exceeds or is equal to the sum of the ore and OB and IB dyke material mined from the mining-cuts belonging to that mining-panel. It is assumed that when a mining-panel is scheduled, all the mining-cuts, blocks or parcels within the mining-panel are extracted uniformly. Equation (3.23) states that the fraction of TCS dyke material produced in each period should be less or equal to the fraction of ore mined for all destinations. This constraint manages the direct relationship between ore and TCS dyke material. TCS dyke material is only generated when ore is processed for bitumen extraction. Equations (3.24) to (3.28) ensure that the total fractions of mining-panel p or mining-cut k mined, or TCS dyke material produced and sent to all destinations in all periods is less or equal to one. This keeps track of the different portions of mining-panels and mining-cuts that are scheduled for various destinations.

3.5.6 The MILGP Model Mining-Panels Extraction Precedence Constraints

The mining-panels extraction precedence in the MILGP model are defined by Equations (3.29) to (3.33). Binary integer decision variable, $b_p^t \in [0,1]$ is used to control precedence of mining-panels extraction. b_p^t is equal to one if the extraction of mining-panel p has started by or in period t, otherwise it is zero.

These equations together implement the vertical and horizontal mining-panel extraction sequence.

$$b_p^t - \sum_{a=1}^{a}\sum_{i=1}^{t} y_s^{a,i} \le 0 \qquad s \in C_p(L) \tag{3.29}$$

$$b_p^t - \sum_{a=1}^{a}\sum_{i=1}^{t} y_r^{a,i} \le 0 \qquad r \in M_p(Z) \tag{3.30}$$

$$b_p^t - \sum_{a=1}^{a}\sum_{i=1}^{t} y_h^{a,i} \le 0 \qquad h \in B_j(H) \tag{3.31}$$

$$\sum_{a=1}^{a}\sum_{i=1}^{t} y_p^{a,i} - b_p^t \le 0 \tag{3.32}$$

$$b_p^t - b_p^{t+1} \le 0 \tag{3.33}$$

For each mining-panel *p*, Equations (3.29) to (3.33) check the set of immediate predecessor mining-panels that must be mined prior to mining mining-panel *p* for all periods and from all locations. This precedence relationship ensures that: 1) all the immediate predecessor mining-panels above the current mining-panel *p* are extracted prior to extraction of mining-panel *p*; represented by the set $C_p(L)$, 2) all the immediate predecessor mining-panels preceding the current mining-panel *p* in the horizontal mining direction are extracted prior to extraction of mining-panel *p*; represented by the set $M_p(Z)$, and 3) all the mining-panels within the immediate predecessor mining phase that precedes the current mining phase, *j* are extracted prior to extraction of mining-panel *p* in the current mining phase; represented by the set $B_j(H)$. The graphical representations of the sets $C_p(L)$, $M_p(Z)$, and $B_j(H)$ can be found in Chapter 4 as Figure 4.1 and Figure 4.3.

Specifically, Equations (3.29) to (3.31) ensure that all the immediate predecessor mining-panels which are members of $C_p(L)$, $M_p(Z)$, and $B_j(H)$ are mined prior to mining mining-panel *p*. Equation (3.32) checks that extraction of mining-panel *p* can start only when the mining-panel has not been extracted before. Equation (3.33) monitors that once the extraction of a mining-panel starts in a period, this mining-panel is available for extraction during the subsequent periods. These equations work together to ensure mining proceeds in the specified horizontal mining direction as the mine goes deeper.

Implementing the mining operation sequencing at mining-panel resolution helps reduce the number of binary variables to be solved for during optimization. It also ensures practical mining sequencing with reduced number of required drop-cuts ensuring efficient equipment utilization. Using mining-cuts to schedule for processing plant and dyke construction also allows for flexible and practical ore and dyke material selective mining that supports our preferred run-of-mine blending strategy.

3.5.7 The MILGP Model Non-Negativity and Integrality Constraints

The MILGP model non-negativity constraints monitor the decision variables to ensure they do not take negative values. The integrality constraint also ensures that the decision variable, b that controls the mining precedence stays integral.

$$d_1^{-,a,t},\ d_2^{-,u,t},\ d_3^{-,u,t},\ d_4^{-,u,t},\ d_5^{-,u,t} \geq 0 \tag{3.34}$$

$$y_p^{a,t},\ x_k^{u,t},\ z_k^{u,t},\ c_k^{u,t},\ s_k^{u,t} \geq 0 \tag{3.35}$$

Equation (3.34) defines the non-negativity of the deviational variables defined to support the goal functions. Equation (3.35) defines the non-negativity of the mining, processing and dyke material decision variables.

3.6 Summary and Conclusions

In summary, the modeling effort, mathematical formulations and theoretical architecture required to integrate the oil sands long-term mine and waste disposal plan has been discussed in this chapter. This integrated mine plan was formalized in an optimization framework using a MILGP mine planning model. The interactions and interrelations of the various processes and procedures in an oil sands conceptual mining model were discussed. The MILGP framework captures the objective of (i) maximizing the net present value of the oil sands mining operation, which includes developing the geologic and economic block models, applying the conceptual mine planning model and generating a production schedule; and (ii) minimizing the waste management cost which consist of the tailings storage management strategy, the waste disposal strategy, the conceptual dyke design and generating a dyke material schedule.

In order to achieve these objectives, the theoretical modeling framework established included the necessary assumptions and limitations based on mine planning and optimization methods. This framework establishes the important aspects of the MILGP model architecture. The model is integrated into appropriate concepts, strategies and formulations for further application analysis and numerical development.

CHAPTER 4

MILGP FORMULATION IMPLEMENTATION

4.1 Background

The mathematical formulations and theoretical architecture development resulted in the MILGP model framework discussed in Chapter 3. This chapter focuses on the development and application of numerical models using a set of procedural instructions and methods in order to achieve the research objectives. The formulation and application of the MILGP model begins with considering its main subcomponents. The three basic subcomponents are: the objective function, the goal functions and the constraints. With the conceptual mining model, these components interact with the economic block model in an optimization framework to achieve the objectives. The conceptual mining model is used in managing the production and waste disposal requirements. The result is an integrated oil sands mine and waste management plan that creates value and is sustainable.

The MILGP formulation development starts with identifying the appropriate numerical modeling platform that can be used in setting up the problem and solving it in a reasonable time. Matlab (Mathworks Inc., 2011) is used as the numerical modeling platform and Tomlab/CPLEX (Holmström, 2009) as the optimization solver. The MILGP model user input interface enables the setting up of the block model data, production and dyke material requirements as well as parameters defining the waste management strategy. The generalized structure used by Tomlab/CPLEX in solving a MILP problem is identified and used as the basis for the numerical modeling of the MILGP formulation. With this in mind, Matlab is used in creating the numerical model of the three main subcomponent of the MILGP formulation to be passed on to Tomlab/CPLEX for optimization. Further numerical modeling techniques in implementing an efficient practical MILGP model for oil sands long term production planning and waste management are discussed. Section 4.2 discusses the numerical implementation of the MILGP model and section 4.3 explains techniques deployed to make the MILGP model efficient. This chapter concludes in section 4.4.

4.2 Numerical Modeling

Using mathematical programming models like the MILGP formulation for mine optimization usually result in large-scale optimization problems. A commercial optimization solver capable of handling such problems is ILOG CPLEX (Bixby, 2009). This optimization solver uses branch and cut algorithm and makes the solving of large-scale problems possible for the MILGP model. Branch and cut is a method of combinatorial optimization for solving integer programming problems. This algorithm is a hybrid of branch-and-bound and cutting plane methods (Horst and Hoang, 1996; Wolsey, 1998).

The MILGP model solver in this research is Tomlab/CPLEX (Holmström, 2009). The user sets an optimization termination criterion in CPLEX known as the gap tolerance (EPGAP). The EPGAP, which is a measure of optimality, sets an absolute tolerance on the gap between the best integer objective and the objective of the best node remaining in the branch and cut algorithm. It instructs CPLEX to terminate once a feasible integer solution within the set EPGAP has been found.

The numerical modeling techniques for the MILGP formulation together with strategies in developing a MILGP problem that can be compiled efficiently are discussed here. This includes compiling the matrices for the objective function, goal functions and constraints. These matrices are compiled using the format as outlined in the Tomlab/CPLEX user's guide (Holmström, 2009).

4.2.1 General Formulation

Tomlab generalizes an MILP problem in the form stated by Equations (4.1) to (4.3). These were subsequently reorganized to the generalized structure of a MILGP problem.

$$\min_{r} f(r) = \mathbf{c}^T.\mathbf{r} \tag{4.1}$$

subject to:

$$\mathbf{r}_L \leq \mathbf{r} \leq \mathbf{r}_U \tag{4.2}$$

$$\mathbf{b}_L \le \mathbf{A.r} \le \mathbf{b}_U \tag{4.3}$$

where

- $\mathbf{c}$ is the linear objective function coefficients of the MILP model; a vector $j \times 1$.
- $\mathbf{r}$ is the decision variables of the MILP model; a vector $j \times 1$.
- $\mathbf{r}_L$ and $\mathbf{r}_U$ defines the lower and upper bounds on the decision variables; vectors $j \times 1$.
- $\mathbf{A}$ represents the coefficients of the constraints of the MILP model; a matrix $i \times j$.
- $\mathbf{b}_L$ and $\mathbf{b}_U$ defines the lower and upper bounds on the constraints; vectors $j \times 1$. Equality constraints are defined by setting the lower bounds equal to the upper bounds for the respective elements of vectors $\mathbf{b}_L$ and $\mathbf{b}_U$.

4.2.2 The MILGP Model Objective Function

The objective of the OSLTPP and waste management problem as defined by Equations (3.7), (3.8), and (3.9) are to: 1) maximize the NPV of the mining operation, 2) minimize dyke construction cost for the waste management plan, and 3) minimize the deviations from the set goals respectively. As shown by Equation (4.1), the general form of the MILP model in Tomlab is to minimize the objective function. Therefore the objective function coefficient vector for Equation (3.7), should be multiplied by a negative sign changing it to: minimize the –NPV of the mining operation. For notation simplification, the matrix vertical concatenation operator, ‘;’ is used. This operator creates a matrix or vector by concatenating them along the vertical dimension of the matrix or vector. The objective function of the MILGP model as represented by Equation (3.10), has a coefficient vector, $\mathbf{c}$, of size $\left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU\right) \times 1$ given by Equation (4.4). In this equation, *K* refers to the number of mining-cuts or mining-panels depending on the variable being set up.

$$\mathbf{c}^{\left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU\right) \times 1} = \left[\mathbf{0}; \mathbf{v}; \mathbf{q}; \mathbf{p}; \mathbf{m}; \mathbf{h}; \mathbf{P}_1\mathbf{a}_1; \mathbf{P}_2\mathbf{a}_2; \mathbf{P}_3\mathbf{a}_3; \mathbf{P}_4\mathbf{a}_4; \mathbf{P}_5\mathbf{a}_5\right] \quad (4.4)$$

where

- $dv \in \{1,...,DV\}$ are the decision variables in the objective function; $dn \in \{1,...,DN\}$ are the deviational variables in the objective function; For simplification, K is the number of mining-cuts and P is the number of mining-panels involved. These are used interchangeably depending on the variable under consideration.
- $\mathbf{0}$ is a $PT \times 1$ vector with all elements equal to zero; P is the maximum number of mining-panels in the model and T is the number of scheduling periods.
- $\mathbf{v}$ is a $KT \times 1$ vector holding the discounted economic values defined by Equation (3.2); K is the maximum number of mining-cuts in the model.
- $\mathbf{q}$ is a $PT \times 1$ vector holding the discounted mining costs shown by Equation (3.3); P is the maximum number of mining-panels in the model.
- **p, m, h** are each a $KTU \times 1$ vector holding the extra discounted cost of mining OB, IB and TCS dyke material respectively shown by Equations (3.4), (3.5) and (3.6); K is the maximum number of mining-cuts in the model; U is the number of dyke construction destinations.
- $\mathbf{P}_1\mathbf{a}_1$, $\mathbf{P}_2\mathbf{a}_2$, $\mathbf{P}_3\mathbf{a}_3$, $\mathbf{P}_4\mathbf{a}_4$, $\mathbf{P}_5\mathbf{a}_5$ are each a $TU \times 1$ vector holding the product of discounted penalty cost and priority parameters for deviating from the mining, processing, OB, IB and TCS dyke material targets respectively.

The objective function coefficient vector and constraints coefficient matrices have different units and order of magnitude. It therefore becomes important to transform them to unitless vectors and matrices. This is done by normalizing the vectors and matrices by dividing them by norm(s) of its multiplier vector(s). For generalization, we define $\overline{\mathbf{v}} = \mathbf{v}/\|\mathbf{v}\|$, where $\|\mathbf{v}\|$ is the norm of $\mathbf{v}$. The objective function coefficient vector will therefore be in the form $\mathbf{c} = \left[\mathbf{0}; \overline{\mathbf{v}}; \overline{\mathbf{q}}; \overline{\mathbf{p}}; \overline{\mathbf{m}}; \overline{\mathbf{h}}; \overline{\mathbf{P}_1\mathbf{a}_1}; \overline{\mathbf{P}_2\mathbf{a}_2}; \overline{\mathbf{P}_3\mathbf{a}_3}; \overline{\mathbf{P}_4\mathbf{a}_4}; \overline{\mathbf{P}_5\mathbf{a}_5} \right]$.

The decision variables vector, $\mathbf{r}$ is also made up of $\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU$ elements to be solved for in the MILGP model during optimization. This is illustrated by Equation (4.5).

$$\mathbf{r}^{\left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU\right)\times 1} = \left[\mathbf{b}; \mathbf{x}; \mathbf{y}; \mathbf{z}; \mathbf{c}; \mathbf{s}; \mathbf{d}_1; \mathbf{d}_2; \mathbf{d}_3; \mathbf{d}_4; \mathbf{d}_5 \right] \tag{4.5}$$

where

- $\mathbf{b}$ is a $PT \times 1$ vector holding the binary integer decision variables controlling the mining-panel extraction precedence; $b_p^t \in \{0,1\}$.
- $\mathbf{x}$ is a $KT \times 1$ vector holding the continuous decision variables representing the ore portion of mining-cut k to be extracted and processed at destination u in period t; $x_k^{u,t} \in [0,1]$.
- $\mathbf{y}$ is a $PT \times 1$ vector holding the continuous decision variables representing the portion of mining-panel p to be mined in period t from location a; $y_p^{a,t} \in [0,1]$.
- $\mathbf{z}$, $\mathbf{c}$, $\mathbf{s}$ are each a $KTU \times 1$ vector holding the continuous decision variables representing respectively the OB, IB and TCS dyke material portions of mining-cut k to be extracted and used for dyke construction at destination u in period t; $z_k^{u,t} \in [0,1]$, $c_k^{u,t} \in [0,1]$, and $s_k^{u,t} \in [0,1]$.
- $\mathbf{d}_1$, $\mathbf{d}_2$, $\mathbf{d}_3$, $\mathbf{d}_4$, $\mathbf{d}_5$ are each a $TU \times 1$ decision vector holding a continuous range of units (tonnes) representing the acceptable deviations from the mining, processing, OB, IB and TCS dyke material targets respectively.

4.2.3 The MILGP Model Goal Functions

We proceed to develop the numerical models for the equality goal functions represented by Equations (3.11) to (3.15). These functions define the mining, processing, OB, IB and TCS dyke material targets required during mining. Equality constraints are defined by setting the lower bounds equal to the upper bounds for each element of the boundary vectors.

4.2.3.1 The Mining Goal Function

The numerical model is represented by Equations (4.6) to (4.8), where $\mathbf{A}_1$ is the coefficient matrix and $\mathbf{b}_1$ is the boundary condition vector.

$$\mathbf{A}_1 \cdot \mathbf{r}+\mathbf{d}_1=\mathbf{b}_1 \tag{4.6}$$

$$\mathbf{A}_1^{T\times\left(\sum_{dv=1}^{DV} KTU+\sum_{dn=1}^{DN} TU\right)} = \begin{bmatrix} \mathbf{0}_1 & \mathbf{0}_1 & \overline{\mathbf{A}}_m & \mathbf{0}_1 & \mathbf{0}_1 & \mathbf{0}_1 & \overline{\mathbf{d}}_m & \mathbf{0}_1 & \mathbf{0}_1 & \mathbf{0}_1 & \mathbf{0}_1 \end{bmatrix} \tag{4.7}$$

$$\mathbf{b}_1^{T\times 1} = \begin{bmatrix} \overline{\mathbf{T}}_m \end{bmatrix} \tag{4.8}$$

where

- $\mathbf{A}_m$ is a $T \times PT$ matrix with elements defining the total tonnage of material in each mining-panel in each period.
- $\mathbf{d}_m$ is a $T \times T$ diagonal unit matrix allowing the acceptable defined mining goal deviation.
- $\mathbf{d}_1$ is a $T \times 1$ coefficient decision variable vector of $\mathbf{d}_m$.
- $\mathbf{T}_m$ is a $T \times 1$ vector of the targeted mining goal.
- $\mathbf{0}_1$ is a zero matrix; the size depends on the decision variable.

4.2.3.2 The Processing Goal Function

The numerical model is represented by Equations (4.9) to (4.11), where $\mathbf{A}_2$ is the coefficient matrix and $\mathbf{b}_2$ is the boundary condition vector.

$$\mathbf{A}_2 \cdot \mathbf{r}+\mathbf{d}_2=\mathbf{b}_2 \tag{4.9}$$

$$\mathbf{A}_2^{T\times\left(\sum_{dv=1}^{DV} KTU+\sum_{dn=1}^{DN} TU\right)} = \begin{bmatrix} \mathbf{0}_2 & \overline{\mathbf{A}}_p & \mathbf{0}_2 & \mathbf{0}_2 & \mathbf{0}_2 & \mathbf{0}_2 & \mathbf{0}_2 & \overline{\mathbf{d}}_p & \mathbf{0}_2 & \mathbf{0}_2 & \mathbf{0}_2 \end{bmatrix} \tag{4.10}$$

$$\mathbf{b}_2^{T\times 1} = \begin{bmatrix} \overline{\mathbf{T}}_p \end{bmatrix} \tag{4.11}$$

where

- $\mathbf{A}_p$ is a $T \times KT$ matrix with elements defining the total tonnage of ore in each mining-cut in each period.
- $\mathbf{d}_p$ is a $T \times T$ diagonal unit matrix allowing the acceptable defined processing goal deviation.
- $\mathbf{d}_2$ is a $T \times 1$ coefficient decision variable vector of $\mathbf{d}_p$.
- $\mathbf{T}_p$ is a $T \times 1$ vector of the targeted processing goal.
- $\mathbf{0}_2$ is a zero matrix; the size depends on the decision variable.

4.2.3.3 The OB Dyke Material Goal Function

The numerical model is represented by Equations (4.12) to (4.14), where $\mathbf{A}_3$ is the coefficient matrix and $\mathbf{b}_3$ is the boundary condition vector.

$$\mathbf{A}_3 \cdot \mathbf{r} + \mathbf{d}_3 = \mathbf{b}_3 \tag{4.12}$$

$$\mathbf{A}_3^{UT\times\left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU\right)} = \begin{bmatrix} \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \overline{\mathbf{A}}_{ob}^{ETF} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \overline{\mathbf{d}}_{ob}^{ETF} & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \overline{\mathbf{A}}_{ob}^{dykeA} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \overline{\mathbf{d}}_{ob}^{dykeA} & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \overline{\mathbf{A}}_{ob}^{dykeB} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \overline{\mathbf{d}}_{ob}^{dykeB} & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \overline{\mathbf{A}}_{ob}^{dykeC} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \overline{\mathbf{d}}_{ob}^{dykeC} & \mathbf{0}_3 & \mathbf{0}_3 \end{bmatrix} \tag{4.13}$$

$$\mathbf{b}_3^{UT\times 1} = \begin{bmatrix} \overline{\mathbf{T}}_{ob}^{ETF} \\ \overline{\mathbf{T}}_{ob}^{dykeA} \\ \overline{\mathbf{T}}_{ob}^{dykeB} \\ \overline{\mathbf{T}}_{ob}^{dykeC} \end{bmatrix} \tag{4.14}$$

where

- $\mathbf{A}_{ob}^{ETF}$, $\mathbf{A}_{ob}^{dykeA}$, $\mathbf{A}_{ob}^{dykeB}$ and $\mathbf{A}_{ob}^{dykeC}$ are each a $T \times KT$ matrix with elements defining the total tonnage of OB dyke material in each mining-cut to be sent to ETF dyke, dyke A, dyke B and dyke C respectively in each period.
- $\mathbf{d}_{ob}^{ETF}$, $\mathbf{d}_{ob}^{dykeA}$, $\mathbf{d}_{ob}^{dykeB}$ and $\mathbf{d}_{ob}^{dykeC}$ are each a $T \times T$ diagonal unit matrix allowing the acceptable defined OB dyke material goal deviation for ETF dyke, dyke A, dyke B and dyke C destinations respectively.
- $\mathbf{d}_3$ is a $TU \times 1$ coefficient decision variable vector of $\mathbf{d}_{ob}^{u}$.
- $\mathbf{T}_{ob}^{ETF}$, $\mathbf{T}_{ob}^{dykeA}$, $\mathbf{T}_{ob}^{dykeB}$ and $\mathbf{T}_{ob}^{dykeC}$ are each a $T \times 1$ vector of the targeted OB dyke material goal defined for ETF dyke, dyke A, dyke B and dyke C destinations respectively.
- $\mathbf{0}_3$ is a zero matrix; the size depends on the decision variable.

4.2.3.4 The IB Dyke Material Goal Function

The numerical model is represented by Equations (4.15) to (4.17), where $\mathbf{A}_4$ is the coefficient matrix and $\mathbf{b}_4$ is the boundary condition vector.

$$\mathbf{A}_4 \cdot \mathbf{r} + \mathbf{d}_4 = \mathbf{b}_4 \tag{4.15}$$

$$\mathbf{A}_4^{UT \times \left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU \right)} =$$
$$\begin{bmatrix} \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \overline{\mathbf{A}}_{ib}^{ETF} & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \overline{\mathbf{d}}_{ib}^{ETF} & \mathbf{0}_4 \\ \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \overline{\mathbf{A}}_{ib}^{dykeA} & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \overline{\mathbf{d}}_{ib}^{dykeA} & \mathbf{0}_4 \\ \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \overline{\mathbf{A}}_{ib}^{dykeB} & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \overline{\mathbf{d}}_{ib}^{dykeB} & \mathbf{0}_4 \\ \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \overline{\mathbf{A}}_{ib}^{dykeC} & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \overline{\mathbf{d}}_{ib}^{dykeC} & \mathbf{0}_4 \end{bmatrix} \tag{4.16}$$

$$\mathbf{b}_4^{UT \times 1} = \begin{bmatrix} \overline{\mathbf{T}}_{ib}^{ETF} \\ \overline{\mathbf{T}}_{ib}^{dykeA} \\ \overline{\mathbf{T}}_{ib}^{dykeB} \\ \overline{\mathbf{T}}_{ib}^{dykeC} \end{bmatrix} \tag{4.17}$$

where

- $\mathbf{A}_{ib}^{ETF}$, $\mathbf{A}_{ib}^{dykeA}$, $\mathbf{A}_{ib}^{dykeB}$ and $\mathbf{A}_{ib}^{dykeC}$ are each a $T \times KT$ matrix with elements defining the total tonnage of IB dyke material in each mining-cut to be sent to ETF dyke, dyke A, dyke B and dyke C respectively in each period.
- $\mathbf{d}_{ib}^{ETF}$, $\mathbf{d}_{ib}^{dykeA}$, $\mathbf{d}_{ib}^{dykeB}$ and $\mathbf{d}_{ib}^{dykeC}$ are each a $T \times T$ diagonal unit matrix allowing the acceptable defined IB dyke material goal deviation for ETF dyke, dyke A, dyke B and dyke C destinations respectively.
- $\mathbf{d}_4$ is a $TU \times 1$ coefficient decision variable vector of $\mathbf{d}_{ib}^{u}$.
- $\mathbf{T}_{ib}^{ETF}$, $\mathbf{T}_{ib}^{dykeA}$, $\mathbf{T}_{ib}^{dykeB}$ and $\mathbf{T}_{ib}^{dykeC}$ are each a $T \times 1$ vector of the targeted IB dyke material goal defined for ETF dyke, dyke A, dyke B and dyke C destinations respectively.
- $\mathbf{0}_4$ is a zero matrix; the size depends on the decision variable.

4.2.3.5 The TCS Dyke Material Goal Function

The numerical model is represented by Equations (4.18) to (4.20), where $\mathbf{A}_5$ is the coefficient matrix and $\mathbf{b}_5$ is the boundary condition vector.

$$\mathbf{A}_5 \cdot \mathbf{r} + \mathbf{d}_5 = \mathbf{b}_5 \tag{4.18}$$

$$\mathbf{A}_5^{UT \times \left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU \right)} = \begin{bmatrix} \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \overline{\mathbf{A}}_{tcs}^{ETF} & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \overline{\mathbf{d}}_{tcs}^{ETF} \\ \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \overline{\mathbf{A}}_{tcs}^{dykeA} & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \overline{\mathbf{d}}_{tcs}^{dykeA} \\ \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \overline{\mathbf{A}}_{tcs}^{dykeB} & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \overline{\mathbf{d}}_{tcs}^{dykeB} \\ \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \overline{\mathbf{A}}_{tcs}^{dykeC} & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \mathbf{0}_5 & \overline{\mathbf{d}}_{tcs}^{dykeC} \end{bmatrix} \tag{4.19}$$

$$\mathbf{b}_5^{UT \times 1} = \begin{bmatrix} \overline{\mathbf{T}}_{tcs}^{ETF} \\ \overline{\mathbf{T}}_{tcs}^{dykeA} \\ \overline{\mathbf{T}}_{tcs}^{dykeB} \\ \overline{\mathbf{T}}_{tcs}^{dykeC} \end{bmatrix} \tag{4.20}$$

where

- $\mathbf{A}_{tcs}^{ETF}$, $\mathbf{A}_{tcs}^{dykeA}$, $\mathbf{A}_{tcs}^{dykeB}$ and $\mathbf{A}_{tcs}^{dykeC}$ are each a $T \times KT$ matrix with elements defining the total tonnage of TCS dyke material in each mining-cut to be sent to ETF dyke, dyke A, dyke B and dyke C respectively in each period.
- $\mathbf{d}_{tcs}^{ETF}$, $\mathbf{d}_{tcs}^{dykeA}$, $\mathbf{d}_{tcs}^{dykeB}$ and $\mathbf{d}_{tcs}^{dykeC}$ are each a $T \times T$ diagonal unit matrix allowing the acceptable defined TCS dyke material goal deviation for ETF dyke, dyke A, dyke B and dyke C destinations respectively.
- $\mathbf{d}_5$ is a $TU \times 1$ coefficient decision variable vector of $\mathbf{d}_{tcs}^{u}$.
- $\mathbf{T}_{tcs}^{ETF}$, $\mathbf{T}_{tcs}^{dykeA}$, $\mathbf{T}_{tcs}^{dykeB}$ and $\mathbf{T}_{tcs}^{dykeC}$ are each a $T \times 1$ vector of the targeted TCS dyke material goal defined for ETF dyke, dyke A, dyke B and dyke C destinations respectively.
- $\mathbf{0}_5$ is a zero matrix; the size depends on the decision variable.

4.2.4 The MILGP Model Grade Blending Constraints

We proceed to develop the numerical models for the MILGP model inequality constraints represented by Equations (3.16) to (3.21). These constraints define the ore bitumen blending, the ore fines percent blending and the IB dyke material fines percent blending for all destinations.

4.2.4.1 The MILGP Model Ore Bitumen Blending Constraints

The numerical model is represented by Equations (4.21) to (4.23), where $\mathbf{A}_6$ is the coefficient matrix and $\mathbf{b}_6$ is the boundary condition vector.

$$\mathbf{A}_6 \cdot \mathbf{r} \le \mathbf{b}_6 \tag{4.21}$$

$$\mathbf{A}_6^{2T\times\left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU\right)} = \begin{bmatrix} \mathbf{0}_6 & \overline{\mathbf{A}}_g & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 \\ \mathbf{0}_6 & -\overline{\mathbf{A}}_g & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{0}_6 \end{bmatrix} \tag{4.22}$$

$$\mathbf{b}_6^{2T\times 1} = \begin{bmatrix} \overline{\mathbf{g}}_u \\ -\overline{\mathbf{g}}_l \end{bmatrix} \tag{4.23}$$

where

- $\mathbf{A}_g$ is a $T \times KT$ matrix of average grade of ore bitumen in each mining-cut in each period.
- $\mathbf{g}_u$ is a $T \times 1$ vector of average ore bitumen grade upper bounds on acceptable average head grade of bitumen.
- $\mathbf{g}_l$ is a $T \times 1$ vector of average ore bitumen grade lower bounds on acceptable average head grade of bitumen.
- $\mathbf{0}_6$ is a zero matrix; the size depends on the decision variable.

4.2.4.2 The MILGP Model Ore Fines Blending Constraints

The numerical model is represented by Equations (4.24) to (4.26), where $\mathbf{A}_7$ is the coefficient matrix and $\mathbf{b}_7$ is the boundary condition vector.

$$\mathbf{A}_7 \cdot \mathbf{r} \le \mathbf{b}_7 \tag{4.24}$$

$$\mathbf{A}_7^{2T\times\left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU\right)} = \begin{bmatrix} \mathbf{0}_7 & \overline{\mathbf{A}}_f & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 \\ \mathbf{0}_7 & -\overline{\mathbf{A}}_f & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 \end{bmatrix} \tag{4.25}$$

$$\mathbf{b}_7^{2T\times 1} = \begin{bmatrix} \bar{\mathbf{f}}_u \\ -\bar{\mathbf{f}}_l \end{bmatrix} \tag{4.26}$$

where

- $\mathbf{A}_f$ is a $T \times KT$ matrix of average ore fines percent in each mining-cut in each period.
- $\mathbf{f}_u$ is a $T \times 1$ vector of average ore fines percent upper bounds on acceptable average head grade of fines percent.
- $\mathbf{f}_l$ is a $T \times 1$ vector of average ore fines percent lower bounds on acceptable average head grade of fines percent.
- $\mathbf{0}_7$ is a zero matrix; the size depends on the decision variable.

4.2.4.3 The MILGP Model IB Dyke Material Fines Blending Constraints

The numerical model is represented by Equations (4.27) to (4.29), where $\mathbf{A}_8$ is the coefficient matrix and $\mathbf{b}_8$ is the boundary condition vector.

$$\mathbf{A}_8 \cdot \mathbf{r} \le \mathbf{b}_8 \tag{4.27}$$

$$\mathbf{A}_8^{2UT\times\left(\sum_{dv=1}^{DV} KTU+\sum_{dn=1}^{DN} TU\right)} = \begin{bmatrix} \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \overline{\mathbf{A}}_d^{ETF} & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 \\ \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \overline{\mathbf{A}}_d^{dykeA} & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 \\ \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \overline{\mathbf{A}}_d^{dykeB} & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 \\ \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \overline{\mathbf{A}}_d^{dykeC} & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 \\ \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & -\overline{\mathbf{A}}_d^{ETF} & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 \\ \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & -\overline{\mathbf{A}}_d^{dykeA} & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 \\ \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & -\overline{\mathbf{A}}_d^{dykeB} & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 \\ \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & -\overline{\mathbf{A}}_d^{dykeC} & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 & \mathbf{0}_8 \end{bmatrix} \tag{4.28}$$

$$\mathbf{b}_8^{2UT\times 1} = \begin{bmatrix} \overline{\mathbf{d}}_u^{ETF} \\ \overline{\mathbf{d}}_u^{dykeA} \\ \overline{\mathbf{d}}_u^{dykeB} \\ \overline{\mathbf{d}}_u^{dykeC} \\ -\overline{\mathbf{d}}_l^{ETF} \\ -\overline{\mathbf{d}}_l^{dykeA} \\ -\overline{\mathbf{d}}_l^{dykeB} \\ -\overline{\mathbf{d}}_l^{dykeC} \end{bmatrix} \tag{4.29}$$

where

- $\mathbf{A}_d^{ETF}$, $\mathbf{A}_d^{dykeA}$, $\mathbf{A}_d^{dykeB}$ and $\mathbf{A}_d^{dykeC}$ are each a $T \times KT$ matrix of average IB dyke material fines percent in each mining-cut in each period for all dyke construction destinations.

- $\mathbf{d}_u^{ETF}$, $\mathbf{d}_u^{dykeA}$, $\mathbf{d}_u^{dykeB}$ and $\mathbf{d}_u^{dykeC}$ are each a $T \times 1$ vector of average IB dyke material fines percent upper bounds on acceptable average grade of fines percent for all dyke construction destinations.
- $\mathbf{d}_l^{ETF}$, $\mathbf{d}_l^{dykeA}$, $\mathbf{d}_l^{dykeB}$ and $\mathbf{d}_l^{dykeC}$ are each a $T \times 1$ vector of average IB dyke material fines percent lower bounds on acceptable average grade of fines percent for all dyke construction destinations.
- $\mathbf{0}_8$ is a zero matrix; the size depends on the decision variable.

4.2.5 The MILGP Model Variables Control Constraints

We proceed to construct the numerical models for the MILGP model variables control constraints represented by Equations (3.22) to (3.34). These constraints monitor the logics of the variables that define mining, processing, dyke materials and goal deviations to ensure they are within acceptable ranges.

4.2.5.1 Ore, OB and IB Dyke Material Scheduled and Material Mined Constraints

The numerical model is represented by Equations (4.30) and (4.31), where $\mathbf{A}_9$ is the coefficient matrix and $\mathbf{b}_9$ is a zero boundary condition vector. Equation (4.30) inequalities ensure that the amount of ore, OB and IB dyke material scheduled from any mining-cut in any given period for all destinations is less than or equal to the amount of rock extracted from the mining-panel that the mining-cut belongs to in any given scheduling period.

$$\mathbf{A}_9 \cdot \mathbf{r} \le \mathbf{b}_9 \tag{4.30}$$

$$\mathbf{A}_9^{PT\times\left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU\right)} = \begin{bmatrix} \mathbf{0}_9 & \mathbf{A}_x & \mathbf{A}_y & \mathbf{A}_z^u & \mathbf{A}_c^u & \mathbf{0}_9 & \mathbf{0}_9 & \mathbf{0}_9 & \mathbf{0}_9 & \mathbf{0}_9 & \mathbf{0}_9 \end{bmatrix} \tag{4.31}$$

where

- u refers to ETF dyke, dyke A, dyke B and dyke C destinations.
- $\mathbf{A}_x$ is a $PT \times KT$ matrix with elements defining the total tonnage of ore in the mining-cuts belonging to mining-panel, p in each period.

- $\mathbf{A}_y$ is a $PT \times PT$ matrix with elements defining the negative of the total tonnage of material in each mining-panel, p in each period.
- $\mathbf{A}_z^u$ is a $PT \times KTU$ matrix with elements defining the total tonnage of OB dyke material in the mining-cuts belonging to mining-panel, p in each period for all destinations.
- $\mathbf{A}_c^u$ is a $PT \times KTU$ matrix with elements defining the total tonnage of IB dyke material in the mining-cuts belonging to mining-panel, p in each period for all destinations.
- $\mathbf{b}_9$ is a $PT \times 1$ zero boundary condition vector.
- $\mathbf{0}_9$ is a zero matrix; the size depends on the decision variable.

4.2.5.2 Ore Processed and TCS Dyke Material Constraints

The numerical model is represented by Equations (4.32) and (4.33), where $\mathbf{A}_{10}$ is the coefficient matrix and $\mathbf{b}_{10}$ is a zero boundary condition vector. Equation (4.32) inequalities ensure that the fraction of ore processed from any mining-cut in any given period is more than or equal to the fraction of TCS dyke material generated from the mining-cut in any given scheduling period for all dyke construction destinations.

$$\mathbf{A}_{10} \cdot \mathbf{r} \leq \mathbf{b}_{10} \tag{4.32}$$

$$\begin{aligned} &\mathbf{A}_{10}^{KT \times \left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU \right)} = \\ &\begin{bmatrix} \mathbf{0}_{10} & \mathbf{A}_x & \mathbf{0}_{10} & \mathbf{0}_{10} & \mathbf{0}_{10} & \mathbf{A}_s^u & \mathbf{0}_{10} & \mathbf{0}_{10} & \mathbf{0}_{10} & \mathbf{0}_{10} & \mathbf{0}_{10} \end{bmatrix} \end{aligned} \tag{4.33}$$

where

- u refers to ETF dyke, dyke A, dyke B and dyke C destinations.
- $\mathbf{A}_x$ is a $KT \times KT$ matrix with an element of -1 for each mining-cut in each period, representing ore variables.
- $\mathbf{A}_s^u$ is a $KT \times KTU$ matrix with an element of 1 for each mining-cut in each period for all destinations, representing TCS dyke material variables.

- $\mathbf{b}_{10}$ is a $KT \times 1$ zero boundary condition vector.
- $\mathbf{0}_{10}$ is a zero matrix; the size depends on the decision variable.

4.2.5.3 Destination Fractions Constraints

The numerical model is represented by Equations (4.34) and (4.35), where $\mathbf{A}_{11}$ is the coefficient matrix and $\mathbf{b}_{11}$ is a boundary condition vector of ones. Equation (4.34) inequalities ensure that the total fractions of mining-panel or mining-cut mined, or TCS dyke material produced and sent to all destinations in all periods is less or equal to one.

$$\mathbf{A}_{11} \cdot \mathbf{r} \leq \mathbf{b}_{11} \tag{4.34}$$

$$\mathbf{A}_{11}^{(4K+P)\times\left(\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU\right)} =$$
$$\begin{bmatrix} \mathbf{0}_{11} & \mathbf{A}_x & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} \\ \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{A}_y & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} \\ \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{A}_z^u & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} \\ \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{A}_c^u & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} \\ \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{A}_s^u & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} & \mathbf{0}_{11} \end{bmatrix} \tag{4.35}$$

where

- u refers to ETF dyke, dyke A, dyke B and dyke C destinations.
- $\mathbf{A}_x$ is a $K \times KT$ matrix with an element of 1 for each mining-cut in all periods, representing ore variables.
- $\mathbf{A}_y$ is a $P \times PT$ matrix with an element of 1 for each mining-panel in all periods, representing mining variables.
- $\mathbf{A}_z^u$ is a $K \times KTU$ matrix with an element of 1 for each mining-cut in all periods for all destinations, representing OB dyke material variables.
- $\mathbf{A}_c^u$ is a $K \times KTU$ matrix with an element of 1 for each mining-cut in all periods for all destinations, representing IB dyke material variables.

- $\mathbf{A}_s^u$ is a $K \times KTU$ matrix with an element of 1 for each mining-cut in all periods for all destinations, representing TCS dyke material variables.
- $\mathbf{b}_{11}$ is a $(4K+P)\times 1$ boundary condition vector of ones.
- $\mathbf{0}_{11}$ is a zero matrix; the size depends on the decision variable.

4.2.5.4 Deviational Variables Non-Negativity Constraints

The numerical model is represented by Equations (4.36) and (4.37), where $\mathbf{A}_{12}$ is the coefficient matrix and $\mathbf{b}_{12}$ is a zero boundary condition vector. Equation (4.36) inequalities define the non-negativity of the deviational variables defined to support the goal functions.

$$\mathbf{A}_{12} \cdot \mathbf{r} \le \mathbf{b}_{12} \tag{4.36}$$

$$\mathbf{A}_{12}^{5UT\times\left(\sum_{dv=1}^{DV} KTU+\sum_{dn=1}^{DN} TU\right)} = \begin{bmatrix} \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{d}_1 & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} \\ \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{d}_2 & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} \\ \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{d}_3^u & \mathbf{0}_{12} & \mathbf{0}_{12} \\ \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{d}_4^u & \mathbf{0}_{12} \\ \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{0}_{12} & \mathbf{d}_5^u \end{bmatrix} \tag{4.37}$$

where

- u refers to ETF dyke, dyke A, dyke B and dyke C destinations.
- $\mathbf{d}_1$, $\mathbf{d}_2$, $\mathbf{d}_3^u$, $\mathbf{d}_4^u$, and $\mathbf{d}_5^u$ are each a $UT \times UT$ matrix with an element of -1 for each scheduling period and destination.
- $\mathbf{b}_{12}$ is a $5UT \times 1$ zero boundary condition vector.
- $\mathbf{0}_{12}$ is a zero matrix; the size depends on the decision variable.

4.2.6 The MILGP Model Mining-Panels Extraction Precedence Constraints

The mining-panels extraction precedence constraints are represented by Equations (3.29) to (3.33). These equations together implement the vertical and horizontal mining-panels extraction sequence. We proceed to construct the numerical model represented by Equation (4.38). An illustrative example will be used to show how the extraction precedence constraint matrix is created.

$$\mathbf{A}_{13} \cdot \mathbf{r} \leq \mathbf{b}_{13} \tag{4.38}$$

Consider a set of mining-panels to be scheduled with the MILGP model as shown in Figure 4.1. Let focus our attention on the five labeled mining-panels. The immediate predecessor mining-panels are illustrated with directed-arcs pointing from the parent to the child node for vertical and horizontal extraction. The extraction precedence relationships between mining-panels are modeled using the directed graph theory. The directed graph lists the mining-panels that must be extracted prior to extracting mining-panel, *p*. For vertical extraction precedence, this set is denoted by $C_p(L)$; for horizontal extraction precedence, this set is denoted by $M_p(Z)$; for pushback extraction precedence, this set is denoted by $B_j(H)$; where L, Z and H are the total number of mining-panels in these sets. The strategy for creating the pushback extraction precedence list has been discussed in more detail in section 4.3.2. Our illustration here will focus on the vertical and horizontal extraction precedence relationship.

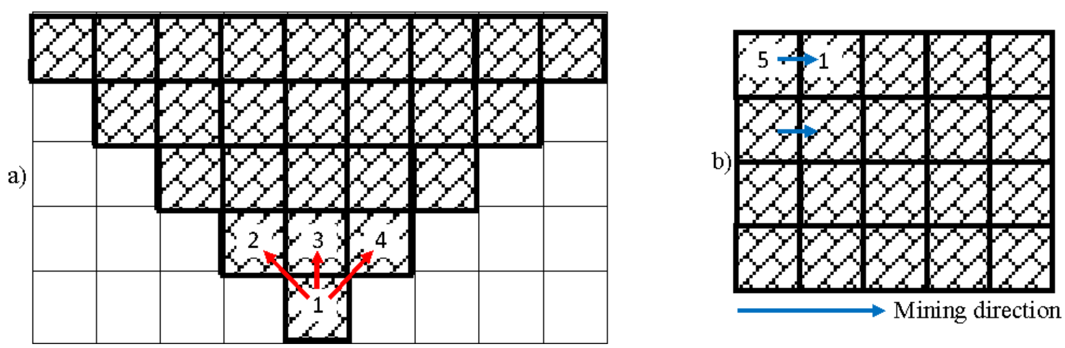

Figure 4.1: Mining-panels extraction precedence in the MILGP formulation modified after Ben-Awuah and Askari-Nasab (2011): a) cross sectional view and b) plan view

To begin, we construct the required matrices that define Equation (3.29) and (3.30). Let assume the five mining-panels $(P = 5)$ shown in Figure 4.1 are to be extracted over four periods $(T = 4)$. For vertical and horizontal extraction, the immediate predecessor mining-panel set for mining-panel 1 is $\{2,3,4,5\}$

representing the sets $C_p(L)+M_p(Z)$. For simplification, we define two vectors that will be used in assembling the matrices constructed from Equations (3.29) and (3.30). These are $1\times P$ vectors denoted by $s1_{vec}$ and $s2_{vec}$ represented by Equations (4.39) and (4.40). These are used in assembling the matrices $s1_{mat}$ and $s2_{mat}$ which are $T\times PT$ matrices defined in Equations (4.41) and (4.42) for each mining-panel; where $\mathbf{0}_{13}$ is a $1\times P$ zero vector. Subsequently, the matrices $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$ are created for all the mining-panels in the model. These are $PT\times PT$ matrices represented by Equations (4.43) and (4.44).

$$\mathbf{s1}_{vec}^{1\times P}=\begin{bmatrix}1 & 0 & 0 & 0 & 0\end{bmatrix} \tag{4.39}$$

$$\mathbf{s2}_{vec}^{1\times P}=\begin{bmatrix}0 & -1 & -1 & -1 & -1\end{bmatrix} \tag{4.40}$$

$$\mathbf{s1}_{mat}^{T\times PT}=\begin{bmatrix}\mathbf{s1}_{vec} & \mathbf{0}_{13} & \cdots & \mathbf{0}_{13}\\ \mathbf{0}_{13} & \ddots & \ddots & \vdots\\ \vdots & \ddots & \ddots & \mathbf{0}_{13}\\ \mathbf{0}_{13} & \cdots & \mathbf{0}_{13} & \mathbf{s1}_{vec}\end{bmatrix} \tag{4.41}$$

$$\mathbf{s2}_{mat}^{T\times PT}=\begin{bmatrix}\mathbf{s2}_{vec} & \mathbf{0}_{13} & \cdots & \mathbf{0}_{13}\\ \mathbf{0}_{13} & \ddots & \ddots & \vdots\\ \vdots & \ddots & \ddots & \mathbf{0}_{13}\\ \mathbf{0}_{13} & \cdots & \mathbf{0}_{13} & \mathbf{s2}_{vec}\end{bmatrix} \tag{4.42}$$

$$\mathbf{A}_{s1}^{PT\times PT}=\left[\mathbf{s1}_{mat1};\mathbf{s1}_{mat2};.....;\mathbf{s1}_{matP}\right] \tag{4.43}$$

$$\mathbf{A}_{s2}^{PT\times PT}=\left[\mathbf{s2}_{mat1};\mathbf{s2}_{mat2};.....;\mathbf{s2}_{matP}\right] \tag{4.44}$$

Next, we construct the matrices generated from Equation (3.32). We define two $1\times P$ vectors represented by Equations (4.45) and (4.46) and denoted by $s3_{vec}$ and $s4_{vec}$. These are used in assembling the matrices $s3_{mat}$ and $s4_{mat}$ which are $T\times PT$ matrices defined in Equations (4.47) and (4.48) for each mining-panel. Subsequently, the matrices $\mathbf{A}_{s3}$ and $\mathbf{A}_{s4}$ are created for all the mining-panels in the model. These are $PT \times PT$ matrices represented by Equations (4.49) and (4.50).

$$\mathbf{s3}_{vec}^{1\times P} = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.45}$$

$$\mathbf{s4}_{vec}^{1\times P} = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.46}$$

$$\mathbf{s3}_{mat}^{T\times PT} = \begin{bmatrix} \mathbf{s3}_{vec} & \mathbf{0}_{13} & \cdots & \mathbf{0}_{13} \\ \mathbf{0}_{13} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \mathbf{0}_{13} \\ \mathbf{0}_{13} & \cdots & \mathbf{0}_{13} & \mathbf{s3}_{vec} \end{bmatrix} \tag{4.47}$$

$$\mathbf{s4}_{mat}^{T\times PT} = \begin{bmatrix} \mathbf{s4}_{vec} & \mathbf{0}_{13} & \cdots & \mathbf{0}_{13} \\ \mathbf{0}_{13} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \mathbf{0}_{13} \\ \mathbf{0}_{13} & \cdots & \mathbf{0}_{13} & \mathbf{s4}_{vec} \end{bmatrix} \tag{4.48}$$

$$\mathbf{A}_{s3}^{PT\times PT} = \left[\mathbf{s3}_{mat1};\mathbf{s3}_{mat2};.....;\mathbf{s3}_{matP}\right] \tag{4.49}$$

$$\mathbf{A}_{s4}^{PT\times PT} = \left[\mathbf{s4}_{mat1};\mathbf{s4}_{mat2};.....;\mathbf{s4}_{matP}\right] \tag{4.50}$$

We proceed to create the matrices generated from Equation (3.33). We define two $1\times P$ vectors represented by Equations (4.51) and (4.52) and denoted by $\mathrm{s5}_{vec}$ and $\mathrm{s6}_{vec}$. These are used in assembling the matrix $\mathrm{s5}_{mat}$ which is a $(T-1)\times PT$ matrix defined in Equation (4.53), for each mining-panel. Subsequently, the matrix $\mathbf{A}_{s5}$ is constructed for all the mining-panels in the model. This is a $P(T-1)\times PT$ matrix represented by Equation (4.54).

$$\mathbf{s5}_{vec}^{1\times P} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.51}$$

$$\mathbf{s6}_{vec}^{1\times P} = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.52}$$

$$\mathbf{s5}_{mat}^{(T-1)\times PT} = \begin{bmatrix} \mathbf{s5}_{vec} & \mathbf{s6}_{vec} & \mathbf{0}_{13} & \cdots & \mathbf{0}_{13} \\ \mathbf{0}_{13} & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \mathbf{0}_{13} \\ \mathbf{0}_{13} & \cdots & \mathbf{0}_{13} & \mathbf{s5}_{vec} & \mathbf{s6}_{vec} \end{bmatrix} \tag{4.53}$$

$$\mathbf{A}_{s5}^{P(T-1)\times PT} = \left[\mathbf{s5}_{mat1};\mathbf{s5}_{mat2};.....;\mathbf{s5}_{matP}\right] \tag{4.54}$$

Now, the inequality constraint represented in Equation (4.38), can be numerically constructed as shown in Equation (4.55); where $\mathbf{A}_{13}$ is the coefficient matrix and $\mathbf{b}_{13}$ is a zero boundary condition vector.

$$\mathbf{A}_{13}^{[2PT+P(T-1)]\times\left(\sum_{dv=1}^{DV}KTU+\sum_{dn=1}^{DN}TU\right)} =$$
$$\begin{bmatrix} \mathbf{A}_{s1} & \mathbf{0}_{14} & \mathbf{A}_{s2} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} \\ \mathbf{A}_{s3} & \mathbf{0}_{14} & \mathbf{A}_{s4} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} \\ \mathbf{A}_{s5} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} \end{bmatrix} \tag{4.55}$$

where

- $\mathbf{A}_{13}$ is a $[2PT\times P(T-1)]\times\left(\sum_{dv=1}^{DV}KTU+\sum_{dn=1}^{DN}TU\right)$ coefficient matrix.
- $\mathbf{b}_{13}$ is a $[2PT\times P(T-1)]\times 1$ zero boundary condition vector.
- $\mathbf{0}_{14}$ is a zero matrix; the size depends on the decision variable it is representing.

Finally, we concatenate all the matrices and vectors representing the goal functions, constraints and bounds into the coefficient matrix, $\mathbf{A}$ and boundary condition vector, $\mathbf{b}$. These are represented by the Equations (4.56) and (4.57). These will be used in solving for the decision variables vector, $\mathbf{r}$.

$$\mathbf{A}=\left[\mathbf{A}_1;\mathbf{A}_2;\mathbf{A}_3;\mathbf{A}_4;\mathbf{A}_5;\mathbf{A}_6;\mathbf{A}_7;\mathbf{A}_8;\mathbf{A}_9;\mathbf{A}_{10};\mathbf{A}_{11};\mathbf{A}_{12};\mathbf{A}_{13}\right] \tag{4.56}$$

$$\mathbf{b}=\left[\mathbf{b}_1;\mathbf{b}_2;\mathbf{b}_3;\mathbf{b}_4;\mathbf{b}_5;\mathbf{b}_6;\mathbf{b}_7;\mathbf{b}_8;\mathbf{b}_9;\mathbf{b}_{10};\mathbf{b}_{11};\mathbf{b}_{12};\mathbf{b}_{13}\right] \tag{4.57}$$

4.3 Implementation of an Efficient MILGP Model

We have progressively developed an efficient and robust MILGP model for solving the OSLTPP and waste management problem which involves multiple destinations, material types, mining locations and pushbacks (Askari-Nasab and Ben-Awuah, 2011; Ben-Awuah and Askari-Nasab, 2011). This leads to a large scale optimization problem with numerous decision variables and constraints that takes large memory overheads and time to solve. Thus, resulting in a sophisticated production scheduling problem which calls for improved numerical modeling and optimization techniques to deliver acceptable results in a timely manner. We have further developed techniques to reduce the number of non-zero decision variables and pushback mining constraints in the production scheduling problem. We also implemented a practical mine production sequencing with mining-cuts and mining-panels which results in reduced number of binary variables to be solved for during optimization.

4.3.1 MILGP Implementation with Fewer Non-Zero Decision Variables

The main set-back in solving large scale MILGP problems is the size of the branch and cut tree. During optimization, the size of the branch and cut tree becomes so large that insufficient memory remains to solve an LP sub-problem. The size of the branch and cut tree depends on the number of decision variables in the formulation. The general strategy in formulating the MILGP for OSLTPP and waste management is therefore to reduce the number of decision variables in the production scheduling problem, thereby reducing the solution time significantly. This is implemented using an initial production schedule generated based on a practical oil sands directional mining strategy and the annual mining capacity.

The general form of the MILGP formulation can be represented by Equation (4.58) as:

$$\min_{r} f(r) = \mathbf{c}^{T}.\mathbf{r} \tag{4.58}$$

subject to: goals and constraints of the MILGP model

The objective function for the OSLTPP problem as stated by Equation (3.10) maximizes the NPV and minimizes the dyke construction cost. The objective function coefficient vector, $\mathbf{c}$, is a column vector containing the discounted revenue and cost values for all mining-panels and mining-cuts in all periods and for all destinations. This is shown by Equation (4.4). The objective function decision variables vector, $\mathbf{r}$, is a column vector containing mining-cut or mining-panel precedence, ore, mining, overburden, interburden and tailings coarse sand production and deviational variables. This is shown by Equation (4.5). The decision variables vector, $\mathbf{r}$ is therefore made up of $\sum_{dv=1}^{DV} KTU + \sum_{dn=1}^{DN} TU$ non-zero elements to be solved for in the MILGP model during optimization. This vector ensures that each mining-cut or mining-panel is available for production scheduling during the entire mine life. As shown in section 4.3.1.1, by having an initial production schedule, the number of non-zero decision variables in $\mathbf{r}$ can be reduced, thereby reducing the size of the production scheduling problem.

4.3.1.1 Generating and Applying an Initial Production Schedule

This technique is based on a practical directional oil sands mining and the continuous depletion of material from a given mining and processing capacity. An initial production schedule can be generated using i) a fast heuristic production scheduling algorithm like Whittle's Fixed Lead algorithm (Gemcom Software International Inc., 2012) or ii) a moving production bin calculated estimate. Before optimization with the MILGP model, Whittle can be used to generate a production schedule and then some periodic tolerance applied to the schedule and used as an initial production schedule. Similarly, a moving production bin can be initiated at one end of the deposit and with the annual mining and processing targets and mining direction, a schedule can be generated. Applying a periodic tolerance, an initial schedule can be deployed for the MILGP model.

Let us consider an oil sands deposit containing say 980 mining-cuts in 2 pushbacks which is to be mined from west to east over 12 periods for the processing plant and 4 dyke construction destinations; as shown in Figure 4.2. The production scheduling and waste disposal planning strategy to be used here is based on a practical directional oil sands mining similar to the conceptual mining model. This includes complete extraction of pushback 1 before the mining of pushback 2 to ensure that pushback 1 can be used for tailings disposal planning. From Figure 4.2, based on the mining and processing goals and direction of mining we can estimate that mining-cut 6 may be mined in say, period 4. Assuming we apply a periodic tolerance of 3, then in the initial schedule for the MILGP model, mining-cut 6 can be said to be extractable over periods 1 to 7;

whilst the rest of the periods are set to zeros. Conventionally, mining-cut 6 will have been modeled to be extractable over the entire 12 years mine life. With this technique, the number of non-zero decision variables, $\mathbf{r}$ to be solved for in the MILGP model during production scheduling will reduce from 176,568 to 94,472. This reduces the size of the production scheduling problem significantly.

Theoretically, this variable reduction technique decreases the solution space for the optimization problem. Thus during optimization, some of the branches in the branch and cut tree are eliminated, ensuring that the solution for the practical production scheduling problem is reached faster. It is important to note that, reducing the solution space unreasonably can cause one to miss the optimal practical production scheduling solution. This method must be applied in accordance to the mining and processing capacities defined.

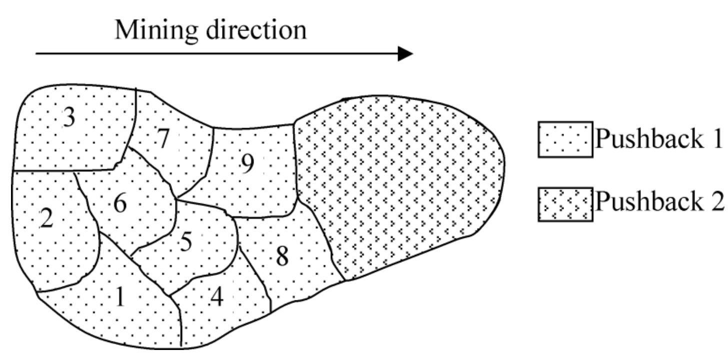

Figure 4.2: Schematic representation of an oil sands deposit showing mining-cuts and pushbacks

4.3.2 MILGP Implementation with Fewer Pushback Precedence Constraints

In OSLTPP and waste management, it is important to have a pushback mining precedence strategy that ties into the waste disposal plan. This requires the development of a well integrated strategy of directional and pushback mining, and tailings dyke construction for in-pit and ex-pit tailings storage management. This includes the complete extraction of one pushback before the mining of the next pushback in the direction of mining, thus enabling the release of the dyke footprints of the recently mined pushback for dyke construction to start and then subsequently tailings deposition. Multiple mines final pits are modeled as pushbacks and the MILGP model applied appropriately.

To implement the complete extraction of pushbacks during optimization, pushback mining precedence constraints must be developed and implemented whilst ensuring that the optimization problem is still feasible within a reasonable time. This requires an efficient modeling of the pushback mining precedence constraints to reduce the number of variables being added to the problem. The strategy used by the MILGP model has been tied into the vertical and horizontal extraction precedence constraints of the mining-panels as defined by Equations (3.29) to (3.33). Three cases and strategies have been identified and are illustrated in Figure 4.3.

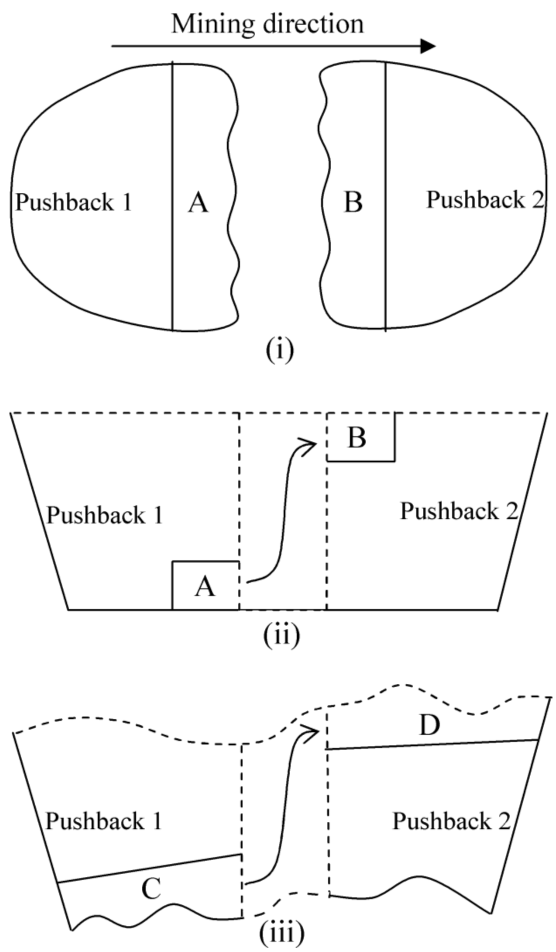

Figure 4.3: Developing pushback mining precedence constraints: (i) Plan view and (ii) Cross sectional view; of final pit with flat topography and bottom showing pushbacks 1 and 2 and the sets of bounding mining-panels (iii) Cross sectional view of final pit with undulating topography and bottom showing pushbacks 1 and 2 and the sets of bounding mining-panels

The first case in Figure 4.3(i) and (ii) assumes that pushbacks in the final pit being used as an input for the MILGP model have flat topography and bottom. This means that with the west to east mining direction, mining will proceed in pushback 1 until it reaches the bottom of the pit where the list of bounding mining-panels in set A becomes the last set of mining-panels for complete extraction of pushback 1 prior to pushback 2. Set B also contains the list of bounding mining-panels at the top of pushback 2 where mining starts. Set A therefore becomes the preceding mining-panels set to set B. The pushback mining precedence constraints here involves identifying the list of bounding mining-panels that belongs to set A and B and applying the mining-panels extraction precedence constraints in Equations (3.31) to (3.33).

The second case in Figure 4.3(iii) is when the final pit has undulating topography and bottom which is almost always the case. Here, we look for the set C which is made up of the bounding mining-panels at the bottom of pushback 1 mined last. The set D also contains the list of bounding mining-panels at the top of pushback 2 which must be mined first when mining of pushback 2 starts. This approach becomes necessary because the mining-panels at the bottom of pushback 1 and top of pushback 2 belong to different mining benches therefore the vertical and horizontal mining-panels extraction precedence constraints are not able to tie the mining of these mining-panels together. Set C becomes the preceding mining-panels set to set D. Similarly, the mining-panels extraction precedence constraints in Equations (3.31) to (3.33) can then be applied to implement the complete extraction of pushback 1 prior to pushback 2.

The third case is when you have a similar situation in Figure 4.3(iii). The strategy here is by adding air mining-panels to the final pit both at the top and bottom, converting it from case 2 to case 1. The case 1 strategy can then be applied to implement the pushback mining precedence constraints.

The strategy used in the second case was implemented in case study 3.

4.4 Summary and Conclusions

In summary, the mathematical models and theoretical architecture developed in Chapter 3 were used as the basis for the MILGP formulation framework development in the first part of this chapter. The model involves the interactions of its three main subcomponents: the objective function, the goal functions and the constraints in an optimization framework to achieve the objectives. The main objectives are to maximize the net present value of the mining operation and minimize dyke construction cost.

The numerical model of the MILGP formulation is developed in Matlab (2011) with the generalized structure used by Tomlab/CPLEX (Holmström, 2009) in solving large scale MILP problems. The MILGP model user input interface enables the setting up of the block model data, production and dyke material requirements as well as parameters defining the waste management strategy. The resulting numerical model is passed on to Tomlab/CPLEX for optimization. Further numerical modeling techniques in implementing an efficient practical MILGP model for oil sands long term production planning and waste management are explored in the second part of the chapter.

CHAPTER 5

APPLICATION OF METHODOLOGY AND DISCUSSION OF RESULTS

5.1 Background

The study proceeds with the application and verification of the models. This chapter will discuss the application of the methodology using the models on two oil sands data sets and the discussion of results for 4 case studies. The mining concepts and strategy and mathematical formulations outlined in Chapter 3 were developed as numerical models representing the MILGP framework application in Chapter 4. Whittle software (Gemcom Software International Inc., 2012) which is based on the 3D LG algorithm (Lerchs and Grossmann, 1965) was used in generating and designing the final pit limit of the oil sands mines. The blocks within the ultimate pit limit were used as the input data for the MILGP model for subsequent integrated long-term production scheduling and waste disposal planning. The four case studies implemented highlights the contributions this research makes in oil sands mine planning. Case study 4 was used for verifying the model by comparing it with an industry standard software, Whittle (Gemcom Software International Inc., 2012).

Verification of the results was done by comparing the results from the MILGP model with Milawa Balanced algorithm used in Whittle software. The best, worst, Milawa NPV and Milawa Balanced case production schedules from Whittle are compared to the practical long-term production schedule generated by the MILGP framework. To enable this comparison, no waste disposal planning was implemented for the MILGP model since Whittle has no tools for that. The annual stripping ratio, average grade, annual ore and waste schedules, and the NPV of the experiments were compared. The advantages of using the MILGP mine planning framework as a preferred method for an integrated oil sands mine planning system is emphasized. The concept of verifying the MILGP model is explained in section 5.2 and the experimental design for the model highlighted in section 5.3. The first case study implementing the application of the MILGP model framework to generate an integrated production schedule and waste disposal plan is discussed in section 5.4. The second case study highlights the robustness of the MILGP model and the sensitivity of some input parameters in section 5.5. Section 5.6 focuses on the deployment of an efficient MILGP model in case study 3. Finally, case study 4 is implemented to enable a comparative analysis between the MILGP model and Whittle software in sections 5.7 and 5.8. The chapter concludes in section 5.9.

5.2 Verification of the MILGP Model

Verification seeks to determine whether the design or system has been built to the set standards or specification. To verify the implementation of the MILGP model, we will seek to answer the question as to whether the developed application conforms to the specifications. As highlighted in Chapters 3 and 4, the main components of the MILGP model is to (i) maximize the NPV of the mining operation and (ii) minimize the dyke construction cost. These are subject to the practical constraints and goals in oil sands mining. The MILGP framework also includes pushback mining strategy that ties into the waste management plan for sustainable mining. Strategies to implement an efficient MILGP model were also discussed. This chapter used four case studies to implement the various aspects of the MILGP mine planning framework. For purposes of verification, case study 4 was simplified by not implementing waste disposal planning to enable Whittle results to be compared to it and analyzed.

5.3 Experimental Design Framework for the MILGP Model

The methodology used in dealing with the integrated oil sands mining and waste management problem in the MILGP framework includes a solution scheme that is based on the branch and cut optimization algorithm (Horst and Hoang, 1996) implemented by Tomlab/CPLEX (Holmström, 2009). To be able to obtain reliable experimental results, the solution scheme employed in solving the problem should be able to capture the complete definition of the integrated oil sands production scheduling and waste disposal planning problem including the conceptual mining framework, the tailings storage management strategy and their corresponding data sets. The assumptions are based on prior knowledge of practical mining environments and the framework for the application of operations research methods in mining.

The MILGP model framework presented in Chapter 3 and the subsequent numerical modeling outlined in Chapter 4 are validated with four case studies using data from two oil sands mining companies. Figure 5.1 shows the general workflow of the experimentation methodology used in this thesis. In this study, an inverse distance weighting methodology is used to construct geologic block models and subsequently the economic block models for the oil sands deposits. The ultimate pit limits were generated and designed using LG algorithm (Lerchs and Grossmann, 1965). The first case study implements the application of the MILGP model framework to generate an integrated production schedule and waste disposal plan. Mining, processing and dyke material scheduling are implemented with mining-cuts as the scheduling units. Case study 2 includes sensitivity analysis for the MILGP model input parameters. Mining, processing and dyke material scheduling are implemented with mining-panels as the mining scheduling units and mining-cuts as the processing and dyke material scheduling units. The third case study focuses on the deployment of an efficient MILGP model. The scheduling units are similar to that in case study 2. Subsequently the best, worst, Milawa NPV and Milawa Balanced case scenarios calculated with the shells node in Whittle (Gemcom Software International Inc., 2012) and the practical annual long-term production schedule generated by the MILGP model are compared for case study 4. No dyke material was scheduled since Whittle does not have tools for this purpose. The experiments compared the stripping ratio, annual production, average grade, and the respective NPVs. Due to the parametric analysis used in Whittle, mathematical optimality is not guaranteed. However it is a standard tool used widely in the industry due to its fast implementation. The MILGP framework on the other hand, uses a solver developed based on exact solution methods for optimization where an optimization termination criterion is set up to define how far our generated solution is from the optimal solution; subject to the practical and technical mining constraints.

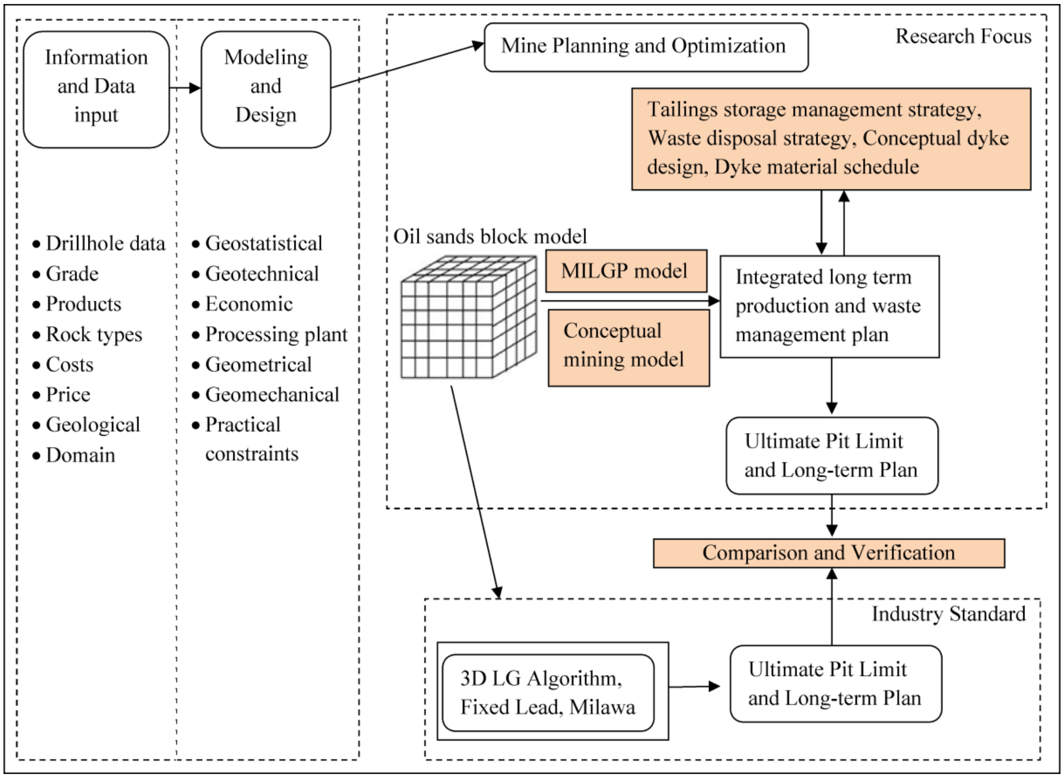

Figure 5.1: General workflow of experimentation methodology

5.4 Case Study 1: Implementation of the MILGP Model

The performance of the proposed MILGP model was analyzed based on NPV, mining production goals, smoothness and practicality of the generated schedules and the availability of tailings containment areas at the required time. The formulation was verified by numerical experiments on a synthetic and an oil sands data set. The application of the model was implemented on a Dell Precision T3500 computer at 2.4 GHz, with 3GB of RAM.

Further implementation of the MILGP model was done for a large scale oil sands deposit covering an area of 8 km x 4 km, which is similar to the conceptual mining model. The rock types in the area are Pleistocene, Clearwater, Upper McMurray, Middle McMurray and Lower McMurray formations. Table 5.1 shows details of the oil sands final pit and the material contained in it. The deposit is to be scheduled over 20 periods equivalent to 20 years.

Table 5.1: Oil sands final pit and production scheduling information

Description	Value
Total tonnage of rock (Mt)	4,866.2
Total ore tonnage (Mt)	2,792.5
Total OI dyke material tonnage (Mt)	1,697.8
Total TCS dyke material tonnage (Mt)	2,110.0
Total waste tonnage (Mt)	375.9
Number of blocks	61,490
Block dimensions (m x m x m)	50 x 50 x 15
Number of benches	5
Bench height (m)	15
Bench elevations (m)	265-325
Number of scheduling periods (years)	20

The designed final pit block model was divided into 4 pushbacks that are consistent with the conceptual mining model. The sizes of the pushbacks are determined in consultation with tailings dam engineers and are based on the required cell capacities and the timelines required in making the cell areas available for tailings containment. The blocks within each pushback are clustered into mining-cuts using fuzzy logic clustering algorithm (Kaufman and Rousseeuw, 1990) to reduce the number of decision variables required in the MILGP model. Clustering of blocks into mining-cuts ensures the MILGP scheduler generates a mining schedule at a selective mining unit that is practical from mining operation point of view. The material in the designed final pit is to be scheduled for the processing plant and 4 dyke construction destinations sequentially, with the objective of maximizing the NPV of the mining operation and minimizing the dyke construction cost. An EPGAP of 2% was set for the optimization of all pushbacks. Mining, processing and dyke material scheduling are implemented with mining-cuts as the scheduling units. A summary of the details for each pushback used for production scheduling are shown in Table 5.2.

For processing plant feed and dyke construction, bitumen grade and fines percent need to be controlled within an acceptable range for all pushbacks and destinations. This requirement has been summarized in Table 5.3. Mining will proceed south starting from pushback 1 to 4. When mining of pushback 1 starts, the OI and TCS dyke material will be used in constructing the key trench, starter dyke, and main dyke of the ETF where the initial fluid fine tailings will be stored. When pushback 1 is completely mined, cell 1 area becomes available and OI and TCS dyke material from pushback 2 can be used in constructing dyke ‘A’ about 100m from the mine face to create cell 1 for in-pit tailings containment to start. This mining and tailings storage management strategy, similar to the conceptual mining model will be utilized until all pushbacks are mined (Figure 3.2).

Table 5.2: Details for each pushback to be used for production scheduling and waste disposal planning

Description	Pushback Value			
	1	2	3	4
Number of blocks	14,535	16,433	16,559	13,963
Number of mining-cuts	971	970	977	999
Tonnage of rock (Mt)	1,144.6	1,303.9	1313.2	1104.5
Ore tonnage (Mt)	631.1	758.7	775.7	627.0
OI dyke material tonnage (Mt)	432.4	434.2	435.6	395.7
TCS dyke material tonnage (Mt)	479.4	568.0	587.0	475.5
Average ore bitumen grade (wt%)	11.7	11.5	11.6	11.6
Average ore fines (wt%)	18.6	21.5	19.4	19.0
Average OI dyke material fines (wt%)	14.1	18.5	15.7	14.5

The aim is to generate a uniform schedule and a smooth mining sequence based on the availability of material, the plant processing capacity, and dyke construction requirements. The dyke construction material scheduled should meet the minimum requirements of material for the specified destination with any excess material being available for other purposes. Further to this, to ensure that the mining equipment capacity is well utilized throughout the mine life, we intend to keep a uniform stripping ratio when the mining of ore starts. Table 5.3 shows the input mining, processing and dyke material goals; and input grade limits for ore and OI dyke material for the MILGP model for 20 periods.

Table 5.3: Mining and processing goals, OI and TCS dyke material goals, ore and OI dyke material grade requirements for all destinations for 20 periods

Production scheduling parameter	Value
Mining goal (Mt)	244
Processing goal (Mt)	140
OI dyke material goal (Mt)	70
TCS dyke material goal (Mt)	106
Ore bitumen grade upper/lower bounds (wt%)	16 / 7
Ore fines percent upper/lower bounds (wt%)	30 / 0
OI dyke material fines percent upper/lower bounds (wt%)	30 / 0

Some of the important features that make this MILGP formulation a robust and flexible platform for mine planning are that, the planner can decide on tradeoffs between NPV maximization or dyke construction cost minimization and goals achievement using the penalty and priority functions. Apart from maximizing NPV and minimizing dyke construction cost, the planner has control over the setting of goals and their deviational variables and the upper and lower limits of grades in each period for all pushbacks and destinations. An advantage of the MILGP model and deviational variables over other optimization formulations like LP or MILP is the fact that the deviational variables take values when an infeasible solution will otherwise have been returned. The planner can then quickly look for the goals that are being relaxed and then change them to obtain different results. The penalty cost and priority parameters used in the MILGP model for this optimization were: 0 for mining; 20 for processing; 30 for OI dyke material; and 30 for TCS dyke material. These generated the required tonnages at the various destinations. Further experiments were conducted in sections 5.4.2 and 5.5 to show how these penalty and priority parameters are calibrated. Table 5.4 summarizes the results from the MILGP model in terms of the NPV and dyke construction cost generated after optimization. The four pushbacks were optimized separately over a total of 20 periods. The overall NPV generated including the dyke construction cost for all pushbacks and destinations is \$14,237M.

Table 5.4: Results from the MILGP model in terms of the NPV and dyke construction cost for all pushbacks and destinations

Pushback #	Decision Variables	Constraints	NPV ($M)	Dyke Construction Cost ($M)	EPGAP (%)
Pushback 1	53495	51224	6,493.77	714.44	2.0
Pushback 2	74816	73671	4,695.34	524.20	2.0
Pushback 3	64590	64357	3,184.72	312.74	1.7
Pushback 4	55035	52661	1,588.65	174.39	1.1

Figure 5.2, Figure 5.3, Figure 5.4 and Figure 5.5 show the mining sequence at levels 280 m, 295 m, 310 m and 325 m for all pushbacks with a north to south mining direction; from pushbacks 1 to 4. The MILGP model generated a practical mining sequence that is smooth and consistent with the mining of oil sands. Mining proceeds in the specified direction to ensure least mobility and increased utilization of loading equipment. This is very important in the case of oil sands mining where large cable shovels are used. The size of the mining-cuts in each period enables good equipment maneuverability and the number and size of active bench phases in each period also reduces the number of loading equipment required as well as providing alternative loading points if needed. Another strategic aspect of mining in the specified direction within each pushback is to ensure that the dyke footprints are released on time as the mining proceeds to enable in-pit dyke construction for tailings containment to start. This is an important integral part of the waste management strategy for oil sands mining operations, and a key driver for profitability and sustainable operations. This also reduces the environmental footprints of the ETF.

The results from Figure 5.6 shows a uniform mining, processing, OI and TCS dyke material schedules, which ensures effective utilization of mining fleet and processing plant throughout the mine life. The schedule ensures that apart from meeting the processing plant requirements to maximize NPV, the required quality and quantity of dyke material needed to build the dykes of the ETF, cells ‘A’, ‘B’, and ‘C’ (Figure 3.2) are provided in a timely manner at a minimum cost for tailings containment. The schedule basically ensures that the minimum dyke material requirements of each dyke construction destination as per the conceptual dykes’ designs are met so that any excess material can be used for other purposes.

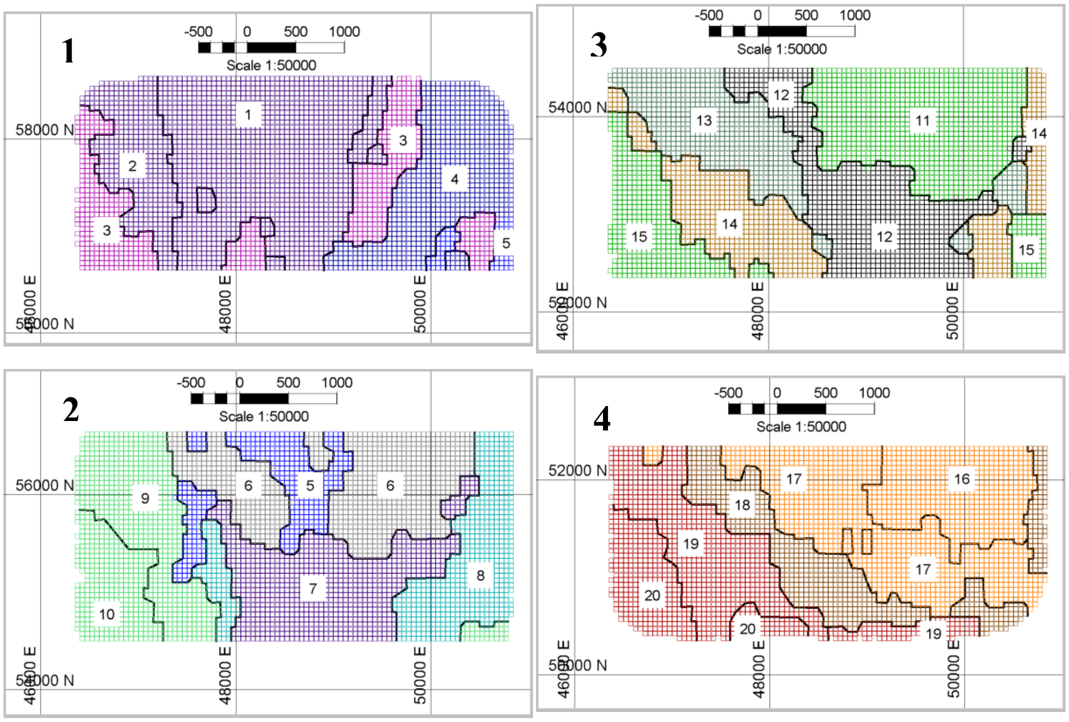

Figure 5.2: Pushbacks 1, 2, 3 and 4 mining sequence at level 280 m

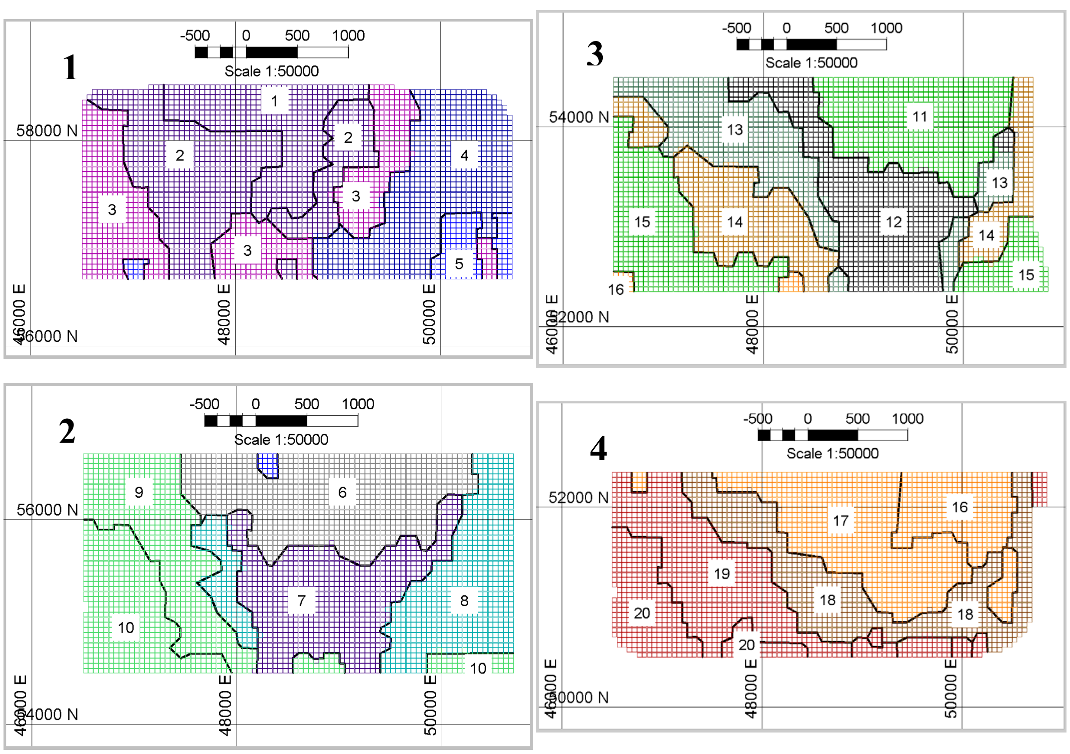

Figure 5.3: Pushbacks 1, 2, 3 and 4 mining sequence at level 295 m

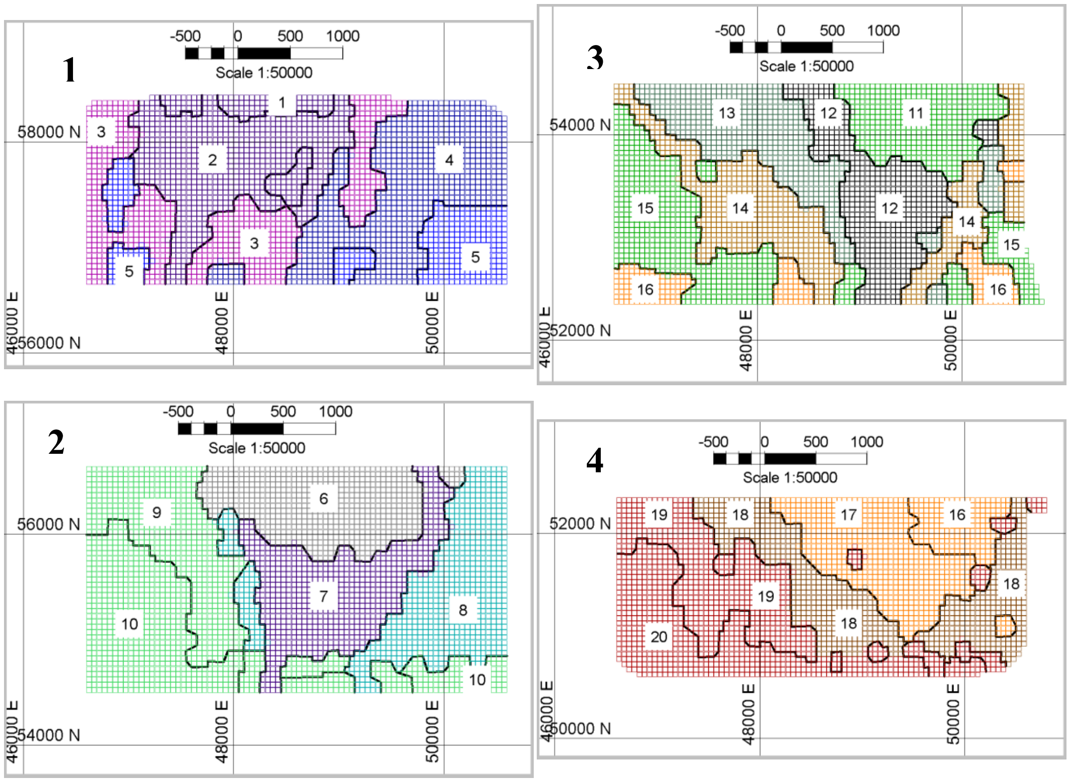

Figure 5.4: Pushbacks 1, 2, 3 and 4 mining sequence at level 310 m

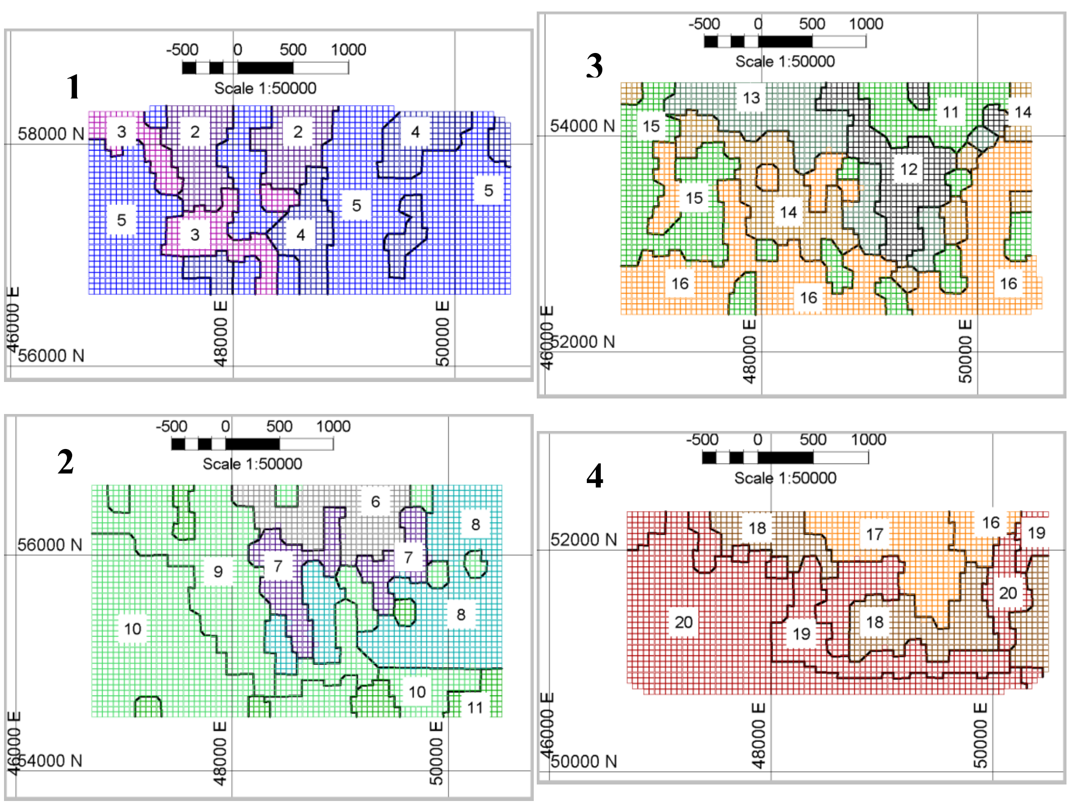

Figure 5.5: Pushbacks 1, 2, 3 and 4 mining sequence at level 325 m

During the first year, due to the requirements of the ETF dyke construction material, less ore and more OI dyke material is mined to facilitate the construction of the key trench and starter dyke and then subsequently, TCS dyke material can be used to continue constructing the main dyke as planned in the conceptual dyke design. This ensures that the tailings containment area is created in time for the storage of fluid fine tailings. Ore becomes available at full processing plant capacity from year 2 until the end of the mine life and subsequently TCS dyke material. The OI dyke material supply was also maintained at a uniform rate throughout the mine life. Figure 5.6 shows the schedules for ore, OI and TCS dyke material, and waste tonnages generated for 20 periods. Figure 5.7 shows the material mined and TCS dyke material tonnage produced in each pushback for 20 periods. Figure 5.8 shows the dyke material tonnage sent to the various dyke construction destinations for 20 periods and Figure 5.9 shows the OI and TCS dyke material volume scheduled for 20 periods. It can be seen from Table 3.2 that 23Mm^3 of OI dyke material is required for the ETF key trench and starter dyke construction and this material requirement has been adequately catered for by scheduling 40Mm^3 of OI dyke material in period 1 as shown in Figure 5.9.

The total material mined was 4866.2Mt. This is made up of 2720.4Mt of ore and 1386.7Mt of OI dyke material whilst 2055.2Mt of TCS dyke material was generated. A total of 1602.1Mm^3 of dyke material was scheduled which is sufficient to construct the in-pit and ex-pit impoundments required to contain the tailings produced. The schedules give the planner good control over dyke material and provides a robust platform for effective dyke construction planning and tailings storage management.

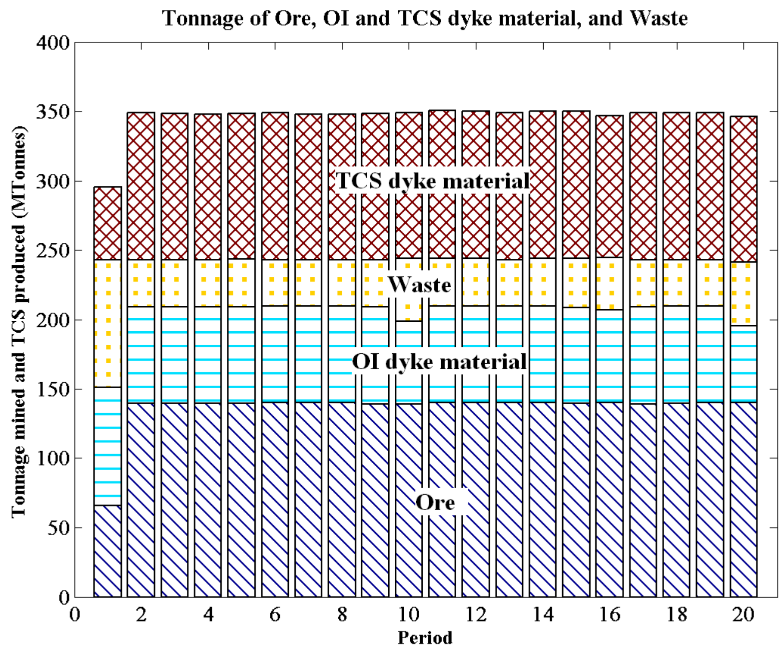

Figure 5.6: Schedules for ore, OI and TCS dyke material, and waste tonnages produced over 20 periods

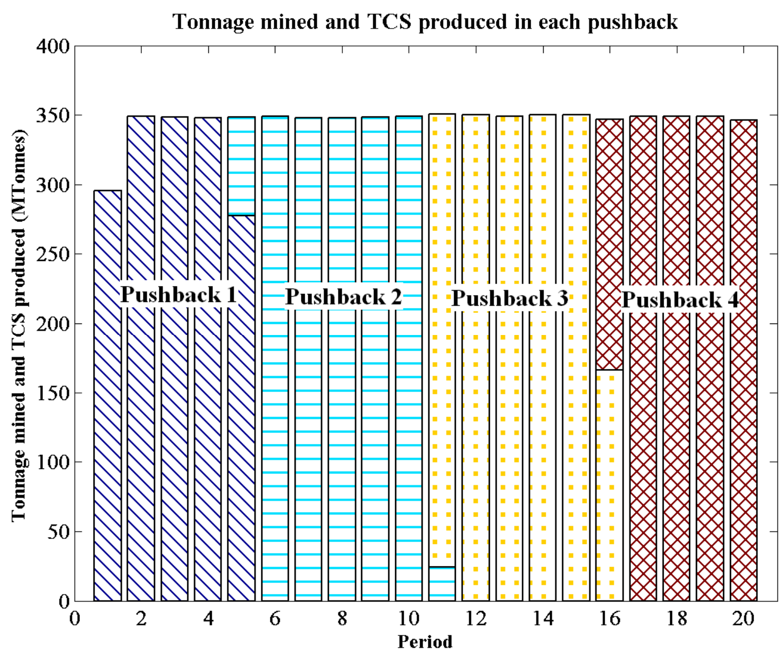

Figure 5.7: Material mined and TCS dyke material tonnage produced in each pushback for 20 periods

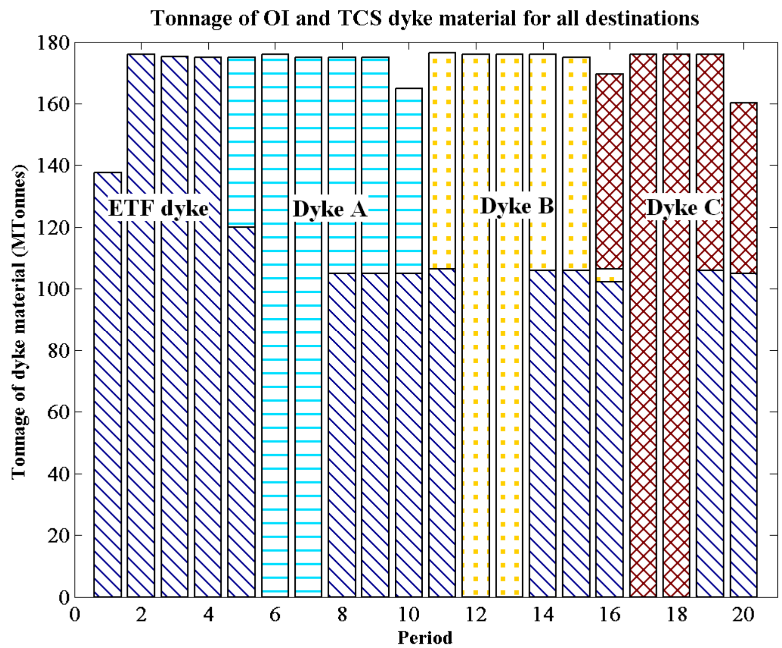

Figure 5.8: Dyke material tonnage sent to the various dyke construction destinations for 20 periods

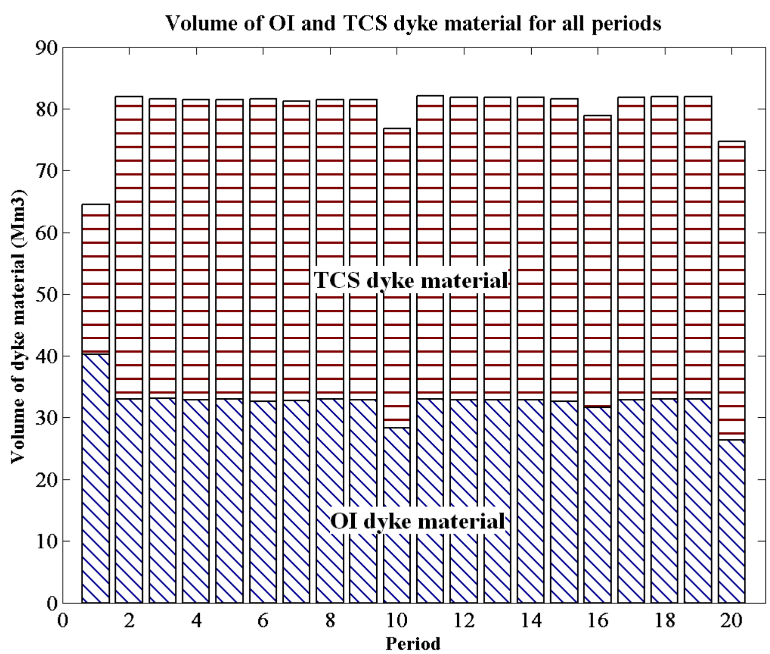

Figure 5.9: OI and TCS dyke material volume scheduled for 20 periods

There is also an inherent task of blending the run-of-mine materials to meet the quality and quantity specifications of the processing plant and dyke construction. The blending problem becomes more prominent as more detailed planning is done in the medium to short term. The processing plant head grade and OI dyke material grade that was set were successfully achieved in all periods for all destinations. With the exception of period 1, the scheduled average ore bitumen grade was between 10.9 and 12.2%. The average ore bitumen grade for period 1 was 10.3% basically due to the emphasis placed on mining OI dyke material for the ETF key trench and starter dyke construction. This was required to construct the initial tailings containment when ore processing starts. The average ore and OI dyke material fines percent were between 14 and 30%, and 10 and 23% respectively. Figure 5.10 and Figure 5.11 show the average ore bitumen grade and ore fines percent for all pushbacks respectively. Figure 5.12 shows the average OI dyke material fines percent for all pushbacks.

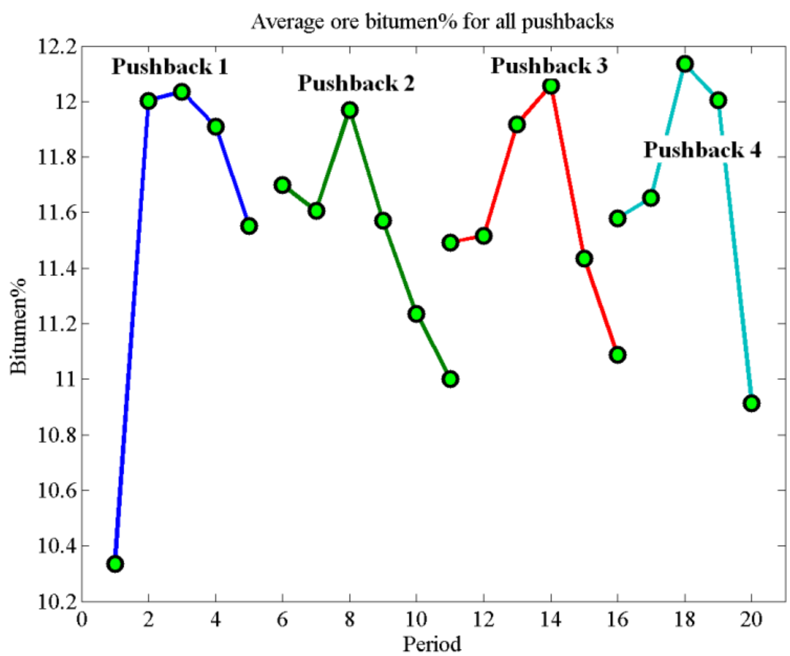

Figure 5.10: Average ore bitumen grade for all pushbacks

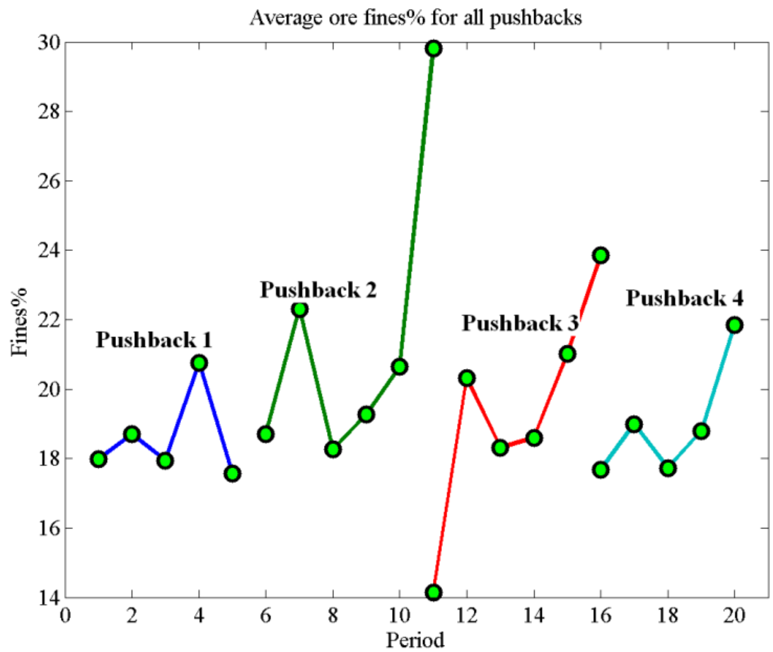

Figure 5.11: Average ore fines percent for all pushbacks

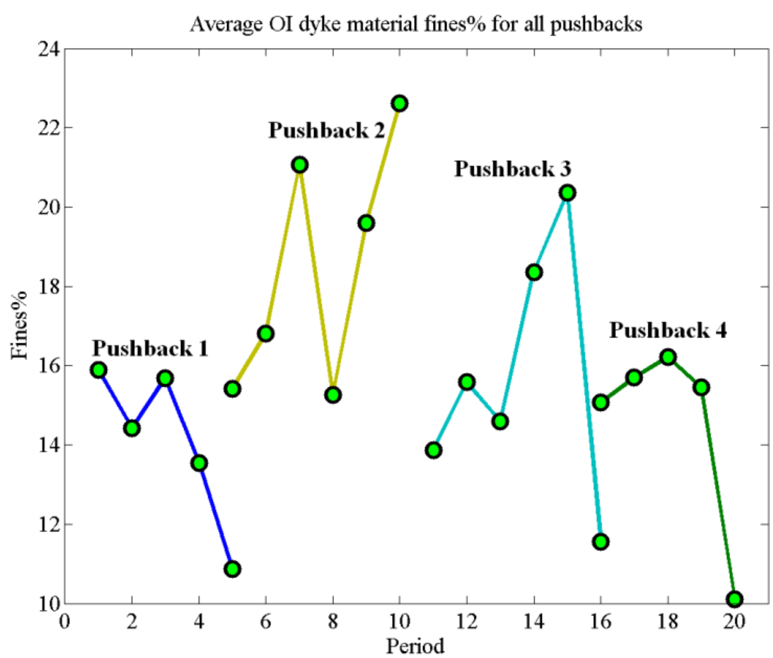

Figure 5.12: Average OI dyke material fines percent for all pushbacks

5.4.1 Waste Disposal Planning and the Environment

Using the conceptual mining model, the MILGP model framework has illustrated how production scheduling can be effectively integrated with waste disposal planning for oil sands mining. Based on dyke construction requirements, schedules are generated to provide the required dyke materials. Providing appropriate dyke material to support engineered dyke construction will help in reducing environmental and public concerns related to the risk of tailings dam failure, seepage, potential water contamination and intergenerational transfer of liability. This will be due to the improved integrity of the constructed dykes for tailings containment.

The directional pushback mining ensures that timely in-pit tailings storage areas are made available for tailings storage thereby reducing the footprints of the ETF and tailings containment in general. This will also help in reducing environmental and public concerns related to large scarred areas, lack of progressive reclamation and return of the land to traditional use since less effort will be required to reclaim a smaller disturbed landscape. Using the MILGP model framework therefore results in better environmental management and sustainable oil sands mining.

5.4.2 Supplementary Experiments

The data shown in Table 5.5 represents the summary of results for other optimization experiments that were conducted prior to selecting the illustration presented in this case study. This illustration corresponds to run 3 on the table. These experiments were designed to highlight some of the basic properties of the MILGP model. The experiments were ranked based on how smooth the mining proceeds from one period to another and the uniformity of tonnages mined per period. The initial optimization experiment conducted was run 1 which schedules for a north-south mining direction. Further work was done by optimizing with a south-north mining direction (run 2) which yielded a lower NPV and a lower dyke material tonnage. The lower NPV results from mining pushbacks with lower economic block values in the early years. Less ore was mined and a less uniform schedule was produced due to the mining direction.

Further investigations were conducted by increasing the number of mining cuts as in run 3. This resulted in an increase in NPV resulting from an increase in the resolution of the optimization problem. The increased resolution increases the flexibility of the problem as well as the number of decision variables thereby increasing the optimization runtime. A smooth and uniform schedule was generated. Another experiment (run 4) was done to test the MILGP model in terms of placing a higher penalty cost and priority (PP) value on one goal as compared to the others. The increased PP value for OI dyke material further constrains the optimization problem decreasing the ore to dyke material ratio and causing a decrease in the overall NPV which includes dyke construction cost. The dyke material tonnes increases and hence the dyke construction cost. Additional experiments were conducted by varying the dyke material PP values to study this trend. As illustrated in Figure 5.13, in general within the set mining constraints, as the PP values for dyke material increases, the NPV decreases as a result of an increase in dyke material tonnes. This approach is useful when more dyke material is required for tailings containment construction to enable a sustainable mining operation.

Comparing these experiments, run 3 was selected because it generates the best overall NPV as well as a good schedule and the required dyke material tonnage.

Table 5.5: Results for supplementary experiments showing that run 3 generates the highest NPV and best schedule

Run #	Total Cuts	Mining dxn	PP values				Run-time (min)	Overall NPV ($M)	Dyke material (Mt)	Schedule uniformity/ smoothness ranking
			Mining	Ore	OI	TCS				
1	1977	NS	0	20	30	30	105	13,810	3315	3
2	1977	SN	0	20	30	30	17	10,713	3012	4
3	3917	NS	0	20	30	30	288	14,237	3442	1
4	3917	NS	0	20	60	30	59	14,121	3460	2

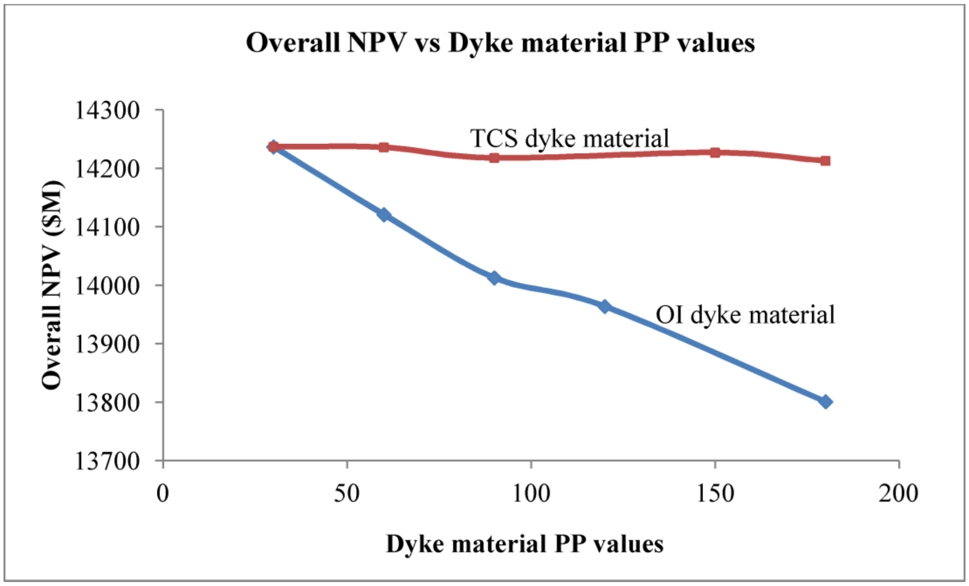

Figure 5.13: General trend of overall NPV with PP values of dyke material

5.4.3 Conclusions: Case Study 1

Oil sands mining requires a carefully planned and integrated mine planning and waste management strategy that generates value and is sustainable. This requires that production schedules are generated for ore, dyke material and waste to ensure that whilst ore is fed to the processing plant, there is enough dyke material available for dyke construction for both the ex-pit and in-pit tailings facilities. This ensures there is adequate storage space for the tailings throughout the mine life whilst reducing the size of the disturbed landscape by making the best use of in-pit tailings facilities and reducing the size of the external tailings facility. The MILGP formulation uses binary integer variables to control mining precedence and continuous variables to control mining of ore and dyke material. There are also goal deviational variables and penalty costs and priorities that must be set up by the planner. The optimization model was implemented in Tomlab/CPLEX environment.

The developed model was able to create value and a sustainable operation by generating a practical, smooth and uniform schedule for ore and dyke material using mining-cuts from block clustering techniques. The schedule gives the planner good control over dyke material and provides a robust platform for effective dyke construction and waste disposal planning. The schedule ensures that the key drivers for oil sands profitability and sustainability, which is maximizing NPV whilst creating timely tailings storage areas are satisfied within an optimization framework. This is in accordance with recent regulatory requirements by Energy Resources Conservation Board (Directive 074) that requires oil sands mining companies to develop an integrated life of mine plans and tailings disposal strategies for in-pit and external tailings disposal systems (McFadyen, 2008). The planner also has the flexibility of choosing goal deviational variables, penalty costs and priorities to achieve a uniform schedule and improved NPV. Similarly, tradeoffs between achieving goals and maximizing NPV or minimizing dyke construction cost can be made.

The overall NPV generated including the dyke construction cost for all pushbacks and destinations is $14,237M. The scheduled average ore bitumen grade was between 10.9 and 12.2%. The average ore and OI dyke material fines percent were between 14 and 30%, and 10 and 23% respectively. The total material mined was 4866.2Mt. This is made up of 2720.4Mt of ore and 1386.7Mt of OI dyke material whilst 2055.2Mt of TCS dyke material was generated.

5.5 Case Study 2: Implementation of the MILGP Model

The oil sands deposit under consideration is located in the province of Alberta, Canada, within the Fort McMurray region. The exploration work for this deposit resulted in 210 drillholes. The final pit covers an area of about 704 ha and the mineralized zone occurs in the McMurray formation. Inverse distance squared interpolation scheme (ArcGIS, 2010) was used in developing the geologic block model. The deposit is to be scheduled for 10 periods for the processing plant and dyke construction locations. The material to be sent to the processing plant includes the minimum regulatory requirement of at least 7% bitumen and the fines content must also support the bitumen extraction process. The material for dyke construction must also contain just enough fines to build dykes of high integrity.

Table 5.6 provides details about the final pit block model used in this case study. The final pit block model was generated using the LG algorithm (Lerchs and Grossmann, 1965) in Whittle (Gemcom Software International Inc., 2012) as documented in section 5.7.1. The final pit was divided into 5 intermediate pushbacks to be used in creating practical mining-panels that will control the mining operation. These mining-panels contain an approximately equal tonnes of material to be mined. Blocks within the mining-panels were clustered into mining-cuts using a hierarchical clustering algorithm (Tabesh and Askari-Nasab, 2011). An EPGAP of 1% was set for optimization. Production scheduling variables that need to be controlled include the mining targets, processing plant feed quality and dyke construction material quality. These parameters have been summarized in Table 5.7. After initial directional mining runs with Whittle, production scheduling will proceed in the west-east mining direction which yielded a higher NPV. Material will be scheduled for the processing plant and 4 dyke construction destinations simultaneously. It is assumed that all the dyke construction destinations are ready to receive dyke material when mining starts.

The performance of the MILGP model was analyzed based on the NPV, mining production goals, smoothness and practicality of the generated schedules and the flexibility that comes with calibrating and using the penalty and priority parameters. The model was implemented on a Quad-Core Dell Precision T7500 computer at 2.8GHz with 24GB of RAM.

Table 5.6: Oil sands deposit characteristics within the final pit limit to be scheduled for 10 periods

Characteristic	Value
Tonnage of rock (Mt)	1,244.8
Ore tonnage (Mt)	394.8
OB dyke material tonnage (Mt)	406.4
IB dyke material tonnage (Mt)	204.4
TCS dyke material tonnage (Mt)	298.8
Waste tonnage (Mt)	239.2
Average ore bitumen grade (wt%)	11.0
Average ore fines (wt%)	14.5
Average IB dyke material fines (wt%)	24.7
Number of blocks	16,985
Number of mining-cuts	968
Number of mining-panels	43
Block dimensions (m)	50 x 50 x 15
Number of benches	9

Table 5.7: Mining and processing goals, OB, IB and TCS dyke material goals, ore and IB dyke material quality requirements for each destination for 10 periods

Production scheduling parameter	Value
Mining goal (Mt)	125
Processing goal (Mt)	47
OB dyke material goal (Mt)	11
IB dyke material goal (Mt)	6
TCS dyke material goal (Mt)	8
Ore bitumen grade upper/lower bounds (wt%)	16 / 7
Ore fines percent upper/lower bounds (wt%)	30 / 0
IB dyke material fines percent upper/lower bounds (wt%)	50 / 0

5.5.1 Analysis

Run 7 in Table 5.9 was chosen for analysis because it generated the required dyke material tonnages. The results after optimization shows an overall NPV including dyke construction cost for all destinations as \$4771M and the total dyke construction cost as \$714M at a 0.99% EPGAP. The conceptual mining model implemented here focuses on a practically integrated OSLTPP and waste management strategy that generates value and is sustainable. This includes mining in the desired direction and releasing completely extracted pushbacks for in-pit dyke construction and subsequently tailings management. This reduces the environmental footprints of the external tailings facility by commissioning in-pit tailings storage areas on time. The mining sequence at level 305m with a west-east mining direction has been shown in Figure 5.14. Figure 5.14 shows a progressive continuous mining in the specified direction ensuring the least mobility of loading equipment and increased utilization. The size of the mining-cuts and mining-panels enables good equipment maneuverability for the large cable shovels and trucks used in oil sands mining. There are also a reduced number of drop cuts required during production development.

The mining, processing and dyke material schedules in Figure 5.15 ensure efficient utilization of mining fleet, processing plant and dyke construction equipment throughout the mine life. The mining targets in periods 9 and 10 were short by 5% (Table 5.8). This is due to the fact that mining any more material will add a negative value to our objective function. As shown in Run 8 in Table 5.9, increasing the mining goal PP value caused all material in the final pit to be mined with more waste thereby reducing the overall NPV. Pre-stripping of ore starts in periods 1 and 2, and ore production starts in period 2, ramping up in periods 3 and 4. The shortfall of 23% in the processing plant target in period 2 was due to the required pre-stripping, the ore grade distribution in the area and the ore feed uniformity required by the processing plant to maximize NPV (Table 5.8, Figure 5.15). The processing plant starts operating at full capacity from period 5 to the end of mine life. The dyke material required at the various dyke construction locations are also mined and scheduled appropriately. The dyke material tonnage required is generated from the conceptual dyke design. This is used as the dyke material target and as shown in Figure 5.20, increasing the dyke material PP values increases the dyke material tonnage mined. This can be used to vary the dyke material requirements. The 11% average shortfall shown in Table 5.8 and Figure 5.16 for periods 2, 4, 5 and 7 in the target dyke material tonnes was allowed because it was assumed that the generated dyke material tonnage was enough to support the dyke construction. By increasing the dyke material PP values more dyke material can be mined at the expense of the NPV. The ore and dyke material quality required was generated by blending the run-of-mine material. The periodic grades can be varied based on the processing plant or dyke construction requirements. These schedules provide an efficient and sustainable platform for an integrated oil sands production scheduling and waste disposal planning strategy. Figure 5.17 and Figure 5.18 show the average ore bitumen grades and ore fines percent over the mine life from the MILGP model. The minimum and maximum average IB dyke material fines percent obtained for all destinations were 9% and 45% respectively.

Table 5.8: Detailed period by period production scheduling results and deviations

Production scheduling parameter	Period									
	1	2	3	4	5	6	7	8	9	10
Mining goal (Mt)	125	125	125	125	125	125	125	125	122	122
Material scheduled (Mt)	125	125	125	125	125	125	125	125	116	116
% deviation	0	0	0	0	0	0	0	0	5	5
Processing goal (Mt)	0	35	39	39	47	47	47	47	47	47
Ore scheduled (Mt)	0	27	39	39	47	47	47	47	47	47
% deviation	0	23	0	0	0	0	0	0	0	0
Dyke material goal (Mt)	58	98	98	98	98	98	98	74	74	57
Dyke material scheduled (Mt)	58	87	98	88	85	96	88	74	73	57
% deviation	0	11	0	10	13	2	10	0	1	0

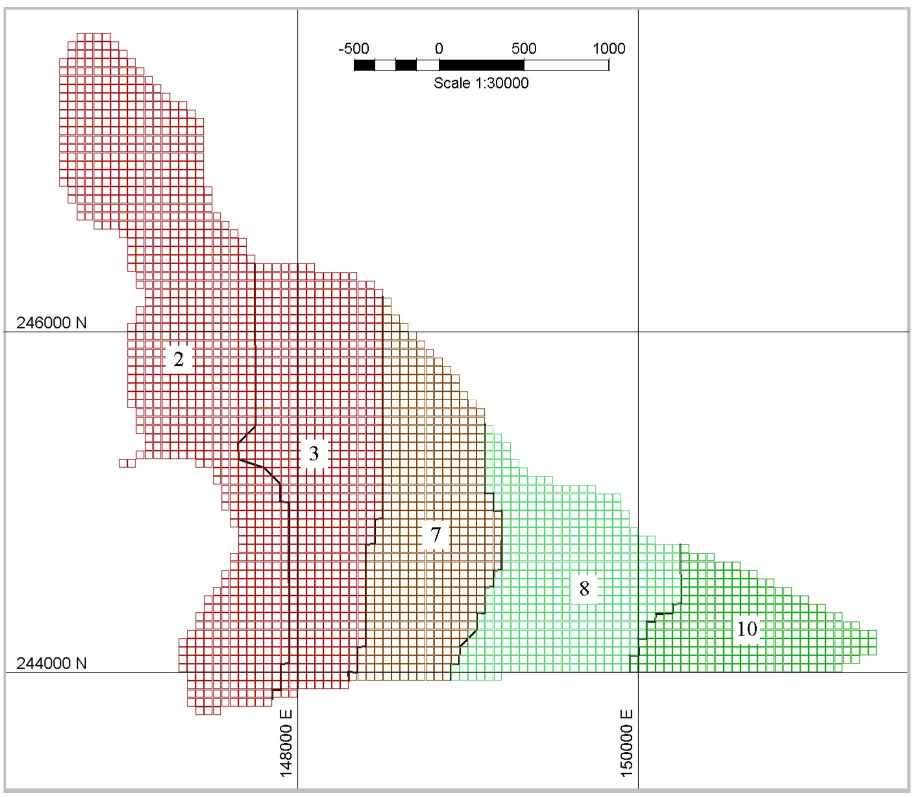

Figure 5.14: Mining sequence at level 305m with a west-east mining direction

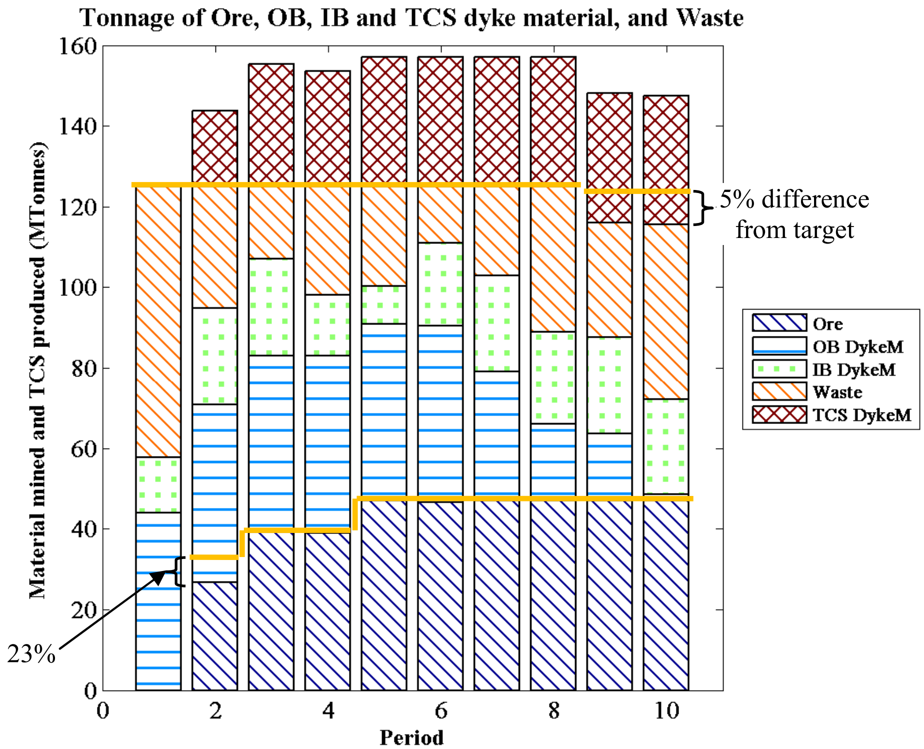

Figure 5.15: Schedules for ore, OB, IB and TCS dyke material, and waste tonnages

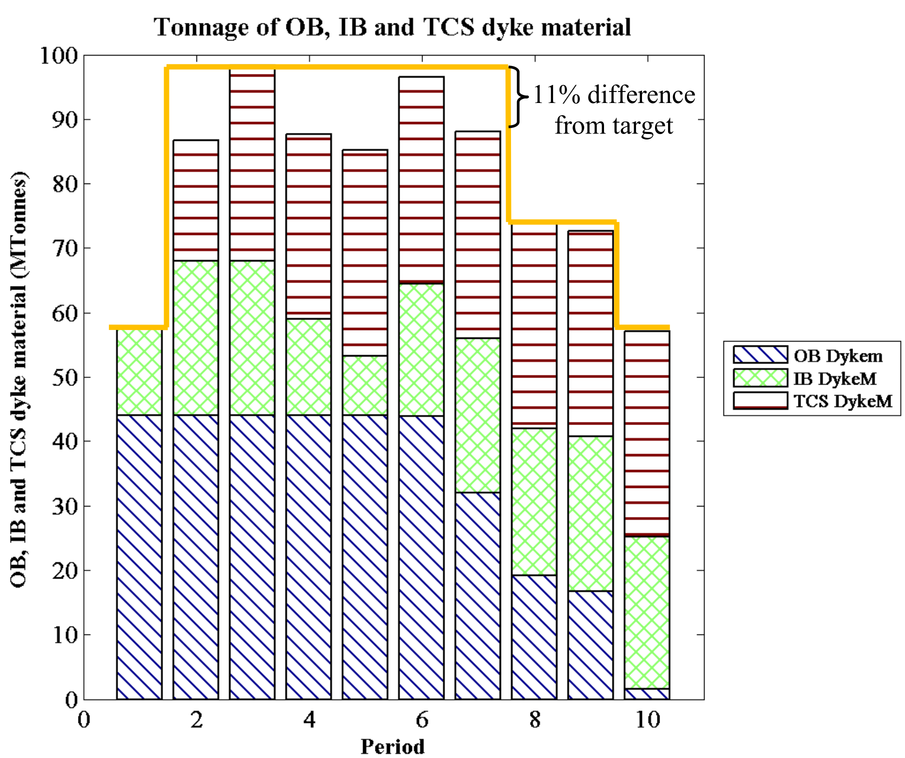

Figure 5.16: Schedules for OB, IB and TCS dyke material

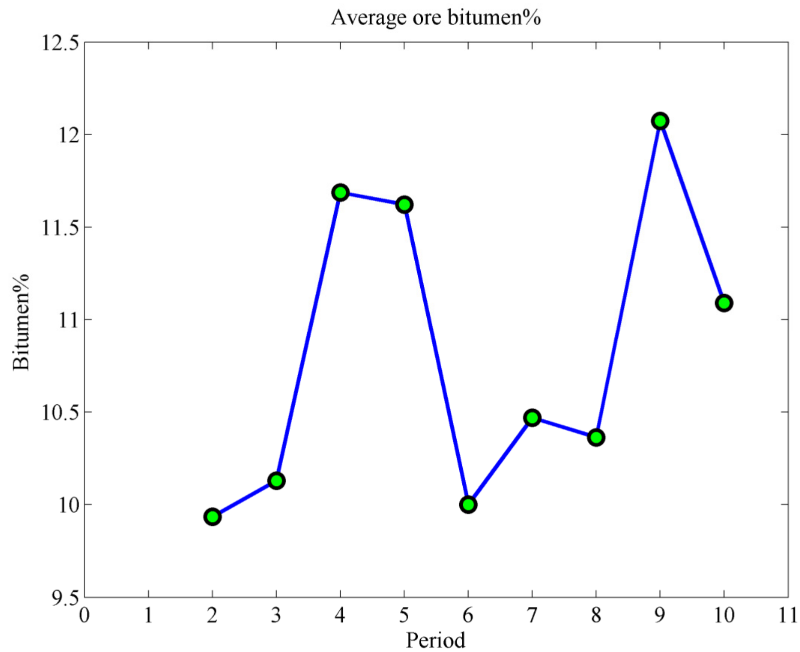

Figure 5.17: Average ore bitumen

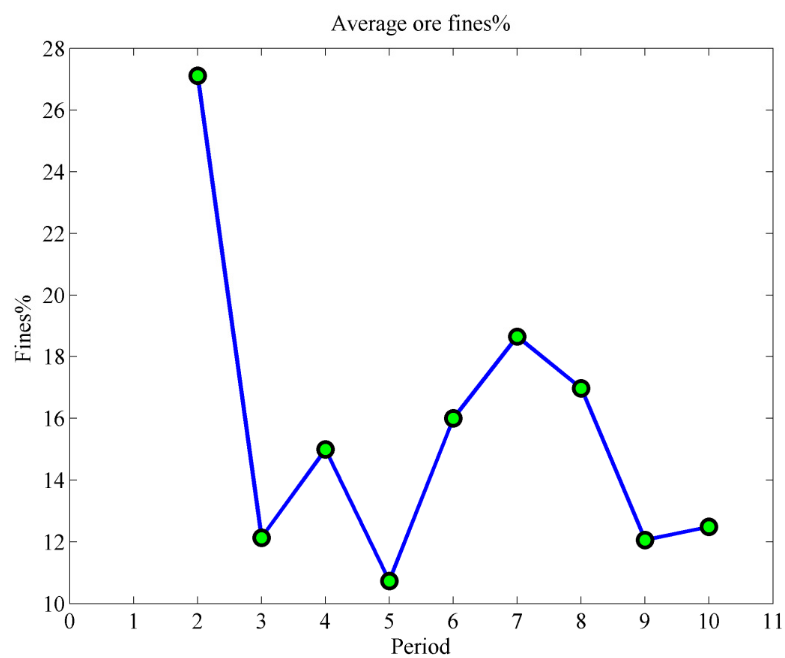

Figure 5.18: Average ore fines

5.5.2 Comparison

An attempt was made to run a set of experiments to highlight the advantages and flexibility that comes with the MILGP model, and the sensitivity of some of the input parameters. Results of these experiments have been summarized in Table 5.9. The initial optimization experiments conducted were runs 1, 2 and 3. These were done to assess the impact of different mining-cut sizes on the NPV generated. The mining-cut sizes are usually controlled by the practicality of the mining units required in the operation. As the mining-cut sizes reduces, the number of mining-cuts increases and hence the number of decision variables. It was observed that the increase in number of mining-cuts generated an increased NPV, though just about 0.4% (Run 3). This is as a result of an increase in the resolution of the optimization problem which increases its flexibility and solution runtime. Figure 5.19 shows a general trend graph of overall NPV with number of mining-cuts.

Subsequent experiments (Runs 3 to 9) were done to test the sensitivity of the MILGP model in terms of varying the penalty and priority (PP) values of different goals. The experiments started with no PP values in Run 3. The investigation proceeded by increasing the dyke material PP values in Runs 4 to 7. This resulted in an increase in dyke material tonnes decreasing the overall NPV accordingly. The increased dyke material PP values further constrain the optimization problem to mine more dyke material, increasing the dyke construction cost and the solution runtime. The ore tonnage mined remains the same. As illustrated in Figure 5.20, in general within the set mining constraints, as the PP values for dyke material increases, the overall NPV decreases as a result of an increase in dyke material tonnes. This approach introduces some flexibility with regards to balancing the dyke material requirements. In Run 8, the PP value for the mining goal was increased. This resulted in an increase in waste tonnes thereby reducing the overall NPV. An increase in the PP values for the ore goal in Run 9 did not affect the ore tonnes mined or the overall NPV. This is the case because the ore tonnes drive the optimization problem and with or without an increase in PP values, the optimal ore schedule will be mined within the defined constraints.

Run 10 was set up for the purposes of comparison with Whittle production scheduling. An attempt was made to run to optimality with zero dyke material targets. Further to this, Run 11 was set up to run the MILGP model to enforce complete extraction of each material type with the highest priority. Several runs showed that, a PP value of 500 for each material type ensures complete extraction of the associated material, subject to the defined constraints. With an OB dyke material PP value of 500, the total available OB dyke material in the mine was completely scheduled with the highest priority. Ore mining was deferred to latter years and ore tonnage was reduced affecting the NPV significantly.

Table 5.9a: Results from the MILGP model showing the sensitivity of number of mining-cuts and penalty and priority parameters

Run #	Blocks/ Mining -Cut	Total Mining -Cuts	Total Panels	Decision Variables	Constraints	Min PP	Ore PP	Dyke Material PP		
								OB	IB	TCS
1	100	212	43	28560	5458	1	1	1	1	1
2	50	380	43	50400	7810	1	1	1	1	1
3	20	968	43	126840	16042	1	1	1	1	1
4	20	968	43	126840	16042	1	1	1.5	1.5	1.5
5	20	968	43	126840	16042	1	1	2	2	2
6	20	968	43	126840	16042	1	1	5	5	5
7	20	968	43	126840	16042	1	1	10	10	10
8	20	968	43	126840	16042	10	1	1	1	1
9	20	968	43	126840	16042	1	10	1	1	1
10	20	968	43	126840	16042	1	1	1	1	1
11	20	968	43	126840	16042	1	1	1	500	1

Table 5.9b: Results from the MILGP model showing the sensitivity of number of mining cuts and penalty and priority parameters

Run #	Tonnage Mined (Mt)	Ore (Mt)	Dyke Material (Mt)			Waste (Mt)	Overall NPV ($M)	NPV %diff	Dyke Cost ($M)	EP-GAP (%)	Run-time (min)
			OB	IB	TCS						
1	1220	387	0	0	112	833	5421	13.6	65	1.00	0.3
2	1225	387	0	0	144	838	5432	13.9	77	0.99	0.9
3	1225	387	0	0	144	838	5443	14.1	77	0.98	3.2
4	1225	387	106	60	270	672	5229	9.6	292	0.89	5.6
5	1225	387	329	186	270	323	4829	1.2	691	1.00	15.7
6	1225	387	333	189	270	316	4809	0.8	703	0.99	17.3
7	1232	387	333	201	270	311	4771	0	714	0.99	29.6
8	1245	387	0	0	144	858	5391	13.0	77	0.99	2.1
9	1225	387	0	0	144	838	5443	14.1	77	1.00	2.3
10	1225	387	0	0	0	838	5522	15.7	0	0.00	0.7
11	1205	335	0	204	134	666	3988	-16.4	280	0.99	71.8

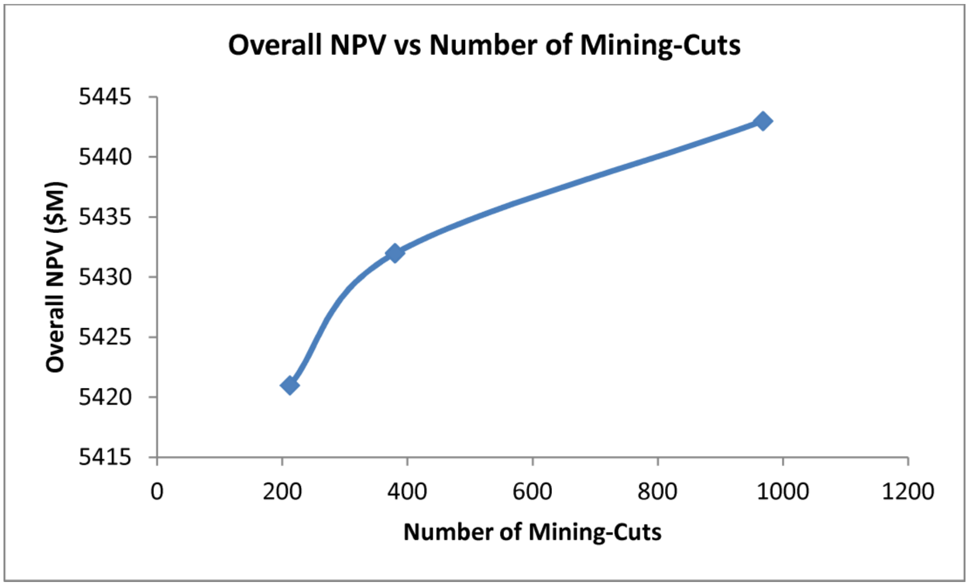

Figure 5.19: General trend of overall NPV with number of mining-cuts

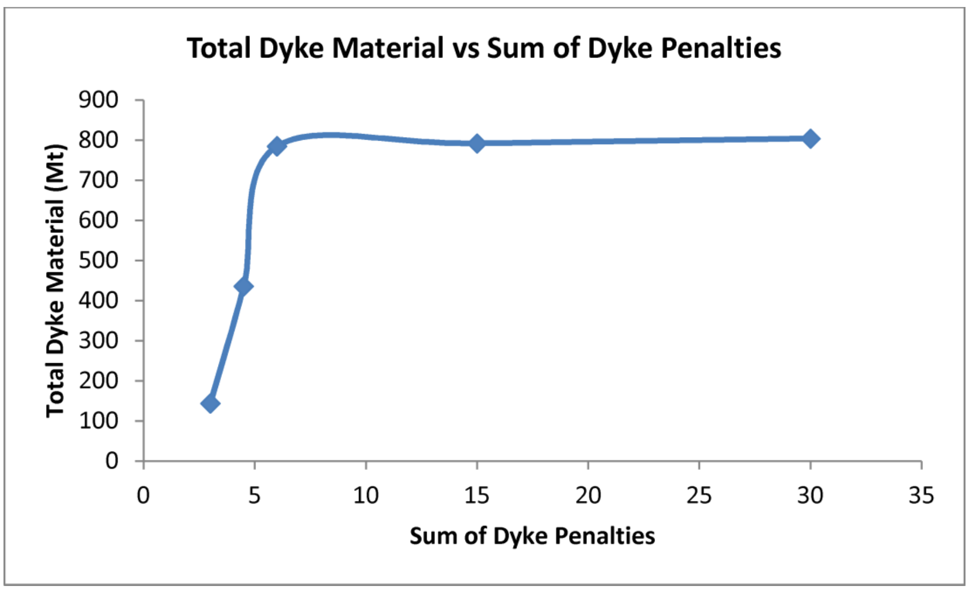

Figure 5.20: General trend of dyke material tonnage with dyke material PP values

5.5.3 Conclusions: Case Study 2

It is important during mine planning to schedule with mining units that is practical for mining operation. The results from this case study show that decreasing the selective mining units increases the NPV of the production schedule due to the increased flexibility during optimization. Also, the dyke material tonnage scheduled can be varied using the dyke material penalty and priority (PP) values to meet the dyke construction requirements from the conceptual dyke design. The increased PP values further constrain the optimization problem to generate more dyke material at the expense of the overall NPV.

The overall NPV generated including the dyke construction cost for all destinations is $4,771M. The scheduled average ore bitumen grade and ore fines percent were between 9.5 and 12.5%, and 10 and 28% respectively. The minimum and maximum average IB dyke material fines percent obtained for all destinations were 9% and 45%. The total material mined was 1232Mt. This is made up of 387Mt of ore and 534Mt of OB and IB dyke material whilst 270Mt of TCS dyke material was generated.

5.6 Case Study 3: Implementation of the MILGP Model

The MILGP model was coded in Matlab (Mathworks Inc., 2011) and implemented on an oil sands deposit which is characterized with 326 drillholes covering an area of about 3900 ha (Figure 5.21). The mineralized zone of this deposit occurs in the McMurray formation and is contained in two final pits. The deposit is to be scheduled for 16 periods equivalent to 16 years for the processing plant and dyke construction destinations. The performance of the proposed MILGP model was analyzed based on NPV, mining production goals, smoothness and practicality of the generated schedules, the availability of tailings containment areas at the required time and the computational time required for convergence. The model was implemented on a Quad-Core Dell Precision T7500 computer at 2.8 GHz, with 24GB of RAM. Table 5.10 provides information about the orebody model within the ultimate pits limits used in the case study. Figure 5.22 shows the general bitumen content distribution in the study area on level 305m.

The area to be mined are divided into 4 pushbacks in consultation with tailings dam engineers based on required tailings cell capacities and the timelines required in making the cell areas available for tailings containment. These 4 pushbacks are further divided into 20 intermediate pushbacks to enable the creation of practical mining-panels to be used in controlling the mining operation (Figure 5.23). These intermediate pushbacks are created using an approximately equal distribution of tonnages to be mined across the deposit. An agglomerative hierarchical clustering algorithm is used in clustering blocks within each intermediate pushback into mining-cuts (Tabesh and Askari-Nasab, 2011). Clustering blocks into mining-cuts ensures the MILGP scheduler generates a schedule at a selective mining unit that is practical from mining operation perspective. Mining, processing and dyke material scheduling are implemented with mining-panels as the mining scheduling units and mining-cuts as the processing and dyke material scheduling units. In solving the MILGP model with CPLEX, the absolute tolerance on the gap between the best integer objective and the objective of the best node remaining in the branch and cut algorithm, referred to as EPGAP, was set at 5% for the optimization of the mining project. The mining targets, processing plant feed, dyke construction requirements, bitumen grade and fines percent need to be controlled within acceptable ranges. These requirements have been summarized inTable 5.11. The mining direction was decided on during the initial production schedule run using the Fixed Lead heuristic algorithm in Whittle (Gemcom Software International Inc., 2012). The mining direction with the best NPV was selected for the MILGP model. Mining will proceed in the west to east direction, from pushback 1 to 4 with complete extraction of each pushback prior to the next. In addition to the processing plant, dyke material requirements for 4 dyke construction destinations will be scheduled simultaneously. It is assumed that all dyke construction destinations are ready to receive dyke material as soon as mining starts. This case study will be implemented with the efficient MILGP model which features an initial production schedule and a pushback mining constraint.

Table 5.10: Oil sands deposit characteristics within the ultimate pit limits to be scheduled for 16 periods

Characteristic	Pit 1	Pit 2		
	Pushback Value			
	1	2	3	4
Tonnage of rock (Mt)	1,244.8	2,165.9	2027.9	2068.7
Ore tonnage (Mt)	394.8	673.0	693.1	549.7
OB dyke material tonnage (Mt)	406.4	667.5	633.9	564.9
IB dyke material tonnage (Mt)	204.4	589.5	597.8	686.0
TCS dyke material tonnage (Mt)	298.8	468.0	454.0	428.0
Waste tonnage (Mt)	239.2	235.9	103.1	268.1
Average ore bitumen grade (wt%)	11.0	11.0	11.5	10.5
Average ore fines (wt%)	14.5	21.8	21.5	22.6
Average IB dyke material fines (wt%)	24.7	37.1	39.1	39.7
Number of blocks	16,985	28,700	26,667	26,393
Number of mining-cuts	380	630	579	564
Number of mining-panels	43	44	40	39
Block dimensions (m)	50 x 50 x 15			
Number of benches	9			

Table 5.11: Mining and processing goals, OB, IB and TCS dyke material goals, ore and IB dyke material grade requirements for each destination for 16 periods

Production scheduling parameter	Value
Mining goal (Mt)	470
Processing goal (Mt)	145
OB dyke material goal (Mt)	36
IB dyke material goal (Mt)	33
TCS dyke material goal (Mt)	26
Ore bitumen grade upper/lower bounds (wt%)	16 / 7
Ore fines percent upper/lower bounds (wt%)	30 / 0
IB dyke material fines percent upper/lower bounds (wt%)	50 / 0

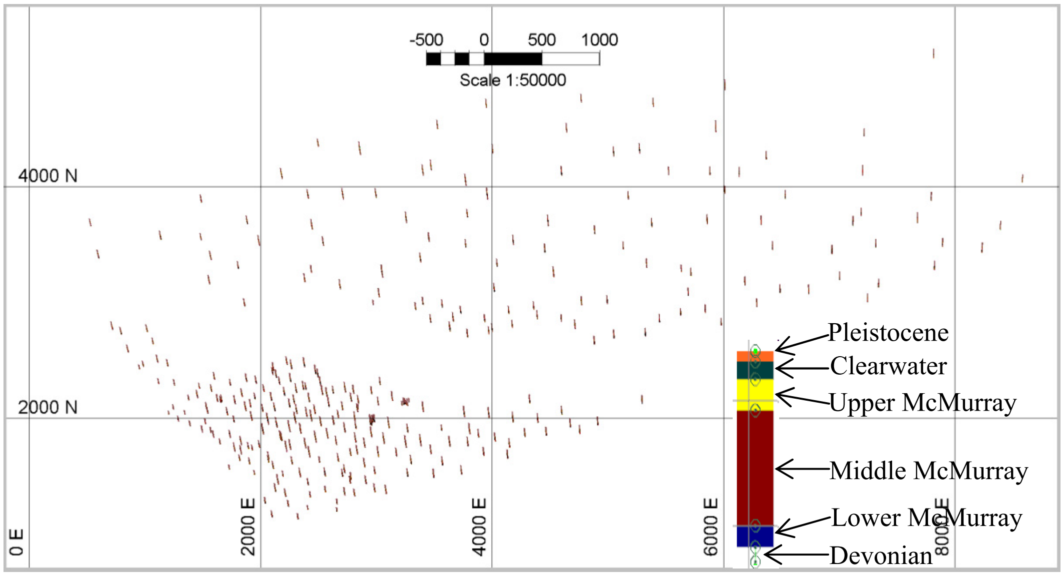

Figure 5.21: A 2D projection of 326 drillholes used for resource modeling and a drillhole cross section

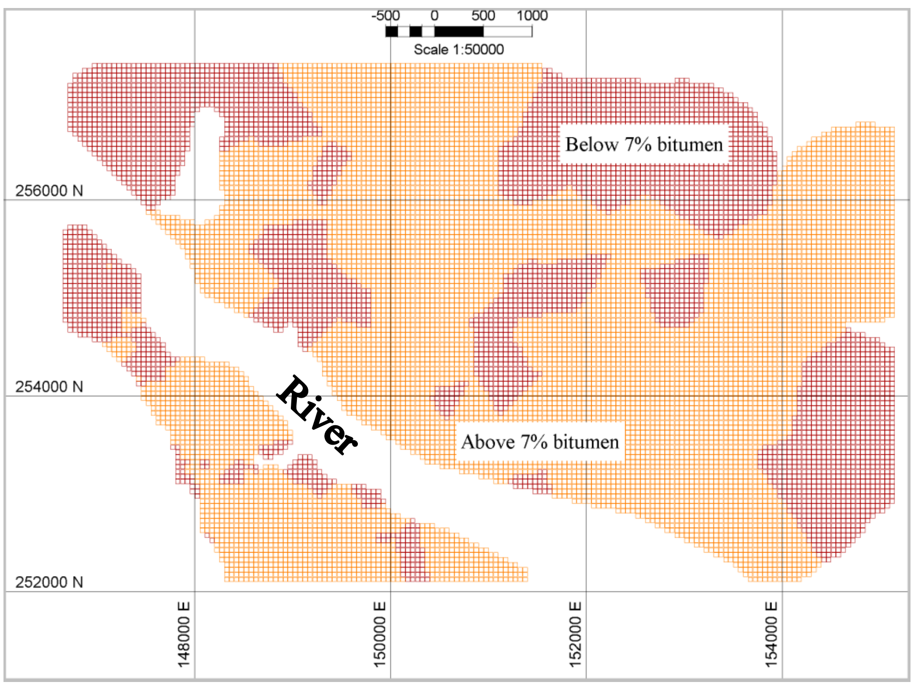

Figure 5.22: General bitumen content distribution in study area on level 305m

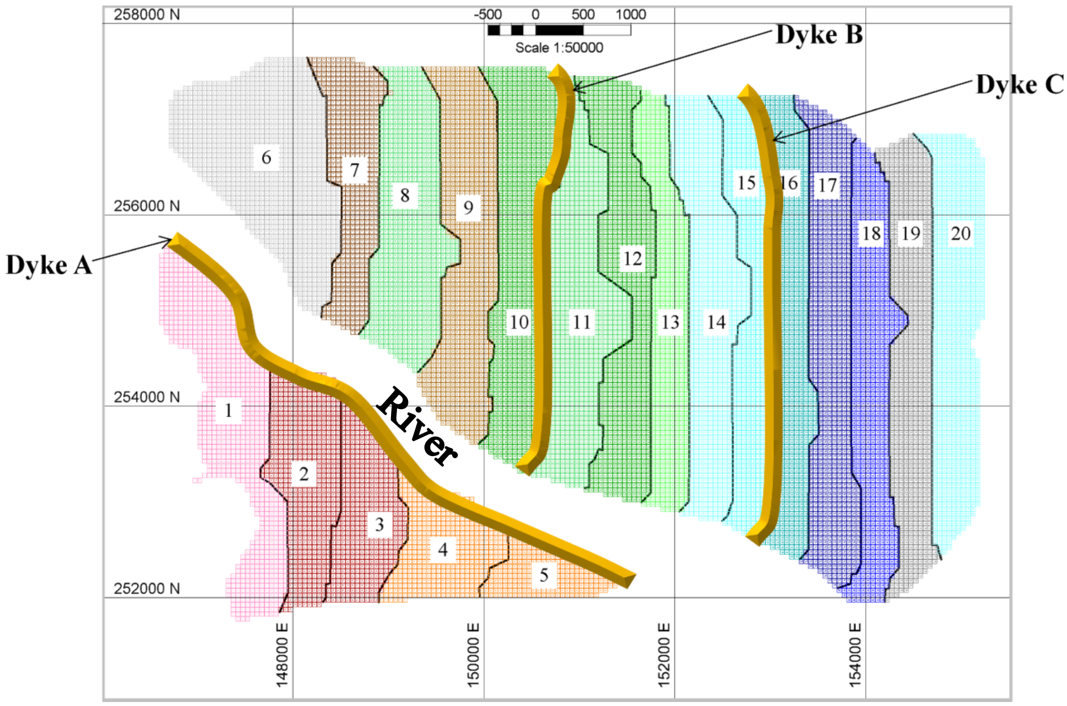

Figure 5.23: Mining-panels and in-pit dyke locations at level 305m

5.6.1 Analysis

Table 5.12 shows a summary of the tonnages scheduled during production planning for 16 periods, which corresponds to Run 2 in Table 5.13. This was chosen for analysis due to its significantly reduced solution time. After optimization, the overall NPV generated including the dyke construction cost for all pushbacks and destinations is \$26,987M and the total dyke construction cost is \$3,821M at a 4.98% EPGAP. The scenario implemented here focuses on a practically integrated OSLTPP and waste management strategy that generates value and sustainability. This includes mining in a specified direction and making completely extracted pushbacks available for in-pit dyke construction and subsequently tailings management. This reduces the environmental footprints of the external tailings facility by commissioning in-pit tailings facilities when the active pushback is completely mined. The mining-panels used for production scheduling and in-pit dyke locations at level 305m are illustrated in Figure 5.23. The mining sequence at levels 320m and 305m for all pushbacks with a west-east mining direction after production scheduling can be seen in Figure 5.24 and Figure 5.25. These figures also show the complete extraction of each pushback prior to mining the next, to support tailings management. The mining sequence shows a progressive continuous mining in the specified direction to ensure least mobility and increased utilization of loading equipment. This is very important in the case of oil sands mining where large cable shovels are used. The size of the mining-cuts and mining-panels also enables good equipment maneuverability and supports multiple material loading operations. The mining-panels enable practical mining to proceed with a reduced number of required drop-cuts.

Table 5.12: Summary of the tonnages scheduled during production planning for 16 periods

Production scheduling results	Tonnage of rock (Mt)	Ore tonnage (Mt)	OB dyke material tonnage (Mt)	IB dyke material tonnage (Mt)	TCS dyke material tonnage (Mt)
Value	7377.4	2225.8	2135.4	1927.1	1570.3

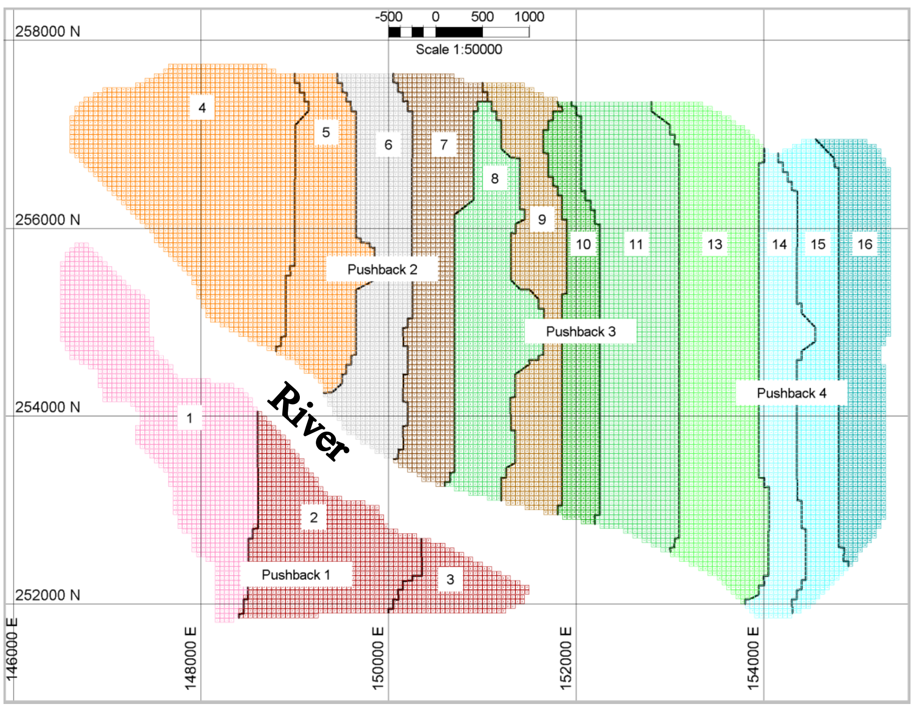

Figure 5.24: Mining sequence at level 320m for all pushbacks with a west-east mining direction

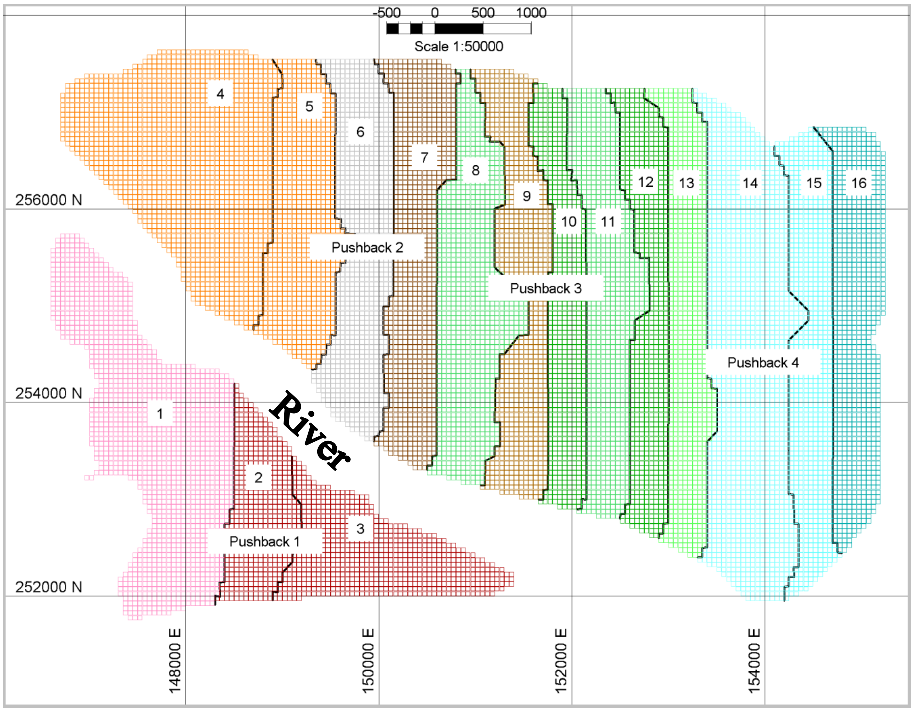

Figure 5.25: Mining sequence at level 305m for all pushbacks with a west-east mining direction

Figure 5.26 shows uniform mining and processing schedules that ensures efficient utilization of mining fleet and processing plant capacity throughout the mine life. The schedule provides the quality and quantity of dyke material needed to build the dykes of the external tailings facility and in-pit tailings cells in a timely manner and at a minimum cost. Pre-stripping of pushback 1 and 2 starts in the first and fourth years, resulting in less ore being mined. Subsequently, uniform ore feed is provided at the current processing plant capacity throughout the mine life. The dyke material mined is sent to the scheduled dyke construction destinations simultaneously. Figure 5.26 shows the total material mined, ore, OB and IB dyke material tonnage mined and TCS dyke material tonnage generated from the processing plant for all destinations. The schedules give the planner good control over dyke material and provides a robust platform for effective dyke construction planning and tailings storage management.

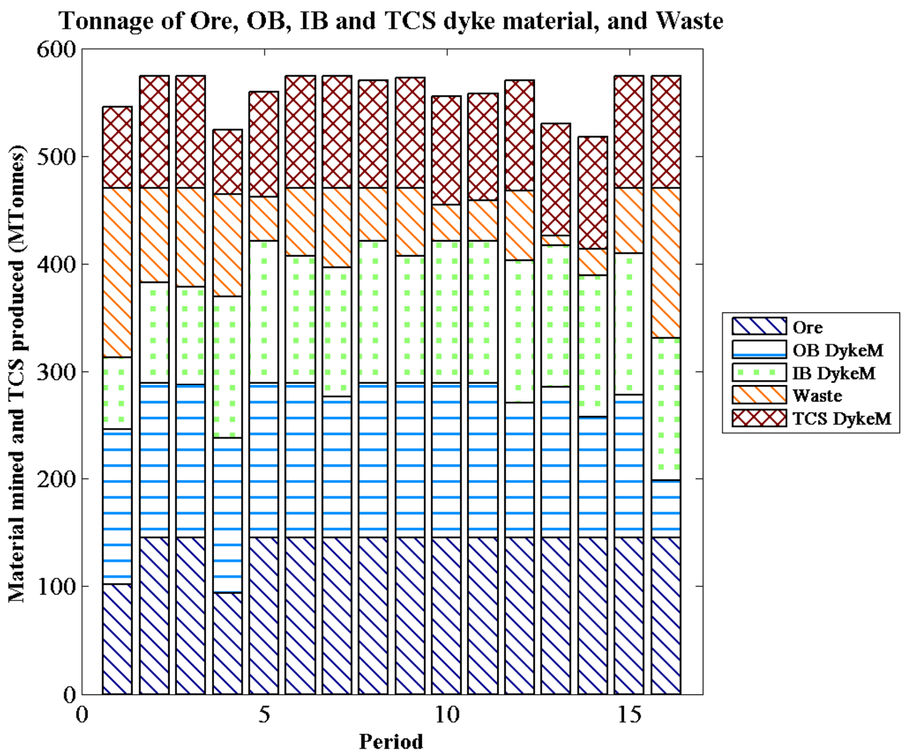

Figure 5.26: Schedules for ore, OB, IB, and TCS dyke material for all destinations, and waste

The ore and dyke material quality is obtained by blending the run-of-mine material. The targeted processing plant head grade and IB dyke material grade that was set were successfully achieved in all periods and for all destinations. We targeted to reduce the periodic grade variability by setting tighter lower and upper grade bounds. The periodic grades in each pushback can be varied depending on the processing plant or dyke construction requirements whilst ensuring a feasible solution is obtained. Figure 5.27 shows the average ore bitumen grades over the mine life. The average ore and IB dyke material fines percent for all destinations can be seen in Figure 5.28, Figure 5.29, Figure 5.30, Figure 5.31 and Figure 5.32.

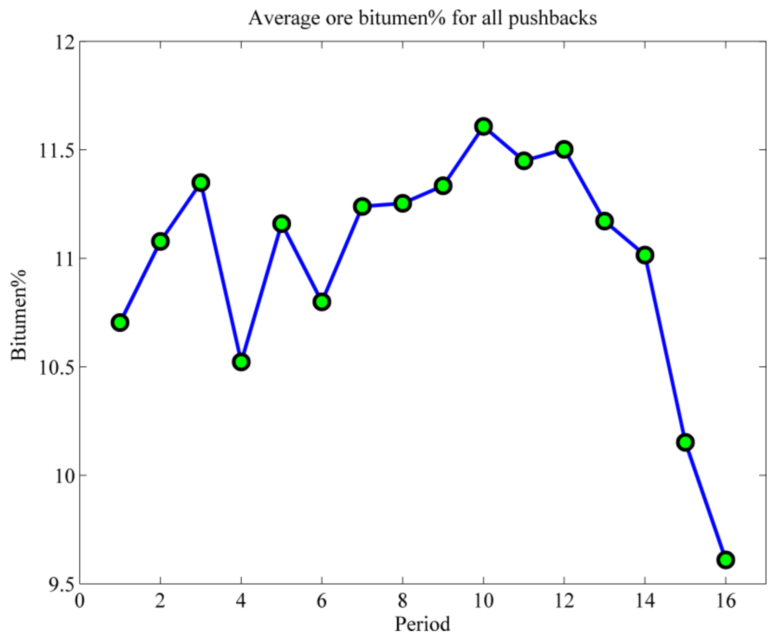

Figure 5.27: Average ore bitumen grades in all periods

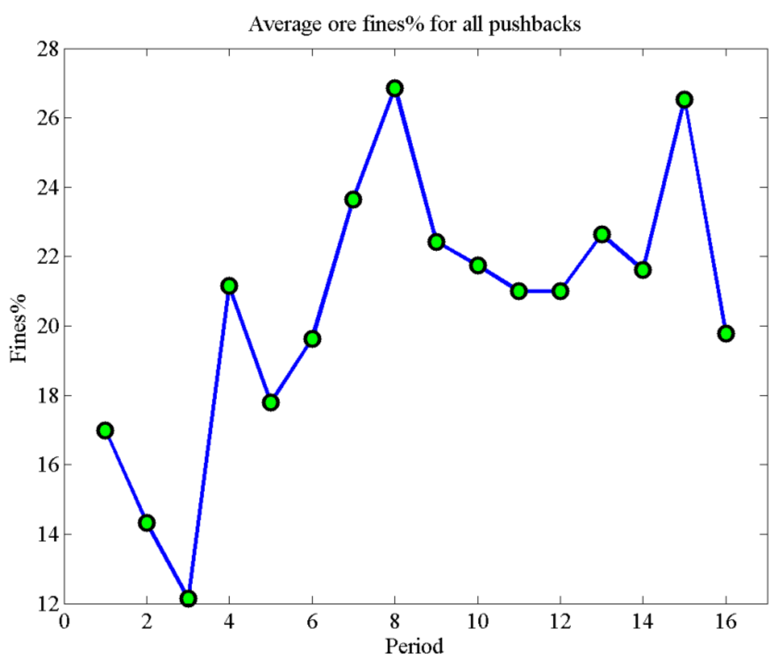

Figure 5.28: Average ore fines percent in all periods

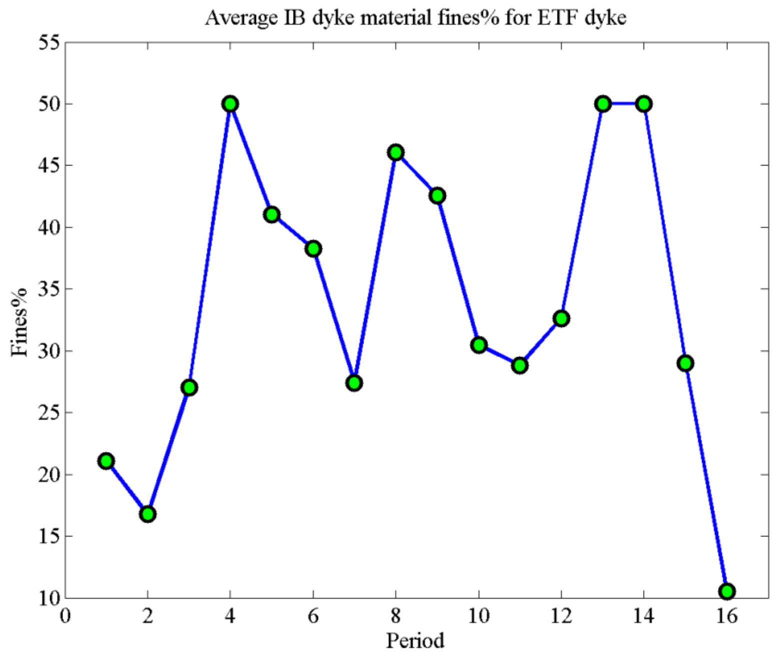

Figure 5.29: Average IB dyke material fines percent for ETF dyke in all periods

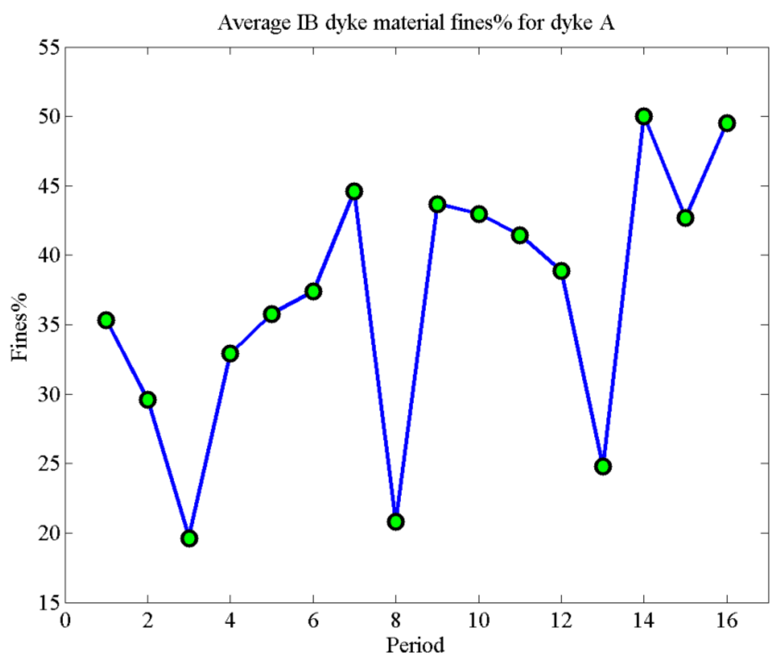

Figure 5.30: Average IB dyke material fines percent for dyke ‘A’ in all periods

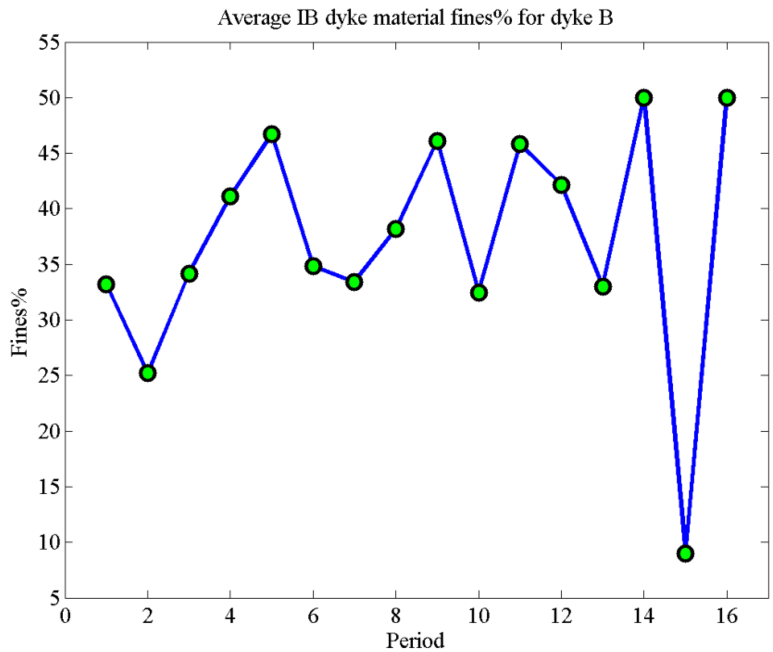

Figure 5.31: Average IB dyke material fines percent for dyke ‘B’ in all periods

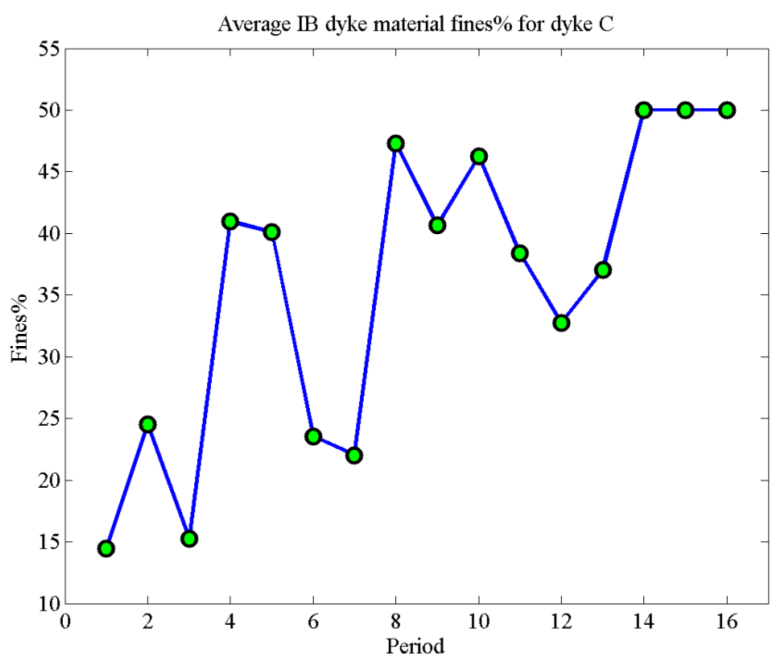

Figure 5.32: Average IB dyke material fines percent for dyke ‘C’ in all periods

5.6.2 Comparison

In implementing the efficient MILGP model with fewer non-zero decision variables, two optimization scenarios were executed to assess our model. Table 5.13 shows a summary of the results of the scenarios with different number of decision variables remaining before and after applying an initial schedule with a periodic tolerance. The results show less than 1% change in NPV and more than 99% change in solution time due to differences in solution space. Run 1 have a lower NPV due to the increase in dyke material tonnage and the associated waste material mined. This resulted in a higher tonnage mined in run 1. The results also show run 2 terminating at a branch closer to the optimal solution than run 1 as shown by the EPGAP. The ore tonnages sent to the processing plant in the two scenarios were the same. However there is a significant decrease in the CPU time as the number of decision variables are reduced using the initial schedule with a periodic tolerance. After applying a periodic tolerance of 2, the number of decision variables in run 1 reduced from 453,360 to 121,884 whilst the CPU time reduced from 243.79 to 0.84 hours which represents over 99% decrease in solution time for run 2. This technique can be used to overcome the long CPU time associated with solving mathematical models like the MILGP model thus bringing its daily use to the front due to its advantages. For a chosen application, the periodic tolerance required to be applied to an initial schedule from a heuristic could be established and used appropriately each time.

In general, it should be noted that the solution time for MILGP models do not depend only on the number of decision variables, but also on the tightness of the model which includes the data set used, the objective function and the constraints. The data used determine the coefficients in the objective function, and coefficients and bounds of the goals and constraints which have major impact on the solution time of an MILGP model.

Table 5.13: Summary of results before and after applying an initial schedule with a periodic tolerance

Run #	Periodic tol. (yrs)	Decision variables	Constraints	NPV (M$)	Tonnage mined (Mt)	Ore (Mt)	Dyke mat. (Mt)	EP-GAP (%)	CPU time (hrs)
1	-	453360	153802	26,791	7504.6	2225.8	5654.2	5.00	243.79
2	2	121884	153802	26,987	7377.4	2225.8	5632.8	4.98	0.84

5.6.3 Conclusions: Case Study 3

We have progressively developed, implemented and verified a MILGP formulation which takes into account practical shovel movements by selecting mining-panels and mining-cuts that are comparable to the selective mining units of oil sands mining operations. Different techniques have been presented for implementing an efficient MILGP model that serves as a guide for optimization of OSLTPP and waste management. The model created value and a sustainable operation by generating a practical, smooth and uniform schedule for ore and dyke material. The schedule gives the planner good control over dyke material and provides a robust platform for effective dyke construction and waste disposal planning. The schedule ensures that the major factors affecting oil sands profitability and sustainability are taken care of within an optimization framework by maximizing NPV whilst creating timely tailings storage areas.

It has been shown that using an initial schedule with a periodic tolerance results in reduced number of decision variables to be solved for in the optimization problem. This variable reduction technique reduced the CPU time by over 99% changing the long CPU times associated with solving mathematical models like the MILGP. In addition to its advantages, the reduced solution time will make the use of such mathematical models more appealing in solving mine planning problems. For a chosen mining application, the periodic tolerance required to be applied to an initial schedule from a heuristic could be established and used appropriately each time. This is useful for mining software developers that use mathematical modeling as the platform for production scheduling.

The total NPV generated including dyke construction cost for all pushbacks and destinations is $26,987M. The average bitumen grade for the scheduled ore was 11.0%. The average ore and IB dyke material fines percent ranges between 12.1 and 26.9, and 9 and 50, respectively. The total material mined was 7377.4Mt, which includes: 2225.8Mt of ore; 2135.4Mt of OB dyke material and 1927.1Mt of IB dyke material whilst 1570.3Mt of TCS dyke material was generated from the processing plant.

5.7 Case Study 4: Whittle and MILGP Long-Term Schedule

5.7.1 The Final Pit Limit Design

The final pit limit was generated using the LG algorithm (Lerchs and Grossmann, 1965) in Whittle (Gemcom Software International Inc., 2012), which is one of the industry standard software. The objective of this algorithm is to generate a pit outline that maximizes the difference between the total value of ore extracted instantaneously and the total extraction cost of ore and waste in the mine. The LG algorithm is mathematically proven to generate optimum solution using the maximum undiscounted cashflow as the criterion for optimization. The algorithm takes in the geologic and economic block models and mining parameters, and progressively creates the set of blocks that should be mined to generate the maximum total value subject to pit slope constraints.

From geotechnical and geo-mechanical analysis, an overall pit slope of 8 degrees was defined for all regions which resulted in an average slope error of 0.2 degrees in Whittle. Whittle generates a set of pit shells by economic parametric analysis using the LG algorithm. The economic and mining data used for pit limit optimization have been summarized in Table 5.14.

Table 5.14: Economic and mining parameters for pit limit optimization

Economic and mining parameter	Value
Mining cost ($/tonne)	4.6
Processing cost ($/tonne)	5.03
Selling price ($/bitumen %mass)	4.5
Mining recovery fraction	1.0
Processing recovery fraction	0.9

Using a set of fixed revenue factors to vary profitability, multiple pit outlines referred to as nested pits are produced. Whittle generated 40 nested pits with their corresponding total ore, waste and NPV. The final pit is therefore the pit outline that corresponds to a revenue factor of 1. This pit has the highest NPV. Other pit outlines corresponding to revenue factors between 0.1 and 1 with 0.02 step sizes can also be referred to as pushbacks. It should be noted that the final pit selected has a direct impact on the expected total profit from the mine project. The sequences of pit expansions must correspond to the evolution of the pit geometry over time. In maximizing NPV and facilitating sustainability in oil sands mining, the revenue factor that produces a pit sufficiently large enough to justify mining and support in-pit tailings storage should be the part of the deposit to be mined first. Likewise, other pushbacks with higher revenue factors which define the highest sustainable NPV evolution of the pit over time are identified. This should be done in consultation with tailings dam engineers to facilitate the integration of pushback selection and in-pit dyke construction. 5 nested pits or pushbacks were selected to be used in production scheduling. These pushbacks were selected in a way that supports the annual production targets and oil sands mining strategy.

The LG algorithm used in Whittle assumes that all mining activities occur simultaneously and instantaneously with no concept of time value of money applied. Time value of money concept can only be applied for any ore or waste block during production scheduling. This usually leads to the selection of a final pit that is larger than the true maximum NPV pit.

5.7.2 Whittle Production Scheduling

In terms of production scheduling, the nested pits helps in identifying which areas to mine and when. The nested pits are used in defining the feasible region for production scheduling. To define the block by block feasible production schedule, Whittle provides some methods that use the set of nested pits; namely best case, worst case and specified case. The specified case could be Milawa NPV, Milawa Balanced or Fixed Lead.

In the best case schedule, each pushback is completely mined before proceeding to the first bench in the subsequent pushback. This helps in exposing and mining ore in the early periods of the mining operation thereby maximizing the NPV. In cases where the mining-width between pushbacks is insufficient, this method of mining may not be feasible. This will require modifications of the bench width between pushbacks resulting in sub optimal production schedules. The worst case schedule on the other hand is associated with completely mining the entire bench across all pushbacks before proceeding to the second bench. This method defers the production of ore to later periods since the entire deposit is pre-stripped before

ore mining starts. Thus, the revenue from the mining operation is delayed and stripping cost placed up front, reducing the projects profitability significantly.

In the specified case schedule, the Milawa algorithm defines a variable bench lead or lag between subsequent pushbacks such that when a fixed number of benches in the initial pushback are mined, mining can start in the next pushback. This results in a vertical lag between benches in different pushbacks. This algorithm iteratively varies the lag between pushbacks and then searches for an optimal combination of lags or leads either in the sense of cashflow (Milawa NPV) or of balancing the removal of ore and waste (Milawa Balanced). Likewise, in the Fixed Lead, the user is allowed to specify the lead or lag between the pushback benches during mining which may result in sub optimal schedules.

In oil sands mining, large cable shovels are used. These shovels require a reasonable amount of mining-width to operate. There are large operating cost associated with moving these shovels during operation and therefore requires production schedules that maximizes equipment utilization and reduces operating cost. Lack of tailings storage areas also require that in-pit tailings storage areas are created as mining proceeds to support the sustainable development of the deposit. These are some reasons that require an integrated oil sands mining strategy that uses directional mining and pushbacks to deal with these operating challenges. Based on the deposit layout, initial production schedule runs were implemented with Whittle using the selected pushbacks and considering two main mining directions; west-east and east-west. The west-east mining direction generated a higher NPV and thus was used for subsequent production scheduling studies. The directional mining algorithm in Whittle uses a mining distance factor which includes a distance expression defined for different mining directions. The mining distance factor is then multiplied to the selling price of the desired element (bitumen) and used as the selling price for production scheduling. This creates a pseudo positive selling price-distance gradient that forces the production scheduling algorithm to mine in the chosen direction to the final pit. This mining direction strategy is also used during the final pit limit design to determine the pushbacks in the defined mining direction.

The Whittle long-term production schedule is generated within the final pit limit designed using the LG algorithm in section 5.7.1. The 5 pushbacks selected were strategically used in conjunction with directional mining. The production scheduling parameters which specify limits on throughputs, the regulatory cut-off grade and the discount rate have been summarized in Table 5.15.

Table 5.15: Production scheduling parameters for Whittle and MILGP

Production scheduling parameter	Value
Mining limit (Mt)	125
Processing limit (Mt)	47
Cut off grade of bitumen (wt%)	7
Discount rate (%)	10

The worst, best and specified case schedules resulted in the NPVs summarized in Table 5.16. The best, worst and Milawa NPV case schedules are illustrated in Figure 5.33, Figure 5.34 and Figure 5.35. It can be seen that there is little control over the ore production stream as the ore and waste are controlled by the geometry of the pushbacks as well as the best and worst case scenarios. The worst case schedule shows pre-stripping in the early years which results in revenue deferment. The best and Milawa NPV case schedules on the other hand show an erratic ore production which will probably be unacceptable for a processing plant and production equipment fleet. These schedules show variable stripping ratios. Thus, the schedules are not feasible to support the mining project. Milawa Balanced algorithm generated a better production schedule that is feasible. However, in the implementation of this algorithm the number of possible schedules is so large that it is not able to generate and evaluate all feasible schedules. Instead, the algorithm strategically samples from the feasible domain and progressively focuses the search until it converges on its solution. The Milawa Balanced case schedule results in a lower NPV compared with the best case schedule. This represents a compromise between feasibility and maximum NPV. The total tonnage of rock mined for the best, worst, Milawa NPV or Milawa Balanced case schedules was 1245Mt which includes 395Mt of ore. Figure 5.37 shows the Milawa Balanced case schedule. Similarly, as shown by Run 10 on

Table 5.9, the total tonnage of rock mined for the MILGP schedule was 1225Mt including 387Mt of ore (Figure 5.36).

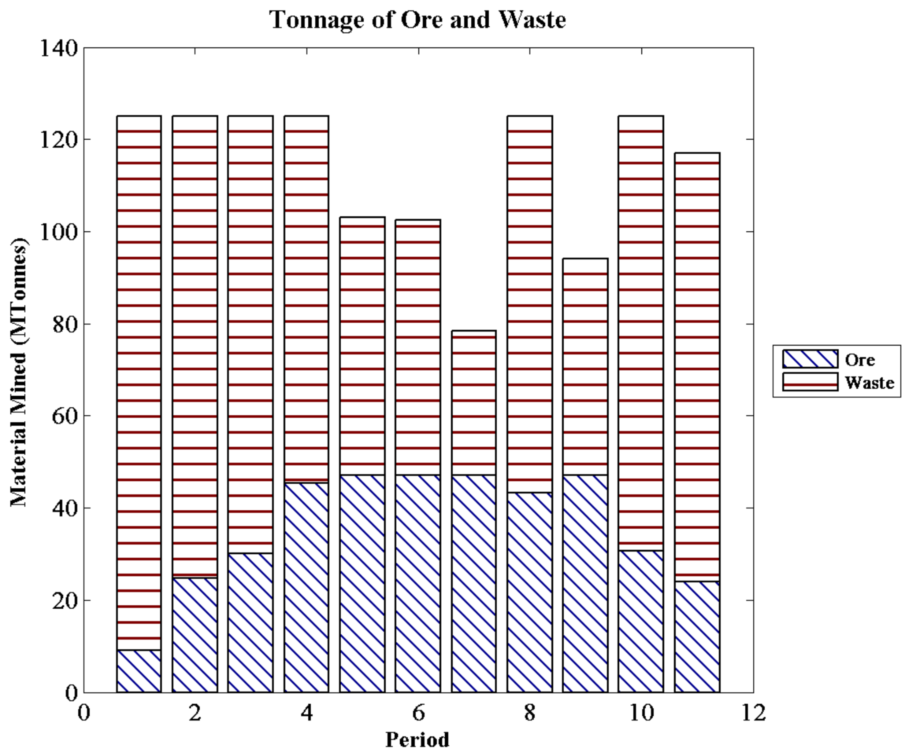

Figure 5.33: Whittle best case schedule

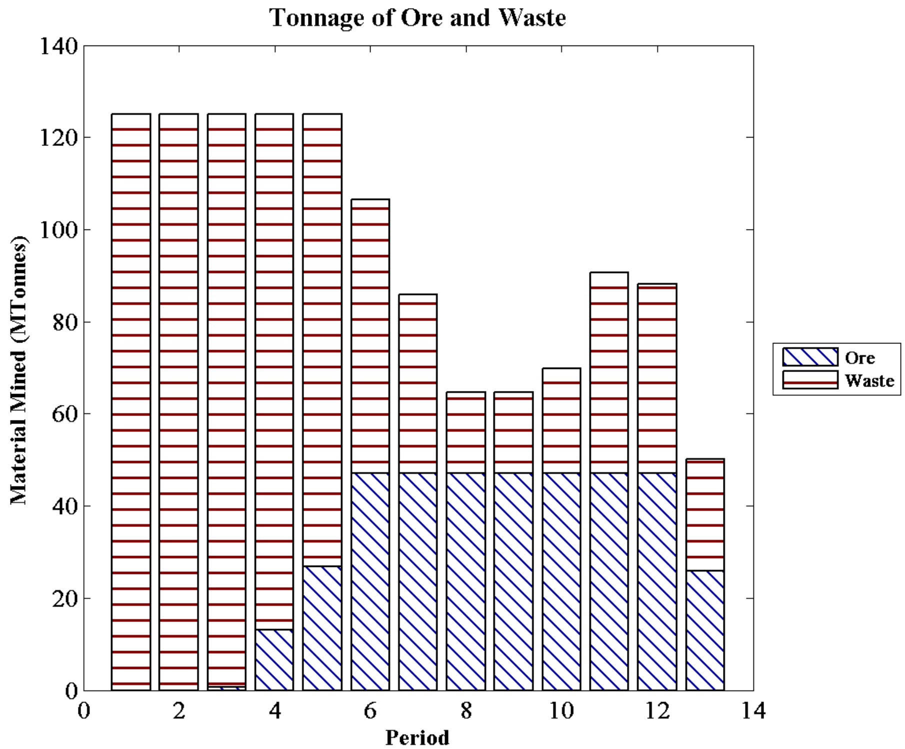

Figure 5.34: Whittle worst case schedule

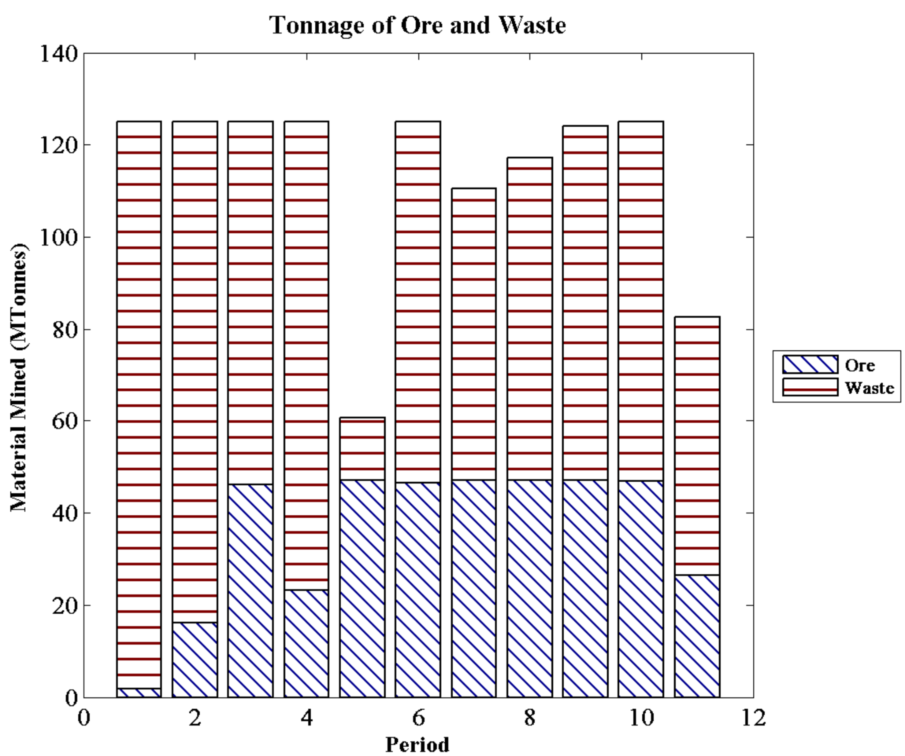

Figure 5.35: Whittle Milawa NPV schedule

5.8 Comparison of MILGP vs Whittle Schedule

An analysis to compare the production schedules from the MILGP model and Whittle Milawa Balanced algorithm was done to validate the results. The objective was to find an extraction sequence that will provide sufficient working space and a steady flow of material to the processing plant. Figure 5.36 and Figure 5.37 show the production plan from the MILGP model and Whittle Milawa Balanced algorithm.

In general, the feasible solution space for Whittle Milawa Balanced algorithm is a region between the worst and best case scenarios. The Milawa Balanced algorithm focuses on maximizing the utilization of production facilities during the mine life instead of maximizing NPV as is the case in Milawa NPV. The comparison of the production schedules shows a uniform mining capacity requirement which implies efficient production fleet utilization. However, the MILGP generated a higher NPV than Whittle Milawa Balanced. As illustrated in Figure 5.38, the MILGP demonstrated a more steady uniform flow of ore to the processing plant than Whittle Milawa Balanced. This is an important requirement for the economics of the processing plant facility.

Figure 5.39 and Figure 5.40 show the average periodic head grade for bitumen and fines percent for the MILGP model and Whittle Milawa Balanced algorithm. The MILGP model generates a consistently higher bitumen head grade than Milawa Balanced which translates to better cashflow (Figure 5.41). The results show that the MILGP model framework provides a robust tool for optimizing long term open pit mines apart from providing a platform for integrating waste management into mine planning.

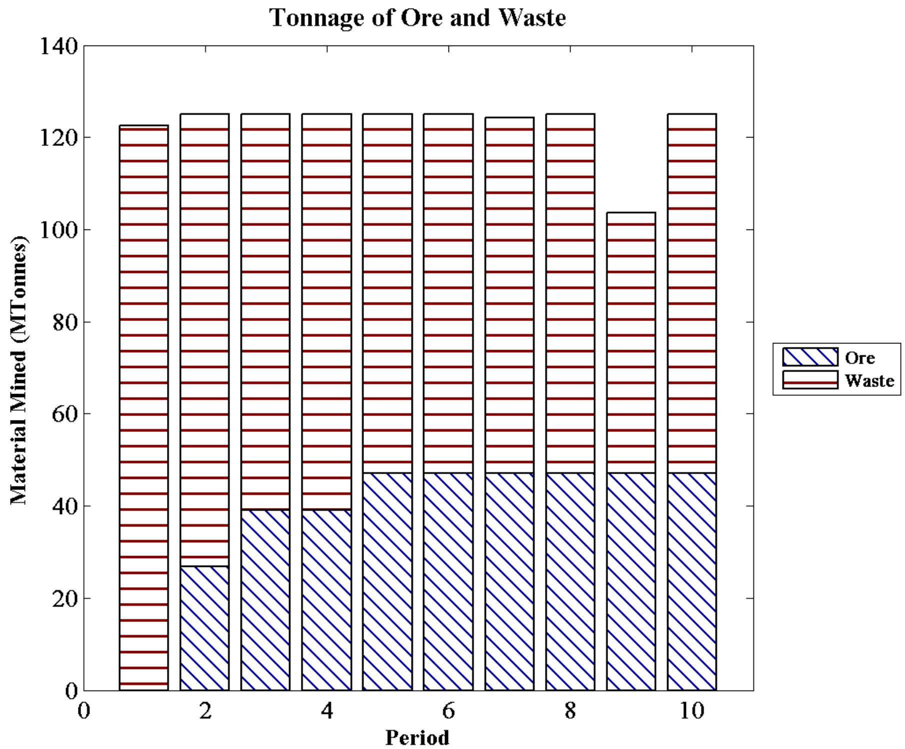

Figure 5.36: MILGP model schedule

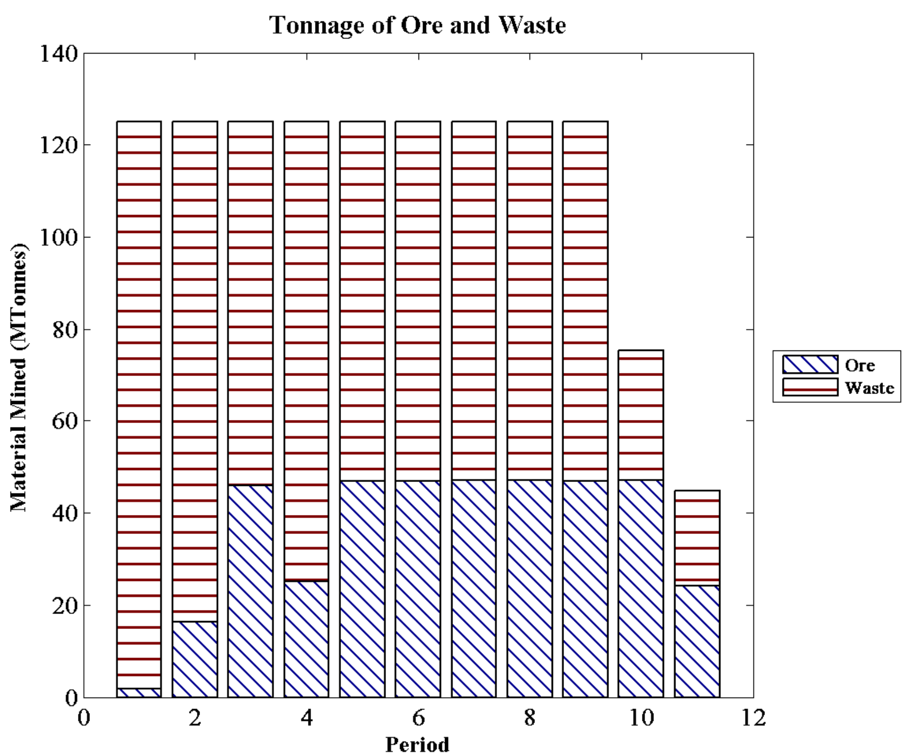

Figure 5.37: Whittle Milawa Balanced schedule

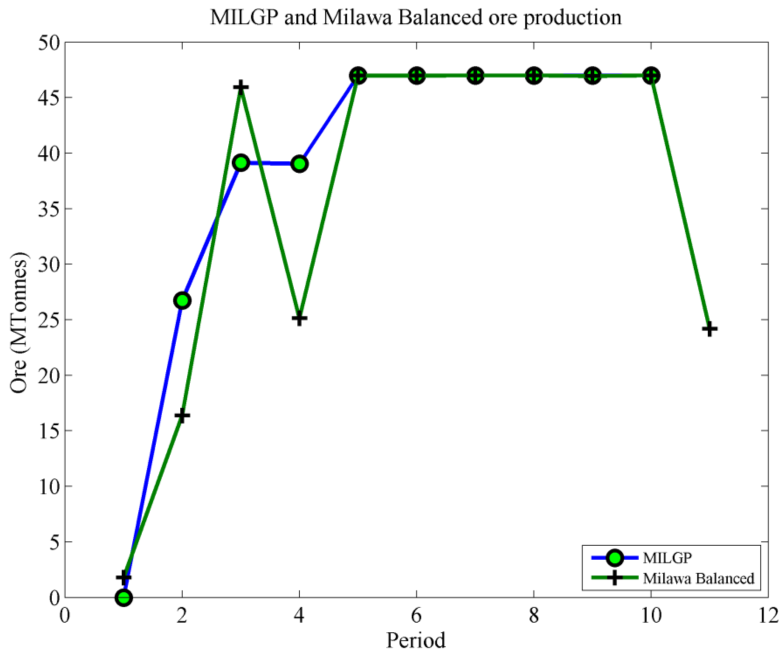

Figure 5.38: MILGP model and Whittle Milawa Balanced ore production

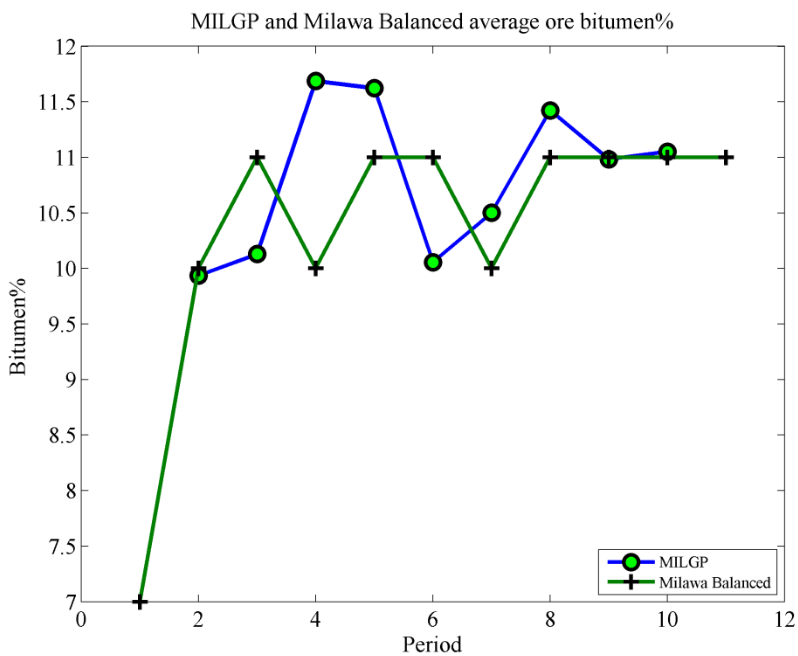

Figure 5.39: MILGP model and Whittle Milawa Balanced average ore bitumen

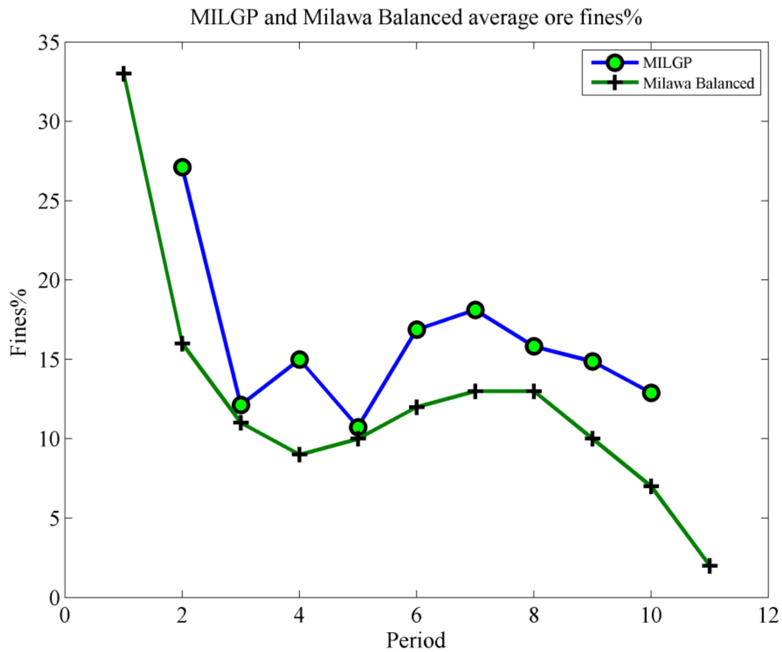

Figure 5.40: MILGP model and Whittle Milawa Balanced average ore fines

5.9 Summary and Conclusions

This chapter covers the verification of the MILGP model through a comparison with Whittle. The first three case studies highlight the techniques and strategies used in the MILGP model to integrate waste disposal planning with production scheduling in oil sands mining. The fourth case study which involves the scheduling of 16,985 blocks was implemented to verify the model. Details of the final pit have been summarized in

Table 5.6. Whittle's LG algorithm was used in generating the final pit limit design. Using a revenue factor between 0.1 and 2, 40 pit shells were generated. Pit shell 40 corresponding to revenue factor 1 was chosen as the optimized final pit limit. This pit contains a total rock of 1245Mt including 395Mt of ore.

The MILGP model framework uses a conceptual mining and dyke design model to integrate mine production scheduling, waste disposal planning and tailings management in oil sands mining. This includes the use of pushbacks and directional mining to strategically synchronize in-pit dyke construction with production scheduling for in-pit tailings storage. The model framework also deploys clustering of blocks to mining-cuts and paneling of mining-cuts to mining-panels to ensure practical mining environments and efficient mining fleet utilization. The clustering and paneling techniques together with an initial schedule and reduced pushback mining constraints are used to significantly reduce the solution runtime of the MILGP model making it a fast practical tool for mine planning.

The practical extraction sequence from the MILGP model was compared with Whittle's worst, best, Milawa NPV and Milawa Balanced case algorithms. The production schedules generated by the worst, best and Milawa NPV case algorithms were not practical. The Milawa Balanced algorithm generated a feasible production schedule which yielded an NPV of \$4818M over a 11 year mine life at an annual discount rate of 10%. The MILGP model generated an optimal practical production schedule with an NPV of \$5522M under the same discount rate and a 10 year mine life. Table 5.16 compares the NPV of the MILGP model and Whittle and their scheduled mine life. The cashflow profile illustrated in Figure 5.41 also shows a more predictable smooth cashflow projection by the MILGP model than Whittle though this was not our primary objective.

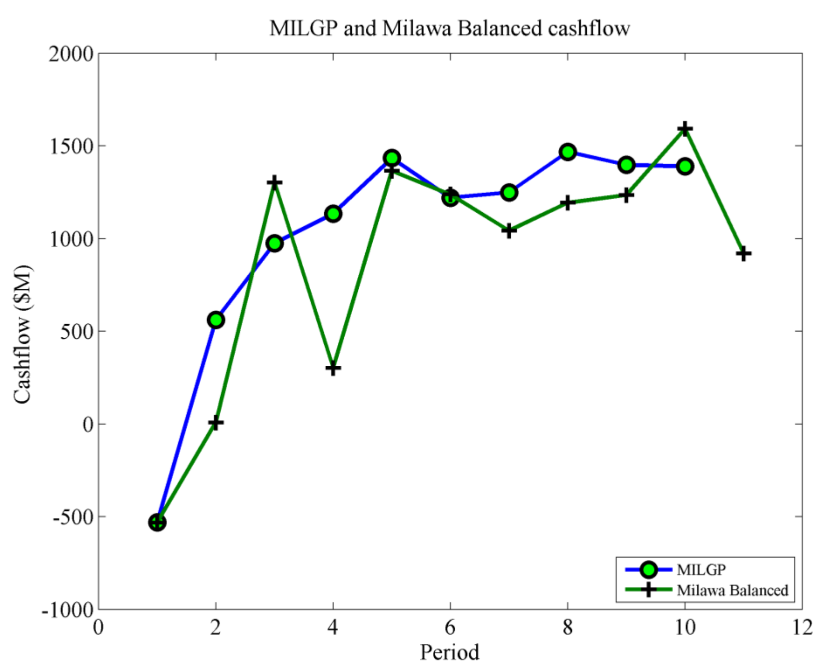

Figure 5.41: MILGP model and Whittle Milawa Balanced cashflow

Table 5.16: Comparison of NPV from production schedules generated by MILGP and Whittle

Method/Scenario	Comment	NPV ($M)	Mine life (yrs)	Optimality Gap (%)
Whittle worst case	Impractical	3338	13	Unknown
Whittle best case	Impractical	5192	11	Unknown
Whittle Milawa NPV	Impractical	4875	11	Unknown
Whittle Milawa Balanced	Feasible	4818	11	Unknown
Practical MILGP model	Feasible	5522	10	0.00

With the parametric analysis used in Whittle, optimality is not guaranteed though it presents a strong heuristic tool for locating high grade ore blocks in the deposit and for maximizing NPV. Whittle is currently one of the most used standard industry software for open pit mine planning. In comparison, the MILGP model generated a production schedule with 13% higher NPV than Whittle Milawa NPV which is not practical, and 15% higher NPV than Whittle Milawa Balanced case which is feasible. This is due to the fact that the MILGP model schedules for more ore in the early years of the mine life than Whittle Milawa Balanced. In addition, the MILGP model schedules the deposit for a shorter mine life than Whittle Milawa Balanced. The MILGP production schedule also shows more uniform ore feed to the processing plant. These results proves that the MILGP model framework provides a powerful tool for optimizing oil sands long term production plans whilst giving us a robust platform for integrating waste disposal planning.

CHAPTER 6

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.1 Summary of Research

Open pit optimization and production scheduling algorithms is continually coming to the forefront as one of the important aspects in determining the viability of mining projects, as the mining industry is faced with lower grades and marginal reserves. Many efforts have been made in recent times to address the open pit optimization and production scheduling problem. In summary, the major bottlenecks of the current planning and optimization techniques are: a) limitations in dealing with large scale problems; b) treatment of stochastic variables as deterministic processes in mining projects; c) deficiency in including the time value of money in pit limit optimization; and d) inability to integrate other systems and processes like waste disposal planning. These inadequacies can cause distortions in the mine plans resulting in sustainability, regulatory and profitability issues. Specifically, in oil sands mining it is required by regulatory instrument (Directive 074) to generate life of mine plans that ties into the waste management system.

Subsequently, a Mixed Integer Linear Goal Programming (MILGP) mine planning model framework has been developed to integrate oil sands production scheduling and waste disposal planning. The results from the research demonstrated the MILGP model framework to be a powerful tool for optimizing oil sands long term production plans whilst providing a robust platform for integrating waste disposal planning. A summary of the research methods and models developed can be seen in Figure 6.1. Matlab (Mathworks Inc., 2011) programming platform was used in capturing the MILGP model framework. The main components of the model include the objective function, goal functions and constraints. These components interact with the block model through the user input parameter definition file. The user input interface facilitates the setting up of the block model, open pit, production and waste disposal parameters. Tomlab/CPLEX (Holmström, 2009) which is a large scale optimization solver developed based on branch and cut algorithm is used for this research.

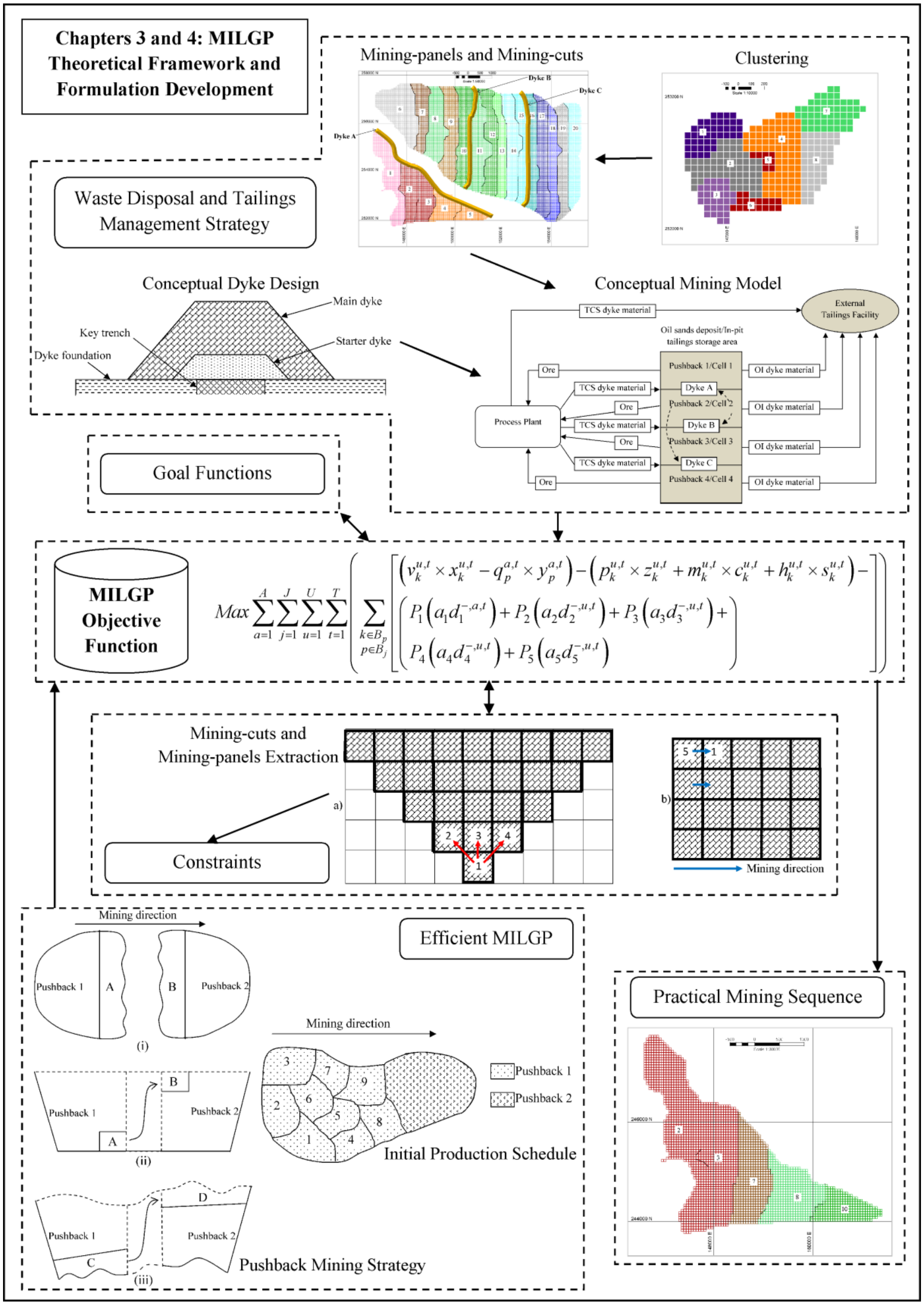

Figure 6.1: Summary of research methods and models developed

In general, the development and implementation of the MILGP optimization model framework was undertaken in three major stages. The results at each stage were published to facilitate continuous feedback from the research community and the oil sands mining industry experts to improve the model (Ben-Awuah and Askari-Nasab, 2010; Askari-Nasab and Ben-Awuah, 2011; Ben-Awuah and Askari-Nasab, 2011; Ben-Awuah et al., 2011; Ben-Awuah et al., 2012; Ben-Awuah and Askari-Nasab, 2012a; Ben-Awuah and Askari-Nasab, 2012b).

The research focuses on two main objectives: (i) maximizing the net present value of the mining operation and (ii) minimizing the waste management cost. The MILGP model framework includes the strategic implementation of pushback and directional mining which ties into the waste management scheme in oil sands mining. This strategy enables the creation of in-pit tailings facility cells in mined out areas as mining proceeds. The model generates a strategic production schedule for the processing plant and a dyke material schedule for in-pit and ex-pit tailings facilities dyke construction. The MILGP model framework was implemented for large scale oil sands mining projects taking into account practical shovel and truck movements. The model deploys the clustering of blocks into mining-cuts and paneling of mining-cuts into mining-panels to model the mining, processing and dyke construction scheduling units. An efficient MILGP model with fewer non-zero decision variables also features the use of an initial production schedule and fewer pushback mining constraints.

The MILGP model framework was verified using numerical experiments on two oil sands datasets for four case studies. The first three case studies highlight the techniques and strategies used in the MILGP model to integrate waste disposal planning with production scheduling in oil sands mining. The fourth case study which involves the scheduling of 16,985 blocks was compared with Whittle software. The LG algorithm in Whittle was used in generating the optimized final pit limits which contained a total of 1245Mt of rock including 395Mt of ore. Figure 6.2 is a schematic comparison of the MILGP model framework and Milawa Balanced algorithm to verify the research.

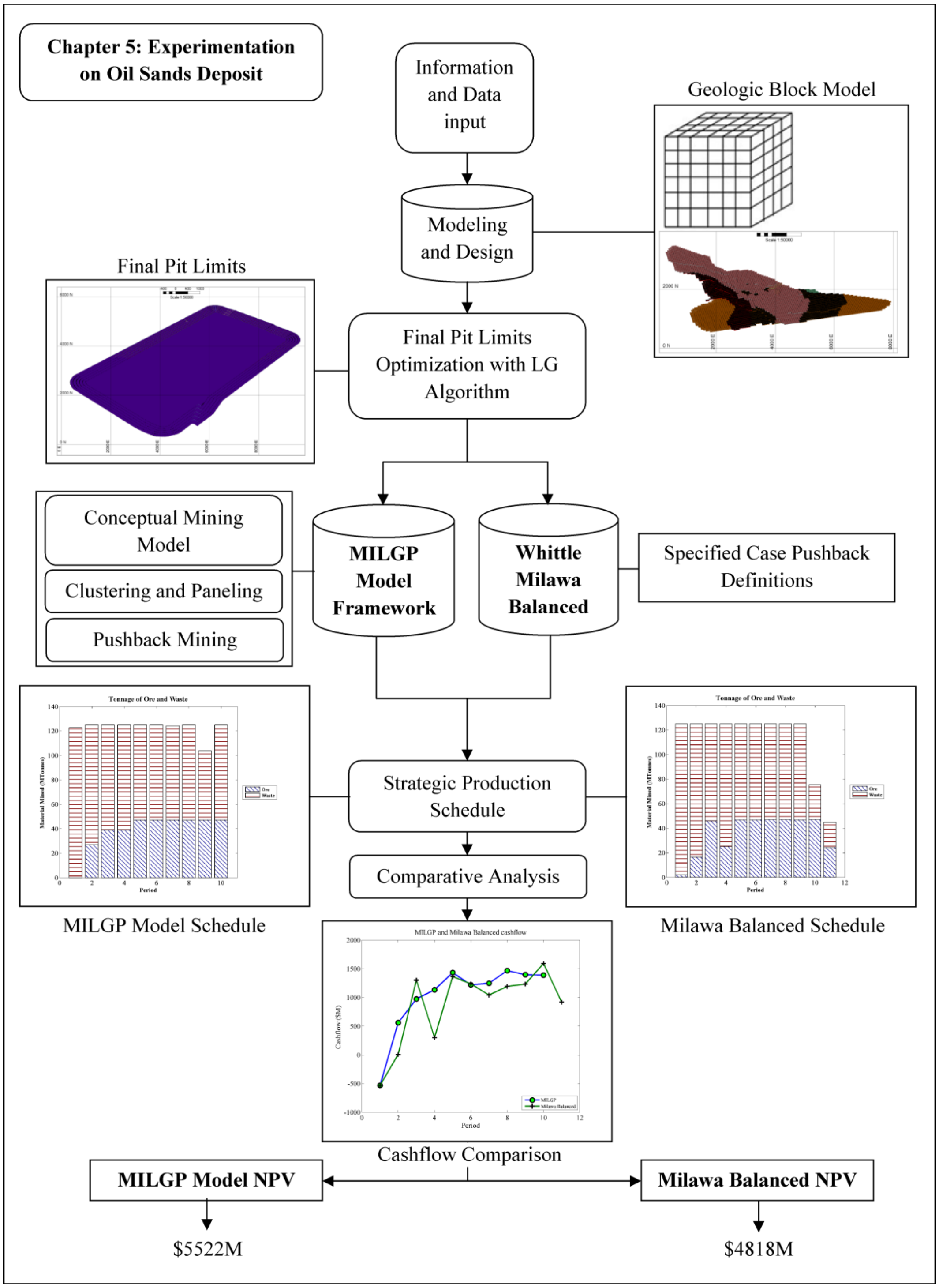

Figure 6.2: Research summary, numerical application and results

The long term mine plans generated by the MILGP model framework and Whittle Milawa Balanced algorithm were compared. The experiments were implemented at a 10% annual discount rate with the MILGP model scheduling the deposit over 10 years whilst Milawa Balanced scheduled the same deposit over 11 years. The analysis compared the annual stripping ratio, average grade, ore production and NPVs. The MILGP model generated a production schedule with 13% higher NPV than Whittle Milawa NPV which is not practical, and 15% higher NPV than the feasible Whittle Milawa Balanced case. This is due to the fact that the MILGP model schedules for more ore in the early years of the mine life than Whittle Milawa Balanced. A summary of the NPVs of Whittle worst, best, Milawa NPV and Milawa Balanced case algorithms and the MILGP model schedules are shown in Table 6.1.

Table 6.1: Summary of NPVs from numerical application

Method/Scenario	Comment	NPV ($M)
Whittle worst case	Impractical	3338
Whittle best case	Impractical	5192
Whittle Milawa NPV	Impractical	4875
Whittle Milawa Balanced	Feasible	4818
Practical MILGP model	Feasible	5522

6.2 Conclusions

In pursuing this research, the literature review conducted established the limitations in the current body of knowledge in production scheduling optimization. The literature showed that there has never been any previous attempt to integrate oil sands production scheduling and waste disposal planning in an optimization framework. The recent regulatory requirement by the Energy Resources Conservation Board (ERCB) (Directive 074) also emphasized the need to develop a systematic workflow towards promoting sustainable oil sands mining. This research therefore pioneers the effort to employ a mathematical programming model in the form of mixed integer linear goal programming to contribute to the body of knowledge and provide a novel understanding in the area of integrated mine planning optimization.

The research objectives outlined in Chapter 1 have been achieved within the research scope. The following conclusions were drawn from the implementation of the MILGP model framework for integrating oil sands production scheduling and waste management:

1. The MILGP model framework generates production and dyke material schedules for large oil sands mining projects using clustering and paneling techniques.
2. The integration of in-pit and ex-pit waste management into production scheduling by the MILGP model is implemented using strategic pushback mining.
3. The MILGP model simultaneously generates production schedules for the processing plant and dyke construction providing the platform for robust waste disposal planning leading to sustainable mining.
4. The MILGP model framework deploys mining-cuts and mining-panels to provide mining-widths for practical shovel and truck movements in oil sands mining.
5. An efficient MILGP model with fewer non-zero decision variables features the use of an initial production schedule and fewer pushback mining constraints that generates production schedules with reduced solution times.
6. The MILGP model framework provides a fast and flexible production scheduling optimization approach through the use of penalty and priority parameters, and goal deviational variables.
7. The MILGP model framework provides a systematic workflow towards promoting sustainable mining as directed by the ERCB Directive 074 regulation.

The comparative analysis of the production schedule generated by the MILGP model and Whittle concludes with the following:

1. The MILGP model framework generated a production schedule with a significantly higher NPV compared to the NPV from Whittle Milawa Balanced algorithm which is an industry standard tool.
2. The comparison of the production schedules generated by the MILGP model and Whittle Milawa Balanced showed a uniform mining capacity requirement which implies efficient production fleet utilization.

3. The MILGP model generated a schedule with shorter mine life than Milawa Balanced.
4. The MILGP schedule provided a more steady flow of ore to the processing plant than Milawa Balanced algorithm.
5. These results proved that the MILGP model framework provides a powerful tool for optimizing oil sands long term production schedules whilst giving us a robust platform for integrating waste disposal planning.

6.3 Contributions of PhD Research

This research has developed a mathematical programming model that deploys multiple material types and multiple destination optimization techniques based on Mixed Integer Linear Goal Programming for oil sands mine planning. The major contributions of this research are as follows:

1. This is a pioneering effort in developing an integrated mathematical programming model for coupling oil sands mine planning and waste management using MILGP in an optimization framework. This research contributes significantly to the body of knowledge on open pit mine planning and design and creates the platform for developing specialized mine planning software packages.
2. The research has developed robust mathematical programming models and techniques that expand the frontiers of mine planning and optimization by generating production schedules with improved net present value compared to current industry software packages.
3. The MILGP model framework enables step-changes in the planning and managing of oil sands mines. It provides a mathematical programming model framework which simultaneously schedules for the processing plant and dyke construction with the objective of maximizing NPV and minimizing dyke construction cost.
4. The MILGP model framework is a novel endeavor to use pushbacks and dyke construction to strategically integrate waste disposal planning and tailings management in an optimization framework. It also provides a

practical mining environment using mining-cuts generated from the clustering of blocks and mining-panels generated from the paneling of mining-cuts. The size of the mining-cuts and mining panels depends on the practical mining-widths and selective mining units required for the operation.

5. Unlike current mathematical programming models, the efficient MILGP model which generates fast results features a fewer non-zero decision variable vector and reduced pushback mining constraints. This sets the foundation for incorporating mathematical programming models into specialized mine planning software packages to handle global optimization problems of large mine planning projects.
6. Novel for the industry, the MILGP model framework provides a systematic workflow towards promoting sustainable mining as directed by the ERCB Directive 074 regulation.

6.4 Recommendations for Further Research

Although the production scheduling and waste disposal planning workflow and models developed in this thesis have provided pioneering efforts for oil sands mine planning and optimization, there is still the need for continued investigation into using mathematical programming models for integrated mine planning in the mineral industry. The following recommendations could improve and add to the body of knowledge in this research area.

- The MILGP model framework assumes that data from the geologic block models are deterministic values and no attribute uncertainties are considered. It is also assumed that the future cost and price data used for the economic block models are constant. This assumption means that as cost and price changes in the future, there is a need for re-optimization of the production schedules. To be able to deal with these limitations, the MILGP model framework should be extended to include stochastic variables like grade and mineral prices during optimization.

- The MILGP model framework considers production scheduling and waste disposal planning for ore and dyke material. For further research, the MILGP model can be extended to include the direct costing and scheduling of reclamation material to facilitate a cradle to grave approach of sustainable oil sands mining.
- The MILGP model framework can also be extended by investigating the penalty and priority parameters and the initial schedule periodic tolerance parameter to optimize them for some selected standard cases.
- To push forward the frontiers of mining, further research into extending the MILGP model framework to optimize the size of the in-pit and ex-pit tailings impoundments should be carried out.

BIBLIOGRAPHY

[1] Akaike, A. and Dagdelen, K. (1999). *A strategic production scheduling method for an open pit mine*. in Proceedings of 28th International Symposium on the Application of Computers and Operations Research in the Mineral Industry, Colorado School of Mines, Littleton, pp. 729-738.

[2] ArcGIS (2010). How inverse distance weighted interpolation works. ArcGIS Resource Center, Retrieved July 19, 2010 from: http://help.arcgis.com/en/arcgisdesktop/10.0/help/index.html#//00310000002m000000.htm

[3] Asa, E. (2002). An intelligent 3-D open pit design and optimization using machine learning: adaptive logic networks and neuro-genetic algorithms. PhD Thesis, University of Alberta, Edmonton, Pages 267.

[4] Askari-Nasab, H. (2006). Intelligent 3D interactive open pit mine planning and optimization. PhD Thesis, University of Alberta, Edmonton, Pages 167.

[5] Askari-Nasab, H. and Awuah-Offei, K. (2009). Mixed integer linear programming formulations for open pit production scheduling. University of Alberta, Mining Optimization Laboratory Report One, Edmonton, pp. 1-31.

[6] Askari-Nasab, H. and Awuah-Offei, K. (2009). Open pit optimization using discounted economic block values. *Transactions of the Institution of Mining and Metallurgy, Section A*, *118* (1), 1-12.

[7] Askari-Nasab, H., Awuah-Offei, K., and Eivazy, H. (2010). Large-scale open pit production scheduling using mixed integer linear programming. *International Journal of Mining and Mineral Engineering*, *2* (3), 185-214.

[8] Askari-Nasab, H. and Ben-Awuah, E. (2011). *Integration of oil sands mine planning and waste management using goal programming*. in Proceedings of 35th International Symposium on the Application of Computers and Operations Research in the Mineral Industry, AusIMM, Wollongong, pp. 329-350.

[9] Askari-Nasab, H., Pourrahimian, Y., Ben-Awuah, E., and Kalantari, S. (2011). Mixed integer linear programming formulations for open pit production scheduling. *Journal of Mining Science*, *47* (3), 338-359.

[10] Azam, S. and Scott, J. D. (2005). Revisiting the ternary diagram for tailings characterization and management. Geotechnical News, The Oil Sands Tailings Research Facility, Edmonton, pp. 43-46.

[11] Ben-Awuah, E. and Akayuli, C. F. A. (2008). Analysis of embankment stability of the water storage facility at Awaso mine. MSc Thesis, University of Mines and Technology, Tarkwa, Pages 86.

[12] Ben-Awuah, E. and Askari-Nasab, H. (2010). *Oil sands mine planning and waste management using goal programming*. in Proceedings of Second International Oil Sands Tailings Conference, University of Alberta, Edmonton, pp. 149-162.

[13] Ben-Awuah, E. and Askari-Nasab, H. (2011). Oil sands mine planning and waste management using mixed integer goal programming. *International Journal of Mining, Reclamation and Environment*, *25* (3), 226-247.

[14] Ben-Awuah, E. and Askari-Nasab, H. (2012a). *A mathematical programming model for oil sands production scheduling and waste management*. in Proceedings of Tailings and Mine Waste Conference, Keystone.

[15] Ben-Awuah, E. and Askari-Nasab, H. (2012b). Incorporating waste management into oil sands long term production planning. *Transactions of the Institution of Mining and Metallurgy, Section A*, *Under Review, Submitted August 24, 2012.*

[16] Ben-Awuah, E., Askari-Nasab, H., and Awuah-Offei, K. (2011). *Waste disposal planning for oil sands mining using goal programming*. in Proceedings of Innovations in Mining Engineering Conference, Missouri S&T, Havener Center.

[17] Ben-Awuah, E., Askari-Nasab, H., and Awuah-Offei, K. (2012). Production scheduling and waste disposal planning for oil sands mining using goal programming. *Journal of Environmental Informatics*, *20* (1), 20-33.

[18] Bixby, R. E. (2009). ILOG CPLEX. Ver. 11.0, Sunnyvale, CA, USA.

[19] Boland, N., Dumitrescu, I., Froyland, G., and Gleixner, A. M. (2009). LP-based disaggregation approaches to solving the open pit mining production scheduling problem with block processing selectivity. *Computers and Operations Research*, *36* (4), 1064-1089.

[20] Boratynec, D. J. (2003). Fundamentals of rapid dewatering of composite tailings. MSc Thesis, University of Alberta, Edmonton, Pages 267.

[21] Caccetta, L. and Giannini, L. M. (1990). *Application of operations research techniques in open pit mining*. in Proceedings of Asian-Pacific Operations Research: APORS'88, Elsevier Science Publishers, Byong-Hun Ahn, pp. 707-724.

[22] Caccetta, L. and Hill, S. P. (2003). An application of branch and cut to open pit mine scheduling. *Journal of Global Optimization*, *27* (2-3), 349-365.

[23] Chanda, E. K. C. and Dagdelen, K. (1995). Optimal blending of mine production using goal programming and interactive graphics systems. *International Journal of Mining, Reclamation and Environment*, *9* (4), 203-208.

[24] Chen, V. Y. X. (1994). A 0-1 goal programming model for scheduling multiple maintenance projects at a copper mine. *European Journal of Operational Research*, *76* (1), 176-191.

[25] Dagdelen, K. (1985). Optimum multi-period open pit mine production scheduling by Lagrangian parameterization. PhD Thesis, University of Colorado, Colorado, Pages 325.

[26] Dagdelen, K. and Johnson, T. B. (1986). *Optimum open pit mine production scheduling by Lagrangian parameterization*. in Proceedings of 19th International Symposium on the Application of Computers and Operations Research in the Mineral Industry, SME, pp. 127-142.

[27] Datamine Corporate Limited (2008). NPV Scheduler. Ver. 4, Beckenham, UK.

[28] Denby, B. and Schofield, D. (1995). Inclusion of risk assessment in open pit design and planning. *Institution of Mining and Metallurgy*, *104* (A), 67-71.

[29] Devenny, D. W. (2009). Overview of oil sands tailings. Alberta Energy Research Institute, Calgary, pp. 76.

[30] Dilay, J. D. (2001). Interim Directive ID 2001-7. Alberta Energy and Utilities Board, Calgary, pp. 9.

[31] Dusseault, M. B. (1977). The geotechnical characteristics of the Athabasca oil sands. PhD Thesis, University of Alberta, Edmonton, Pages 500.

[32] Esfandiri, B., Aryanezhad, M. B., and Abrishamifar, S. A. (2004). Open pit optimization including mineral dressing criteria using 0-1 non-linear goal programming. *Transactions of the Institutions of Mining and Metallurgy: Section A*, *113* (1), 3-16.

[33] Fauquier, R., Eaton, T., Bowie, L., Treacy, D., and Horton, J. (2009). In-pit dyke construction planning. Shell Upstream Americas, Ft. McMurray, pp. 15.

[34] Feng, L., Qiu, M.-H., Wang, Y.-X., Xiang, Q.-L., Yang, Y.-F., and Liu, K. (2010). A fast divisive clustering algorithm using an improved discrete particle swarm optimizer. *Pattern Recognition Letters*, *31* (11), 1216–1225.

[35] Ferland, J. A., Berrada, I., Nabli, I., Ahiod, B., Michelon, P., Gascon, V., and Gagne, E. (2001). Generalized assignment type goal programming problem: Application to nurse scheduling. *Journal of Heuristics*, *7* (4), 391-413.

[36] Fort Hills Energy Corporation (2009). Annual tailings managment plan. Suncor Energy, Calgary, pp. 124.

[37] Gemcom Software International (2012). Gemcom GEMS. Ver. 6.3, Vancouver.

[38] Gemcom Software International (2012). Whittle strategic mine planning software. Ver. 4.4, Vancouver.

[39] Gershon, M. E. (1983). Optimal mine production scheduling: evaluation of large scale mathematical programming approaches. *International Journal of Mining Engineering*, *1* (4), 315-329.

[40] Hannan, E. L. (1985). An assessment of some criticisms of goal programming. *Computers and Operations Research*, *12* (6), 525-541.

[41] Hein, F. J., Cotterill, D. K., and Berhane, H. (2000). An Atlas of Lithofacies of the McMurray Formation, Athabasca Oil Sands Deposit, Northeastern Alberta: Surface and Subsurface. Alberta Geological Survey, Edmonton, Alberta, pp. 217.

[42] Hochbaum, D. S. and Chen, A. (2000). Performance analysis and best implementations of old and new algorithms for the open-pit mining problem. *Operations Research*, *48* (6), 894-914.

[43] Holmström, K. (2009). TOMLAB /CPLEX (Version 11.2). Tomlab Optimization, Pullman, WA, USA.

[44] Horst, R. and Hoang, T. (1996). *Global optimization: deterministic approaches.* Springer, New York, 3rd ed, Pages 727.

[45] Hustrulid, W. A. and Kuchta, M. (2006). *Open pit mine planning and design.* Taylor and Francis/Balkema, 2nd ed, Pages 735.

[46] Jääskeläinen, V. (1969). A goal programming model of aggregate production planning. *Swedish Journal of Economics*, *71* (1), 14-29.

[47] JackpineMine (2009). Tailings managment plan. Shell Canada Limited, Calgary, pp. 102.

[48] Johnson, S. (1967). Hierarchical clustering schemes. *Psychometrika*, *32* (3), 241–254.

[49] Johnson, T. B. (1969). *Optimum open-pit mine production scheduling*. in Proceedings of 8th International Symposium on the Application of Computers and Operations Research in the Mineral Industry, Salt Lake City, Utah, pp. 539-562.

[50] Kalantari, S. (2011). Linkage of annual oil sands mine plan to composite tailings plan. MSc Thesis, University of Alberta, Edmonton, Pages 98.

[51] Kaufman, L. and Rousseeuw (1990). *Finding groups in data: an introduction to cluster analysis.* J. Wiley, New York, Pages 342.

[52] Kearl Oil Sands Project (2009). Annual tailings plan submission. Imperial Oil Resources, Calgary, pp. 31.

[53] Khalokakaie, R., Dowd, P. A., and Fowell, R. J. (2000a). Incorporation of slope design into optimal pit design algorithms. *Transactions of the Institution of Mining and Metallurgy, Section A*, *109* (2), 70-76.

[54] Khalokakaie, R., Dowd, P. A., and Fowell, R. J. (2000b). The Lerchs-Grossmann algorithm with variable slope angles. *Transactions of the Institute of Mining and Metallurgy*, *109* A77-A85.

[55] Khalokakaie, R., Dowd, P. A., and Fowell, R. J. (2000c). A windows program for optimal open pit design with variable slope angles. *International Journal for Surface Mining, Reclamation and Environment*, *14* (4), 261-276.

[56] Laurich, R. (1990). *Planning and design of surface mines.* Port City Press, Baltimore, 2nd ed, Pages 1206.

[57] Lee, J., Kang, S., Rosenberger, J., and Kim, S. B. (2010). A hybrid approach of goal programming for weapons systems selection. *Computers and Industrial Engineering*, *58* (3), 521-527.

[58] Lerchs, H. and Grossmann, I. F. (1965). Optimum design of open-pit mines. *Transactions of the Canadian Mining and Metallurgical Bulletin*, *68* 17-24.

[59] Leung, S. C. H., Wu, Y., and Lai, K. K. (2003). Multi-site aggregate production planning with multiple objectives: a goal programming approach. *Production Planning and Control*, *14* (5), 425-436.

[60] Liang, F. and Lawrence, S. (2007). A goal programming approach to the team formation problem. Leeds School of Business, University of Colorado, pp. 8.

[61] Maptek Software Pty Ltd (2012). Maptek Vulcan Chronos. Ver. 8.0, Sydney, Australia.

[62] Masliyah, J. (2010). *Fundamentals of oilsands extraction.* University of Alberta, Edmonton, Pages C1-2.

[63] Mathworks Inc. (2011). MATLAB Software. Ver. 7.13 (R2011b).

[64] McFadyen, D. (2008). Directive 074. Energy Resources Conservation Board, Calgary, pp. 14.

[65] Morgan, G. (2001). An energy renaissance in oil sands development. *World Energy*, (4), 46-53.

[66] Mukherjee, K. and Bera, A. (1995). Application of goal programming in project selection decision: a case study from the Indian coal mining industry. *European Journal of Operational Research*, *82* (1), 18-25.

[67] Muskeg River Mine (2009). Tailings management plan. Shell Canada Limited, Calgary, pp. 103.

[68] Newman, A. M., Rubio, E., Caro, R., Weintraub, A., and Eurek, K. (2010). A review of operations research in mine planning. *Interfaces*, *40* (3), 222-245.

[69] Nja, M. E. and Udofia, G. A. (2009). Formulation of the mixed-integer goal programming model for flour producing companies. *Asian Journal of Mathematics and Statistics*, *2* (3), 55-64.

[70] Oraee, K. and Asi, B. (2004). *Fuzzy model for truck allocation in surface mines*. in Proceedings of 13th International Symposium on Mine Planning and

Equipment Selection, Routledge Taylor and Francis Group, Wroclaw, pp. 585-593.

[71] Pana, M. T. and Davey, R. K. (1965). *The simulation approach to open pit design*. in Proceedings of 5th International Symposium on the Application of Computers and Operations Research in the Mineral Industry, University of Arizona, Arizona, pp. zz1-1124.

[72] Picard, J. C. (1976). Maximum closure of a graph and applications to combinatorial problems. *Management Science*, *22* 1268-1272.

[73] Ramazan, S. (2001). Open pit mine scheduling based on fundamental tree algorithm. PhD Thesis, Colorado School of Mines, Colorado, Pages 164.

[74] Ramazan, S. (2007). *Large-scale production scheduling with the fundamental tree algorithm: Model, case study and comparisons*. in Proceedings of Orebody Modelling and Strategic Mine Planning, AusIMM, Perth, pp. 121-127.

[75] Ramazan, S., Dagdelen, K., and Johnson, T. B. (2005). Fundamental tree algorithm in optimising production scheduling for open pit mine design. *Transactions of the Institutions of Mining and Metallurgy: Section A*, *114* (1), 45-54.

[76] Ramazan, S. and Dimitrakopoulos, R. (2004a). *Recent applications of operations research and efficient MIP formulations in open pit mining*. in Proceedings of SME Annual Meeting, SME, Cincinnati, Ohio, pp. 73-78.

[77] Runge Limited (2009). XPAC Autoscheduler. Ver. 7.8.

[78] Sego, D. C. (2010). Mine waste management. Course notes, University of Alberta, Geotechnical Center, Edmonton, pp. 83.

[79] Selen, W. J. and Hott, D. D. (1986). A mixed-integer goal-programming formulation of the standard flow-shop scheduling problem. *Journal of the Operational Research Society*, *37* (12), 1121-1128.

[80] Suncor Energy Incorporated Oil Sands (2009). Annual tailings managment plan. Suncor Energy, Calgary, pp. 93.

[81] Syncrude Aurora North (2009). Annual tailings plan submission. Syncrude Canada Limited, Fort McMurray, pp. 45.

[82] Syncrude Aurora South (2009). Annual tailings plan submission. Syncrude Canada Limited, Fort McMurray, pp. 24.

[83] Syncrude Mildred Lake (2009). Annual tailings plan submission. Syncrude Canada Limited, Fort McMurray, pp. 45.

[84] Tabesh, M. and Askari-Nasab, H. (2011). Two stage clustering algorithm for block aggregation in open pit mines. *Transactions of the Institution of Mining and Metallurgy, Section A*, *120* (3), 158-169.

[85] Underwood, R. and Tolwinski, B. (1998). A mathematical programming viewpoint for solving the ultimate pit problem. *European Journal of Operational Research*, *107* (1), 96-107.

[86] Vick, S. G. (1983). *Planning, design, and analysis of tailings dams.* John Wiley and Sons, New York, Pages 369.

[87] Whittle, J. (1988). *Beyond optimization in open pit mining*. in Proceedings of First Canadian Conference on Computer Applications in Mineral Industry, pp. 331-337.

[88] Whittle, J. (1989). The facts and fallacies of open pit design. Whittle Programming Pty Ltd, North Balwyn, Victoria, Australia.

[89] Wik, S., Sparks, B. D., Ng, S., Tu, Y., Li, Z., Chung, K. H., and Kotlyar, L. S. (2008). Effect of bitumen composition and process water chemistry on model oilsands separation using a warm slurry extraction process simulation. *Fuel*, *87* (7), 1413-1421.

[90] Wolsey, L. A. (1998). *Integer programming.* J. Wiley, New York, Pages 264.

[91] Zeleny, M. (1980). Multiple objectives in mathematical programming: Letting the man in. *Computers and Operations Research*, *7* (1-2), 1-4.

[92] Zhang, Y. D., Cheng, Y. P., and Su, J. (1993). Application of goal programming in open pit planning. *International Journal of Mining, Reclamation and Environment*, *7* (1), 41-45.

[93] Zhao, Y. and Kim, Y. C. (1992). *A new optimum pit limit design algorithm*. in Proceedings of 23rd International Symposium on the Application of Computers and Operations Research in the Mineral Industry, SME, Littleton, pp. 423-434.